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ORIGINAL RESEARCH PAPER

Influence of Wind Energy Source on Congestion Management in Power System Transmission Network: a Novel Modified Whale Optimization Approach

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Abstract
This manuscript proposes a Modified Whale Optimization Algorithm for power system congestion cost problem based on the optimal real power rescheduling with integration of wind farm. Bus sensitivity factor and wind availability factor are utilized for the wind farm integration in the framework. The bus sensitivity factor signifies the most sensitive bus for the integration of the wind that will impact the power flow in the congested lines. The wind availability factor determines the optimal geographic location of wind availability factor based on the wind speed and availability of space. Wind Farm Position Factor has been developed for the optimal wind farm placement considering the combined weightage of bus sensitivity factor signifies and wind availability factor. The Modified Whale Optimization Algorithm has been developed with the incorporation of two correction factors at the stages of exploration and exploitation of Whale Optimization Algorithm to overcome its tendency of confining itself into local optima region with premature convergence. The performance of Modified Whale Optimization Algorithm has been assessed based on the standard benchmark functions. IEEE-30 bus system is considered to evaluate the potency of the proposed Modified Whale Optimization Algorithm for the transmission congestion management problem. The results opted with Modified Whale Optimization Algorithm based on the congestion cost, bus voltage magnitudes, system losses, and computational time are found to be superior when contrasted with other optimization techniques.

Keywords Wind energy · Cost minimization · Optimization techniques · Renewable energy sources · Whale Optimization Algorithm

Introduction

The deregulated nature of the electricity market has raised the competition among the market players. The aim of profit maximization among the various market players has resulted in the operation of the power transmission channels close to their transfer limits. The transfer limits are basically designated as the thermal, voltage, and stability limits (Patel et al., 2021). It becomes important to maintain or create power generation planning infrastructure that would satisfy the sudden or future growth in the power demand for maintaining the power system transfer limits within its desirable boundaries (Serrano-Arévalo et al., 2020). The congestion in the transmission framework of power system can occur due to the violation of any of these limits. This scenario may also lead to the unstable operation of the entire power system framework. This operational failure of the power system may also lead to both economic and social consequences due to cascading backouts (Hasan & Kargarian, 2020). Thus, Transmission Congestion Management (TCM) becomes an integral strategy to observe and maintain these transfer limits.

The TCM includes Generator Rescheduling (GR), curtailment of loads, transformer tap setting, and implementation of FACTS devices as some of the conventional approaches for congestion control (Farzana & Mahadevan, 2020).

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Razmjooy et al. (2021) formulated a TCM approach considering the optimal power bidding strategies based on the operation of the electricity market. In their research, they developed a bidding scheme that will determine the optimal power production of the generators to manage the congestion. Improved word cup optimization technique has been implemented to determine the optimal pricing scheme of the power delivered by the generator to maximize the social welfare. Ullah and Park (2021) considered the influence of bilateral and pool market structures on the TCM. A peer-to-peer distributed pricing scheme has been developed based on the system voltage and congestion levels and an Alternating Direction Method of Multipliers algorithm for optimizing the willingness for bilateral trading. Sayed et al. (2021) conducted Congestion Management (CM) based on optimal load shedding and voltage stability enhancement. They implemented thyristor controlled switched capacitor to an optimal position in the power system network using the moth flame optimization algorithm in order to reduce the system loadability and minimize the congestion. Numan et al. (2021) proposed a CM technique considering the dynamic thermal line rating for reconfiguration of the power system network considering the influence of wind energy sources. The integration of the renewable energy sources for CM in their research has been done based on the data achieved by optimal coordination between the transmission line reconfiguration and the dynamic thermal ratings of the lines.

The Independent System Operator (ISO) usually adopts the GR techniques for TCM as this approach does not necessitates the change in the framework/topology of the power system for CM. Kumar et al. (2004) adopted GR for the generators located in the congested zones based on the transmission distribution factors to mitigate congestion. The identification of the congested zones has been done based on the transmission congestion distribution factors, which has been computed considering the sensitivity of the power flow in the congested lines. Dutta and Singh (2008) implemented optimal GR based on the Particle Swarm Optimization (PSO) to achieve optimal generator power output for CM. The sensitivity analysis has been utilized to sort and select the generators that will contribute to the GR process. In another research, Reddy (2016) formulated a multi-objective TCM problem addressing maximization of social welfare with real power rescheduling of the thermal generators. The research projected a multi-objective CM solution based on the combined optimal solution considering the real power rescheduling and load shedding cost minimization along with social welfare maximization. Verma and Mukherjee (2016) implemented the Firefly Algorithm (FFA) control the congestion by optimally rescheduling the active power generations. Paul et al. (2021) performed congestion alleviation by optimal rescheduling of real power adjustment of the generators with Bat Algorithm (BA).

In the dynamic power market, as the conventional fuel sources tends to be depleted with the time of usage, it is essential to focus on the renewable energy sources (Hernandez et al., 2021). Among the renewable energy sources, the wind energy has been very efficient due to its economical operation and maintenance cost (Deb et al., 2015). Tena-García et al. (2022) developed an optimal design strategy to manage the data sets required for the effective operation of the renewable energy systems for power system operation. The optimal data management system designed for the renewable energy system aids in the reduction in the data loss and lowers the computational cost for optimal operation of power system. Mahmoud et al. (2022) designed a wind energy system based on the permanent magnet synchronous generator for analyzing its performance in various harsh power system operating condition. WOA has been utilized to design the PI controller for optimally controlling its torque and current for the maximum power point tracking. Proper placement of the Wind Energy Sources (WES) in the power system results in the congestion relief with reduction in the system loss and appreciable improvement in the bus voltages (Deb et al., 2015). Parihar and Malik (2022) developed a probabilistic approach to combinedly control the uncertainties in the load demand and the intermittent behavior of the renewable energy systems to manage the power flow in the distribution network for controlling congestion in the distribution side of the power system framework. A TCM based on the Locational Marginal Pricing with the integration of the Wind Farm (WF) has been reported in Sood and Singh (2010). WES application based on the sensitivity analysis for the TCM has been discussed in Deb et al. (2015). However, the location for the positioning of the WF in Deb et al. (2015) has been done without considering the availability of the wind status at that location.

Considering the efficient performance of the power system, the implementation of the WF to mitigate congestion should adhere to the following aspects:

a) Appropriate availability of desirable proportion of wind.
b) The locational sensitivity that influences the WF positioning for congestion mitigation.

In view of these aspects, a new methodology has been proposed based on the Wind Availability Factor (WAF) and Bus Sensitivity Factor (BSF) to identify the most suitable position for WF installation.

In the power system r

esearch, the problem of power flow and optimal power generations has been solved considering several conventional techniques like quadratic programming (Quintana & Santos-Nieto, 1989), non-linear programming (Sachdeva & Billinton, 1973), and mixed integer programming (Aoki et al., 1988). The conventional optimization approaches have certain impediment such as complex algorithmic structures, sensitivity to initial search point, and poor convergence criteria. Thus, meta-heuristic algorithms that are mostly inspired from the physical and biological behavior of natural events have been developed and implemented to overcome the drawbacks. The meta-heuristic approaches bear efficient searching capabilities for the global optima (Nazari-Heris et al., 2018).

The Whale Optimization Algorithm (WOA) is one of such efficient optimization technique that has been developed considering the bubble net hunting approach of the humpback whales by Mirjalili and Lewis (2016). The performance of WOA has been appreciable in the engineering optimization problems (Gharehchopogh & Gholizadeh, 2019). Dasu et al. (2019) enhanced the optimal performance of power system stabilizer with the implementation of WOA to suppress the oscillations and improve the system stability. Mishra et al. (2022) implemented WOA for determining the optimal data sets and measure the sustainable performance of the laser drilling machine. Sahoo and Hota (2021) utilized the WOA to find the optimal bidding scenario in the presence of Renewable Energy System (RES). Uniyal and Sarangi (2021) sorted the optimal location of the Distributed Generation (DG) based on the network reconfiguration and probabilistic power flow. Prasad et al. (2021) formulated an Optimal Power Flow (OPF) based on WOA while considering the variation in the network temperature. In another research, Amroune et al. (2019) utilized WOA to optimally curtail the risk of voltage instability for development of an emergency demand response strategy. ben oualid Medani et al. (2018), in their research, performed optimal reactive power dispatch with WOA.

In WOA, the parameters are reliant on the path of random distribution and have a propensity to reach a state of premature convergence. During the execution process, the candidate solution position update is performed based on the guidance of the fittest search agent. This scenario may result in a lag in the coordination phases between the stages of exploration and exploitation. This stochastic nature of WOA drives the complete process to confine itself towards the region of local optima. Thus, a Modified Whale Optimization Algorithm (MWOA) is proposed with the incorporation of two correction factors IF_1 and IF_2 in the exploration and exploration phases of the algorithm to obtain efficient and appreciable outcome.

The objectives and contribution of the proposed TCM strategy are:

- Development of a TCM approach based on the implementation of WF. BSF and WAF are introduced to select the most optimal bus for WF placement based on the bus sensitivity and availability of wind respectively.
- Implement the proposed MWOA for the TCM problem considering the effect of the WF to relive the over burdening of the transmission lines while performing the optimal power rescheduling to achieve minimum rescheduling cost.
- The effectiveness of the proposed method is tested on IEEE-30 bus. In order to evaluate the effectiveness of WF and MWOA for TCM, two scenarios have been considered for the research work. Scenario 1 which analyze the TCM without WF and Scenario 2 that analyzes the influence of WF for TCM with MWOA. The same optimization problem has been also solved with PSO, Differential Evolution (DE), Flower Pollination Algorithm (FPA), Gravitational Search Algorithm (GSA), and WOA and the results opted with MWOA have been compared with the results of FFA (Verma & Mukherjee, 2016), PSO [solved], DE [solved], FPA [solved], GSA [solved], and WOA [solved], to evaluate the efficiency of adopted methodology.
- A comparative evaluation has been established between MWOA and the other optimization techniques based on the congestion cost, power flow after TCM, system losses, bus voltages, computational time, and convergence characteristics.

The remaining structure of the manuscript has been organized as follows: The framing of the problem has been covered in the "Problem Formulation" section. The fundamental overview of WOA has been depicted in the "Whale Optimization Algorithm" section. The formulation of MWOA for TCM has been portrayed in the "Modified Whale Optimization Algorithm" section. The "MWOA Performance Analysis" section embodies the performance efficiency analysis of MWOA. The "Results and Discussions" section illustrates the results and discussion. And the "Conclusion" section states the Conclusion.

Problem Formulation

The placement of the Wind Farm (WF) is performed based on the Bus Sensitivity Factor (BSF) and availability of wind:

Bus Sensitivity Factor

The BSF can be defined as the alteration in the power flow "ΔP_{ij}" in the over burden line "k" existing between the buses "i-j" due the injection of real power "ΔP_n" at n^{th} bus. The BSF can be represented as:

$$BSF_k^n = \frac{\Delta P_{ij}}{\Delta P_n} \tag{1}$$

In the TCM, the placement of the WF is done at the load bus. The BSF values are important for identifying the most sensitive buses, which can control the overloaded line power flow with a minor variation in power injection. The buses with the most deviating BSF values are taken into consideration for WF incorporation.

Wind Availability Factor

The WF's incorporation in the power system architecture not only helps to alleviate transmission channel congestion, but also generates profit for market participants. The WAF is a critical aspect in determining the location of the WF. The WAF comprises two factors: the availability of wind and the availability of space for WF installation. The availability of wind in each area is determined by the place's geographical topography. The wind speed maps for almost any region across the globe are maintained in all the weather station of that country. In the proposed TCM, the WAF has been determined using the wind speed map referred in Hetzer et al. (2008) and Moussavi et al. (2011).

Wind availability, on the other hand, is a critical aspect to consider. Apart from reducing congestion, this will promote financial rewards in terms of profit for the investors. Each place has a wind availability map that rates the buses based on their wind availability. Furthermore, sufficient space should be available for WF installation outside of urban areas. In light of these circumstances, the WAF for a given region may be expressed as follows:

$$\begin{aligned} WAF_i &= f_i(AOS_i, WAS_i) \\ 0 \le AOS_i &\le 1,\ 0 \le WAS_i \le 1 \end{aligned} \tag{2}$$

The "AOS_i" is the availability of space for a region "i" and "WAS_i" is wind average speed in that region. "f_i" is the function of both these factors that allocates weights to these factors. The function can be defined as:

$$f_i(AOS_i, WAS_i) = AOS_i * WAS_i \tag{3}$$

The space factor can have a value of 0 or 1. The space factor is one if there is enough room for wind turbines; otherwise, it is zero.

Wind Farm Placement

Taking both the BSF and WAF values into account, a possible WF location can be determined. Wind Farm Position Factor (WFPF) is proposed to identify the optimal site for WF placement. The WFPF is defined as follows:

$$WFPF_i = f_i(BSF_i, WAF_i) \tag{4}$$

The function can be expressed as:

$$f_i(BSF_i, WAF_i) = BSF_i + \mu_i WAF_i \tag{5}$$

The weighing factor μ_i lies in the range of $0 \le \mu_i \le 1$. The most significant aspect in mitigating the congestion is the detection of the power system buses that are more responsive towards the change in the power flow associated with the congested line. Taking this situation into account, the BSF can be weighted more than WAF. Thus, in relation to this, the bus that reflects the highest value of WFPF is selected for the positioning of the WF. It can be noted that both the BSF and WAF play an important aspect in determining the optimal position for WF placement for CM alleviation. Figure 1 illustrates the optimal positioning approach of WF for CM.

Problem Formulation

The integral objective of the TCM is to have optimal power generation to relieve the congestion. The implementation

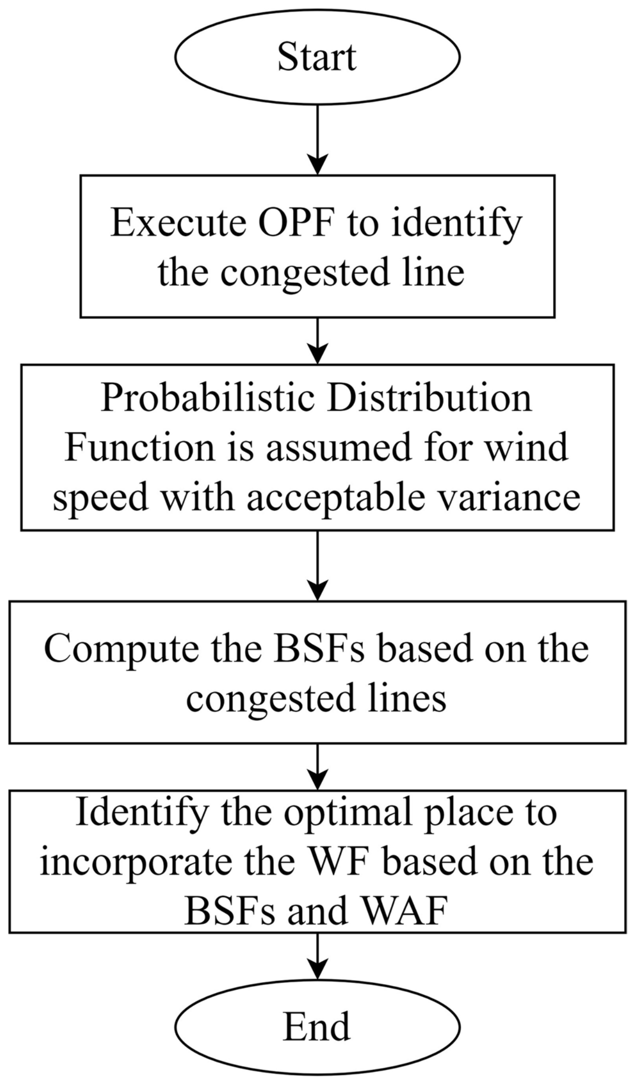


Fig. 1 Optimal wind farm placement based on bus sensitivity factor and wind availability factor

of WF alone can also mitigate congestion but the power generation by the WF is quite random. Thus, a rescheduling approach is proposed combining the generators and the wind power generation for effective alleviation of congestion. The complete power rescheduling of the existing generators is computed considering the bids of the generators taking part in the TCM. The congestion cost as the objective function can be represented as:

$$CC_i = \sum_{i=1}^{N_g} (C_i^u \Delta P_{gi}^u + C_i^d \Delta P_{gi}^d) + C_w P_{wf} \tag{6}$$

Subjected to system constraints:
Inequality constraints:
Power generation limits:

$$\Delta P_{gi}^{\min} \le \Delta P_{gi} \le \Delta P_{gi}^{\max} \tag{7}$$

$$P_{gi} - P_{gi}^{\min} = \Delta P_g^{\min} \& P_{gi}^{\max} - P_{gi} = \Delta P_{gi}^{\max}$$

Voltage limit constraints:

$$V_i^{\min} \le V_i \le V_i^{\max} \tag{8}$$

Reactive power generation constraints:

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max} \tag{9}$$

Power flow limits for transmission lines:

$$F_t \le F_t^{\max} \tag{10}$$

Equality constraints:

$$P_i = V_i \sum_{i=1}^{N} V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] \tag{11}$$

$$Q_i = V_i \sum_{i=1}^{N} V_j [G_{ij} \sin(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] \tag{12}$$

Here, ΔP_{gi} is the rescheduled active power. N_g is the total generator count, P_{wf} is the WF power output, and C_i^u and C_i^d are the incremental and the decremental price bids submitted by the generators respectively. As wind is a natural source of energy, bidding costs for wind C_w is presumed to be 0. $P_{gi}^{\min}$ and $P_{gi}^{\max}$ are the minimum and maximum limits of real power generations. V_i is the voltage at the buses that ranges between its upper limit $V_i^{\max}$ and lower limit $\mathrm{V}_{\mathrm{i}}^{\min}$. $F_t^{\max}$ is the maximum power flow in the transmission line and F_t is the actual power plow in the line in MW respectively. The power balance equations are represented in Eq. (11) and (12). P_i and Q_i are the real and reactive power injected in the buses, respectively. The bus voltages are designated as V_i and V_j for the i^{th} and j^{th} bus, respectively. δ_i represents the voltage angle corresponding to bus i and δ_j denotes the voltage angle at bus j. G_{ij} is the conductance and B_{ij} is the susceptance exiting between the i^{th} and j^{th} buses.

The fitness function for the TCM problem is formed by transforming the constraints that are dependent variable to penalty functions and hence adding those to the objective function. Thus, the fitness function is represented as:

$$T = CC + \sum_{j=1}^{N_l} VP_j + \sum_{j=1}^{N_g} QP_j + \sum_{j=1}^{N_t} FP_j \tag{13}$$

Here, N_g, N_l, and N_t in Eq. (33) represent the generator buses, load buses, and power system framework transmission lines respectively. The penalty terms are designated as VP_j, QP_j, and FP_j for the violation of voltage limits, reactive power generation limits, and transmission line power flow limits, respectively. These can be represented as:

$$VP_j = \begin{cases} K_c(V_j - V_j^{\max})^2 \text{ if } V_j > V_j^{\max} \\ K_c(V_j - V_j^{\min})^2 \text{ if } V_j < V_j^{\max} \\ 0 \text{ otherwise} \end{cases} \tag{14}$$

$$QP_j = \begin{cases} K_d(Q_j - Q_j^{\max})^2 \text{ if } \mathrm{Q}_j > Q_j^{\max} \\ K_d(Q_j - Q_j^{\min})^2 \text{ if } \mathrm{Q}_j < Q_j^{\max} \\ 0 \ \text{ otherwise} \end{cases} \tag{15}$$

$$FP_j = \begin{cases} K_t(F_j - F_j^{\max})^2 \text{ if } \mathrm{F}_j > F_j^{\max} \\ 0 \text{ otherwise} \end{cases} \tag{16}$$

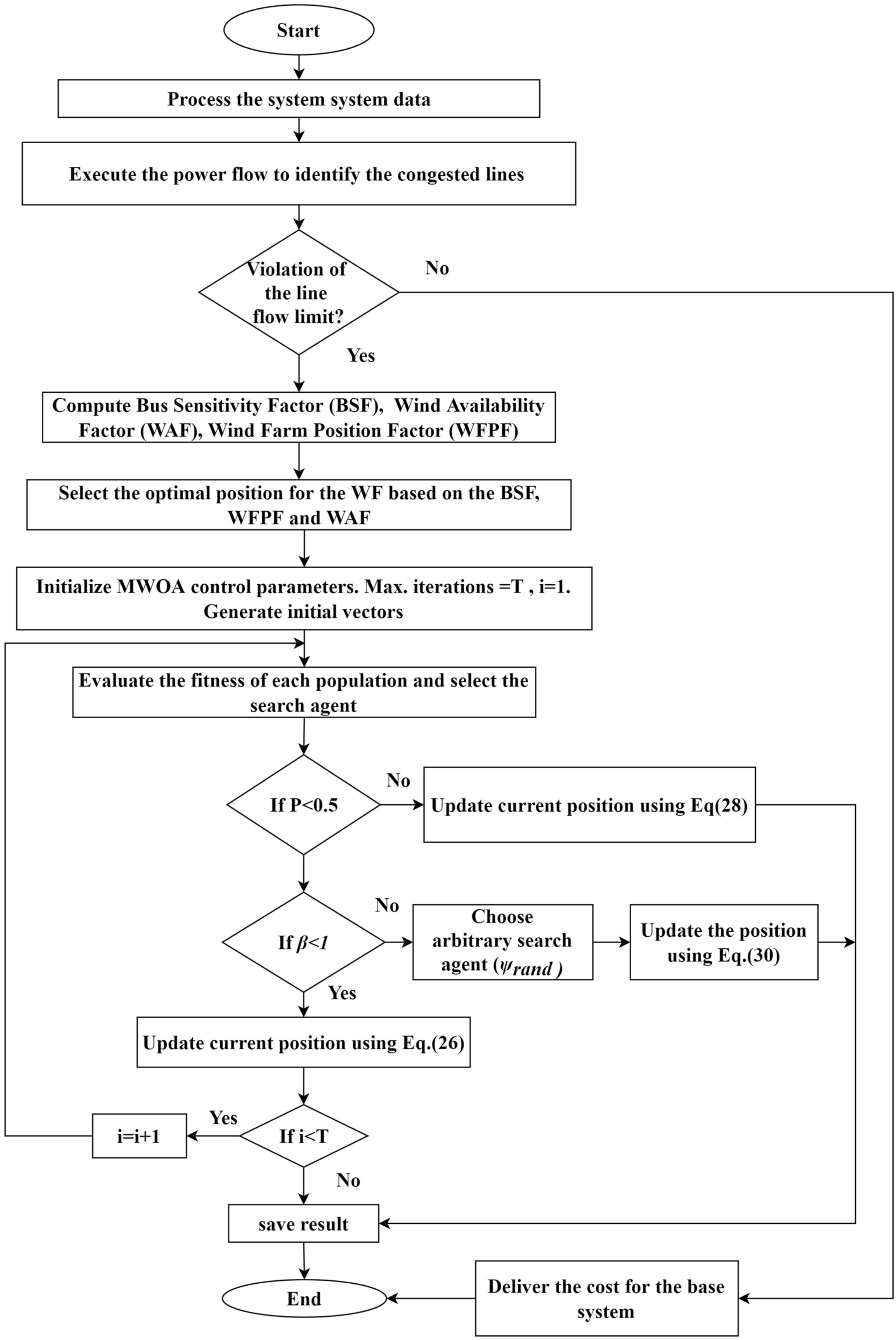
Here, K_c, K_d, and K_t are designated as the penalty factors for the TCM problem.

Whale Optimization Algorithm

Mirjalili and Lewis developed the Whale Optimization Algorithm (WOA) mimicked from the hunting strategy of the whales (Mirjalili & Lewis, 2016). The feature of bubble net surfing for the whale with spiral encircling procedure of hunting provides a very potent ability to catch its prey. The complete hunting procedure has been mathematically represented as follows:

Encircling Prey

The initial hunting mechanism proceeds with the encircling of the prey (fittest candidate solution). The position


Start
Process the system system data
Execute the power flow to identify the congested lines
Violation of the line flow limit?
No
Yes
Compute Bus Sensitivity Factor (BSF), Wind Availability Factor (WAF), Wind Farm Position Factor (WFPF)
Select the optimal position for the WF based on the BSF, WFPF and WAF
Initialize MWOA control parameters. Max. iterations =T , i=1. Generate initial vectors
Evaluate the fitness of each population and select the search agent
If P<0.5
No
Update current position using Eq(28)
If β<1
No
Choose arbitrary search agent (ψrand)
Update the position using Eq.(30)
Yes
Update current position using Eq.(26)
If i<T
Yes
i=i+1
No
save result
End
Deliver the cost for the base system

◂**Fig. 2** Flow chart for Modified Whale Optimization Algorithm for congestion management with wind farm

is updated based on the fittest solution. The encircling phenomenon has been portrayed as:

$$\vec{\xi} = \left| \vec{\chi} \cdot \vec{\psi}^{*}(t) - \vec{\Psi}(t) \right| \tag{17}$$

$$\vec{\Psi}(t+1) = \vec{\psi}^{*}(t) - \vec{\beta} \cdot \vec{\xi} \tag{18}$$

Here, "t" is the latest iteration number. β and χ are the coefficient vectors. ψ resembles the position vector corresponding to the best candidate solution and the ψ^{*} signifies the position vector. During each generation, ψ^{*} is updated for the search operation towards better solution. β and χ are computed as:

$$\vec{\beta} = 2.\vec{\sigma}.\eta - \vec{\sigma} \tag{19}$$

$$\vec{\chi} = 2.\eta \tag{20}$$

Here, σ has a linear decrement from 2 to 0 and $\eta \in [0,1]$.

Bubble Net Preying Strategy (Exploitation Stage)

The position update between the whale and the prey during the attacking phase is represented by the spiral equation:

$$\vec{\xi}' = \left| \vec{\psi}^{*}(t) - \vec{\Psi}(t) \right| \tag{21}$$

$$\vec{\Psi}(t+1) = \vec{\xi}' .f^{gl}.\cos(2\pi l) + \vec{\psi}^{*}(t) \tag{22}$$

In Eq. (21), $\vec{\xi}'$ represents the effective distance that prevails between position of the humpback whale and its designated prey. In Eq. (22), logarithmic spiral is designated as g and $l \in [0,1]$. There is a probability of 50% for the encircling mechanism to follow logarithmic oriented pathway or shrinking encircle. This is represented as:

$$\left.\begin{aligned} \vec{\Psi}(t+1) &= \vec{\psi}^{*}(t) - \vec{\beta} \cdot \vec{\xi}\,; p < 0.5 \\ \vec{\Psi}(t+1) &= \vec{\xi}' .f^{gl}.\cos(2\pi l) + \vec{\psi}^{*}(t); p > 0.5 \end{aligned}\right\} \tag{23}$$

Here, p is the probability of encircling path having a range [0,1].

Searching Strategy for Prey (Exploration Stage)

In this phase, β is employed for conducting the exploration process which aims towards searching of the prey. The range of β ranges from a minimum value of − 1 to 1. The exploration phase is represented as:

$$\vec{\xi} = \vec{\chi}.\vec{\Psi}_{rand} - \vec{\Psi} \tag{24}$$

$$\vec{\Psi}(t+1) = \vec{\Psi}_{\mathrm{rand}}(t) - \vec{\beta}.\vec{\xi} \tag{25}$$

Here, $\vec{\Psi}_{\mathrm{rand}}$ is taken as random position vector.

Modified Whale Optimization Algorithm

The target prey in the initial stage of WOA is the current fittest candidate solution, which is represented as the current fittest candidate solution. Because of this, the search agents are forced to adjust their positions in the direction of the current best solution determined by Eqs. (17) and (18). Due to the lack of information about the fittest search agent in the initial phase of WOA, the revising technique for position update may lead to premature convergence towards non-optimal solution. Thus, two correction factors IF_1 and IF_2 are implemented in the search stages of MWOA which makes the whales to traverse in small steps towards its prey to enhance its exploration performance. The modified equation of MWOA are:

$$\vec{\xi} = \left| \vec{\chi} \cdot \vec{\psi}^{*}(t) - \vec{\Psi}(t) \right| / IF_1 \tag{26}$$

$$\vec{\Psi}(t+1) = (\vec{\psi}^{*}(t) - \vec{\beta} \cdot \vec{\xi}) / IF_1 \tag{27}$$

In the same way, the modifications are incorporated in the exploitation phase for the spiral updating mechanism in Eq. (18) of WOA. The modified equation for MWOA is:

$$\vec{\Psi}(t+1) = (\vec{\xi}' .f^{gl}.\cos(2\pi l) + \vec{\psi}^{*}(t)) / IF_2 \tag{28}$$

The modified Eq. (28) with the correction factor enhances the phase of the exploitation by withering the shrinking circle that resembles the searching area for the whale for its prey. In WOA, the position revising is obtained with Eqs. (24) and ((25). This makes the search and traversing mechanism of the whale to be arbitrary in the case of WOA. Thus, to improve this situation, correction factors are incorporated for the phase of position update in MWOA. The modified exploration phase is represented by Eqs. (29) and (30):

$$\vec{\xi} = (\vec{\chi}.\underset{\mathrm{rand}}{\vec{\Psi}} - \vec{\Psi}) / IF_1 \tag{29}$$

$$\vec{\psi}(t+1) = (\vec{\psi}_{rand}(t) - \vec{\beta}\,.\,\vec{\xi})/IF_2 \quad (30)$$

The value of IF_1 and IF_2 are taken a 3.5 and 2.5 based on numerous hit and trail method The flow chart for the TCM with WF and MWOA is shown in Fig. 2.

MWOA Performance Analysis

The potency of MWOA is analyzed based on the standard benchmark functions. The expressions, ranges, and dimensions of the unimodal and multi-modal benchmark function are illustrated in Tables 1 and 2. The outcome of MWOA are compared to PSO, DE, FPA, GSA, and WOA. In this analysis, 30 search agents are taken and 300 maximum iterations with 30 independent trials have been performed.

The exploitation capacity of MWOA is tested with unimodal function. From Table 3, it is observed that MWOA has performed efficiently for six unimodal functions in comparison to FPA, DE, GSA, and WOA. The MWOA has outperformed PSO over four functions. MWOA has proved superior in contrast to all the considered optimization approaches for the functions (*f1*, *f2*, *f3*, *f7*) and for function (*f6*) MWOA has outperform WOA. Thus, it is observed that the performance of MWOA is appreciable in the stages of exploitation. In the case of the multi-modal

Table 1 Representation of unimodal benchmark functions

Function name	Mathematical representation	Dimensions, limits
Sphere	$f_1(z) = \sum_{i=1}^{k} z_i^2$	30, [− 100, 100]
Schwefel 2.22	$f_2(z) = \sum_{i=1}^{k} \lvert z_i \rvert + \Pi_{i=1}^{k} \lvert z_i \rvert$	30, [− 10, 10]
Schwefel 1.2	$f_3(z) = \sum_{i=1}^{k} \left(\sum_{j=1}^{n} z_j \right)^2$	30, [− 100, 100]
Schwefel 2.21	$f_4(z) = \max_i \{ \lvert z_i \rvert, 1 \le i \le k \}$	30, [− 100, 100]
Rosenbrock	$f_5(z) = \sum_{i=1}^{k-1} \left[100(z_{i+1} - z_i^2)^2 + (z_i - 1)^2 \right]$	30, [− 30, 30]
Step	$f_6(z) = \sum_{i=1}^{k} ([z_i + 0.5])^2$	30, [− 100, 100]
Quartic	$f_7(z) = \sum_{i=1}^{k} i z_i^4 + \text{random}(0, 1)$	30, [− 1.28, 1.28]

Table 2 Representation of multi-modal benchmark functions

Function name	Mathematical representation	Dimensions, limits
Schwefel	$f_8(z) = \sum_{i=1}^{k} -z_i + \sin(\sqrt{\lvert z_i \rvert})$	30, [− 500,50]
Rastrigin	$f_9(z) = \sum_{i=1}^{k} [z_i^2 - 10\cos(2\Pi z_i) + 10]$	30, [− 5.12, 5.12]
Ackley	$f_{10}(z) = -20\exp\left(-0.2\sqrt{\frac{1}{k}\sum_{i=1}^{n} z_i^2}\right) - \exp\left(\frac{1}{k}\sum_{i=1}^{n}\cos(2\Pi z_i)\right) + 20 + e$	30, [− 32, 32]
Griewank	$f_{11}(z) = \frac{1}{4000}\sum_{i=1}^{k} z_i^2 - \Pi_{i=1}^{n}\cos\left(\frac{zl}{\sqrt{i}}\right) + 1$	30, [− 600, 600
Penalized	$f_{12}(z) = \frac{\Pi}{k}\left\{ 101\sin(\Pi d_1) + \sum_{i=1}^{k-1}(d_i - 1)^2[1 + 10\sin^2(\Pi d_{i+1}) + (d_n - 1)^2 \right\} + \sum_{i=1}^{n} v(z_i, 10, 100, 4)$ where $d_i = 1 + \frac{z_i+1}{4}$ and $u(z_i, a, j, n) = \begin{cases} j(z_i - a)^n z_i \rangle a \\ 0 - a \langle z_i \langle a \\ j(-z_i - a)^m z_i \langle -a \end{cases}$	30, [− 50, 50]
Penalized 2	$f_{13}(z) = 0.1\left\{ \sin^2(3\Pi z_i) + \sum_{i=1}^{k} \begin{matrix} (z_i - 1)^2[1 + \sin^2(3\Pi z_i + 1)] \\ +(z_i - 1)^2[1 + \sin^2(3\Pi z_k] \end{matrix} \right\} + \sum_{i=1}^{k} v(z_i, 5, 100, 4)$	30, [− 50, 50]

Table 3 Performance assessment of MWOA other optimization methods for unimodal functions

Functions	MWOA		WOA		PSO		FPA		DE		GSA	
	Avg	SD	Avg	SD	Avg	SD	Avg	SD	Avg	SD	Avg	SD
f_1	0	0	1.46×10^{-30}	4.92×10^{-30}	8.1×10^{-14}	6.0×10^{-14}	1.34×10^{-4}	2.01×10^{-4}	5.6×10^{-4}	1.4×10^{-4}	2.35×10^{-16}	9.76×10^{-16}
f_2	6.3230×10^{-278}	0	1.05×10^{-21}	2.48×10^{-21}	1.5×10^{-09}	9.9×10^{-09}	4.3124×10^{-2}	4.5612×10^{-2}	7.9×10^{-4}	7.8×10^{-4}	5.6384×10^{-2}	0.19462
f_3	0	0	5.46×10^{-07}	2.95×10^{-06}	6.6×10^{-11}	7.3×10^{-11}	70.21623	23.7134	1.5×10^{-2}	1.2×10^{-2}	876.4753	319.5598
f_4	1.8360×10^{-253}	0	7.5218×10^{-2}	0.39648	0	0	1.074684	0.342856	0.3	0.7	7.43856	1.648726
f_5	28.9224	0.3758	26.6837	0.78621	0	0	96.73238	61.76884	5.03	5.82	68.43814	62.33452
f_6	0.9890	0.3879	3.21992	0.54924	0	0	1.03×10^{-4}	8.37×10^{-05}	0	0	2.4×10^{-16}	1.87×10^{-16}
f_7	9.6400×10^{-05}	1.00810×10^{-4}	1.438×10^{-3}	1.148×10^{-3}	4.65×10^{-3}	1.2×10^{-3}	0.124654	4.576439	0.1267	0.3623	8.9332×10^{-2}	4.558×10^{-2}

Table 4 Performance assessment of MWOA and other optimization methodologies for multi-modal functions

Functions	MWOA		WOA		PSO		FPA		DE		GSA	
	Avg	SD	Avg	SD	Avg	SD	Avg	SD	Avg	SD	Avg	SD
f_8	1.0462×10^{-04}	0.3026	5082.67	659.75	11,047.2	576.4	4821.92	1163.315	1268.2	51.8	2932.05	494.735
f_9	0	0	0	0	68.43	39.2	46.76341	12.4326	4.3×10^{-2}	1.3×10^{-2}	24.68934	6.74363
f_{10}	8.8923×10^{-16}	0	7.6403	9.983673	9.4×10^{-8}	4.6×10^{-8}	0.360175	0.40801	1.7×10^{-3}	2.2×10^{-3}	6.3046×10^{-2}	0.24836
f_{11}	0	0	2.98×10^{-4}	1.468×10^{-4}	0	0	9.1635×10^{-3}	7.6487×10^{-3}	1.5×10^{-2}	2.3×10^{-2}	28.0648	5.15372
f_{12}	8.58×10^{-2}	3.89×10^{-2}	0.34026	0.21682	7.8×10^{-15}	8.02×10^{-15}	6.871×10^{-3}	2.3602×10^{-3}	9.3×10^{-6}	3.8×10^{-6}	1.68897	0.93164
f_{13}	5.780×10^{-1}	0.3879	1.985634	0.209367	5.3×10^{-14}	4.6×10^{-14}	6.74836×10^{-3}	8.709×10^{-3}	1.5×10^{-4}	7.2×10^{-4}	8.93462	7.03836

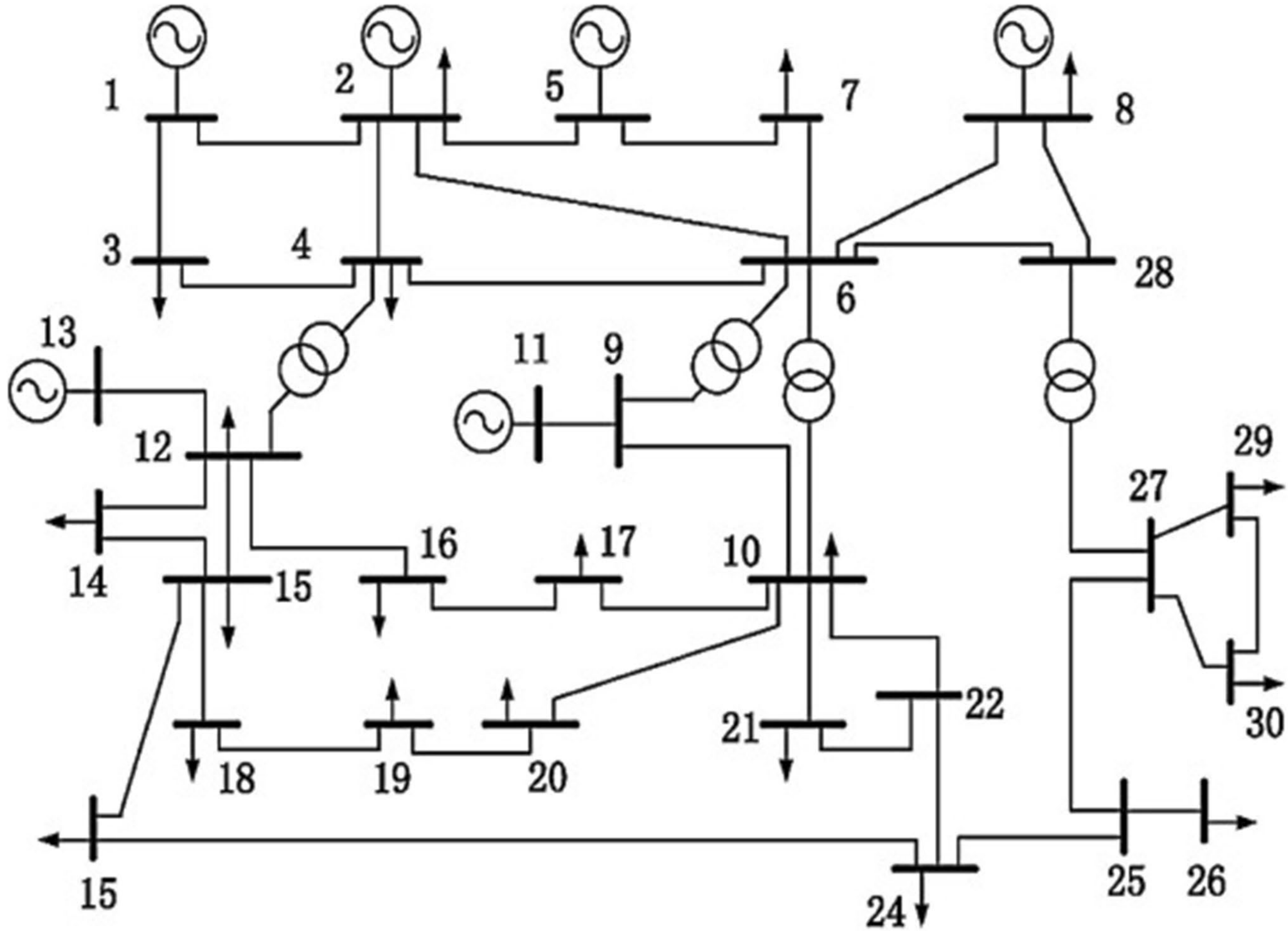


Fig. 3 Single line representation of IEEE 30 bus system

functions (*f8*, *f9*, *f10*, *f11*), portrayed in Table 4, the performance behavior of MWOA is significantly appreciable than the other optimization approaches considered in this research. For the function (*f12*, *f13*), MWOA proves to be superior to GSA and original WOA.

Results and Discussions

The proposed TCM problem is tested on IEEE 30 bus system to evaluate its efficacy [32]. The depiction of IEEE-30 is shown in Fig. 3. The complete execution of the codes and algorithms for the TCM problem is performed on MATLAB 2016(a) with i7 processor and 8 GB

Table 5 Optimization techniques parameters used for transmission congestion management

Algorithms	Parameters of the optimization techniques
MWOA	Size of population: 40. Correction factors: IF_1 and IF_2 are 3.5 and 2.5, respectively. Maximum generations: 300. Coefficient vectors β and $\chi \in [0,1]$
WOA	Size of population: 40. Maximum iterations: 300. Coefficient vectors β and $\chi \in [0,1]$
DE	Size of population: 40. Scaling factor = 0.8 and crossover ratio = 0.8. Maximum iterations: 300
PSO	Size of population: 40; min and max inertia weights are 0.9 and 0.4, respectively. Acceleration constants: C1 and C2 = 2. Maximum iterations: 300
FPA	Size of population: 40, attractiveness coefficient ($\mathscr{L}=10$), absorption coefficient ($\hbar=0.5$). Maximum iterations: 300
GSA	Size of population: 40. Acceleration constant (α) = 10. Gravitational constant $G_0=100$. Maximum iterations: 300

Table 6 Congested lines power flow

Congested lines	Power flow (MW)	Max. Line limit (MW)	Excess power flow (MW)
1–3	170.36	130	40.36
3–4	162.20	130	32.20
4–6	103.75	190	13.75

Table 7 Generators price bids

Bus No:	Price bids ($/MWh)	
	R_u	R_d
1	22	18
2	21	19
5	42	38
8	43	37
11	43	35
13	41	39

RAM laptop. To establish a comprehensive analysis, the TCM problem has been solved considering two scenarios: (i) without WF and (ii) with WF. The same problem is also solved with PSO [solved], DE [solved], FPA [solved], GSA [solved], and WOA [solved] along with the proposed MWOA to analyze the efficacy of the proposed TCM approach. For the TCM problem, 30 independent trial runs are performed for the iteration count of 300 for each of the considered cases. The parameters of the applied optimization approaches for the TCM are listed in Table 5. Based on the contingency analysis, line (1–2) is tripped with increase in system load by 20% which led to the congestion in lines (1–3), (4–6), and (3–4). The congested line power flows are shown in Table 6. The generator bids are represented in Table 7.

Table 9 Sorted values of BSF, WAF, and WFPF for optimal placement of wind farm

Sl. No	Bus No	BSF	WAF	WFPF
1	3	−0.8439	0.12	0.8909
2	16	−0.5980	0.17	0.6380
3	18	−0.6329	0.39	0.7882
4	**20**	**−0.9997**	**0.61**	**1.2436**
5	23	−0.6346	0.17	0.6882
6	26	−0.5479	1.26	1.0218
7	29	−0.5621	1.26	1.0641

Determination of Wind Farm Location

The computed values of BSF are represented in Table 8. The most deviated negative values of BSF are opted as the probable location for WF placement. It is observed that the buses 3, 16, 18, 20, 23, 26, and 29 show the most deviated BSF values for the congested lines, which are marked in bold. Thus, the injection of power at these buses will significantly influence the power flow in the over burden lines. Therefore, these selected buses are marked as the most responsive buses. Table 8 also represents the hypothetical WAF values corresponding to each bus (Moussavi et al., 2011).

Most sensitive buses are sorted based on the WFPFs to establish the optimal placement of the WF. The WFPF values are calculated by applying a weighting factor of $\mu = 0.4$ to Eq. (4) (Moussavi et al., 2011). Table 9 displays the WFPF values. Considering the WFPF values, bus 20

Table 8 Bus sensitivity factor and wind availability factor values for the congested lines at load buses

Sl. No	Bus No	Lines with congestion			WAF	Sl. No	Bus No	Lines with congestion			WAF
		1–3	3–4	4–6				1–3	3–4	4–6	
1	3	**−0.8439**	**−0.6784**	**−0.2671**	**0.12**	13	19	0.2361	0.1326	0.6732	0.20
2	4	−0.2362	−0.2015	−0.0882	0.32	14	20	**−0.9997**	**−0.7402**	**−0.2895**	**0.61**
3	6	0.5063	0.9784	0.4368	0.24	15	21	0.1151	0.0971	0.0358	0.60
4	7	−0.0868	−0.0748	−0.0821	0.31	16	22	−0.4164	−0.1648	−0.0572	0.15
5	9	−0.4054	−0.1038	−0.0801	0.12	17	23	**−0.6346**	**−0.5169**	**−0.1862**	**0.17**
6	10	03,468	0.2671	0.1038	0.31	18	24	−0.2152	−0.1637	−0.0642	0.38
7	12	0.1802	0.1447	0.0536	0.23	19	25	−0.4175	−0.2369	−0.0485	0.96
8	14	0.3136	0.2579	0.1013	0.62	20	26	**−0.5479**	**−0.4629**	**−0.1883**	**1.26**
9	15	−0.2376	−0.1970	−0.0730	0.60	21	27	−0.4368	−0.2544	−0.0163	0.84
10	16	**−0.5890**	**−0.4693**	**−0.1879**	**0.17**	22	28	−0.3276	−0.3894	−0.0788	0.98
11	17	0.2273	0.1768	0.0784	0.14	23	29	**−0.5621**	**−0.6684**	**−0.2633**	**1.26**
12	18	**−0.6329**	**−0.5124**	**−0.1979**	**0.39**	24	30	0.1890	0.1576	0.0542	0.87

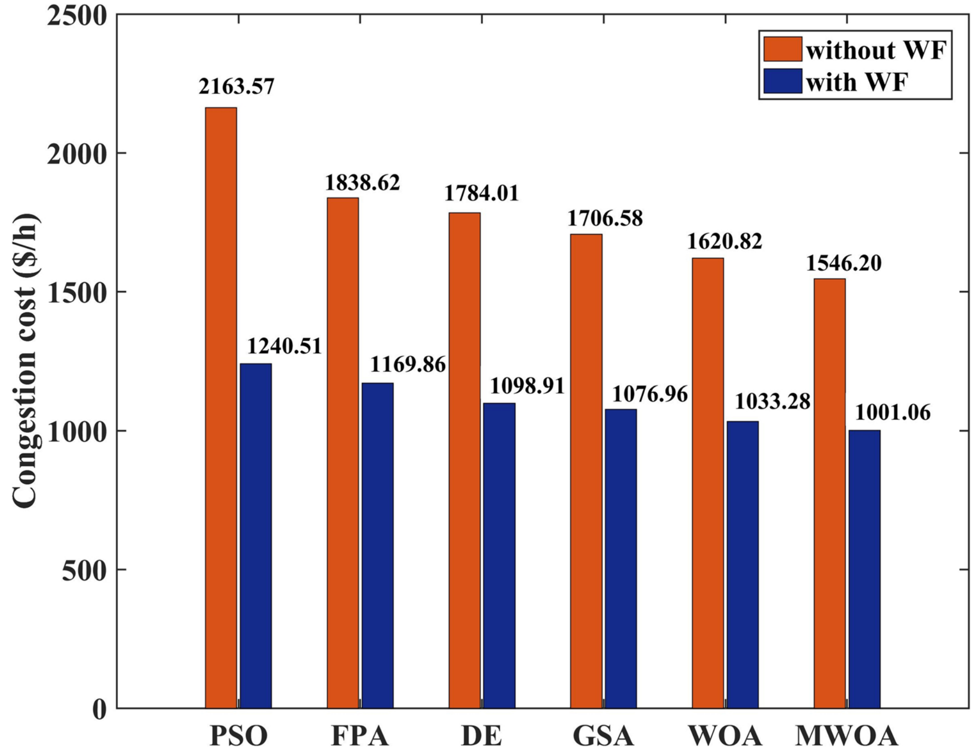


Fig. 4 Comparative congestion cost (i) without wind farm and (ii) with wind farm

exhibits the most optimal position for the WF placement, which is marked in bold. It should be noted that the WF incorporation at the other buses would also reduce the power flow in the congested transmission channel but depending upon the BSF and WFPF values, bus 20 exhibits most optimal and significant impact on the location and power flowing in the congested lines. Therefore, bus 20 has been considered for the WF placement.

Analysis of MWOA on Transmission Congestion Management

The proposed MWOA approach has been applied successfully to relieve the over-burdened lines from the state of congestion. The complete analysis of the TCM problem for the two scenarios, (i) without WF and (ii) with WF, is highlighted in Tables 8 and 9 respectively. In Table 8, the

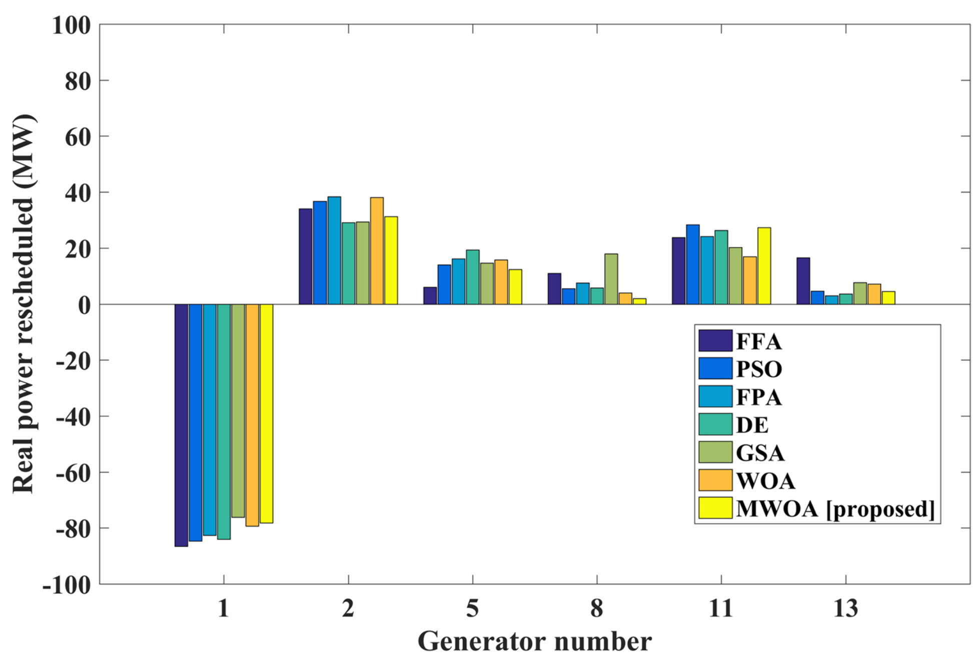


Fig. 5 Power rescheduled with various optimization algorithm without wind farm

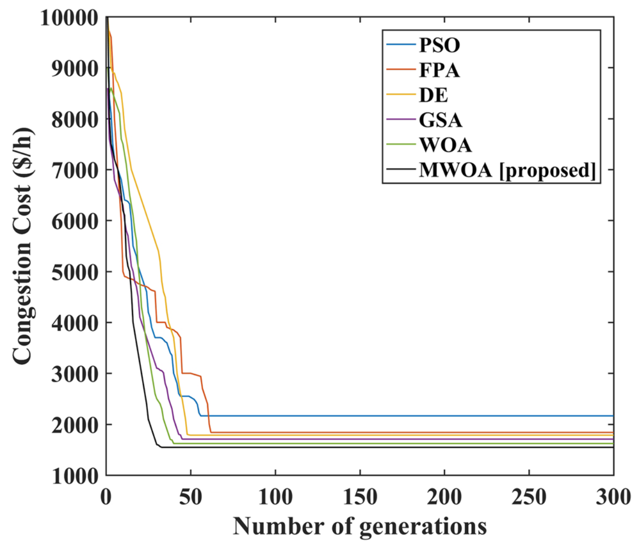


Fig. 6 Convergence profile without wind farm with the application of Modified Whale Optimization Algorithm and other optimization techniques

power rescheduling with MWOA shows that congested lines' power flows have been reduced below its maximum limit. The congestion cost achieved with MWOA without WF is 1546.20$/h which is least among the cost achieved with WOA [solved], DE [solved], PSO [solved], FPA [solved], and GSA [solved]. The graphical representation of congestion cost, amount of the real power adjusted, and the convergence profiles achieved with the various optimization approaches for TCM without WF are shown in Figs. 4, 5, and 6, respectively.

From Table 11, it can be observed that the installation of WF has effectively reduced congestion with optimal minimization of congestion cost. The congestion cost accomplished with the impact of WF and MWOA is 1001.06$/h. When established a comparative analysis, it is seen that the cost accomplished with the influence of WF placement and MWOA is lower among all the rescheduling cost achieved with WOA [solved], DE [solved], PSO [solved], FPA [solved], and GSA [solved]. The comparative congestion cost representation is shown in Fig. 4. It is observed that there is a considerable amount of reduction in congestion cost due to the WF integration in the power system when compared to the results opted without WF integration. From comparative analysis of Tables 10 and 11, it can be noticed that there is a significant reduction on the amount of power flow on the congested lines with the influence of WF. The power rescheduled for each of the generators with the MWOA and WF is shown in Fig. 7.

The convergence characteristics for the optimal cost obtained in the presence of WF with optimization algorithms are shown in Fig. 8. It is observed that with WF, MWOA has converged at 27th iteration for the best solution. Thus, proposed MWOA with WF has a faster convergence in contrast to other techniques.

Table 12 highlights the system losses and voltages before and after TCM. During congestion, the loss in the system

Table 10 Output achieved with various algorithms for transmission line congestion management without wind farm

	FFA (Verma & Mukherjee, 2016)	PSO [Solved]	FPA [Solved]	DE [Solved]	GSA[Solved]	WOA [Solved]	MWOA [Proposed]
Approx. cost of rescheduling ($/h)	2769.53	2163.57	1838.62	1784.01	1706.58	1620.82	1546.20
Best cost	NR	2163.57	1838.62	1784.01	1709.58	1620.82	1546.20
Worst cost	NR	3118.48	2082.37	2058.04	2031.38	2016.47	1964.23
Average value	NR	2046.26	1247.08	1186.31	1179.75	1138.65	1142.63
Line 1–3 flow post TCM (MW)	129.70	129.74	129.28	129.60	129.68	129.42	129.06
Line 3–4 flow post TCM (MW)	129.91	129.88	129.82	129.33	129.46	129.01	129.23
Line 4–6 flow post TCM (MW)	89.64	89.33	89.94	89.02	89.46	88.98	88.92
ΔP_1 (MW)	−86.57	−84.68	−82.68	−84.01	−76.14	−79.36	−78.21
ΔP_2 (MW)	34.09	36.73	38.35	29.10	29.36	38.10	31.30
ΔP_3 (MW)	6.05	14.00	16.15	19.29	14.59	15.83	12.39
ΔP_4 (MW)	11.02	5.49	7.60	5.77	17.95	4.05	2.02
ΔP_5 (MW)	23.83	28.37	24.13	26.30	20.20	16.91	27.3
ΔP_6 (MW)	16.51	4.63	3.01	3.57	7.70	7.20	4.5
Total amount (MW)	177.79	173.86	171.79	168.04	165.94	161.45	156.02

NR not reported

Table 11 Output achieved with various optimization algorithms for transmission congestion management with wind farm

	FFA (Verma & Mukherjee, 2016)	PSO [Solved]	FPA [Solved]	DE [Solved]	GSA [Solved]	WOA [Solved]	MWOA [Proposed]
Approx. cost of rescheduling ($/h)	2769.53	1240.51	1169.86	1098.91	1076.96	1033.28	1001.06
Best cost	NR	1240.51	1169.86	1098.91	1076.96	1033.28	1001.06
Worst cost	NR	1549.36	1487.10	1556.08	1496.48	1463.77	1386.49
Average value	NR	1336.74	1247.08	1186.31	1179.75	1138.65	1142.63
Post CM line 1–3 (MW)	129.70	127.30	128.28	127.60	126.68	126.42	126.06
Post TCM line 3–4 (MW)	129.91	128.42	127.82	128.33	127.46	126.01	126.23
Post TCM line 4–6 (MW)	89.64	87.96	85.94	86.02	84.46	84.98	84.62
ΔP_1 (MW)	−86.57	−56.36	−54.01	−49.57	−49.14	−46.38	−40.67
ΔP_2 (MW)	34.09	17.98	19.20	13.56	19.35	14.97	12.93
ΔP_5 (MW)	6.05	19.92	14.84	25.32	12.47	7.42	5.21
ΔP_8 (MW)	11.02	9.85	7.60	5.77	3.12	3.06	2.32
ΔP_{11} (MW)	23.83	3.68	8.55	6.30	8.29	9.14	8.93
ΔP_{13} (MW)	16.51	5.43	3.01	2.01	2.23	1.4	1.01
P_{Wf}	NR	34.98	34.64	32.98	35.28	32.04	30.76
Total amount (MW)	177.79	148.48	141.31	135.51	129.88	114.41	101.83

NR not reported

was 59.9 MW. It is seen that the losses have reduced to 56.02 MW with WF and MWOA after TCM. The system voltage achieved is 0.9730p.u with MWOA post TCM. The enhancement in the system voltage level is significant

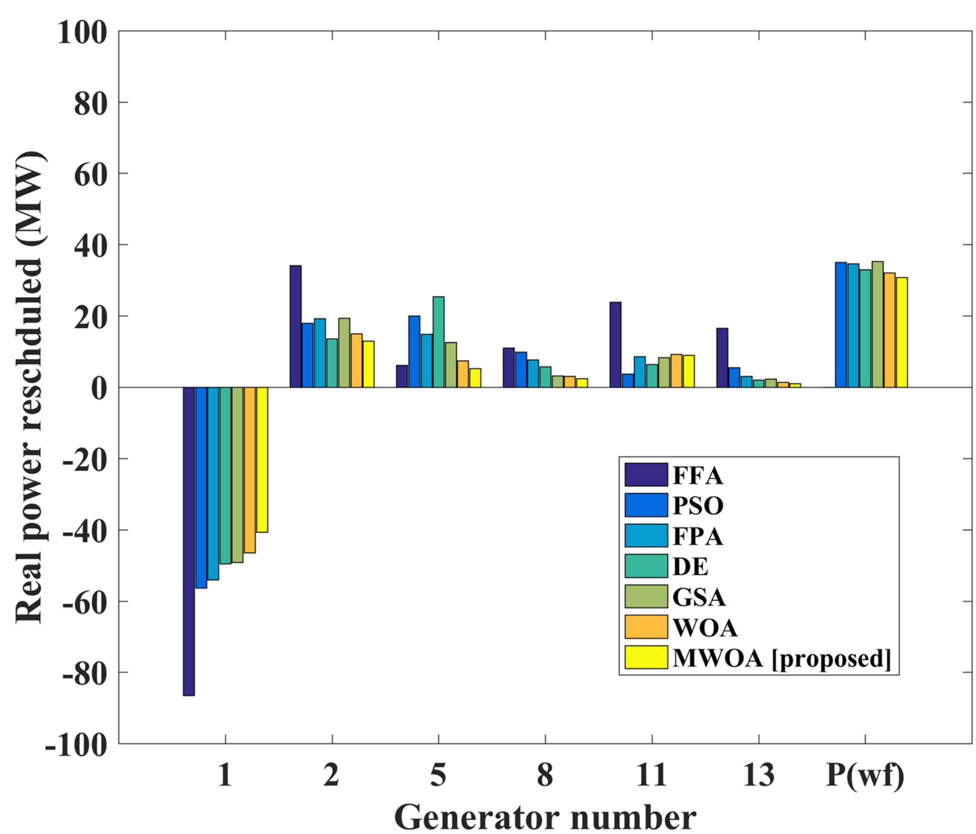


Fig. 7 Power rescheduled with various algorithms with wind farm

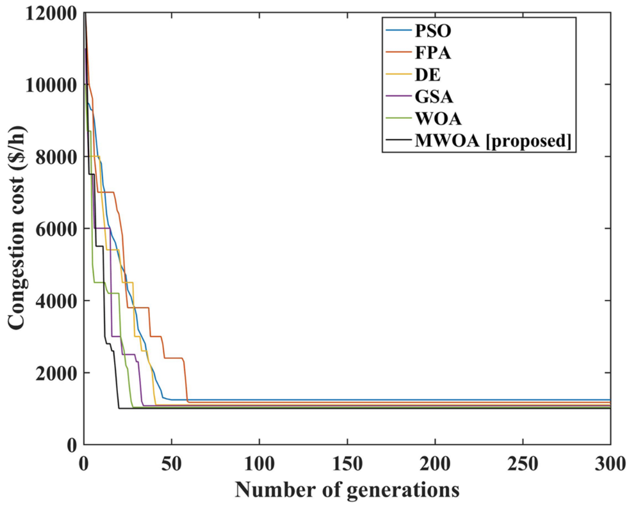


Fig. 8 Convergence characteristics for optimization algorithms with wind farm

with MWOA and WF in comparison to other optimization approaches and is listed in Table 12. The voltages at each bus with WF opted with the optimization techniques after congestion alleviation are represented in Fig. 9. The computational time of MWOA and other adopted optimization technique applied for the TCM with WF and without WF are given in Table 13. It can be observed that the computational time for MWOA is comparatively less for both the scenarios in comparison to other optimization techniques for the TCM.

Conclusion

In this manuscript, a congestion alleviation mechanism based on the integration of WF has been proposed for the power system transmission lines. The BSF has been employed to ascertain the most sensitive bus towards the power injection, which will modify the power flow in the overloaded line when the power injection occurs. In association to this, WAF is also considered that determines the WF placement based on the wind speed and availability of space at a particular region. The TCM problem is formulated as the congestion cost minimization problem considering the active power injection by the WF as one of the control variables. The proposed MWOA exhibits that it is a potent optimization approach for the TCM that converges towards

Table 12 Analysis of system parameters

Parameters	Without wind farm	With wind farm						
		FFA (Verma & Mukherjee, 2016)	PSO [Solved]	FPA [Solved]	DE [Solved]	GSA [Solved]	WOA [Solved]	MWOA [Proposed]
P_{Loss} (MW)	59.9	58.73	59.14	59.6	58.9	58.63	58.25	57.12
V_{min} (p.u)	0.935	0.9417	0.9408	0.9475	0.9518	0.9604	0.9698	0.9730

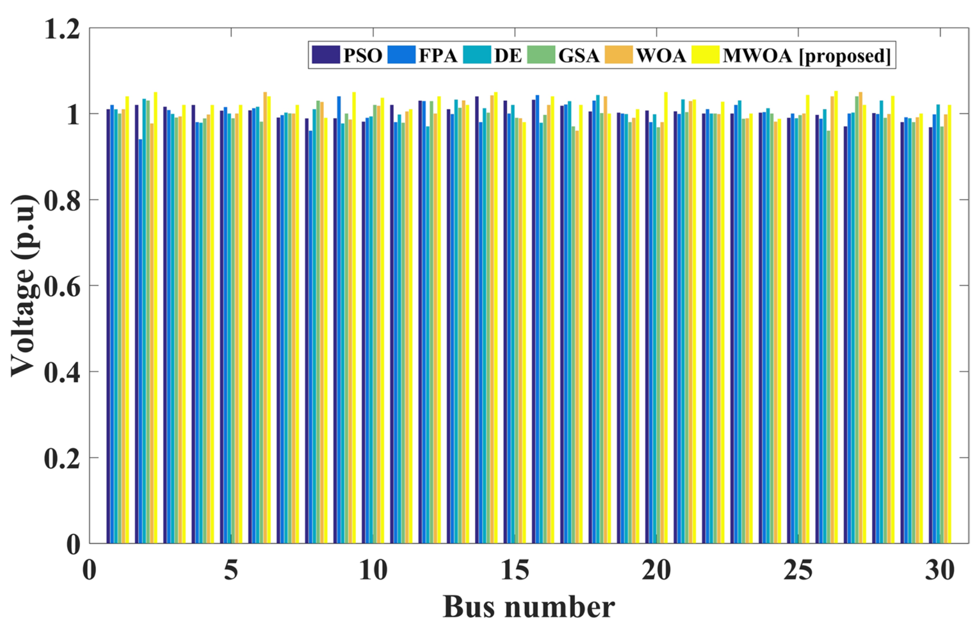


Fig. 9 Comparative bus voltages with various optimization approaches post transmission congestion management with wind farm

Table 13 Comparative computational time between Modified Whale Optimization Algorithm and other optimization techniques

	Average Computational Time (Sec)					
	PSO [Solved]	FPA [Solved]	DE [Solved]	GSA [Solved]	WOA [Solved]	MWOA [Proposed]
Iterations/trials	300/30	300/30	300/30	300/30	300/30	300/30
Without wind farm	4.63	4.77	4.26	3.4	3.85	2.74
With wind farm	4.06	4.12	4.01	3.72	3.69	2.62

the global optimal solution without confining itself into local optima. The proposed TCM problem with MWOA is verified on IEEE-30 bus system. A comprehensive comparative analysis is portrayed based on the output opted with WF integration and without the influence of WF. Results achieved with PSO, FPA, DE, GSA, and WOA are also highlighted for the TCM problem to portray a comparative performance analysis with MWOA.

The proposed MWOA for TCM has made it possible to achieve the lowest possible congestion cost while simultaneously reducing overburdening of the transmission channels. The introduction of the correction factors in the exploration and exploitation stages has assisted in achieving a faster rate of convergence for MWOA with a better ability to search for global optima. There has been a reduction of 21.06%, 19.30%, 14.42%, 8.90%, 7.04%, and 3.11% in congestion cost accomplished with MWOA and incorporation of WF when compared to FFA, PSO, FPA, DE, GSA, and WOA respectively. This signifies that the performance of MWOA for congestion cost minimization is appreciable when compared to the optimization methods like FFA, PSO, FPA, DE, GSA, and WOA for reduction of congestion cost. The system real power loss has been diminished by 2.78 MW with MWOA post-CM when compared to the congested scenario. When compared to the loss reduction for the post-CM scenario, it has been found that with MWOA, the system losses have been reduced by 1.61 MW, 2.02 MW, 2.48 MW, 1.78 MW, 1.51 MW, and 1.13 MW when compared to losses achieved with FFA, PSO, FPA, DE, GSA, and WOA for the post-congestion scenario. There has been a significant improvement in the system bus voltages and appreciable reduction in the computational time with MWOA. Therefore, the integration of WF along with MWOA is a cost-effective and efficient method to control the congestion in transmission network.

Data Availability Data will be made available on reasonable request.

Declarations

Conflict of Interest The authors declare no competing interests.

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