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Stochastic Modeling for Wind Energy and Multi-Objective Optimal Power Flow by Novel Meta-Heuristic Method

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ABSTRACT Wind energy is considered one of the most important alternative energy sources for generating electricity. But the stochastic nature of wind, leads to use the distribution function to present the wind system. The two-parameter Weibull distribution is often used in the wind speed presentation. The two-parameter Weibull distribution has scale and shape parameters that are important in wind energy applications, thus selecting the optimum method for estimation them is important. The unpredictability in wind speed leads to uncertainty in devolved power which leads to difficult system operation. In this study, two novel artificial intelligence (AI) methods called Mayfly algorithm (MA) and Aquila Optimizer (AO) are used for calculating the Weibull distribution parameters. Results are compared with four classical numerical methods called the Maximum likelihood approach, Energy pattern factor method, Graphical method, and Empirical method. The two AI methods prove superiority and robustness for evaluating two-parameter of Weibull distribution as they give lower errors and higher correlation coefficients. Moreover, to prove the accuracy of the MA method in solving the optimal power flow (OPF) problem, single and multi-objective OPF is applied on a standard IEEE-30 bus system to minimize fuel cost, power loss, thermal unit emissions, and voltage security index (VSI), and results are compared with other metaheuristic methods. The results prove the validity and robustness of the MA method in solving the OPF problem. Then, single and multi-objective stochastic optimal power flow (SCOPF) is applied to modified IEEE-30 which contains two wind farms to minimize total generation cost, power loss, thermal unit emission, and VSI. The fuzzy-based Pareto front technique is utilized in multi-objective optimization (MOO) to obtain the best compromise point solution. The objective function of SCOPF considers reserve cost for overestimation and penalty cost for underestimation of wind energy. Finally, this paper studies the effect of changing Weibull parameters, penalty cost coefficient, and reverse cost coefficient in wind energy generation cost. The proposed MA method could be valuable to system operators as a decision-making aid when dealing with hybrid power systems.

INDEX TERMS Aquila optimizer, mayfly algorithm, Weibull distribution, optimal power flow, multi-objective optimization, stochastic optimal power flow, wind energy.

ABBREVIATION

AI	Artificial intelligence.
MA	Mayfly algorithm.
AO	Aquila Optimizer.
OPF	Optimal power flow.
SCOPF	Stochastic optimal power flow.
MOO	Multi-objective optimization.
MO-OPF	Multi-objective optimal power flow.
MO-SCOPF	Multi-objective stochastic optimal power flow.
VSI	Voltage security index.

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R^2	Correlation coefficient.
X^2	Chi-square.
RMSE	Root mean square error.
C	Weibull scale parameter.
K	Weibull shape parameter.
PDF	Probability distribution function.
$f(v)$	Weibull probability distribution function.
$F(v)$	Weibull cumulative distribution function.
v	wind speed (m/s).
Γ (x)	Gamma function.
P_{wind}	Output power from a wind turbine.
v_{cut-in}	Cut-in speed for wind turbine.
$v_{cut-off}$	Cut-off speed for wind turbine.
C_R	Overestimation cost.
C_P	Underestimation cost.
$P_{scheduled}$	Scheduled power by wind farm.
$P_{available}$	Available power by wind farm.

I. INTRODUCTION

A. MOTIVATION

Wind energy is a type of solar energy that occurs because of the Earth's uneven heating. About 1% to 2% of the energy emitted by the Sun is converted to wind energy. For ages, this type of energy has been employed to power windmills, water pumps, and ships. Wind energy has lately regained popularity due to its enormous potential for producing electrical energy [1], [2]. It is motivated by efforts to reduce pollution and its harmful effects on the global environment, like electric power plants, which use fossil fuels, are one of the largest greenhouse gas generators. Wind, on the other hand, is a renewable, long-lasting, and environmentally benign energy source. Due to the uncertainty of wind power, integrating wind energy into the power system is a complicated system operation [1].

In wind system modeling, the wind speed variable is the most essential parameter. Wind speed is a random variable that varies over time and is influenced by geographical and climatic factors in the area [3]. Forecasting wind speed is important for determining wind energy potential and the efficiency of wind energy conversion equipment. The probability distribution function of the obtained data is determined to investigate the wind speed data. These are also used to determine wind quality for power generation, together with wind speed indicators and statistical descriptors. As a result, enormous data sets are reduced to a handful of parameters. Many researchers have looked at numerous probability distribution functions and compared them to find the one that fits the best [4]. The Weibull distribution gives the best fit of the collected wind speed data [5]. The parameters of the Weibull distribution can be estimated using a variety of methods [6]. Because the Weibull distribution parameters are so significant in wind speed applications, it's critical to examine a number of approaches for estimating the Weibull distribution parameters to find the best fit.

Wind energy is now widely used in the electricity market, and the electrical system is becoming more complex. The complexity of the system is for a variety of reasons, including the fact that they cover enormous areas and include multiple power sources like thermal generator and wind turbine. The traditional OPF problem considers thermal power plants only. With the growing use of wind energy in the grid, a study of OPF is required to account for the uncertainties associated with these renewable energy sources [7].

The OPF is one of the most significant techniques for analyzing such systems [8]. The basic goal of OPF is to find the system's optimal control variables, which optimize an objective function under the limitations of the system. In the OPF problem, many control variables are used, such as the real power output of generators and the voltage of generators. The overall fuel cost of generation units, the rate of emission, active power losses, and the voltage security index (VSI) are among the objective functions [9], [10]. If more than one of these objective functions needs to be optimized simultaneously, a multi-objective optimal power flow (MO-OPF) problem is utilized [11]–[13].

The OPF problem is a large-scale non-linear non-convex optimization problem with many constraints [14]. This problem can be solved using a variety of mathematical strategies [15]. All of these strategies have the potential to become stuck in local minima, preventing the algorithm from obtaining the genuine optimal solution. The significant computational effort and time consumption of these techniques are also drawbacks. Meta-heuristic algorithms offer a new strategy for dealing with the drawbacks of these mathematical methodologies. The Novel Aquila optimizer [16] and Mayfly algorithm [17] are two recently developed strategies for solving optimization problems. Meta-heuristic approaches have several advantages, including the ability to find the global optimal solution, the ability to process problems with many qualitative constraints, the ability to solve multi-objective optimization problems better than classical methods, and the ability to simultaneously locate multiple local optimal solutions. The main advantages of MA and AO over other Meta-heuristic algorithms are that they are algorithm-parameter-free techniques, meaning their efficiency is unaffected by the algorithm parameters.

B. LITERATURE REVIEW

The Weibull distribution function [18] is used to describe wind speed distribution,. The parameters of the Weibull probability distribution function (PDF) can be estimated using a variety of numerical ways in recent years [19]–[22]. The method's efficiency can be affected by sample size, sample data distribution, sample data type, and the goodness of fit test [23]. The classical approaches for calculating the Weibull parameter are not always correct, and they are typically iterative methods with large computation costs. As a result, intelligent optimization techniques that employ fitness as an objective function to find the best fitting parameters can be used to compute the optimal parameters [24]–[26].

Many studies deal with conventional generators only in OPF study using population-based strategies [27]. Hazra and Sinha [28] provided a MO-OPF technique that uses particle swarm optimization to reduce two competing objectives at the same time: generating cost and emission, Basu [29] offered a differential evolution algorithm to handle the MO-OPF problem, taking into account generation cost, emissions, and power losses, Kumari and Maheswarapu [30] presented enhanced genetic algorithm with quadratic load flow solution to solve MO-OPF problem based on strength Pareto evolutionary method, Khunkitti *et al.* [31] proposed a hybrid dragonfly and particle swarm optimization techniques in solving MO-OPF to minimize fuel cost, emission, and power loss.

Traditional OPF treats only thermal power sources; however, rising fuel prices and environmental concerns have encouraged countries to look into renewable energy sources like wind power, solar power, and wave energy [32]–[34]. The penetration of wind energy should be considered in the power system. As a result, it is necessary to incorporate wind generation costs into the standard OPF problem in order to obtain the best operation for a system with wind energy sources; this problem is known as a stochastic optimal power flow (SCOPF) [35]–[37]. Shi *et al.* [38] provided a method for assessing the cost of wind-generated electricity in systems that include both thermal and wind generators based on the Weibull distribution and a function approximation wind turbine model, Kathiravan and Devi [39] provided a novel OPF model for packaged power scheduling and dispatch for wind and solar energy, Tyagi *et al.* [40] presented improved stochastic fractal search method to solve MO-OPF problem for the hybrid power system, Hmida *et al.* [41] applied hybrid imperialist competitive and grey wolf methods to solve MO-OPF with wind energy penetration in IEEE-30 and IEEE-118 bus systems, Ma and Qin [42] presented non-dominated sorting genetic algorithm to solve MO-OPF bases on energy hub model with wind power penetration.

C. PAPER CONTRIBUTION AND ORGANIZATION

This work proposed two novels AI meta-heuristic methods called Mayfly and Aquila Optimizer algorithms which are developed in 2020 and 2021, respectively to estimate Weibull distribution parameters. AI methods can improve the determination of the Weibull parameters and, as a result, reduce wind turbine energy production estimation mistakes. In this paper, the maximum likelihood method (MLM), Energy pattern (EP) technique, graphical method (GM), and Empirical method (EM) were investigated and compared with the two AI approaches. All six techniques are studied and compared using real-time 10min interval wind speed data for 12 months in a site located in the UK [43]. The correlation coefficient (R^2), root mean square error (RMSE), and chi-square (X^2) are used to compare the methods, AI methods give minimum error and higher correlation which prove their superiority over traditional numerical methods.

Moreover, this study presents a solution for single and multi-objective OPF and SCOPF problems using the MA method. First, traditional OPF and MO-OPF will be solved using the MA method on the standard IEEE-30 bus system then results compared to other metaheuristic techniques to prove validity and accuracy of the proposed approach. The objective functions are minimizing fuel cost, active power loss, emission, and VSI. The proposed MA technique gives the best results for the four-objective function. Then, single and multi-objective SCOPF will be solved on a modified IEEE-30 bus system which contains 2 wind farms. The cost of dispatching wind power has two components: wind power underestimation cost and wind power overestimation cost. The underestimation cost is the cost of using more reserve capacity, whereas the overestimation cost is the cost of the system operator having to purchase additional power from wind farms that they had not expected to be available. The objective functions of SCOPF are minimizing fuel cost, wind generation cost, power loss, thermal unit emission, and VSI.

Because the MOO problem's objectives are conflicting, a fuzzy membership function technique was utilized to find the optimal compromise solution after collecting a collection of Pareto front solutions.

The remainder of this paper is organized as follows: Section II describes the Weibull distribution for wind speed and power. Section III presents the problem formulation of single and multi-objective OPF problems. The numerical methods used to estimate Weibull parameters are described in Section IV. Section V presents the algorithms of the two proposed optimization methods. Section VI presents the three statistical errors used to compare Weibull distribution functions. The results obtained in this work along with a discussion about these results are described in Section VII. Finally, the conclusion is drawn in Section VIII.

II. WEIBULL DISTRIBUTION

The Weibull distribution is developed by Weibull [44]. The two-parameter of Weibull distribution's PDF $f(v)$ and cumulative distribution function $F(v)$ are given by.

$$f(v) = \frac{k}{c^k} v^{v-1}\, exp(-\left(\frac{v}{c}\right)^k) \tag{1}$$

and

$$F(v) = 1 - exp(-\left(\frac{x}{c}\right)^k), \tag{2}$$

where the wind speed is v, the dimensionless shape parameter is k, and the scale parameter is c.

The Weibull distribution's mean E(v) and variance V(v) are given by

$$E(v) = c\Gamma(\,1 + \frac{1}{k}) \tag{3}$$

$$V(v) = c^2(\Gamma\left(1 + \frac{2}{k}\right) - \Gamma^2\left(1 + \frac{1}{k}\right)), \tag{4}$$

where Γ (x) is the gamma function $\int_0^\infty t^{x-1} e^{-t} dt$.

The output power from a wind turbine is computed as follows:

$$P_{wind} = \begin{cases} 0 & v \leq v_{cut-in} \text{ or } v \geq v_{cut-off} \\ \frac{1}{2}\rho A C_P v^3 & v_{cut-in} < v \leq v_{rated} \\ P_{rated} & v_{rated} < v < v_{cut-off} \end{cases} \quad (5)$$

where, ρ is the density of the air, A is the blade area, C_P is the coefficient of performance, v_{cut-in} and $v_{cut-off}$ are the cut-in and cut-off speed, respectively, v_{rated} is the speed that's given max output power, P_{rated} is the wind generator's maximum power.

The wind farm's power output probability distribution is calculated using the Weibull wind speed distribution and a function approximation wind turbine model. The frequency distribution of wind speed can be calculated using Monte Carlo simulation with sample size N = 8000.

III. OPTIMAL POWER FLOW

The following sections cover the problem formulations for single and multi-objective optimal power flow problems:

A. SINGLE OBJECTIVE OPF PROBLEM

Only one objective function is optimized at a time in single-objective optimization. This can be stated as follows:

$$Min\, f(x) \quad (6)$$

Subjected to:

$$g(x) = o \quad (7)$$

$$h(x) \leq o, \quad (8)$$

where x is the problem variables, $g(x)$ and $h(x)$ are equality and inequality constraints, respectively.

B. MULTI-OBJECTIVE OPF PROBLEM

More than one objective will be optimized simultaneously in a general MOO problem. A set of equality and inequality constraints is imposed on the optimization problem, which must be met by the solution. The MOO problem is stated as follows:

$$Min\, f_i(x) \quad i = 1, 2, \ldots\ldots.., N_{obj} \quad (9)$$

Subjected to:

$$g_i(x) = o \quad i = 1, 2, \ldots\ldots.., M_{eq} \quad (10)$$

$$h_i(x) \leq o \quad i = 1, 2, \ldots\ldots.., N_{ineq}, \quad (11)$$

where, N_{obj} is the number of objective functions, M_{eq} and N_{ineq} are the number of equality and inequality constraints, respectively.

In a MOO, the solution $x1$ dominates $x2$ if the following criteria are met: [45]

$$f_i(x1) \leq f_i(x2), \quad \forall i \in N_{obj} \quad (12)$$

The Pareto front solutions are the dominant solutions over the whole search space. A fuzzy membership function μ_i can be expressed as follows to represent the i_{ih} objective function f_i:

$$\mu_i = \begin{cases} 1 & f_i \leq f_i^{min} \\ \dfrac{f_i^{max} - f_i}{f_i^{max} - f_i^{min}} & f_i^{min} < f_i < f_i^{max} \\ 0 & f_i \geq f_i^{max} \end{cases} \quad (13)$$

For each Pareto front k, the membership function μ^k is computed as follows:

$$\mu^k = \frac{\sum_{i=1}^{N_{obj}} \mu^k{}_i}{\sum_{k=1}^{M} \sum_{i=1}^{N_{obj}} \mu^k{}_i} \quad (14)$$

The maximum value of μ^k is the best compromise solution.

C. OBJECTIVE FUNCTIONS

1) FUEL COST

The goal of this objective function is to reduce the running costs of conventional thermal generators $C_t(\$/hr)$.

$$Min\; C_t = \sum_{i=1}^{n} a_i + b_i p_{gi} + c_i p_{gi}^2 \quad (15)$$

where, n is the number of thermal units, (a_i, b_i, c_i) are the coefficient of thermal units, p_{gi} is the generator active power.

2) WIND GENERATION COST

The goal of this objective function is to reduce the running costs of wind generation $C_w(\$/hr)$.

$$Min\; C_w = C_R + C_P \quad (16)$$

where, C_R and C_P are the overestimation and underestimation costs, respectively.

When the available real wind power is less than the planned wind power, electricity must be obtained from other sources, resulting in an increase in the operation cost known as overestimation cost (C_R). If the actual available wind power exceeds the planned amount, the operator will have to purchase additional electricity from wind farms that they did not expect and deal with it, a fee is known as underestimation cost (C_P) [46].

The costs of overestimating and underestimation are computed as follows:

$$C_R = K_R(P_{scheduled} - P_{available}) \quad (17)$$

$$C_P = K_P(P_{available} - P_{scheduled}), \quad (18)$$

where, K_R and K_P and are the overestimating and underestimation cost coefficients, respectively, $P_{scheduled}$ is the scheduled power, and $P_{available}$ is the available power by the wind farm.

3) ACTIVE POWER LOSSES

The goal of this objective function is to minimize active power losses T_L (MW).

$$Min\ T_L = \sum_{i=1}^{N} \sum_{\substack{j=1 \\ i \neq j}}^{N} R_{ij} \frac{(|V_i|^2 + |V_j|^2 - 2|V_i||V_j| \cos\delta_{ij})}{|Z_{ij}|^2}, \tag{19}$$

where, N is the number of buses, $|V_i|$ is the voltage magnitude at bus i, R_{ij} and Z_{ij} are the resistance and impedance between buses i and j, respectively, δ_{ij} is the difference between δ_i *and* δ_j.

4) VOLTAGE SECURITY INDEX

The goal of this objective function is to minimize voltage security index VSI.

$$Min\ VSI = \sum_{i=1}^{N} \left(\frac{|V_i| - V_{avg}}{dV} \right)^2 \tag{20}$$

where, $V_{avg} = \left(\frac{|V_{max}|+|V_{min}|}{2} \right)$, $dV = \left(\frac{|V_{max}|-|V_{min}|}{2} \right)$, $|V_{max}|$ and $|V_{min}|$ are the maximum and minimum voltage magnitudes, respectively.

5) EMISSION FUNCTION

The goal of this objective function is to reduce the emissions from the thermal unit $E_t(ton/hr)$.

$$Min\ E_t = \sum_{i=1}^{n} \alpha_i + \beta_i p_{gi} + \gamma_i p_{gi}^2 + \xi_i \exp(\lambda_i p_{gi}) \tag{21}$$

where, α_i, β_i, γ_i, ξ_i, and λ_i are the emission coefficients.

D. PROBLEM CONSTRAINTS

The equality constraints $g(x)$ represent the load flow equations. It can be formulated as follows:

$$\sum_{i=1}^{n} p_{gi} = P(loss) + P(load) \tag{22}$$

$$\sum_{i=1}^{n} Q_{gi} = Q(loss) + Q(load), \tag{23}$$

where $P(loss)$ and $Q(loss)$ are the transmission line losses. While the $P(load)$ and $Q(load)$ are the connected load power.

The inequality constraints $h(x)$ represents system operating constraints. It can be formulated as follows:

$$p_{gi}min \leq p_{gi} \leq p_{gi}max \tag{24}$$

$$Q_{gi}min \leq Q_{gi} \leq Q_{gi}max \tag{25}$$

$$V_{gi}min \leq V_{gi} \leq V_{gi}max, \tag{26}$$

where Q_{gi} is the generator's reactive power V_{gi} is the generator bus voltage.

IV. NUMERICAL METHODS FOR ESTIMATING WEIBULL PARAMETERS

A. MAXIMUM LIKELIHOOD METHOD

The Weibull distribution's likelihood function is given by

$$L(k, c) = \prod_{t=1}^{t=n} \frac{k}{c^k} v_t^{x-1} exp(-\left(\frac{v}{c}\right)^k) \tag{27}$$

By differentiating the log of the likelihood function with respect to k and c, respectively, and equal them to zero, we obtain

$$\frac{\partial L(k, c)}{\partial k} = \frac{n}{k} - n\, lnc - \frac{\sum_{i=1}^{n} v_i^k \ln v_i - \ln c \sum_{i=1}^{n} v_i^k}{c^k} + \sum_{i=1}^{n} \ln v_i = 0 \tag{28}$$

$$\frac{\partial L(k, c)}{\partial c} = -\frac{nk}{c} - \frac{k}{c^{k+1}} \sum_{i=1}^{n} v_i^k = 0 \tag{29}$$

Rearrange above two equations, the shape parameter k and the scale parameter c can be estimated by.

$$\frac{1}{k} - \frac{\sum_{i=1}^{n} v_i^k\, ln\, v_i}{\sum_{i=1}^{n} v_i^k} + \frac{1}{n} \sum_{i=1}^{n} ln\, v_i = 0 \tag{30}$$

$$c = \left(\frac{1}{n} \sum_{i=1}^{n} v_i^k \right)^{\frac{1}{k}} \tag{31}$$

The values of k and c can be obtained by solving the above two equations using the numerical newton method.

B. THE EMPIRICAL METHOD

The empirical method is a subset of the moment method, where the Weibull parameters k and c are determined by the formulas below [47].

$$k = \left(\frac{\sigma}{v} \right)^{-1.086} \tag{32}$$

$$\bar{v} = c\Gamma \left(1 + \frac{1}{k} \right) \tag{33}$$

where, $\bar{v}$ is mean of wind speed and σ is the standard deviation of the observed data.

C. ENERGY PATTERN FACTOR METHOD

Energy pattern factor (E_{pf}) method is based on the averaged dataset of wind speed and is described by the following equations [23].

$$E_{pf} = \frac{\overline{v^3}}{\overline{(v)^3}} \tag{34}$$

$$k = 1 + \frac{3.69}{E_{pf}^2} \tag{35}$$

$$\bar{v} = c\Gamma \left(1 + \frac{1}{k} \right) \tag{36}$$

D. GRAPHICAL METHOD

The cumulative distribution function is used to develop the graphical method [47]. The wind speed dataset is interpolated by a straight line using the least squares. A double logarithmic transformation can be used to describe the equation for this method as follow.

$$\ln\{-\ln(1-F(v))\} = k\ln(v) - k\ln(c) \tag{37}$$

V. ARTIFICIAL OPTIMIZATION ALGORITHM

Artificial intelligence optimization algorithms are one method of achieving the best answers. Most of these algorithms are inspired by natural events, with an objective function serving as a test criterion for the distance from the best answers. The most essential aspect impacting the results is the objective function selection.

A. MAYFLY ALGORITHM

Mayflies are insects that belong to the Balaenoptera family of insects. Mayflies develop from their eggs as aquatic nymphs, then climb to the surface when fully grown, where they live for only a few days before breeding and dying. A Male Mayfly (MM) performs a nuptial dance movement around a water body in order to mate with a Female Mayfly (FM); FMs mate with MMs in the air and eventually drop offspring/eggs, and the life cycle continues [17]. The proposed MA optimization procedures are divided into four categories:

1. Movement of MMs
2. Movement of FMs
3. Mating
4. Mutation

1) MOVEMENT OF MMS

MMs congregate in swarms around a body of water. This means that their position and movement speed are modified in response to the swarm's other mayflies. The position of MMs can be formulated as follows:

$$x_i^{t+1} = x_i^t + v_i^{t+1}, \tag{38}$$

where, x_i^t and x_i^{t+1} are the current position and next position of MM number i, and v_i^{t+1} is the MM velocity. x_i represent the power output by a generator in the OPF problem.

The Mayfly velocity can be indicated as:

$$v_i^{t+1} = v_i^t + ae^{-\beta r_p{}^2}\left(pbest_i - x_i^t\right) + be^{-\beta r_g{}^2}\left(gbest - x_i^t\right), \tag{39}$$

where a and b are +ve constants, $pbest$ and $gbest$ are current best position and global best position, respectively, r_p and r_g are the distance between x_i and current best position and global best position, respectively, β is the fixed visibility coefficient. $pbest$ and $gbest$ are representing the local and global minimum generation cost in the OPF problem, respectively,

2) MOVEMENT OF FMS

FMs y_i do not congregate in swarms; instead, they travel towards the male's position in order to procreate. The following equation can be used to estimate the change in this position.

$$y_i^{t+1} = y_i^t + w_i^{t+1}, \tag{40}$$

where y_i represent the power output by a generator in the OPF problem. w_i^{t+1} is the velocity of FMs which can be indicated as follows:

$$w_i^{t+1} = w_i^t + be^{-\beta r_m{}^2}\left(x_i^t - y_i^t\right) \tag{41}$$

where, r_m is the distance between MM and FM

3) MATING

The offspring are chosen in the same way that the FMs select their MMs for breeding. To develop and offspring, the best MM couples with the best FM. All MMs and FMs are ranked in the same way. The following equations are used to determine the mayfly crossover:

$$offspring1 = L \times x_i + (1-L) \times y_i \tag{42}$$

$$offspring2 = L \times y_i + (1-L) \times x_i \tag{43}$$

where L is a random number between 0 to 1. Offspring represent the power output by a generator in the OPF problem

4) MUTATION

The offspring are changed in order to keep the algorithm from becoming trapped on a local minimum which can be formulated as the following equation:

$$offspring_n' = offspring_n + N_{(0,1)}, \tag{44}$$

where $N_{(0,1)}$ is the normal distribution with mean=0 and standard deviation = 1.

The pseudo-code of the Mayfly algorithm is shown in FIGURE 1.

Objective function $f(x)$
Initialize the male mayfly population x_i $(i = 1,2,\ldots,N)$
Initialize the female mayfly population y_i $(i = 1,2,\ldots,M)$
Evaluate solutions and find global best $gbest$
Do While stopping criteria are not met
  Update positions of male and female Mayflies
  Evaluate solutions
  Rank the Mayflies
  Mate the Mayflies
  Evaluate offspring
  Separate offspring to male and female randomly
  Replace worst solutions with the best new ones
  Update pbest and gbest
end while

FIGURE 1. Pseudo code of the Mayfly algorithm.

B. AQUILA OPTIMIZER

This strategy was inspired by the Aquila's natural habits while catching its prey [16]. The proposed AO algorithm's optimization procedures are divided into four categories:

1. Choosing the search space at a vertical stoop.
2. Explore in a diverge search space with a contour flight and a short attack.

3. Explore in a converge search space with a low flight and a slow attack.
4. Swooping with a walk and grab prey.

AO is a population-based approach, the optimization algorithm starts with a population of potential solutions (X), The following is a mathematical model of the AO [16].

1) STAGE 1: EXPANDED EXPLORATION x_1

By a high soar with the vertical stoop, the Aquila recognizes the prey area and chooses the optimum hunting place.

$$x_1(t+1)=x_{best}(t)*\left(1-\frac{t}{T}\right)+(x_M(t)-x_{best}(t)*rand), \tag{45}$$

where $x_1\,(t+1)$ is the solution of the next step of t which is produced by the 1^{st} search approach x_1, $x_{best}(t)$ is the best-obtained result, rand is a random value between zero and one, and t and T present the current step and the maximum number of iterations. x_1 represent the power output by a generator in the OPF problem in the expanded exploration phase. x_{best} represent the best-obtained power output by a generator that has minimum generation cost in the OPF problem

2) STAGE 2: NARROWED EXPLORATION x_2

When the prey location is discovered from a high vantage point, the Aquila circles over the target prey prepares the land and then attacks. This technique is known as contour flight with a brief glide attack.

$$x_2\,(t+1)=x_{best}(t)*Levy_D+x_R(t)+(y-x)*rand), \tag{46}$$

where $x_2\,(t+1)$ is the result of the next step of t which is produced by the 2^{nd} search approach. x_2 represent the power output by a generator in the OPF problem in the narrowed exploration phase. D is the dimension space, and Levy (D) is the levy flight distribution function given by

$$Levy_D=s*\frac{v*\sigma}{|v|^{\frac{1}{\beta}}}, \tag{47}$$

where s is a constant number equal to 0.01, u and v are random numbers from o to 1.

3) STAGE 3: EXPANDED EXPLOITATION x_3

When the prey location is precisely specified and the Aquila is ready to land and strike, the third step (X_3) is used. The Aquila descends vertically with a preliminary attack to detect the prey reaction.

$$x_3(t+1)=(x_{best}(t)-x_M(t))\alpha-rand+((UB-UL)*rand+LB)*\delta, \tag{48}$$

where UL and UB are the lower and upper bound of problem and α, δ are exploitation adjustment const=0.1.x_3 represent the power output by a generator in the OPF problem in the expanded exploitation phase

4) STAGE 4: NARROWED EXPLOITATION x_4

When the Aquila approaches the prey in the fourth step, it attacks the prey over land based on its stochastic motions.

$$x_4(t+1)=x_{best}(t)*Qf-(G1*X(t)*rand-G2*Levy_D+G1*rand, \tag{49}$$

where Qf stands for a quality function that is used to balance the search tactics and G1 denotes the AO's numerous motions. x_4 represent the power output by a generator in the OPF problem in the exploitation phase. The pseudo-code of the AO method is shown in FIGURE 2.

Objective function $f(x)$
Initialize the population x_i $(i=1,2,\ldots,N)$
Initialize the parameters of the AO method $(\alpha,\delta,..etc)$
Evaluate solutions and find global best $gbest$
Do While stopping criteria are not met
  Update the mean value of the current solution $X_M(t)$
If t $\le \frac{2}{3}T$, Then
  If Rand $\le$ 0.5, Then
   Update the current solution using **Expanded exploration** x_1
  End
  If Rand $>$ 0.5, Then
   Update the current solution using **Narrowed exploration** x_2
  End
End
If t $> \frac{2}{3}T$, Then
  If Rand $\le$ 0.5, Then
   Update the current solution using **Expanded exploitation** x_3
  End
  If Rand $>$ 0.5, Then
   Update the current solution using **Narrowed exploitation** x_4
  End
End
  Update pbest and gbest
end while

FIGURE 2. **Pseudo code of the Aquila optimizer.**

VI. STATISTICAL ERROR ANALYSIS

The performance and accuracy of the procedures used to estimate Weibull parameters are evaluated and compared using statistical error methodologies. The coefficient of determination (R^2), root mean square (RMSE), and chi-square (X^2) are the statistical approaches used. These laws can be described as follows [48]:

$$RMSE=\sqrt{\frac{1}{2}\sum_{i=1}^{n}(y_i-x_i)^2} \tag{50}$$

$$R^2=\frac{\sum_{i=1}^{n}(y_i-m)^2-\sum_{i=1}^{n}(x_i-m)^2}{\sum_{i=1}^{n}(y_i-m)^2} \tag{51}$$

$$X^2=\frac{1}{N-n}\sum_{i=1}^{n}(y_i-x_i)^2, \tag{52}$$

where n represents the number of wind speed classes, N is the number of observations, y_i represents the i^{th} wind speed from real data, x_i represents the predicted i^{th} wind speed and m represents the average wind speed.

VII. RESULTS AND DISCUSSION

This work presents several case studies to demonstrate the stochastic modeling of wind energy and its application in the electrical power system. First, the parameters of Weibull PDF will be estimated using four numerical and two AI methods, and the results are compared. Then, eight case studies will be applied to study the OPF in the standard IEEE-30 bus system and modified IEEE-30 bus system which contains 2 wind farms.

The OPF will be applied with different objective functions using the MA method. Then, three cases of multi-objective optimal power flow will be applied using the multi-objective MA method. After that, single and multi-objective SCOPF will be applied to the modified IEEE-30 bus system. The numerical and AI methods are developed using the MATLAB program. The Newton-Raphson technique was used to calculate power flow using the MATPOWER program [49]. The generators fuel cost coefficients and emission coefficients of the standard IEEE-30 bus system are shown in TABLE 1

Case 1 (Weibull Distribution Function): In this case study, the parameters of Weibull distribution functions are estimated using four numerical methods and two AI methods. The four numerical methods are MLM, EM, GM, and EP, while the two AI methods are AO and MA. FIGURE 3 shows the fitting of Weibull PDF using the six methods with wind speed frequency distribution.

TABLE 1. Fuel cost and emission coefficients for IEEE-30 bus system.

	G1	G2	G5	G8	G11	G13
			Generators fuel cost coefficients			
a	0.00375	0.0175	0.0625	0.0083	0.025	0.025
b	2	1.75	1	3.25	3	3
c	0	0	0	0	0	0
			Generators Emission coefficients			
α	0.04091	0.02543	0.04258	0.05326	0.04258	0.06131
β	-0.0555	-0.0604	-0.0509	-0.0355	-0.0509	-0.0555
γ	0.0649	0.05638	0.04586	0.0338	0.04586	0.05151
ξ	0.0002	0.0005	0.000001	0.002	0.000001	0.00001
λ	2.857	3.333	8	2	8	6.667

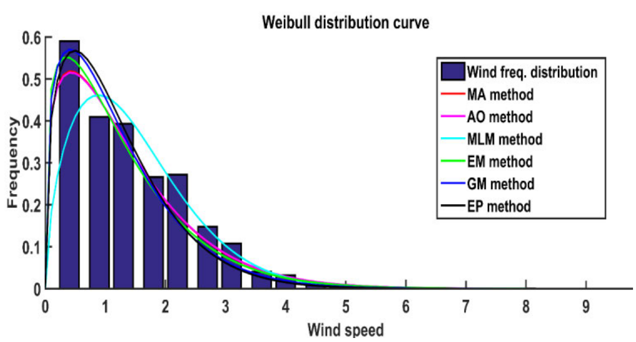

FIGURE 3. Weibull distribution Curve.

TABLE 2 shows the performance of the Weibull distribution models for numerical and AI methods used. Comparing the four numerical methods and the AI methods, AI methods have a better performance for the estimation of the Weibull parameters as they give minimum RMSE than numerical methods. Also, AI methods give better R^2 than numerical methods. These results prove the superiority of AI methods over traditional methods in evaluating Weibull distribution parameters and hence designing a stochastic wind speed model for the power system.

TABLE 2. Performance of the Weibull distribution models.

	MLM	EM	GM	EP	MA	AO
K	1.5916	1.2361	1.298	1.2936	1.2736	1.2746
C	1.6467	1.3477	1.2903	1.3613	1.4233	1.4319
RMSE	0.0563	0.0356	0.0388	0.0353	0.0342	0.0343
R^2	0.8808	0.9561	0.9531	0.9560	0.9573	0.9569
X^2	0.00055	0.00022	0.00026	0.00022	0.00020	0.00021

It is clear that AI methods have better modeling accuracy than classical techniques. From Table 1, MA and AO have RMSE around 0.0343 while the classical methods (MLM, EM, GM, and EP) have RMSE 0.0563, 0.0356, 0.03878, and 0.03533 respectively. Moreover, the coefficient of determination in the AI method is around 0.957 while the classical methods (MLM, EM, GM, and EP) have $R^2$0.88, 0.956, 0.953, and 0.956 respectively.

Case 2 (Single Objective Optimal Power Flow): In this case study, four single objective OPF are employed to minimize fuel cost, active power loss, VSI, and Emission using the MA method. The convergence curves for fuel cost, power loss, emission, and VSI minimization are shown in FIGURE 4, FIGURE 5, FIGURE 6, and FIGURE 7, respectively. The optimal control variable and optimal results are shown in TABLE 3. Results from differential evolution (DE), particle swarm optimization (PSO), improved particle swarm optimization (IPSO), harmony search algorithm (HAS), modified differential evolution (MDE), Genetic Algorithm (GA), shuffled frog leaping algorithm (SFLA), Gray wolf optimizer (GWO), and tabu search (TS) are compared to the results from proposed MA. The comparisons for the four objective functions were given in TABLE 4, TABLE 5, and (FIGURE 8 - FIGURE 11). The results prove the accuracy of the proposed MA method.

Case 3 (Multi-Objective Optimal Power Flow): Three scenarios of MO-OPF are presented which are (fuel cost-power Loss) minimization, (fuel cost-VSI) minimization, and (fuel cost-emission) minimization using the MO-MA algorithm for the standard IEEE 30-bus system. The Pareto optimal

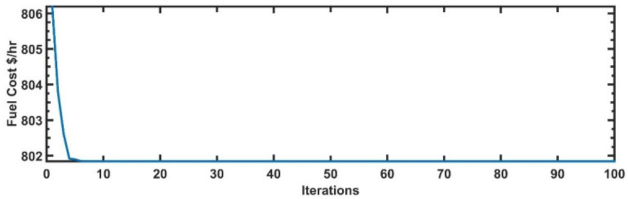

FIGURE 4. Convergence curves for Fuel cost minimization.

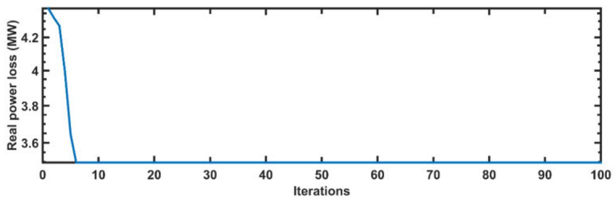

FIGURE 5. Convergence curves for power loss minimization.

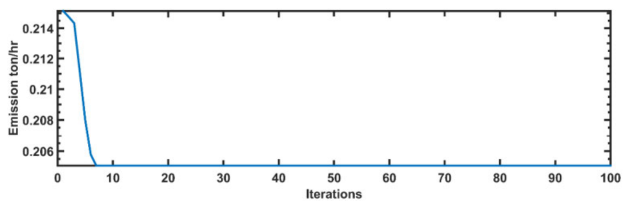

FIGURE 6. Convergence curves for Emission minimization.

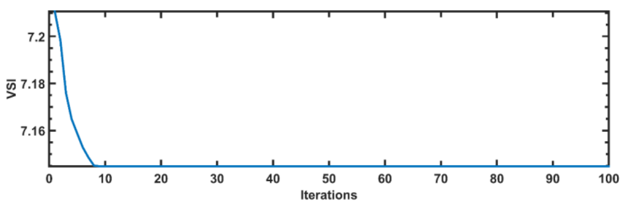

FIGURE 7. Convergence curves for VSI minimization.

TABLE 3. Optimal control variable and optimal data using MA method.

	Fuel Cost minimization ($/hr)	Power Loss minimization (MW)	VSI minimization	Emission minimization (ton/hr)
P_{G1}	176.7303	51.8973	177.4726	64.2915
P_{G2}	48.8300	80.0000	20.0000	67.7120
P_{G5}	21.4738	50.0000	15.0000	50.0000
P_{G8}	21.6481	30.0000	10.0000	35.0000
P_{G11}	12.0937	35.0000	30.0000	30.0000
P_{G13}	12.0000	40.0000	40.0000	40.0000
Fuel Cost	**801.8436**	968.5621	849.9497	945.4828
Power Loss	9.3760	**3.4973**	9.0726	3.6035
VSI	7.5942	7.2140	**7.1449**	7.2122
Emission	0.3652	0.2075	0.3627	**0.2050**

TABLE 4. Comparison of fuel cost and power loss optimization for the IEEE 30-bus system.

Method	Fuel cost Minimization ($/hr)	Method	Power Loss Minimization (MW)
MA	**801.84**	MA	**3.49**
GWO [50]	801.86	HSA [51]	3.51
DE [52]	802.39	Enhanced GA [30]	3.62
MDE-OPF [52]	802.37		
GA [53]	801.96		
TS [54]	802.29		
SFLA [55]	802.51		

TABLE 5. Comparison of emission and VSI optimization for the IEEE 30-bus system.

Method	Emission Minimization (ton/hr)	Method	VSI Minimization
MA	**0.2050**	**MA**	**7.1449**
GA [56]	0.20723	DE [57]	8.2367
PSO [56]	0.2063	GWO [57]	8.268
Improved PSO [56]	0.2058		

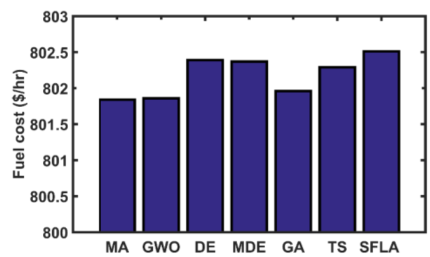

FIGURE 8. Comparisons of fuel cost for the IEEE 30-bus system.

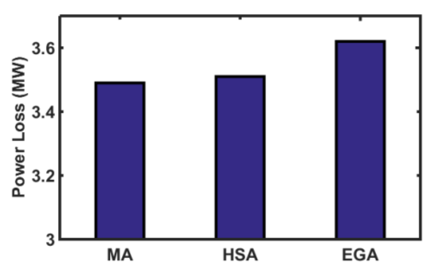

FIGURE 9. Comparisons of power loss for the IEEE 30-bus system.

solutions and the obtained best compromise solutions for the three scenarios are shown in (FIGURE 12- FIGURE 14). The compromise control variables and data for the three scenarios are shown in TABLE 6. Comparison for the compromise solution in case of (fuel cost-power loss) MOO with other methods is presented in TABLE 7.

Case 4 (Single Objective Stochastic Optimal Power Flow): The MA approach will be used to apply SCOPF to the modified IEEE-30 bus system in order to obtain optimal scheduled wind power from wind farms. The IEEE 30-bus system's buses 2 and 5 were transformed into wind farms with a rated power of 80MW and 50MW, respectively. The objective

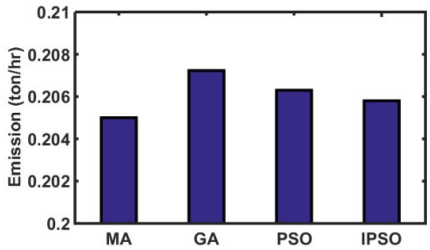

FIGURE 10. Comparisons of emission for the IEEE 30-bus system.

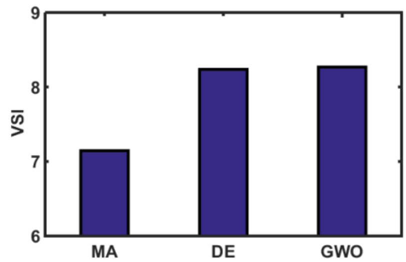

FIGURE 11. Comparisons of VSI for the IEEE 30-bus system.

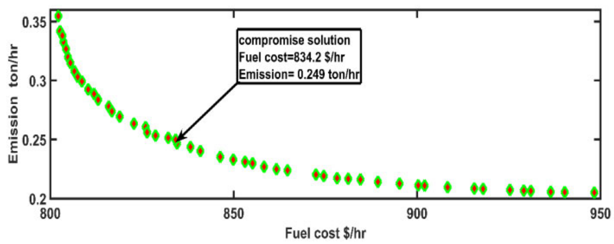

FIGURE 12. Best compromise and Pareto optimal solutions for (fuel cost-emission) minimization.

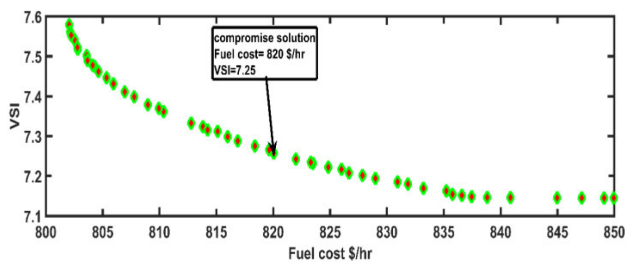

FIGURE 13. Best compromise and Pareto optimal solutions for (fuel cost-VSI) minimization.

functions for SCOPF in this case study are minimization of total operation cost, active power loss, VSI, and Emission. The Weibull PDF parameters are fixed at k=2 and c=10. The reserve cost coefficient is $K_R = 4$ and Penalty cost coefficient $K_P = 1$. (FIGURE 15 - FIGURE 18) show the convergence curves for the four objective functions. The optimal control variable and optimal results are shown in TABLE 8

Case 5 (Multi-Objective Stochastic Optimal Power Flow): In this part, three scenarios of MO-SCOPF are applied in the modified IEEE-30 bus system using MO-MA. The objective functions are minimization for (total generation cost-power

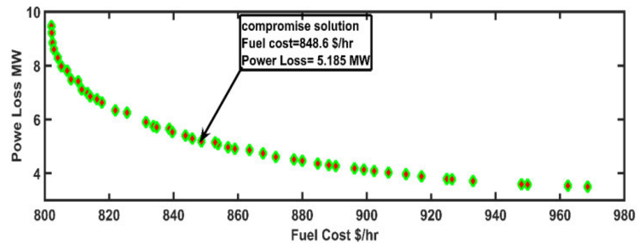

FIGURE 14. Best compromise and Pareto optimal solutions for (fuel cost-power loss) minimization.

TABLE 6. Control variables and optimal data for compromise solutions using MO-MA method.

	Fuel Cost($/hr)-power loss(MW) minimization	Fuel Cost($/hr)-VSI minimization	Fuel Cost($/hr)-emission(ton/hr) minimization
P_{G1}	109.6951	158.9354	116.5261
P_{G2}	53.9780	45.9933	63.4771
P_{G5}	35.4460	18.8608	27.4643
P_{G8}	34.8389	10.1768	35.0000
P_{G11}	29.4622	28.6885	30.0000
P_{G13}	25.1645	29.0540	16.8310
Fuel Cost	**848.6486**	**820.0397**	**834.1692**
Power Loss	**5.1847**	8.3088	5.8985
VSI	7.3405	**7.2575**	7.4118
Emission	0.2366	0.3157	**0.2499**

TABLE 7. Comparison of best compromise solution for (fuel cost-power loss) minimization.

Method	Fuel cost($/hr)	Power Loss(MW)
MA	848.6486	5.1847
PSO [58]	847.01	5.67
HSA [51]	823.89	5.77
DE [57]	820.85	6.13

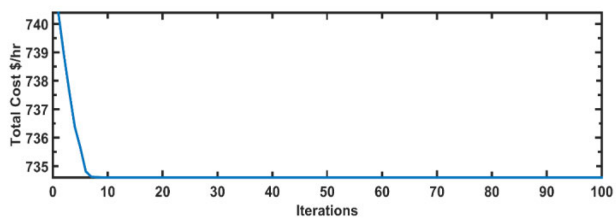

FIGURE 15. Convergence curves for total cost minimization.

Loss), (total generation cost -VSI), and (total generation cost - emission). The Pareto optimal solutions and the obtained best compromise solutions for the three scenarios are shown in (FIGURE 19- FIGURE 21). The compromise control variables and data for the three scenarios are shown in TABLE 6. All parameters in this case study are the same as case 4.

Case 6 (Wind Cost Versus Scheduled Power): The Weibull PDF parameters are fixed at k=2 and c=10. The reserve cost coefficient is $K_R = 4$ and Penalty cost coefficient $K_P = 1$.

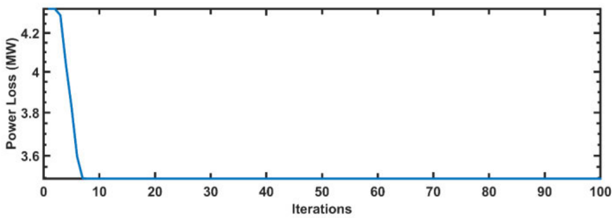

FIGURE 16. Convergence curves for power loss minimization.

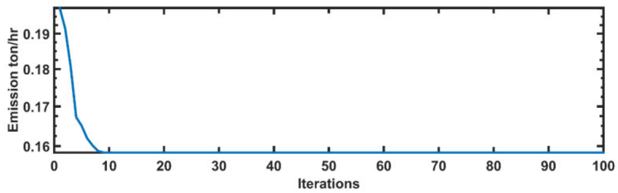

FIGURE 17. Convergence curves for emission minimization.

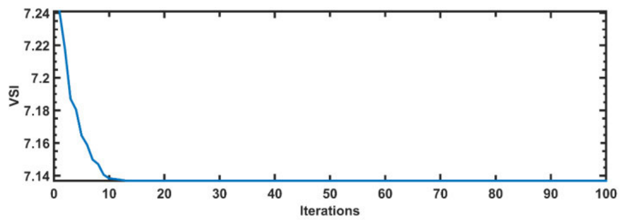

FIGURE 18. Convergence curves for VSI minimization.

TABLE 8. Optimal control variable and optimal data using MA method with wind energy penetration.

	Total Cost ($/hr)	Power Loss (MW)	VSI	Emission (ton/hr)
P_{G1}	145.8310	51.8973	200.0000	51.8973
$P_{scheduled2}$	67.1468	80.0000	0.0000	80.0000
$P_{scheduled5}$	45.9789	50.0000	0.0000	50.0000
P_{G8}	10.0000	35.0000	10.0000	35.0000
P_{G11}	10.0000	30.0000	30.0000	30.0000
P_{G13}	12.0000	40.0000	40.0000	40.0000
Fuel cost	476.8420	510.3121	2386.2894	510.3121
Wind power cost	257.7630	316.8303	51.9425	312.0770
Total Cost	**734.6050**	827.1424	2438.2319	822.3891
Power Loss	7.5567	**3.4973**	11.9046	3.4973
VSI	7.6119	7.2140	**7.1370**	7.2140
Emission	0.2568	0.1584	0.3816	**0.1584**

The scheduled wind power for G_2 is varied from 0 to 80 MW. The Variations of penalty cost, reserve cost, and total cost are shown in FIGURE 22.

Case 7 (Wind Costs Versus Wind Weibull Parameter): In this case study, the Weibull scale parameter is varied from 1 to 15 with fixed shape parameter $k = 2$ to monitor change in wind power costs of G_2. The scheduled power of G_2 is fixed at 40 MW and the reserve cost and penalty cost coefficients are fixed at $K_R = 4$ and $K_P = 1$. FIGURE 23 depicts wind costs vs. Weibull scale parameter. It can be indicated

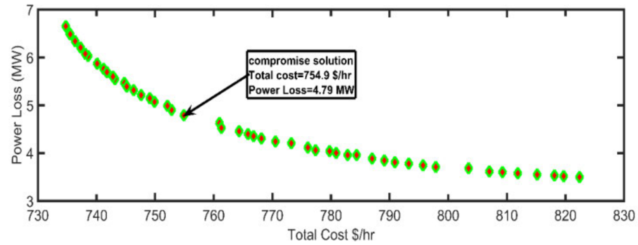

FIGURE 19. Compromise and Pareto optimal solutions for (total cost-power loss) minimization in SCOPF problem.

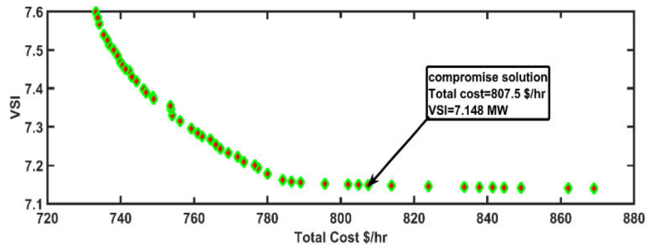

FIGURE 20. Compromise and Pareto optimal solutions for (total cost-VSI) minimization in SCOPF problem.

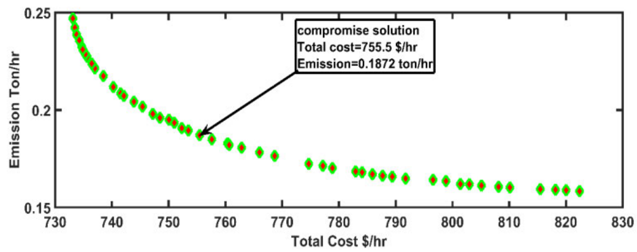

FIGURE 21. Compromise and Pareto optimal solutions for (total cost-emission) minimization in SCOPF problem.

TABLE 9. Control variables and optimal data for compromise solutions using MOMA method.

	Total Cost($/hr)-power loss (MW) minimization	Total Cost($/hr)-VSI minimization	Total Cost($/hr)--emission(ton/hr) minimization
P_{G1}	99.7495	138.4251	95.5307
$P_{scheduled2}$	68.4471	58.4628	80.0000
$P_{scheduled5}$	50.0000	14.2500	50.0000
P_{G8}	34.9765	10.0028	24.6067
P_{G11}	19.4746	29.9827	18.6344
P_{G13}	15.5423	39.9976	19.6302
Fuel cost	481.2101	654.4558	443.3899
Wind power cost	273.7032	153.0843	312.0770
Total Cost	**754.9133**	**807.5402**	**755.5000**
Power Loss	**4.7900**	7.7210	5.0020
VSI	7.5354	**7.1484**	7.4841
Emission	0.1910	0.2303	**0.1872**

from FIGURE 23 that when the scale parameter increases, overestimation and total costs decrease, but underestimation cost increases.

Case 8 (Wind Costs Versus Penalty Cost Coefficient): Except for the penalty cost coefficients, all of the factors in this case study are the same as in Case 4. The penalty cost coefficients K_P ranged from 1 to 4. FIGURE 24 shows the

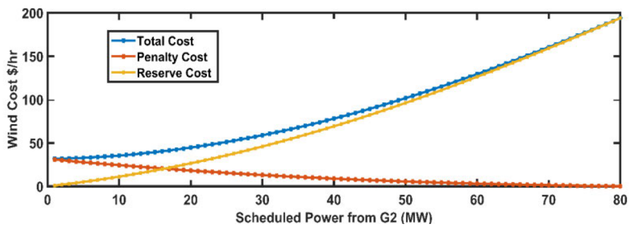

FIGURE 22. Variation of wind power costs vs scheduled power for G2.

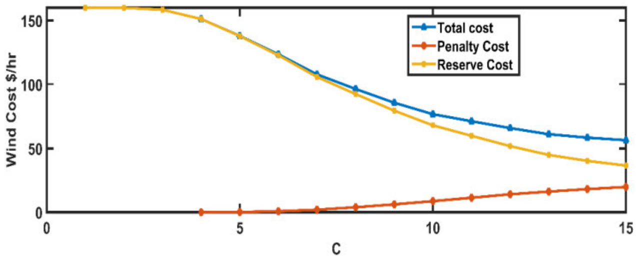

FIGURE 23. Variation of wind power costs vs Weibull scale parameter for G2.

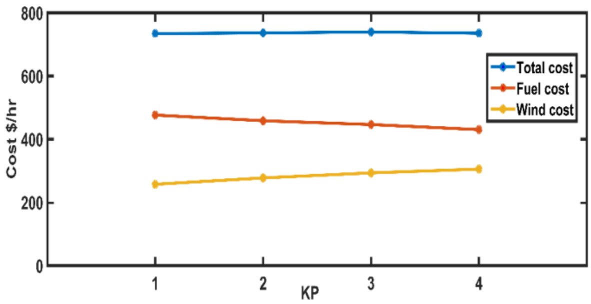

FIGURE 24. Variation of generation cost vs penalty cost coefficients.

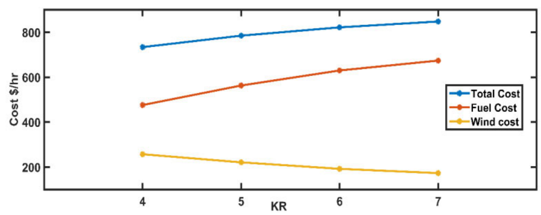

FIGURE 25. Variation of generation cost vs penalty cost coefficients.

variation of fuel, wind, and total cost versus penalty cost coefficients. Scheduled output power from wind farms tends to grow when the penalty cost coefficient rises, as increasing the scheduled power would help to lower the penalty cost.

Case 9 (Wind Costs Versus Reserve Cost Coefficient): Except for the reserve cost coefficients, all of the factors in this case study are the same as in Case 4. The reserve cost coefficients K_R ranged from 4 to 7. FIGURE 25 shows the variation of fuel, wind, and total cost versus reserve cost coefficients. The optimum Scheduled power for the two wind farms drops as K_R rises, as a decrease in scheduled power necessitates less spinning reserve. When K_R rises, thermal generators adjust for lower outputs from wind farms, raising total generation costs.

VIII. CONCLUSION

In this paper, two novel AI algorithms are employed to estimate Weibull parameters and results compared to four well-known numerical methods. The two AI methods gave the best performance which was proved by error analysis. After that, the MA method is employed to address the single objective and multi-objective OPF problem in order to minimize fuel cost, power loss, VSI, and emission. The suggested method's performance was evaluated on standard IEEE-30 bus systems, and the results were compared with those of alternative optimization strategies available in the literature. The results showed that the MA method produced the best results, which was demonstrating the MA method's validity and accuracy. Moreover, the MA method is utilized to solve single objective and multi-objective SCOPF on a modified IEEE-30 bus system that contains two wind farms. The results gave the best wind schedule under several conditions. It can be concluded that, Mayfly algorithm (MA) method had superior performance in determining Weibull parameters over other numerical methods and in solving single and multi-objective OPF problems with wind energy penetration over other meta-heuristic methods. Moreover, it had better performance in obtaining the best wind schedule for the SCOPF.

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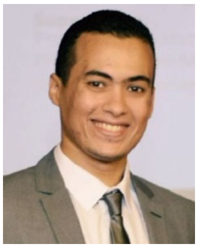

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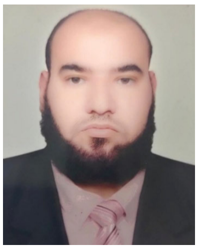

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