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Optimal Active Power Rescheduling for Transmission Congestion Management Using Competition of Tribes and Cooperation of Members Algorithm

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ABSTRACT- Congestion management in transmission systems is one of the key challenges in deregulated electricity markets for independent system operators. This issue can be solved by optimal rescheduling of active power generation in congested transmission systems. This paper introduces a metaheuristic-based methodology for solving the congestion problem in the transmission lines. The proposed approach employs the competition of tribes and cooperation of members (CTCM) algorithm for effective optimal rescheduling of active output power generation in congested transmission systems. This method mitigates the congestion in transmission lines by optimally adjusting the active power output generation while obeying constraints such as line thermal limits, bus voltage magnitude limits, and generator capacity constraints. The suggested methodology is tested on a modified IEEE-30 bus transmission system and a modified IEEE-57 bus transmission system under two critical cases. Further simulation results prove that the proposed methodology helps to mitigate congested lines with minimum rescheduling cost. Further, a performance comparison with established algorithms from the literature study has been presented. It shows the effectiveness of the proposed method in solution quality and computational reliability for congestion management applications.

Keywords: Congestion Management, Optimization, Voltage Constraints, Deregulation.

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1. INTRODUCTION

The operational landscape for independent system operators has changed due to the restructuring of power systems from vertically integrated monopolies to deregulated competitive markets [1]. In this market, congestion in transmission networks has emerged as one of the most challenging operational concerns, which leads to power flow exceeding transmission line thermal limits and deviations in voltage levels above permissible limits [2].

The operational and economic consequences of congestion in transmission systems are substantial. It restricts market competition, creates inefficiencies through increased transmission costs, and results in higher electricity prices for consumers. Therefore, effective congestion management schemes are required to confirm secure and economic management of deregulated power networks [3]. Generation rescheduling has arisen as a promising option for congestion management in transmission systems [4].

This scheme seeks the optimal rescheduling of generator output to alleviate burdened transmission lines while curtailing the total congestion cost [5]. However, this optimization problem is complex, requiring satisfaction of multiple operational constraints, including transmission line thermal limits, generator capacity limits, and bus voltage constraints. This makes it a difficult multi-constraint optimization problem that imposes robust solution methodologies.

The congestion management trial *via* optimal generation rescheduling has received much attention from many researchers, leading to the development of various metaheuristic-based optimization algorithms [6]-[18]. These methods aim to determine the optimal generator output adjustments that alleviate the congestion in transmission network lines while minimizing operational costs. In [6], authors have adopted the artificial bee colony (ABC) method for optimal rescheduling of generation output. In [7][8], particle swarm optimization (PSO) has been adopted to demonstrate initial efficacy in generator rescheduling. In [9], the firefly algorithm (FFA) has been adopted for congestion management with efficient global searches in deregulated markets. In [10], [11] teaching-learning-based optimization (TLBO) and Ant Lion Optimizer (ALO) have been employed for the congestion problem in transmission networks, respectively, while their efficiency diminishes in extensive systems with several limitations. Recent algorithms include the Symbiotic Organism Search (SOS) [12], Circulatory System Based Optimization (CSBO) [13], Innovative Gunner Algorithm (IGA) [14], Gravitational Search Algorithm (GSA) [15], improved Manta Ray Foraging Optimization (IMRFO) [16], improved Monarch

Butterfly Optimization (IMBO) [17], and Nutcracker Optimizer Algorithm (NOA) [18], which have been employed for optimal rescheduling of generation output for congestion management. Although these methods demonstrate incremental advancements, the majority continue to struggle with premature convergence or inadequately balanced exploration and exploitation.

Competition of Tribes and Cooperation of Members (CTCM) is a meta-heuristic-based method inspired by the operations of primitive tribal societies [19]. In this CTCM algorithm, the exploration-exploitation tradeoff uses two complementary mechanisms, such as collaboration among tribe members with analogous traits and competition among disparate tribes pursuing enhanced solutions. Further, an erratic loyalty updating procedure periodically reallocates members to various tribes. This method maintains population diversity and prevents premature convergence. This paper presents an application study investigating the CTCM algorithm for congestion management in deregulated electricity markets. The implementation of CTCM is suggested to determine the optimal generator output adjustments that mitigate the congestion in transmission lines while minimizing operational costs. Further, CTCM has been compared with different algorithms such as PSO, FFA, TLBO, ALO, SOS, and CSBO on the IEEE 30-bus transmission test system under critical cases.

2. MATHEMATICAL PROBLEM FORMULATION

The main aim of the congestion management is to reduce the total congestion cost while maintaining voltage magnitude, line thermal, and generator capacity constraints. In this work, the congestion problem in transmission lines has been solved by adjustments to the active power generator outputs. While the adjustment in active power output is related to total congestion cost, which varies on the price bids suggested by generator companies (GENCOs). The objective of congestion management is expressed as given in *equation (1)*.

$$Minimize\ T_{cost} = \sum_{i\epsilon N_g}\left(C_{g,i}\Delta P_{g,i}^{+} + D_{g,i}\Delta P_{g,i}^{-}\right) \quad (1)$$

Where, $D_{g,j}$, $C_{g,j}$ represents the decrement and increment price bids ($/MWh), $\Delta P_{g,j}^{-}$, $\Delta P_{g,j}^{+}$ represents the active power output decrement and increment of generator (MW).

The current optimization problem is constrained by both inequality and equality conditions as given below.

2.1. Equality Constraints

The constraints of power flow in the transmission network are defined by equality, which are expressed as given in *equations (2) to (5)*.

$$P_{g,i} - P_{d,i} = \sum_{j=1}^{N_b}\left(|V_i||V_j|\left[G_{ij}cos(\delta_i - \delta_j) + B_{ij}sin(\delta_i - \delta_j)\right]\right) \quad (2)$$

$$Q_{g,i} - Q_{d,i} = \sum_{j=1}^{N_b}\left(|V_i||V_j|\left[G_{ij}sin(\delta_i - \delta_j) - B_{ij}cos(\delta_i - \delta_j)\right]\right) \quad (3)$$

$$P_{g,i} = P_{g,i}^{C} + \Delta P_{g,i}^{+} - \Delta P_{g,i}^{-} \quad (4)$$

$$P_{d,i} = P_{d,i}^{C} \quad (5)$$

where $Q_{g,i}$ and $P_{g,i}$ indicate the reactive and active power generation at node *i*, respectively. $Q_{d,i}$ and $P_{d,i}$ indicate the reactive and active power consumption at node *i*, respectively. V_i and V_j represent voltage bus magnitudes at nodes *i* and *j*, respectively. δ denotes voltage phase angles. *Bij* and *Gij* represent susceptance and conductance of the transmission branches connecting nodes. *Nb* denotes the total number of network nodes. $P_{g,i}^{C}$ and $P_{d,i}^{C}$ denote the baseline active power generation and consumption at node *i*.

2.2. Inequality Constraints

The constraints of the power network are stated by inequalities, which set the operational and physical limits. Operational restrictions and generator limitations are described in *equations (6) to (10)*.

$$P_{g,i}^{min} \le P_{g,i} \le P_{g,i}^{max} \quad (6)$$

$$Q_{g,i}^{min} \le Q_{g,i} \le Q_{g,i}^{max} \quad (7)$$

$$\left(P_{g,i} - P_{g,i}^{min}\right) = \Delta P_{g,i}^{min} \le P_{g,i} \le \Delta P_{g,i}^{max} = \left(P_{g,i}^{max} - P_{g,i}\right) \quad (8)$$

$$V_i^{min} \le V_i \le V_i^{max} \quad (9)$$

$$|S_{ij}| \le S_{ij}^{max} \quad (10)$$

Where, $P_{g,i}^{max}$ /$P_{g,i}^{min}$ denotes the maximum/ minimum active power output limits, respectively. The same applies to reactive power, where $Q_{g,i}^{min}$and $Q_{g,i}^{max}$define how much reactive power the generator can produce or absorb. Bus voltages must stay between V_i^{min} and $V_i^{max}$to avoid damaging equipment or causing stability problems. For the transmission line connecting nodes *i* and *j*, the apparent power flow (*Sij*) cannot exceed maximum limit (S_{ij}^{max}), which is set by the thermal rating of that line. Violating any of these limits during optimization means the solution isn't physically realizable.

3. CTCM ALGORITHM FOR CONGESTION MANAGEMENT

This section shown the experimental result of our novel ANN-FLC-Nanofluid-Lyapunov A framework -Nanofluid-Lyapunov A framework is employed for a 400 kVA, 33/0.38 kV, ONAN transformer at the Nasiriyah Electrical Research Laboratory. All verifications were carried out under harsh operating conditions: 40°C ambient, 140% overload, 5.2% THD, and +15°C step fluctuation.

3.1. Tribal Organization and Social Structure

The CTCM algorithms mimic the operation of early human tribes, in which the population was divided into tribes settling (*n*) different locations and migrating to find better resources. Each tribe is led by a chief, who controls the best resources and guides the tribe's movement direction [19]. Tribe members will

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search for better resources based on both their own experience and the chief's instructions. Tribe members typically follow their chief; they can think independently and may change the chief if they discover more fertile land. When two tribes encounter each other, they compete for resources, and the weaker tribe will retreat to avoid conflict and losses.

3.2. Mathematical Model and Algorithm

CTCM algorithm's mathematical structure based on the interactions of tribes and their members

3.2.1. Population Initialization

Across *m* tribes, *n* number of populations has been created by using *equation (11)*

$$X_{n,m,d} = X_{min} + rand(0,1) \times (X_{max} - X_{min}) \tag{11}$$

where n = 1,2,...,p (individuals), m = 1,2,...,tribes, and d = 1,2,...,dimensions

where Xn,m,d denotes the d^{th} dimension of the n^{th} individual within the m^{th} tribe, p represents the aggregate count of individuals (generators engaged in congestion management), and the dimensions signify the power system parameters (generation rescheduling variables).

3.2.2. Tribal Assignment and Chieftain Selection

The population is divided into tribal groups, each with about p tribe members. The leader of each tribe is chosen based on the best fitness evaluation, which means the lowest congestion cost, within that tribe. Each person has a velocity vector that determines where they will go next. The complete velocity matrix V for a basic human society is shown as

$$V = [V_1 \quad V_2 \quad \cdots \quad V_p]^T \in \mathbb{R}^{p\times d} \tag{12}$$

The velocity matrix is formulated as

$$V_n = \begin{bmatrix} V_{n,1,1} & \cdots & V_{n,1,d} \\ \vdots & \ddots & \vdots \\ V_{n,m,1} & \cdots & V_{n,m,d} \end{bmatrix} \in \mathbb{R}^{m\times d} \tag{13}$$

3.2.3. Cooperation of Members (Exploitation)

The chief, as the foremost leader, holds the primary responsibility for strategic oversight and developmental initiatives. Nonetheless, individual tribe members retain their cognitive liberty, resulting in variations in their devotion over time. This commitment exhibits chaotic traits, with the magnitude of this disorderly conduct strengthened by the size of the tribal community. Therefore, sine chaotic representation is applied to show these transformations in loyalty, considering how the number of tribes, shown as n, affects the chaotic states. Individual member loyalty, shown as rt, is shown as follows:

$$r_t = \begin{cases} U(0,1) & if\ t = k.m, k \in \mathbb{Z} \\ sin\left(\frac{\pi}{2} r_{t-1}\right) & else \end{cases} \tag{14}$$

The equation for modifying the position in collaboration is

$$V_{n,m,d}^{t+1} = \frac{3}{5}V_{n,m,d}^{t} + c_1 r_1\left(X_{n,m,d}^{best} - X_{n,m,d}^{t}\right) + c_2 r_2\left(X_{tribe}^{best} - X_{n,m,d}^{t}\right) \tag{15}$$

Where, $V_{n,m,d}^{t+1}$ is the velocity of the nth member of the mth tribe at iteration *t+1*. Coefficient 3/5 is the inertia parameter and $V_{n,m,d}^{t}$ is the velocity at iteration *t*. $X_{n,m,d}^{best}$ shows where the tribe found the best fitness during the search period. X_{tribe}^{best} shows the position at iteration t. c_1 and c_2 denote the experience factor and obey factor, respectively. r_1 and r_2 represent the loyalty coefficients of particular members.

3.2.4 Competition of Tribes (Exploration)

Inter-tribal conflicts demonstrate the competitive dynamics involved. These arguments often come from tribes opposing over resources, such as more efficient generator scheduling methods, which force less competitive tribes to back down. Conflicts between tribes can happen by accident, causing the weaker group to leave while the stronger tribe stays safe. The equation $I_{rival} = rand(n))$ shows a random interaction with a tribe chosen from n tribes. Subsequently, the expression of velocity is modified as given in the below *equations (17)*.

$$R_{n,m,d}^{t} = c_3 r_3\left(X_{n,m,d}^{t} - X_{rival}^{best}\right) \tag{16}$$

$$V_{n,m,d}^{t+1} = \begin{cases} V_{n,m,d}^{t+1} - R_{n,m,d}^{t}, & if\ F_n^{best} < F_{rival}^{best} \\ V_{n,m,d}^{t+1} & else \end{cases} \tag{17}$$

where X_{rival}^{best}represents the optimal position identified by the competing tribe, f_n^{best} denotes the superior value of the n-th tribe and f_{rival}^{best}signifies the best value of the competing tribe. Parameter c_3 denotes the tribal retreat coefficient and r_3 constitutes a chaotic stochastic parameter characterizing the withdrawal velocity. Subsequently, the positions of tribal participants are modified according to:

$$X_{n,m,d}^{t+1} = X_{n,m,d}^{t} + V_{n,m,d}^{t+1} \tag{18}$$

When the revised position of a tribal participant $X_{n,m,d}^{t+1}$ surpasses the permissible solution space boundaries $[X_{min}, X_{max}]$ where X_{min}defines the lower boundary of the domain and X_{max}specify the upper boundary of the designated domain, the position information undergoes correction.

$$V_{n,m,d}^{t+1} = -V_{n,m,d}^{t+1} \tag{19}$$

Concurrently, the tribal member's position receives appropriate adjustment. The framework of CTCM is established, and its algorithmic procedure is presented in *Algorithm 1*.

Algorithm 1 The algorithm of CTCM for Congestion Management

Input: *Maximum iteration count: $iter_{max}$, total number of humans (n), number of tribal groups (m), Weighting coefficients: experience factor (c_1), obey factor (c_2), escape factor (c_3)*

Output: X^{best}, T_{cost}^{best}

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while *iter< iter$_{max}$ do*
  for *Each human do*
    revise the loyalty factor r_1, and, r_2, by Eq. (14)
    revise the velocity $V_{n,m,d}^{t+1}$ by Eq. (15)
    // Apply generator power constraints (6) – (10)
    if $X_{n,m,d}^{t} < P_{g,i}^{min}$ *or* $X_{n,m,d}^{t} > P_{g,i}^{max}$ *then*
      $V_{n,m,d}^{t+1} = -V_{n,m,d}^{t+1}$
    randomly select rival tribe k and revise V_{rival}^{t+1} by Eq. (17)
    if $T_{cost,n}^{best} < T_{cost,rival}^{best}$ *then*
      revise the loyalty factor by Eq. (14)
    revise the human position $X_{n,m,d}^{t+1}$ by Eq. (18)
    if $X_{n,m,d}^{t+1}$*is out of bound then*
      $V_{n,m,d}^{t+1} = -V_{n,m,d}^{t+1}$
    // Evaluate congestion management fitness
    Run AC power flow analysis
    Check power flow constraints (6)-(8)
    Check voltage constraints (9)
    Check line thermal constraints (10)
    Calculate congestion cost (T_{cost}) (1)
    if *constraint violations exist then*
      $T_{cost} = T_{cost}$ *+ penalty_factor × total_violations*
    compute the fitness T_{cost}
    if $T_{cost} < T_{cost,tribe}^{best}$ *then*
      $X_{cost,tribe}^{best} = X$
      $T_{cost,tribe}^{best} = T_{cost}$
    if $T_{cost} < T_{cost}^{best}$ *then*
      $X^{best} = X$
      $T_{cost}^{best} = T_{cost}$
  end for
  get the current position
  iter = iter + 1
end while
return X^{best}, T_{cost}^{best}

4. COMPUTATIONAL PROCEDURE OF CTCM FOR CONGESTION MANAGEMENT

The following steps for congestion management by optimally adjusting the active power generator outputs using the CTCM algorithm

Step 1: Set up the system parameters by importing data about network nodes, line characteristics, and CTCM algorithm required parameters

Step 2: Initialize the population of generator active power by using *equation (11)*.

Step 3: Conduct the AC load analysis using the Newton-Raphson method, obeying the equality constraints given in *equations (2)* to *(5)*. Obtain the fitness value of each tribal member by using *equation (1)*, which is the minimization of total congestion cost.

Step 4: Divide the population into n tribal groups and set up a hierarchy by choosing chiefs based on the best fitness with minimal congestion costs.

Step 5: Update the loyalty coefficients *r1* and *r2* by using *equation (14)*.

Step 6: Update the velocity variations of each member by using *equation (15)*.

Step 7: At this stage, tribes oppose one another. A competitor tribe is selected by less congestion cost, and velocity variations are calculated by using equation (17).

Step 8: The loyalty coefficients are modified based on the chaotic mapping given in equation (14).

Step 9: At this stage, all constraints are evaluated. Generator outputs must conform to permissible limits (constraints 6-10).

Step 10: Positions are revised in accordance with equation (18).

Step 11: If the maximum number of iterations is achieved, proceed to Step 12. Otherwise, increase the iteration counter (t = t + 1) and revert to Step 3 for further optimization.

Step 12: Obtain the optimal active power generator output with the minimum congestion cost (T_{cost}^{best}), and the related generation dispatch schedule (X^{best}) is then produced, and the algorithm stops.

5. SIMULATION RESULTS AND DISCUSSION

In this study, the suggested CTCM approach has been implemented using MATLAB R2023b program on an Intel Core i7 Processor with 2.4GHz and associated with 32 GB of RAM. To validate the efficacy of the proposed CTCM approach in solving the congestion problem, simulation experiments are presented on a modified IEEE 30-bus transmission system [9] and modified IEEE 57-bus transmission system [9]. Here, generator increment and decrement price bids have been taken from reference [11], which is also given in *table 1*.

Table 1. Generator Increment and Decrement Price Bids

IEEE 30-Bus			IEEE 57-Bus		
Generator	Increment ($/MWh)	Decrement ($/MWh)	Generator	Increment ($/MWh)	Decrement ($/MWh)
G1	22	18	G1	44	41
G2	21	19	G2	43	39
G3	42	38	G3	42	38
G4	43	37	G4	43	37
G5	43	35	G5	42	39
G6	41	39	G6	44	40
----	----	-----	G7	44	41

The proposed CTCM methodology has been evaluated for 50 individual trial runs. Here, tribal size is set as 20, and the number of tribal groups (m) is set as 20, which governs the allocation of persons among tribal groups. Weighting

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coefficients: experience factor (c_1) is set as 2, which determines the impact of self-learning from prior optimal settings; obey factor (c_2) is set as 1, which directs the degree to which each tribe complies with their chieftain's authority; escape factor (c_3) is set as 0.5, which governs the retreat in competitive interactions among tribes.

5.1. Modified IEEE 30-Bus Transmission System

In the modified IEEE 30-bus transmission system, two critical cases have been considered to evaluate the execution of the suggested method as given below.

Case 1: Single line outage analysis
Case 2: Single line outage with a 50% load increase across all buses

5.1.1 Case 1: Single line outage Analysis

In this case, a single line outage (1-2) is considered. *Table 2* depicts the recorded active power loaded values on lines 1-7 and 7-8 in the transmission network, which are about 147.46 MW and 136.29 MW, respectively, resulting in 13.43% and 4.84% overload. After implementation of congestion management (CM) via the proposed CTCM approach, these values have been 129.982 MW and 120.784 MW, respectively.

Figure 1 illustrates the power flow throughout the system prior to and after congestion control. The loading on Line 1-7 decreased to 99.986% utilization, while Line 7-8 was reduced to 92.911% utilization; both lines operated safely within their thermal limits.

Table 2. Congestion Analysis of IEEE 30 bus system for Case 1

Line	Limit (MW)	Before CM (MW)	Loading Before (%)	After CM (MW)	Loading After (%)
1-7	130	147.463	113.43	129.982	99.986
7-8	130	136.292	104.84	120.784	92.911

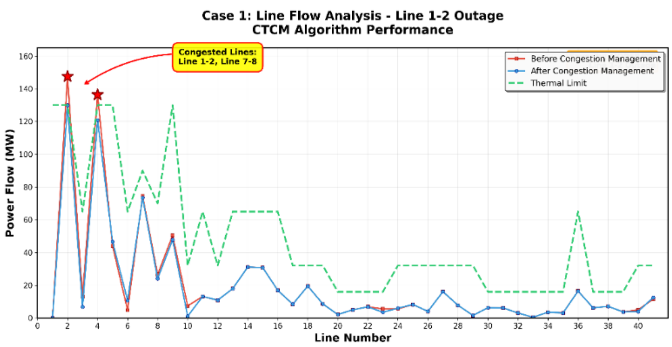

Figure 1. Line flow comparison after and before congestion management for Case 1

Table 3 depicts the results of different algorithms; it shows that our proposed CTCM reduced generator G1's output by 8.65 MW while increasing generator G2's production by 14.53 MW. Generators G3 through G6 maintained their original dispatch schedules. CTCM achieved a total congestion expense of \$460.74/h, which is the minimum including all methods tested. This statistic represents substantial savings of about 14.52% below PSO (\$538.95/h), 9.99% below FFA (\$511.87/h), 6.86% below TLBO (\$494.66/h), 3.37% below NOA (\$476.84/h), and 4.02% below ALO (\$480.04/h). CTCM also outperformed the recent SOS and CSBO algorithms (both at \$460.83/h) by \$0.09/h. While this margin appears small, such incremental improvements translate to significant annual savings in large-scale power systems under continuous operation.

Table 3. Comparison of simulation results of IEEE 30 bus system for case 1

Algorithm	Generators re-dispatching (MW)						Total cost (\$/h)
	ΔPg1	ΔPg2	ΔPg3	ΔPg4	ΔPg5	ΔPg6	
PSO [8]	-8.61	10.40	3.03	0.02	0.85	-0.01	538.95
FFA [9]	-8.78	15	0.11	0.06	0.17	-0.62	511.87
TLBO [10]	-8.59	12.99	0.46	0.73	0.01	0.40	494.66
ALO [11]	-9.09	15.07	0.00	0.00	0.00	0.00	480.04
SOS [12]	-8.6	14.58	0	0	0	0	460.83
CSBO [13]	-8.75	14.43	0	0	0	0	460.83
NOA [18]	-7.7642	10.4476	0.3487	0.6178	0.0074	0.2877	476.84
CTCM (ours)	**-8.65**	**14.53**	**0**	**0**	**0**	**0**	**460.74**

5.1.2. Case 2: Single line outage with 50% load Increase

In this case, single line outage (1-7) with a 50% load increase across all buses is considered. *Table 4* depicts the recorded active power loaded values on lines 1-2, 2-8, and 2-9 in the network, which are about 310.92 MW, 97.35 MW, and 103.52 MW respectively, resulting in 139.17%, 49.77%, and 59.27% overload. After implementation of congestion management (CM) *via* proposed CTCM approach, these values have been 129.787 MW, 63.661 MW, and 64.991 MW, respectively.

Figure 2 illustrates the power flow throughout the system prior to and after congestion control. The loading on Line 1-2 decreased to 99.836% utilization, Line 2-8 decreased to 97.94% utilization, and Line 2-9 was reduced to 99.986% utilization; all lines operated safely within their thermal limits.

Table 4. Congestion Analysis of IEEE 30 bus system for Case 2

Line	Limit (MW)	Before CM (MW)	Loading Before (%)	After CM (MW)	Loading After (%)
1-2	130	310.917	239.17	129.787	99.836
2-8	65	97.353	149.77	63.661	97.94
2-9	65	103.524	159.27	64.991	99.986

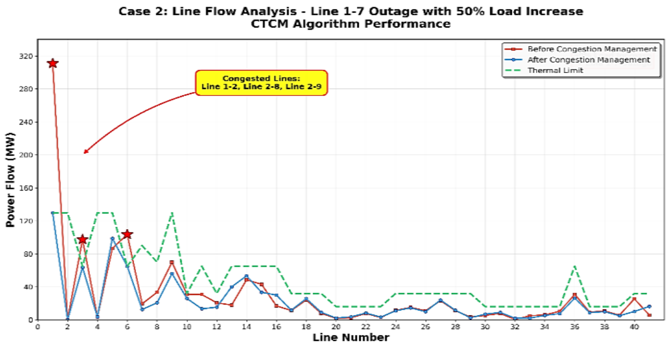

Figure 2. Line flow comparison after and before congestion management for Case 2

Table 5 depicts the results of different algorithms, similar to case 1. It shows that in the proposed CTCM method, the generator G1 output is increased by 8.803 MW, while generators G2 to G6 noted increases of 75.604 MW, 1.44 MW, 46.146 MW, 22.09 MW, and 13.07 MW, respectively. By this, the proposed method achieved the lowest total congestion cost of $5276.64/h. This results in significant savings of about 1.10% below PSO ($5,335.50/h), 0.52% below FFA ($5,304.40/h), 0.56% below TLBO ($5,306.50/h), and 0.38% below ALO ($5,296.75/h). Further, the proposed CTCM also outperformed recent algorithms such as SOS ($5,303.00/h) with 0.50% savings and 0.28% below CSBO ($5,291.34/h).

Table 5. Comparison of simulation results of IEEE 30 bus system for case 2

Algorithm	Generators re-dispatching (MW)						Total cost ($/h)
	ΔPg1	ΔPg2	ΔPg3	ΔPg4	ΔPg5	ΔPg6	
PSO [8]	----	----	----	----	----	----	5335.5
FFA [9]	-8.58	74.02	0.06	42.99	23.83	16.51	5304.4
TLBO [10]	-8.587	75.65	0.012	34.357	31.4791	17.83	5306.5
ALO [11]	-8.588	76.4	0.056	42.844	24.571	15.525	5296.75
SOS [12]	-8.76	76.46	0	41.08	30.23	11.62	5303
CSBO [13]	-8.76	76.21	0	53.03	18.98	10.64	5291.34
CTCM (ours)	**-8.803**	**75.604**	**1.44**	**46.146**	**22.09**	**13.07**	**5276.64**

5.2. Modified IEEE 57-Bus Transmission System

In the modified IEEE 57-bus transmission system, two critical cases have been considered to evaluate the execution of the suggested method as given below

Case 1: reduction in capacity of lines 5-6 and 6-12 from 200 to 175 MW and from 50 to 35 MW, respectively

Case 2: reduction in capacity of lines 2-3 from 85 to 20 MW

5.2.1 Case 1

In this case, reduction in capacity of lines 5-6 and 6-12 from 200 to 175 MW and from 50 to 35 MW, respectively. *Table 6* depicts the recorded active power loaded values on lines 5-6 and 6-12 in the transmission network, which are about 195.971 MW and 49.351 MW respectively, resulting in 11.983% and 41.003% overload. After implementation of congestion management (CM) via the proposed CTCM approach, these values have been 174.95 MW and 34.95 MW, respectively, which are under limits.

Table 6. Congestion Analysis of IEEE 57 bus system for Case 1

Line	Limit (MW)	Before CM (MW)	Loading Before (%)	After CM (MW)	Loading After (%)
5-6	175	195.971	111.983	174.95	99.971
6-12	35	49.351	141.003	34.95	99.857

Table 7 depicts the different algorithms validated for the modified IEEE 57-bus system under case 1. The comparison shows that our proposed CTCM reduced Generator G1's output, which is increased by 0.946 MW, and G2's output, which is decreased by 10.728 MW. Similarly, the G3 to G6 output is decreased to 4.812 MW, 44.2612 MW, 50.321 MW, and 33.868 MW, respectively. Generator G7 had a small increase of 0.465 MW. The total cost of congestion for CTCM was $5,618.179/h, which is the lowest of all reported methods. The result is a significant savings of about 19.19% less than PSO ($6,951.9/h), 7.14% less than FFA ($6,050.1/h), 6.07% less than TLBO ($5,981.3/h), and 4.72% less than ALO ($5,896.548/h).

Table 7. Comparison of simulation results of IEEE 57 bus system for case 1

Algorithm	Generators re-dispatching (MW)							Total cost ($/h)
	ΔPg1	ΔPg2	ΔPg3	ΔPg4	ΔPg5	ΔPg6	ΔPg7	
PSO [8]	23.13	12.44	7.49	-5.38	-81.21	0	39.03	6951.9
FFA [9]	5.6351	2.523	0.5098	0.107	-39.1514	-35.1122	62.1938	6050.1
TLBO [10]	38.1219	0.7801	9.0766	0.0179	-43.2018	-29.9082	22.8093	5981.3
ALO [11]	34.367	1.609	0	-1.867	-42.254	-31.596	30.327	5896.548
CTCM (ours)	**0.946**	**-10.728**	**-4.812**	**-44.2612**	**-50.321**	**-33.868**	**0.465**	**5618.179**

5.2.2. Case 2

In this case, reduction in capacity of lines 2-3 from 85 to 20 MW. *Table 8* depicts the recorded active power loaded values on lines 2-3 in the network, which is about 37.048, resulting in 85.24% overload. After implementation of congestion management (CM) via the proposed CTCM approach, this value is about 19.85 MW, which is under the limit.

Table 8. Congestion Analysis of IEEE 57 bus system for Case 2

Line	Limit (MW)	Before CM (MW)	Loading Before (%)	After CM (MW)	Loading After (%)
2-3	20	37.048	185.240	19.850	99.250

Table 9 depicts the different algorithms validated for Case 1, the modified IEEE 57-bus system. The study shows that our suggested CTCM increased the output of generator G1 by 1.761 MW and decreased the output of generator G2 by 0.413 MW. Generator G3 increased by 23.049 MW, while the output of Generators G4 to G6 decreased by 0.330 MW, 11.008 MW and 0.500 MW respectively. Generator G7 output is increased to 17.007 MW. CTCM had the lowest total congestion cost of $2,271.564/h, which is the lowest of all the methods tested. The result is a big savings of about 27.14% less than PSO ($3,117.6/h), 13.23% less than FFA ($2,618.1/h), 22.11% less than TLBO ($2,916.4/h), and 1.99% less than ALO ($2,317.6/h).

Table 9. Comparison of simulation results of IEEE 57 bus system for case 2

Algorithm	Generators re-dispatching (MW)							Total cost ($/h)
	ΔPg1	ΔPg2	ΔPg3	ΔPg4	ΔPg5	ΔPg6	ΔPg7	
PSO [8]	---	----	----	-----	-----	----	-----	3117.6
FFA [9]	0.3704	-27.5084	31.6294	0.3308	-2.254	-1.9354	-0.5101	2618.1
TLBO [10]	-1.01	-24.6365	36.0991	-6.2282	-0.2811	-1.254	-2.5732	2916.4
ALO [11]	-0.10	-28.2907	28.593	0.1338	-0.0503	-0.008	-0.0218	2317.6
CTCM (ours)	**1.761**	**-0.413**	**23.049**	**-0.330**	**-11.008**	**-0.500**	**17.007**	**2271.564**

5.3. Voltage and Reactive Power Constraints Handling

Figure 3 and *figure 4* portray the voltage profile of the system under both cases with the proposed methodology in the IEEE 30 bus and IEEE 57 bus systems, respectively. The figures reveal that voltage magnitudes are within permissible limits, *i.e.*, 0.9 to 1.1 pu. This graphic shows the proposed method obeying the voltage constraints.

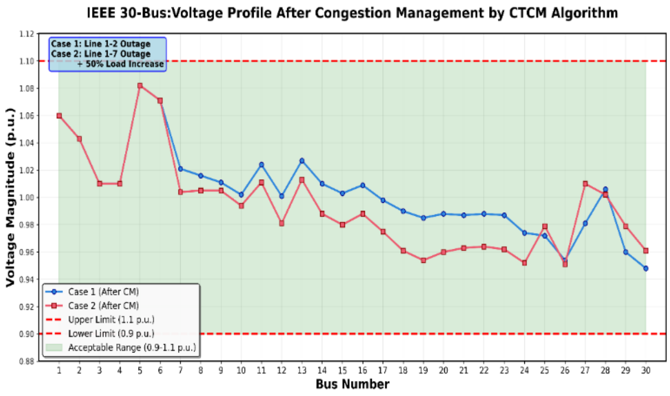

Figure 3. voltage profile of IEEE 30 bus after congestion management for Case 1 and Case 2

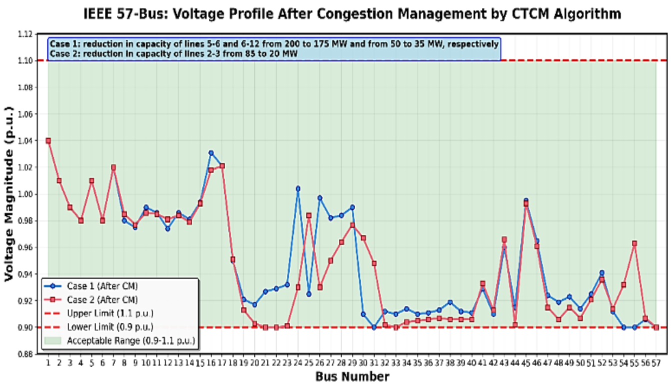

Figure 4. voltage profile of IEEE 57 bus after congestion management for *Case 1* and *Case 2*

Figure 5 and *figure 6* portray the reactive power dispatch in the system under both cases after performing the proposed methodology in the IEEE 30 Bus and IEEE 57 Bus systems, respectively. It is noticed that all six generators have been operated within their reactive power limits (*i.e.*, -30 to 150 MVAr) for IEEE 30 bus system. Similarly, all seven generators have been operated within their reactive power limits (*i.e.*, -150 to 200 MVAr) for the IEEE 30 bus system. This graph shows the proposed method obeying the reactive power constraints.

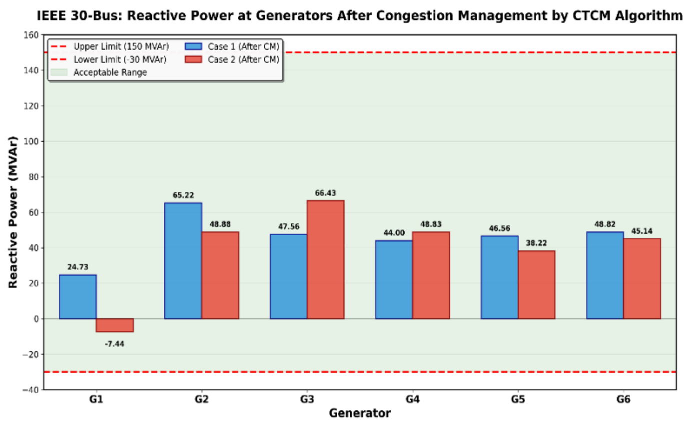

Figure 5. Reactive power at generators of IEEE 30 bus after congestion management for *Case 1* and *Case 2*

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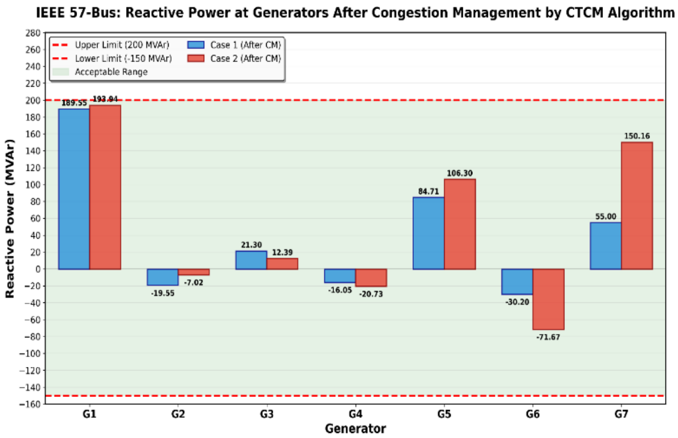

Figure 6. Reactive power at generators of IEEE 57 bus after congestion management for Case 1 and Case 2

5.4. Statistical Robustness and Performance Consistency Analysis

Table 10 depicts the statistical evaluation of the IEEE 30 bus of different algorithms over 50 independent runs and visual presentation in *figure 7*. Among all methods, the proposed CTCM achieved a significantly low total congestion cost of about 460.74 \$/h (*Case 1*) and 5276.64 \$/h (*Case 2*). The proposed CTCM achieved a significantly low total congestion cost mean of about 510 \$/h (Case 1) and 5984.53 \$/h (*Case 2*), and also the standard deviations are significantly low, of about 68.20 \$/h (*Case 1*) and 1006.11 \$/h (*Case 2*), respectively, which results in a variability that is 2.7-3.7 times less than that of PSO and 1.7-1.8 times less than the performance of the SOS and CSBO algorithms.

Table 10. Statistical Performance of IEEE 30 Bus: Comparison Over 50 Independent Runs

Algorithm	Case 1: Single line 1-2 Outage				Case 2: Single line 1-7 Outage + 50% Load			
	Best	Mean	Worst	Std Dev	Best	Mean	Worst	Std Dev
PSO	538.95	751.86	2062.12	250.41	5335.5	7270.42	24428.69	2890.16
FFA	511.87	649.16	1649.7	184.72	5304.4	6814.93	19542.95	2208.45
TLBO	494.66	649.91	1649.7	186.37	5306.5	6826.69	19542.95	2401.9
NOA	476.84	579.16	1402.24	148.3	—	—	—	—
ALO	480.04	567.57	1402.24	152.28	5296.75	6428.97	16611.51	1734.46
SOS	460.83	554.83	1237.27	123.13	5303	6831.41	14657.21	1556.09
CSBO	460.83	525.91	1237.27	118.5	5291.34	6460.16	14657.21	1614.25
CTCM (ours)	**460.74**	**510**	**824.85**	**68.2**	**5276.6**	**5984.5**	**9771.47**	**1006.11**

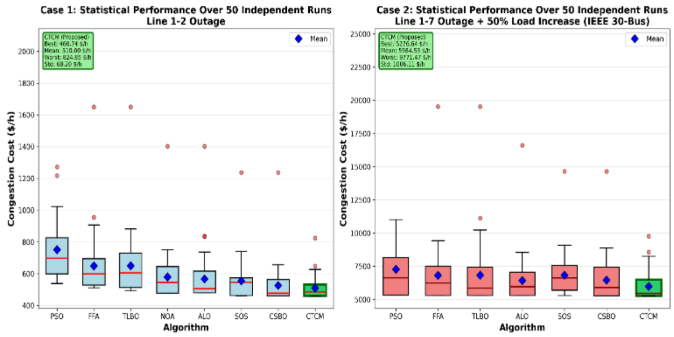

Figure 7. Statistical performance of different algorithms after congestion management for Case 1 and Case 2: IEEE 30-Bus

Table 11. Statistical Performance Comparison of IEEE 57 Bus: Over 50 Independent Runs

Algorithm	Case 1				Case 2			
	Best	Mean	Worst	Std Dev	Best	Mean	Worst	Std Dev
PSO	6951.90	9698.22	26599.22	3230.03	3117.60	4248.20	14273.99	1688.76
FFA	6050.10	7672.81	19498.80	2183.32	2618.10	3363.65	9645.84	1090.03
TLBO	5981.30	7858.54	19947.74	2253.54	2916.40	3751.88	10740.61	1320.06
ALO	5896.55	6971.72	17224.35	1870.52	2317.60	2813.00	7268.39	758.92
CTCM (ours)	**5618.18**	**6218.85**	**10058.07**	**831.62**	**2271.56**	**2576.31**	**4206.56**	**433.12**

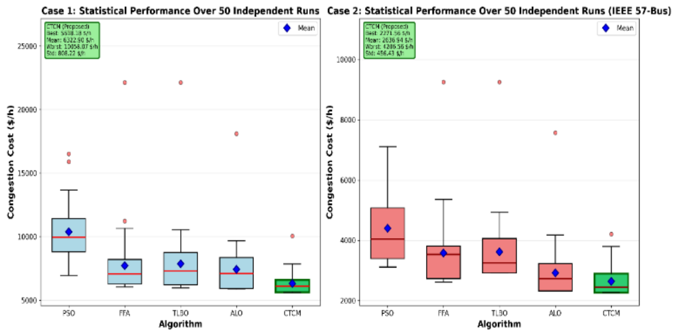

Figure 8. Statistical performance of different algorithms after congestion management for *Case 1* and *Case 2*: IEEE 57-Bus

Table 11 depicts the statistical evaluation of the IEEE 57 bus of different algorithms over 50 independent runs with a visual presentation in *figure 8*. Among all methods, the proposed CTCM achieved a significantly low total congestion cost of 5,618.18 \$/h (*Case 1*) and 2,271.56 \$/h (*Case 2*). More importantly, CTCM demonstrated superior consistency with mean costs of 6,218.85 \$/h (*Case 1*) and 2,576.31 \$/h (*Case 2*), representing the lowest average performance across all 50 runs. The standard deviations were remarkably low at 831.62 \$/h (*Case 1*) and 433.12 \$/h (*Case 2*), respectively, which results in variability that is 3.88 times less than PSO (3,230.03 \$/h vs. 831.62 \$/h for Case 1) and 3.90 times less than PSO (1,688.76 \$/h vs. 433.12 \$/h for *Case 2*). Compared to the second-best performer, ALO, CTCM still demonstrates 2.25 times lower standard deviation in *Case 1* (831.62 $/h vs. 1,870.52 $/h) and 1.75 times lower in *Case 2* (433.12 $/h vs. 758.92 $/h).

5.5. Enhanced Statistical Validation

This subsection examines thorough non-parametric tests conducted on the data from *Case 1* in *table 12*, derived from 50 independent trials for the IEEE 57-bus system (*Case 1*). *tables 10 and 11* depicts the basic statistical measures (best, mean, worst, and standard deviation) for the IEEE 30-bus and IEEE 57-bus cases, respectively. However, detailed non-parametric hypothesis testing was conducted only for the larger IEEE 57-bus *Case 1* to demonstrate CTCM's scalability and robustness on more complex systems.

The Friedman test [20], a non-parametric substitute for ANOVA, indicates statistically significant differences among all five algorithms ($\chi^2 = 194.3$, $p < 0.001$). The exceedingly low p-value (< 0.001) indicates over 99.9% confidence that the performance differences are genuine rather than attributable to chance.

Table 12: Statistical Significance Analysis (IEEE 57-Bus System: case 1)

Comparison	Mean Diff. ($/h)	Cohen's d	p-value
CTCM vs PSO	-3479.37	1.91	< 0.001
CTCM vs FFA	-1453.96	0.88	< 0.001
CTCM vs TLBO	-1639.69	0.97	< 0.001
CTCM vs ALO	-752.87	0.52	< 0.001

(Note: Negative mean differences indicate CTCM achieves lower costs. All comparisons significant at p < 0.001)

Table 12 illustrates the results of paired Wilcoxon signed-rank tests comparing CTCM to its competitors. The mean difference column shows the average cost reduction executed by CTCM throughout 50 iterations. Negative values show that CTCM typically indicates to lower congestion costs. In the IEEE 57-bus system (*Case 1*), CTCM costs $752.87 less per hour than the ALO algorithm and up to $3,479.37 less per hour than the PSO algorithm. All comparisons yield *p*-values inferior to 0.001, indicating statistically significant superiority with considerable confidence.

In *table 12*, it is observed that Cohen's *d* values, which ranged from 0.52 to 1.91, show a medium to very big effect in real life, based on known benchmarks ($d = 0.2$: modest, $d = 0.5$: medium, $d = 0.8$: significant effect). A Cohen's d value of 1.91 for CTCM compared to PSO shows a good improvement, while a value of 0.52 for ALO shows a moderate but still significant advantage over the second-best method.

5.6. Computational Performance Analysis

Different algorithms were executed in MATLAB R2023b on an Intel Core i7-8700K processor (3.7 GHz, 32 GB RAM) with uniform parameters: a population size of 50, a maximum of 100 iterations, and 50 independent runs, as seen in *table 13*. CTCM is more efficient at computing on both test systems (IEEE 30 bus and 57 bus). CTCM runs the IEEE 30-bus system the fastest, taking 14.8 seconds, which is 19.6% faster than PSO and 8.6% faster than TLBO. The lower standard deviation (±1.6 s) means that the computer is more likely to behave the same way as its competitors (±1.8-3.5 s).

For the IEEE 57-bus system, CTCM has an average execution time of 35.2 seconds, which is 16.8% faster than PSO and 9.5% faster than TLBO. Besides, CTCM needs fewer iterations than other algorithms (58 for IEEE 30-bus and 71 for IEEE 57-bus). These results show that CTCM not only finds better solutions, as shown in *section 5.2*, but also converges faster and more reliably. This makes it a beneficial choice for managing congestion in real time.

Table 13. Computational Performance Comparison

System	IEEE 30-Bus System		IEEE 57-Bus System	
Algorithm	Avg. CPU Time (s)	Avg. Iterations	Avg. CPU Time (s)	Avg. Iterations
PSO [8]	18.4 ± 2.1	68 ± 12	42.3 ± 4.8	82 ± 16
FFA [9]	22.7 ± 3.5	72 ± 15	51.6 ± 6.2	88 ± 18
TLBO [10]	16.2 ± 1.8	64 ± 10	38.9 ± 3.9	78 ± 14
ALO [11]	19.5 ± 2.4	70 ± 13	45.1 ± 5.1	85 ± 17
CTCM	**14.8 ± 1.6**	**58 ± 9**	**35.2 ± 3.5**	**71 ± 12**

5.7. Parameter Sensitivity Analysis

A sensitivity study was conducted on the critical parameters of CTCM employing 30 independent simulations on the IEEE 57-bus system. Evaluate each parameter individually while maintaining the others at their baseline levels.

Table 14 presents the results of the sensitivity analysis for various parameters such as tribal size, groups (m), experience factor (C_1), obey factor (C_2) and escape factor (C_3). The optimal number of tribes is 20, which achieves the most favourable balance between solution quality and efficiency. While the values were lower (10–15), the mean congestion costs increased by 2.8% and 0.8%, respectively. This reveals ineffective population choice for effective analysis. In contrast, increased levels (25–30) lead to a 24–60% increase in CPU time with only minimal improvements in quality (0.2–0.4% cost escalation), representing deteriorating gains.

The tribal group, $m = 20$, indicates an optimal balance between sufficient variety for a global search and flexible computational complexity. Values below 20 demonstrated inferior execution, with mean congestion costs 1.2% (m=10) and 0.6% (m=15) above the optimal level. Values exceeding 20 exhibited minor cost escalations of 0.1% to 0.3% without any associated advantages. This indicates that 20 groups represent an optimal equilibrium between exploration and exploitation.

The experience factor C_1 = 2.0 enables sufficient learning from optimal historical solutions while preventing rapid convergence. Reduced values (C_1 = 1.5) ineffectively use historical knowledge AND lead to AN increased congestion cost of 0.8% and a standard deviation from 28.3 to 41.8. When C_1 *is* 2.5 or 3.0, the algorithm is trapped in local optima. This increases congestion cost by 0.5% and 1.1%, respectively.

The obey factor C_2 = 1.0 achieves an optimal equilibrium between the authority of the leader and the autonomy of the members. Values below 1.0 (C_2 = 0.5) hinder cooperation among leaders, lead to 0.7% increase in congestion cost and a 39.2% increase in standard deviation. Values above 1.0 reduce member independence, hence decreasing population variety and increasing costs by 0.5% (C_2 = 1.5) to 0.9% (C_2= 2.0).

The escape factor C_3 = 0.5 delivers optimal execution, while C_3 = 0 exhibits nearly equivalent efficacy, with a congestion cost variance of only 0.03%. Increased values (C_3 = 1.0 and 1.5) result in a 10% and 26% rise in computation time, respectively, while deteriorating solution quality by 0.1–0.2%. This reveals that excessive escape behavior hinders convergence. The standard deviations remain reasonable across all evaluated c_3 values (28.3–32.8), pointing out that this parameter has minimal impact on solution reliability. This study reveals that CTCM method performs well across several parameters. Even when parameters are not optimized, costs remain within 1.2% of the optimal range.

Table 14. Parameter Sensitivity Analysis Results

Parameter	Value	Mean Cost ($/h)	Std. Dev. ($/h)
Tribal Size	10	2,334.80	52.4
	15	2,289.50	38.7
	20	**2,271.56**	**28.3**
	25	2,275.90	31.2
	30	2,281.40	35.8
Groups (m)	10	2,298.30	47.6
	15	2,284.70	39.2
	20	**2,271.56**	**28.3**
	25	2,274.80	32.5
	30	2,279.10	36.9
Experience (c_1)	1.5	2,289.40	41.8
	2	**2,271.56**	**28.3**
	2.5	2,283.60	37.5
	3	2,295.80	44.2
Obey (c_2)	0.5	2,287.20	39.4
	1	**2,271.56**	**28.3**
	1.5	2,281.90	34.6
	2	2,292.70	42.1

6. CONCLUSION

This paper introduces a new optimization method for the congestion problem in transmission systems for independent system operators. The proposed CTCM methodology is successfully executed to minimize the total congestion cost while maintaining constraints such as bus voltage magnitude, line thermal, and generator capacity constraints. The suggested approach is justified on both the modified IEEE 30-bus system and the modified IEEE 57-bus system under two critical cases, and the simulation outcomes are evaluated with different well-known methods and recent algorithms such as PSO, FFA, TLBO, NOA, ALO, SOS, and CSBO. The proposed method extensively mitigates the congestion problem while keeping line loadings within acceptable limits and achieves the lowest total congestion cost compared to all algorithms under both critical congestion cases. The statistical performance of different algorithms over 50 independent runs for both cases confirms that the proposed CTCM exhibits superior robustness and consistency, with significantly lower standard deviation and minimal performance variations. Finally, these results verify that the suggested CTCM methodology is reliable and computationally efficient for practical congestion management in transmission systems.

Future research will extend the framework to incorporate reactive power optimization and renewable energy penetration and handle load and generation uncertainties through stochastic formulations for enhanced practical applicability in modern power grids.

Conflicts of Interest: The authors declare no conflict of interest.

Ethical Approval: The material is the author's original work, which has not been previously published.

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