Short Term Load Forecasting in Interconnected Greek Power System using ANN: Confidence Interval Estimation using a Novel Re-sampling Technique with Corrective Factor

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Abstract: - The modern methods for power system load prediction are usually based on Artificial Neural Networks (ANN), which present satisfactory results. However, the estimation of the confidence intervals can not be applied directly, unlike to the classical forecasting methods. One of the most commonly used methods is the re-sampling technique, which calculates the respective confidence interval based on the training data set. The limits of the training set confidence interval are also applied in the case of the real prediction giving satisfactory but slightly underestimated results. The targets of this paper are: (1) to apply the basic re-sampling method for the short term forecasting of the next day load in the interconnected Greek power system using an optimized ANN proving the aforementioned disadvantage and (2) to propose a modified re-sampling technique using a proper corrective multiplication factor. Finally, the next day load demand of the test set is estimated using the best ANN structure and the modified confidence intervals.

Key-Words: - artificial neural networks, confidence interval, re-sampling technique, short-term load forecasting

1 Introduction

In a liberalized electric energy market, the load demand has to be predicted with the highest possible precision in different time periods: very short-term (for the next few minutes), short-term (for the next few hours to a week), midterm (for the next few weeks to few months) and long-term (for the next few months to years). Especially, short-term load forecasting is very crucial problem, because its accuracy affects other operational issues of power systems, such as unit commitment, scheduling of spinning reserve, available transfer capability, system stability, application of load demand management programs, etc succeeding higher reliability and lower operational costs for power systems. During last decade several forecasting methods have been implemented with different levels of success, such as ARMAX models [1], regression [2], ANNs [3], fuzzy logic [4], hybrid systems [5-6] etc. Specifically, in Greece, ANNs have been used successfully either for the interconnected power system [7-11], or autonomous big islands [9, 12-13]. Some techniques belong to classical ANNs [7-12] or specialized ones [13] or they are based on ANNs combined with fuzzy logic algorithms [14].

All forecasting models lead to a prediction value which is rarely equal to the real one. The variance between the prediction and the real value should be quantified in advance. In regression and other classical statistical models this is expressed by the confidence interval based on analytical calculations. In case of ANNs, the three commonly used methods are: (a) the error output, (b) the re-sampling, (c) the multi-linear regression adapted to ANN [15]. In [11] and [15] the theoretical and practical superiority of the re-sampling technique has been proved. In [16] a new adaptive confidence interval method based on the re-sampling technique has been proposed presenting a full version of the respective statistical background and giving satisfactory results. For fuzzy logic based methods the standard deviation has been calculated analytically working out at the same time the respective problem [17].

In this paper a novel confidence interval estimation method based on the re-sampling technique is presented. Specifically, the ANN short-term load forecasting method of the next day in interconnected Greek power system is presented briefly using the scaled conjugate gradient training algorithm which is properly optimized based on the evaluation data set [9]. Afterwards, the theoretical determination of the confidence intervals using the re-sampling technique is analyzed and it is applied proving that the confidence intervals between the training, evaluation and test sets differ for the same probability in tail. In order to correct this mismatch, the corrective multiplication factor is introduced and three different practical estimation methods are presented: (a) the mean value of the hourly ratios of the limit of the test set and the limit of the evaluation set of the previous year, (b) the maximum value of all hourly ratios of the limit of the test set and the limit of the evaluation set of the previous year, (c) the hourly ratio of the limit of the test set and the limit of the evaluation set of the previous year. Finally, the proposed method is applied for actual hour load data of the Greek intercontinental power system and the practical superiority of the last estimation method is proved.

2 ANN Methodology for Short-term Load Forecasting

The short-term load forecasting is achieved by applying an ANN methodology through the proper selection of the parameters of the scaled conjugate gradient algorithm. This methodology includes the following basic steps and its flow chart is shown in Figure 1.

(a) *Data selection*: In this step the input variables for load forecasting of the *d*-th day are formed according to Kiartzis et al [7-8], Tsekouras et al [9-10] including:

(1) the hourly actual loads of the two previous days,

(2) the maximum mean temperature per three hours and the minimum mean temperature per three hours for Athens and for Thessalonica, for the current and the previous day,

(3) the temperature difference between the maximum mean temperature per three hours of the current day and the respective one of the last day for Athens and Thessalonica,

(4) the temperature dispersion from comfortable living conditions temperature for Athens and for Thessalonica, for the current and the previous day,

(5) seven-digit binary numbers, which express the kind of the week day,

(6) two sinusoidal functions $\cos(2\pi d/T)$ and $\sin(2\pi d/T)$), which express the seasonal behavior of the current day, where T is the number of the days of the current year. So, each input vector comprises 71 elements, while the output variables are the 24 hourly actual load demand of the current day.

(b) *Data preprocessing*: Data are examined, in order to modify or delete the values that are obviously wrong (noise suppression). Due to the great non linearity of the problem, non linear activation functions are preferably used. In that case, saturation problems may occur. These problems can be attributed to the use of sigmoid activation functions that present non-linear behavior outside the region [-1, 1]. In order to avoid saturation problems, the input and the output values are normalized.

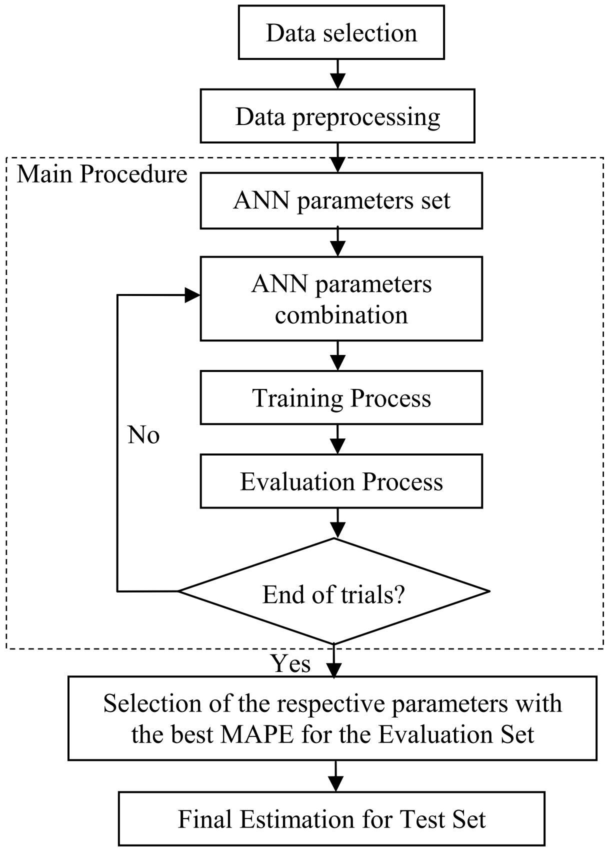

Fig. 1. Flowchart of the ANN methodology for the proper selection of ANN parameters for short-term load forecasting for different kind of input variables

(c) *Main procedure*: The ANN is trained using the scaled conjugate gradient algorithm (SCGA), whose basic steps have been presented in [10, 18]. The basic disadvantage of the SCGA algorithm is that its calculation complexity per iteration is twofold of the basic steepest descent method. Its basic advantage is that the error function decreases monotonically. The respective parameters of the neural network are selected through a set of trials. Specifically for each ANN parameter (such as the neurons of the hidden layer, the type of the activation functions (hyperbolic tangent, logistic, linear), the parameters of the activation functions, the maximum number of epochs, the SCGA algorithm parameters) the training algorithm is separately executed for the respective range of values (i.e. 20 to 70 neurons with step 1) based on the error function (sum of the square of errors for all neurons per epoch) for the training set and the regions with satisfactory results (minimum Mean Absolute Percentage Error (*MAPE)* for evaluation set) are identified. It is noted that the *MAPE* index between the measured and the estimated values of hourly load demand for the evaluation set' days is given by:

$$MAPE_{ev} = 100\% \cdot \frac{1}{m_{ev}} \cdot \sum_{d=1}^{m_{ev}} \sum_{i=1}^{24} \frac{\left|\hat{L}(d,i) - L(d,i)\right|}{L(d,i)} \quad (1)$$

where $L(d,i)$ is the measured value of load demand for the i-th hour of d-th day of the evaluation set, $\hat{L}(d,i)$ the respective estimated value, m_{ev} the population of the evaluation set. This index is a practical measure, which reflects the approximation of the actual load demand independently from its measurement units.

Following, the training algorithm is repeatedly executed, while all parameters are simultaneously adjusted to their respective regions, so that the combination with the smallest *MAPE* for the evaluation set is selected. It is also noted that:

(1) The ANN is solved by using one hidden layer and properly calibrating the number of neurons according to Kolmogorov's theorem.

(2) During the training process for each ANN three stopping criterions are used: stabilization of the weights, the respective error function not to be decreased or the violation of the maximum number of epochs [9].

(d) *Final estimation for the test set*: The actual load demand (in MW) for the days of the test set is finally estimated by using the respective ANN parameters.

The best result for the *MAPE* index of the evaluation set is 1.487% for the case of Greek intercontinental power system with training years 1997-1999 (the training and the evaluation sets consist of the 90% and 10% of the normal days without holidays, respectively), while the respective test set consists of the normal days of the year 2000. The *MAPE* indexes for the training and the test set are 1.294% and 1.781% respectively. These are obtained for an ANN with 52 neurons in the hidden layer using hyperbolic tangent activation function in both layers (tanh(0.5·x) for the hidden layer, tanh(0.25·x) for the output layer, where x is the respective sum of the properly weighted inputs of the neuron) (see [10, paragraph 4] for more details).

3 Confidence interval estimation by re-sampling technique

The estimation of the confidence intervals for ANN models is not applied directly, unlike to the classical models. Three techniques have been mentioned in [15]: (a) the output error, (b) the re-sampling, (c) the multi-linear regression adapted to ANN.

In [11] the theoretical superiority of the re-sampling technique has been proved, because the output error technique doubles the number of the ANN's outputs increasing the respective number of the ANN weights and the respective computational time significantly, while the multi-linear regression adapted to ANN technique allows only the use of the linear activation function for the output layer, which deteriorates the *MAPE* results. On the contrary, the re-sampling technique does not affect the computational time and the *MAPE* results.

In order to estimate the confidence interval using the re-sampling technique, the prediction and the respective error are calculated for each set and for all available *m* input vectors. These errors are sorted in ascending order considering the signs and the cumulative sample distribution function of the prediction errors can be estimated by:

$$S_m(z) = \begin{cases} 0, & z < z_1 \\ r/m, & z_r \le z < z_{r+1} \\ 1, & z_m \le z \end{cases} \quad (2)$$

When m is large enough, $S_m(z)$ is a good approximation of the true cumulative probability distribution $F(z)$. The confidence interval is estimated by keeping the intermediate z_r and discarding the extreme values, according to the desired confidence degree. The intervals are computed in order to be symmetrical in probability (not necessarily symmetric in z). The number of cases to discard in each tail of the prediction error distribution is $n \cdot p$, where p is the probability in each tail. If $n \cdot p$ is a fractional number, the number of cases to discard in each tail is $\lfloor n \cdot p \rfloor$ for safety reasons. If the cumulative probability distribution $F(Z_p)$ equals to p, then there is a probability p that an error is less than or equal to Z_p , which indicates that Z_p is the lower confidence limit. Consequently, Z_{1-p} is the upper limit and there is a $(1-2p)$ confidence interval for future errors.

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4 Application of the Re-sampling technique for Short-term Load Forecasting in Interconnected Greek Power System based on ANN STLF Methodology

In [10] the application of ANN STLF methodology is described analytically. After the selection of the best ANN the 90% confidence interval is estimated using the re-sampling technique with 5% probability in each tail. In Fig. 2 the prediction errors of a typical summer day for Greek interconnected power system in 2000 (Thursday 8-6-2000) are presented for the training, evaluation and test sets respectively, while in Fig. 3 the respective measured and estimated load values are presented together with the 90% confidence intervals from the evaluation set and from the test set.

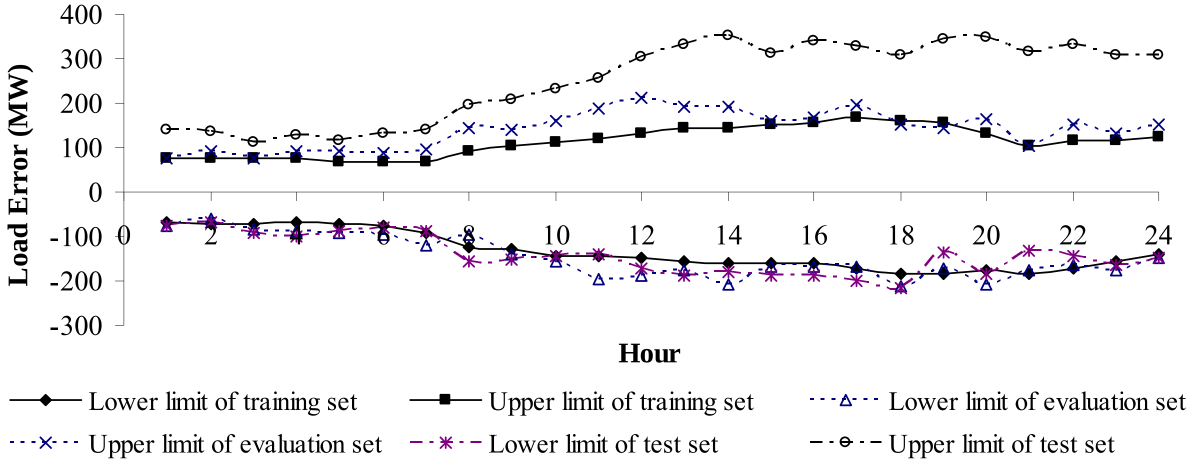

Fig. 2. 90% confidence interval limits with respect to the training, evaluation and test sets for the best ANN model for 8-6-2000 in Greek interconnected power system

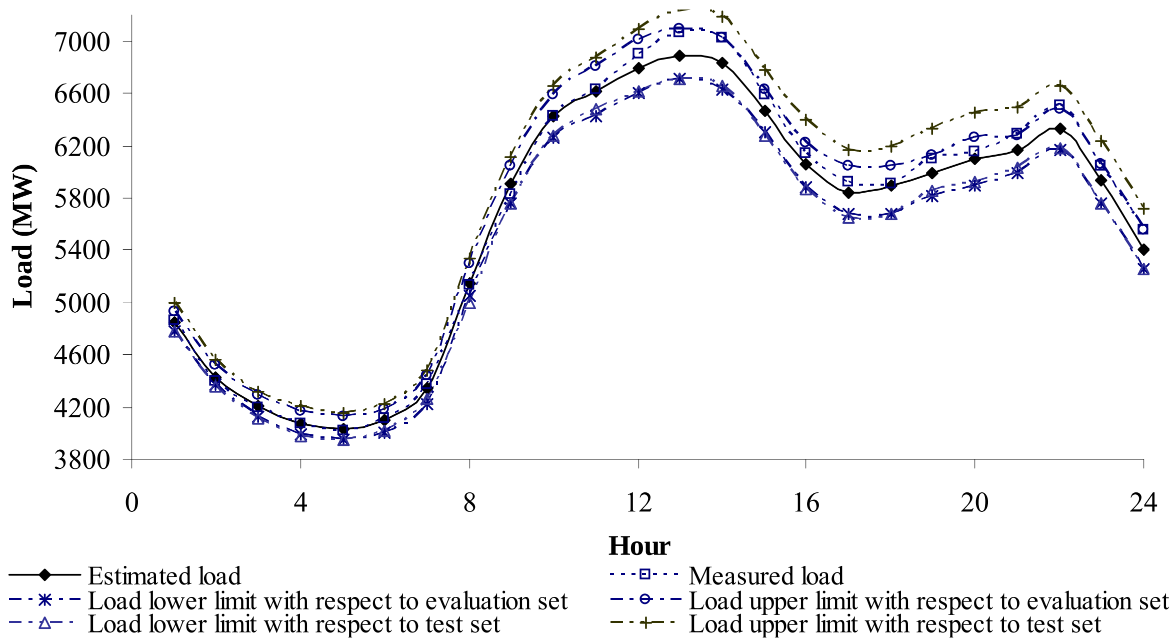

Fig.3. Chronological active load curves of the measured load, the estimated load, the estimated load with the 5% lower limit with respect to evaluation set, the estimated load with the 5% upper limit with respect to evaluation set, the estimated load with the 5% lower limit with respect to test set, the estimated load with the 5% upper limit with respect to test set for the best ANN model for 8-6-2000 in Greek interconnected power system

From Fig. 2 it is observed that the lower limits of the confidence intervals for the three sets are quite similar. The ratio of the lower hourly error of the test set to the respective one of the evaluation set varies between 0.71 and 1.60, while the mean value is practically 1. However, the upper limit of the confidence intervals for the test set is almost the double of the respective one of the evaluation set. The ratio of the upper limit error load of the test set to the respective one of the evaluation set varies between 1.22 and 3.02, while the mean value is equal to 1.78. From Fig. 3 it is observed that the confidence interval of the test set is broader than the respective one of the evaluation set. Similar behavior is observed for all days studied.

This is obvious in Table 1, where the ratios between (a) the 5% lower limit with respect to test set to the 5% lower limit with respect to training set, (b) the 5% upper limit with respect to test set to the 5% upper limit with respect to training set, (c) the 5% lower limit with respect to test set to the 5% lower limit with respect to evaluation set, (d) the 5% upper limit with respect to test set to the 5% upper limit with respect to evaluation set, are presented. The respective abbreviations of the ratios are r_1, r_2, r_3 and r_4. Specifically, the ratios of the lower limits are closer to 1, while the ratios of the upper limits are significantly larger than 1, which means that the upper limit of load error is underestimated. It is also observed that the mean ratios based on the evaluation set approach are closer than the ones based on the training set, although the respective interval ([min hourly ratio, max hourly ratio]) is broader. In fact the limits of the test set are unknown in real applications, which means that they should be corrected based on the estimation of the confidence interval from the training or evaluation set.

5 Modification of the Re-sampling technique using the Corrective Factor

According to the results of §4 the estimation of the confidence interval of the test set using either the confidence interval limits of the training set or the respective ones of the evaluation set directly, is not completely satisfactory. This problem can be solved practically by multiplying the limits of the training or evaluation set with a proper number so as to remove this dissimilarity.

Next, three candidates of corrective multiplication factors for each limit are examined:

(a) the mean value of the hourly ratio of the limit of the test set with respect to the limit of the evaluation set,

$$f_{mean} = \frac{1}{24}\sum_{h=1}^{24}\frac{\text{limit error}_{test\ set}(h)}{\text{limit error}_{evaluation\ set}(h)} \qquad (3)$$

(b) the maximum value of the hourly ratio of the limit of the test set with respect to the limit of the evaluation set,

$$f_{\max} = \max_{h=1,\dots,24}\left\{\frac{\text{limit error}_{test\ set}(h)}{\text{limit error}_{evaluation\ set}(h)}\right\} \qquad (4)$$

(c) the hourly ratio of the limit of the test set with respect to the limit of the evaluation set, which entails 24 different values for each limit:

$$f(h) = \frac{\text{limit error}_{test\ set}(h)}{\text{limit error}_{evaluation\ set}(h)} : h=1,\dots 24 \qquad (5)$$

These ratios are calculated for the previous year e.g. if the forecasting year is 2000 with training years 1997-99, the corrective factors will be calculated using as forecasting year 1999 and training years 1996-98. It is noted that if a factor is smaller than 1, it will be set equal to 1 for safety reasons.

The proposed method is applied for actual hourly load data of the Greek interconnected power system for the case study of [10]. In Fig. 4 the hourly 5% upper limit load error of the confidence interval is presented for: (i) the evaluation set (10% of normal days of the training years 1997-99), (ii) the test set (normal days of the year 2000), (iii) the estimation of the test set based on the mean value of hourly ratio of the upper limit of the test set with respect to the respective one of the evaluation set, (iv) the estimation of the test set based on the maximum value of hourly ratio of the upper limit of the test set with respect to the respective one of the evaluation set, (v) the estimation of the test set based on the hourly ratio of the upper limit of the test set with respect to the respective one of the evaluation set.

It is obvious that the estimation of the confidence interval using the mean value of the hourly ratio (1st candidate) overestimates the real confidence interval of the test set for 08.00-12.00, while it underestimates it for 17.00-23.00 (especially for 21.00). The estimation of the confidence interval using the maximum value of the hourly ratio (2nd candidate) overestimates the real confidence interval of the test set significantly and it is a over-conservative solution with extremely extended limits. The estimation of the confidence interval using the hourly ratio of the limit of the test set with respect to the limit of the evaluation set (3rd candidate) is the closest one to the real confidence interval of the test set.

In this way the practical superiority of the last candidate factor is proved and it is proposed for use.

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TABLE 1
ANN SHORT-TERM LOAD FORECASTING IN GREEK INTERCONNECTED POWER SYSTEM FOR PREDICTION YEAR 2000 WITH TRAINING YEARS 1997-99: RATIOS BETWEEN THE 5% LOWER LIMIT OF TEST SET TO THE 5% LOWER LIMIT OF TRAINING SET (r_1) & OF EVALUATION SET (r_3), RATIOS BETWEEN THE 5% UPPER LIMIT OF TEST SET TO THE 5% UPPER LIMIT OF TRAINING SET (r_2) & OF EVALUATION SET (r_4)

Hour	1	2	3	4	5	6	7	8	9	10	11	12
r_1	1.11	0.95	1.28	1.48	1.25	1.03	0.98	1.26	1.19	0.99	0.97	1.17
r_2	1.80	1.81	1.46	1.68	1.68	1.90	2.05	2.15	2.00	2.07	2.14	2.31
r_3	1.02	1.10	1.09	1.16	0.99	0.81	0.73	1.60	1.09	0.93	0.71	0.91
r_4	1.84	1.48	1.45	1.35	1.22	1.51	1.44	1.35	1.48	1.44	1.37	1.44
Hour	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
r_1	1.21	1.12	1.19	1.18	1.15	1.18	0.73	1.04	0.72	0.84	1.04	1.07
r_2	2.29	2.46	2.04	2.16	1.95	1.92	2.21	2.66	3.04	2.89	2.65	2.44
r_3	1.07	0.86	1.13	1.13	1.18	1.03	0.79	0.87	0.76	0.89	0.94	1.02
r_4	1.71	1.85	1.94	2.03	1.67	2.05	2.41	2.14	3.02	2.18	2.37	2.01

From all days		
Min	Max	Mean
0.72	1.48	1.09
1.46	3.04	2.16
0.71	1.60	0.99
1.22	3.02	1.78

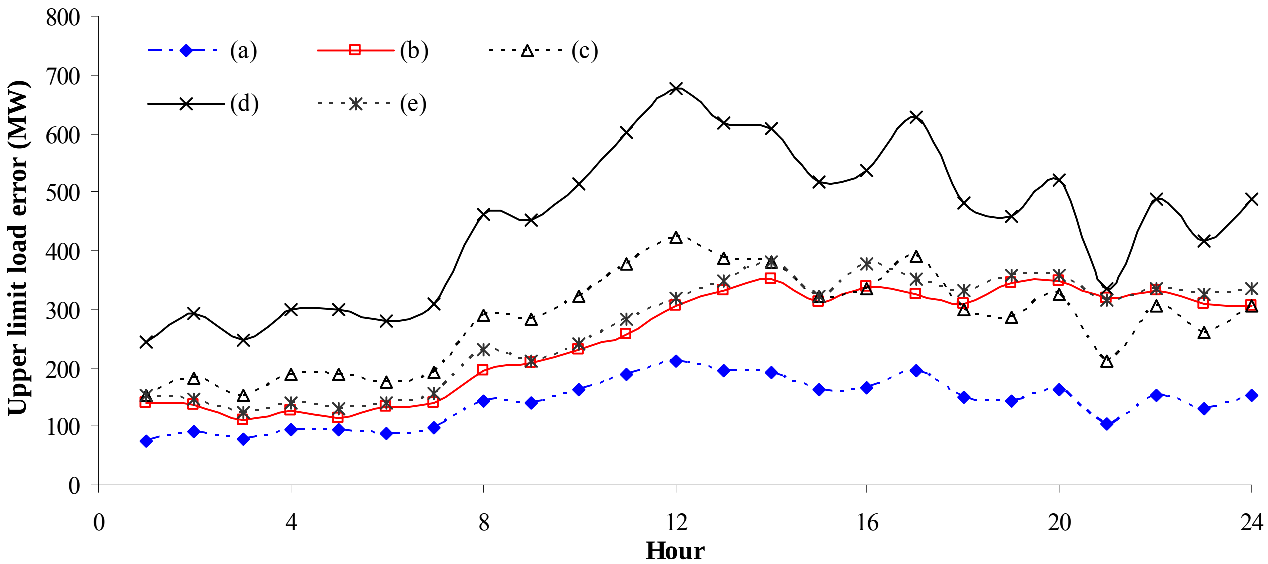

Fig. 4. Hourly curves of (a) the 5% upper limit load error for the evaluation set, (b) the 5% upper limit load error for the test set, (c) the 5% estimated upper limit load error for the test set based on the mean value of the hourly ratio of the limit of the test set with respect to the limit of the evaluation set of the previous year, (d) the 5% estimated upper limit load error for the test set based on the maximum ratio of the hourly ratio of the limit of the test set with respect to the limit of the evaluation set of the previous year, (e) the 5% estimated upper limit load error for the test set based on the hourly ratio of the limit of the test set with respect to the limit of the evaluation set of the previous year in Greek interconnected power system

6 Conclusions

This paper presents the improved features of the re-sampling technique for the ANN confidence interval estimation in case of the short term load forecasting. Specifically, the basic re-sampling method for confidence interval estimation is applied for the short term forecasting of the next day load in the interconnected Greek power system using an optimized ANN. The obtained results have proved that the confidence interval limits of the test set are underestimated using the respective ones either of the evaluation or the training set (especially for the upper limit the difference has been tripled). This has led to propose a modified re-sampling technique using a proper corrective multiplication factor between the limit of the test set and the respective one of the evaluation set. Three candidates factors have been examined: (a) the mean value of the hourly ratios of the limit of the test set to the limit of the evaluation set of the previous year, (b) the maximum value of all hourly ratios of the limit of the test set to the limit of the evaluation set of the previous year, (c) the hourly ratio of the limit of the test set to the limit of the evaluation set of the previous year. From the comparison of the applied methods for actual hour load data of the Greek interconnected power system in year 2000 the superiority of the hourly ratios of the limit of the test set to the limit of the evaluation set of the previous year has been proved and it is proposed for use.

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