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Optimal Power Generation in Energy-Deficient Scenarios Using Bagging Ensembles

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ABSTRACT This paper presents an improved technique for optimal power generation using ensemble artificial neural networks (EANN). The motive for using EANN is to benefit from multiple parallel processor computing rather than traditional serial computation to reduce bias and variance in machine learning. The load data is obtained from the load regulation authority of Pakistan for 24 hours. The data is analyzed on an IEEE 30-bus test system by implementing two approaches; the conventional artificial neural network (ANN) with feed-forward back-propagation model and a Bagging algorithm. To improve the training of ANN and authenticate its result, first the Load Flow Analysis (LFA) on IEEE 30 bus is performed using Newton Raphson Method and then the program is developed in MATLAB using Lagrange relaxation (LR) framework to solve a power-generator scheduling problem. The bootstraps for the EANN are obtained through a disjoint partition Bagging algorithm to handle the fluctuating power demand and is used to forecast the power generation. The results of MATLAB simulations are analyzed and compared along with computational complexity, therein showing the dominance of the EANN over the traditional ANN strategy that closed to LR.

INDEX TERMS Artificial neural networks, bootstrap aggregation, bagging algorithm, disjoint partition, economic dispatch, optimal power generation.

I. INTRODUCTION

Interconnected power systems are foundations on which modern civilization rests. The economy of any developing country, like Pakistan, is based on the provision of cheap and abundant sources of electrical energy. Thus, optimal power generation using better scheduling of available generating units is essential to supply economical energy to consumers and thus enhance the sustainability of power systems.

The foremost economic influences on any modern power system are the cost of generating active power and reducing system reactive power flow. In practical power systems, hundreds of generating units run in parallel to meet the load demand. So, it is essential to run power plants economically.

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The economic operation of a power plant is a sub-problem of the unit commitment (UC) [1]. The generation scheduling problem for energy deficient scenarios or large UC has become the subject of considerable discussion during the last few years [2]–[6]. Mathematical programming and heuristic methods have been extensively used to define UC for power plants [2], [5].

Economic dispatch (ED) problems have been investigated through various heuristic, intelligent and hybrid techniques such as; evolutionary programming (EP) [7], artificial bee colony algorithm (ABC) [8], particle swarm optimization (PSO) [9], hopfield neural network with quadratic programming (HNN-QP) [10] and some others are summarized in the Table 1. Although the discussed methods are useful in optimizing the production cost for ED problems, but does not converge rapidly [11], [12]; particularly in the case when generation schedule is on an hourly basis to overcome the

TABLE 1. Economic dispatch investigation via heuristic, intelligent and hybrid techniques.

Technique	Methods	Constraints
Artificial Intelligence	Improved PSO [12]	Valve point loading effect
Artificial Intelligence	Differential Evaluation (DE) [13]	Valve point loading effects
Heuristic	Dynamic Programming [14]	Non-smooth cost functions and transmission losses
Hybrid	EP and sequential quadratic programming (SQP) [15]	Non-smooth incremental fuel cost function
Heuristic	Gradient projection method [16]	Spinning reserves and ramp rate constraints
Hybrid	EP-PSO-SQP [17]	Prohibited operating zones
Artificial Intelligence	Hopfield Neural Network [18]	Parallel processing
Hybrid	HNN-QP [10]	Transmission Line losses

power shedding in an under-developed country like Pakistan. Artificial neural networks (ANN) attracted attention to solving ED problems optimally as it has high computational speed, a high convergence rate even for short intervals and self-error correction ability, unlike other intelligence techniques [19], [20].

In [19], a dynamic neural network is employed to solve the combined economic and emission dispatch problem with fast convergence. Fukuyama *et al.* employed neural network techniques to solve the ED problem considering security constraints [21]. Liang applied neural network based re-dispatch method for solving the spinning reserve constrained ED problem [18]. Chan *et al.* presented an artificial neural network and genetic algorithm to optimize the load distribution for a chiller plant [20]. However, ANN alone may undergo premature convergence and a tendency to be trapped at a local optimum [22], which results in a significant error in learning. The error in ANN learning is reduced by using bootstrap aggregation [23], which gives better precision, improved generalization, and prediction along with reduced machine learning errors like bias and variance. Thus, a research objective is to overcome the mentioned shortcomings and to explore economic-dispatch optimally using Lagrange relaxation with an enhanced neural network (NN) by adopting a bootstrap aggregation algorithm for energy deficient scenarios. Such an enhanced neural network is termed an ensemble of artificial neural networks (EANN).

The proposed neural network ensemble approach is applied to the IEEE 30-bus system and evaluated for a day on an hourly basis. There are six generators and twenty load buses. The constraints considered are generator limits, transmission line losses, and the power demand. The input data for the neural network is described by a 20 × 24 matrix which gives the power demand distribution among 20 buses during 24 hours. The target data for the neural network is via a 6 × 24 matrix that describes the generation of six generators for a day. Multiple neural networks are incorporated by applying a Bagging algorithm to create an ensemble of neural networks. The predictions from the individual neural networks are aggregated by an algebraic method to get the ensembled output. Finally, a comparison between ANNs and EANNs show the predominance of the proposed method.

The remainder of the paper is organized as follows: problem formulation of economic dispatch is described in section II. In section III, system description and power dispatch is discussed. In sections IV and V, the artificial neural network with feed-forward back-propagation model and ensemble of artificial neural network with Bagging are presented, respectively. Simulation results are presented in section VI, with conclusions then drawn.

II. ECONOMIC DISPATCH PROBLEM FORMULATION

Thermal power plants operate in parallel to fulfill the demand of different load centers. Typically, cost of power generation is not the same for each generating unit as this depends upon the operating efficiency and fuel cost of a unit, and transmission losses. For optimal generation, minimization of the cost of real power generated from all units must be achieved. The amount of fuel consumed by a generating unit, and in turn the fuel cost, depends upon the produced power at a specific operating point as shown in Fig. 1 [1].

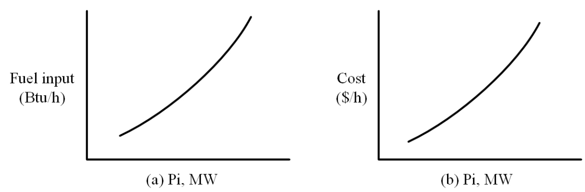

FIGURE 1. (a) Heat-rate curve (b) Fuel-cost curve.

A generating unit is assumed to have a quadratic cost function in terms of its produced active power [1]:

$$C_{Gi} = \alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 \tag{1}$$

where C_{Gi} is the cost of the i^{th} power generating unit, P_{Gi} is the real power generated by the i^{th} generating unit, and α_i, β_i and γ_i are the cost coefficients.

The constraint equations for optimal generation are given by (2), (3) and (4):

$$\sum_{i=1}^{n} P_{Gi} = P_D + P_L \tag{2}$$

where 'n' is the total number of generating plants, P_D is the load demand, and P_L is the total transmission loss.

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_{Gi}B_{ij}P_{Gj} + \sum_{i=1}^{n} B_{0i}P_{Gi} + B_{00} \tag{3}$$

Transmission losses as a function of generator powers are expressed through B-coefficients and given by Kron's loss formula is described in [24]:

Where P_{Gi} and P_{Gj} are real power generation at the i^{th} and j^{th} generating units, respectively. B_{ij} and B_{0i} are the loss coefficients (constant for certain conditions), and B_{00} is a loss constant. However, the generation limits of units are given by:

$$P_{Gi(min)} \leq P_{Gi} \leq P_{i(max)} \tag{4}$$

From the Lagrange method, the overall objective function, including constraint limits and transmission line losses, becomes:

$$F = C_t + \lambda(P_D + P_L - \sum_{i=1}^{n} P_{Gi}) + \sum_{i=1}^{n} \mu_{i(max)}(P_{Gi} - P_{Gi(max)}) + \sum_{i=1}^{n} \mu_{i(min)}(P_{Gi} - P_{Gi(min)}) \tag{5}$$

The constant $\mu_{i(max)} = 0$ when $P_i < P_{i(max)}$ and $\mu_{i(min)} = 0$ when $P_i > P_{i(min)}$. These constants play an active role when constraints are violated, specifically $P_i > P_{i(max)}$ and $P_i < P_{i(min)}$. C_t and $\lambda$are the total cost and incremental cost of all generating units, respectively, and C_t is defined as:

$$C_t = \sum_{i=1}^{n} C_{Gi} \tag{6}$$

The following conditions hold if the function 'F' is to be a minimum:

$$\frac{\partial F}{\partial P_{Gi}} = 0 \quad \frac{\partial F}{\partial \lambda} = 0 \tag{7}$$

$$\frac{\partial F}{\partial \mu_{i(max)}} = P_{Gi} - P_{Gi(max)} = 0 \tag{8}$$

$$\frac{\partial F}{\partial \mu_{i(min)}} = P_{Gi} - P_{Gi(min)} = 0 \tag{9}$$

If P_{Gi} is within its limits, then $\mu_{i(min)}$ and $\mu_{i(max)}$ are zero and the Lagrange (λ) of (7) is:

$$\frac{\partial C_t}{\partial P_G} + \lambda(0 + \frac{\partial P_L}{\partial P_{Gi}} - 1) = 0 \tag{10}$$

The incremental transmission line losses are incorporated as the partial derivative of (3) with respect to the real power generation P_{Gi}:

$$\frac{\partial P_L}{\partial P_{Gi}} = 2\sum_{j=1}^{n} B_{ij}P_{Gj} + B_{0i} \tag{11}$$

Substituting (1) and (11) into (6) and simplifying gives:

$$\left(\frac{\gamma_{Gi}}{\lambda} + B_{ii}\right) P_{Gi} + \sum_{\substack{j=1 \\ j \neq 1}}^{n} B_{ij}P_{Gj} = \frac{1}{2}\left(1 - B_{0i} - \frac{\beta_{Gi}}{\lambda}\right) \tag{12}$$

Equation (12) for all units, results in matrix form, equation (13), for all linear equations.

Solving (13) gives ED for an estimated value of λ. An iterative approach is employed to find optimal generation, until all constraints are satisfied, the P_G matrix from (13) is calculated and the total cost of generation is obtained from (6). More details of the Lagrange method can be found in [1].

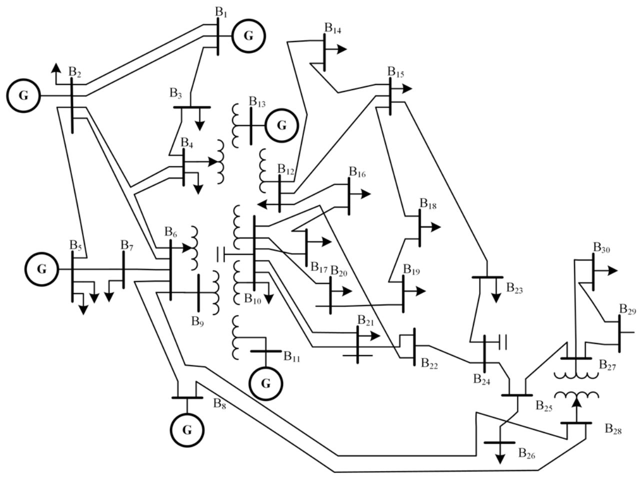

FIGURE 2. Single line diagram of the IEEE 30-bus test system.

TABLE 2. Cost function parameters of the generators.

Gen. Bus	P_{min} (MW)	P_{max} (MW)	α	β (MW)	γ (MWh)
Bus -01	50	200	0	2.00	0.00375
Bus -02	20	80	0	1.75	0.01750
Bus -05	15	50	0	1.00	0.06250
Bus -08	10	35	0	3.25	0.00834
Bus -11	10	30	0	3.00	0.02500
Bus -13	12	40	0	3.00	0.02500

$$\begin{pmatrix} \frac{\gamma_{G1}}{\lambda} + B_{11} & B_{12} & \cdots B_{1n} \\ B_{21} & \frac{\gamma_{G2}}{\lambda} + B_{22} & \cdots B_{2n} \\ \vdots & & \ddots \vdots \\ B_{n1} & \vdots & \\ & B_{n22} & \cdots \frac{\gamma_{Gn}}{\lambda} + B_{nn} \end{pmatrix} \begin{pmatrix} P_{G1} \\ P_{G2} \\ \vdots \\ P_{Gn} \end{pmatrix} = \frac{1}{2} \begin{pmatrix} 1 - B_{01} - \frac{\beta_{G1}}{\lambda} \\ 1 - B_{02} - \frac{\beta_{G2}}{\lambda} \\ \vdots \\ 1 - B_{0n} - \frac{\beta_{Gn}}{\lambda} \end{pmatrix} \tag{13}$$

III. SYSTEM DESCRIPTION AND POWER DISPATCH

Lagrange relaxation and the ensembled artificial neural network (EANN) are applied on the IEEE 30-bus system, as shown in Fig. 2, to not only solve the ED problem optimally but also to boost and enhance system learning. Generation scheduling is done on an hourly basis to overcome the power shedding. EANN is explained in detail in section 5.

The beta loss coefficients matrix 'B_{ij}' of order 6 × 6 for the IEEE 30-bus system with 6 generators is obtained from the

TABLE 3. Optimal power generated by employing lagrange relaxation method for supervised learning of the ANN.

Sr. No.	Bus_1, P_1 (MW)	Bus_2, P_2 (MW)	Bus_3, P_3 (MW)	Bus_4, P_4 (MW)	Bus_5, P_5 (MW)	Bus_6, P_6 (MW)	Total Loss (MW)	Total Power Gen. (MW)	Cost $/h
1	51.01	20.00	15.00	10.00	10.0	12.0	0.01	118.01	288.20
2	58.01	20.00	15.00	10.00	10.0	12.0	0.01	125.01	305.14
3	84.71	25.30	15.00	10.00	10.0	12.0	0.02	157.02	386.33
4	118.4	32.53	15.11	10.00	10.0	12.0	0.05	198.04	499.68
5	200.0	59.44	22.65	34.81	16.6	16.6	0.12	350.11	1007.2
6	200.0	80.00	47.14	35.00	30.0	40.0	0.15	432.14	1384.0
7	200.0	66.82	24.71	35.00	21.7	21.8	0.13	370.15	1086.5
8	170.9	43.81	18.27	10.00	10.0	12.0	0.08	265.08	706.48
9	155.2	40.44	17.33	10.00	10.0	12.0	0.07	245.08	641.90
10	124.6	33.87	15.49	10.00	10.0	12.0	0.05	206.05	522.90
11	117.6	32.36	15.06	10.00	10.0	12.0	0.04	197.04	496.70
12	200.0	51.49	20.42	18.14	11.0	12.0	0.11	313.11	870.50
13	200.0	59.73	22.73	35.00	16.8	16.8	0.12	351.18	1011.0
14	200.0	50.75	20.21	16.60	10.5	12.0	0.11	310.11	859.98
15	200.0	56.29	21.76	28.23	14.4	14.4	0.11	335.11	950.60
16	182.7	46.34	18.98	10.00	10.0	12.0	0.10	280.09	756.40
17	102.0	29.01	15.00	10.00	10.0	12.0	0.03	178.02	443.06
18	147.4	38.76	16.86	10.00	10.0	12.0	0.06	235.06	610.50
19	123.8	33.71	15.44	10.00	10.0	12.0	0.04	205.04	520.00
20	153.7	40.10	17.23	10.00	10.0	12.0	0.07	243.06	635.60
21	181.9	46.17	18.93	10.00	10.0	12.0	0.09	279.09	753.00
22	156.8	40.78	17.42	10.00	10.0	12.0	0.07	247.07	648.30
23	53.01	20.00	15.00	10.00	10.0	12.0	0.01	120.01	293.00
24	67.41	21.59	15.00	10.00	10.0	12.0	0.01	136.01	332.33

power flow calculations using the Newton-Raphson method and is given by (14), as shown at the bottom of this page, [23]. Other loss coefficients, B_{0i} and B_{00}, are also presented.

The cost function parameters of the six generators in the IEEE 30-bus system are given in Table 2. [25].

α, β and γ are the cost coefficients in Table 2. The column 'Gen. Bus' give the bus to which a generator is connected. The maximum generation from all the six generators is 435 MW while the minimum generation is 117 MW. The daily load data is obtained from the National Power Control Centre (NPCC) of Pakistan and is shown in Fig. 3, and is used for optimal generation.

Optimal generation for the IEEE 30-bus system is obtained by applying the Lagrange method for supervised learning of the ANN, as given in Table 3.

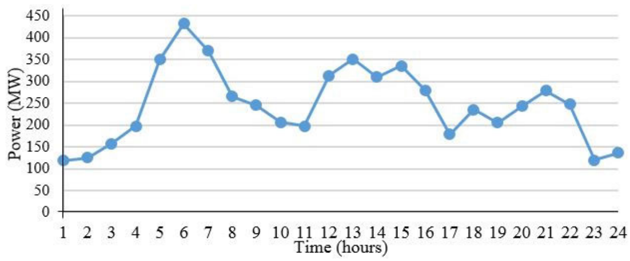

FIGURE 3. Daily load curve obtained from NPCC-Pakistan.

IV. FEED-FORWARD BACK-PROPAGATION NEURAL NETWORK

The artificial neural network is derived from the biological neural network (BNN). ANNs are not as complex but the data handling method is similar to the BNN. The organization of an ANN is shown in Fig. 4. It is an interconnected system that is capable of quickly solving highly non-linear issues.

A multilayer feed-forward back-propagation neural network is employed here instead of a single layer neural network.

Each layer is associated with the neighboring layer which means all the neurons in each layer are connected to all the neurons in a neighboring layer, as shown in Fig. 5 for a three-layer feed forward back-propagation NN. The first

$$
\begin{aligned}
B_{ij} &= \begin{pmatrix}
2.18E-04 & 1.03E-04 & 9.00E-06 & -1.00E-05 & 2.00E-06 & 2.70E-05 \\
1.03E-04 & 1.81E-04 & 4.00E-06 & -1.50E-05 & 2.00E-06 & 3.00E-05 \\
9.00E-06 & 4.00E-06 & 4.17E-04 & -1.31E-04 & -1.53E-04 & -1.07E-04 \\
-1.40E-04 & -1.50E-05 & -1.31E-04 & 2.21E-04 & 9.40E-05 & 5.00E-05 \\
2.00E-06 & 2.00E-06 & -1.53E-04 & 9.40E-05 & 2.43E-04 & 0.00E+00 \\
2.70E-05 & 3.00E-05 & -5.00E-05 & 5.00E-04 & 0.00E+00 & 3.58E-04
\end{pmatrix} \\
B_{0i} &= [\,1.40E-05\,] \\
B_{00} &= [\,-3.00E-06 \quad 2.10E-05 \quad -5.60E-05 \quad 3.40E-05 \quad 1.50E-05 \quad 7.80E-05\,]
\end{aligned} \tag{14}
$$

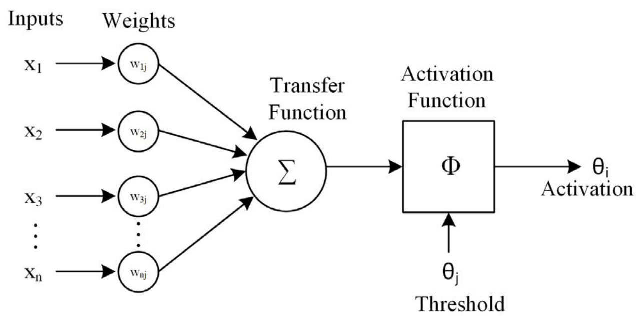

FIGURE 4. Basic construction of an ANN.

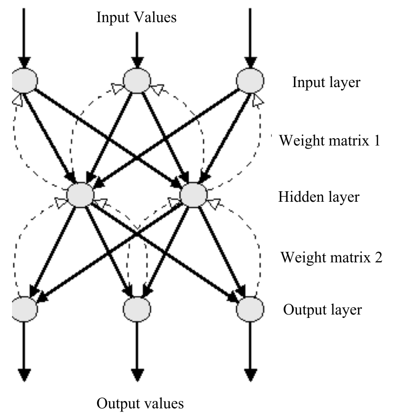

FIGURE 5. A three-layer feed-forward back-propagation neural network.

layer is the input layer, the last layer is the output layer and the intermediate layer is termed a hidden layer. The number of hidden layers and selection of neurons affects the results [26]. Because of this composition, a multilayer feed forward neural network is trained (by back-propagation) to learn non-linear patterns in linear space. Back-propagation is a form of supervised training, where a network is provided with both sample inputs and target values.

The input values are fed directly to the output layer via a weight matrix as in Fig. 4. Inputs (x_1, $x_2 \ldots$, x_N) and their respective weights (w_{1j}, w_{2j}, ..., w_{nj}) are sent to the transfer functions (TF) of the hidden layers. Activation function O_j is added to TF to check whether or not the output is produced through comparison with the threshold value θ_j. TF governs the threshold values. The difference between the ANN and desired values gives the error, which controls ANN training. Thus, the error is fed-back to re-set the weights, until the ANN outputs resemble the desired values. Neural network training is a repetitive process. Repetition continues until the stopping criteria is met, namely a specified mean square error (MSE).

In this study, the developed supervised neural network is trained using the parameters in Table 4. The input to the neural network is power demand which is divided among 20 load busses while the output of the neural network is the power generated on 6 busses, obtained from the Lagrange relaxation method. This generated power fulfills the system constraints and hence optimizes generation cost.

TABLE 4. Training parameter of a single neural network.

Parameters	Specifications
Input Neurons	20 , load demand at 20 busses
Output neurons	6, generated power at 6 busses
Hidden layers	10
Neural network topology	Feed-forward Back-propagation
Neural network training Algorithm	Levenberg–Marquardt Back Propagation (LMBP)
Adaptation learning function	Gradient Descent
Activation function for layer 1	Transig
Activation function for layer 2	Purelin
Performance function	Mean squared error (MSE)
Data division of original data set	70% training set,15% validation set,15% test set
Maximum number of epoch	1000
Learning rate	0.010
Maximum validation failures	6.000
Error threshold	0.001
Weight update method	Batch

V. ENSEMBLE OF ARTIFICIAL NEURAL NETWORK

A. BOOTSTRAP AGGREGATION

Artificial neural network performance is satisfactory for specified values but when the data values constantly vary, as in this study, in hours, then the ANN experiences under or over fitting because of reduced generalization ability. Difference between the anticipated and actual values occurs even after several ANN times training periods. This error occurs because of the flawed learning process. The three main error factors in learning are: variance, noise and bias [26].

$$\text{Error} = \text{Variance} + \text{Noise} + \text{Bias} \tag{15}$$

Large variance is the reason of over fitting and large bias causes under fitting of the data. Generalization of the ANN to adjust with the new values increases variance and bias are reduced to a minimum, and then the data-set will not undergo under and over fitting. Additionally, the percentage change in input and output values during the learning process decreases, hence prediction improves.

Thus, bootstrap aggregating is employed to refine and enhance the precision and stability of the machine learning algorithm, ANN. It reduces variance and bias which helps avoid over and under fitting, respectively [26], [27]. The Bagging structure is shown in Fig. 6. Bootstrap aggregating is also called bagging and is classified as follows:

1. Disjoint partitions
2. Small bags
3. No replication small bags
4. Disjoint bags

Disjoint partitions bagging is implemented here, by using MATLAB, as it is more effective and thus outperform other

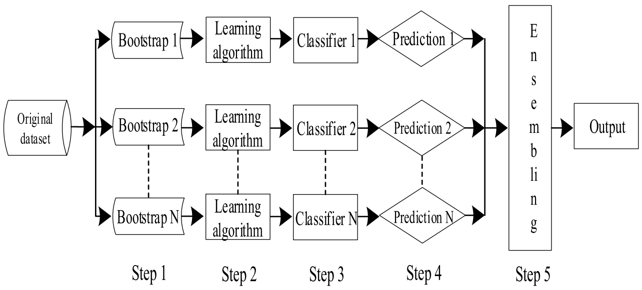

FIGURE 6. A typical idea for the ensemble of neural networks.

A	B	C	D	E	F	G	H	I	J	K	L

FIGURE 7. Original dataset D.

A	B	C	D

E	F	G	H

I	J	K	L

FIGURE 8. Disjoint partitions (3 bootstraps).

techniques [28]–[30]. To understanding disjoint partitions, assume the data set D as shown in Fig. 7. A subset is formed by random selection of elements from the defined data set without replication. For this, each certain element is taken only once as shown in Fig. 8. These subsets are called Bootstraps.

B. PROPOSED METHOD

The proposed method for optimal generation uses the following steps:

1. Real data set generation
2. ANN design
3. Bootstrap design

STEP 1: The employed dataset (power demand against each hour) is from the National Power Control Centre (NPCC) in-charge of controlling and monitoring electric power flow in Pakistan's power system, shown in Fig. 3. This dataset is tested on the IEEE 30-bus system. The worst-case scenario of zero spinning reserve is considered for optimal power generation.

STEP 2: The initial step for the formation of the ANN classifier, is the selection of the target and input datasets. The input data for the neural network is power demand, a 20×24 matrix, among 20 buses during 24 hours. The target values for the NN are a 6×24 matrix that describes the generation of six generators for a day. The target data is obtained from the Lagrange method for supervised learning. The biases and weights of each neuron are randomly generated. The specifications in Table 4 are used for ANN classifiers.

The training of the classifiers employs the Levenberg–Marquardt Back Propagation algorithm, for fast convergence with reduced error. Gradient descent is employed to reset the bias and weights in the adaption learning process since the convergence of 'batch gradient descent with momentum' is fast enough for feed-forward networks. Gradient descent also reduces the mean square error (MSE) [31]:

$$\mathrm{MSE} = \frac{1}{n}\sum_{I=1}^{n} e(i)^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - z_i)^2 \tag{16}$$

where n is the number of samples, x_i is the prediction and is the target value.

The data is divided as: 70% is used for training, 15% is for validation to reduce over-fitting, and the remaining 15% is used to predict the ANN final value.

STEP 3: Several ANN training sessions reveal a deviation from the target value; mainly when the input dataset varies abruptly. So Hypothetical 30 bootstraps are created with different Network topology and Training Algorithms. Bootstraps re-sample the initial data before ANN training to improve the generalization ability. The Bootstrap ANN (EANN) result is closer to the target with reduced percentage error. EANN and ANN outputs are compared and presented in the result section.

The proposed methodology is described in the algorithm as:

1. Initialization of the original training data set D for $i = 1, 2, 3 \ldots n$.
2. Formation of a fresh data set Di called bootstrap of the same size D by arbitrary choosing some data of training samples from the set D (several samples can be selected recurrently, and some of the samples may not be selected at all, i.e. with or without replacement).
3. Training and learning of a specific classifier Ni of Di by some machine learning procedures which depend on the actual training set Di.
4. Combining the predictions of n classifiers by taking an average.

The flow chart of optimal power generation, using a Bagging/Bootstrap algorithm, is shown in Fig. 9 and further explained via following algorithm:

1. START
2. Define system for economic dispatch:
   a. IEEE 30 bus system which includes 6 generator buses, 20 load busses
3. Obtained the data for economic dispatch:
   a. Sum of power demands at 20 load busses at a particular hour from daily load curve
   b. Beta loss coefficients matrix (Transmission losses) obtained after Load Flow Analysis
   c. Generator maximum and minimum power generated limits in MW including cost coefficients
4. Find out the dispatch using Lagrange Relaxation (LR) method in MATLAB:
   a. Active power generation in MW at 6^{th} generator busses to fulfil the daily load demand
   b. The cost in $/hr to fulfil power demands
5. Prepared the N number of Neural Networks in MATLAB:

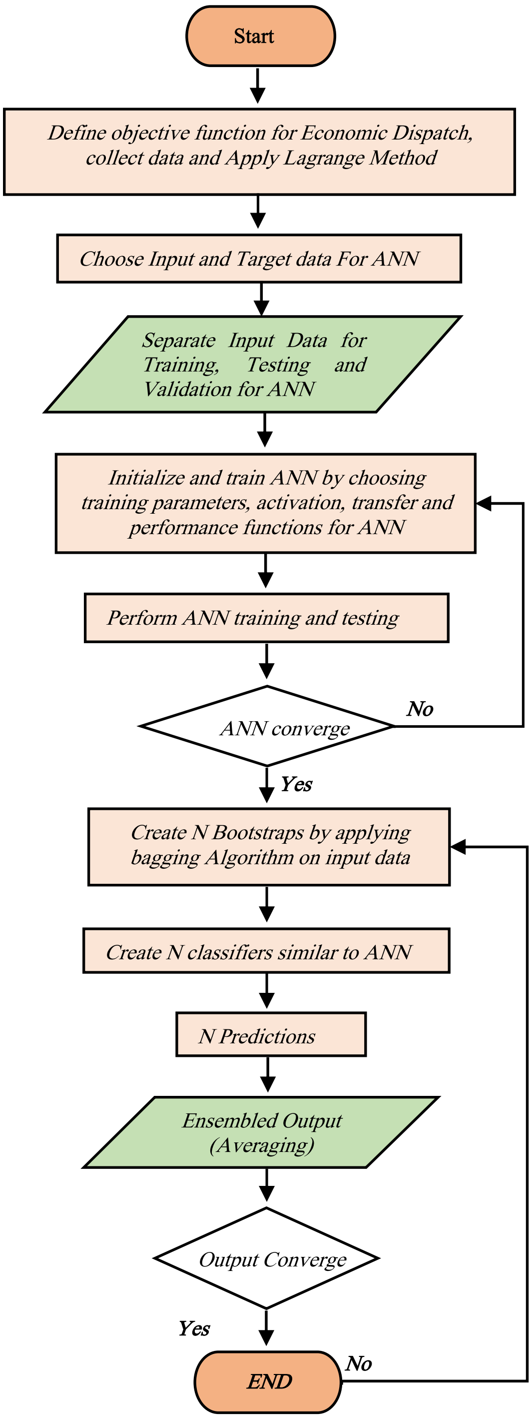

FIGURE 9. **Flowchart of ensemble neural network using bootstrap aggregating.**

a. For each Neural Network, selection of the input data set i.e. bootstraps of order 20*24
b. Selection of target data set of order 6*24 obtained from LR

6. Setting the parameters of Neural Network:
   a. Data division, hidden layers, number of neurons in the hidden layers, training function, performance function etc.
7. Separate training, testing and validation data for Neural Network
8. Run ANN
9. Check ANN converge. If YES, go to step 10. Otherwise go to step 6
10. Create N Bootstraps by applying bagging algorithm on input data
11. Create N classifiers similar to ANN
12. Aggregating the Ensemble Neural Network to get final prediction
13. Check EANN converge. If YES, go to step 14. Otherwise, go to step 10
14. Print the output results
15. END

VI. SIMULATION RESULTS

The performance of ANN with regression analysis, comparison of ANN prediction with target data, the formation of an ensemble of neural networks with bootstrap aggregation, and its influence on the predicted values along with regression analysis and error histograms, are discussed in this section. The optimal solution for the IEEE 30-bus system in Table 3, is obtained by applying the Lagrange method.

The training window is presented in appendix, Fig. 10, representing the mapping of IEEE 30-bus system into the neural network.

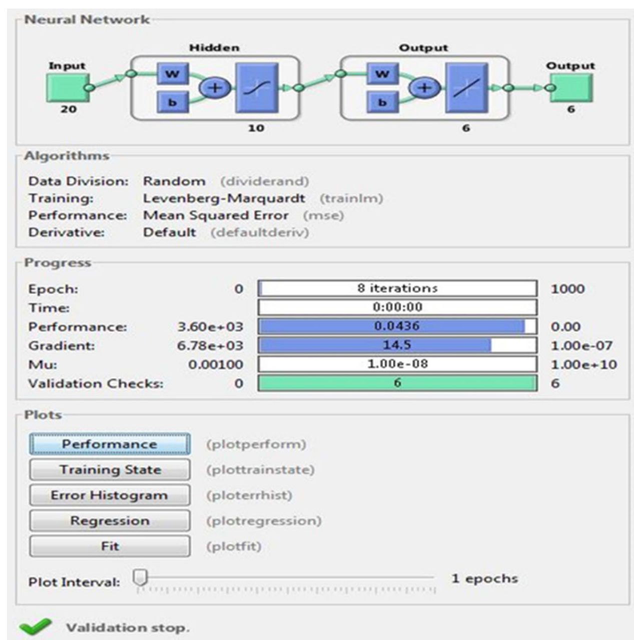

FIGURE 10. **Training window of the artificial neural network.**

The data division is 'Random' and Levenberg-Marquardt is selected as a training method which is further employed with MSE performance functions. This is the most effective training method for feed-forward neural networks with respect to the training precision [32].

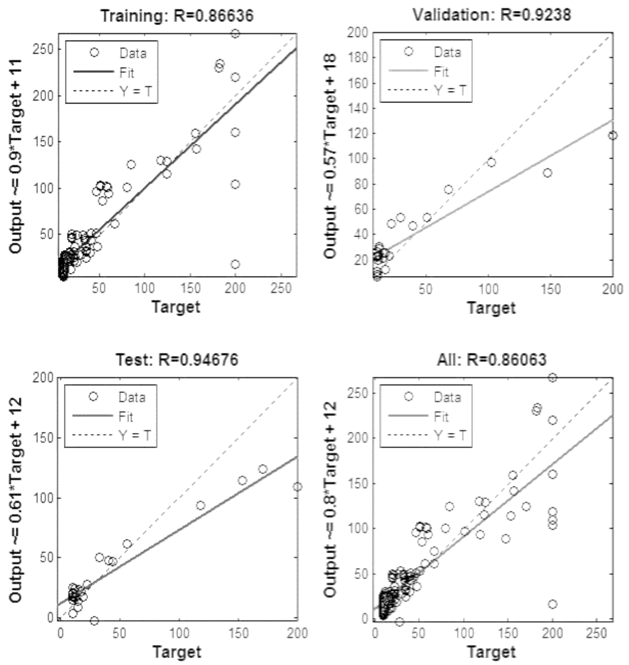

FIGURE 11. Regression plots obtained during the training of artificial neural network.

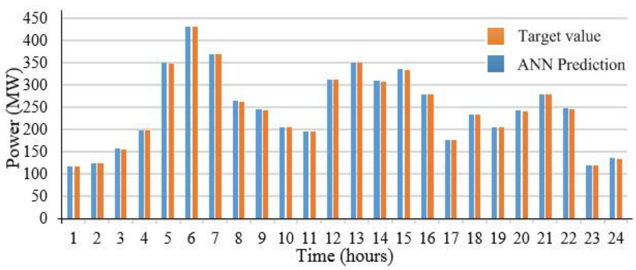

FIGURE 12. Comparison between target data and ANN prediction.

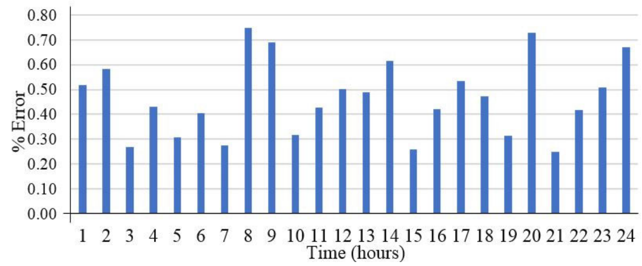

FIGURE 13. Error histogram of target and ANN predictions.

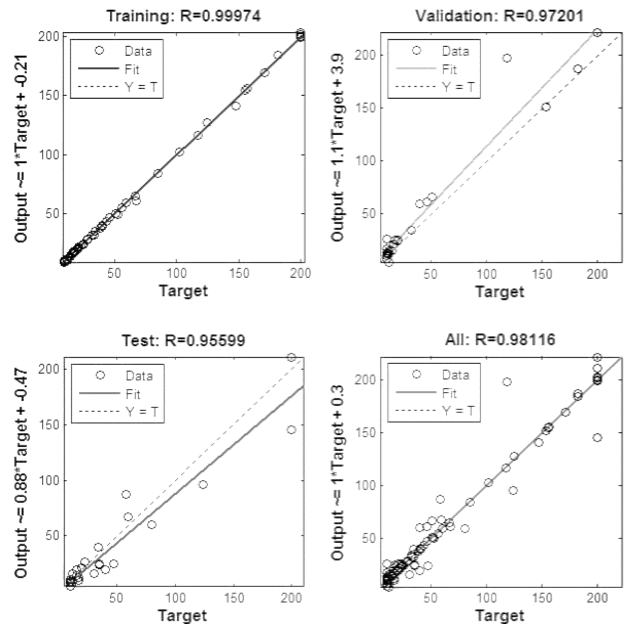

FIGURE 14. Regression plots obtained during the training of ensembled artificial neural network.

The relation between the anticipated value (target data) and the actual value (ANN output) is shown in the regression plots of Fig. 11. The regression plots (R) gives the relation between the desired and actual output for training, testing, validation, and overall data. Ideally, data division (circles) should be on the line for good generalization, representing $y = x$, which shows output is equal to the target value and thus 'R' is unity. The ANN value at $R = 0.86$ does not match with the target value because of the load change each hour which indicates the lack of good generalization ability of ANN.

Comparison of the target value (real power generation) and the ANN prediction is shown in the Fig. 12. The comparative analysis shows that the ANN forecast does not match precisely with the actual power demand resulting in the sub-optimal and uneconomical dispatch. The closer difference is represented by the error histogram of ANN as shown in the Fig. 13.

The error histogram in Fig. 13 shows the percentage error between the target power generation and the EANN forecast against each hour of the day. The maximum percentage error is at the 8^{th} hour that is 0.747% and the minimum percentage change is at 21^{st} hour, which is 0.247%. Although the percentage error is small against each hour, but the application of EANN reflects the significant improvement in the percentage error, better generalization ability and faster convergence with the reduction in bias and variance under the same training parameters and operating conditions. The ANN has trained again for the re-sampled data to enhance its ability and to adapt to new values speedily, after creating the Bootstrap data by using the Bagging algorithm for the formation of EANN. The Bagging algorithm to produce Bootstraps is implemented in MATLAB by following the steps described in section V.

The trials are done 50 times, and average value is taken to analyze the results. It is shown in the results that the neural network ensembles make fewer errors than the simple ANN alone. The regression analysis of EANN is provided in the Fig. 14. $R = 0.98$ shows the improved performance of the classifiers. The data division is so aligned that $y = x$ and have a very little deviation in training, validation and test data sets as compared to ANN.

TABLE 5. Accuracy percentage of EANN.

Time (Hours)	Power Demand (MW)	Actual Gen. (MW)	ANN Prediction (MW)	EANN Prediction (MW)	EANN % Accuracy
1	118	118.01	117.4	117.81	99.83
2	125	125.01	124.28	124.81	99.84
3	157	157.02	156.6	156.79	99.85
4	198	198.05	197.2	197.69	99.82
5	350	350.12	349.04	349.75	99.89
6	432	432.15	430.4	431.49	99.85
7	370	370.13	369.1	369.5	99.83
8	265	265.08	263.1	264.59	99.82
9	245	245.07	243.38	244.58	99.8
10	206	206.05	205.4	205.8	99.88
11	197	197.04	196.2	196.75	99.85
12	313	313.11	311.54	312.65	99.85
13	351	351.12	349.4	351.01	99.97
14	310	310.11	308.2	309.8	99.9
15	335	335.11	334.24	334.6	99.85
16	280	280.1	278.92	279.71	99.86
17	178	178.03	177.08	177.73	99.83
18	235	235.06	233.95	234.8	99.89
19	205	205.04	204.4	204.77	99.87
20	243	243.07	241.3	242.8	99.89
21	279	279.09	278.4	278.6	99.82
22	247	247.07	246.04	246.7	99.85
23	120	120.01	119.4	119.83	99.85
24	136	136.02	135.1	135.81	99.85

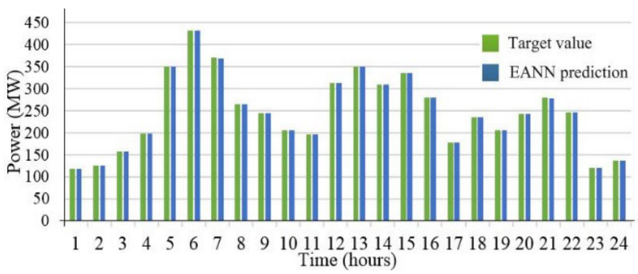

FIGURE 15. Comparison between target data and EANN prediction.

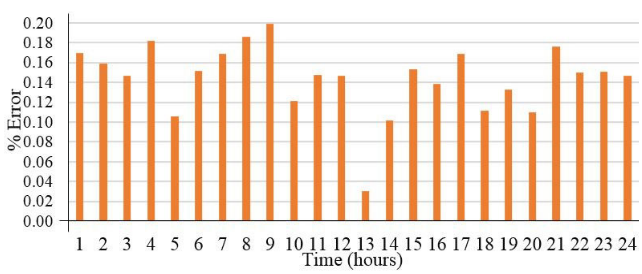

FIGURE 16. Error histogram of target and EANN predictions.

Comparison of the target value and the EANN prediction is shown in the Fig. 15. The EANN prediction is more close to the target value (power generation) incorporating better generalization ability as than ANN. The percentage change of the EANN is shown via error histogram of Fig. 16.

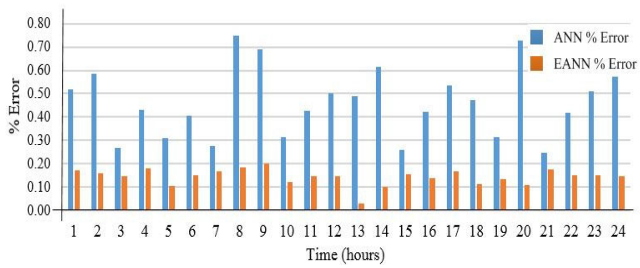

FIGURE 17. Comparison of percentage errors between ANN and EANN.

It is noticed that the maximum percentage error is at the 9th hour that is 0.199% and the minimum percentage error is at the 13th hour, which is 0.031%. The significant reduction in the percentage error shows the superiority of EANN over ANN with reduced bias and variance due to the inherent property of the Bootstrap aggregation.

Fig. 17 shows the comparison of percentage errors between ANN and the proposed EANN. The comparison graphically portrays the dominance of the Bootstraps algorithm over the conventional ANN.

To summarize the results of ANN and EANN, the accuracy percentage is measured and is shown in the Table 5.

A. VALIDATION OF PROPOSED ALGORITHM

As the load data could change day by day, so the proposed algorithm is implemented on seven days' data sets.

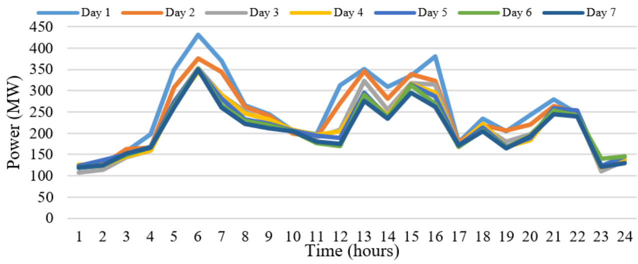

FIGURE 18. Weekly load curve obtained from NPCC-Pakistan.

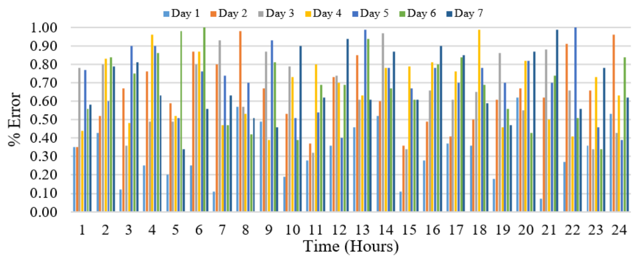

FIGURE 19. Error histogram of ANN predictions for a week.

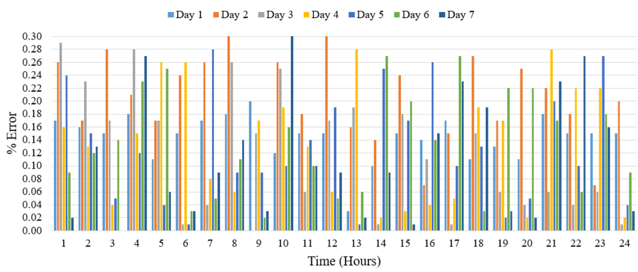

FIGURE 20. Error histogram of EANN predictions for a week.

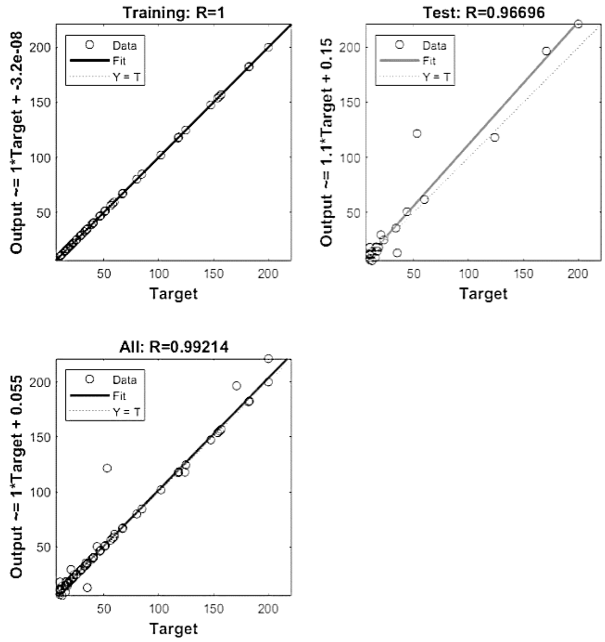

FIGURE 21. Regression plots obtained during the training of ensembled artificial neural network for a week.

The weekly load curve is shown in Fig. 18 for twenty-four hours.

The error analysis of ANN forecast for a full week is shown in the Fig. 19. It is noted that the error is 1% percent, resulting in the sub-optimal and uneconomical dispatch.

The error analysis of EANN forecast for a full week is shown in the Fig. 20 of appendix and noted that the error ranges from 0.0%-0.3%, which is far less than the errors produced by ANN. Thus, the proposed algorithm is valid for the variation in datasets.

The regression analysis of EANN during a week is provided in the Fig. 21. R = 0.99 shows the significant improvement in the proposed algorithm when the dataset is varied.

B. COMPARATIVE STUDY

To check the accuracy of the proposed method, we utilized four standard performance measures: Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) and Mean Error Deviation (MAD) on various persistence models. The MSE is discussed before while others performance measures are defined as:

$$\mathrm{MAD} = \frac{1}{n}\sum_{i=1}^{n}(x_i - z_i) \tag{17}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - z_i)^2} \tag{18}$$

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{(x_i - z_i)}{x_i}\right| \tag{19}$$

The errors have been computed independently for training, testing and the Validation data. Their values are important indicators of the practical usefulness of the forecasting framework. The performance of EANN is compared with other state-of-the-art machine learning algorithms namely Artificial Neural Network-Multilayer perceptron (ANN-MLP), Support vector machines (SVM), Radial basis function (RBF). Table 6 shows the performance metric of these models.

The results show that using an EANN resulted in higher accuracy than using other classifiers, for all four performance metric. The improvements in terms of MAPE for the validation data, averaged over all case studies are 0.14, 0.46, 0.95 and 0.87 for EANN, ANN, SVM, RBF respectively. The computational cost of training an ensemble is higher than for a single ANN but suitable for both offline and online practical applications.

C. COMPUTATIONAL COMPLEXITY ANALYSIS

EANN is a bootstrapping technique, mainly influenced by the learning phase. The resampling step, along with training

TABLE 6. Models performance metric.

		EANN	ANN	SVM	RBF
Testing 15%	MAD	4.26	3.45	5.2	4.53
	MSE	2.15	3.48	3.09	2.97
	RMSE	1.47	1.87	1.76	1.72
	MAPE	1.221	2.24	3.54	3.86
Training 15%	MAD	2.33	5.65	4.23	3.89
	MSE	1.65	2.54	3.2	3.18
	RMSE	1.28	1.59	1.79	1.78
	MAPE	0.97	1.21	1.54	2.16
Validation 70%	MAD	0.35	1.11	2.31	1.06
	MSE	0.14	1.44	1.74	1.65
	RMSE	0.37	1.2	1.32	1.28
	MAPE	0.14	0.46	0.95	0.87

TABLE 7. Computational complexity analysis.

	Training	Search	Inference
EANN	σ(B(N+R))	σ(N)	σ(B)
ANN	σ(N)	σ(N)	σ(N)
SVM	σ(N)	$\sigma(2^N)$	σ(N)

of the classifier for a certain number of bags leads to an expensive approach than a simple ANN and SVM. Three phases are considered, distinguished as training, search of the optimal ensemble and inference, to show computational complexity of ensemble techniques. Let N represents the number of classifiers, R represents number of replacements and B represents number of bags. If σ represents the time complexity in terms of learning a computational complexity of EANN, ANN and SVM is presented in the Table 7.

In terms of optimal searching, the SVM is the most time intense approach characterized by an exponential time complexity of $\sigma(2^N)$ compared to the linear ANN and Bagging. However, EANN (bagging) shows a bit computational complexity due to number of bags (B) and replacements(R), defined by the term σ(B (N + R)) which is by definition greater than one. However, this can be tolerated as compared with SVM and ANN.

To measure the time complexity of the model with experimental dataset at a particular load, comparisons of 50 individual trials have been done and the values are averaged. RMSE (for training, testing and validation), and prediction accuracy (under the tolerance of 15%) are used as indicators to evaluate the models. The time complexity of SVM, ANN and EANN (15 bootstraps) ANN and SVM is given in Table 8.

In general, the forecast results of any classifiers are acceptable that have lower RMSEs. Table 8 show that the EANN have lowest RMSEs (1.28) and having the prediction accuracy of 99.50% with the tolerance of 15%.

TABLE 8. Time complexity analysis.

		EANN	ANN	SVM
RMSE	Training	1.28	1.59	1.79
	Testing	1.47	1.87	1.76
	Validation	0.37	1.20	1.32
Total Time (Sec)		43.87	25.43	19.45
Prediction Accuracy (%)		99.50	99.25	99.13

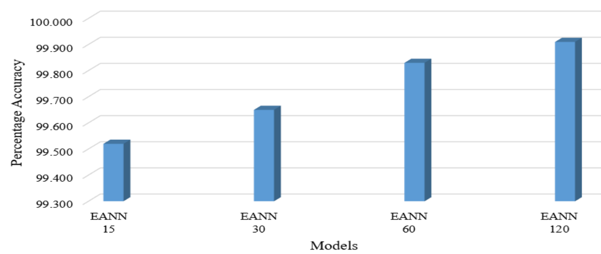

FIGURE 22. EANN performance over the number of bootstraps.

However, with increase in number of classifiers the error of ensemble learning is greatly reduced but the total time including (training, testing and validation) is increased subsequently. To show the effectiveness of the proposed approach, further EANN performance over the number of bootstraps is analyzed. In Fig. 22, EANN performance varies over the number of bootstraps employed in the model. Higher the bootstraps in the model higher the accuracy and time it takes. EANN is bit computationally intensive because of the complex network architecture and greater spatial dimensions. However, the runtime still allows the use of the model for a real-time estimation with the advantage of a better and robust performance.

VII. CONCLUSION

A solution for the optimal power generation problem using an ensemble of artificial neural networks through bootstrap aggregation is proposed in this paper. Load demand data for Pakistan's power system has been considered for a day and then validated for a week. Lagrange Relaxation method is developed and used to train the several conventional ANNs. The proposed algorithm EANN is then applied to analyze the results.

Results show that the feed forward back propagation of the ANN model alone is not suitable for power scheduling as it produces significant errors for the simulated and actual generations. It is shown that when the proposed EANN is used to deal with ED problem, a great deal of improvement is witnessed compared with the ANN. EANN approach shows better generalization ability, faster convergence with reduced bias and variance due to the inherent property of the Bootstrap aggregation, under the same operating conditions.

The ANN is accurate for the given set of data during different scenarios of overloading and contingencies in the Pakistan's power system but when load changes are rapid or change in the following hour, the ANN suffers under or overfitting. These ANN limitations lead to inaccuracy during load shedding and disturb power system stability. The computational complexity analysis for the proposed EANN shows real-time estimation with better and robust performance. Thus, proposed EANN algorithm is preferred for scenarios where the load sheds/changes rapidly, solving the shortcomings of an ANN.

APPENDIX

See Figure. 10.

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