

A Hybrid GSF–CHMBO Framework for Cost Effective Congestion Management in Power Systems

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Abstract: - The advent of competitive power markets in recent decades has facilitated a substantial rise in transactions between producers and consumers to meet the rapidly growing load demand. Power transactions in modern electricity markets are carried out through bilateral or multilateral agreements, either directly between market participants or through common trading platforms. These transactions require the transmission network to transfer electricity from generating stations to consumers, and excessive power transfers may lead to congestion when line capacity limits are exceeded. Such congestion affects the secure and economical execution of scheduled transactions and may increase operating costs. Therefore, the Independent System Operator (ISO) plays an important role in maintaining reliable system operation by managing congestion and ensuring that all network security constraints are satisfied. This study aims to reduce transmission congestion by controlling overloaded line flows, maintaining operational limits, improving system stability, and minimizing transmission losses. Generator Sensitivity Factor (GSF) is used to identify the generating units that significantly influence congested transmission lines and require suitable rescheduling. Two enhanced Monarch Butterfly Optimization approaches, namely Improved MBO with a Linear Weighting factor (IMBO-LW) and Chaos-Embedded MBO (CHMBO), are employed to determine optimal generator rescheduling strategies. The proposed methods simultaneously minimize rescheduling cost and changes in generator power output. Their performance is evaluated using standard benchmark functions and further validated on a modified IEEE 30-bus test system, demonstrating their effectiveness in achieving secure, reliable, and economically efficient congestion management.

Key-Words: - Independent System Operator, Congestion, Rescheduling, Generator sensitivity, Monarch butterfly optimization. Chaos theory.

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1 Introduction

The electricity industry has undergone a major structural transformation over the past several years, moving away from the traditional regulated monopoly model toward a competitive and deregulated environment. This restructuring has fundamentally changed the manner in which power systems are organized and operated. Instead of functioning as a single vertically integrated utility, the industry is now divided among independent participants such as generation companies (GenCos), transmission companies (TransCos), distribution companies (DisCos), retailers, and electricity consumers. This competitive structure is intended to improve resource utilization, promote economic operation, and enhance the overall efficiency, security, and reliability of the electrical network. However, deregulation has also introduced several complex challenges, including the

development of appropriate market policies, management of ancillary services, and effective assessment and mitigation of financial risks. Among these challenges, transmission congestion remains particularly significant because it can influence market power and alter the bidding behavior of generation companies. If congestion is not properly controlled, the expected economic benefits and incentives associated with electricity deregulation may be weakened. A transmission network is considered congested when proposed electricity transactions between sellers and buyers cause one or more system transfer limits to be reached or violated [1]. Increasing competition among market participants has substantially increased the volume of power transactions, thereby placing greater pressure on available transmission corridors and affecting the economic performance of the system [2]. The feasible transfer of electrical power is

restricted by several network constraints, including MVA capacity, voltage operating limits, and stability requirements. When congestion occurs, inexpensive generators located in certain areas may be unable to supply the desired amount of power, forcing the system to depend on more expensive generation resources. As a result, congestion can increase dispatch costs, influence market bids and prices, and adversely affect the security and stability of the power network. Therefore, rapid identification and effective mitigation of congestion are essential for maintaining an efficient and economically viable electricity market.

Considerable research has been devoted to the development of congestion management (CM) approaches that balance the interests of electricity producers and consumers while improving overall market welfare [3]. In [4], the optimal installation locations of FACTS devices for CM are determined through a conflicting multi-objective formulation that simultaneously considers generation and emission costs. Similarly, the studies in [5] and [6] investigate congestion management under three-block bidding arrangements using FACTS technologies such as STATCOM, SSSC, and UPFC. The influence of the constant impedance, current, and power (ZIP) load representation on congestion related costs has also been investigated [7]. Network limitations can significantly affect market settlement by changing the effective bidding strategies of participating generation companies. To address this issue, [8] formulates a two-tier optimization framework for developing an effective producer strategy. Market splitting has also been used to study congestion by separating the market into surplus and deficit pricing regions. In [9], a congestion management mechanism based on locational marginal pricing (LMP) is introduced to reduce transmission line overloads. The work in [10] applies the ant lion optimizer to modify the real-power outputs of generators for congestion relief. A curtailment algorithm is presented in [11], where the influence of congestion on the profit function is also analyzed. Furthermore, [12] develops a multi-objective congestion management formulation incorporating voltage dependent load characteristics, and Pareto-based solutions are used to identify an appropriate compromise among competing objectives.

A method for estimating transmission congestion costs in pool-based and bilateral electricity markets is presented in [13] using power flow tracing derived from Bialek's theory. In [14], DC power flow is incorporated into the market clearing process to account for transmission network constraints.

Although DC power flow can provide reasonably accurate approximations, its simplifying assumptions limit its ability to represent actual system behavior comprehensively [15]. The transmission constrained residual demand derivative (TCRDD) technique is adopted in [16] to maximize producer profit in a transmission limited market environment. However, this approach requires all generating units belonging to a seller to be connected to the same bus. In [17], tap-changing transformers and phase-shifting devices are utilized to support the ISO in managing congestion while minimizing deviations from preferred operating schedules. Meanwhile, [18] investigates two approaches, the highest LMP method and the total congestion rent (TCR) method, for determining the optimal location and capacity of Distributed Generation (DG) units to reduce transmission line overloads.

Numerous methods for reducing congestion in transmission systems have been reported in the literature [19]. A robust optimization-based framework employing energy storage (ES) is proposed in [20] to reduce peak demand and alleviate congestion. Similarly, [21] demonstrates that the coordinated integration of Distributed Generation (DG) and Energy Storage (ES) can improve Available Transfer Capability (ATC) compared with a system employing DG alone. Real time congestion mitigation is addressed in [22] through the use of quasi-dynamic thermal ratings instead of conventional static ratings for transmission lines. The study introduces a congestion clearance time index and incorporates it into the objective function, enabling the system operator to respond rapidly to congestion during severe contingency conditions and thereby reduce the possibility of widespread system damage. In [23], [24] a modified whale optimization algorithm (MWOA) is employed to determine an effective generator rearrangement strategy for congestion reduction. An artificial immunity algorithm (AIA) based on transmission switching is also applied to relieve overloaded lines while controlling operational costs and maintaining network reliability. A price responsive demand shifting mechanism is introduced in [25] to influence LMP values and reduce congestion. In [26], generator active power rescheduling is determined using relative electrical distance (RED) to relieve overloaded transmission paths. Although this technique improves voltage characteristics and reduces system losses, individual generator bids and generator rescheduling costs are not considered. In addition, the method does not explicitly minimize

the number of generators participating in the congestion management process.

Generator rescheduling for congestion control requires the coordinated adjustment of multiple generating units while satisfying nonlinear objective functions and numerous network constraints. Consequently, the problem is nonlinear, complex, and combinatorial in nature, making meta heuristic optimization techniques attractive alternatives to conventional solution approaches. Several optimization methods have therefore been applied to determine suitable generator rescheduling strategies. Particle Swarm Optimization is used in [27] to modify generator outputs and reduce overloaded transmission lines. Nevertheless, PSO may experience premature convergence and can become trapped in local optimum regions. Teaching Learning Based Optimization (TLBO) is employed for CM in [28], although its computational and memory requirements can be considerable. In [29], satin bowerbird optimization (SBO) is applied to the generator rescheduling problem and produces better results than the two previously discussed approaches; however, its exploitation performance and solution accuracy are strongly influenced by parameter selection. The flower pollination algorithm (FPA) is utilized in [30] to solve a multi objective capacity management problem involving the determination of appropriate Distributed Generation (DG) capacities. Despite its advantages, FPA may converge prematurely and exhibit insufficient exploitation capability, potentially producing suboptimal solutions. A hybrid approach combining the firefly algorithm (FA) with differential evolution (DE) is proposed in [31] for congestion reduction through the optimal allocation of Distributed Generators (DGs). However, the tendency of FA to stagnate around local optima and its relatively slow convergence can reduce its effectiveness in complex optimization environments. An optimal power flow based congestion management method using an improved genetic algorithm (GA) is presented in [32], whereas [33] introduces a multi-objective GA for simultaneously reducing power losses and relieving congestion through the optimal placement and rating of TCSC devices. Nevertheless, genetic algorithms can be highly dependent on the initial population and may converge prematurely toward local solutions because of excessive elitist behavior [34]. Monarch Butterfly Optimization (MBO), introduced in [35], is a relatively recent nature inspired meta heuristic algorithm that has been applied successfully to various power system optimization problems [36], [37], [38]. Its notable characteristics

include simple implementation, fast convergence, and suitability for parallel computation. Evidence from applications across different optimization domains indicates that MBO can provide competitive solutions when compared with several alternative approaches. Motivated by these characteristics, the present study employs MBO and its proposed enhanced variants to determine effective generator redispatch strategies for relieving transmission line congestion.

2 Problem Formulation

Transmission congestion occurs when power flows in one or more transmission lines exceed their permissible thermal limits due to contingencies, load variations, or increased market transactions. In a deregulated power system, congestion management must be performed in a secure and economical manner while satisfying all operational constraints. Among the available mitigation strategies, generator rescheduling is an effective approach due to its rapid implementation and operational flexibility. However, all generators do not contribute equally to congestion in overloaded transmission lines. Therefore, only those generators that significantly influence the power flow of congested lines should participate in the rescheduling process. To achieve this, a Generator Sensitivity Factor (GSF) based selection mechanism is adopted, followed by an optimization framework that minimizes the total rescheduling cost while ensuring system security and reliability.

2.1 Generator Sensitivity Factor

The Generator Sensitivity Factor quantifies the impact of a change in generator real power output on the active power flow of a congested transmission line. For a transmission line l connecting buses m and n , the GSF of generator g is defined as:

$$GSF_g = \frac{\Delta P_{mn}}{\Delta P_g} \quad (1)$$

The active power flow in the transmission line is expressed as:

$$P_{mn} = -V_m^2 G_{mn} + V_m V_n G_{mn} \cos(\theta_m - \theta_n) + V_m V_n B_{mn} \sin(\theta_m - \theta_n) \quad (2)$$

By linearizing the above expression and neglecting higher-order terms and P-V coupling, the GSF can be approximated as:

$$GSF_g = \left(\frac{\partial P_{mn}}{\partial \theta_m} \right) \left(\frac{\partial \theta_m}{\partial P_g} \right) + \left(\frac{\partial P_{mn}}{\partial \theta_n} \right) \left(\frac{\partial \theta_n}{\partial P_g} \right) \quad (3)$$

The required partial derivatives are obtained using the reduced Jacobian matrix of the power flow equations, considering the slack bus as the reference. Generators with large and non-uniform GSF values are selected for rescheduling, thereby reducing computational complexity and unnecessary economic burden.

2.2 Objective Function

The objective of congestion management is to minimize the total cost incurred due to generator rescheduling. The objective function is formulated as:

$$\min_{\Delta P_g} RC = \sum_{g=1}^{N_g} C_g(\Delta P_g) \Delta P_g \quad (4)$$

where ΔP_g denotes the change in real power output of generator g , $C_g(\Delta P_g)$ represents the incremental/decremental bid price submitted by the generator, and N_g is the number of generators participating in rescheduling.

2.3 Constraints

The optimization problem is subject to the following constraints:

$$\text{Power Balance Constraint } \sum_{g=1}^{N_g} \Delta P_g = 0 \quad (5)$$

Transmission Line Flow Constraints

$$\sum_{g=1}^{N_g} (GSF_g \cdot \Delta P_g) + T_l^0 \leq T_l^{\max}, \forall l \quad (6)$$

Generator Rescheduling Limits

$$\Delta P_g^{\min} \leq \Delta P_g \leq \Delta P_g^{\max} \quad (7)$$

$$\Delta P_g^{\min} = P_g - P_g^{\min}, \quad \Delta P_g^{\max} = P_g^{\max} - P_g \quad (8)$$

Generator Operating Limits

$$P_g^{\min} \leq P_g + \Delta P_g \leq P_g^{\max} \quad (9)$$

Voltage Magnitude Constraints

$$V_i^{\min} \leq V_i \leq V_i^{\max}, \quad \forall i \quad (10)$$

2.4 Severity Index

To quantify the extent of congestion under contingency conditions, a Severity Index (SI) is defined as:

$$SI = \sum_{l=1}^{OL} \left(\frac{P_{mn}}{P_{mn}^{\max}} \right)^{2k} \quad (11)$$

where OL denotes the set of overloaded transmission lines and k is an integer constant (set to 1). The contingency corresponding to the highest SI value is considered the most critical and is selected for congestion mitigation.

3 Monarch Butterfly Optimization (MBO)

Monarch Butterfly Optimization (MBO) is a nature-inspired metaheuristic that models the long-distance seasonal migration of monarch butterflies between two geographical regions (often represented as Land 1 and Land 2). In nature, monarchs migrate from northern regions to warmer habitats for overwintering, and this collective movement guided by an internal navigation mechanism motivates the exploration behavior in the MBO search process. MBO begins by generating a population of candidate solutions (butterflies), where each butterfly represents a feasible solution vector in the search space. The full population is then divided into two subpopulations corresponding to two lands. This division is controlled by a migration ratio p , which determines how many butterflies belong to each land (subpopulation). Let the total population size be NP . Each butterfly is represented as:

$$\mathbf{X}_i = [x_{i,1}, x_{i,2}, \dots, x_{i,D}] \quad (12)$$

where D is the dimension of the optimization problem.

The population is divided into two lands using the migration ratio p :

$$NP_1 = [p \cdot NP], \quad NP_2 = NP - NP_1 \quad (13)$$

where $NP_1 \rightarrow$ butterflies in Land 1, $NP_2 \rightarrow$ butterflies in Land 2

MBO updates butterfly positions using two complementary mechanisms: A) Migration Operator (MO): The Migration Operator is responsible for creating new offspring solutions by exchanging information between the two lands. A portion of butterflies (governed by p) are updated through migration, which promotes global exploration by allowing solutions to inherit characteristics from butterflies in different regions. MO performs “cross-land mixing” of decision variables. It helps the algorithm explore diverse regions and escape premature convergence. B) Butterfly Adjusting Operator (BAO): The remaining butterflies are refined using the Butterfly Adjusting Operator, which improves solution quality by locally adjusting positions. BAO acts like a fine-tuning step

(exploitation), making controlled changes to move solutions toward promising regions. To further enhance diversity and widen the search capability, BAO incorporates Lévy flight, which introduces occasional long jumps in the search space (helpful to avoid local optima).

The Migration Operator is applied to butterflies in Land 1 and is responsible for global exploration. A new position for the i -th butterfly in dimension j is generated as:

$$x_{i,j}^{t+1} = \begin{cases} x_{r_1,j}^t, & \text{amp; if } rand \leq p \\ x_{r_2,j}^t, & \text{amp; otherwise} \end{cases} \quad (14)$$

where r_1 and r_2 are randomly selected butterflies from Land 1 and Land 2, respectively. $rand \in [0, 1]$ is a uniformly distributed random number, t denotes the current iteration.

This operator enables information sharing between subpopulations, enhancing global search capability. The Butterfly Adjusting Operator is applied to butterflies in Land 2 to perform local exploitation.

The position update is defined as:

$$x_{i,j}^{t+1} = x_{best,j}^t + \alpha \cdot (x_{r,j}^t - x_{i,j}^t) \quad (15)$$

where x_{best}^t is the global best butterfly, is a randomly selected butterfly, α is the weighting factor controlling the adjustment step.

To improve diversity, Lévy flight is occasionally applied:

$$x_{i,j}^{t+1} = x_{i,j}^t + Levy(\lambda) \quad (16)$$

This helps the algorithm escape local optima and improves convergence reliability.

Although conventional MBO provides good exploration, its performance may degrade due to random selection during migration and a rapidly decreasing weighting factor. To overcome these limitations, an Improved MBO with Linear Weighting (IMBO-LW) is introduced. Instead of using an exponentially decreasing weighting factor, IMBO-LW employs a linearly varying weighting factor defined as:

$$\alpha_{mod}(iter) = \alpha_{max} - \left(\frac{\alpha_{max} - \alpha_{min}}{iter_{max}} \right) \times iter \quad (17)$$

where α_{max} and α_{min} are the maximum and minimum weighting values, $iter$ is the current iteration, $iter_{max}$ is the maximum number of iterations. This linear reduction allows: Strong global exploration in early iterations, Enhanced local exploitation in later stages.

Figure 1 illustrates the complete workflow of the proposed CHMBO-based congestion management framework. The process begins with contingency analysis and congestion identification, followed by generator selection using GSF. Subsequently, CHMBO optimization is applied to determine the optimal generator rescheduling strategy. The graphical representation has been redesigned with improved layout, clearer labels, and enhanced visual quality to provide a professional illustration of the proposed methodology.

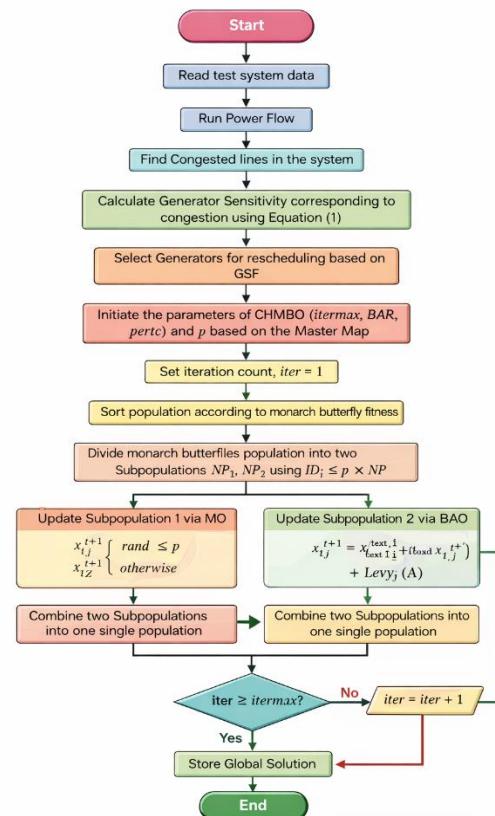


Fig. 1: Flowchart of congestion management using the proposed CHMBO algorithm

Source: created by the authors

Subsequently, the CHMBO algorithm parameters, including population size, migration ratio, butterfly adjusting rate, and maximum iteration count, are initialized. The monarch butterfly population is then generated randomly and evaluated based on the congestion management objective function. The population is sorted according to fitness and divided into two subpopulations. The first subpopulation is updated using the Migration Operator (MO) to enhance global exploration, while the second subpopulation is refined using the Butterfly Adjusting Operator (BAO) combined with Lévy flight and chaotic mapping to strengthen local exploitation and avoid

premature convergence. The updated subpopulations are merged, and the stopping criterion is checked. If the maximum number of iterations is not reached, the iteration counter is incremented and the process repeats. Once convergence is achieved, the optimal rescheduling solution that minimizes congestion and cost is stored, and the algorithm terminates. This flowchart clearly demonstrates how CHMBO effectively balances exploration and exploitation to achieve secure and economical congestion management.

4 Results and Discussions

The proposed CHMBO algorithm is compared with several well-known optimization techniques including PSO, TLBO, SBO, and conventional MBO. The comparison considers multiple performance indicators such as congestion management cost, total rescheduled power, convergence speed, and post-rescheduling transmission line flows. These additional evaluations provide a more comprehensive assessment of the proposed method under stressed network conditions.

To provide a more comprehensive evaluation of the proposed method, additional performance metrics and comparative analyses have been incorporated. The performance of the CHMBO algorithm is evaluated in terms of congestion management cost, total rescheduled power, convergence speed, and post-rescheduling transmission line flows. A detailed comparison with established optimization techniques such as PSO, TLBO, SBO, and conventional MBO is also carried out. The results clearly indicate that the proposed CHMBO algorithm outperforms existing methods by achieving lower congestion management cost and reduced generator rescheduling requirements. This improvement is primarily attributed to the effective balance between exploration and exploitation achieved through chaotic mapping and enhanced butterfly adjustment mechanisms. Moreover, the convergence characteristics demonstrate that CHMBO attains optimal solutions in fewer iterations, making it computationally efficient for real-time applications. In addition, the impact of generator sensitivity factor (GSF) based selection is analyzed. It is observed that selecting only the most influential generators significantly reduces unnecessary participation, thereby minimizing operational complexity and cost. This validates the effectiveness of the proposed hybrid strategy combining sensitivity analysis with intelligent optimization.

This section evaluates the effectiveness of the proposed Chaos-Embedded Monarch Butterfly Optimization (CHMBO) algorithm for transmission congestion management. All simulations are performed in a MATLAB® environment on the modified IEEE 30-bus test system to validate the capability of the proposed approach in mitigating line overloads while minimizing generator rescheduling cost. The IEEE 30-bus system consists of 6 generator buses, 21 load buses, and 41 transmission lines. Bus 1 is designated as the slack bus. The total system load is approximately 283 MW active power and 131 MVAR reactive power. Generator bids, line limits, and operating constraints are adopted from standard test system data used in congestion management studies. To examine system behavior under stressed conditions, line outage contingencies are intentionally introduced and ranked using the Severity Index (SI). The contingency resulting in the highest SI value is selected for congestion mitigation analysis.

4.1 Contingency Analysis and Congestion Identification

Transmission congestion in the IEEE 30-bus system is examined under contingency conditions using a severity-based screening approach. Line outage contingencies are deliberately introduced to simulate stressed operating conditions, and the resulting system response is evaluated using the Severity Index (SI). The severity index quantifies the extent of line overloading by comparing actual line power flow with the corresponding thermal limits. The contingency associated with the highest SI value is considered the most critical and is selected for congestion mitigation analysis. In this study, two prominent single-line outage scenarios are investigated: outage of line 1–2 and outage of line 1–3. For both cases, power flow analysis is carried out while keeping system loading unchanged. The resulting overloaded transmission lines, magnitude of power violations, and severity index values are summarized in Table 1 (Appendix).

From Table 1 (Appendix), it is evident that the outage of line 1–2 results in more severe congestion compared to the outage of line 1–3. Specifically, the line 1–2 contingency causes simultaneous overloading of transmission lines 1–7 and 7–8, with power flows exceeding their thermal limits by approximately 12–13% and 6–7%, respectively. The cumulative power violation in this case is around 25 MVA, yielding a severity index value of approximately 2.41. In contrast, the outage of line 1–3 leads to relatively lower congestion, affecting lines 2–1 and 9–2 with smaller overload magnitudes

and a lower cumulative violation of approximately 10 MVA. Consequently, the corresponding severity index is also lower, at approximately 2.26. Since the line 1–2 outage exhibits the highest severity index, it is identified as the worst contingency and is therefore selected for further congestion mitigation analysis using the proposed CHMBO-based generator rescheduling framework.

Table 2 (Appendix) demonstrates that the proposed CHMBO method achieves the lowest congestion management cost and minimum total rescheduled power among all compared techniques. Although traditional methods such as PSO, TLBO, and SBO relieve congestion, they require higher rescheduling magnitudes and incur greater economic cost. CHMBO efficiently mitigates congestion while maintaining post-rescheduling line flows within permissible limits and exhibits faster convergence compared to other optimization approaches. Table 2 (Appendix) presents a detailed comparison of the proposed CHMBO algorithm with PSO, TLBO, SBO, MBO, and IMBO-LW. The results indicate that CHMBO achieves the lowest congestion management cost (\$339.8/h), minimum total rescheduled power (15.26 MW), and fastest convergence time (5.48 s), demonstrating its superiority in both economic and technical performance. Traditional algorithms such as PSO and TLBO require larger adjustments in generator outputs, leading to higher operational cost. In contrast, CHMBO efficiently identifies optimal rescheduling strategies with minimal intervention. Furthermore, the proposed method maintains transmission line flows within permissible limits without introducing new violations. The improved convergence behavior, as illustrated in Figure 4, confirms that CHMBO avoids premature convergence and ensures stable performance. These results demonstrate the superiority of the proposed approach in terms of both economic and technical performance.

Figure 2 illustrates the relationship between the Generator Sensitivity Factor (GSF) and the corresponding rescheduling magnitude of participating generators under the selected contingency. Generators with higher absolute GSF values undergo larger power adjustments, confirming the effectiveness of sensitivity-based generator selection in identifying the most influential units for congestion mitigation.

Figure 3 compares transmission line power flows under congested and post-rescheduling conditions. It is observed that the proposed CHMBO-based rescheduling successfully reduces the overloaded line flows to within their thermal limits without

introducing new violations elsewhere in the network, thereby maintaining overall system security.

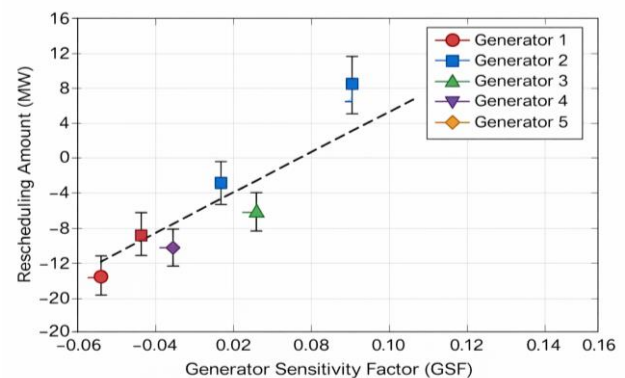


Fig. 2: Generator sensitivity factor versus rescheduling amount

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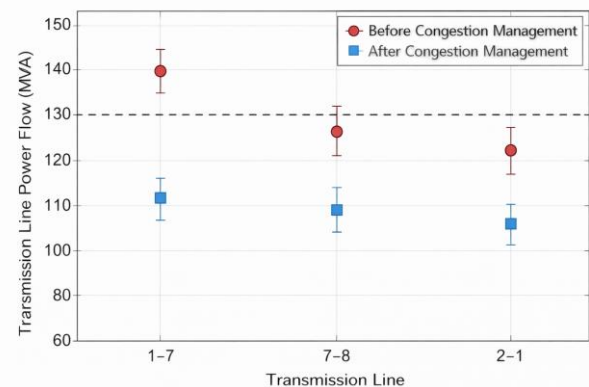


Fig. 3: Transmission line power flows before and after congestion management

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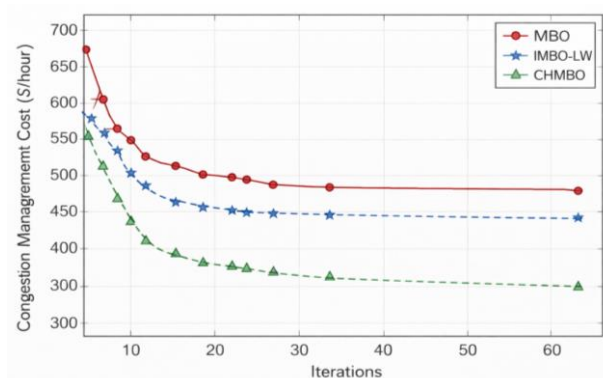


Fig. 4: Convergence characteristics of optimization algorithms

Source: created by the authors

Figure 4 presents the convergence behavior of MBO, IMBO-LW, and CHMBO for the IEEE 30-bus system. While conventional MBO shows slower convergence and early stagnation, IMBO-LW

improves convergence stability, and the proposed CHMBO achieves faster convergence with a lower objective value due to enhanced exploration through chaotic dynamics. To further analyze the effectiveness of the proposed CHMBO algorithm, its performance is compared with other optimization techniques in terms of convergence characteristics and congestion management cost. The convergence curves indicate that CHMBO reaches the optimal solution faster than MBO and IMBO-LW due to the incorporation of chaotic mapping, which enhances global exploration while preventing premature convergence.

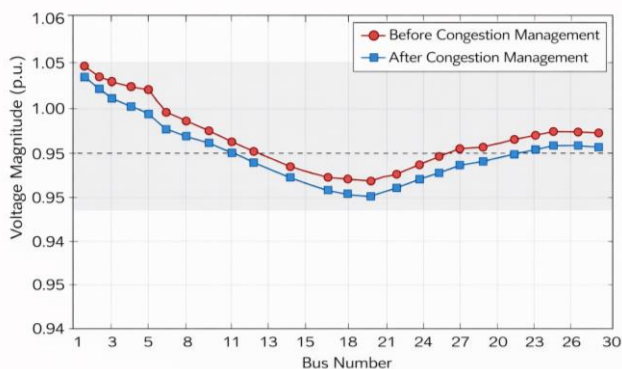


Fig. 5: Voltage profile of the IEEE 30-bus system after congestion management

Source: created by the authors

Figure 5 depicts the voltage magnitude profile of all buses in the IEEE 30-bus system before and after applying the proposed CHMBO-based congestion management strategy. It can be observed that the bus voltages remain well within the permissible operating limits of 0.95–1.05 p.u. after rescheduling. Compared to the congested case, slight voltage improvements are noticed at weak buses, indicating reduced system stress and enhanced voltage stability. These results confirm that the proposed method not only alleviates transmission congestion but also preserves overall voltage security of the system.

In a deregulated power market, generator price bids play a crucial role in determining market clearing prices and congestion management costs. Under normal operating conditions, generators submit incremental and decremental bids based on fuel cost, operational constraints, and expected market demand. However, when transmission congestion occurs, the influence of generator price bids becomes significantly pronounced, as only a subset of generators can effectively contribute to congestion relief. Congestion alters the economic dispatch by restricting power transfer across congested corridors, thereby limiting the

participation of low-cost generators located electrically far from load centers. As a result, generators located near congested areas or with higher sensitivity to congested lines gain greater market influence, often leading to increased congestion management costs. These generators may submit higher incremental bids due to their strategic importance in relieving congestion, which directly affects the overall rescheduling cost.

In the IEEE 30-bus system considered in this study, congestion caused by critical line outages leads to selective generator participation based on Generator Sensitivity Factors (GSFs). Generators with higher GSF values exhibit a stronger impact on congested line flows and are therefore preferred for rescheduling. Consequently, their submitted price bids have a greater influence on the final congestion management outcome. This selective participation prevents unnecessary rescheduling of generators with low congestion influence, thereby reducing excessive market intervention. The proposed CHMBO-based congestion management framework effectively mitigates the adverse impact of congestion on generator price bids by optimally balancing economic and technical considerations. By minimizing total rescheduling cost while satisfying network constraints, the algorithm limits the exploitation of market power by strategically located generators. This results in a fairer and more economically efficient congestion management process. The numerical results demonstrate that transmission congestion not only affects power flows but also reshapes generator bidding behavior and market outcomes. Efficient congestion management strategies, such as the proposed CHMBO approach, are therefore essential to ensure cost-effective operation, prevent price manipulation, and maintain market transparency under stressed network conditions.

5 Conclusion

This paper presents an effective congestion management framework based on the proposed Chaos-Embedded Monarch Butterfly Optimization (CHMBO) algorithm and validates its performance on the IEEE 30-bus test system. Transmission congestion resulting from critical line outages is first identified through severity index-based contingency analysis. To reduce computational burden and unnecessary generator participation, Generator Sensitivity Factors (GSFs) are employed to select only the most influential generators for rescheduling. The proposed approach successfully alleviates congestion while satisfying all operational

constraints, including transmission line thermal limits and bus voltage limits. Comprehensive simulations demonstrate that CHMBO outperforms existing optimization techniques such as PSO, TLBO, SBO, MBO, and IMBO-LW in terms of congestion management cost, total rescheduled power, and convergence speed. The incorporation of chaotic dynamics significantly enhances the exploration capability of the optimization process, preventing premature convergence and improving solution quality. The proposed framework also effectively limits the adverse impact of congestion on generator price bids, thereby reducing opportunities for market power exploitation and promoting fair economic operation. Post-rescheduling results confirm that system security and voltage stability are maintained throughout the congestion mitigation process.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

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APPENDIX

Table 1. Power Flow Details Under Line Outage Contingencies

Root of Contingency	Congested Line	Power Flow (MVA)	Line Limit (MVA)	Power Violation (MVA)	Overload (%)	Severity Index
Line 1–2 outage	1–7	146.8	130	16.8	12.9	2.41
	7–8	138.6	130	8.6	6.6	
Total Violation	–	–	–	25.4	–	–
Line 1–3 outage	2–1	134.5	130	4.5	3.5	2.26
	9–2	70.4	65	5.4	8.3	
Total Violation	–	–	–	9.9	–	–

Source: created by the authors

Table 2. Comparison of Results for Congestion Mitigation

Parameters	PSO [27]	TLBO [28]	SBO [29]	MBO	IMBO-LW	CHMBO
ΔP_1 (MW)	–8.54	–8.61	–8.48	–1.62	–0.21	–0.51
ΔP_2 (MW)	10.32	13.14	7.44	8.06	14.88	13.58
ΔP_3 (MW)	2.91	0.53	0.41	2.19	–1.54	–0.62
ΔP_4 (MW)	0.05	0.34	1.02	3.37	0.18	–0.26
ΔP_5 (MW)	0.64	–0.06	0.61	1.04	–0.69	–0.29
ΔP_6 (MW)	–0.04	0.42	0.49	NC	NC	NC
$\sum \Delta P$ (MW)	22.49	23.11	18.45	15.26	17.58	15.26
RC (\$/h)	542.3	498.9	426.7	446.5	432.4	339.8
PF_{AR} (MVA) (1–7)	129.6	130.0	129.8	129.3	127.9	128.4
PF_{AR} (MVA) (7–8)	121.1	121.0	123.2	125.8	127.2	129.4
CT (seconds)	NA	NA	NA	7.25	5.61	5.48

Source: created by the authors