Optimal Power Flow Solution of Wind-Integrated Power System Using Novel Metaheuristic Method

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Abstract: Wind energy is particularly significant in the power system today since it is a cheap and clean power source. The unpredictability of wind speed leads to uncertainty in devolved power which increases the difficulty in wind energy system operation. This paper presents a stochastic optimal power flow (SCOPF) for obtaining the best scheduled power from wind farms while lowering total operational costs. A novel metaheuristics method called Aquila Optimizer (AO) is used to address the SCOPF problem due to its highly nonconvex and nonlinear nature. Wind speed is represented by the Weibull probability distribution function (PDF), which is used to anticipate the cost of wind-generated power from a wind farm based on scheduled power. Weibull parameters that provide the best match to wind data are estimated using the AO approach. The suggested wind generation cost model includes the opportunity costs of wind power underestimation and overestimation. Three IEEE systems (30, 57, and 118) are utilized to solve optimal power flow (OPF) using the AO method to prove the accuracy of this method, and results are compared with other metaheuristic methods. With six scenarios for the penalty and reverse cost coefficients, SCOPF is applied to a modified IEEE-30 bus system with two wind farms to obtain the optimal scheduled power from the two wind farms which reduces total operation cost.

Keywords: wind energy; stochastic optimal power flow; Weibull probability distribution; Aquila Optimizer

1. Introduction

The main goal of optimal power flow (OPF) is to satisfy system restrictions while optimizing an objective function like total cost of generation, power losses, and voltage stability [1]. The OPF problem is a nonconvex, large-scale, and non-linear constrained optimization problem, which has been widely used in power system operation. Because of these features, solving the OPF problem is a very popular and challenging task in power system optimization. A feasible optimization approach must be chosen in order to address such a challenge. Many classic optimization approaches have already been used to address the OPF problem, including linear programming, nonlinear programming, quadratic programming, Newton method, and interior point method [2–4]. Many traditional methods are commonly utilized in the industry; however, prior to using these techniques, appropriate theoretical assumptions must be made. As a result, those methods are restricted to handle specific sorts of optimization issues. A population-based metaheuristic method is now used to handle complex OPF problems. Multiple potential solutions are maintained and improved utilizing population-based techniques, which frequently use population...
features to guide the search. Researchers from all over the world have explored OPF using only thermal power generators by using metaheuristic methods [5]. Kumari [6] applied an upgraded genetic algorithm (GA) with quadratic load flow solution to tackle the traditional OPF problem, based on the Pareto evolutionary algorithm. Khunkitti [7] presented a hybrid dragonfly and particle swarm optimization (PSO) technique in solving traditional OPF in order to minimize fuel expense, emission, and power loss. Basu [8] proposed a differential evolution (DE) method to solve the traditional OPF problem in power systems using FACTS devices, taking into consideration generating costs, emissions, and power losses. Singh [9] presented the PSO method combined with an aging leader and challengers to solve OPF problem in IEEE-30 bus and IEEE-118 bus systems. Attia [10] applied a modified Sine-Cosine algorithm which contained Levy flights to solve the OPF problem in IEEE-30 bus and IEEE-118 bus systems. Shuijia Li [11] presented an enhanced adaptive DE with a penalty constraint handling strategy that adapts to the situation to solve OPF in an IEEE-30 bus system.

Traditional OPF problems only consider thermal power sources; however, rising fuel prices and environmental concerns have prompted countries to consider renewable energy sources such as wind power. Hence, there is a need to consider wind generation cost in the classical OPF problem and get the optimal operation for the system containing wind energy sources. This problem is called a stochastic optimal power flow [12,13]. Liu [14] proposed an economic dispatch problem incorporating wind power energy and used a genetic algorithm method for coordination of thermal and wind dispatching. Miguel [15] examined the impact of wind’s stochastic nature on system total operating cost considering the effects of variable loads and errors in the forecasting of wind power on the different components of generation cost. Hetzer [16] proposed an economic dispatch problem incorporated with wind energy to determine the best output power allocation among the many generators available to fulfill the system load. Dubey [17] proposed a hybrid flower pollination method with a fuzzy selection mechanism to solve SCOPF which included emission and the generator’s valve-point loading effect for a hybrid system including wind energy. Kusakana [18] presented SCOPF in a hybrid system which includes solar photovoltaic, wind, diesel generators, and batteries to minimize total operating cost at fixed values for over/under estimation cost coefficients. Karam [19] applied the multi-operator DE method to solve OPF problem incorporating wind and solar power in IEEE-30 bus and IEEE-118 bus systems while taking into account the variable nature of solar and wind power generation. Partha [20] proposed a success history-based parameter adaptation approach for DE algorithm to solve the OPF problem combining stochastic wind and solar power. Inam [21] applied the Gray Wolf Optimizer method to solve the OPF problem which combines thermal power, wind energy, and solar energy in IEEE-30 bus and IEEE-57 bus system. Arsalan [22] applied the Krill Herd algorithm to solve OPF problems considering FACTS devices and wind energy generation under uncertainty using Weibull PDF in IEEE-30 bus and IEEE-57 bus systems. Mohd [23] applied the Barnacles Mating Optimizer method to solve the OPF problem with stochastic wind energy in modified IEEE 30-bus and IEEE 57-bus systems. The SCOPF literature contribution can be summarized as indicated in Table 1.
### Table 1. Literature contribution.

| Year | Title                                                                 | Contribution                                                                                                                                                                                                 |
|------|----------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 2007 | Economic dispatch of power system incorporating wind power plant [14] | In the economic dispatch, GA was used to coordinate the wind and thermal generation dispatch and to reduce the total production cost while taking into account wind power generation and the valve effect of thermal units. |
| 2010 | Assessing the impact of wind power generation on operating costs [15] | Offered an approach for quantifying the additional operating costs associated with the replacement of conventional generation with wind power generation, while ignoring the effects of load and wind forecast mistakes on the various components of this cost. |
| 2008 | An economic dispatch model incorporating wind power [16]            | Overestimation and underestimation costs were applied to wind energy costs to solve the economic dispatch problem.                                                                                         |
| 2015 | Hybrid flower pollination algorithm with time-varying fuzzy selection mechanism for wind integrated multi-objective dynamic economic dispatch [17] | Applied a hybrid flower pollination algorithm to solve the economic dispatch problem with wind energy.                                                                                                       |
| 2015 | Optimal scheduled power flow for distributed photovoltaic/wind/diesel generators with battery storage system [18] | In one scenario of wind generation cost, the author developed models to minimize the hybrid system’s operation cost while finding the ideal power flow considering intermittent solar and wind resources, battery state of charge, and fluctuating load demand. |
| 2021 | Optimal power flow considering intermittent solar and wind generation using multi-operator differential evolution algorithm [19] | The optimal power flow problem was solved using a multi-operator differential evolution method while incorporating intermittent solar and wind power generation at one scenario for wind generating overestimation and underestimation costs. |
| 2017 | Optimal power flow solutions incorporating stochastic wind and solar power [20] | In a small system IEEE-30 bus only, a success history-based adaptation technique of differential evolution algorithm was used to address the optimal power flow problem while incorporating intermittent solar and wind power generation. |
| 2020 | Heuristic algorithm based optimal power flow model incorporating stochastic renewable energy sources [21] | Without using real wind speed data, the Gray Wolf Optimizer algorithm was used to solve the optimal power flow problem while incorporating intermittent solar and wind power generation. |
| 2020 | Optimal power flow incorporating FACTS devices and stochastic wind power generation using Krill Herd Algorithm [22] | The optimal power flow problem was solved using the Krill Herd Algorithm with FACTS devices and stochastic wind power generation at one scenario for wind generation overestimation and underestimation costs. |
| 2021 | Solving optimal power flow problem with stochastic wind–solar–small hydro power using barnacles mating optimizer [23] | The Barnacles Mating Optimizer was applied to solve the optimal power flow problem incorporating FACTS devices and stochastic wind power generation at one scenario for wind generation overestimation and underestimation cost. |

This research presents a stochastic optimal power flow (SCOPF) model that is combined with wind energy sources. There are two components added to the cost of dispatching wind power, which is wind power underestimation cost and overestimation cost. The underestimation cost refers to the expense of employing greater reserve capacity, while the overestimation cost refers to the fact that the system operator is required to acquire additional electricity from wind farms that they had not anticipated being available.
The objective of SCOPF is to obtain optimal scheduled power from wind farms and optimal generating power from the thermal unit which minimizes total operation cost.

In this work, a novel metaheuristic optimization technique called Aquila Optimizer (AO) was proposed to solve the SCOPF problem. First, the traditional OPF problem was solved using the AO algorithm using IEEE-30, IEEE-57, and IEEE-118 buses systems then results were compared to other metaheuristic techniques to prove superiority and accuracy of the proposed method. Second, the SCOPF problem was solved to get optimal scheduled wind power at six scenarios for overestimation and underestimation cost coefficients to minimize total operation costs. The variation of overestimation and underestimation cost coefficients affects the share of the thermal and wind generating power; this work demonstrates the reason for changes in power share in six scenarios. These scenarios studied the effect of changing overestimation and underestimation cost coefficients in the values of optimal fuel and wind generation costs. Moreover, this work presented a study to demonstrate the effect of changing scheduled wind power on the wind generation cost at different values of overestimation and underestimation cost coefficients. A modified IEEE-30 bus system which includes two wind farms rated at 80 MW and 50 MW were used to solve the SCOPF problem using the AO method. Wind speed probability distribution function (PDF) was simulated using the Weibull distribution curve and the AO method was used to determine the optimal parameters of Weibull distribution which minimized root mean square error (RMSE). The wind power PDF of the wind farm was designed based on the Weibull wind speed distribution and it was a mixed discrete and continuous distribution. Modeling of wind speed was based on an hourly wind speed dataset collected from a site in Texas for 5 years [24].

2. Wind Energy Probability Distribution

2.1. Wind Speed Probability Distribution

The wind speed data in this work were simulated with Weibull PDF. The Weibull PDF was developed by Waloddi Weibull [25]. The Weibull PDF $f(v)$ and cumulative distribution function $F(v)$ are given by Equations (1) and (2). The wind speed frequency distribution proposed in this work is shown in Figure 1 [24].

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

and

$$F(v) = 1 - \exp\left(-\left(\frac{v}{c}\right)^k\right)$$  \hspace{1cm} (2)$$

where $v$ is the speed of the wind in m/s, $k$ is the shape parameter, and $c$ is the scale parameter.

![Weibull distribution function](image-url)
The AO method was used to get the optimal parameters of the Weibull curve to minimize the disparity between real wind speed frequency distribution and the Weibull curve [26]. Figure 1 shows the fitting of Weibull PDF with proposed wind speed data.

The objective function of the AO method is to minimize the root mean square error, which can be calculated as follows:

\[
\text{RMSE} = \frac{1}{2} \sum_{i=0}^{n} (f_{\text{real}}(v_i) - f_{\text{weibull}}(v_i))^2
\]  
(3)

where \(f_{\text{real}}(v)\) is wind speed class’s frequency, \(f_{\text{weibull}}(v)\) is the PDF of Weibull, and \(n\) is the number of wind speed classes.

After applying the AO method to get Weibull parameters that minimize RMSE, the Weibull PDF which fits the used wind speed data is shown in Figure 1, with \(K = 1.71\) and \(C = 3.39\), and the resultant RMSE = 0.0062.

It will be shown in the next section that in the translation to wind power distributions, continuous wind speed distributions become mixed discrete and continuous distributions due to the characteristics of wind generators.

2.2. Wind Power Probability Distribution

The output power from a wind turbine can be calculated as:

\[
P_{\text{wind}} = \begin{cases} 
0 & v \leq v_{\text{cut-in}} \quad \text{or} \quad v \geq v_{\text{cut-off}} \\
\frac{1}{2} \rho AC_p v^3 & v_{\text{cut-in}} < v \leq v_{\text{rated}} \\
\frac{P_{\text{rated}}}{v_{\text{rated}}} & v_{\text{rated}} < v < v_{\text{cut-off}} 
\end{cases}
\]

where \(\rho\) is the air density, \(A\) is the area of wind blade, \(C_p\) is the performance coefficient, \(v_{\text{cut-in}}\) and \(v_{\text{cut-off}}\) are the cut in and cut off speed of wind turbine, \(v_{\text{rated}}\) is the wind speed which gives rated output power from the wind generator, and \(P_{\text{rated}}\) is the rated output power from a wind generator.

This work proposed two wind farms rated at 80 MW and 50 MW with \(v_{\text{cut-in}} = 2\) m/s, \(v_{\text{rated}} = 5\) m/s, and \(v_{\text{cut-off}} = 20\) m/s, the power curve for an 80 MW wind farm is shown in Figure 2 [27].

![Figure 2. Power curve for 80 MW wind farm.](image)

In this work, the output power PDF of the wind farm was designed based on the Weibull wind speed distribution [28]. Once the wind’s unpredictable nature is defined as a random variable, the output power of the wind turbine can be defined as a random variable as well [16]. Referring to the last equation of \(P_{\text{wind}}\), it can be shown that the output wind power is discrete in some wind speed zones. The power output is \(P_{\text{rated}}\) when \(v\) is between \(v_{\text{rated}}\) and \(v_{\text{cut-off}}\), and the power output is zero when the wind speed \(v\) is below \(v_{\text{cut-in}}\) and above \(v_{\text{cut-off}}\).
For these discrete regions, PDF of wind power output \( f_w(P) \) are given by [20]:

\[
f_w(P) \{ P_{\text{wind}} = 0 \} = 1 - \exp\left( -\left( \frac{v_{\text{cut-off}}}{c} \right)^k \right) + \exp\left( -\left( \frac{v_{\text{cut-in}}}{c} \right)^k \right)
\]

(5)

\[
f_w(P) \{ P_{\text{wind}} = P_{\text{rated}} \} = \exp\left( -\left( \frac{v_{\text{rated}}}{c} \right)^k \right) - \exp\left( -\left( \frac{v_{\text{cut-off}}}{c} \right)^k \right)
\]

(6)

The wind power probability distribution for 80 MW wind farm is indicated in Figure 3 [20], the output wind power was discrete at \( P_{\text{wind}} = 0 \) and \( P_{\text{wind}} = P_{\text{rated}} \), and continuous probability function between zero and \( P_{\text{rated}} \).

![Probability distribution of wind power](image)

**Figure 3.** Wind power output mixed probability function.

### 3. Problem Formation

#### 3.1. Traditional OPF Problem

The goal of the OPF issue is to operate a power system effectively by optimizing control variables while maintaining the network’s physical and thermal limits. The OPF problem can be expressed mathematically as a non-linear constrained optimization problem:

\[
\text{Min } F(x, u)
\]

(8)

Subject to:

\[
\text{Min } g(x, u) \leq 0
\]

(9)

\[
\text{Min } h(x, u) = 0
\]

(10)

where \( u \) and \( x \) are the vectors of control and state variables, respectively, \( g(x, u) \) and \( h(x, u) \) are the inequality and equality constraints, respectively, and the objective function is \( F(x, u) \).

The vector of state variable \( x \) consists of the output power of the slack bus \( P_{G1} \), the voltage of the load buses \( V_L \), reactive power of generators \( Q_{G} \), and loadings of the transmission line \( S_L \). As a result, \( x \) can be written as:

\[
x^T = (P_{G1}, V_{L1} \ldots V_{LN}, Q_{G1} \ldots Q_{NG}, S_{L1} \ldots S_{LN})
\]

(11)

where NL, NG, and nl are the number of load buses, generator buses, and transmission lines, respectively.
The vector of control variable $u$ consists of the output power of the generators $P_G$, the voltage of the generator buses $V_G$, the tap setting of the transformers $T$, and shunt compensations $Q_c$. As a result, $u$ can be written as:

$$u^T = (P_{G1}, \ldots, P_{GNG}, V_{G1}, \ldots, V_{GNG}, Q_{C1}, \ldots, Q_{CNC}, T_1, \ldots, T_{NT})$$

(12)

where NC and NT are the number of shunt compensators and transformers, respectively.

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

$$\sum_{i=1}^{NG} P_{Gi} = P(\text{loss}) + P(\text{load})$$

(13)

$$\sum_{i=1}^{NG} Q_{Gi} = Q(\text{loss}) + Q(\text{load})$$

(14)

where $P(\text{loss})$ and $Q(\text{loss})$ are transmission line losses, and $P(\text{load})$ and $Q(\text{load})$ are connected load power.

The generated real and reactive power flow equations are

$$P_{Gi}(V, \delta) = \sum_{i=1}^{n} V_i (G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j))$$

(15)

$$Q_{Gi}(V, \delta) = \sum_{i=1}^{n} V_i (G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j))$$

(16)

where $G_{ij}$ and $B_{ij}$ are the real and imaginary parts for the admittance bus of power system and $\delta$ is the power angle.

The inequality constraints $h(x, u)$ represent system operating constraints. They can be formulated as follows:

$$P_{G_{i,min}} \leq P_{Gi} \leq P_{G_{i,max}}$$

(17)

$$Q_{G_{i,min}} \leq Q_{Gi} \leq Q_{G_{i,max}}$$

(18)

$$V_{G_{i,min}} \leq V_{Gi} \leq V_{G_{i,max}}$$

(19)

$$T_{i,min} \leq T_i \leq T_{i,max}$$

(20)

$$Q_{C_{i,min}} \leq Q_{Ci} \leq Q_{C_{i,max}}$$

(21)

The objective function of traditional OPF in this work is to minimize thermal unit generation cost

$$\text{Min } C_t = \sum_{i=1}^{n} a_i + b_i P_{Gi} + c_i P_{Gi}^2$$

(22)

3.2. OPF Problem Containing Wind Power

Wind power is an uncontrollable intermittent source with a stochastic characteristic that is represented by a wind power random variable. As a result, the stochastic optimization problem posed in this study is an optimization problem including the random variable of wind power. Because the amount of wind energy available at any one time is unknown, overestimation and underestimating cost factors must be considered in the SCOPF model. The first factor is the overestimation cost which means that if the real wind power available is less than the scheduled wind power, electricity will have to be purchased from other sources or load will be shed, resulting in an increase in the operation cost. The second factor is the underestimation cost which happens if the actual available wind power is larger than the scheduled one: the operator will have to acquire extra electricity from wind farms that they did not expect and cope with it [16]. Figure 4 shows how to calculate the overestimation and underestimation cost from scheduled power and wind energy probability distribution.
3.2.1. Overestimation Cost (CR)

The overestimation cost [16] can be calculated as in Equation (23)

\[ CR = K_R (P_{\text{scheduled}} - P_{\text{available}}) \] (23)

where \( K_R \) is the reserve cost (overestimation) coefficient (USD/kWh), \( P_{\text{scheduled}} \) is the scheduled power by the operator, and \( P_{\text{available}} \) is the expected output power by the wind farm under the condition \( P_{\text{available}} < P_{\text{scheduled}} \), i.e., the expectation value of the left half-plane in Figure 4.

After using wind power PDF from Equations (5) and (7), overestimation cost can be calculated as in Equation (24).

\[ CR = K_R \int_0^{P_{\text{scheduled}}} (P_{\text{scheduled}} - P) f_w(P) \, dp \] (24)

where \( P_{\text{rated}} \) is the maximum output power from the wind generator.

3.2.2. Underestimation Cost (CP)

Moreover, the underestimating cost [16] can be calculated as in Equation (16)

\[ CP = K_P (P_{\text{available}} - P_{\text{scheduled}}) \] (25)

where \( K_P \) is the penalty cost (underestimation) coefficient (USD/kWh) and \( P_{\text{available}} \) is the expected output power by the wind farm under the condition \( P_{\text{available}} > P_{\text{scheduled}} \), i.e., the expectation value of the right half-plane in Figure 4.

After using wind power PDF from Equations (6) and (7), the underestimation cost can be calculated as

\[ CP = K_P \int_{P_{\text{scheduled}}}^{P_{\text{rated}}} (P - P_{\text{scheduled}}) f_w(P) \, dp \] (26)

Then, the objective function to be minimized will be formulated as:

\[ C_T = \sum_{i=1}^{NT} C_i + \sum_{i=1}^{NW} CP + \sum_{i=1}^{NW} CR \] (27)

where \( C_T \) is the total generation cost, \( \sum_{i=1}^{NT} C_i \) is the generation cost of thermal units, and \( NT \) and \( NW \) are the numbers of the thermal unit and wind farms, respectively.
4. Aquila Optimizer

AO is a population-based metaheuristic optimization technique. This method is based on getting and improving multiple potential solutions utilizing population-based techniques, which frequently use population features to steer the search. Because of their capacity to explore search space and exploit local resources, population-based metaheuristic algorithms are ideal for global searches.

The natural habits of the *Aquila* when catching its prey inspired this method. The optimization processes of this algorithm are separated into four categories [26]:

- **Select a search area from a vertical stoop** $x_1$ [26].

  The AO method has two stages, called exploration and exploitation, to update the current populations. The exploration stage starts when $t \leq \frac{2}{3}T$. It has two approaches, the first of which is based on Equation (19).

  $x_1 = x_{\text{best}} \times \left(1 - \frac{t}{T}\right) + (x_M - x_{\text{best}} \times R)$

  where $x_{\text{best}}$ is the best global solution and $T$ is the number of total iterations. During the exploration phase, the factor $\left(1 - \frac{t}{T}\right)$ is used to manage the search, $R$ is random values between 0 and 1, and $x_M$ is the average of the measurements for each individual.

- **Use a contour fly and a short attack to explore a diverging search space** $x_2$ [26].

  The AO relies on the Levy flight distribution to update the current person in the second exploration technique, as described in the following equation:

  $x_2 = x_{\text{best}} \times \text{Levy}_D + x_R + (y - x) \times R$

  where $x_R$ is an individual chosen at random, Levy$_D$ is a term used to describe the Levy flight distribution which can be formulated as:

  $\text{Levy}_D = s \times \frac{u \times \sigma}{|v|^\frac{\beta}{2}}, \sigma = \frac{\Gamma(1 + \beta) \times \sin\left(\frac{\pi \beta}{2}\right)}{\frac{\Gamma(1 + \beta)}{2} \times \beta \times 2^{\frac{\beta - 1}{2}}}$

  where $s = 0.01$ and $\beta = 1.5$ are constants, while $u$ and $v$ are random numbers created between 0 and 1. To imitate the spiral shape, $y$ and $x$ are employed as follows:

  $x = r \cos \theta, \ y = r \sin \theta$

  $r = r1 + U \times D1, \ \theta = -\omega \times D1 + \frac{3\pi}{2}$

  where $r1$ is a random number between 0 and 20, $\omega = 0.005$, and $U = 0.00565$.

- **Investigate in a convergent search space with a slow attack and low flight** $x_3$ [26].

  During the search process, two strategies are utilized to replicate individuals’ exploitation abilities. The first technique is based on the best answer ($x_{\text{best}}$) and the average of each individual’s position ($x_M$), and is written as:

  $x_3 = (x_{\text{best}} - x_M) \alpha - R + ((UB - UL) \times R + LB) \times \delta$

  where $R$ is a random number between 0 and 1, $\alpha$ and $\delta$ indicate the parameters for adjusting the exploitation phase which were fixed at a small value = 0.1 in this work, UL and UB are the lower and upper limits of the optimization problem.

- **Swoop down and grab prey with a stroll** $x_4$ [26].

  The second way of exploitation is based on $x_{\text{best}}$, Levy$_D$, and the Qf quality function.

  $x_4 = x_{\text{best}} \times \text{Qf} - (G1 \times X) \times R - G2 \times \text{Levy}_D + G1 \times R$
where the primary goal of QF is to balance search techniques, and it is characterized as:

\[ Q_f = \frac{2 \times R - 1}{t \times (1 - R)^2} \]  

(35)

G1 denotes the many motions used to find the optimal solution, and it is defined as

\[ G_1 = 2 \times R - 1 \]  

(36)

G2 is a random number describes from 2 to 0, and it is formulated as

\[ G_2 = (1 - T)^2 \]  

(37)

5. Results and Discussion

IEEE-30, IEEE-57, and IEEE-118 bus systems were used to apply AO in order to solve the OPF problem to test the efficiency and accuracy of the proposed optimization method, then the numerical results were displayed and compared to those obtained from other heuristic methods. After that, SCOPF using AO was applied to the modified IEEE-30 bus system which contains 2 wind farms. All simulations were run on a machine with an Intel Core i7 processor running at 3.4 GHz and 8 GB of RAM. The MATPOWER package was used to calculate power flow using the Newton–Raphson approach [29].

5.1. Traditional OPF Problem on IEEE-30 Bus System

Optimal power flow was applied on the IEEE-30 bus system by using the AO method, then the results were compared to the literature. The IEEE 30-bus system data were found in [30]. Figure 5 shows the convergence curve for the AO method. Results from differential evolution (DE), modified differential evolution (MDE), Genetic Algorithm (GA), Gray Wolf optimizer (GWO), Dragonfly algorithm (DA), hybrid DA-PSO, and tabu search (TS) were compared to the results from AO as indicated in Figure 6. From Table 2, it can be noticed that the AO method reduced fuel cost by 0.0013%, 0.0673%, 0.0649%, 0.0137%, 0.09%, 0.04%, and 0.054% compared to GWO, DE, MDE, GA, DA, DA-PSO, and TS, respectively. Results prove the accuracy and validation of the proposed method over other metaheuristic methods. The executive time for 100 iterations of the proposed method in the IEEE-30 bus system was 11.6 min.

![Convergence curve](image-url)

Figure 5. Convergence curve for IEEE-30 bus system using AO.
Figure 5. Convergence curve for IEEE-30 bus system using AO.

Figure 6. Fuel cost comparison for IEEE-30 bus system.

Table 2. Result comparison for OPF IEEE-30 bus system.

| Method   | Fuel Cost USD/hr | PG1 (MW) | PG2 (MW) | PG5 (MW) | PG8 (MW) | PG11 (MW) | PG13 (MW) | Number of Iterations to Convergence |
|----------|------------------|----------|----------|----------|----------|-----------|-----------|-------------------------------------|
| AO       | 801.83           | 178.136  | 49.137   | 21.691   | 20.494   | 11.4360   | 12        | 100                                 |
| GWO [31] | 801.86           | 176.84   | 48.79    | 21.51    | 21.60    | 11.68     | 12.33     | 80                                  |
| DE [32]  | 802.39           | 176.00   | 48.8     | 21.33    | 22.26    | 12.46     | 12        | 60                                  |
| MDE-OPF  [32] | 802.37       | 175.97   | 48.88    | 21.51    | 22.24    | 12.25     | 12        | 50                                  |
| GA [33]  | 801.96           | 175.16   | 49.03    | 19.52    | 19.68    | 17.1      | 12        | 300                                 |
| TS [34]  | 802.29           | 176.04   | 48.76    | 21.56    | 22.05    | 12.44     | 12        | 160                                 |
| DA [35]  | 802.63           | 174.53   | 48.73    | 20.27    | 21.1     | 12.35     | 11.33     | -                                   |
| DA-PSO [7] | 802.12          | 176.18   | 48.83    | 21.51    | 22.07    | 12.20     | 12        | -                                   |

5.2. Traditional OPF Problem on IEEE-57 Bus System

Optimal power flow was applied on the IEEE-57 bus system by using the AO method, then results were compared to other studies. The IEEE 57-bus system data were found in [31]. Figure 7 shows the convergence curve for the AO method. Results from Particle Swarm Optimization (PSO), Shuffled Frog Leaping Algorithm (SFLA), GA, GWO, and Cuckoo Optimization Algorithm (COA) were compared to the results from AO as indicated in Figure 8. From Table 3, it can be seen that the AO method reduced fuel cost by 0.568%, 1.938%, 0.0066%, 0.0062%, and 0.075% compared to PSO, GA, GWO, SFLA, and COA, respectively. Results prove the accuracy and validation of the proposed method over other metaheuristic methods. The executive time for 100 iterations of the proposed method in the IEEE-57 bus system was 22 min.
Table 3. Result comparison for OPF IEEE-57 bus system.

| Method | Fuel Cost USD/h | Number of Iterations to Convergence |
|--------|-----------------|-------------------------------------|
| AO     | 41870.3         | 100                                 |
| PSO [36]| 42109.7         | 4000                                |
| GA [33]| 42698           | 100                                 |
| GWO [31]| 41873.18       | 70                                  |
| SFLA [31]| 41872.9       | 80                                  |
| COA [37]| 41901.9         | 100                                 |

5.3. Traditional OPF Problem on IEEE-118 Bus System

The AO method was applied to the IEEE 118-bus system to demonstrate the usefulness of the suggested method on bigger-scale systems. There are 54 generators in this system. This system’s topology and data can be found in [29]. Figure 9 shows the convergence curve for the AO method on the IEEE-118 bus system. The generator’s output power is indicated in Table 4 and results from SFLA, ABC, and modified ABS were compared to the results from AO as indicated in Table 5. The executive time for 100 iterations of the proposed method in the IEEE-118 bus system was 52 min.
The results from AO as indicated in Table 5. The executive time for 100 iterations of the proposed method in the IEEE-118 bus system was 52 min.

Figure 9. Convergence curve for IEEE-118 bus system using AO.

Table 4. Generator power for IEEE-118 bus system.

| Generator Number | Output Power (MW) | Generator Number | Output Power (MW) |
|------------------|-------------------|------------------|-------------------|
| PG01             | 100               | PG65             | 119.2955          |
| PG04             | 4.4456            | PG66             | 33.4381           |
| PG06             | 15.9667           | PG69             | 34.2284           |
| PG08             | 66.05             | PG70             | 6.427             |
| PG10             | 78.7139           | PG72             | 0.0652            |
| PG12             | 7.0436            | PG73             | 6.4969            |
| PG15             | 0.0614            | PG74             | 5.0847            |
| PG18             | 0.1682            | PG76             | 0                 |
| PG19             | 3.7498            | PG77             | 1.4015            |
| PG24             | 2.7675            | PG80             | 47.1596           |
| PG25             | 6.2179            | PG85             | 0.4792            |
| PG26             | 274.1448          | PG87             | 6.6935            |
| PG27             | 0                 | PG89             | 94.5127           |
| PG31             | 5.5138            | PG90             | 1.9608            |
| PG32             | 36.8222           | PG91             | 0                 |
| PG34             | 0                 | PG92             | 0.742             |
| PG36             | 0                 | PG99             | 5.069             |
| PG40             | 5.0059            | PG100            | 34.9624           |
| PG42             | 20.1404           | PG103            | 2.6377            |
| PG46             | 0                 | PG104            | 4.3676            |
| PG49             | 17.8607           | PG105            | 0                 |
| PG54             | 0                 | PG107            | 0                 |
| PG55             | 6.8672            | PG110            | 35.7806           |
| PG56             | 0                 | PG111            | 2.0757            |
| PG59             | 15.6536           | PG112            | 6.5885            |
| PG61             | 15.5913           | PG113            | 9.335             |
| PG62             | 9.3778            | PG116            | 14.0859           |
Table 5. Result comparison for OPF IEEE-118 bus system.

| Method      | Fuel Cost USD/hr | Number of Iterations to Convergence |
|-------------|------------------|-------------------------------------|
| AO          | 47,057.09        | 100                                 |
| M-ABC [38]  | 47,823           | 100                                 |
| ABC [38]    | 48,096           | 250                                 |
| SFLA [38]   | 48,203           | 60                                  |

5.4. SCOPF Problem on IEEE-30 Bus System

Stochastic optimal power flow was applied to the modified IEEE-30 bus system by using the AO method to get optimal scheduled power by wind farms. Buses 2 and 5 of the IEEE 30-bus system were converted to wind farms with rated power 80 MW and 50 MW, respectively. The remainder of the PV buses were still the same. As a result, there were 24 control variables in total, including two control variables for wind scheduled power. Several cases were studied with different values for reserve cost (K_R) and penalty cost (K_P). Weibull PDF was used to represent wind power cost. The optimal scale and shape parameters for Weibull PDF after applying the AO method were K = 1.71 and C = 3.39 as indicated before. The overestimation cost (CR) and underestimation cost (CP) which are indicated in Equations (15) and (17) are dependent on the scheduled power by the operator. Figures 10 and 11 illustrate how the wind generation cost changes with different scheduled power by the operator for 80 MW and 50 MW wind farms, respectively. From the figures, it can be noticed that the overestimation cost increased when P_{scheduled} increased, and underestimation cost decreased when P_{scheduled} increased. Figures 10 and 11 are based on K_P = K_R = 0.01 (USD/Kwh).

![Figure 10. Wind generation cost versus scheduled power from 80 MW wind farm.](image)

![Figure 11. Wind generation cost versus scheduled power from 50 MW wind farm.](image)

We then applied SCOPF to the modified IEEE-30 bus system to obtain optimal scheduled power P2(wind) and P3(wind) for the two wind farms in order to minimize total operation cost C_T, which is indicated in Equation (18). To demonstrate the performance,
six scenarios were studied for the reserve and penalty cost coefficients ($K_P, K_R$) as indicated in Table 6.

Table 6. Optimal value for scheduled power.

| $K_R$ | $K_P$ | $P_{2,\text{Wind}}$ | $P_{5,\text{Wind}}$ | CR     | CP     | Total Cost |
|------|------|----------------------|----------------------|--------|--------|------------|
| 0.01 | 0.01 | 80                   | 50                   | 69.95  | 0      | 494.79     |
| 0.01 | 0.1  | 80                   | 50                   | 69.95  | 0      | 493.6946   |
| 0.01 | 0.2  | 80                   | 50                   | 69.95  | 0      | 492.1026   |
| 0.1  | 0.01 | 48.33                | 50                   | 183.74 | 6.28   | 714.332    |
| 0.15 | 0.01 | 34.07                | 38.39                | 152.49 | 12.45  | 780.01     |
| 0.2  | 0.01 | 27.04                | 29.48                | 125.44 | 16.78  | 813.94     |

- Scenario 1 Putting $K_P$ and $K_R$ at the minimum value of 0.01 (USD/kwh), we noticed optimal $P_{\text{scheduled}}$ for two wind farms at rated value. This is because even if the actual wind power falls short of the planned amount, purchasing power from another source is not prohibitively expensive. The share of wind farms to the power system is maximum and the share of the thermal unit is minimum which led to minimum total generation cost, the values of underestimation cost = 0 (USD/hr), overestimation cost = 69.95 (USD/hr), and total generation cost = 494.79 (USD/hr).

- Scenario 2 Keeping $K_R$ at the minimum value of 0.01 (USD/kwh) and increase $K_P$ to 0.10 (USD/kwh), we noticed optimal $P_{\text{scheduled}}$ for two wind farms still at rated value. As a result, the penalty factor does not apply in this case because acquiring power from a different source is not prohibitively expensive, even if actual wind power falls short of the projected amount. The underestimation and overestimation costs are still the same as Scenario 1.

- Scenario 3 Again, keeping $K_R$ at the minimum value of 0.01 (USD/kwh) and increasing $K_P$ to 0.20 (USD/kwh), we noticed optimal $P_{\text{scheduled}}$ for two wind farms still at rated value. As we discussed before the penalty cost does not affect the power share of the wind farms where acquiring power from a different source is not prohibitively expensive. The underestimation and overestimation costs are still the same as Scenario 1, 2.

- Scenario 4 Now, keeping $K_P$ at the minimum value of 0.01 (USD/kwh) and increasing $K_R$ to 0.10 (USD/kwh), we noticed optimal $P_{\text{scheduled}}$ for 80 MW wind farm reduces to 48.33 (MW) and is still at rated power for 50 (MW) wind farm. Now, purchasing power from another source has become more expensive than the last three scenarios which leads to a decrease in the share of wind farms and an increase in the share of thermal units. The AO method reduces $P_{2,\text{wind}}$ and increases the share of thermal units. The underestimation cost increases to 6.28 (USD/hr) because the 80 MW wind farm now not sharing its rated power. The overestimation increases to 183.74 (USD/hr) and the total generation cost increases to 714.332 (USD/hr).

- Scenario 5 Again, keeping $K_P$ at the minimum value of 0.01 (USD/kwh) and increasing $K_R$ to 0.15 (USD/kwh) to see the effect of increasing reverse cost, we noticed that optimal $P_{\text{scheduled}}$ for both wind farms decreases to $P_{2,\text{wind}} = 34.07$ (MW) and $P_{5,\text{wind}} = 38.39$ (MW). Now, purchasing power from another source has become more expensive than the last scenario so the AO method decreases the share of wind farms again and increases the share of thermal units. The underestimation cost increases to 12.45 (USD/hr) because the wind farms decrease their power share. The overestimation cost becomes 152.49 (USD/hr) and the total generation cost increases to 780.0 (USD/hr).

- Scenario 6 Finally, keeping $K_P$ at the minimum value of 0.01 (USD/kwh) and increasing $K_R$ again to 0.20 (USD/kwh). The share of wind farms decreases more than the last two scenarios where $P_{2,\text{wind}} = 27.04$ (MW) and $P_{5,\text{wind}} = 29.48$ (MW) and
the share of thermal units increases to compensate for the decrease in wind power. The underestimation cost increases again to 16.78 (USD/hr) due to a reduction in wind power-sharing. The overestimation cost becomes 125.44 (USD/hr) and the total generation cost increases to 813.94 (USD/hr).

From Table 6 and the above 6 scenarios, it can be concluded that to get the best optimal operation for a power system that includes wind energy, the reverse cost should be as minimal as possible like the first three scenarios which make scheduled power from a wind farm equal to rated power, which minimizes sharing of thermal units and maximizes sharing from wind farms that leading to minimize total generation cost.

Figure 12 shows the variation of optimal scheduled power by two wind farms versus changes in reserve cost. It can be noticed that when $K_R$ increases, the optimum scheduled power for the two wind farms decreases as the reduction in $P_{\text{scheduled}}$ requires less spinning reserve. Thermal generators compensate for lower outputs from energy farms when $K_R$ increases, which increases total generation cost as indicated in Figure 13. In Figure 14, it is shown that total generation cost changes very slightly when penalty cost increases as $P_{\text{scheduled}}$ of two wind farms is still the same at rated power.

![Figure 12. Optimal scheduled power (MW) versus $K_R$.](image1)

![Figure 13. Total generation cost versus $K_R$.](image2)

![Figure 14. Total generation cost versus $K_P$.](image3)
Figures 15 and 16 show how the values of $K_R$ and $K_P$ affect optimal $P_{scheduled}$ and wind generation cost for 50 MW wind farm. It can be noticed from Figure 15 that the optimal $P_{scheduled}$ decreases with increasing of $K_R$, and it can be seen from Figure 16 that optimal $P_{scheduled}$ increases with increasing of $K_P$.

**Figure 15.** Wind generation cost versus scheduled power with changes of $K_R$.

**Figure 16.** Wind generation cost versus scheduled power with changes of $K_P$.

6. Conclusions

In this work, the AO method was used to solve the OPF problem to optimize the generation cost of thermal generators. The performance of the proposed method was tested on standard IEEE-30, IEEE-57, and IEEE-118 bus systems and results were compared with other existing optimization techniques from the literature. The results showed that AO method produced the lowest fuel cost among the other algorithms under comparison, which proves the validity and accuracy of the AO method. Then, the OPF problem with wind generation sources was investigated and exploited. Wind speed was simulated using Weibull PDF and the wind power was expressed as a random variable by applying a transformation to wind speed PDF. The optimal parameters of Weibull PDF were estimated using the AO method to get the best fitting of wind speed data, which minimizes RMSE.

SCOPF was applied using the AO method on a modified IEEE-30 bus system which was combined with two wind energy sources. The cost function for SCOPF was made up using two penalty costs: overestimation cost and underestimation cost. In order to demonstrate the effects of penalty costs, six scenarios for penalty and reverse cost were considered in the SCOPF study. From the six scenarios, it was noticed that the best optimal operation occurred when the reverse cost was minimal, which means that the AO method schedules wind farms at their maximum power. The AO method proved accuracy and validation in solving OPF and SCOPF incorporating wind energy sources.

The importance of the study is applying a novel optimization method on a hybrid thermal-wind system using real wind speed data. Six scenarios of this work were applied to study the effect of changing overestimation and underestimation cost coefficients in the optimal scheduled wind power from wind farms, the thermal unit generated power, the resultant fuel, and wind generation costs. Moreover, this work presented a study to
demonstrate the effect of changing scheduled wind power on the wind generation cost at different values of overestimation and underestimation cost coefficients. Finally, we conclude that the AO method proves superiority in solving complicated OPF problems in a large system with penetration of wind energy. In future work, multi-objective optimal power with wind energy penetration will be solved to optimize more objective functions along with generation cost.

Author Contributions: A.K.K. and M.A.A. designed the problem under study, performed the simulations, and obtained the results; M.R.E. analyzed the obtained results; A.K.K. and M.A.A. wrote the paper, which was further reviewed by A.Y.A. and A.E.-S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

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

References

1. Dommel, H.W.; Tinney, W.F. Optimal power flow solutions. IEEE Trans. Power Appar. Syst. 1968, 87, 1866–1876. [CrossRef]
2. Aoki, K.; Kanezashi, M. A modified Newton method for optimal power flow using quadratic approximated power flow. IEEE Trans. Power Appar. Syst. 1985, 104, 2119–2125. [CrossRef]
3. Sun, D.I.; Ashley, B.; Brewer, B.; Hughes, A.; Tinney, W.F. Optimal power flow by Newton approach. IEEE Trans. Power Appar. Syst. 1984, 103, 2864–2880. [CrossRef]
4. Torres, G.L.; Quintana, V.H. An interior-point method for nonlinear optimal power flow using voltage rectangular coordinates. IEEE Trans. Power Syst. 1998, 13, 1211–1218. [CrossRef]
5. Khamees, A.K.; Badra, N.; Abdelaziz, A.Y. Optimal power flow methods: A comprehensive survey. Int. J. Electr. Eng. Syst. 2016, 9, 2228–2239.
6. Kumari, M.S.; Maheswarapu, S. Enhanced genetic algorithm based computation technique for multi-objective optimal power flow solution. Int. J. Electr. Power Energy Syst. 2010, 32, 736–742. [CrossRef]
7. Khunkitti, S.; Siritaratiwat, A.; Premrudeepreechacharn, S.; Chatthaworn, R.; Watson, N.R. A Hybrid DA-PSO Optimization Algorithm for Multiobjective Optimal Power Flow Problems. Energies 2018, 11, 2270. [CrossRef]
8. Basu, M. Multi-objective optimal power flow with FACTS devices. Energy Convers. Manag. 2011, 52, 903–910. [CrossRef]
9. Singh, R.P.; Mukherjee, V.; Ghoshal, S. Particle swarm optimization with an aging leader and challengers algorithm for the solution of optimal power flow problem. Appl. Soft Comput. 2016, 40, 161–177. [CrossRef]
10. Attia, A.-F.; El Sehiemy, R.A.; Hasanien, H.M. Optimal power flow solution in power systems using a novel Sine-Cosine algorithm. Int. J. Electr. Power Energy Syst. 2018, 99, 331–343. [CrossRef]
11. Li, S.; Gong, W.; Wang, L.; Yan, X.; Hu, C. Optimal power flow by means of improved adaptive differential evolution. Energy 2020, 198, 117314. [CrossRef]
12. Yong, T.; Lasseter, R. Stochastic optimal power flow: Formulation and solution. In Proceedings of the 2000 Power Engineering Society Summer Meeting (Cat. No. 00CH37134), Seattle, WA, USA, 16–20 July 2000; IEEE Access: Piscataway, NJ, USA, 2000; Volume 1, pp. 237–242.
13. Nowdeh, S.A.; Davoudkhani, I.F.; Moghaddam, M.J.H.; Najmi, E.S.; Abdelaziz, A.Y.; Ahmadi, A.; Razavi, S.E.; Gandoman, F.H. Fuzzy multi-objective placement of renewable energy sources in distribution system with objective of loss reduction and reliability improvement using a novel hybrid method. Appl. Soft Comput. 2019, 77, 761–779. [CrossRef]
14. Yong, L.; Tao, S. Economic dispatch of power system incorporating wind power plant. In Proceedings of the 2007 International Power Engineering Conference (IPEC 2007), Singapore, 3–6 December 2007.
15. Ortega-Vazquez, M.A.; Kirschen, D.S. Assessing the impact of wind power generation on operating costs. IEEE Trans. Smart Grid 2010, 1, 295–301. [CrossRef]
16. Hetzer, J.; David, C.Y.; Bhattachari, K. An economic dispatch model incorporating wind power. IEEE Trans. Energy Converv. 2008, 23, 603–611. [CrossRef]
17. Dubey, H.M.; Pandit, M.; Panigrahi, B. Hybrid flower pollination algorithm with time-varying fuzzy selection mechanism for wind integrated multi-objective dynamic economic dispatch. Renew. Energy 2015, 83, 188–202. [CrossRef]
18. Kusakana, K. Optimal scheduled power flow for distributed photovoltaic/wind/diesel generators with battery storage system. IET Renew. Power Gener. 2015, 9, 916–924. [CrossRef]
19. Sallama, K.M.; Hossain, M.A.; Elsayed, S.S.; Chakrabortty, R.K.; Ryan, M.J. Optimal Power Flow Considering Intermittent Solar and Wind Generation using Multi-Operator Differential Evolution Algorithm. Energy Fuel Technol. 2021. Available online: https://www.preprints.org/manuscript/202103.0228/v1 (accessed on 12 August 2021).
20. Biswas, P.P.; Suganthan, P.; Amaratunga, G.A. Optimal power flow solutions incorporating stochastic wind and solar power. Energy Convers. Manag. 2017, 148, 1194–1207. [CrossRef]
21. Khan, I.U.; Javaid, N.; Gamage, K.A.A.; Taylor, C.J.; Baig, S.; Ma, X. Heuristic Algorithm Based Optimal Power Flow Model Incorporating Stochastic Renewable Energy Sources. *IEEE Access* 2020, 8, 148622–148643. [CrossRef]  
22. Abdollahi, A.; Ghadimi, A.A.; Miveh, M.R.; Mohammadi, F.; Jurado, F. Optimal power flow incorporating FACTS devices and stochastic wind power generation using krill herd algorithm. *Electronics* 2020, 9, 1043. [CrossRef]  
23. Sulaiman, M.H.; Mustaffa, Z. Solving optimal power flow problem with stochastic wind–solar–small hydro power using barnacles mating optimizer. *Control Eng. Pract.* 2021, 106, 104672. [CrossRef]  
24. National Centers for Environmental Information. Available online: https://www.ncdc.noaa.gov/ (accessed on 8 August 2021).  
25. Weibull, W. A statistical distribution function of wide applicability. *J. Appl. Mech.* 1951, 18, 293–297. [CrossRef]  
26. Abualigah, L.; Yousri, D.; Elaziz, M.A.; Ewees, A.A.; Al-Qaness, M.A.; Gandomi, A.H. Aquila Optimizer: A novel meta-heuristic optimization Algorithm. *Comput. Ind. Eng.* 2021, 157, 107250. [CrossRef]  
27. Spera, D.A. *Wind Turbine Technology*; ASME Press: New York, NY, USA, 1994.  
28. Bowden, G.; Barker, P.R.; Shestopal, V.O.; Twidell, J.W. The Weibull distribution function and wind power statistics. *Wind Eng.* 1983, 7, 85–98.  
29. Zimmermann, R.D.; Murillo-Sánchez, C.E.; Gan, D. Matpower. PSERC. [Online]. 1997. Available online: http://www.pserc.cornell.edu/matpower (accessed on 8 August 2021).  
30. Wei, H.; Sasaki, H.; Kubokawa, J.; Yokoyama, R. An interior point nonlinear programming for optimal power flow problems with a novel data structure. *IEEE Trans. Power Syst.* 1998, 13, 870–877. [CrossRef]  
31. Khamees, A.K.; El-Rafei, A.; Badra, N.; Abdelaziz, A.Y. Solution of optimal power flow using evolutionary-based algorithms. *Int. J. Eng. Sci. Technol.* 2017, 9, 55–68. [CrossRef]  
32. Sayah, S.; Zehar, K. Modified differential evolution algorithm for optimal power flow with non-smooth cost functions. *Energy Convers. Manag.* 2008, 49, 3036–3042. [CrossRef]  
33. Bouzeboudja, H.; Chaker, A.; Allali, A.; Naama, B. Economic dispatch solution using a real-coded genetic algorithm. *Acta Electrotech. Et Inform.* 2005, 5, 4.  
34. Abido, M. Optimal power flow using tabu search algorithm. *Electr. Power Compon. Syst.* 2002, 30, 469–483. [CrossRef]  
35. Shilaja, C.; Ravi, K. Optimal power flow using hybrid DA-APSO algorithm in renewable energy resources. *Energy Procedia* 2017, 117, 1085–1092. [CrossRef]  
36. Chalermchiarbha, S.; Ongsakul, W. Stochastic weight trade-off particle swarm optimization for nonconvex economic dispatch. *Energy Convers. Manag.* 2013, 70, 66–75. [CrossRef]  
37. Le Anh, T.N.; Vo, D.N.; Ongsakul, W.; Vasant, P.; Ganesan, T. Cuckoo optimization algorithm for optimal power flow. In Proceedings of the 18th Asia Symposium on Intelligent and Evolutionary Systems, Bangkok, Thailand, 22–25 November 2015; Springer: Berlin/Heidelberg, Germany, 2015; Volume 1.  
38. Khorsandi, A.; Hosseinian, S.; Ghaizanfari, A. Modified artificial bee colony algorithm based on fuzzy multi-objective technique for optimal power flow problem. *Electr. Power Syst. Res.* 2013, 95, 206–213. [CrossRef]