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Original Article

Managing Network Congestion in Deregulated Environments Using Chaotic Butterfly-Optimized CNN Approach with Modified Back Propagation

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Abstract *- Power system congestion challenges are a common problem brought on by line, voltage and thermal limits. This process results in voltage instability, loss growth and voltage drop in the power system. Thus, considering all the known restrictions, efficient management of congestion should be carried out in order to ensure system operability. In this work, a Congestion Management (CM) method using a modified Back Propagation (BP) algorithm based on a Convolutional Neural Network (CNN) with a Chaotic Butterfly Optimization Algorithm (CBOA) is designed to reduce congestion and encourage Independent System Operators (ISOs). The primary objective of the proposed work is to produce improved estimation outputs with lower error values for congestion management. The proposed strategy is effectively verified for its operation on systems tested for various dimensions by implementing it on customized IEEE 118-bus, IEEE 57-bus and IEEE 30-bus test systems. The simulation is made using MATLAB Simulink software to acquire the most significant data for the test system, including congestion cost, change in real power, convergence profile and voltage magnitude.*

Keywords *- Convolutional Neural Network, Chaotic Butterfly Optimization, Congestion management, Modified back propagation algorithm.*

1. Introduction

Electric power is being transformed from a vertically integrated industry to a decontrolled utility. Vertical utility systems control all transmissions, distributors, and generation. The fact that distribution, transmission, and generation systems are independent of their surroundings makes it difficult for ISOs to maintain an unregulated utility system. CM is essential for the deregulated power market. The limits on voltage, stability and temperature place a limit on the amount of power that can be delivered across the transmission system [1].

CM is crucial for Distribution System Operators (DSOs) to manage congested distribution network assets to increase system security [2]. Examples of the former include network reconfiguration, congested line aging, transformer taps, phase shifters, and Flexible AC Transmission (FACTS) devices. The latter involves techniques like load reduction, generation rescheduling and generation prioritization. When a particular line is congested, ISO notifies consumers and allows load change while adhering to the system's limitations. Customers experience troubles as a result of CM, which is sometimes carried out by halting transactions [3].

The main approaches ISO uses to reduce congestion are both complementary and costly techniques [4]. When a line is congested, ISO alerts customers and enables them to modify their loads within the system's parameters. CM is occasionally implemented by physically blocking the exchange of funds despite the inconvenience to customers [5].

By using Soft Open Points (SOPs) to control low-voltage Active Distribution Networks (ADN) congestion, it is possible to balance the flow of power across various feeders, maximize their capability for regulation, and raise the system's overall power quality. A highly adjustable power electronic device known as a Soft Open Point (SOP) was placed to exchange normally open points to achieve precise and quick control of reactive and active power flow between feeders [6].

In [7], an innovative demand response system to reduce congestion is proposed. The proposed model and the ideal time for DRPs to run using wind power were validated on the IEEE 39-bus system network. For CM in a deregulated power system, work [8] presents an effective meta-heuristic Satin Bowerbird Optimization (SBO) method. A generation rescheduling-based strategy is used to ease transmission line congestion while meeting all requirements. To anticipate short-term solar power output, a hybrid ensemble deep learning architecture is designed [9]. This research in [10] analyses the operation of a Thyristor-Controlled Series Compensator (TCSC) for transmission line optimisation and congestion with the design of an algorithm that improves working measures of contingency analysis, placement, and control of TCSC. The ideal site for TCSC in terms of enhancing power transmission effectiveness, reducing instability and maintaining voltage stability in power systems [11]. In order to improve transient response and congestion control, TCSC is employed in power systems. The maximization of societal benefit, reducing load shedding, and enhancing load served were all mentioned in objective models for minimizing costs and load shedding [12].

A genetic algorithm is utilized to determine the best generation schedule for CM in an unregulated power system [13]. Grasshopper Algorithm [14], Firefly Algorithm (FA) [15], Grey Wolf Algorithm [16], Flower Pollination Algorithm [17], and Bat Algorithm [18] etc. are examples of nature-inspired swarm intelligence-based algorithms that have proven their worth and are now widely used by academics. Despite its advantages, it still has problems with things like slow convergence and local optima prediction. The proposed approach addresses the shortcomings of existing algorithms by combining CNN networks based on BPs and CBOA, a modern optimisation approach that excels in congestion control.

As a result of the proposed work, the following benefits will be achieved;

- To control congestion in a deregulated power system, a novel hybridization of BP-based CNN, this study offers an immediate/ready solution for generation rescheduling.
- To provide efficient and accurate output, even with an unbalanced data set, the Modified BP-CNN detects congested and non-congested loading conditions.
- To reduce the losses and costs associated with congestion,
- Using the proposed system, evaluate the effectiveness of different test systems, namely 30-bus, 57-bus and IEEE 118-bus.

The overall system was evaluated using MATLAB software and Simulink software, and the effectiveness of the system has been proposed is observed.

2. Proposed System Modelling

2.1. Congestion Management

Adjusting the generator's schedule handles the congestion management issue, which reduces congestion at the lowest possible organizing cost. As a result, Equation (1) demonstrates precisely that the entire problem may be expressed as a restricted minimization function. Assuming a change in power as ΔP_p:$0 \leq p \leq N_g$(MW) which is to be reorganized for a cost of $co(\Delta P_p)$ in \$ for p^{th} generator unit. The minimization problem is characterized, just as denoted in Equation (1) and subjected to specific restrictions.

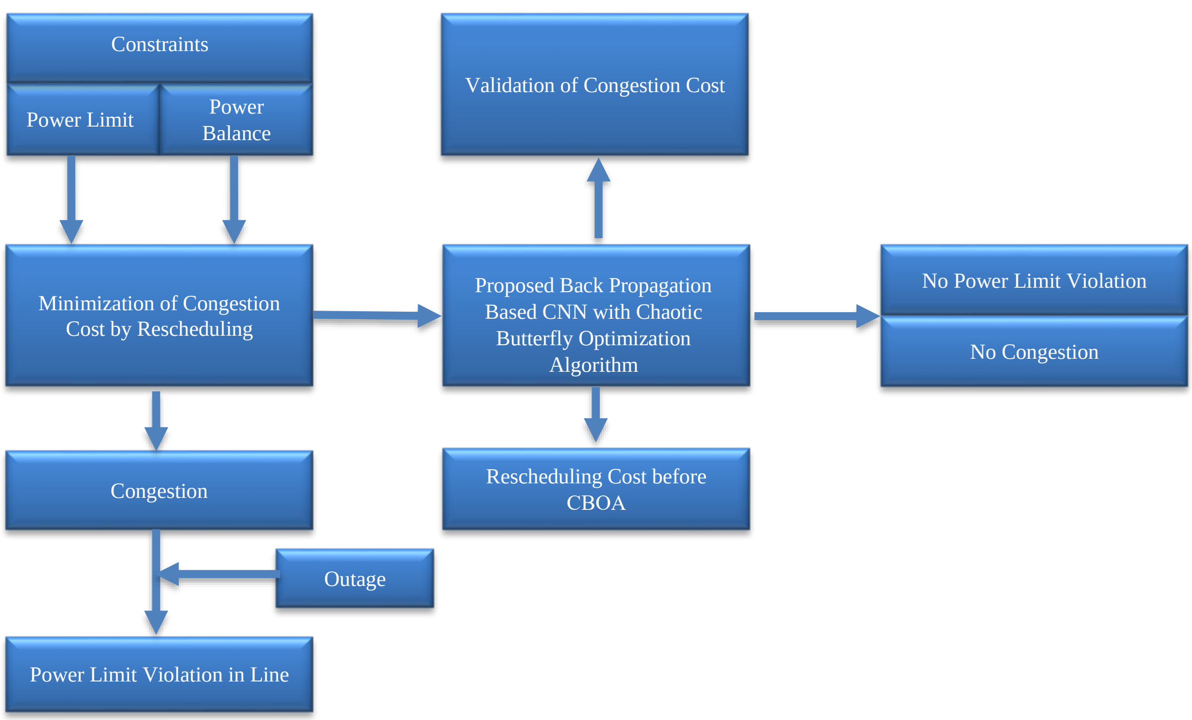


Fig. 1 Congestion management in a deregulated system

$$GE^* = \underset{\Delta P_p}{arg} \underset{\forall p}{min} \sum_{p=1}^{N_g} c(\Delta P_p) \quad (1)$$

By rearranging the active power output schedule of generators reduces the congestion cost, which is explained in the following.

2.2. Congestion Cost

In real terms, this rearranging is accomplished both by reducing or increasing active power output. This change in active power output, however, is subject to a charge that is represented by price bids. As a result, in Equation (2), the congestion cost is denoted as the cost of rescheduling.

$$CO_{total} = \sum_{j \in N_g}(CO_j \Delta P_p^+(j) + B_j \Delta P_p^-(j))\$/n \quad (2)$$

Where CO_{total} represents the overall expense of active power output modification ($/n), $CO_j: j = 1, 2, .., N_g$ and B_j displays the price offers to maximize power and reduce power in $/MWn by j^{th} iteration. Furthermore, active power change exposes disparities between the submitted price in attendance hour (n) and the hour before, as shown in Equation (3).

$$\Delta P_p = |P_p(n-1) - P_p(n)| \quad (3)$$

Whereas ΔP_p indicates the change in active power. Generated active power at (n-1) is denoted as $P_p(n-1)$, and currently, the power generated is denoted as $P_p(n)$.

The hybridization of modified BP-based CNN optimized by CBOA proposed for the management of congestion and a schematic diagram of work is presented in Figure 1. Moreover, the proposed work is evaluated by comparing its performance with metaheuristic techniques including Simulated Annealing (SA), FA, Random Search method (RSM) and PSO.

2.3. Modified BP Based CNN

Convolutional, activation and pooling layers are the basic layers that make up most contemporary CNNs. One additional node has been considered biased in the input and hidden layers. In the training process, two phases such as Forward Propagation (FP) and BP, update kernels to develop certain functionalities. In this work, a CNN trained by a modified BP method is proposed for detecting congested and non-congested Loading Situations (LSs). With the relevant partial derivatives of a cost function, BP updates kernels to detect congested loading situations. Figure 2 illustrates the structure for modified BP-based CNN.

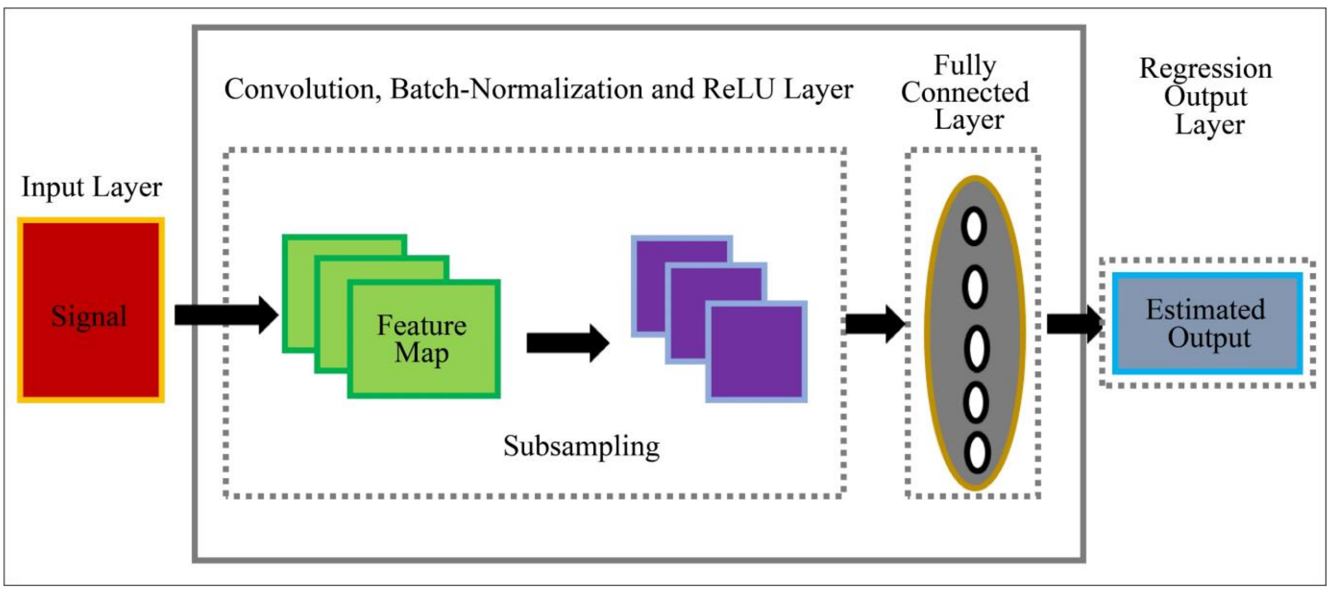


Fig. 2 Structure for modified BP-based CNN

Two steps are involved in the BP stage in training CNN, such as δ propagation and kernel updating. The partial derivative of cost function J concerning output feature map y in FP is known as δ. Due to the propagating relationship of y between layers and the chain rule of the partial derivatives, s is capable of being computed via propagations. The dimensions of δ's and y's remain constant since each constituent of y has its derivative. However, the calculations for propagation differ. The Kernel Update (KU) stage determines which kernels' partial derivatives are used for optimization. The gradient descent is an optimization algorithm, and it is stated in the equation as follows;

$$Ker[i,j] = ker[i,j] - \alpha \frac{\partial J}{\partial Ker[i,j]} = Ker[i,j] - \alpha \sum_{(r,c)\epsilon\delta} \delta[r,c].x[r+i,c+j] \quad (4)$$

Where the input window is represented as x[r+i,c+j] and α denotes the learning rate constant. As a result, windows of the input feature maps and corresponding elements of the maps can determine the partial derivatives of kernels. Table 1 represents the CNN architecture utilized in the proposed work.

Table 1. Architecture for CNN layer

Layers	No. of Filters	Filter Size
Convolution-ReLU	32	3× 3
Max-pooling	32	2× 2
Convolution-Maxout	32	2× 2
Max-Pooling	32	2× 2
Convolution-Maxout	48	2× 2
Max-Pooling	48	2× 2
Convolution-Maxout	64	2× 2
Max-Pooling	64	2× 2
Full-connected	512	2× 2

The hybridization of modified BP algorithm based CNN is then optimized using the optimization technique in which the following section explains the optimization approach proposed in this work.

2.4. Chaotic BOA

It is a nature-based metaheuristic algorithm that originates from an algorithm related to BOA. While flying in the environment, butterflies in BOA exhibit fragrance. There are five of them (taste, touch, smell, sight, and hearing). It assists animals in finding food, locating mates for mating, traveling from one location to another, and avoiding predators. Butterflies in motion emit powerful smells. Depending on the potency of the scent, other butterflies will be attracted to it. Every butterfly's fragrance is stated in the following,

$$P_i = M_s . I_S^Y ; i \in (1,2,..,N), \tag{5}$$

Where I_S denotes impulsive intensity, M_S indicates the modality of the sensor, P_i denotes i^{th} butterfly's fragrance magnitude and Y indicate the power component. Butterfly movement takes place in three stages: global exploration phase, local search phase, and determining outcomes analysis. The motion of butterflies during their exploration stage is stated in equation (6),

$$m_i^{t+1} = m_i^t + (n^2 \times q^* - m_i^t). P_i \text{ where } n \in [0,1] \tag{6}$$

The random number is denoted as n, and the best solution's solution vector of i^{th} the butterfly is denoted as m and q^* respectively. During the local search, butterflies are expressed as,

$$m_i^{t+1} = m_i^t + (n^2 . m_g^t - m_h^t) \times P_i \tag{7}$$

Where m_h and m_g are h^{th} and g^{th} butterflies assisted in searching for space. The third phase, solution evaluation, uses the smell's potency as the objective function. Due to other randomness in the process, equations demonstrate that butterflies get confused while trying to discover the ideal value that is denoted as n^2. BOA's involvement with local optimum and inadequate convergence rate are its main downsides.

A novel technique is proposed to overcome these problems, in which chaotic maps in the proposed CBOA play a function of BOA's independent character. Enabling BOA to attain a global minimum and avoid getting stuck at the local minimum, in addition to chaotic maps, enhances its behavior randomly and accelerates the pace of convergence. The following steps represent the procedure for the CBO algorithm;

1. A chaotic map is used for updating butterfly's position rather than random variables in which the Equations (6) and (7) are replaced as follows;

$$m_i^{t+1} = m_i^t + \left(C_j \times q^* - m_i^t\right). P_i \tag{8}$$

$$m_i^{t+1} = m_i^t + (C_j . m_g^t - m_h^t) \times P_i \tag{9}$$

Where the chaotic map is represented as C_j in which $j = 1, 2, \dots 0.10$.

2. CBOA is anticipated to be far more robust than binary CBOA in the context of binary values [0, 1], allowing for adaptive feature space searching for best feature combinations. Equation (10) represents binary CBOA,

$$x_i^{t+1} = \begin{cases} 1 & if\ \left(s\left((x_i^{t+1}\right)\right) \geq rand\ (), \\ & 0, \quad otherwise, \end{cases} \tag{10}$$

Where transfer function is denoted as s, $rand$ () denotes a number randomly that is obtained from a uniform distribution [0, 1] and x_i^{t+1} represents updated solutions;

$$s(x_i^{t+1}) = \frac{1}{1+exp^{10\left(x_i^{t+1}\right)-0.5}} \tag{11}$$

The proposed algorithms clearly improve the dependability of optimal performance and quality of outputs, according to statistical findings and success rates of CBOAs. The improvement in the trade-off between exploration and exploitation caused by the addition of regular signals that are chaotic is the fundamental cause of CBOAs' improved performance. The chaotic variable also enables CBOAs to explore search space more casually, aiding algorithms in avoiding local optimization ineffective and accelerating optimization.

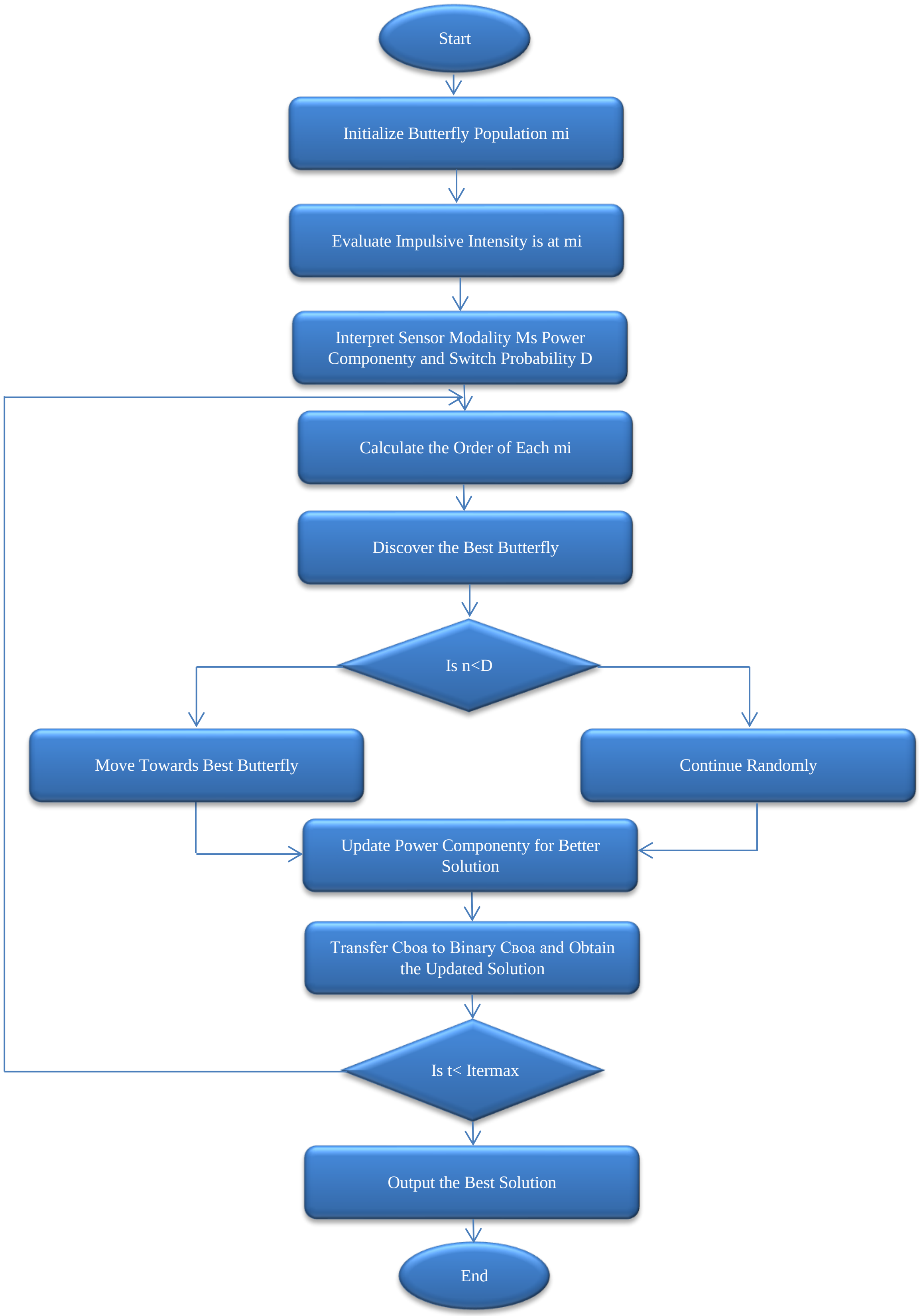


Fig. 3 Flowchart for CBOA

3. Results and Discussion

In this work, the congestion problem in an uncontrolled environment is solved using a CNN built on a modified BP base that has been CBOA optimized. With decreased congestion cost, optimized CNN allows for active power rescheduling of generators. Modified BP-based CNN receives three inputs: active, apparent and reactive power load. Additional pre-processing, such as eliminating outliers and transforming the data into a time-series format, is necessary after the data is collected at the scheduled times. Information is arranged into tensors or arrays, where rows stand for time steps and columns for features like active power load. The prepared data are used as input by the CNN built using the modified BP architecture. The proposed research is validated on various networks, comprising IEEE 118-bus, IEEE 57-bus and IEEE 30-bus and confirmed by implementation in MATLAB. Table 2 provides the test systems considered to evaluate the effectiveness of CBOA-optimized modified BP-based CNN for CM.

Table 2. Details of testing system

Test case	1A	1B	2A	2B	3
System on test	Improved	IEEE 30-bus	Improved	IEEE 57- bus	IEEE 118-bus
Contingency taken into account	Outage of line across 1 and 2	Between 1 and 7 outages in the line	Line ability reduction between 50-35	Line capacity reduction between 2 and 3 lines	Between 5 and 8, a line outage takes place.

3.1. System Test on IEEE 30-Bus

We propose to use an updated version of the IEEE 30-bus system, which includes 6 generator buses, 41 transmission lines, and 24 load buses, to fully grasp the opportunities of the modified BP-based CNN-based CM method. Here, two distinct cases are taken into consideration. Case 1A: A power outage produces traffic congestion on lines 1-7 and 7-8; Case 1B: Bus load increases to 50%, causing traffic congestion on lines 1-2, 2-8, and 2-9. Table 3 provides specifics about the results, indicating that the proposed work yields better results in cases 1A (22.036) and 1B (165.148).

Table 3. Test system results

	Techniques	TC, $/h	ΔP_{G_1}	ΔP_{G_2}	ΔP_{G_3}	ΔP_{G_4}	ΔP_{G_5}	ΔP_{G_6}	TRRG
Case 1A	RSM[19]	731.25	-8.900	3.141	3.456	4.102	3.213	3.412	26.224
	SA[19]	750.86	-9.090	3.341	3.741	3.243	3.521	2.943	25.879
	FA[20]	520.91	-8.900	16	1.012	1.151	1.1786	-1.521	29.762
	PSO[19]	560.90	-8.80	11.5	3.421	0.52	1.01	-1.02	26.271
	Proposed	410.50	-7.800	8.43	1.424	1.496	1.658	1.2281	22.036
Case 1B	RSM[19]	6321	-	-	-	-	-	-	175.9
	SA[19]	7125.6	-	-	-	-	-	-	178.32
	FA[20]	5496.1	-8.815	76.21	1.032	43.5	24.51	17.21	171.277
	PSO[19]	5635.2	-	-	-	-	-	-	174.8
	Proposed	5548.6	-9.706	63.5	35.12	2.912	30.41	23.50	165.148

TC-Total, TRRG-Total Real power Rescheduling Generator

Figure 4 shows computational findings for case 1A. When the figure is analysed, it is found that the proposed CM technique employing CBOA-optimised Modified BP-based CNN has the lowest possible congestion cost. Real-power losses are also substantially lower than before, going from 16.13 MW to 12.65 MW, demonstrating the success of the proposed methodology. The voltage magnitude is also maintained within a reasonable range (0.9 to 1.1) following CM.

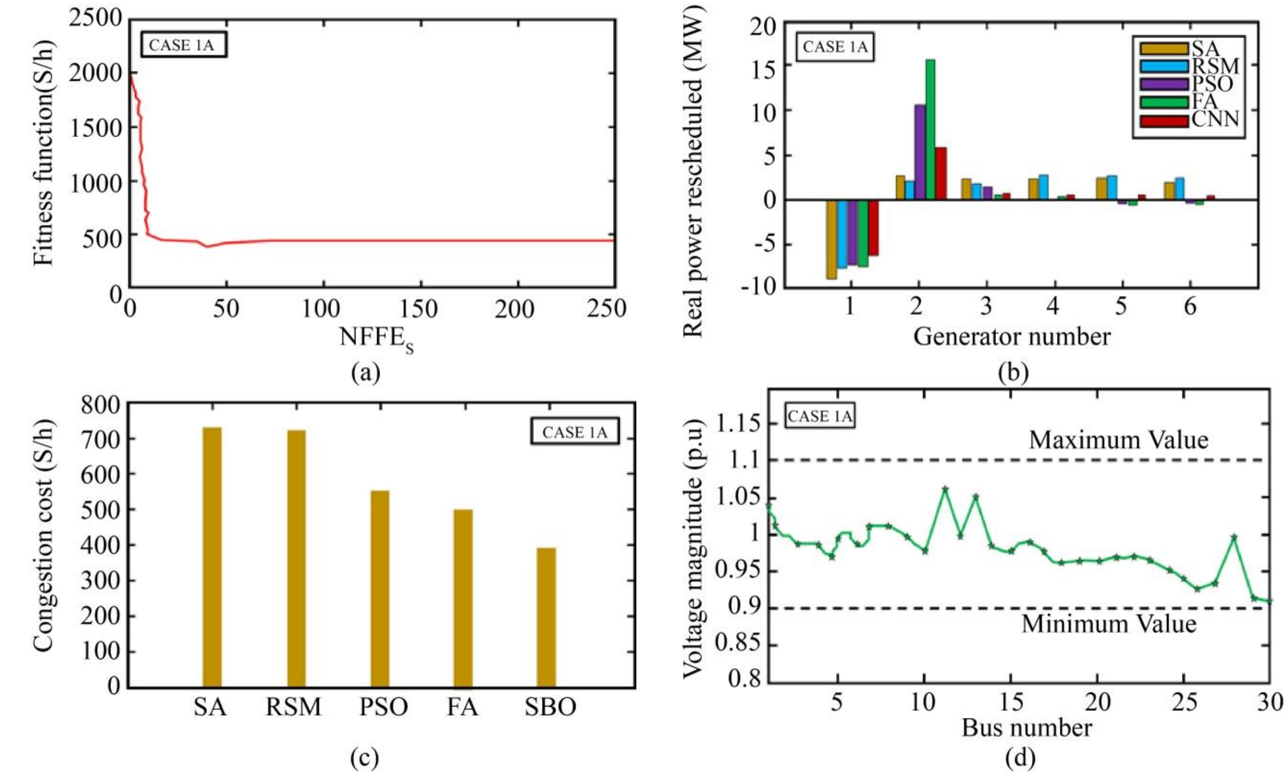


Fig. 4 Simulation findings of case 1A (a) Rate of convergence, (b) Real power alteration, (c) Congestion cost, and (d) Magnitude of voltage.

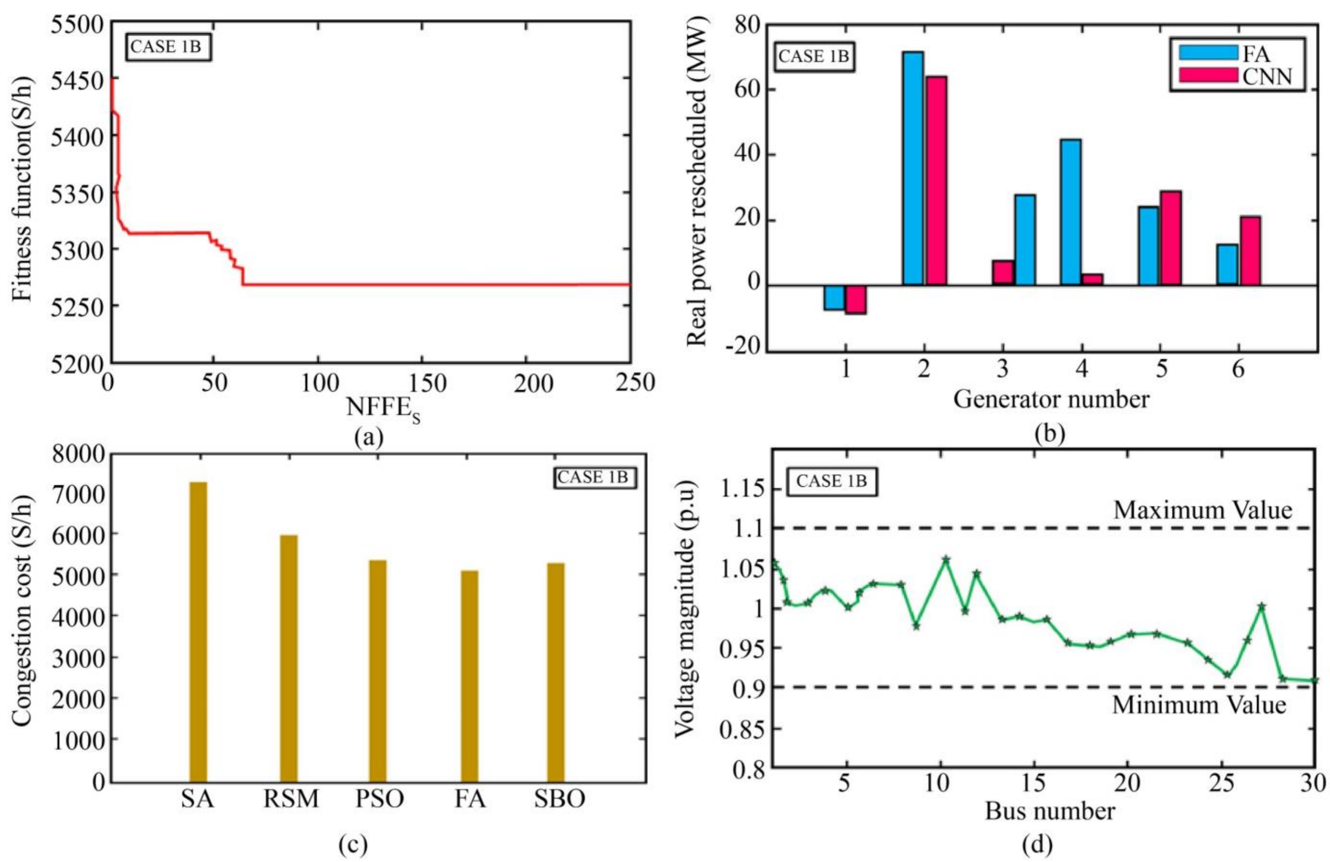


Fig. 5 Simulation findings of case 1B (a) Convergence rate, (b) Real power comparison, (c) Congestion cost, and (d) Magnitude shown for voltage.

Table 4. Test system results

	Techniques	TC, \$/h	ΔP_{G_1}	ΔP_{G_2}	ΔP_{G_3}	ΔP_{G_4}	ΔP_{G_5}	ΔP_{G_6}	ΔP_{G_7}	TRRG
Case 2A	RSM[19]	7912.1	60.2	0	40.1	-49.5	-64.5	0	0	214.3
	SA[19]	7212.1	79.1	0	-3.21	10.2	-89.2	0	0	181.71
	FA[20]	6412.3	6.13	3.21	3.2	2	-49.6	-40.5	65.2	169.84
	PSO[19]	6921.4	25.6	14.2	9.21	-7.31	-83.4	0	40.1	179.82
	Proposed	5614.2	-0.07	-11.9	-6.01	-45.3	-52.1	-35.1	-0.71	151.19
Case 2B	RSM[19]	4312.7	-	-	-	-	-	-	-	70.3
	SA[19]	4321.4	-	-	-	-	-	-	-	72.5
	FA[20]	2994	0.42	-28.6	32.4	0.72	-2.91	-2.12	-1.32	68.49
	PSO[19]	3912.2	-	-	-	-	-	-	-	69.91
	Proposed	2613.1	0.94	1.2	23.042	0.21	-11.6	-11.1	16.91	37.37

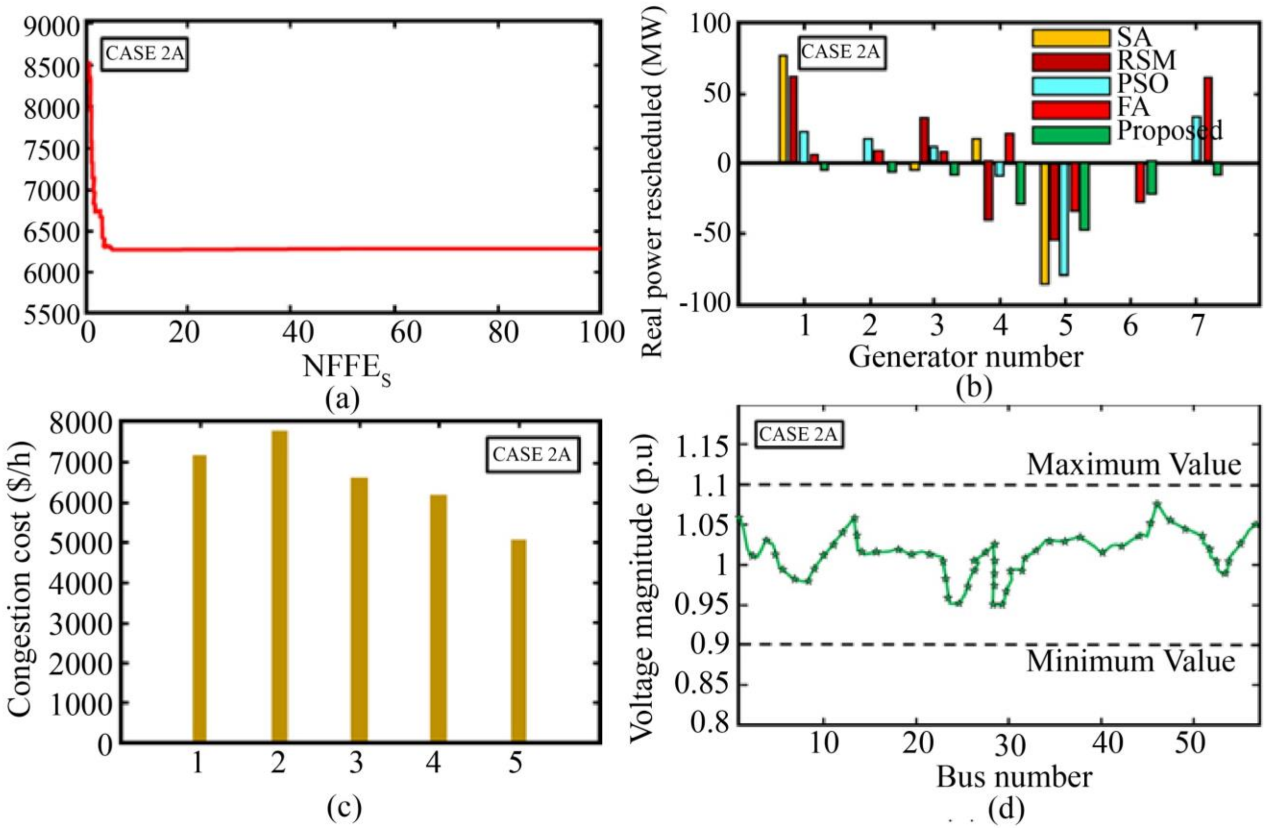


Fig. 6 Simulation findings of case 2A (a) Speed of convergence, (b) Real power changes, (c) Congestion cost, and (d) Magnitude change in voltage.

In Figure 6, model results for case 2A are displayed. Case 2A reduces the line restrictions for lines 6-12 and 5-6 from 50 MW to 35 MW and 200 MW to 175 MW, correspondingly.

There is an overload among lines 6-12 and 5-6 when congestion occurs. After CM in case 2A utilising the suggested methods, the system loss dramatically decreased from 69.64 MW to 24.558 MW.

Figure 7 shows simulated findings of case 2B in contrast. By lowering the line limit between lines 2-3 from 85 MW to 20 MW, case 2B causes line overloading. Analysis of Table 4 reveals that the proposed approach performs comparably better in Case 2A as well. In this instance, system losses decreased significantly from their initial value of 78.23 MW before CM to 28.22 MW. Overall, optimised real-power rescheduling reduces the violation of overloading lines.

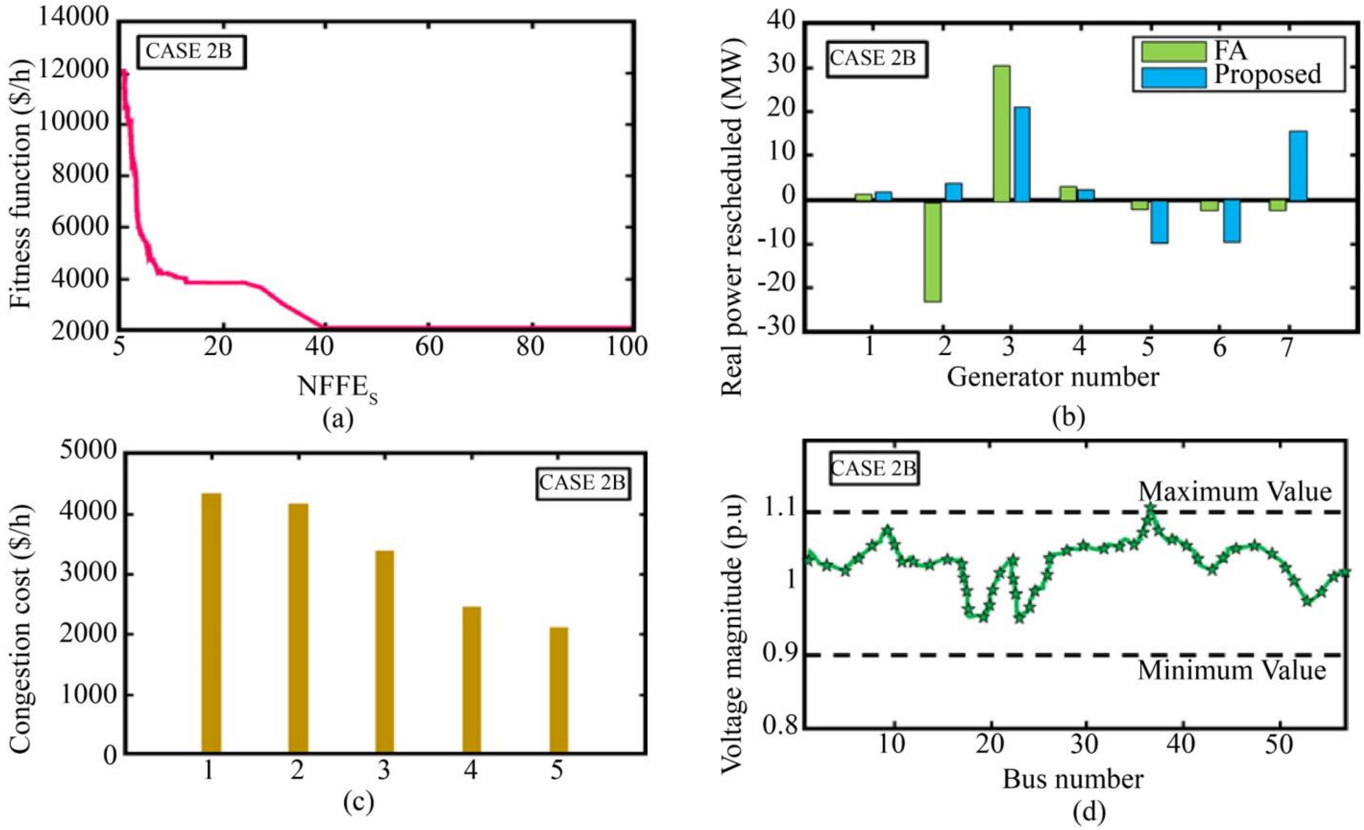


Fig. 7 Simulation findings of case 2B (a) Profile of convergence speed, (b) Real-power change, (c) Congestion cost, and (d) Voltage magnitude.

3.2. System Test on IEEE 118-Bus

By implementing the proposed Modified BP-based CNN for CM in a redesigned approach of a 118-bus test system composed of 64 load buses, 54 generator buses and one 186 transmission line, its performance in other test systems is also assessed. In this instance, loads across lines 20 and 11 are enlarged by 1.57 times when lines 5 and 8 are unplugged. The results that are simulated for Case 3 are shown in Figure 8.

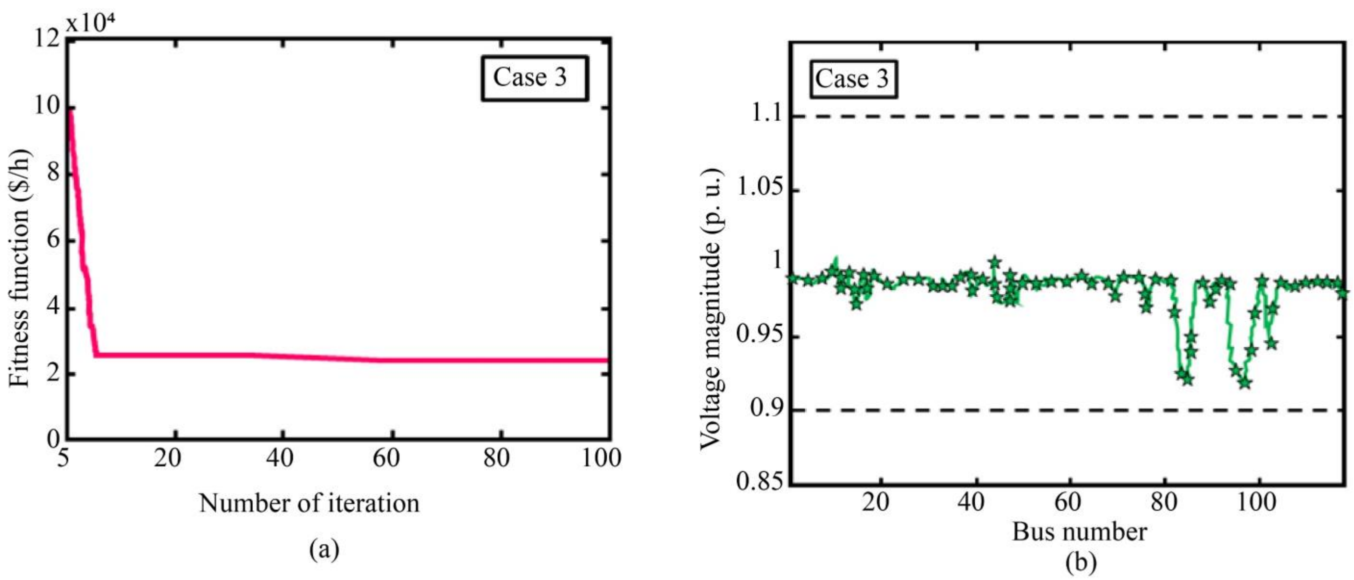
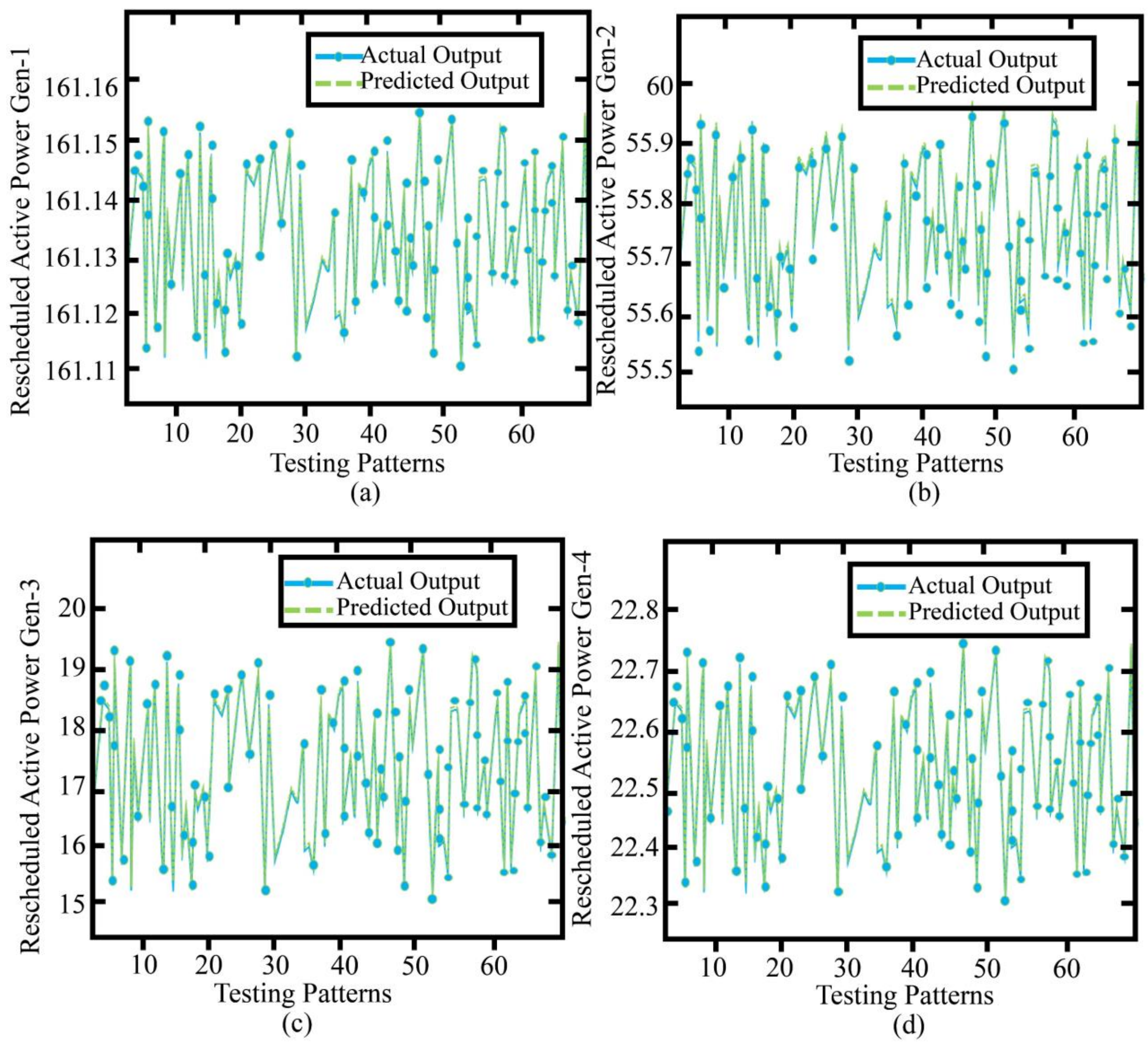


Fig. 8 Simulation findings of case 3 (a) Convergence profile, and (b) voltage magnitude.

Table 5. IEEE 30-bus system generator rescheduling comparison

Approaches	Outcomes	G1	G2	G3	G4	G5	G6
DNN[21]	Predicted	179.111	46.416	21.605	23.640	18.901	-
	Actual	179.098	45.973	21.831	23.637	19.086	-
	% Error	0.007	0.964	1.038	0.014	0.970	-
Proposed CBOA-Modified BP-Based CNN	Predicted	161.146	55.84	18.707	22.672	18.353	32.876
	Actual	161.149	55.945	19.527	22.676	18.384	32.915
	% Error	0.002	0.105	0.82	0.004	0.031	0.039



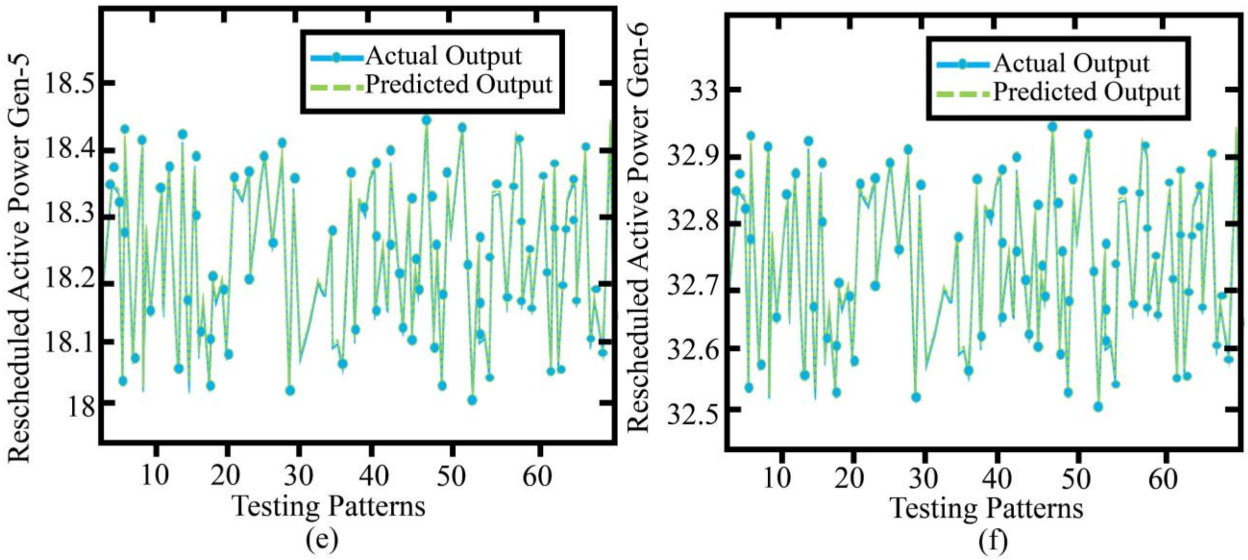


Fig. 9 (a-f) Actual and predicted outputs

The proposed CBOA-Modified BP-based CNN for generator rescheduling is compared to existing works in Table 4, and the relevant graphs are shown in Figsures 9(a-f).

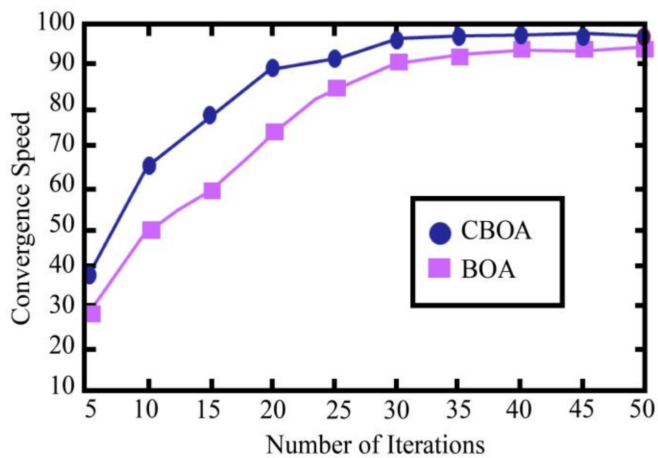


Fig. 10 Convergence speed comparison

The provided values show that the suggested work performs better than competing ones, with improved prediction results showing a lower error. The proposed CBOA algorithm achieves a faster convergence speed than BOA, illustrated in Figure 10.

4. Conclusion

This study offers a quick fix for congestion control in a power system without regulation using generation rescheduling. In order to lessen congestion by reducing fuel/congestion costs, a novel hybridization of a modified BP-based CNN has been developed in this study for generation rescheduling. The newly developed hybrid CNN comprises a cascading combination of a generation rescheduling module and a screening module. For all unknown congested loading conditions, the proposed Neural Network offers active power rescheduling of generators very quickly with minimal congestion costs. Once trained, the proposed hybrid Neural Network forecasts active power generation rescheduling as soon as possible. As a result, it is possible to demonstrate that the proposed CBOAs' convergence values are better. In the proposed work, MATLAB simulations, and simulation outcomes, the CBOA-modified BP-based CNN demonstrates excellent performance in reducing congestion losses and costs.

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