

OPTIMAL WIND-THERMAL ECONOMIC DISPATCH CONSIDERING VOLTAGE STABILITY IMPROVEMENT USING MANTA RAY FORAGING OPTIMIZATION ALGORITHM

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ABSTRACT

This paper investigates the adaptation and the application of one of the recently proposed meta-heuristic optimization algorithm namely Manta Ray Foraging (MRFO) algorithm to solve the Optimal Power Flow (OPF) problem with the presence of wind power generation. The wind generation cost model includes direct cost, expected penalty cost and expected reserves cost to account for wind power generation imbalance. The methodology for maximizing voltage stability margin in the system is also presented in this study and the line voltage stability index is used as indicator to investigate voltage stability assessment. The effectiveness of the proposed methodology is tested on IEEE 30-bus power system for different objective functions. The obtained results are compared with the recently published methods in the case of conventional OPF as well as in the case of OPF incorporating wind sources. The comparison study demonstrates the effectiveness of the proposed methodology.



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I. INTRODUCTION

The integration of renewable energy, especially wind power, in power systems has become a new task for researcher. The integration of wind generation in power systems has been continuously increased in recent years due to the environmental benefits. The insertion of such energy sources into modern power systems has introduced new kind of challenges for operating and managing the power systems [1]. Optimal power flow (OPF) is one of the widely used tools in the planning and managing of the power systems. Its main goal is to optimize a specified objective function while satisfying a set of equality and inequality constraints. However, in last years, solving the OPF problem has become more convoluted with immense integration of renewable energy resources. A variety of optimization techniques have been successfully used to solve the OPF problem with incorporating of wind power generation. Authors in [2] proposed the use of Gravitational Search Algorithm (GSA) to solve the economic emission load dispatch problem for system with thermal power and wind generators. OPF solution of power grid incorporating stochastic wind power with the implementation of Gbest guided artificial bee colony algorithm is addressed in [3]. According to [4] proposed a new optimization algorithm called Modified Bacteria Foraging Algorithm (MBFA) and introduced Doubly Fed Induction Generator (DFIG) model in OPF problem. Authors in [5] used concepts from the fuzzy set theory with a new cost model in OPF problem. The cost model is based on the addition of a penalty cost in the classical economic dispatch problem representing compensation payment to private owners of wind farms for not using the available wind power capacity. In the same way, a supplementary cost term for overestimation of the available wind power has been added in OPF problem along with use probability functions to describe the wind speed profiles [6], [7]. According to [8] Modeled the uncertainties of wind power penetration in the power system through probability density functions and solved the economic emission load dispatch problem with genetic algorithm. Authors in [9] used a new hybrid flower pollination algorithm with time-varying fuzzy selection mechanism to solve the OPF problem incorporating wind power, emission and valve-point loading effect of generators. Quantum-inspired particle swarm optimization algorithm is proposed by [10] for OPF problem solving considering wind power uncertainty and carbon tax.

According to [11] employed entropy weight–TOPSIS method to comprehensively assess the performance of different power producers, based on which a multi-objective security-constrained economic dispatch model. In [12] proposes an Enhanced Moth-Flame Optimization (EMFO) algorithm for solving the non-convex economic dispatch problem with valve point effects and emissions. In this paper, the wind-thermal OPF problem with voltage stability enhancement is solved using a recently proposed optimization algorithm named Manta Ray Foraging Optimization (MRFO). The wind generation cost model is introduced into the conventional OPF program as objective function, and voltage stability improvement is investigated as well. The OPF objective function includes: the fuel cost of thermal units, the cost of wind power and the line voltage stability index (L_{mn}). In turn, wind power cost includes: the expected cost of wind power to be purchased, the expected penalty cost for not exploiting available wind power and the expected reserve cost due the shortage of wind power [10]. The proposed method is tested on IEEE 30-bus test system. The simulation results show the efficiency of the proposed method compared to other methods available in literature. The rest of the paper is organized as follows. Section 2 deals with the OPF problem with wind energy subject to equality and inequality constraints. The general framework of MRFO and its implementation for solving the OPF problem is discussed in Section 3 whereas Section 4 illustrates the simulation and results of the proposed method. Finally, conclusions are given in Section 5.

II. PROBLEM FORMULATION

The wind–thermal economic dispatch problem with voltage stability improvement can be formulated mathematically as the following constrained nonlinear optimization problem with some equality and inequality constraints.

II.1 THERMAL GENERATORS COST FUNCTION

Generation cost or the total fuel cost can be expressed in terms of the real power output by the quadratic function and hence the fuel cost function to be minimized can be described as:

$$f_1 = \min \sum_{i=1}^{NG} f_i = \sum_{i=1}^{NG} [a_i + b_i P_i + c_i P_i^2] \quad (\$/h) \quad (1)$$

Where f_i is the fuel cost of the i_{th} generator, a_i , b_i and c_i are the basic, the linear and the quadratic cost coefficients of the i_{th} thermal generator, P_i represents the power output of the i_{th} thermal generator; NG denotes the number of generating units

II.2 WIND GENERATORS COST FUNCTION

Considering the influence on power system produced by the uncertainty of wind power, the operating cost of wind power can be divided into three parts: direct cost, underestimated cost and overestimated cost. Typically wind power units are owned by private parties and grid operators pay for wind power purchased from wind farm operator based on the power purchase agreement. A direct cost for power derived from the wind generators is given by Equation (2) [3].

$$WPCost_{dir,j} = d_j w_j \quad (2)$$

Where $WPCost_{dir,j}$ is the direct cost for generation of wind power, which is directly proportional to output wind power; d_j is the direct cost coefficient for j_{th} wind farm. The underestimation cost is considered when available power of wind farm is not used and it can be computed using the following equation

$$WPCost_{ue} = \sum_{j=1}^m (C_{pwj} \times E(Y_{ue,j})) \quad (3)$$

Where

$$E(Y_{ue,j}) = \begin{cases} w_j \left\{ 1 - \exp\left(-\left(v_{IN}/c\right)^K\right) + \exp\left(-\left(v_{OUT}/c\right)^K\right) \right\} \\ + \left(\left(w_R v_{IN} / v_R - v_{IN} \right) + w_j \right) \left(\exp\left(-v_{IN}^K / c^K\right) - \exp\left(-v_j^K / c^K\right) \right) \\ + \left(\left(w_R c / v_R - v_{IN} \right) \right) \left(\Gamma\left[1+1/K, \left(v_{IN}/c\right)^K\right] - \Gamma\left[1+1/K, \left(v_j/c\right)^K\right] \right) \end{cases} \quad (4)$$

$WPCost_{ue,j}$ is the scaled average cost of underestimation for j_{th} wind turbine; C_{pwj} is the cost coefficients for underestimation; $E(Y_{ue,j})$ is the expected value of wind power underestimation for j_{th} wind turbine; w_j is the available active power from j_{th} wind power source; w_R is rated wind power output; v_R is rated velocity of wind; v_{IN} is cut in velocity of wind; v_{OUT} is cut-out velocity of wind. The overestimation cost is calculated for buying power from alternate sources (reserves) or load shedding. It can be expressed as follow

$$WPCost_{oe} = \sum_{j=1}^m (C_{rwj} \times E(Y_{oe,j})) \quad (5)$$

Where

$$E(Y_{oe,j}) = \begin{cases} w_j \left\{ 1 - \exp\left(-\left(v_{IN}/c\right)^k\right) + \exp\left(-\left(v_{OUT}/c\right)^k\right) \right\} \\ + \left(\left(w_R v_{IN}/v_R - v_{IN} \right) + w_j \right) \left(\exp\left(-v_{IN}^K/c^K\right) - \exp\left(-v_j^K/c^K\right) \right) \\ + \left(\left(w_R c/v_R - v_{IN} \right) \right) \left(\Gamma \left[1+1/K, (v_{IN}/c)^K \right] - \Gamma \left[1+1/K, (v_j/c)^K \right] \right) \end{cases} \quad (6)$$

Where $WPCost_{oe}$ is the scaled average cost of overestimation for j_{th} wind turbine; C_{rwj} is the cost coefficients for overestimation of j_{th} wind turbine. Similarly, $E(Y_{oe,j})$ is the expected value of wind power overestimation for j_{th} wind turbine. The total cost of wind-generated power from the wind farm can be represented as the sum of the direct, underestimation and overestimation costs:

$$f_2 = \min \sum_{j=1}^m (WPCost_{dir,j} + WPCost_{oe,j} + WPCost_{ue,j}) \quad (7)$$

II.3 VOLTAGE STABILITY INDEX

It is conspicuous that a power system operating at the pinnacle of the unstable condition is conspicuously referring to the voltage magnitude approaching to its limit and it is presented by the voltage stability indices [13]. Several methods have been introduced to assess the voltage stability and to determine the stability margins. In this part voltage stability enhancement is considered through optimization of the line voltage stability index (L_{mn}) [14]. The L_{mn} index is defined as follows:

$$L_{mn} = \frac{4XQ_r}{[V_s \sin(\theta - \delta)]^2} \leq 1.0 \quad (8)$$

Where X is the line reactance, Q_r is the reactive power at the receiving end, V_s is the sending end voltage, θ is the line impedance angle and δ is the angle difference between the supply voltage and the receiving voltage. The value of L_{mn} index ranges from 0 (no load) to 1 (voltage collapse) and it must be less than 1 for stable systems. The improvement of the voltage stability of the system can be reached by minimization of the line voltage stability index at all branches in the system. The function described the line voltage stability index is expressed as follows [15]:

$$f_3 = \min \sum_{k=1}^{NB} L_{mn} \quad (9)$$

Where NB is the number of power system branches.

II.4 ACTIVE POWER LOSSES MINIMIZATION

The first objective aims to minimize the total active P_{loss} by optimally adjusting the control variables. This objective can be defined mathematically as follows:

$$f_4 = \min(P_{Loss}) = \min \left[\sum_{i=1}^{N_L} G_{ij} (V_i^2 + V_j^2 - 2 \times V_i \times V_j \cos \delta_{ij}) \right] \quad (10)$$

The total objective function including thermal generation cost, wind generation cost, voltage stability enhancement and active power losses minimization is expressed as follows:

$$F = f_1 + f_2 + f_3 + f_4 \quad (11)$$

The OPF objective is subject to system equality and inequality constraints. Equality constraints: equality constraints are the power balance equations where the generated real and reactive powers must be equal to the demand and losses.

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_{ij}) + B_{ij} \sin(\delta_{ij})] = 0 \quad (12)$$

$$Q_{gi} - Q_{di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\delta_{ij}) + B_{ij} \cos(\delta_{ij})] = 0 \quad (13)$$

Where, P_{gi} and Q_{gi} are real and reactive powers of i_{th} generator, whereas P_{di} and Q_{di} is real and reactive load of i_{th} bus, respectively. $\delta_{ij} = \delta_i - \delta_j$ is the voltage angle difference between buses i and j . G_{ij} and B_{ij} are the ij branch conductance and susceptance, respectively. Inequality constraints: The inequality constraints of the OPF reflect the limits on physical devices present in the power system as well as the limits created to guarantee system security. These inequality constraints are as follows

$$P_{gi}^{\min} \leq P_{gi} \leq P_{gi}^{\max} \quad (14)$$

$$Q_{gi}^{\min} \leq Q_{gi} \leq Q_{gi}^{\max} \quad (15)$$

$$P_{wi}^{\min} \leq P_{wi} \leq P_{wi}^{\max} \quad (16)$$

$$Q_{wi}^{\min} \leq Q_{wi} \leq Q_{wi}^{\max} \quad (17)$$

$$V_{gi}^{\min} \leq V_{gi} \leq V_{gi}^{\max} \quad (18)$$

$$T_i^{\min} \leq T_i \leq T_i^{\max} \quad (19)$$

$$Q_{Ci}^{\min} \leq Q_{Ci} \leq Q_{Ci}^{\max} \quad (20)$$

P_{wi} and Q_{wi} represent the real and reactive powers output of i th wind turbine generator, respectively; V_{gi} represents the voltage magnitude of i th generator bus; T_i represents the tap settings of i th transformer; Q_{Ci} represents the i th shunt VAR compensation.

III. IMPLEMENTATION OF MRFO ALGORITHM IN OPF PROBLEM

Manta rays are marine organisms distinguished by a flattened body and a pair of expansive pectoral fins Figure 1. They mostly consume plankton due to the absence of sharp teeth. The Manta Ray Foraging Optimization (MRFO) method is derived from the distinctive foraging habits demonstrated by manta rays in its native environment [16]. These activities are exemplified by three primary foraging mechanisms: the chain, the cyclone and the somersault. The MRFO method commences by initializing a population of candidate solutions that are randomly dispersed inside the search space, as articulated by the subsequent equation [16]:

$$X_i(t) = X_{\min} + r \times (X_{\max} - X_{\min}) \quad (21)$$

Where $X_{\min}$ and $X_{\max}$ denote the bounds of the design parameters, respectively, and r represents an arbitrary number uniformly distributed between 0 and 1. Subsequent to the initialization procedure, the three foraging techniques are implemented in succession to replicate the feeding behavior of manta rays, as elaborated in the following subsections [16].



Figure 1: Picture of the manta ray.

Source: Authors, (2026).

III.1 CHAIN FORAGING

This strategy indicates that manta rays navigate towards areas with the greatest abundance of plankton. In this procedure, manta rays arrange themselves in a line, creating a chain structure to enhance foraging efficiency. With the exception of the foremost individual, each manta ray in the population advances concurrently toward the direction of the food source and the person directly ahead of it. This synchronized action facilitates efficient information exchange and alignment towards ideal feeding areas. The chain foraging mechanism of The MRFO method can be theoretically articulated as follows [16]:

$$X_i^d(t+1) = \begin{cases} X_i^d(t) + r(X_{best}^d(t) - X_i^d(t)) + \alpha(X_{best}^d(t) - X_i^d(t)), i = 1 \\ X_i^d(t) + r(X_{i-1}^d(t) - X_i^d(t)) + \alpha(X_{best}^d(t) - X_i^d(t)), i = 2, 3, \dots, N \\ \alpha = 2r\sqrt{|\log(r)|} \end{cases} \quad (22)$$

$X_i^d(t)$ represents the position of the i_{th} manta ray at iteration t in dimension d . X_{best} denotes the individual exhibiting the optimal fitness. r represents a random variable inside the interval $[0,1]$, N signifies the population size, and α denotes the weight coefficient. The chain hunting procedure is shown in Figure 2 [16].

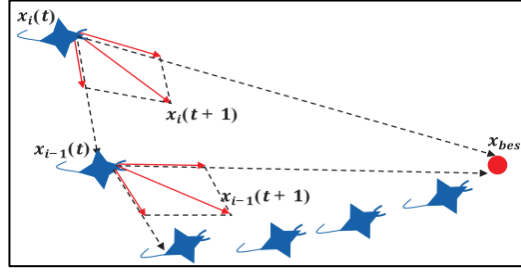


Figure 2: The chain foraging strategy.
Source: Authors, (2026).

III.2 CYCLONE FORAGING

In this phase, every manta ray executes two fundamental tasks to discover food effectively. Initially, it navigates towards the plankton-abundant zone, adhering to a spiral path that mimics the natural vortex movement characteristic of authentic manta ray behavior. Secondly, it concurrently advances towards the individual situated immediately in front inside the sequence [17]. This synchronized movement improves local search functionality and signifies the exploitation phase of the MRFO algorithm, whereby solutions are optimized in proximity to favorable areas inside the search field. The cyclone foraging behavior can be defined as follows [16]:

$$X_i^d(t+1) = \begin{cases} X_{best}^d(t) + r(X_{best}^d(t) - X_i^d(t)) + \beta(X_{best}^d(t) - X_i^d(t)), & i=1 \\ X_{best}^d(t) + r(X_{i-1}^d(t) - X_i^d(t)) + \beta(X_{best}^d(t) - X_i^d(t)), & i=2, \dots, N \\ \beta = 2e^{-\frac{r_1 t_{max} - t + 1}{t_{max}}} \times \sin(2\pi r_1) \end{cases} \quad (23)$$

Where β represents the weight coefficient, r_1 is an arbitrary number within the interval $[0,1]$, and t_{max} signifies the extreme number of iterations. To enhance their foraging ability, manta rays conduct a global search for a new feeding location, distancing themselves from the present optimal site. This mechanism can be articulated analytically as follows:

$$X_i^d(t+1) = \begin{cases} X_{rand}^d(t) + r(X_{rand}^d(t) - X_i^d(t)) + \alpha(X_{rand}^d(t) - X_i^d(t)), & i=1 \\ X_{rand}^d(t) + r(X_{i-1}^d(t) - X_i^d(t)) + \alpha(X_{rand}^d(t) - X_i^d(t)), & i=2, \dots, N \\ X_{rand}^d(t) = LL^d + r \times (UL^d - LL^d) \end{cases} \quad (24)$$

Where X_{rand} denotes a random point within the search space, while LL_d and UL_d signify the boundaries of dimension d . Figure 3 illustrates the cyclone foraging method [16].

III.3 SOMERSAULT FORAGING

In this procedure, each manta ray navigates around the food location and does a somersault to reach a new food spot. They consistently adjust their locations toward the area with the largest quantity of plankton.

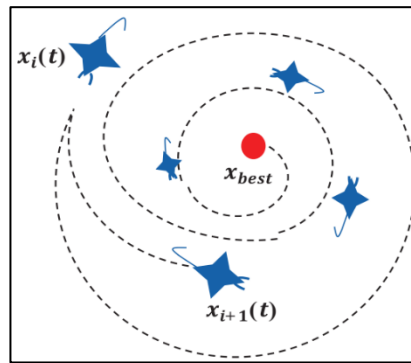


Figure 3: The cyclone foraging strategy.
Source: Authors, (2026).

The mathematical representation of somersault foraging is as follows [16]:

$$X_i^d(t+1) = X_{rand}^d(t) + SF(r_2 X_{best}^d(t) - r_3 X_i^d(t)), i=1, \dots, N \quad (25)$$

Where r_2 and r_3 are stochastic variables inside the interval $[0,1]$. SF represents the somersault factor, which is set at a value of 2 as advised in [16]. Figure 4 illustrates the somersault foraging mechanism.

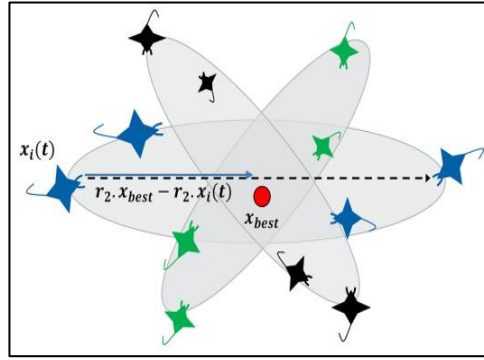


Figure 4: The somersault foraging strategy.
Source: Authors, (2026).

IV. RESULTS AND DISCUSSIONS

In this section, the MRFO algorithm is applied to solve the OPF problem on standard and modified IEEE 30-bus test system for three case studies.

Case 1: Optimal power flow without incorporating wind power

In this case, the performance of the MRFO algorithm is tested on the standard IEEE 30-bus test system without incorporating wind power where the objective is to minimize the fuel cost of thermal generators given by Equation 1. The test system contains six thermal generators at buses 1, 2, 5, 8, 11 and 13 interconnected with 41 branches [18]. The cost characteristics and power limits of the thermal generators are shown in Table 1. The OPF problem is solved and the total cost obtained under the constraint optimization is **798.9211 \$/h**. Figure 5 depicts the convergence characteristic of MRFO algorithm during this case. The simulation results obtained by MRFO algorithm are compared with other optimization algorithms reported in the literature. These optimization algorithms include Sine-Cosine Algorithm (SCA) [19], Modified Sine-Cosine Algorithm (MSCA) [19], Gbest guided Artificial Bee Colony (GABC) [3], (SF-DE) [20] and (GAME) [21]. The results of this comparison are given in Table 1. It is clearly seen from this Table that the proposed method gave better results in the terms of fuel cost and power loss minimization.

Case 2: Optimal power flow with wind power

This case aims to simultaneously optimize the fuel cost of thermal generators and the cost of wind power. The IEEE 30-bus system is modified by replacing the thermal power plants located at buses 5, 11, and 13 with wind farms. The wind farm at bus 5 consists of ten wind turbine generators with a total capacity of 60 MW. Similarly, the wind farms at buses 11 and 13 each consist of ten wind turbines with a total capacity of 60 MW. Cost coefficients associated with the wind farms are reported in [22]. The convergence characteristic of MRFO for this case is shown in Figure 6. The best cost and real power losses calculated by MRFO algorithm are **798.7147 \$/h** and **4.8862 MW**, respectively. The corresponding system total cost and real power loss are relatively low compared with the system without wind farms. In other words, buses 5, 11 and 13 are the fittest integrated positions from viewpoint of system total cost and power loss reduction. Analyzing and interpreting the results is part of the discussions, their importance, achievements and limitations, highlighting the innovative aspects of the practical applications of the study and the conclusions derived from them, delimiting unresolved issues. If necessary, recommendations can be proposed.

Case 3: Optimal power flow with wind power and voltage stability enhancement

With the same simulation conditions given in case 2, after considering voltage stability improvement, the total cost and the active power transmission losses are found to be **799.606\$/h** and **4.9512 MW**, respectively. The convergence characteristic of MRFO is shown in Figure 7. Compared with the obtained results without considering voltage stability improvement, it can be observed that the total cost and the power losses are increased with **0.8913\$/h** and **0.065 MW**, respectively. However, in the terms of voltage magnitudes and L_{mn} index, the results achieved are better compared with the obtained results without considering voltage stability index as shown in Figure 8, 9 and 10. Detailed comparison of the optimal obtained results under the studied cases is represented in Table 2. The results achieved in case 3 displays that the active power losses are greatly reduced compared to the case 1 as well as the $\sum L_{mn}$ index is decreased compared to the case 1 and 2, thus, the distance to the collapse point is enhanced.

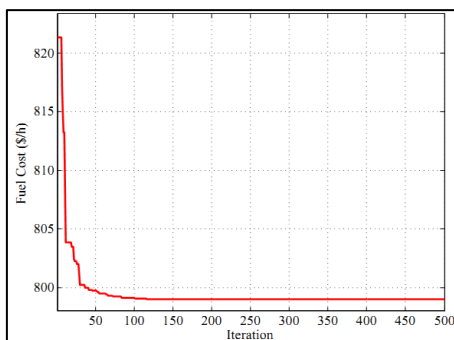


Figure 5: Convergence characteristic of MRFO for Case 1.
Source: Authors, (2026).

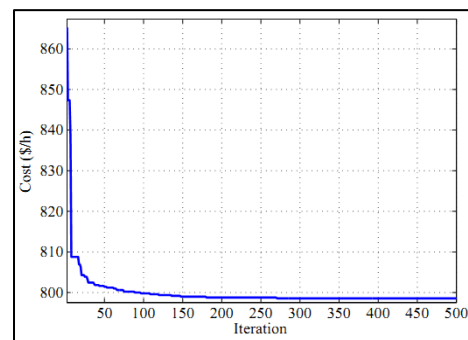


Figure 6: Coverage curves of MFO for Case 2.
Source: Authors, (2026).

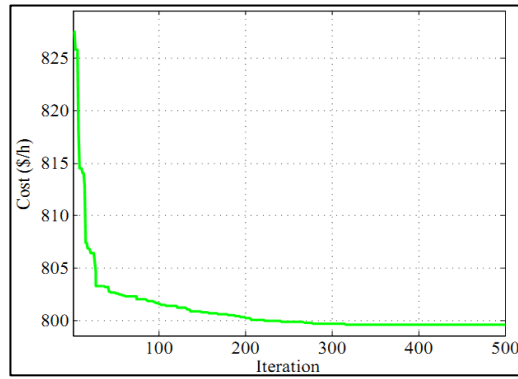


Figure 7: Convergence curves of MRFO for Case 3.
Source: Authors, (2026).

Table 1: Comparison of MRFO and other algorithms reported in the literature for the Case 1.

Control variable	Min	Max	SCA[19]	MSCA [19]	GABC [3]	SF-DE [20]	GAMS [21]	MRFO
P ₁ (MW)	50	200	140.21	177.40	177.23	-	177.1	177.11
P ₂ (MW)	20	80	49.00	48.63	48.70	48.72	48.8	48.72
P ₅ (MW)	15	50	20.26	21.23	21.35	21.35	21.4	21.23
P ₈ (MW)	10	35	22.00	20.86	21.13	21.19	21.5	21.08
P ₁₁ (MW)	10	30	11.00	11.93	11.89	11.90	12	11.78
P ₁₃ (MW)	12	40	11.00	12.00	12.00	12.00	12	12.00
V ₁ (p.u.)	0.95	1.1	1.10	1.1	1.09	-	1.08	1.10
V ₂ (p.u.)	0.95	1.1	1.10	1.08	1.07	1.08	1.06	1.08
V ₅ (p.u.)	0.95	1.1	1.05	1.06	1.04	1.06	1.03	1.06
V ₈ (p.u.)	0.95	1.1	1.10	1.09	1.04	1.03	1.03	1.06
V ₁₁ (p.u.)	0.95	1.1	1.10	1.10	1.06	1.04	1.01	1.10
V ₁₃ (p.u.)	0.95	1.1	1.10	1.10	1.04	1.08	1.04	1.10
T ₁₁ (p.u.)	0.9	1.1	0.97	1.04	1.02	1.04	NA	1.04
T ₁₂ (p.u.)	0.9	1.1	0.95	0.91	0.93	1.05	NA	0.90
T ₁₅ (p.u.)	0.9	1.1	0.96	1.03	0.96	0.92	NA	0.97
T ₃₆ (p.u.)	0.9	1.1	0.97	0.99	0.98	0.96	NA	0.96
Q _{C10} (MVAR)	0	5	5.00	0.02	3.05	0.97	NA	4.97
Q _{C12} (MVAR)	0	5	4.80	2.56	2.51	3.63	NA	5.00
Q _{C15} (MVAR)	0	5	4.99	4.58	4.39	2.60	NA	5.00
Q _{C17} (MVAR)	0	5	5.00	2.40	5.00	3.86	NA	4.94
Q _{C20} (MVAR)	0	5	4.60	4.63	4.38	4.98	NA	3.09
Q _{C21} (MVAR)	0	5	4.40	0.36	5.00	4.18	NA	5.00
Q _{C23} (MVAR)	0	5	5.00	3.14	3.13	3.15	NA	5.00
Q _{C24} (MVAR)	0	5	5.00	4.84	5.00	4.98	NA	4.99
Q _{C29} (MVAR)	0	5	2.50	3.94	2.29	2.39	NA	2.37
Fuel cost (\$/h)	-	-	800.102	799.31	800.0963	800.4131	799.1116	798.9211
Power loss (MW)	-	-	9.0633	8.7327	8.9340	9.0104	8.63	8.5984

Source: Authors, (2026).

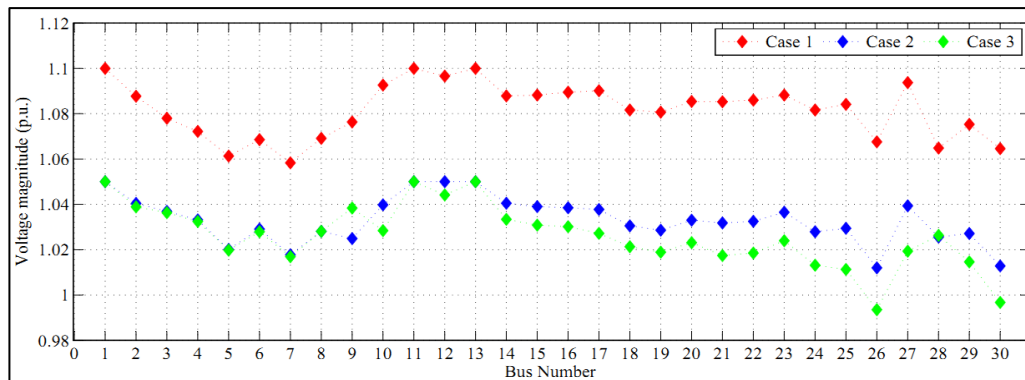


Figure 8: Voltage magnitudes comparison.
Source: Authors, (2026).

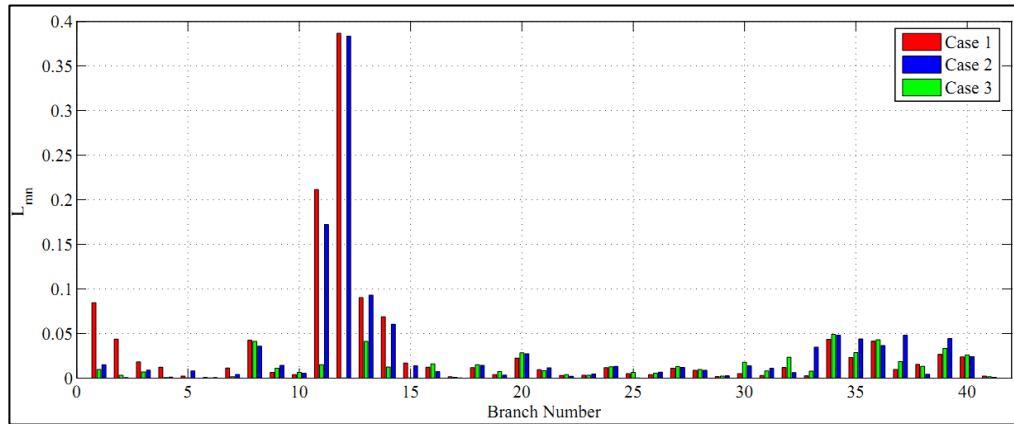


Figure 9: Line voltage stability index comparison.
Source: Authors, (2026).

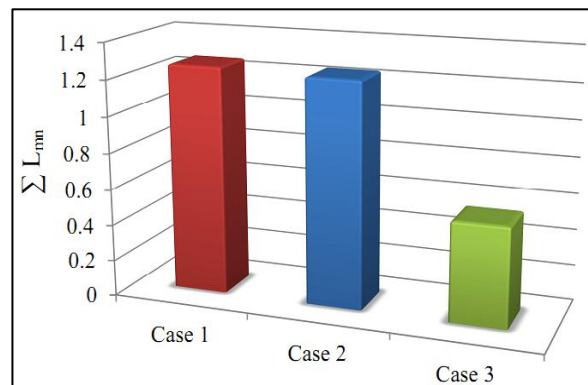


Figure 10: Comparison of $\sum L_{mn}$ index.
Source: Authors, (2026).

Table 2: Comparison of optimal results for different Cases.

Control variable	Case 1	Case 2	Case 3
Total generation cost (\$/h)	798.9211	798.7147	799.6060
Power loss (MW)	8.5984	4.8862	4.9512
$\sum L_{mn}$ index	1.2835	1.3763	0.6879

Source: Authors, (2026).

V. CONCLUSIONS

This paper presents the solution of OPF problem incorporating wind power generation and voltage stability enhancement using one of the most recently proposed optimization algorithms namely Manta Ray Foraging Optimization (MRFO) algorithm. This method used to optimize the power flows in the system in order to minimize the operating cost and to enhance the voltage stability. The efficiency of the proposed MRFO algorithm has been tested through its application to the IEEE 30-bus power system. The results demonstrate that the proposed algorithm to solve OPF incorporating wind power and line voltage stability index decreases the operating cost and improves the voltage stability of the power system.

VI. AUTHOR'S CONTRIBUTION

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