HYBRID DEEP NEURAL NETWORK BASED GENERATION RESCHEDULING FOR CONGESTION MITIGATION IN SPOT POWER MARKET

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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 (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 adaptive 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 competitive 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.

B. MINIMIZATION OF GENERATION COST

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

$$
\min C_G = \min \sum_{i=1}^{N_G} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \quad i = 1, 2, 3 \ldots \ldots N_G
$$

where, $P_{Gi}$ 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.

C. EQUALITY AND INEQUALITY CONSTRAINTS

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

$$
P_{Gi} - P_{Di} - V_i \sum_{j=1}^{N_B} V_j \left[G_{ij} \cos(\delta_{ij} - \delta_i) + B_{ij} \sin(\delta_{ij} - \delta_i)\right] = 0 \quad (2)
$$

$$
Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{N_B} V_j \left[G_{ij} \sin(\delta_{ij} - \delta_i) - B_{ij} \cos(\delta_{ij} - \delta_i)\right] = 0 \quad (3)
$$

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

Minimum and maximum generation limits can be expressed as:

$$
P_{G\min} \leq P_{Gi} \leq P_{G\max} \quad i = 1, 2, 3 \ldots \ldots N_G \quad (4)
$$

$$
Q_{G\min} \leq Q_{Gi} \leq Q_{G\max} \quad i = 1, 2, 3 \ldots \ldots N_G \quad (5)
$$

where, $Q_{Gi}$ is the reactive power generation at $i^{th}$ generating unit.

Minimum and maximum voltage limits can be be given as:

$$
V_{j\min} \leq V_j \leq V_{j\max} \quad j = 1, 2, 3 \ldots \ldots N_B \quad (6)
$$

$$
V_{G\min} \leq V_{Gi} \leq V_{G\max} \quad i = 1, 2, 3 \ldots \ldots N_G \quad (7)
$$

where, $N_B$ represents the total number of load buses, $V_j$ and $V_{Gi}$ are the voltage at $j^{th}$ and $i^{th}$ load and generating bus respectively.

Transmission line limits can be given as:

$$
S_{\max} \leq S_l \quad l = 1, 2, 3 \ldots \ldots N_{\text{line}} \quad (8)
$$

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

D. 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]:

$$
\text{Minimize } C_C = \text{minimize } \sum_{i=1}^{N_G} C_i \Delta P_{Gi} + \sum_{i=1}^{N_G} D_i \Delta P_{Gi} \quad (9)
$$

where, $C_i$ and $D_i$ are the cost coefficients for incremental and decremental rescheduling bid for $i^{th}$ generator. $\Delta P_{Gi}$ and $\Delta P_{Gi}$ are the positive and negative deviation in real power generation from their preferred schedule for $i^{th}$ generator.

The re-scheduled generation at $i^{th}$ generator $P_{Gi}^*$ can be expressed as:

$$
P_{Gi}^* = P_{Gi} \pm \Delta P_{Gi} \quad (10)
$$

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:

$$
\Delta P_{G\min} \leq \Delta P_{Gi} \leq \Delta P_{G\max} \quad (11)
$$

E. 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:

$$
P_{Gi} - P_{Di} = 0 \quad (12)
$$

where, $P_{Gi}$ is the power injected at seller bus $s$ and $P_{Di}$ 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:

$$
\sum_{s} P_{G_{si}}^k - \sum_{b} P_{D_{bi}}^k = 0 \quad k = 1, 2, 3 \ldots \ldots t \quad (13)
$$

where, $P_{G_{si}}^k$ is the power injected at seller bus $s$ for the $k^{th}$ transaction and $P_{D_{bi}}^k$ is the power withdrawn at buyer bus $b$. 

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for $k$th transaction. Here $t$ is the total number of multilateral transactions.

$$\Delta P_{G_i}^{\text{min}} \leq \Delta P_{G_i} \leq \Delta P_{G_i}^{\text{max}}$$ (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 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).

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

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 suited 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. 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

IV. DEEP NEURAL NETWORK-BASED GR MODULE
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]:

$$\text{RMSE} = \sqrt{\frac{\sum_{n=1}^{N} (y_n - \hat{y}_n)^2}{N}}$$  \hspace{1cm} (18)

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

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 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. 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, ±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/ multi-lateral 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 ±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 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, 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 3×21×1 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 3×21×1 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.
| Loading Scenario | Target | Predicted | % Error  |
|-----------------|--------|-----------|----------|
| 1               | 179.0989 | 179.1119 | 0.00726  |
|                 | 45.97318 | 46.41644 | 0.96417  |
|                 | 21.83195 | 22.32291 | 1.03843  |
|                 | 23.63709 | 21.52447 | 0.01476  |
|                 | 19.08656 | 18.90128 | 0.97074  |
| 2               | 175.3584 | 175.2703 | 0.05025  |
|                 | 48.8095  | 48.414   | 0.8103   |
|                 | 22.53253 | 22.50306 | 0.80385  |
|                 | 21.75304 | 21.5975  | 0.3393   |
|                 | 19.08656 | 18.90128 | 0.97074  |
| 3               | 175.4749 | 175.3492 | 0.07164  |
|                 | 48.82962 | 48.58421 | 0.50258  |
|                 | 22.53253 | 22.50306 | 0.08385  |
|                 | 21.75304 | 21.5975  | 0.2593   |
|                 | 19.08656 | 18.90128 | 0.97074  |
| 4               | 173.7909 | 173.9033 | 0.06469  |
|                 | 49.55614 | 49.21436 | 0.1598   |
|                 | 22.43512 | 22.17122 | 0.61629  |
|                 | 23.07435 | 22.07786 | 0.5768   |
|                 | 17.63755 | 16.48621 | 0.573    |
| 5               | 178.3165 | 178.3749 | 0.03273  |
|                 | 49.55614 | 49.47695 | 0.1598   |
|                 | 22.43512 | 21.32051 | 0.61629  |
|                 | 23.07435 | 22.20591 | 0.5768   |
|                 | 17.63755 | 16.48621 | 0.573    |
| 6               | 177.8092 | 177.8287 | 0.01099  |
|                 | 46.79847 | 46.72582 | 0.1523   |
|                 | 21.7035  | 21.71584 | 0.05685  |
|                 | 23.07435 | 22.07786 | 0.35207  |
|                 | 17.63755 | 16.48621 | 0.573    |
| 7               | 174.1286 | 174.1684 | 0.02287  |
|                 | 45.69988 | 45.62999 | 0.1523   |
|                 | 21.3471  | 21.41974 | 0.34028  |
|                 | 21.6356  | 21.25477 | 0.43098  |
|                 | 16.92444 | 16.84757 | 0.45423  |
| 8               | 177.9146 | 177.9213 | 0.06879  |
|                 | 49.46039 | 49.23149 | 0.46279  |
|                 | 22.48788 | 22.74548 | 1.14551  |
|                 | 22.8216  | 22.65393 | 0.73469  |
|                 | 14.43141 | 14.48376 | 0.3627   |
| 9               | 176.6856 | 176.7388 | 0.03012  |
|                 | 47.8743  | 47.86917 | 0.01071  |
|                 | 21.61862 | 21.81928 | 0.92818  |
|                 | 22.22949 | 22.62725 | 0.19903  |
|                 | 16.08847 | 16.21521 | 0.78163  |
| 10              | 174.842  | 174.9293 | 0.04996  |
|                 | 47.16143 | 46.83521 | 0.69171  |
|                 | 21.39301 | 21.6158  | 1.04141  |
|                 | 22.45109 | 22.41705 | 0.15166  |
|                 | 15.02671 | 15.19864 | 1.14419  |
| 11              | 175.9004 | 175.8283 | 0.04097  |
|                 | 46.27024 | 46.1896  | 0.17428  |
|                 | 21.49173 | 21.45492 | 0.17129  |
|                 | 23.46564 | 23.38742 | 0.33332  |
|                 | 16.04721 | 16.19836 | 0.94197  |
| 12              | 177.0782 | 177.0474 | 0.01742  |
|                 | 45.73852 | 45.9035  | 0.36072  |
|                 | 21.62605 | 21.48647 | 0.6454   |
|                 | 22.55374 | 22.67164 | 0.52276  |
|                 | 18.46094 | 18.30997 | 0.8178   |
| 13              | 175.3839 | 175.4477 | 0.03636  |
|                 | 46.95522 | 46.7444  | 0.44899  |
|                 | 21.49945 | 21.74885 | 1.16003  |
|                 | 21.42545 | 21.36275 | 0.29267  |
|                 | 16.5075  | 16.56455 | 0.34561  |
| 14              | 175.1053 | 175.1552 | 0.09097  |
|                 | 45.03031 | 45.17921 | 0.36072  |
|                 | 21.41913 | 21.18758 | 0.6454   |
|                 | 23.07884 | 23.00815 | 0.52276  |
|                 | 16.77638 | 16.97227 | 0.8178   |
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.

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