IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received February 20, 2022, accepted March 5, 2022, date of publication March 8, 2022, date of current version March 21, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3157846

Hybrid Deep Neural Network-Based Generation Rescheduling for Congestion Mitigation in Spot Power Market

ANJALI AGRAWAL[1], SEEMA N. PANDEY[2], LAXMI SRIVASTAVA[1], (Senior Member, IEEE), PRATIMA WALDE[3], SAUMYA SINGH[3], (Student Member, IEEE), BASEEM KHAN[4], (Senior Member, IEEE), AND R. K. SAKET[3], (Senior Member, IEEE)

[1]Department of Electrical Engineering, Madhav Institute of Technology and Science, Gwalior, Madhya Pradesh 474001, India
[2]Department of Electrical Engineering, Dr. Bhim Rao Ambedkar Polytechnic College, Gwalior, Madhya Pradesh 474001, India
[3]Department of Electrical Engineering, Indian Institute of Technology (BHU), Varanasi, Uttar Pradesh 221005, India
[4]Department of Electrical and Computer Engineering, Hawassa University, Hawassa 05, Ethiopia

Corresponding authors: R. K. Saket (rksaket@ieee.org) and Baseem Khan (baseem.khan04@gmail.com)

ABSTRACT In the open-access power market environment, the continuously varying loading and accommodation of various bilateral and multilateral transactions, sometimes leads to congestion, which is not desirable. In a day ahead or spot power market, generation rescheduling (GR) is one of the most prominent techniques to be adopted by the system operator (SO) to release congestion. In this paper, a novel hybrid Deep Neural Network (NN) is developed for projecting rescheduled generation dispatches at all the generators. The proposed hybrid Deep Neural Network is a cascaded combination of modified back-propagation (BP) algorithm based ANN as screening module and Deep NN as GR module. The screening module segregates the congested and non-congested loading scenarios resulting due to bilateral/multilateral transactions, efficiently and accurately. However, the GR module projects the re-scheduled active power dispatches at all the generating units at minimum congestion cost for all unseen congested loading scenarios instantly. The present approach provides a ready/instantaneous solution to manage congestion in a spot power market. During the training, the Root Mean Square Error (RMSE) is evaluated and minimized. The effectiveness of the proposed method has been demonstrated on the IEEE 30-bus system. The maximum error incurred during the testing phase is found 1.191% which is within the acceptable accuracy limits.

INDEX TERMS Bilateral/multilateral transactions, congestion management, deep neural network, generation rescheduling, modified back propagation algorithm-based ANN.

I. INTRODUCTION

The most important characteristic of an electric power market is its continuously changing loading scenario. Apart from it, participants in competitive power markets try to get electricity from the cheapest available source. This tendency sometimes causes the transmission networks to operate beyond transfer limits and the system is said to be congested. Congestion management (CM) is supposed to be one of the most crucial issues of restructured power system [1]. In the emerging day-ahead hybrid power market, some effective financial tools are inevitable to manage congestion in which bid-based generation rescheduling (GR) is found to be most eminent [2]. For bid-based GR, three types of bids are required to be submitted by suppliers. One is the initial bid and the remaining two are the post congestion bids which are incremental and decremental rescheduling bids. According to them, suppliers have to amend their real power generation along with optimizing flows and thus support in mitigation of congestion [2]. In the literature, different approaches have been suggested for this purpose based on the classical method [3], [4]. The conventional optimization methods have become outmoded as these are very slow, containing complex structure and data dependency, while evolutionary computing (EC) based optimization techniques have been found superior in terms of ease of use, no dependency on initial guesses, and type of functions. Several EC algorithms, like adaptive bacterial foraging algorithm with Nelder-Mead [5], fuzzy adaptive bacterial foraging algorithm [6], Particle swarm optimization

The associate editor coordinating the review of this manuscript and approving it for publication was Mostafa Rahimi Azghadi.

(PSO) [7], [8], PSO with distributed acceleration constant [9], Ant lion optimizer [10] and satin bowerbird optimization-based algorithm [11] have been suggested for generation rescheduling. For enhancing the performance of PSO, hybrid Nelder-mead-fuzzy adoptive PSO [12], hybridization of fuzzy along with GSA and PSO [13], a fitness distance ratio and fuzzy adaptive-PSO [14] have also been suggested for generation rescheduling to manage congestion.

The performance of evolutionary computing techniques is affected by the selection of basic parameters like exploration and exploitation parameters, weighting coefficients, size of the population, number of iterations, etc. In most of the EC techniques during the exploitation phase, optimum solutions are selected from global best, while local best solutions are rejected which may cause loss of more accurate results [15]. Also, the EC algorithms evaluate the fitness function iteratively each time that makes them slow.

For each requested transaction and each variation of load, the complete OPF program has to be run repeatedly, which results in a sluggish response. On the other hand, artificial neural network (ANN) based techniques have been developed to exploit the tolerance for imprecision, uncertainty, partial truth, and robustness. Once an appropriate ANN model has been developed, accurate and instant prediction can be obtained, irrespective of any missing or partially corrupted data [16]. The most popular and commonly used multi-layer perceptron (MLP) neural networks are developed usually with one input layer, one or two hidden layers, and one output layer. A successive development in the field of artificial intelligence has suggested the deep architecture of neural networks with many hidden layers. The conjugacy between adjacent hidden layers makes training and testing remarkably efficient and fast [17].

The recent and emerging development in a power system has made its operation more complex and challenging due to its large size and restructuring. Minor variation in the load or any constraint makes the operation more tedious. To overcome this difficulty, a deep learning Convolution neural network (CNN) model has exhibited its excellent identification in this field even with large data size. Few Deep learning-based applications like a multiple-input deep NN to forecast photovoltaic power [18], CNN based deep learning to forecast day-ahead photovoltaic power [19], Long short term memory (LSTM) based NN to forecast short-term photovoltaic power generation in a time series manner [20], CNN-LSTM to forecast short term wind speed [21], CNN in a combination of LightGBM algorithm to forecast ultra-short-term wind power [22], a genetic algorithm-based optimized deep NN to forecast Locational Margin Price [23], a recurring neural network combining dynamic time wrapping to forecast daily peak load [24] and an adaptive CNN to detect the faulty line in the distribution network [25], etc. have been suggested in the literature.

To the best of the authors' knowledge, in the recent competitive power market scenario, a hybrid Deep neural network application for generation rescheduling-based congestion management has not been developed yet. Even ANN application for generation rescheduling has not been found in the literature. A cascaded combination of screening ANN and Deep NN for GR has been employed in the proposed approach. The screening ANN is a modified back-propagation (BP) algorithm based ANN developed for filtering out the non-congested cases, while the GR module is a Deep NN developed for predicting re-scheduled active power generation at all the generating units. In the present paper, congested loading scenarios have been created by perturbing the load at each load bus and implementing bilateral/multilateral transactions. Congestion management has been carried out by rescheduling the active power generation at various generating units using their incremental/decremental bids to minimize the total congestion cost.

The proposed hybrid Deep NN approach for GR has been implemented on the IEEE 30-bus system [5]. The main contributions of this paper are:

- This paper presents an instant/ready solution for bid-based generation rescheduling to manage congestion in a spot power market, based on a novel hybrid Deep NN.
- The developed hybrid Deep NN is a cascaded combination of a screening module and GR module.
- A modified back-propagation learning algorithm-based ANN has been developed as a screening module.
- The screening module classifies congested and non-congested loading scenarios efficiently and accurately even for an imbalanced data set.
- A Deep NN has been developed as a generation rescheduling module and projects the rescheduled active power generation dispatch at all the generating units, accurately and almost instantaneously for all the unseen congested loading scenarios.
- The proposed Deep NN mitigates congestion and enhances the flexibility of power market operations.

The following document is composed as: Part 2 presents the problem formulation, part 3 and part 4 present developments of the screening module and GR module. In part 5, the flow chart of the proposed hybrid Deep NN-based approach for GR has been given. In part 6, the demonstration of the proposed approach on the IEEE 30-bus system has been presented. The conclusion and future scope of the work are included in part 7.

II. PROBLEM FORMULATION

In this paper, the congestion management problem has been formulated as minimization of generation cost, active power rescheduling, and minimization of congestion cost, subject to various equality and inequality constraints. Any optimization method for OPF may be used. PSO is one of the established population-based evolutionary computing techniques and has been successfully implemented for optimization in various fields including generation rescheduling [7]–[9]. Hence, PSO based optimal power flow program [26] has been employed to obtain minimization of fuel and congestion cost as well as re-scheduled active power generation. Modeling of bilateral/multilateral transactions has also been presented in this section.

A. MINIMIZATION OF GENERATION COST

Objective function for minimization of generation cost C_G (\$/hr) can be written as follows:

$$\min\ C_G = \min \sum\nolimits_{i=1}^{N_G} \left(a_i + b_i P_{G_i} + c_i P_{G_i}^2\right) \quad i = 1,2,3\ldots \mathrm{N_G} \tag{1}$$

where, P_{G_i} is the real power generation at i^{th} generating unit and $a_i\, b_i, c_i$ are the fuel cost coefficients of i^{th} generating unit. N_G represents the total number of generating units.

B. EQUALITY AND INEQUALITY CONSTRAINTS

Including static load flow equations for both real and reactive power balance; these have been expressed as follows:

$$P_{G_i} - P_{D_i} - V_i \sum\nolimits_{j=1}^{N_B} V_j \left[G_{ij}\cos\left(\delta_i - \delta_j\right) + B_{ij}\sin\left(\delta_i - \delta_j\right)\right] = 0 \tag{2}$$

$$Q_{G_i} - Q_{D_i} - V_i \sum\nolimits_{i=1}^{N_B} V_j \left[G_{ij}\sin\left(\delta_i - \delta_j\right) + B_{ij}\cos\left(\delta_i - \delta_j\right)\right] = 0 \tag{3}$$

where, P_{D_i} and Q_{D_j} are the real and reactive power demand respectively of the j^{th} customer.

Minimum and maximum generation limits can be expressed as:

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max} \quad i = 1,2,3\ldots N_G \tag{4}$$

$$Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max} \quad i = 1,2,3\ldots N_G \tag{5}$$

where, Q_{G_i} is the reactive power generation at ith generating unit.

Minimum and maximum voltage limits can be can be given as:

$$V_j^{\min} \le V_j \le V_j^{\max} \quad j = 1,2,3\ldots N_D \tag{6}$$

$$V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max} \quad i = 1,2,3\ldots N_G \tag{7}$$

where, N_D represents the total number of load buses, V_i and V_{G_i} are the voltage at j^{th} and i^{th} load and generating bus respectively.

Transmission line limits can be given as:

$$S_{\max_l} \ge S_l \quad l = 1,2,3\ldots N_{BR} \tag{8}$$

where $S_{\max_l}$ is the loading capacity in MVA and S_l is the MVA flow over l^{th} line.

C. MINIMIZATION OF CONGESTION COST

Power scenarios resulting from bilateral/multilateral transactions may give rise to a violation of the line loading limit of transmission lines and consequently may create congestion. For mitigating this congestion, active power generation rescheduling has been proposed. For achieving generation rescheduling, some amount of generation has been suggested to be added or subtracted from the preferred schedule based on their incremental and decremental rescheduling bids. These bids are constrained within up and down ramp limits. The congestion cost has been evaluated and minimized employing these rescheduling bids and deviation in real power generation at all the generators as follows [23]:

$$\mathit{Minimize}\ C_c = \mathit{minimize} \sum\nolimits_{i=1}^{N_C} C_i \Delta P_{G_i+} + \sum\nolimits_{i=1}^{N_C} D_i \Delta P_{G_i-} \tag{9}$$

where, C_i and D_i are the cost coefficients for incremental and decremental rescheduling bid for ith generator. ΔP_{G_i+} and ΔP_{G_i-} are the positive and negative deviation in real power generation from their preferred schedule for ith generator. The re-scheduled generation at ith generator P'_{G_i} can be expressed as:

$$P'_{G_i} = P_{G_i} \pm \Delta P_{G_{i\pm}} \tag{10}$$

All the equality and inequality constraints given by "(2),"– "(8)," have been considered while minimizing the congestion cost (CC). In addition to this, minimum and maximum ramp limits for rescheduling of the ith generator has been considered as:

$$\Delta P_{G_i}^{\min} \le \Delta P_{G'_{i+}} \Delta P_{G_{i-}} \le \Delta P_{G_i}^{\max} \tag{11}$$

D. BILATERAL AND MULTILATERAL TRANSACTION

Bilateral transactions are based on a contractual agreement between seller and buyer for their traded volume and price. However, accommodation of these transactions in a power market depends upon the feasibility of these transactions evaluated by SO as per available transmission facility to avoid any security violation [3]. The mathematical expression for bilateral transactions can be modeled as follows:

$$P_{G_S} - P_{D_b} = 0 \tag{12}$$

where, P_{G_S} is the power injected at seller bus s and P_{D_b} is the power withdrawn at buyer bus b.

The concept of bilateral transactions can be extended to multilateral transactions, where sellers may inject power at several buses and buyers may withdraw power from several buses. This also requires power balance such that total power injection is equal to the total power withdrawn for each transaction. Mathematically, *the* k^{th} multilateral transaction involving more than one seller and buyer can be expressed as follows:

$$\sum\nolimits_S P_{G_S}^k - \sum\nolimits_b P_{D_b}^k = 0 \quad k = 1,2,3\ldots t \tag{13}$$

where, $P_{G_S}^k$ is the power injected at seller bus s for the k^{th} transaction and $P_{D_b}^k$ is the power withdrawn at buyer bus b for k^{th} transaction. Here t is the total number of multilateral transactions.

$$\Delta P_{G_i}^{\min} \le \Delta P_{G'_{i+}} \Delta P_{G_{i-}} \le \Delta P_{G_i}^{\max} \tag{14}$$

III. MODIFIED BP-ANN BASED SCREENING MODULE

For screening congested and non-congested loading scenarios (LSs), a Feed-Forward ANN trained by a modified back-propagation algorithm has been developed in this paper [27]–[30]. The architectural diagram of this screening module has been presented in Fig. 1. In the input and hidden

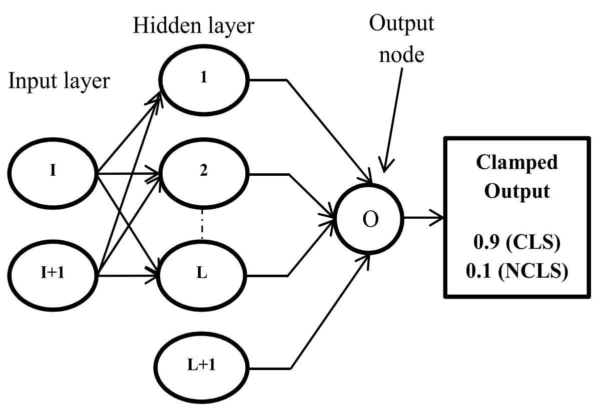

FIGURE 1. Architecture of modified BP – ANN based screening module.

layer, one extra node has been considered as bias. This ANN provides single clamped output, one at a time for each loading scenario to classify congested and non-congested loading scenarios. In the present work, the training of this screening ANN has been done such that the target output is high (0.9) when presented with a sample from congested loading scenarios (CLS) and low (0.1) when coming across with a non-congested loading scenario (NCLS).

The training data set for the proposed screening ANN contains a higher number of epitomes for dominance class (CLS) in comparison to subordinate class (NCLS). Hence, it is supposed to be an imbalanced data set. When such ANN is trained with the standard back-propagation algorithm, the rate of convergence of net output error is very low. Because the negative gradient vector computed by standard back-propagation algorithm does not initially reduce the error for the subordinate class. As a result of this, the error in the subordinate class increases remarkably high. To overcome this problem, the modified back-propagation algorithm tries to equalize the error reduction in both classes proportionally by computing a descent vector in weight space [27]. Therefore for the imbalanced data set, the learning rate has been accelerated by one order of magnitude employing adaptive learning.

IV. DEEP NEURAL NETWORK-BASED GR MODULE

In this paper, convolution NN-based deep learning has been applied for predicting generation rescheduling and the Deep learning toolbox of Matlab has been used for this purpose. The convolution NN comprises multiple hidden layers and is best suitable for analyzing the image data. CNN can be used for classification tasks and also for the prediction of continuous data (regression). In the case of image classification, its last (output) layer is the fully connected classification layer while in the case of regression task; its last layer is the fully connected regression layer. In the present work for congestion management, generation rescheduling has been predicted for continuously changing loading scenarios, hence for obtaining continuous output, the regression layer has been considered as the last layer.

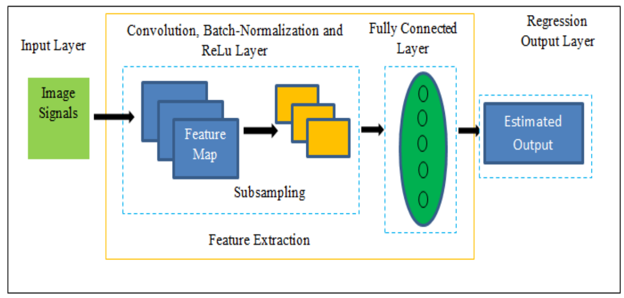

FIGURE 2. Structural block diagram of deep NN.

The developed generation rescheduling module based on a deep neural network (CNN) has been shown in Fig. 2.

This Deep NN consists of 6 types of layers. The first layer is the input layer, which provides data set in the form of an image to the next layer which is the convolution layer. This is a multi-dimensional layer. However, in the present work, it is 2-D.

The convolution layer comprises a set of parallel features which are composed by sliding different filters connected with one or more feature map channels. These are known as kernel filters. Kernel filters move vertically and horizontally and convolution operation takes place between input images and these kernel filters, by which feature mapping is performed. Feature mapping can be further improved by optimizing the hyper-parameters padding, stride, and pooling. In the convolution layer, some features like sparse connectivity of adjacent layers, parameter sharing, and spatial sub-sampling, effectively reduce the dimension and learning parameters of Deep NN. This makes DNN faster and easy as compared to traditional ANNs. The third layer is the Batch normalization layer, which is used to standardize the input feature maps for scaling and shifting the activation functions. The batch normalization layer reduces the number of epochs by providing data set in the form of mini-batches, thus it enhances the training and testing performance of Deep NN. The fourth layer is the ReLu layer, which is a rectified linear unit layer comprised of non-linear decision functions. This layer improves the accuracy of Deep NN by performing repeated learning from the data set. The fifth layer is a fully-connected layer, where each of the inputs is connected to each output, with dissimilar weights. The final layer where continuous prediction is obtained is known as the Regression output layer. This layer is dense at the end with one dimension for every single output and contains no non-linear activation function. The final output of Deep NN is the minimized value of the loss function. In this work, root mean square error (RMSE) has been taken as a loss function. The RMSE function framed for this work can be given as follows [7]:

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N} (y_n - \hat{y}_n)^2}{N}} \tag{15}$$

where, y_n and $\hat{y}_n$ are the target and predicted outputs for N size data set.

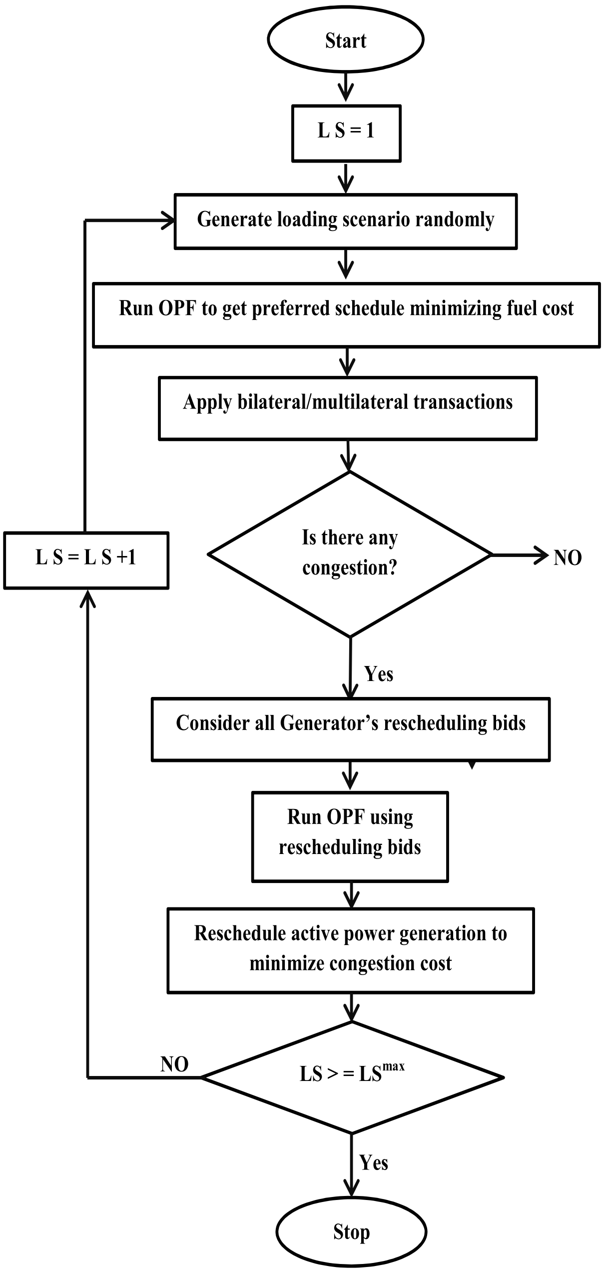

FIGURE 3. Flowchart for generating loading scenarios.

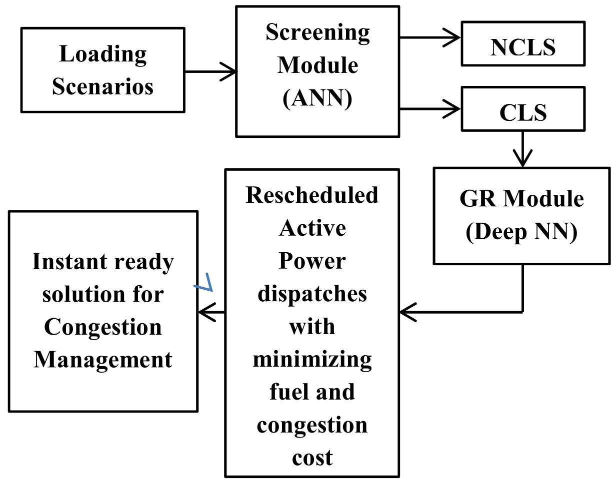

FIGURE 4. Schematic block diagram of proposed approach of CM.

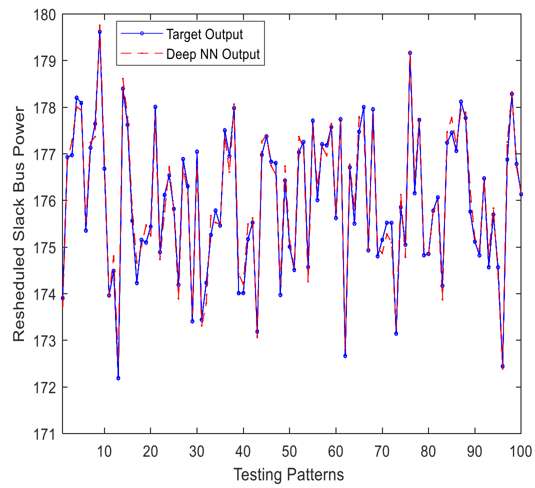

FIGURE 5. Target and actual output of deep NN for slack bus.

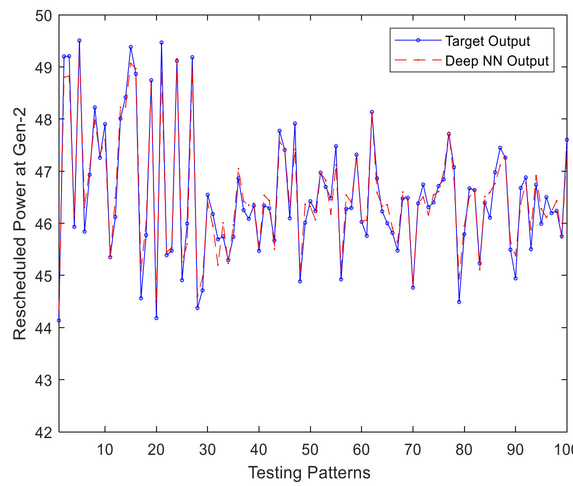

FIGURE 6. Target and actual output of deep NN for generator 2.

V. METHODOLOGY OF PROPOSED WORK

The proposed approach addresses the problem of congestion, which takes place through continuously varying loading scenarios and by implementing various bilateral and multilateral transactions. For this purpose, continuously varying loading scenarios have been generated by perturbing active and reactive power loads at each load bus and implementing various bilateral and multilateral transactions. The systematic steps for generating loading scenarios are shown in Fig. 3.

The schematic block diagram of the proposed approach for active power generation rescheduling for mitigating congestion has been shown in Fig. 4. In this approach, a cascade combination of screening module and GR module has been developed. The screening module is a modified BP algorithm-based feed-forward ANN, while the GR module is a Deep NN. Several loading scenarios have been

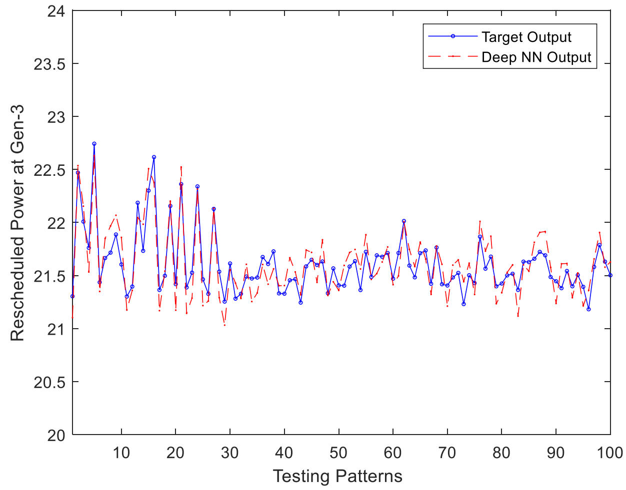

FIGURE 7. Target and actual output of deep NN for generator 3.

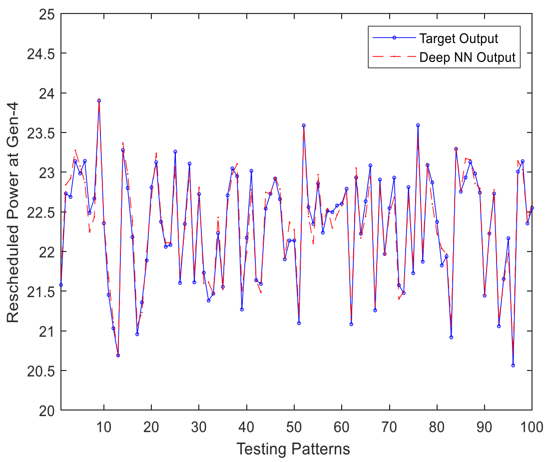

FIGURE 8. Target and actual output of deep NN for generator 4.

applied to the screening ANN module, which classifies them into congested loading scenarios (CLS) and non-congested loading scenarios (NCLS). Only congested loading scenarios have been applied to the Deep NN as input. The Deep NN is trained to provide actual output (regression output) as close as possible to the target outputs which are re-scheduled active power generation at various generating units.

Thus, the output of the proposed Deep NN is the re-scheduled active power generation for all the 5 generating units with minimum fuel cost and congestion cost. By mitigating congestion accurately, the proposed approach provides a ready solution for a spot power market that enhances the flexibility of market operation.

VI. RESULT AND DISCUSSION

The performance of the proposed hybrid Deep NN has been examined on an IEEE 30-bus system. The IEEE 30-bus system comprises 41 transmission lines, 24 load buses, and 6 generator buses. Generating units are at bus nos. 1, 2, 5, 8, 11, and 13. The lower voltage limit for all the buses is the same i.e. 0.95 pu. However, the upper voltage limit for generator buses is 1.1 pu and for all remaining buses, it is 1.05 pu.

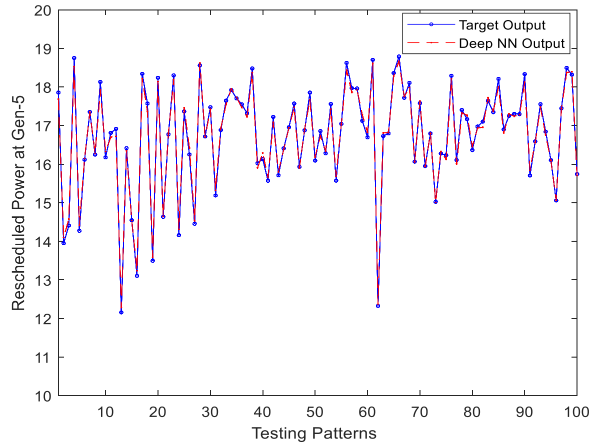

FIGURE 9. Target and actual output of deep NN for generator 5.

Out of 24 load buses, only 21 buses are there which are having non-zero loads. All the data for the IEEE 30-bus system has been taken from [5]. For obtaining continuously varying loading scenarios, $\pm 10\%$ perturbation in real and reactive loads has been implemented at all the 21 load buses with non-zero loads. For further creating congestion, various bilateral and multi-lateral transactions have been implemented [5]. For GR, the details of incremental/decremental rescheduling bids along with up and down ramp limits of generators have been taken from [5]. In the current competitive power market, the participants try to get maximum profit with available sources. The continuously varying loads and bilateral/multilateral transactions may create large disturbances in the economic operation of the power market. To simulate the realistic power market operation and for including maximum possible loading conditions, several loading patterns are required to develop an artificial neural network. For this purpose, as many as 501 loading scenarios have been generated by perturbing load at each load bus by $\pm 10\%$ of the base condition and by implementing various bi-lateral and multi-lateral transactions in this paper. These generated 501 loading scenarios (input-output patterns) have been divided into two parts and used for training and testing of the proposed Hybrid Deep NN. For training, 78% of the patterns were utilized, while for testing, the remaining 22% unseen loading scenarios were used. Various trials were taken by considering different architectures of the Deep NN, and the best results obtained by testing the developed Hybrid Deep NN are given in this paper.

During training, out of 390 loading scenarios, 378 scenarios have been classified as congested while only 12 as non-congested loading scenarios. During testing, the screening module classified all the congested and non-contested cases accurately. Out of 111 unseen patterns, 100 loading scenarios, were been classified as congested loading scenarios and the remaining 11 as non-congested cases. Classification performance of the proposed screening module has been found quite satisfactory for the given imbalanced data set comprising more epitomes in the dominant class and less in the subordinate class. However, many other screening

TABLE 1. Target and predicted output of deep NN for all 5 generators.

Loading Scenario	Output	RP_{G1}	RP_{G2}	RP_{G3}	RP_{G4}	RP_{G5}
1	Target	179.0989	45.97318	21.83195	23.63709	19.08656
	Predicted	179.1119	46.41644	21.60524	23.64058	18.90128
	% Error	0.00726	0.96417	1.03843	0.01476	0.97074
2	Target	175.3584	48.8095	22.32291	21.52447	13.87383
	Predicted	175.2703	48.414	22.50306	21.5975	13.94069
	% Error	0.05025	0.8103	0.80701	0.3393	0.48188
3	Target	175.4749	48.82962	22.53253	21.75304	13.54292
	Predicted	175.3492	48.58421	22.51364	21.80945	13.67755
	% Error	0.07164	0.50258	0.08385	0.25933	0.99414
4	Target	173.7909	44.96363	21.30251	22.20591	16.39228
	Predicted	173.9033	45.21436	21.17122	22.07786	16.48621
	% Error	0.06469	0.55762	0.61629	0.57668	0.573
5	Target	178.3165	49.55614	22.43512	23.07435	14.63851
	Predicted	178.3749	49.47695	22.50606	22.96611	14.79268
	% Error	0.03273	0.1598	0.31622	0.46912	1.05321
6	Target	177.8092	46.79847	21.7035	23.12369	17.63561
	Predicted	177.8287	46.72582	21.71584	23.2051	17.61468
	% Error	0.01099	0.15523	0.05685	0.35207	0.11871
7	Target	174.1286	45.69989	21.3471	21.16356	16.92444
	Predicted	174.1684	45.62399	21.41974	21.25477	16.84757
	% Error	0.02287	0.16608	0.34028	0.43098	0.45423
8	Target	177.9146	49.46039	22.48788	22.8216	14.43141
	Predicted	177.7923	49.23149	22.74548	22.65393	14.48376
	% Error	0.06879	0.46279	1.14551	0.73469	0.3627
9	Target	176.6856	47.8743	21.61862	22.26725	16.21521
	Predicted	176.7388	47.86917	21.81928	22.22294	16.08847
	% Error	0.03012	0.01071	0.92818	0.19903	0.78163
10	Target	174.842	47.16143	21.39301	22.45109	15.02671
	Predicted	174.9293	46.83521	21.6158	22.41705	15.19864
	% Error	0.04996	0.69171	1.04141	0.15166	1.14419
11	Target	175.9004	46.27024	21.49173	23.46564	16.04721
	Predicted	175.8283	46.1896	21.45492	23.38742	16.19836
	% Error	0.04097	0.17428	0.17129	0.33332	0.94197
12	Target	177.0782	45.73852	21.62605	22.55374	18.46094
	Predicted	177.0474	45.9035	21.48647	22.67164	18.30997
	% Error	0.01742	0.36072	0.6454	0.52276	0.8178
13	Target	175.3839	46.95522	21.49945	21.42545	16.5075
	Predicted	175.4477	46.7444	21.74885	21.36275	16.56455
	% Error	0.03636	0.44899	1.16003	0.29267	0.34561
14	Target	175.1053	45.03031	21.41913	23.07584	16.77638
	Predicted	175.1552	45.17921	21.18758	23.00815	16.97227

modules like classical ANN, extreme learning machine module (ELM), deep neural network, and the probabilistic neural network did not provide accurate classification when implemented for such a high dimension and complex non-linear problem.

The Deep NN has been trained and tested with input-output patterns. This has been observed that re-scheduled active power generation at generator bus no. 13 is 12 MW (Minimum limit of PG) for all the generated loading scenarios. As per the data taken from [5], for the generator at bus no. 13,

TABLE 1. *(Continued.)* **Target and predicted output of deep NN for all 5 generators.**

	% Error	0.0285	0.33069	1.08102	0.29335	1.16766
15	Target	173.706	48.39474	22.3696	20.66821	13.32363
	Predicted	173.8813	48.2675	22.26488	20.89131	13.42408
	% Error	0.1009	0.26292	0.46814	1.07944	0.75394
16	Target	178.098	49.48895	22.74084	22.91888	14.24903
	Predicted	178.1177	49.31714	22.93247	22.90858	14.28675
	% Error	0.01104	0.34717	0.84268	0.04496	0.26475
17	Target	176.244	46.62529	21.6101	21.94534	17.21908
	Predicted	176.2824	46.52008	21.8059	21.94482	17.13377
	% Error	0.02182	0.22564	0.90609	0.0024	0.49544
18	Target	177.6908	49.39774	22.52365	22.87079	14.35427
	Predicted	177.7862	49.07821	22.62161	22.96547	14.52377
	% Error	0.05368	0.64685	0.43494	0.41399	1.18086
19	Target	178.4062	46.55471	21.76482	23.37187	18.27965
	Predicted	178.4167	46.5607	21.7639	23.49807	18.15386
	% Error	0.00591	0.01285	0.00422	0.53998	0.68814
20	Target	173.9337	46.69501	21.32415	21.11206	15.8838
	Predicted	174.0233	46.59935	21.39662	21.31093	15.75414
	% Error	0.05151	0.20486	0.33984	0.94196	0.81629

the rescheduling incremental bid is 48 \$/MWhr which is quite high as compared to its rescheduling decremental bid i.e. 25 \$/MWhr. Hence to minimize congestion cost, it provides a constant output of 12 MW (Minimum limit of PG13) for various loading scenarios even after several trials. Thus, out of 6 generators, only 5 generators reschedule their generation for all the congested loading scenarios. Hence, the GR module has been developed for providing the re-scheduled active power generation at 5 generating units only.

The 378 congested loading scenarios have been used to accomplish training of the GR module to provide re-scheduled active power generation at the 5 generator buses (bus no. 1, 2, 5, 8 and 11). Bus number 1 is the slack bus. The inputs for Deep NN are the active power load, the reactive power load, and the apparent power load at all the non-zero 21 load buses. In this way, total inputs are 63, while the dimension of the input layer is taken as $3 \times 21 \times 1$ for Deep NN. After having several trials, the optimum size of various layers of Deep NN has been determined.

Thus, training of Deep NN has been accomplished with $3 \times 21 \times 1$ inputs using 378 loading scenarios. For testing, 100 unseen congested loading scenarios have been given to the trained Deep NN. Fig. 5 shows the re-scheduled active power at slack bus obtained by PSO-OPF method as well as by Deep NN for all the 100 testing loading scenarios. Fig. 6 to Fig. 9 show the plot of actual and target output of Deep NN for all 100 congested loading scenarios for generators at bus nos. 2, 5, 8, and 11 respectively. It can be observed from these figures that the predicted outputs closely follow the target values as obtained by PSO-OPF method. Precise predictions have been obtained for all the 100 testing loading scenarios.

However, prediction for only 20 loading scenarios has been shown in Table 1 due to limited space. Table 1 shows the re-scheduled power generation (RPG) at all the 5 generators, predicted by the proposed hybrid Deep NN-based approach and computed by PSO-OPF as target outputs. Maximum percentage testing errors for all the 5 generating units have been found as 0.10784, 0.096417, 1.17018, 1.18053, and 1.19151 respectively. Among these, the highest testing % error is 1.19151, which is quite satisfactory. It can be concluded that the proposed approach can provide an accurate prediction of re-scheduled generation at different generators almost instantaneously. This provides a ready solution for congestion management in a spot power market.

VII. CONCLUSION

This paper presents an instant/ready solution for congestion management for a spot power market deploying bid-based generation rescheduling. In this paper, a novel hybrid Deep Neural Network has been developed for generation rescheduling to mitigate congestion by minimizing fuel/congestion cost. The developed hybrid Deep NN is a cascaded combination of screening module and generation rescheduling module. The screening module is a modified BP-ANN, while the GR module is a Deep NN.

The developed Deep NN as GR module provides active power rescheduling of generators with minimum fuel/congestion cost almost instantly and accurately for all the unseen congested loading scenarios. Continuously load changing scenario of electricity market forces the EC based optimization algorithms to restart from initialization process that makes them slower while the proposed hybrid

Deep NN once trained, estimates active power generation rescheduling almost instantaneously. Demonstration of the proposed approach has been carried out on the IEEE 30-bus system with very accurate results. As this hybrid Deep NN-based approach is found to be superior in terms of computing time and accuracy, it may be used for practical power systems as well.

ACKNOWLEDGMENT

Authors sincerely acknowledge the Director, Madhav Institute of Technology and Science, Gwalior, and the Principal Dr. Bhim Rao Ambedkar Polytechnic College, Gwalior, India, to provide academic and research environment to carrying out this research work.

REFERENCES

[1] A. Narain, S. K. Srivastava, and S. N. Singh, "Congestion management approaches in restructured power system: Key issues and challenges," *Electr. J.*, vol. 33, no. 3, Apr. 2020, Art. no. 106715, doi: 10.1016/j.tej.2020.106715.

[2] M. Sarwar, A. S. Siddiqui, Z. A. Jaffery, and D. P. Kothari, "Bid responsive generation rescheduling for congestion management in electricity market," *Eng. Rep.*, vol. 3, no. 5, May 2021, Art. no. e12331, doi: 10.1002/eng2.12331.

[3] A. Kumar, S. C. Srivastava, and S. N. Singh, "A zonal congestion management approach using real and reactive power rescheduling," *IEEE Trans. Power Syst.*, vol. 19, no. 1, pp. 554–562, Feb. 2004, doi: 10.1109/TPWRS.2003.821448.

[4] Y. P. Verma and A. K. Sharma, "Congestion management solution under secure bilateral transactions in hybrid electricity market for hydro-thermal combination," *Int. J. Electr. Power Energy Syst.*, vol. 64, pp. 398–407, Jan. 2015, doi: 10.1016/j.ijepes.2014.06.077.

[5] B. K. Panigrahi and V. R. Pandi, "Congestion management using adaptive bacterial foraging algorithm," *Energy Convers. Manage.*, vol. 50, no. 5, pp. 1202–1209, May 2009, doi: 10.1016/j.enconman.2009.01.029.

[6] C. Venkaiah and D. M. V. Kumar, "Fuzzy adaptive bacterial foraging congestion management using sensitivity based optimal active power re-scheduling of generators," *Appl. Soft Comput.*, vol. 11, no. 8, pp. 4921–4930, Dec. 2011, doi: 10.1016/j.asoc.2011.06.007.

[7] S. Dutta and S. P. Singh, "Optimal rescheduling of generators for congestion management based on particle swarm optimization," *IEEE Trans. Power Syst.*, vol. 23, no. 4, pp. 1560–1569, Nov. 2008, doi: 10.1109/TPWRS.2008.922647.

[8] K. S. Pandya and S. K. Joshi, "Sensitivity and particle swarm optimization-based congestion management," *Electr. Power Compon. Syst.*, vol. 41, no. 4, pp. 465–484, Feb. 2013, doi: 10.1080/15325008.2012.749555.

[9] N. K. Yadav, "Rescheduling-based congestion management scheme using particle swarm optimization with distributed acceleration constants," *Soft Comput.*, vol. 23, no. 3, pp. 847–857, Feb. 2019, doi: 10.1007/s00500-017-2792-3.

[10] S. Verma and V. Mukherjee, "Optimal real power rescheduling of generators for congestion management using a novel ant lion optimiser," *IET Gener., Transmiss. Distrib.*, vol. 10, no. 10, pp. 2548–2561, Jul. 2016.

[11] J. Chintam and M. Daniel, "Real-power rescheduling of generators for congestion management using a novel satin bowerbird optimization algorithm," *Energies*, vol. 11, no. 1, p. 183, Jan. 2018, doi: 10.3390/en11010183.

[12] J. J. D. Nesamalar, P. Venkatesh, and S. C. Raja, "Managing multi-line power congestion by using hybrid Nelder–Mead—Fuzzy adaptive particle swarm optimization (HNM-FAPSO)," *Appl. Soft Comput.*, vol. 43, pp. 222–234, Jun. 2016, doi: 10.1016/j.asoc.2016.02.013.

[13] R. Peesapati, A. Yadav, V. K. Yadav, and N. Kumar, "GSA–FAPSO-based generators active power rescheduling for transmission congestion management," *IEEE Syst. J.*, vol. 13, no. 3, pp. 3266–3273, Sep. 2019, doi: 10.1109/JSYST.2018.2869672.

[14] S. S. Reddy and S. A. Wajid, "Swarm intelligent-based congestion management using optimal rescheduling of generators," *Int. J. Bio-Inspired Comput.*, vol. 13, no. 3, pp. 159–168, 2019, doi: 10.1504/IJBIC.2019.099172.

[15] S. S. Aote, M. M. Raghuwanshi, and L. Malik, "A brief review on particle swarm optimization: Limitations & future directions," *Int. J. Comput. Sci. Eng.*, vol. 2, no. 5, pp. 196–200, 2013.

[16] S. N. Pandey, S. Tapaswi, and L. Srivastava, "Integrated evolutionary neural network approach with distributed computing for congestion management," *Appl. Soft Comput.*, vol. 10, no. 1, pp. 251–260, Jan. 2010, doi: 10.1016/j.asoc.2009.07.008.

[17] C.-H. Chang, "Deep and shallow architecture of multilayer neural networks," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 26, no. 10, pp. 2477–2486, Oct. 2015, doi: 10.1109/TNNLS.2014.2387439.

[18] C.-J. Huang and P.-H. Kuo, "Multiple-input deep convolutional neural network model for short-term photovoltaic power forecasting," *IEEE Access*, vol. 7, pp. 74822–74834, 2019, doi: 10.1109/ACCESS.2019.2921238.

[19] H. Zang, L. Cheng, T. Ding, K. W. Cheung, Z. Wei, and G. Sun, "Day-ahead photovoltaic power forecasting approach based on deep convolutional neural networks and meta learning," *Int. J. Electr. Power Energy Syst.*, vol. 118, Jun. 2020, Art. no. 105790, doi: 10.1016/j.ijepes.2019.105790.

[20] H. Zhou, Y. Zhang, L. Yang, Q. Liu, K. Yan, and Y. Du, "Short-term photovoltaic power forecasting based on long short term memory neural network and attention mechanism," *IEEE Access*, vol. 7, pp. 78063–78074, 2019, doi: 10.1109/ACCESS.2019.2923006.

[21] Y. Chen, Y. Wang, Z. Dong, J. Su, Z. Han, D. Zhou, Y. Zhao, and Y. Bao, "2-D regional short-term wind speed forecast based on CNN-LSTM deep learning model," *Energy Convers. Manage.*, vol. 244, Sep. 2021, Art. no. 114451, doi: 10.1016/j.enconman.2021.114451.

[22] Y. Ju, G. Sun, Q. Chen, M. Zhang, H. Zhu, and R. U. Mujeeb, "A model combining convolutional neural network and light GBM algorithm for ultra-short-term wind power forecasting," *IEEE Access*, vol. 7, pp. 28309–28318, 2019, doi: 10.1109/ACCESS.2019.2901920.

[23] Y.-Y. Hong, J. V. Taylar, and A. C. Fajardo, "Locational marginal price forecasting using deep learning network optimized by mapping-based genetic algorithm," *IEEE Access*, vol. 8, pp. 91975–91988, 2020, doi: 10.1109/ACCESS.2020.2994444.

[24] Z. Yu, Z. Niu, W. Tang, and Q. Wu, "Deep learning for daily peak load forecasting—A novel gated recurrent neural network combining dynamic time warping," *IEEE Access*, vol. 7, pp. 17184–17194, 2019, doi: 10.1109/ACCESS.2019.2895604.

[25] J. Liang, T. Jing, H. Niu, and J. Wang, "Two-terminal fault location method of distribution network based on adaptive convolution neural network," *IEEE Access*, vol. 8, pp. 54035–54043, 2020, doi: 10.1109/ACCESS.2020.2980573.

[26] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. Int. Conf. Neural Netw. (ICNN)*, Nov. 1995, pp. 1942–1948, doi: 10.1109/ICNN.1995.488968.

[27] R. Anand, K. G. Mehrotra, C. K. Mohan, and S. Ranka, "An improved algorithm for neural network classification of imbalanced training sets," *IEEE Trans. Neural Netw.*, vol. 4, no. 6, pp. 962–969, Nov. 1993, doi: 10.1109/72.286891.

[28] L. Srivastava, S. N. Singh, and J. D. Sharma, "A hybrid neural network model for fast voltage contingency screening and ranking," *Int. J. Electr. Power Energy Syst.*, vol. 22, no. 1, pp. 35–42, 2000, doi: 10.1016/S0142-0615(99)00024-1.

[29] S. N. Singh, L. Srivastava, and J. D. Sharma, "Fast voltage contingency screening and ranking using cascade neural network," *Electr. Power Syst. Res.*, vol. 53, no. 3, pp. 197–205, 2000, doi: 10.1016/S0378-7796(99)00059-0.

[30] V. Sharma, P. Walde, R. K. Saket, and S. Mekhilef, "Optimization of distributed generation size based on line sensitivity using transmission congestion cost," *Int. Trans. Electr. Energy Syst.*, vol. 31, no. 10, Oct. 2021, Art. no. e12695.

ANJALI AGRAWAL received the B.E. degree in electrical engineering and the M.E. degree in industrial system and drives from the Madhav Institute of Technology and Science, Gwalior, Madhya Pradesh, India, in 2003 and 2006, respectively. She is currently a Research Scholar with the Department of Electrical Engineering, Madhav Institute of Technology and Science. Her research interest includes deregulated power systems.

SEEMA N. PANDEY received the B.E. degree in electrical engineering and the M.E. degree in power systems from the Madhav Institute of Technology and Science, Gwalior, India, in 1998 and 2003, respectively, and the Ph.D. degree from ABVIIITM, Gwalior, in 2010. She is currently a Senior Lecturer with the Electrical Engineering Department, Dr. Bhim Rao Ambedkar Polytechnic College, Gwalior. Her research interests include deregulated power systems and power system operation and control.

LAXMI SRIVASTAVA (Senior Member, IEEE) received the B.E. and Ph.D. degrees in electrical engineering from the University of Roorkee (presently IIT Roorkee), India, and the M.Tech. degree in electrical engineering from the IIT, Kanpur.

She worked at various positions at the Department of Electrical Engineering, M.I.T.S. Gwalior, India. She has published/presented more than 245 research papers in reputed international/national journals and conference proceedings. She is currently involved in research in AI applications in power system security analysis, optimization, and control. She is a fellow of the Institution of Engineers, IE(I), and a Life Member of the Indian Society for Technical Education (ISTE), the Institution of Electronics & Telecommunication Engineers (IETE), the Computer Society of India (CSI), and the Indian Women Scientist Association (IWSA). She worked as a reviewer of research articles of various international journals of repute.

PRATIMA WALDE received the B.E. degree in electrical engineering from the Government Engineering College, Jabalpur, Madhya Pradesh, India, in 1998, the M.E. degree from the Madhav Institute of Technology and Science, Gwalior, Madhya Pradesh, in 2003, and the Ph.D. degree from the Indian Institute of Technology (BHU), Varanasi, Uttar Pradesh, India, in 2009. From January 2003 to April 2008, she worked as a Senior Research Fellow with the Department of Electrical Engineering, Banaras Hindu University, Varanasi. From 2012 to 2020, she was associated with Galgotias University, Greater Noida, India, as an Associate Professor with the Electrical Engineering Department. Her research interests include power system deregulation, power system optimization, and AI application to power systems.

SAUMYA SINGH (Student Member, IEEE) received the B.Tech. degree in electrical engineering from Dr. A. P. J. Abdul Kalam Technical University, Lucknow, Uttar Pradesh, India, in 2009, and the M.Tech. degree in power system from Bhagwant University, Ajmer, Rajasthan, India, in 2013. She is currently working as an Assistant Professor with the Department of Electrical Engineering, Christian College of Engineering and Technology, Bhilai, Chhattisgarh, India. She is also associated with the Academic and Research Team of Prof. R. K. Saket with the Department of Electrical Engineering, Indian Institute of Technology (Banaras Hindu University), Varanasi, Uttar Pradesh, India. Her research interests include renewable energy resources, reliability enhancement of grid integrated renewable energy systems, power system reliability, hybrid electric vehicle, and reliability issues related to power electronics converters.

BASEEM KHAN (Senior Member, IEEE) received the B.Eng. degree in electrical engineering from Rajiv Gandhi Technological University, Bhopal, India, in 2008, and the M.Tech. and D.Phil. degrees in electrical engineering from the Maulana Azad National Institute of Technology, Bhopal, in 2010 and 2014, respectively. He is currently working as a Faculty Member at Hawassa University, Ethiopia. He has published more than 125 research articles in indexed journals, including IEEE Transactions, IEEE Access, *Computer and Electrical Engineering* (Elsevier), *IET GTD*, *IET PRG*, and *IET Power Electronics*. Further, he has authored and edited books with Wiley, CRC Press, and Elsevier. His research interests include power system restructuring, power system planning, smart grid technologies, meta-heuristic optimization techniques, reliability analysis of renewable energy systems, power quality analysis, and renewable energy integration.

R. K. SAKET (Senior Member, IEEE) is currently a Professor with the Department of Electrical Engineering, Indian Institute of Technology (Banaras Hindu University) Varanasi, Uttar Pradesh, India. Previously, he was a Faculty Member at the Government Engineering College, Rewa, Madhya Pradesh, India; the Birla Institute of Technology and Science, Pilani, Rajasthan, India; the Sam Higginbottom University of Agriculture, Technology and Sciences, Allahabad, Uttar Pradesh; and the University Institute of Technology, Rajiv Gandhi University of Technology, Bhopal, Madhya Pradesh. He has provided his industrial services to the Electrical Safety Division of the M. P. Electricity Board, Government of Madhya Pradesh, Ujjain Division, Madhya Pradesh, as an Electrical Safety Engineer. He has more than 21 years of academic, industrial, and research experience. He is the author/coauthor of six national/international patents, approximately 150 scientific articles, book chapters, and research papers in indexed international journals and prestigious conference proceedings. He has supervised 12 Ph.D. research scholars and 50 M.Tech. students. He has delivered many technical talks and honored as a resource person of the power system reliability engineering. His research interests include reliability engineering, electrical machines and drives, power system reliability, reliability enhancement of industrial components and systems, and reliability aspects in renewable energy systems. He is a fellow of the Institution of Engineers, India, a member of IET, U.K., and a Life Member of the Indian Society for Technical Education, New Delhi, India. He is an Editorial Board Member of the *Journal of Electrical Systems*, France, and *Engineering, Technology and Applied Science Research*, Greece. He has received many awards, honors, and recognitions for his excellent academic and research contributions, including the Prestigious Gandhian Young Technological Innovation Award–2018 appreciated by the Hon'ble President of India at Rashtrapati Bhavan, New Delhi, India; the Design Impact Award–2018 appreciated by Padma Vibhushan Ratan Tata at Mumbai, India; and the Nehru Encouragement Award–1988 & 1990 awarded by the Hon'ble Chief Minister of M. P. State Government, Bhopal. He is an Associate Editor of the *IET Renewable Power Generation*, U.K., *IET Electrical Systems in Transportation*, U.K., and IEEE Access, USA.