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ABSTRACT

In a developing country like Pakistan, where the electrical power demand is more than the generated power, maintaining the power system stability is a big challenge. In such cases it becomes, thus, essential to shed just the right amount of load to keep a power system stable. This paper presents a case study of Pakistan's power system where the generated power, the load demand, frequency deviation and the load shed during a 24-h duration have been provided. The data have been analyzed using two techniques; the conventional artificial neural network (ANN) by implementing feed forward back propagation model and the Bootstrap aggregating or bagging algorithm. The simulation results reveal the superiority of the Bootstrap aggregating algorithm over a conventional ANN technique using feed forward back propagation model.

Introduction

The demand of power is increasing with each passing day which requires more resources of generation and construction of new grids. The developing countries that do not have sufficient resources have to perform load shedding in order to achieve 'power system stability'. When the load increases, the generators connected to a power system start slowing down that in turn results in reduced electrical frequency. The minimum threshold value for frequency in Pakistan is 49.5 Hz. When frequency decreases below its threshold value due to a sudden increase in load or tripping of major power plants (or transmission lines), the whole system becomes vulnerable to losing its stability. The tripping of one major generator (or power plant) or a transmission line results in the re-distribution of load on other generators or transmission lines and if they are not able to bear this increased load (particularly in case when they already are operating near their rated capacities), the whole system could collapse. This condition is known as cascaded failure or blackout [1].

The cascaded failures are a major threat to power systems. They should not be allowed to happen as they can prove detrimental to the equipment and personnel. One of the earliest blackout occurred in 1965 popularly known as Northeast Blackout, which left more than 30 million people without electricity for almost 6 days. The biggest cascaded failure that affected more than 300 million people occurred in India on 30 July 2012. In the last decade Pakistan also suffered with three major cascaded failures.

Optimal load shedding means shedding of just minimum load which can guarantee the system stability [2]. There are two worse-case scenarios in a power system:

(i) When the system generation is less than the load demand, frequency falls which could ultimately cause the generators to shut down.
(ii) When system generation is greater than the load demand, the speeding up of the generators will increase the system frequency and in the absence of a control mechanism will make the generators lose synchronism with the rest of the power system.

The upper threshold value of the frequency in Pakistan is 50.5 Hz. Fig. 1 presents a beautiful illustration, in the form of a balance, of the variation of frequency with the change in load or the generation: 50 Hz will be the frequency when generation exactly matches with the load, ignoring losses. Increasing power generation above the balance point will increase the frequency, whereas increased load will result in the decrease of the frequency.

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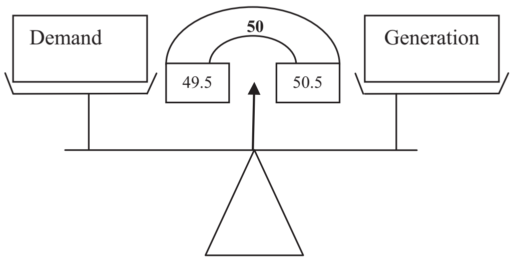

Fig. 1. Effect of supply and demand on system frequency.

Automatic generation control (or load–frequency control) mechanism, equipped with every generator, completely solves the second problem (when generation is more than the load demand by a governor action to decrease the flow of steam in case of steam-driven generators and water in case of hydel generators) but partially in the first scenario (when the load demand is more than the generation). In this case the control mechanism tries to adjust the speed of a generator by increasing the flow of steam, in case of a steam-driven generator for example, to compensate for the slow speed of the machine. However, if the machines are already operating at their maximum limits (generally the rated values) then the only option left is shedding some load to avoid a cascaded failure [3]. There are numerous ways to shed load such as breaker-interlock method, under-frequency relay, programmable logic controller based and intelligent load shedding scheme. The problems with these methods are that they are too slow and not efficient to calculate the correct amount of load needed to be shed.

Optimal load shedding has been studied using various conventional and artificial intelligence techniques. Traditional methods take more time than that by artificial neural network (ANN) to calculate the correct amount of load to be shed [3,4]. The convergence rate and execution time of ANNs are faster than those of many other artificial intelligence techniques [5,6]. The error in the learning of artificial neural network can be reduced by Bootstrap aggregating, also called bagging, algorithm that will increase the accuracy of a system [7]. The objective of this study is to explore optimal load shedding by using bagging algorithm. Power generation, power demand and the rate of change of frequency will play key roles in the training of neural networks, and to shed the correct amount of load. After training the neural network, a comparison of the target and the neural network output has been made which shows that there still was a significant difference between the two. Bagging technique is then used to reduce this error.

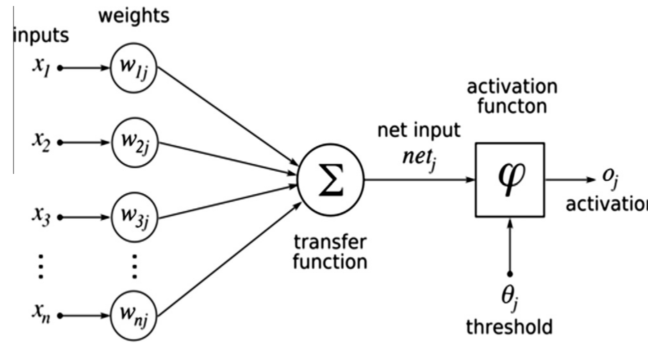

Fig. 3. Data propagation in an ANN.

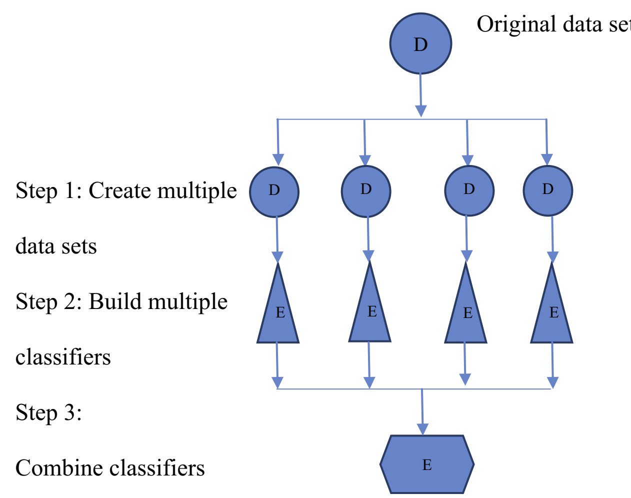

Fig. 4. General idea of bagging.

Levenberg–Marquardt back-propagation artificial neural network

A biological neural network forms the basic design of an artificial neural network. ANN is, however, not as complex as biological neural networks but the way of information processing resembles with those of biological neural systems. ANN is an interconnected system which is able to solve highly non-linear functions in a short time. The structure of an ANN is shown in Fig. 2.

Suitable data are required to extract enough information between input and output to train an ANN. The selection of the

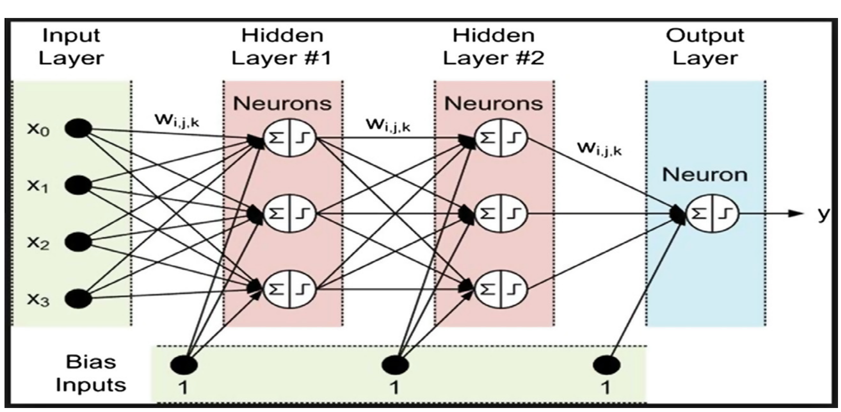

Fig. 2. Structure of an ANN.

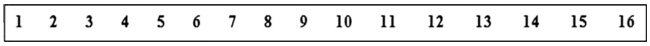

Fig. 5. Original data set.

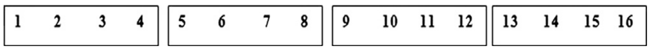

Fig. 6. Disjoint partition.

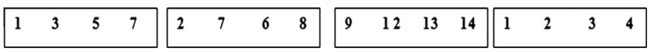

Fig. 7. Small bags.

number of hidden layers also affects the results. Most of the time the size of hidden layers is 10% of the input layers [8]. The data propagation from input layers to output layers is shown in Fig. 3.

The weights of inputs ($x_1, x_2, \ldots, x_n$) are determined by w_{1j}, w_{2j}, …, w_{nj} that determine their strength. Inputs and their respective weights are fed to the transfer function. An activation function that is added to the transfer function will decide whether the signal is generated or not by comparison to some threshold value. A transfer function determines the threshold value. The difference of ANN output and desired output represents the error that depicts that the training of ANN is required. The error is propagated backward to adjust the weights of input so that desired output matches the neural-networks' output.

Bootstrap aggregating

An ANN works well for a given data set but when data set changes in the next hour or the next day for example, it suffers the problem of over-fitting or under-fitting due to its reduced generalization ability. Even after training several times of ANN the result between the actual and desired values does not match. The reason for this error is in the learning process. Error in learning is because of three main factors; bias, variance and noise [7].

$$\text{Error} = \text{Noise} + \text{Bias} + \text{Variance} \tag{1}$$

Large bias causes under-fitting while large variance causes over-fitting of data. Generalization of an ANN to adapt to the new data set will increase much if bias and variance are reduced to minimum as data will not suffer the problem of over-fitting and under-fitting anymore. Moreover, the error in learning also reduces and overall prediction improves.

Table 1
Power generation, load demand and change in frequency.

Time	Power generation	Load demand	Change in frequency
00:00:00	8151.2	11651.22	−0.22
01:00:00	7891.6	11394.93	−0.20
02:00:00	7725.8	11225.8	−0.50
03:00:00	7696.3	11196.3	−0.28
04:00:00	7713.12	11213.12	−0.29
05:00:00	8521.29	11694.62	0.16
06:00:00	9524.38	11524.39	−0.30
07:00:00	9897.81	11897.76	−0.09
08:00:00	9536.1	11746.1	−0.07
09:00:00	9792.77	12392.88	−0.15
10:00:00	9800.39	12400.39	−0.16
11:00:00	9828.43	12428.48	−0.02
12:00:00	9826.83	12426.85	−0.01
13:00:00	9555.35	12155.39	0.00
14:00:00	9796.15	12396.14	−0.04
15:00:00	9659.27	12259.21	0.03
16:00:00	9510.74	12110.77	−0.15
17:00:00	9568.38	12543.49	−0.03
18:00:00	9886.25	13386.21	0.07
19:00:00	9723.15	13223.17	−0.03
20:00:00	9726.16	12801.17	−0.15
21:00:00	9272.85	12272.83	−0.08
22:00:00	8809.23	11809.23	0.17
23:00:00	8424.41	11157.92	0.14

Table 2
Load management data.

Time	Short generation	Transmission O/L (NTDC)	Industrial cuts	DISCO'S constraints	Emergency L/M	Total
Load management						
0000	1167	0	24	1272	0	2463
0100	1095	0	14	1266	0	2375
0200	1160	0	14	1240	0	2414
0300	1068	0	17	1262	0	2347
0400	1024	0	18	1271	0	2313
0500	977	0	17	1261	0	2255
0600	1091	0	141	1255	0	2487
0700	1318	0	93	1230	0	2641
0800	1468	0	182	1201	0	2851
0900	1520	0	80	1172	0	2772
1000	1685	0	43	1086	0	2814
1100	1700	0	182	1168	0	3050
1200	1709	0	188	1166	0	3063
1300	1735	0	100	1209	0	3044
1400	1629	0	50	1191	0	2870
1500	1481	0	90	1231	0	2802
1600	1605	0	102	1282	0	2989
1700	1512	0	237	1182	0	2931
1800	1711	0	101	1207	0	3019
1900	1837	0	260	1097	0	3194
2000	1739	0	214	1093	0	3046
2100	1473	0	19	1105	0	2597
2200	1394	0	25	1139	0	2558
2300	1445	0	26	1231	0	2702

Table 3
Specification of the ANN.

Number of input neurons	3 (P_G,P_L, d*f*/d*t*)
Number of output neurons	1 (Pshed)
Number of hidden-layer neurons	10
Neural network model	Feed forward back propagation
Training function	Levenberg–Marquardt Back Propagation (LMBP)
Adaptation learning function	Gradient descent with momentum weight and bias
Number of layers	2
Activation function for layer 1	Trans sigmoid
Activation function for layer 2	Pure linear
Performance function	Mean Square Error (MSE)
Percentage of using information	Train (70%), test (15%), cross validation (15%)
Maximum of epoch	1000
Learning rate	0.01
Maximum validation failures	6
Error threshold	0.001
Weight update method	Batch

Bagging is used to improve the stability and precision of an ANN algorithm. It minimizes the variance which further helps in reducing the over-fitting [9]. The description of this technique is illustrated in Fig. 4.

Classifications of bagging are [10]:

(i) Small bags.
(ii) Disjoint partition.

In this study disjoint partition is implemented by using MATLAB. It is considered more effective than small bags method [9–11]. Let us consider the original data set, given in Fig. 5, to understand the disjoint partition.

Disjoint partition will make the subsets of the original data set in such a way that the number of subsets will be equal to that of the original data set. In this case each particular number will be selected only once as shown in Fig. 6.

In case of small bags the union of subsets may not necessarily be equal to the original data set because of the repetition of numbers as shown in Fig. 7.

Proposed method

The proposed method involves three steps:

1. Real data set generation.
2. Design of ANN.
3. Design of Bootstrap.

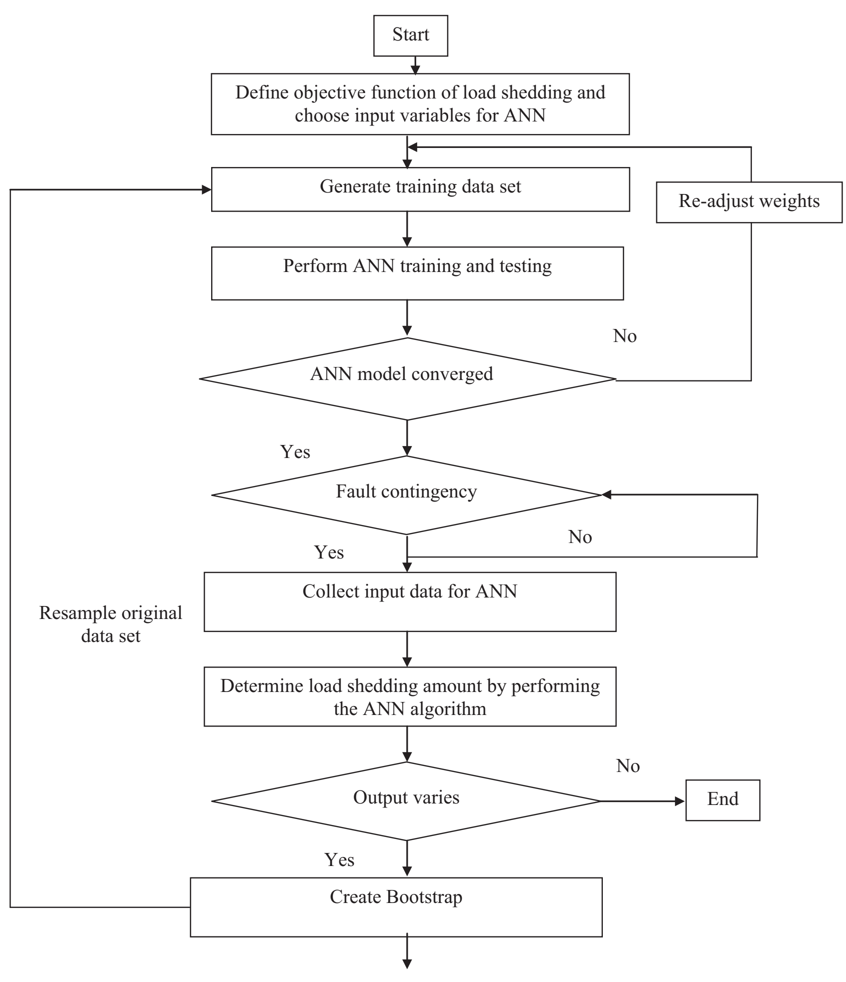

Fig. 8. Flowchart of optimal load shedding using bagging algorithm.

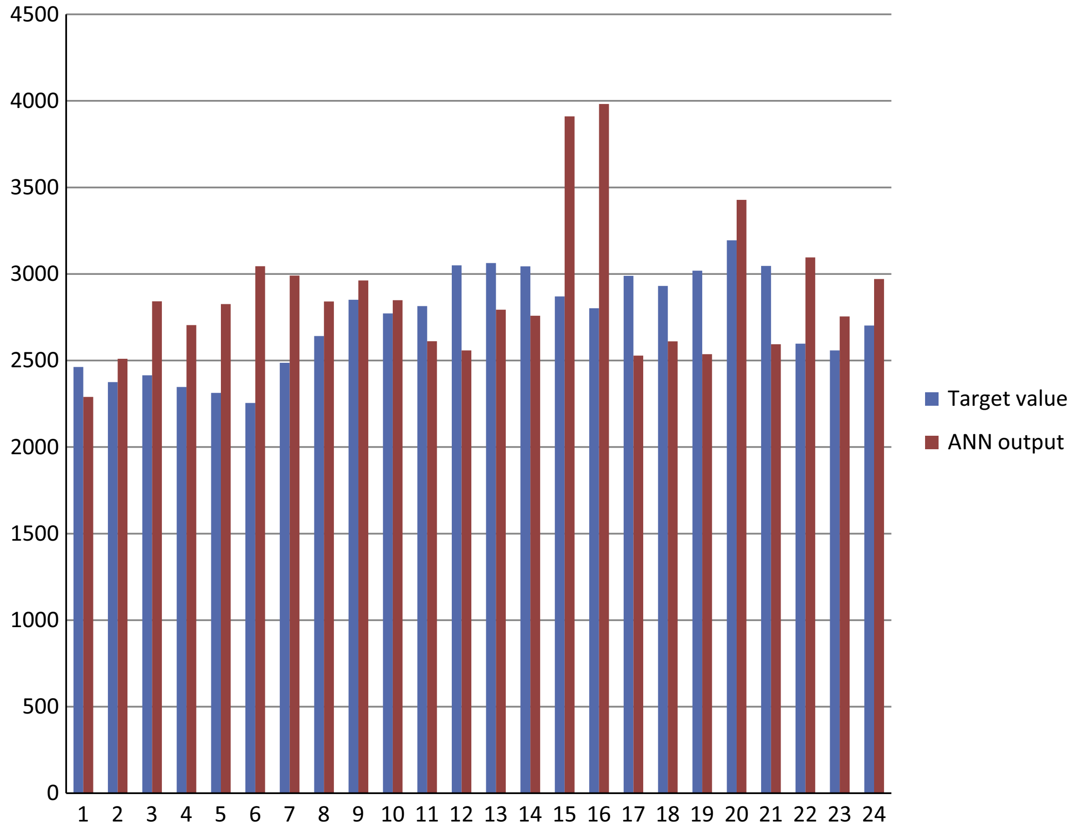

Fig. 9. Comparison of the target values against the ANN values.

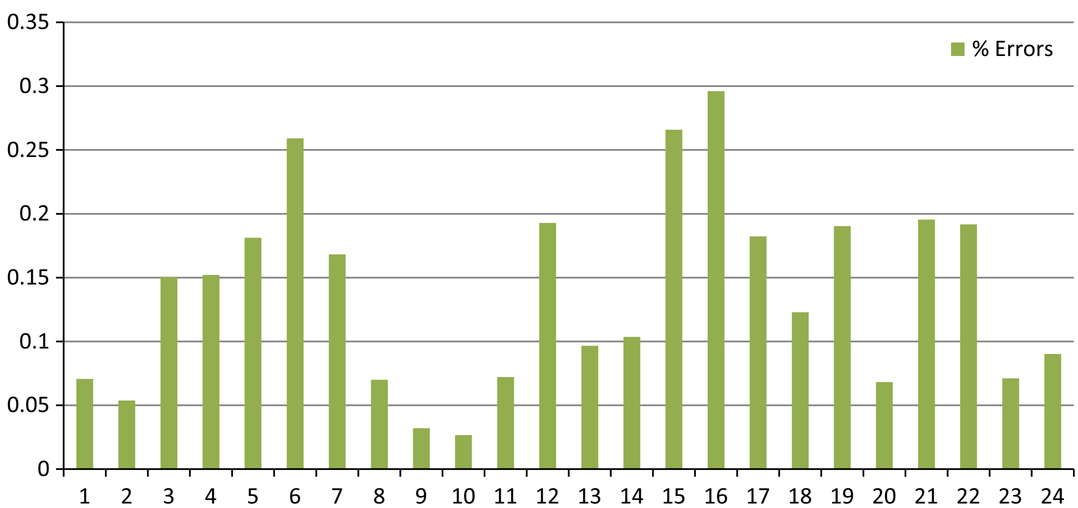

Fig. 10. Percentage errors of the target and ANN values.

Step 1: Data set from Pakistan's state-owned electric utility Water and Power Development Authority (commonly known as WAPDA) that includes power generation, power demand, the rate of change of frequency and the load shed against each hour has been used. The data, given in Table 1, were provided by Pakistan's National Power Control Centre (NPCC) which is responsible to monitor and control the power flow in Pakistan's power system.

Not only the reduced power generation, when compared with the demand, but also the transmission and distribution constraints are responsible for load shedding. The transmission constraints, as shown in Table 2, are zero as the National Transmission and Dispatch Company of Pakistan (commonly known as NTDC) transmits the entire power that it receives while the DISCOs (distribution companies) constraints are not zero because each distribution company has a certain capacity to distribute the load. A stable power system has to have sufficient reserve capacity. The data of load management (a soft name for load shedding), provided by WAPDA (Table 2), depict an unfortunate scenario of having zero spinning reserve in Pakistan's power system.

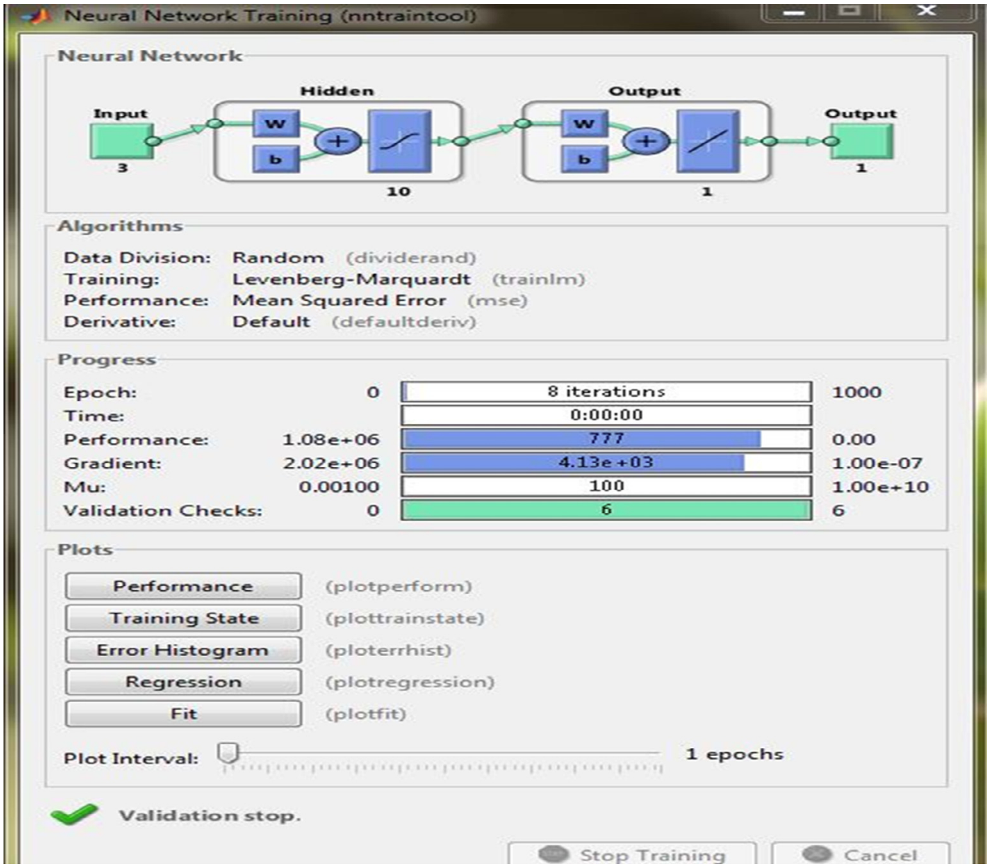

Fig. 11. Training window of ANN.

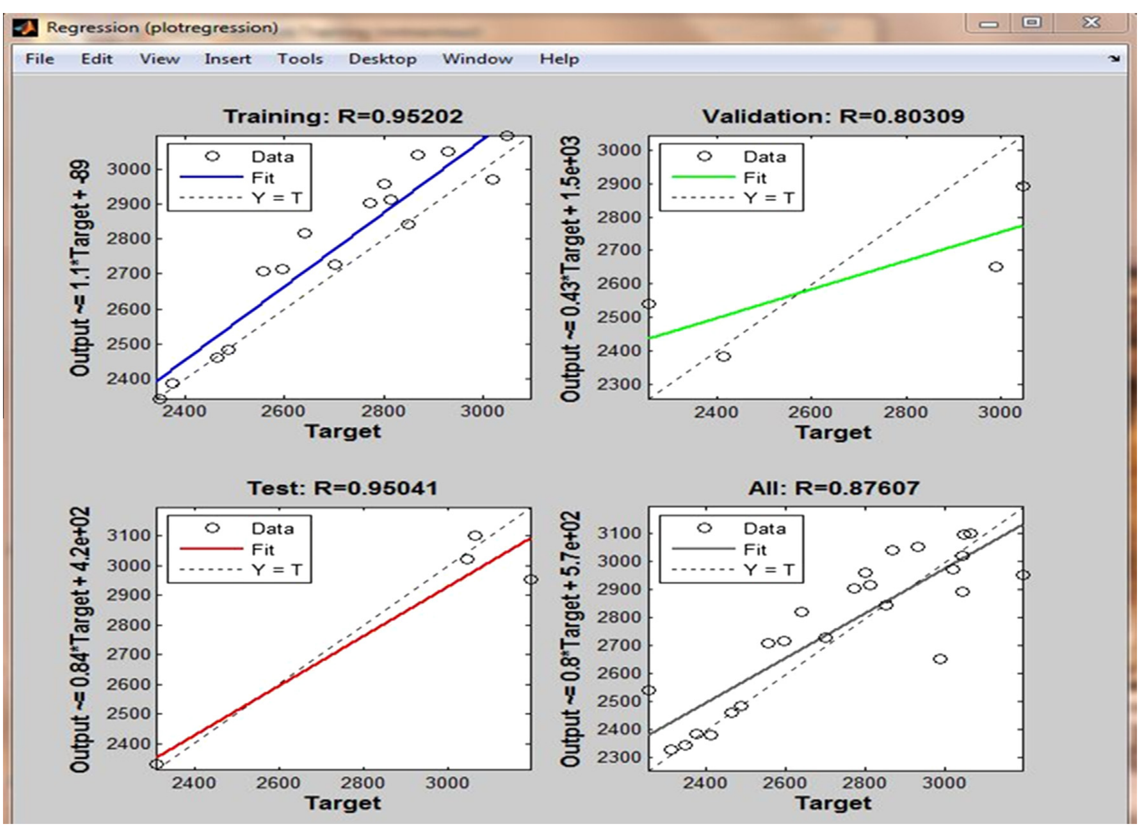

Fig. 12. Regression plot of ANN.

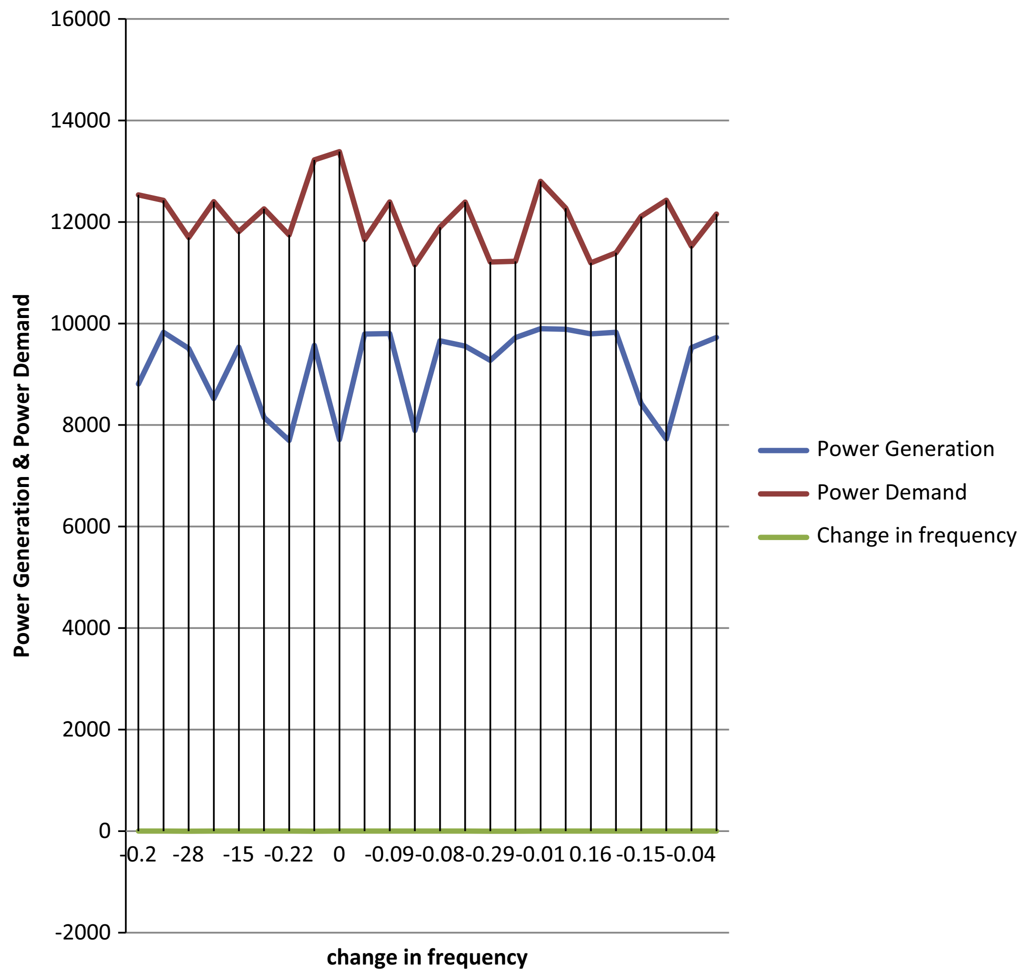

Fig. 13. Bootstraps data.

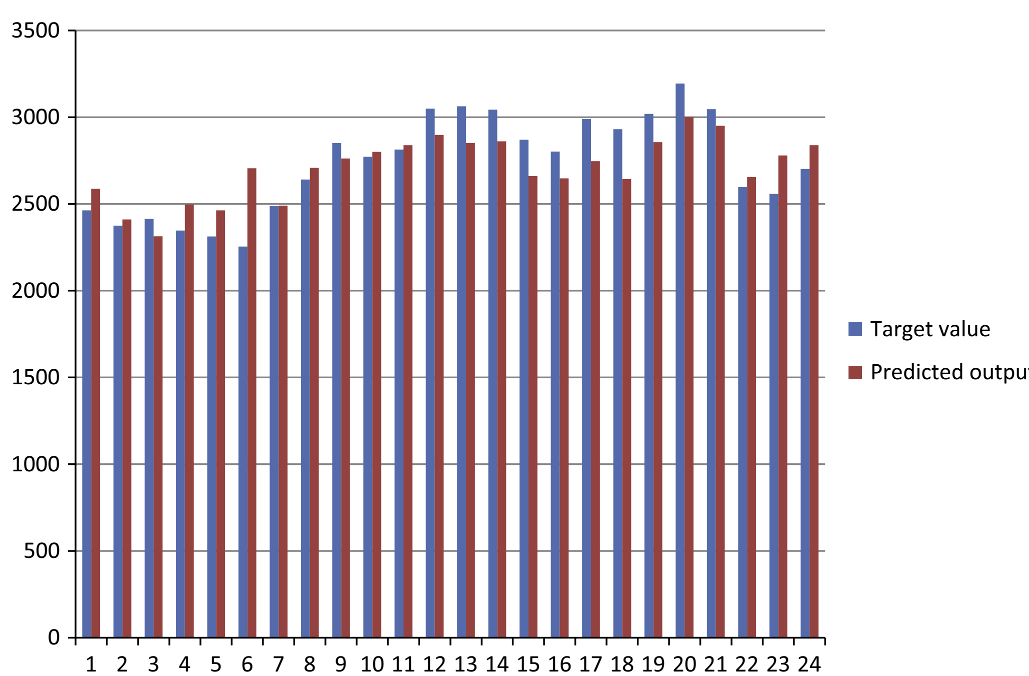

Fig. 14. Comparison between target value and the final predicted value.

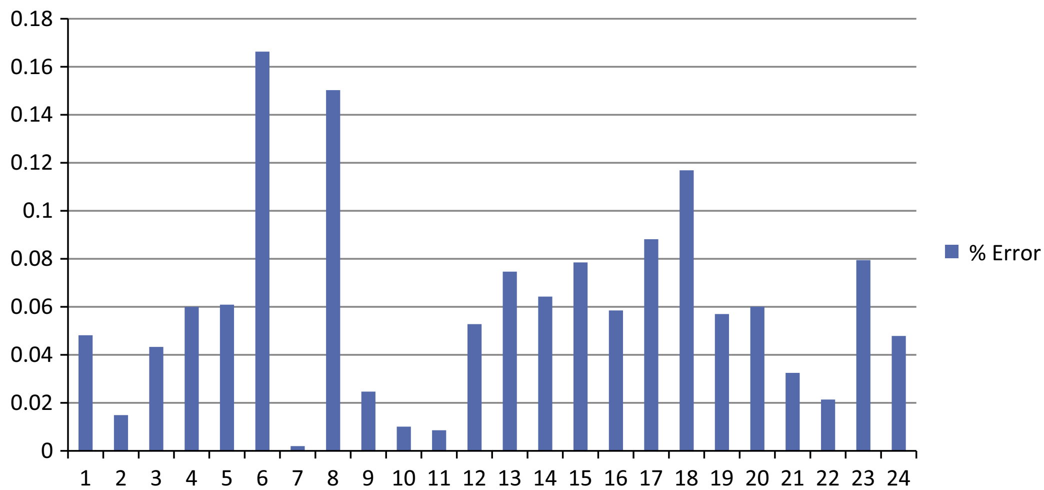

Fig. 15. Percentage errors of the target and ANN values after implementing Bootstrap aggregating algorithm.

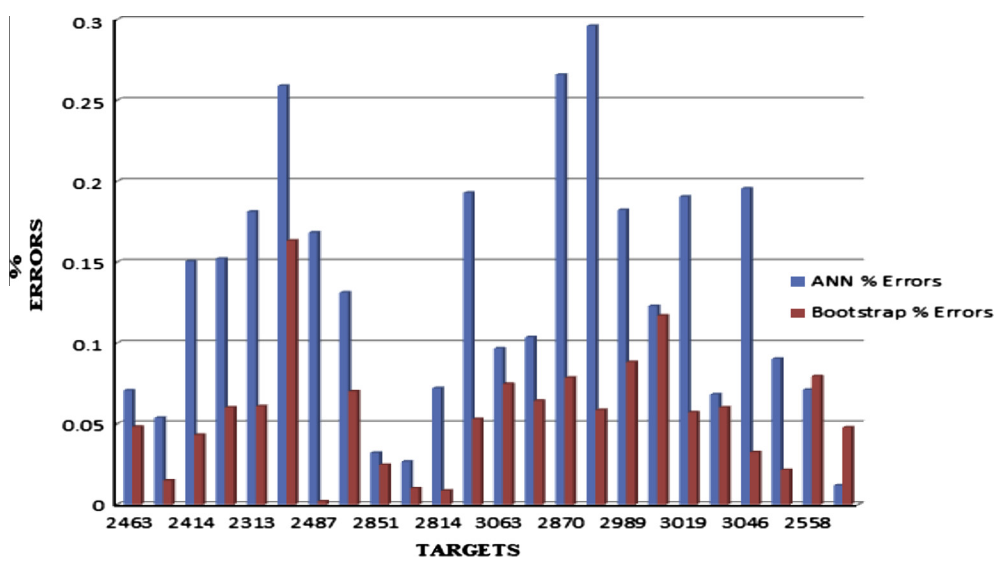

Fig. 16. Comparison of the percentage errors.

Step 2: The first step in designing the ANN is the selection of inputs and target function. The power generation (P_G), power demand (P_L) and the rate of change of frequency (df/dt) are selected as inputs while the load shed during each hour by NPCC is selected as target. The specifications of the ANN structure, in detail, are presented in Table 3.

Once inputs and targets are selected, and weights and biases have been initialized the neural network is ready for training. The training of ANN is done by using LMBP algorithm because of least error and fast convergence [12]. '*Gradient descent*' is used to update the weight and bias in the adaptation learning process. The reason for using this technique is that the convergence rate of '*batch gradient descent with momentum*' is fastest for feedforward networks [12]. The '*mean square error (MSE)*' is reduced using gradient descent method.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} e(i)^2 = \frac{1}{n}\sum_{i=1}^{n}(t_i - y_i)^2 \tag{2}$$

where, n is the number of examples, t_i is the desired target value and y_i is the output of target.

The entire data are divided in different percentages; 70% of the data used for training, 15% for validation in order to reduce overfitting while 15% is used for testing (necessary to predict the final output of the ANN).

Step 3: After training the ANN several times the results still show deviation from the target; especially when data set changes the results deviate more from the desired output. The creation of Bootstraps that resample the original data set many times, before training the ANN, improves the results. The ANN does now work more accurately because of its increased generalization ability. The Bootstrap ANN output is compared with the previous ANN output. It has been observed that the Bootstrap output is closer to the target value and the percentage error is reduced. The flowchart of optimal load shedding using Bootstrap or bagging algorithm is illustrated in Fig. 8.

Simulation and results

In this section the ANN outputs, their comparison with the target, creation of Bootstraps and final predicted outputs of the ANN on the Bootstrap are shown.

The target value against each ANN output is shown in Fig. 9. The difference of the ANN output and the target, termed as error, is shown in Fig. 10.

Fig. 11 shows *dividerand* function illustrating that the LMBP training method is used with mean square error (MSE) performance function.

Regression plot presents the relation between the desired output (target) and the actual output (ANN output). $R = 0.87$ in Fig. 12 depicts that ANN output does not exactly match with the target, which is the load shed by the WAPDA against each hour.

The creation of Bootstrap that resamples the original data set is shown in Fig. 13.

After creating the Bootstrap data, the ANN is trained again on the re-sampled data to increase its ability to opt to the new data set. Fig. 14 shows the comparison between target value and final predicted value while Fig. 15 shows the reduced percentage errors.

Fig. 16 shows the final predicted output of the ANN on Bootstrap and graphically depicts the superiority of the Bootstraps algorithm over the conventional ANN.

Conclusion

In this study a successful implementation of an optimal load-shedding strategy by using ANN and Bootstrap aggregating or bagging algorithm has been accomplished. The data for Pakistan's power system have been considered which consist of generated power, load demand, the rate of change of frequency and the load shed against each hour in 24-h period. When analyzed using feed forward back propagation model of the ANN there was significant error in the simulated and actual results (the load shed against each hour). When bagging algorithm applied on the same data the results significantly improved which illustrates the superiority of the algorithm.

The hourly data set of one complete day consists of P_G, P_L, df/dt and load shed against each hour. For different operating scenarios of power system of Pakistan like contingencies and overloading ANN performs accurately for the given training data, but when the training data set changes for the next hour the ANN faces some problems like over-fitting or under-fitting. These issues may disturb the system accuracy during shedding the load or may disrupt the power system stability. These problems must be solved to shed the same amount of load that is required.

To overcome these problems, and thus increasing the system accuracy and also enhancing the generalization ability of ANN, the Bagging algorithm has been used in which the prediction does not suffer the problem to opt to new data set.

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