



Article Optimal Power Flow Solution of Power Systems with Renewable Energy Sources Using White Sharks Algorithm

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Abstract: Modern electrical power systems are becoming increasingly complex and are expanding at an accelerating pace. The power system's transmission lines are under more strain than ever before. As a result, the power system is experiencing a wide range of issues, including rising power losses, voltage instability, line overloads, and so on. Losses can be minimized and the voltage profile can be improved when energy resources are installed on appropriate buses to optimize real and reactive power. This is especially true in densely congested networks. Optimal power flow (OPF) is a basic tool for the secure and economic operation of power systems. It is a mathematical tool used to find the instantaneous optimal operation of a power system under constraints meeting operation feasibility and security. In this study, a new application algorithm named white shark optimizer (WSO) is proposed to solve the optimal power flow (OPF) problems based on a single objective and considering the minimization of the generation cost. The WSO is used to find the optimal solution for an upgraded power system that includes both traditional thermal power units (TPG) and renewable energy units, including wind (WPG) and solar photovoltaic generators (SPG). Although renewable energy sources such as wind and solar energy represent environmentally friendly sources in line with the United Nations sustainable development goals (UN SDG), they appear as a major challenge for power flow systems due to the problems of discontinuous energy production. For overcoming this problem, probability density functions of Weibull and Lognormal (PDF) have been used to aid in forecasting uncertain output powers from WPG and SPG, respectively. Testing on modified IEEE-30 buses' systems is used to evaluate the proposed method's performance. The results of the suggested WSO algorithm are compared to the results of the Northern Goshawk Optimizer (NGO) and two other optimization methods to investigate its effectiveness. The simulation results reveal that WSO is more effective at finding the best solution to the OPF problem when considering total power cost minimization and solution convergence. Moreover, the results of the proposed technique are compared to the other existing method described in the literature, with the results indicating that the suggested method can find better optimal solutions, employ less generated solutions, and save computation time.

Keywords: white shark optimizer; optimal power flow; thermal power; renewable energy; generation cost

1. Introduction

Currently, the electrical power system has become a more complex network that is growing day by day. The electrical grid's transmission system has more risk than it has ever had previously. As a result, for congested networks, the power system faces numerous issues such as increased power loss, voltage instability, line overloading, and so on. As



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Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). a result, the optimum power flow (OPF) problem has become a more significant tool for electrical power system design and management. OPF is necessary for operators of electricity grids in effectively meeting consumers' energy demands and ensuring the power system's reliability [1]. Carpentier was the first to formulate the problem of optimum power flow in [2].

Several different objectives are considered in the OPF problem, including the total cost of power generating fuel, total power loss, maximum pollutant emissions, voltage stability and voltage deviation, and others. Furthermore, OPF problems must adhere to a variety of physical and operational constraints imposed by hardware and network constraints, such as generator active and reactive power, transformer tap, bus voltage, and transmission line capacity limits. In general, OPF control variables include the generators' active power, the voltage magnitude in the generating bus, transformer tap settings, and other variables, such as the reactive power of the generators [3]. OPF problems have been solved with a wide range of traditional optimization tools, mostly based on derivatives and gradient methods, such as non-linear and quadratic programming [4].

In this article, in addition to using modern methods, non-conventional or renewable energy sources have also been introduced into the power system, by which the OPF problem has been solved. Although these systems are characterized by sustainability and low-pollutant emissions, they represent a major challenge in solving the problems of OPF due to the uncertain nature of these systems. In the literature, several approaches for modelling uncertainties in load demand and renewable energy sources (RESs) have been proposed. Ref. [5] provides a G-best guided artificial bee colony to improve OPF findings with uncertain power sources. In [6], the authors created a modified bacterial foraging algorithm that integrates a mixed system for thermal, wind, and a static compensator to obtain the best OPF solution (STATCOM). The authors of [7] used a particle swarm optimization approach to investigate the OPF problem with and without wind power, simulating uncertain wind power generation with the Weibull distribution function. Other methods include Tabu search algorithm (TS) [8], modified honeybee mating optimization (MHBMO) [9], mathematical programming algorithm (MPA) [10], gravitational search algorithm (GSA) [11], artificial bee colony algorithm (ABCA) [12], modified imperialist competitive algorithm (MICA) [13], cuckoo optimization algorithm (COA) [14], and grey wolf optimization algorithm (GOA) [15].

Ref. [16] addressed an OPF problem with a detailed model of uncertainty in solar and wind power based on a mix of success history-based differentiated development and the superior of feasible solution (SF), a constraints management method. The authors of [17] examined the OPF problem and its numerous formulations in depth. Traditional energy sources, renewable energy sources, and energy storage technologies are used to research the OPF. The enhanced slime mold algorithm (ESMAOPF), instead of the conventional SMA, for solving the optimal power flow problem, was presented by the authors in [18]. Gaussian bare-bones imperialist competitive algorithm (GBBICA) [19], improved electromagnetism-like mechanism algorithm (IELMA) [20], improved colliding bodies optimization algorithm (ICBOA) [21], differential search algorithm (DSA) [22], stud krill herd algorithm (SKHA) [23], and shuffle frog leaping algorithm (SFLA) [24] have also been developed for solving the OPF issue in the literature. The essential contributions of this paper can be summarized as follows:

- The white shark optimizer (WSO), a novel meta-heuristic algorithm proposed in [25], is employed to efficiently solve the OPF issue in this study;
- The proposed algorithm is developed to test an IEEE-30 bus system with double wind farms and a single solar photovoltaic to determine if it can discover the best results for the OPF problem using renewable power in both unpractical and real scenarios;
- Three other application algorithms, Smell Agent Optimization (SAO) [26], Northern Goshawk Optimization (NGO) [27], and Pelican Optimization Algorithm (POA) [28], are used in the proposed model in order to compare their outputs to those of WSO;

- The four algorithms were prepared to find the optimal solution after 10 runs and 300 iterations. The best three solutions are selected among the ten to be presented in the results and used to study the convergence for each case in terms of reaching the optimal solution for scheduling and using power from different power plants;
- In addition, the solutions of the proposed method are compared with the method (ESMAOPF) that the authors used in [18], where the enhanced slime mold algorithm was used instead of conventional SMA, for solving the optimal power flow problem. The comparison showed the success of WSO over ESMAOPF in terms of achieving a lower total generating cost.

The next sections make up the remainder of this paper. The OPF problem's mathematical model and its related constraints are shown in Section 2. Section 3 introduces the WPG and SPG uncertainty output models. Section 4 develops a new proposal for applying WSO to OPF, which contains the uncertain RES. For each of the four methods under examination, Section 5 presents simulation results from a range of real-world studies wherein WSO was used to solve the OPF problem under the same conditions as other algorithms to see if it was legitimate. In Section 6, the conclusions of this work are stated. Finally, future work is presented in Section 7.

2. Optimal Power Flow Mathematical Models

OPF is a general optimization problem that aims to optimize a certain objective function through the optimal setting of control variables within operational, equality, and inequality constraints.

The optimization problem can be formulated as follows:

$$Minimize F(x, u) \tag{1}$$

Subject to

$$g_i(x,u) = 0 \ i = 1, 2, 3, \dots, m$$
 (2)

$$h_j(x,u) \le 0 \ j = 1, 2, 3, \dots, n$$
 (3)

where *F* is the objective function, *x* is the state variable's vector, *u* is the control variable's vector, g_i , h_j are the equality and inequality constraints, and *m*, *n* are the number of equality and inequality constraints.

The state variables (dependent variables) can be expressed in a vector form as follows:

$$x = |P_{G1}, V_{L1} \dots V_{LNPO}, Q_{G1} \dots Q_{GNPV}, S_{TL1} \dots S_{TLNTL}|$$

$$\tag{4}$$

where P_{G1} is the generated power of slack bus, V_L is the voltage of load bus. NPQ is the number of load buses. Q_G is the reactive power output of generators. NPV is the number of generation buses. S_{TL} is the apparent power flow in transmission line. N_{TL} is the number of transmission lines.

The control variables (independent variables) can be expressed in a vector as follows:

$$u = [P_{G2} \dots P_{GNG}, V_{G1} \dots V_{GNG}, Q_{C1} \dots Q_{CNC}, T_1 \dots T_{NT}]$$
(5)

where P_G is the output active power of generator, NG is the number of generators. VG is the voltage of the generation bus. Q_C is the injected reactive power of the shunt compensator. NC is the number of shunt compensators. T is the tap setting of transformers. NT is the number of transformers.

Table 1 lists the basic specifications of the upgraded IEEE-30 bus network. Figure 1 shows a single line diagram of the modified network. Three main types of power-generating resources are included in the upgraded network: constant-output thermal energy generators (TG), variable-output solar photovoltaics generator (SPG), and variable-output wind farms (WPG). This volatility in photovoltaic/wind production should be compensated by

combining all power stations and backup power, resulting in a total cost of production that includes all generator operating costs, reserve expenses, and penalty costs.

Table 1. The basic specifications of the modified IEEE network with 30 buses [1].

Items	Quantity	Details
Buses	30	[29]
Branches	41	[29]
Thermal Generators (TG1, TG2, TG3)	3	Bus 1 (Swing), Bus 2, and Bus 8.
Wind Generators (WPG1, WPG2)	2	Bus 5 and bus 11.
Solar PV (SPG)	1	Bus 13.
Control variables	11	The planned power of five generators (TG2, TG3, WPG1, WPG2 and SPG) as well as six generating hus voltages
Connected load	-	283.4 MW, 126.2 MVAR
Allowable voltage range for load buses	24	[0.95–1.05] p.u.



Figure 1. Upgraded IEEE-30 bus power system.

2.1. Thermal Power Generation Cost

TPGs are powered by fossil fuels. The fossil fuel cost (USD/h) of all TPGs can be calculated using Equation (6).

$$C_{T0}(P_{TG}) = \sum_{i=1}^{N_{TG}} a_i + b_i P_{TGi} + c_i P_{TGi}^2$$
(6)

where the cost coefficients of the *i*th thermal power unit generating power *P* are *a*, *b*, and *c*. The network's total number of thermal generators is N_{TG} . Because valve point loading influences the overall cost of fuel, accounting for it results in a more accurate and reliable cost, as shown in Equation (7).

$$C_T(P_{TG}) = \sum_{i=1}^{N_{TG}} a_i + b_i P_{TGi} + c_i P_{TGi}^2 + \left| d_i \times \sin\left(e_i \times \left(P_{TGi}^{\min} - P_{TGi}\right)\right) \right|$$
(7)

Table 2 lists all of the cost and emission coefficients for the TPGs that are utilized in cost calculations. These were taken, as in ref. [30], to be used in the calculations of the total cost of generation.

Table 2. Cost and emission coefficients of thermal power generators [18].

Gen.	Bus	а	b	с	1	т	α	β	γ	ω	μ	P ⁰ _{TGi} (MW)	DR _i (MW)	UR _i (MW)
TG1	1	0	2	0.00375	18	0.037	4.091	-5.554	6.49	0.0002	6.667	99.211	20	15
TG2	2	0	1.75	0.0175	16	0.038	2.543	-6.047	5.638	0.0005	3.333	80	15	10
TG3	8	0	3.25	0.00834	12	0.045	5.326	-3.55	3.38	0.002	2	20	8	4

2.2. Direct Cost of Wind and Solar Photovoltaic

There is no need for fossil fuels in wind and solar power generators. If the independent system operator (ISO) owns the plants, the cost function may not exist unless ISO wants to attribute a payback cost to the initial expenditure for the plants or assign this as a maintenance and renewal cost.

The concept specifies the total costs of wind electricity produced by *j*th wind generator in relation to its planned power in (8).

$$C_{w,j} = h_j P_{w,j} \tag{8}$$

Similarly, the direct cost of the *k*th solar power photovoltaics power generation is as follows:

$$C_{s,k} = g_k P_{s,k} \tag{9}$$

2.3. Cost Estimation for Wind Power with Uncertain Output

Two situations are possible because of the discontinuous generation of wind power. When wind plant's output power falls short of the expected output power, the first scenario occurs. This is referred to as an overvaluation of power level. In this case, the system operator employs spinning reserve to maintain a consistent source of electricity to customers. In order to fix this problem, committed reserve power units need to pay reserve costs. For the *j*th WPG, this cost can be calculated as follows:

$$C_{rw.j}(P_{ws.j} - P_{wa.j}) = K_{rw.j}(P_{ws.j} - P_{wa.j}) = K_{rw.j} \int_{0}^{P_{ws.j}} (P_{ws.j} - P_{w.j}) \times f_w(P_{w.j}) dP_{w.j}$$
(10)

The second situation occurs when the wind power plant's output exceeds the expected the output power value. This is referred to as an underestimate of output power. As a result,

if the leftover power cannot be consumed by reducing the output power of conventional generators, it will be lost. In this case, ISO is obligated to pay a penalty cost linked with the remaining power. For the *j*th WPG, this cost can be calculated as follows:

$$C_{pw.j}(P_{wa.j} - P_{ws.j}) = K_{pw.j}(P_{wa.j} - P_{ws.j}) = K_{pw.j} \int_{P_{ws.j}}^{P_{wr.j}} (P_{w.j} - P_{ws.j}) \times f_w(P_{w.j}) dP_{w.j}$$
(11)

2.4. Cost Estimation for Solar Power with Uncertain Output

Solar energy, as with wind energy, has an unpredictable and intermittent production. Undervaluation and overvaluation of the photovoltaic electrical output should be addressed in the same way that the undervaluation and overvaluation of the wind electrical output are addressed in theory. To make computations easier, penalty and reserve simulation methods are developed using the methods provided in ref. [31]. This is due to the fact that solar irradiation following a lognormal PDF [32], which is notably different from the Weibull PDF applied for wind velocity distribution.

The solar PV power plant *k*th surplus cost is computed by the following formula:

$$C_{rs,k}(P_{ss,k} - P_{sa,k}) = K_{rs,k}(P_{ss,k} - P_{sa,k}) = K_{rs,k} \times f_s(P_{sa,k} < P_{ss,k}) \times [(P_{ss,k} - Ex(P_{sa,k} < P_{ss,k}))]$$
(12)

The calculation for the penalization cost related to the *k*th solar photovoltaic power is shown in Equation (13).

$$C_{ps.k}(P_{sa.k} - P_{ss.k}) = K_{ps.k}(P_{sa.k} - P_{ss.k}) = K_{ps.k} \times f_s(P_{sa.k} > P_{ss.k}) \times [(Ex(P_{sa.k} > P_{ss.k}) - P_{ss.k})]$$
(13)

2.5. Emission

Using traditional energy sources to generate electricity is widely known for releasing greenhouse gases into the atmosphere. SO_x and NO_x are two of these hazardous gases, and their emissions rise in tandem with the amount of power generated by traditional power producers. Equation (14) illustrates the link between emissions in (t/h) and output power (in p.u. MW):

$$E = \sum_{i=1}^{N_{TG}} \left[\left(\alpha_i + \beta_i P_{TG,i} + \gamma_i P_{TGi}^2 \right) \times 0.01 + \omega_i e^{(\mu_i P_{TGi})} \right]$$
(14)

where α_i , β_i , γ_i , ω_i , and μ_i are emission coefficients. Table 2 shows the values of emission coefficients connected to the thermal power generator, which are close to the numbers in [30].

As shown in Equations (7)–(13), the optimum objective for OPF is generated by combining all cost function models. Emission cost is ignored in the objective function (F1). The objective function (F2) is created, incorporating emission cost, to elucidate the variation in generation scheduling while considering an emission, as shown in Equation (15).

$$F1 = C_T(P_{TG}) + \sum_{j=1}^{N_{WG}} \begin{bmatrix} h_j P_{w,j} + K_{rw,j} (P_{ws,j} - P_{wa,j}) \\ + K_{pw,j} (P_{wa,j} - P_{ws,j}) \end{bmatrix} + \sum_{j=1}^{N_{SG}} \begin{bmatrix} g_k P_{s,k} + K_{rs,k} (P_{ss,k} - P_{sa,k}) + K_{ps,k} (P_{sa,k} - P_{ss,k}) \end{bmatrix}$$
(15)

Minimize the second objective function.

$$F2 = F1 + E \tag{16}$$

Several system equality and inequality requirements apply to the above-mentioned OPF objective functions.

2.6. Equality Constraints

Power flow balancing is subject to equality requirements, which requires that produced real and reactive power are equivalent to the demand and the losses of the network. The following are the equality constraints [16]:

$$P_{Gi} = P_{Di} + V_i \sum_{i=1}^{NB} V_J \left[G_{ij} \cos(\delta_{ij}) + B_{ij} \sin(\delta_{ij}) \right] \forall i \in NB$$
(17)

$$Q_{Gi} = Q_{Di} + V_i \sum_{i=1}^{NB} V_J \left[G_{ij} \sin(\delta_{ij}) + B_{ij} \cos(\delta_{ij}) \right] \forall i \in NB$$
(18)

 $\Delta_{ij} = (\delta_i - \delta_j)$ denotes the angle of voltage difference, NB = network number, P_{Di} , Q_{Di} , P_{Gi} , and Q_{Gi} denote active and reactive components of load demand and generation, respectively, for any of the energy resources, whether traditional or renewable. G_{ij} and B_{ij} , = conductance and susceptance, respectively.

2.7. Inequality Constraints

The operational limits of components and equipment in a power system are represented by the inequality constraints. Safety limitations on transmission lines and load buses are among these constraints.

2.7.1. Generator's Constraints

Equations (19)–(21) indicate the active power generation limits for thermal generators, wind generators, and solar PV generators, respectively.

$$P_{TGi}^{\min} \le P_{TGi} \le P_{TGi}^{\max} \dots \forall i \in N_{TG}$$
(19)

$$P_{ws,j}^{\min} \le P_{ws,j} \le P_{ws,j}^{\max} \tag{20}$$

$$P_{ss,k}^{\min} \le P_{ss,k} \le P_{ss,k}^{\max} \tag{21}$$

The reactive power limits of all generators employing the same configuration are represented by Equations (22)–(24). N_G stands for the number of generator buses or generators.

$$Q_{TGi}^{\min} \le Q_{TGi} \le Q_{TGi}^{\max} \dots \forall i \in N_{TG}$$
(22)

$$Q_{ws,j}^{\min} \le Q_{ws,j} \le Q_{ws,j}^{\max}$$
(23)

$$Q_{ss,k}^{\min} \le Q_{ss,k} \le Q_{ss,k}^{\max} \tag{24}$$

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max} \tag{25}$$

The voltage constraints on generator buses are shown in Equation (25).

2.7.2. Safety Constraints

Equation (26) depicts the voltage limits applied to load buses, whereas (27) depicts transmission line capacity constraints.

$$V_{L_P}^{\min} \le V_{L_P} \le V_{L_P}^{\max} \tag{26}$$

$$S_{Lq} \le S_{L_q}^{\max} \tag{27}$$

where V_{Lp} is line voltage limits subjected to PQ buses (load buses). When studying the OPF problem, power losses (P_{loss}) in transmission lines and voltage deviation (V_d) are additional

and important elements to consider. It is impossible to prevent power losses from power transmission lines due to their persistent resistance. The grid's P_{loss} is determined by:

$$P_{loss} = \sum_{i=1}^{NL} \sum_{j \neq 1}^{NL} \left(G_{ij} \times \left[V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_{ij}) \right] \right)$$
(28)

where V_i and V_j represent the voltages applied to buses *i* and *j*, respectively. The voltage deviation (V_d) in a power system specifies how far load bus voltages diverge from the nominal voltage level, which is typically 1 p.u. The voltage deviation (V_d) is a measurement of how far load bus voltages deviate from a nominal voltage value, which is commonly 1 p.u. V_d indicates the voltage quality of the power system.

$$V_d = \sum_{p=1}^{NL} |V_{LP} - 1|$$
(29)

3. Estimation of the Uncertain Power of Renewable Energy Sources

3.1. Renewable Energy Source Probability Distribution

For wind turbine mean power estimates, ref. [31] indicated that the wind speed distribution follows the Weibull probability density function (PDF). According to the Weibull PDF, the probability of wind speed is given by:

$$f_{v}(v) = \left(\frac{k}{c}\right) + \left(\frac{v}{c}\right)^{(k-1)} e^{-(v/c)^{k}} \text{ for } 0 < v < \infty$$
(30)

v = wind speed in m/s, k represents form coefficient, c represents the scale coefficient. The Weibull PDF:

$$M_{wbl} = c \times \Gamma\left(1 + k^{-1}\right) \tag{31}$$

where Γ is gamma function which is defined as follows:

$$\Gamma(x) = \int_0^\infty e^{-t} t^{x-1} dt \tag{32}$$

In this paper, as shown in Figure 1, the IEEE system with 30 buses has been updated by changing two thermal generators on buses 5 and 11 with two wind turbine generators, as well as replacing thermal generators at bus 13 with Solar PV. Table 3 shows the settings for the Weibull scale (c) and shape (k) variables that are used. Figure 2 shows the results of the Weibull fitting for wind frequency distributions. They were obtained by an 8000-iteration Monte Carlo simulation [16].

Table 3. The PDF parameters for wind and solar PV power plants.

Wind Power Farm						Solar Power Plan	t
Wind Power Generator	No. of Turbines	Rated Power (MW)	Weibull PDF Parameters	Weibull Mean, M _{wbl}	Rated Power (MW)	Lognormal PDF Parameters	Lognormal
1 (at bus 5)	25	75	K = 2, c = 9	$v = 7.976 \ (m/s)$	E(a + b + a + 12)	$u = 6 \delta = 0.6$	D 402 M/ 2
2 (at bus 11)	20	60	K = 2, c = 10	v = 8.862 (m/s)	50 (at bus 15)	$\mu = 0, v = 0.0$	$K = 483 \text{ W} / \text{m}^2$



Figure 2. The Weibull PDF Distribution for wind speed: (a) WPG1, bus 5, and (b) WPG2, bus 11.

The output of a photovoltaic generator is determined by sun irradiation (R); it has a log-normal probability distributer (PDF) [32]. The probability of sun irradiation (R) is provided by the following log-normal PDF:

$$f_T(R) = \frac{1}{R\sigma\sqrt{2\pi}} e^{\{\frac{-(\ln x - \mu)^2}{2\sigma^2}\}} \text{ for } R > 0$$
(33)

Figure 3 depicts the frequency distribution and lognormal probability for solar irradiation derived from an 8000-iteration Monte Carlo simulation. Table 3 shows the lognormal PDF parameter values that are used.





3.2. Power Models for Wind Generator and Solar Photovoltaic

The new IEEE-30 bus power system has two WPGs, as previously described in Figure 1. WPG1 is connected to bus 5 and has a total active power of 75 megawatts. WPG2 is connected to bus no. 11 and has a total power of 60 MW. The relationship between output power and wind speed is expressed as:

$$P_{w}(v) \begin{cases} 0, & for \ v \leq v_{in} \ and \ v > v_{out} \\ P_{wr}\left(\frac{(v-v_{in})}{(v_{r}-v_{in})}\right) & for \ v_{in} \leq v \leq v_{r} \\ P_{wr} & for \ v_{r} \leq v \leq v_{out} \end{cases}$$
(34)

 v_r = rated speed, v_{out} = cut-out speed, v_{in} = cut-in speed of the wind turbine. P_{wr} = rated output power according to the product datasheet for (Enercon E82-E4) wind turbine. The generation of solar PV energy is measured in terms of solar radiation (*R*) [33].

$$P_{S}(v) \begin{cases} P_{Sr}\left(\frac{R^{2}}{R_{std}T_{c}}\right) & for \ 0 < R < T_{c} \\ P_{Sr}\left(\frac{R}{R_{std}}\right) & for \ R \ge T_{c} \end{cases}$$
(35)

The histogram in Figure 4 represents the solar PV plant's stochastic output power. The line depicts the planned power that the solar generator is meant to send to the network. It is important to remember that planned production solar power is a changeable value.



Figure 4. Available power distribution of solar PV (MW) at bus 13.

As a result, the ISO and the developer of the solar photovoltaic plant have entered into a power sharing arrangement.

Equations (36) and (37) are utilized in the model to calculate the overvaluation and undervaluation costs of solar PV electricity, respectively:

$$C_{rs.k}(P_{ss} - P_{sa}) = K_{rs}(P_{ss} - P_{sa}) = K_{rs}\sum_{n=1}^{N^{-}} [P_{ss} - P_{sn-}] * fsn-$$
(36)

$$C_{sp.k}(P_{sav} - P_{ss}) = K_{ps}(P_{sa} - P_{ss}) = K_{ps} \sum_{n=1}^{N^+} [P_{sn+} - P_{Ss}] * fsn+$$
(37)

The shortfall and excess power are represented by P_{Sn} and P_{Sn+r} respectively.

4. The Basis of the Proposed Method's Development

This study introduces the white shark optimizer (WSO), which is a new optimization algorithm inspired by white sharks' scholastic behaviors when hunting in the wild to assist them in the ocean depths. The authors in [25] developed this algorithm within aim to solve real-world optimization problems that are difficult to solve using current techniques, both limited and unrestricted.

Many types of problems demand more flexibility than WSO can supply; hence, the suggested WSO provides several benefits for complex optimization problems, including its predicted adaptability in dealing with various types of optimization problems.

WSO's mathematical approach makes it applicable to a wide range of engineering optimization problems, particularly those with high dimensionality. Its simplicity and resilience should allow it to identify the global optimum problems to challenging optimization problems quickly and precisely [25].

4.1. White Shark Optimizer (WSO)

The mathematical models of the proposed WSO to solve the OPF problem, which were built to define the actions of white sharks when hunting, are detailed in this section. This involves tracking and killing prey.

4.2. Initialization of WSO

As shown in the following 2d matrix, a population of n WSO, in a d search domain space, with the location of every shark indicating a suggested solution to these problems [25].

$$w = \begin{bmatrix} w_1^1 & w_2^1 & \dots & w_d^1 \\ w_1^2 & w_2^2 & \dots & w_d^2 \\ \vdots & \vdots & \ddots & \vdots \\ w_1^n & w_2^n & \dots & w_d^n \end{bmatrix}$$
(38)

where *w* represents the location of all sharks in the search domain, *d* denotes the number of choice variables for a given task.

4.3. Speed of Movement towards Prey

A white shark recognizes a prey's location by hearing a pause in the waves as the prey moves, as illustrated in Equation (39).

$$u_{k+1}^{i} = \mu \left[u_{k}^{i} + p_{1} \left(w_{gbest_{k}} - w_{k}^{i} \right) \times c_{1} + p_{2} \left(w_{best}^{v_{k}^{i}} - w_{k}^{i} \right) \times c_{2} \right]$$
(39)

i = 1, 2, ..., n = index of size *n*, and the new speed vector of the *i*th shark is denoted by v_{k+1}^i . v^i is the *i*th index vector of sharks attaining the optimal location, as indicated by Equation (40).

$$v = \lfloor n \times rand \ (1, n) \rfloor + 1 \tag{40}$$

where *rand* (1, n) = randomly generated numbers having a distribution in the domain [0, 1].

$$p_1 = p_{\max} + (p_{\max} - p_{\min}) \times e^{-(4k/k)^2}$$
(41)

$$p_2 = p_{\min} + (p_{\max} - p_{\min}) \times e^{-(4k/k)^2}$$
(42)

where k = current, K = maximum iterations, and p_{min} and p_{max} denote the starting and subordinate velocities for white shark motion. After a thorough examination, the values of p_{min} and p_{max} were discovered to be 0.5 and 1.5, respectively.

$$\mu = \frac{2}{\left|2 - \tau - \sqrt{\tau^2 - 4\tau}\right|}\tag{43}$$

 τ signifies the accelerating factor, which is 4.125, as was discovered after extensive research [25].

4.4. Movement in the Direction of the Optimal Prey

In this context, the position updating strategy defined in Equation (44) was used to describe the behavior of white sharks as they move towards prey.

$$w_{k+1}^{i} = \begin{cases} w_{k}^{i} \to \oplus w_{0} + u.a + l.b; rand < mv \\ w_{k}^{i} + u_{k}^{i} / f; rand \ge mv \end{cases}$$
(44)

Equations (45) and (46), respectively, define *a* and *b* as binary vectors.

$$a = \operatorname{sgn}\left(w_k^i - u\right) > 0 \tag{45}$$

$$b = \operatorname{sgn}\left(w_k^i - 1\right) < 0 \tag{46}$$

$$w_0 = \oplus(a, b) \tag{47}$$

where \oplus is the result of a bitwise xor operation. The frequency of a white shark's wavy motion and the multitude of times the shark attacks its target are described by Equations (48) and (49), respectively.

$$f = f_{\min} + \frac{f_{\max} - f_{\min}}{f_{\max} + f_{\min}}$$
(48)

$$mv = \frac{1}{(a_0 + e^{(k/2 - k)/a_1})} \tag{49}$$

where a_0 and a_1 are location constants that are used for control exploration and exploitation.

4.5. Movement in the Direction of the Optimal Shark

Sharks can keep their place in front of the most advantageous one who is near to the target. Equation (50) shows how this phenomenon is expressed.

$$w'_{k=1}^{i} = w_{gbestk} + r_1 \overrightarrow{D}_w \operatorname{sgn}(r_2 - 0.5) r_3 < S_s$$
 (50)

 w'_{k+1} = upgraded shark's location, sgn($r_2 - 0.5$) returns 1 or -1 to modify the search path, r_1 , r_2 , and $r_3 = rand$. No. in the domain of [0, 1], D_w = length for both target and shark, is given in Equation (51). S_s is a parameter that has been proposed to reflect the power of white sharks, as specified in Equation (52).

$$\vec{D}_w = \left| rand \times \left(w_{gbest} - w_k^i \right) \right| \tag{51}$$

$$S_s = \left| 1 - e^{\left(-a_2 \times k/k \right)} \right| \tag{52}$$

where a_2 is a location factor used to regulate exploration and exploitation. Algorithm 1, the pseudo code of WSO [25].

Alg	orithm 1: Code summarizing the iterative optimization process of WSO.
1:	Initialize the parameters of the problem
2:	Initialize the parameters of WSO
3:	Randomly generate the initial positions of WSO
4:	Initialize the velocity of the initial population
5:	Evaluate the position of the initial population
6:	while $(k < K)$ do
7.	Update the parameters v , p_1 , p_2 , μ , a , b , w_0 , f , m_v and S_s using Equations (40)–(43), (45)–(49) and (52),
7.	respectively.
8:	for $i = 1$ to n do
9:	$v_{k+1}^{i} = \mu \left[v_{k}^{i} + p_{1} \left(w_{gbestk} - w_{k}^{i} \right) \times c_{1} + p_{2} \left(w'^{vk}_{best} - w_{k}^{i} \right) \times c_{2} \right]$
10:	end for
11:	$\mathbf{for} \ \mathbf{i} = 1 \ \mathbf{to} \ n \ \mathbf{do}$
12:	if rand < mv then
13:	$w^i{}_{k+1} = w^i{}_k \cdot - \oplus w_0 + u \cdot a + l \cdot b$
14:	else
15:	$w^i{}_{k+1} = w^i{}_k + v^i{}_k/f$
16:	end if
17:	end for
18:	$\mathbf{for}\ \mathbf{i} = 1\ \mathbf{to}\ n\ \mathbf{do}$
19:	if $rand \leq S_s$ then
20:	$\vec{D}_{w} = rand \times (w_{abest} - w_{L}^{i}) $

Alg	orithm 1: Cont.
21:	if $i == 1$ then
22:	$w_{k+1}^i = w_{ebestk} + r_1 \vec{D}_w \operatorname{sgn}(r_2 - 0.5)$
23:	else
24:	$w'_{k=1}^{i} = w_{gbestk} + r_1 \vec{D}_w \operatorname{sgn}(r_2 - 0.5)$
25:	$w_{k-1}^i = \frac{w_k^i + w_{k+1}^{i}}{2 \times rand}$
26:	end if
27:	end if
28:	end for
29:	Adjust the position of the white sharks that proceed beyond the boundary
30:	Evaluate and update the new positions
31:	k = k + 1
32:	end while

33: Return the optimal solution obtained so far

4.6. Fish School Behavior

The following formula was presented to define white shark fish school behavior:

$$w_{k=1}^{i} = \frac{w_{k}^{i} + w_{k+1}^{\prime i}}{2 \times rand}$$
(53)

where *rand* denotes a uniformly distributed random number in the range [0, 1]. As proven by Equation (52), the sharks are able to adjust their location based on the optimal shark who has arrived at the optimal location, which is very near to target. The end location of sharks is someplace ideally around the prey in the search space. The collective behavior of WSO is identified by fish action and the movement of sharks to the greatest shark, and improved local and global search capabilities.

4.7. Implementation and Analysis of WSO

During the process of function evaluations, white sharks always aim to move closer to the globally optimum solution. The reason is that white sharks are more likely to find a best answer by exploring and utilizing the search space's surroundings. The location of the optimal sharks and their target is used to accomplish this ability. As a result, sharks are can constantly investigate and contribute to potentially prey-rich locations. The major steps of the algorithm in Algorithm 1 can be used to summaries the pseudo code of WSO.

WSO starts the optimization process by creating white shark positions at random, according to the algorithm in Algorithm 1. At each function execution, Equation (44) has been used to update the location of white sharks. WSO's simulated steps will return them to the search region if they pass outside of the search space. To discover the white shark with the best fit value, a fitness process is used to estimate the optimal solution, with the fitness criterion being regenerated for every process estimation. The best stance for a white shark hunting prey is said to be the most suited solution [25].

5. Simulation Results and Comparison

In this section, the upgraded IEEE-30 bus power system is studied to find the optimal solution for the PF problem. The results of using the WSO to reduce the total power generation cost are provided and explained. Northern Goshawk Optimizer (NGO) and two alternative optimization algorithms, SAO and POA, are also applied to verify the validity of WSO. The optimization algorithms are simulated using MATLAB (2018b) on a computer that has the following specifications: Intel[®] Core^(TM) i5-3210M processor, 2.5 GHz, and 8 GB of RAM.

The four algorithms were prepared to find the optimal solution after 10 runs and 300 iterations. The statistical results in Table 4 show that WSO and NGO's values are always close to the optimal solution, with a standard deviation of 0.6722 and 0.3766, respectively. However, WSO is the best of the four in terms of convergence time, with an average of 524 s for one run. Figure 5 shows the boxplots for distributing the statistics of



the results to all the methods, it's clear that the boxplots of the WSO technique are narrow compared to the other techniques, where POA in Figure 5c contains one suspected outlier.

Figure 5. The boxplots for all algorithms for the statistical results: (**a**) boxplot for WSO, (**b**) boxplot for NGO, (**c**) boxplot for POA (red + = suspected outliers), (**d**) boxplot for SAO, (**e**) boxplots for all.

Table 4. The results of total generation cost and statistical results for the proposed WSO algorithm and other recent algorithms.

The Results of Total Generation Cost for 10 Runs and 300 Iterations								
	WSO	NGO	POA	SAO				
1st Run	782.6698	782.313	782.8485	907.0226				
2nd Run	783.7659	782.9944	785.3441	846.683				
3rd Run	782.5018	782.5711	782.5089	843.0099				
4th Run	781.8318	782.1243	782.4893	905.917				
5th Run	781.7552	781.8438	782.1865	872.6064				
6th Run	782.3621	782.2253	782.3702	851.711				
7th Run	781.733	782.9235	782.2994	811.187				
8th Run	783.3357	782.1109	782.4652	887.9602				
9th Run	782.4915	782.1162	782.9073	949.768				
10th Run	782.1152	782.1276	783.033	823.5738				

The Statistical Results of Total Generation Cost for 10 Runs and 300 Iterations							
	WSO	NGO	POA	SAO			
Best	781.733	781.8438	782.1865	811.187			
Worst	783.7659	782.9944	785.3441	949.768			
Mean	782.4562	782.335	782.8452	869.9439			
Std	0.6722	0.3766	0.9205	42.9133			
Average time of one run (s)	524	1024	1610	1790			

Table 4. Cont.

The best three solutions were selected among the ten to be presented in the results and to study the convergence for each case in terms of reaching the lowest value of the total power generation cost by finding the optimal solution for scheduling and using power from different power plants according to Equation (15). The simulation results for all four algorithms were as follows:

5.1. White Shark Optimizer (WSO)

The white shark optimizer (WSO) was implemented and used to obtain an optimal solution to the problem of scheduling the generation power to minimize the total generation cost by performing 10 runs each time with 300 iterations. Among all 10 runs, three were given preference: the seventh, the fifth, and the fourth, achieving a generation cost of 781.733, 781.755, and 781.831 USD/h, respectively, as shown in Figure 6a. Thus, the seventh run was chosen to be the best performer at the lowest total generating cost of 781.733 USD/h.



Figure 6. The WSO results for the best 3 runs: (**a**) characteristics of convergence for the best three runs of WSO algorithm; (**b**) profile voltages of load buses for the best three runs of WSO.

The voltages of the load buses play a significant part in the OPF investigation. As a result, dealing with the voltage constraints of load buses is critical. The buses of load in the IEEE system with 30 buses must have voltages between [0.95: 1.05] p.u. Where Figure 6b shows the voltage levels in the load buses for the best three runs of WSO. It is obvious from the figure that all voltages for the load buses fall within the safe limits for operation.

5.2. Northern Goshawk Optimization (NGO)

As the same in WSO, the NGO was implemented to minimize the total generation cost by doing 10 runs each time with 300 iterations. Among of all 10 runs, three were given preference: the fifth, the fourth, and the first, achieving a generation cost of 781.843, 782.124, and 782.313 USD/h, respectively, as shown in Figure 7a. Thus, the fifth run was chosen to be the best performer at the lowest total generating cost of 781.843 USD/h. Figure 7b provides load bus voltage characteristics for the best three runs of NGO. It is obvious from the figure that all voltages for the load buses fall within the safe limits for operation.



Figure 7. The NGO results for the best 3 runs: (**a**) characteristics of convergence for the best three runs of NGO algorithm; (**b**) profile voltages of load buses for the best three runs of NGO.

5.3. Pelican Optimization Algorithm (POA)

As the same in WSO and NGO, the POA was implemented to minimize the total generation cost by doing 10 runs each time with 300 iterations. Among of all 10 runs, three were given preference: the fifth, seventh and third, achieving a generation cost of 782.186, 782.299, and 782.508 USD/h, respectively, as shown in Figure 8a. Thus, the fifth run was chosen to be the best performer at the lowest total generating cost of 782.186 USD/h. Figure 8b provides load bus voltage characteristics for the best three runs of POA.



Figure 8. The POA results for the best 3 runs: (**a**) characteristics of convergence for the best three runs of POA algorithm; (**b**) profile voltages of load buses for the best three runs of POA.

It is obvious from the figure that all voltages for the load buses fall within the safe limits for operation.

5.4. Smell Agent Optimization (SAO)

As in the previous cases, the SAO was implemented to minimize the total generation cost by doing 10 runs each time with 300 iterations. Among of all 10 runs, three were given preference: the seventh, sixth and second, achieving a generation cost of 811.187, 851.711, and 846.683 \$/h, respectively, as shown in Figure 9a. Thus, the seventh run was chosen to be the best performer at the lowest total generating cost of 811.187 USD/h. Figure 9b provides load bus voltage characteristics for the best three runs of SAO. It is obvious from the figure that all voltages for the load buses almost fall within the safe limits for operation.



Figure 9. The SAO results for the best 3 runs: (**a**) characteristics of convergence for the best three runs of SAO algorithm; (**b**) profile voltages of Load buses for the best three runs of SAO.

5.5. Comparison of the Results of Different Optimization Techniques and Discussion

In this section, the results of WHO and the other three algorithms mentioned above, in addition to ESMAOPF in [18], have been compared to verify the validity of WSO to optimize schedule power generation from all power plants connected to the upgraded system in order to achieve the minimum total power cost. Table 5 records optimal schedule power and overall generation cost for all algorithms including ESMA [18], reactive power (Q), control variables, and other essential estimated values.

Table 5. Detail simulation results of the different	optimization al	gorithms (in addi	tion to	ESMA)	ļ.
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Control Variables	Min	Max	WSO	NCO	POA	\$40	ESMA [19]
Control variables	IVIIII	IVIAX	W30	NGO	IUA	SAU	ESIMA [10]
PTG1 (MW)	50	140	134.9165	134.9041	134.9076	113.404	134.9143
PTG2 (MW)	20	80	27.57455	29.36321	26.6666	26.64171	27.688
PTG3 (MW)	10	35	10.00492	10.0109	10.02834	18.70488	10.0125
PwG1 (MW)	0	75	43.05681	43.73514	43.27867	46.21081	43.5782
PwG2 (MW)	0	60	36.12732	36.71591	38.29961	43.67977	37.4508
PsG1 (MW)	0	50	37.52105	34.45914	35.97858	39.90458	35.5275
V1 (p.u)	0.95	1.1	1.070752	1.071513	1.072656	1.017665	1.0699
V2 (p.u)	0.95	1.1	1.056697	1.056241	1.056156	1.004626	1.0568
V5 (p.u)	0.95	1.1	1.034903	1.034296	1.029249	1.095148	1.0334
V8 (p.u)	0.95	1.1	1.0401	1.041903	1.043762	1.105398	1.088
V11 (p.u)	0.95	1.1	1.099687	1.099531	1.099998	1.084872	1.097
V13 (p.u)	0.95	1.1	1.056971	1.054164	1.049375	1.109471	1.052
Parameters	Min	Max	WSO	NGO	POA	SAO	ESMA [18]
QTG1 (MVAr)	-20	150	-4.43953	-1.8199	1.326721	-6.41329	-6.588
QTG2 (MVAr)	-20	60	14.28056	10.49797	12.42993	-3.53766	16.436
QTG3 (MVAr)	-15	40	23.31959	22.32038	17.85702	35	40
QwG1 (MVAr)	-30	35	35.7025	39.00757	40	40	21.181
QwG2 (MVAr)	-25	30	30	30	30	30	29.548
QwG1 (MVAr)	-20	25	18.19068	17.01745	15.63321	25	16.472
Total power cost (USD/h)			781.733	781.8438	782.1865	811.1871	781.9375
Emissions (t/h)			1.763241	1.761466	1.7625	0.510854	1.7629
P_{loss} (MW)			5.80114	5.788415	5.759369	5.145789	5.7715
V_d (p.u)			0.468569	0.465172	0.44752	0.68291	0.45868

The convergence curves of the various (OPF) optimizer applications applied in this investigation are illustrated in Figure 10. The success and effectiveness of the algorithm (WSO) among the rest of the others in reaching the optimal solution for scheduling the generated power and reducing the total generation cost is clear from the results in this figure.



Figure 10. Convergence curves for various optimization applications.

It is clear from zooming in on the convergence curves that the curve of WSO reached its lowest value between the 290 and 300 iteration and achieved the lowest cost of 781.733 USD/h. While the algorithm NGO achieved a total generation cost of 781.844 USD/h, followed by the algorithm POA at a cost of 782.186 %/h; finally, SAO achieved a cost of 811.187 USD/h. Moreover, by comparing the results of the total generation cost presented in Table 5, it becomes clear that the efficiency of the algorithm WSO is better than ESMA, which the authors used in [18], and in which it achieved a cost of 791.937 USD/h, while both WSO and NGO achieved a lower cost.

The effectiveness of WSO can be shown in the simulation results when compared to ESMA in [18] and other optimization techniques used for NGO, POA, and SAO. As a result, the suggested method has a higher solution quality and several advantages, including easier application, fewer control parameters, less time spent adjusting control parameter values, faster convergence to optimal solutions, and more steady search capabilities.

Table 5 also shows the bus voltage values for the generation buses, which are six buses. Figure 11 shows the voltage values for all buses of loads for all the applications of the previously mentioned optimization algorithms. It becomes clear that most of the efforts are within the acceptable limits.



Figure 11. Load buses' voltages for the different optimization algorithms.

Figure 12 shows the results of all optimization algorithms for optimizing the power cost of thermal, wind, and solar power plants. The lack of output power from wind and solar PV sources is compensated by thermal power generators. As a result, the cost of a thermal power generation system rises, as shown in the cost characteristic of a thermal power source (TPG) in Figure 12, whereas the cost of WPG and SPG steadily reduces to a certain level.



Figure 12. Costs variation of all generators for all algorithms.

Figure 13a depicts the optimal results of the planned powers of thermal, wind, and solar power generators. When sun irradiation or wind speed are great, ideal planned power from wind and solar PV facilities improves because raising the planned produced power helps to minimize the penalization cost. The planned reactive power from all power plants is depicted in Figure 13b. In several cases, the generators TG3 and WG2 run at their maximum reactive power (Q) capability by following the constraints of reactive power (Q), as indicated in Table 5. As a result, whenever an optimization technique is implemented, the limitations on Q must be considered.





6. Conclusions

In this study, a novel meta-heuristic optimization algorithm, so called the white shark optimizer (WSO), has been proposed for providing an optimal solution for the OPF problem in the IEEE-30 bus power system which has been upgraded with unpredictable wind and solar photovoltaic energy sources. Weibull and lognormal probability density functions (PDFs) were used to describe the uncertain outputs of wind and solar energy sources, respectively. The WSO and another three optimization algorithms have been used to optimize the scheduling of power generation with both traditional thermal power plants and renewable power sources to minimize the total electricity generation cost. To verify the WSO performance, the results of the proposed algorithm has been compared with the results obtained from the other three optimizers (NGO, POA, and SAO).

The results showed the effectiveness of the WSO algorithm in solving the OPF problem and in achieving the minimum total generation cost (781.733 USD/h) among the other three algorithms and ESMA, where the overall power produced cost from all power plants was optimally minimized. Moreover, the results of WSO and the other three application algorithms also reveal that the environmental and safety constraints are in the system operator's stated boundaries. In addition, the results were compared with the ESMA method that the authors used in [18], and the comparison showed the success of WSO over ESMAOPF in terms of achieving a lower total generating cost.

As a result, the algorithm has advantages over ESMA and the other three proposed algorithms in this paper, such as simpler application, fewer control parameters, less time spent tuning control parameter values, faster convergence to optimal solutions, fewer generated new solutions, shorter simulation time, and more stable search ability. Therefore, we can conclude that WSO is a powerful method for dealing with optimal power flow problems where optimization of single objectives is required.

7. Future Work

- Apply the proposed methods to solve optimal power flow in a larger power system;
- Incorporate more renewable energy sources (such as hydropower plants) into the larger power system;
- Apply of more than one case study that takes into account factors other than the minimization of generation cost, such as emissions, carbon tax, reserve cost, penalty cost, and the dynamic nature of generating facilities' control;
- Studying multi-objective optimal power flow in a power system with renewable energy sources.

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