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ESMA-OPF: Enhanced Slime Mould Algorithm for Solving Optimal Power Flow Problem

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Abstract: In this work, an enhanced slime mould algorithm (ESMA) based on neighborhood dimension learning (NDL) search strategy is proposed for solving the optimal power flow (OPF) problem. Before using the proposed ESMA for solving the OPF problem, its validity is verified by an experiment using 23 benchmark functions and compared with the original SMA, and three other recent optimization algorithms. Consequently, the ESMA is used to solve a modified power flow model including both conventional energy, represented by thermal power generators (TPGs), and renewable energy represented by wind power generators (WPGs) and solar photovoltaic generators (SPGs). Despite the important role of WPGs and SPGs in reducing CO₂ emissions, they represent a big challenge for the OPF problem due to their intermittent output powers. To forecast the intermittent output powers from SPGs and WPGs, Lognormal and Weibull probability density functions (PDFs) are used, respectively. The objective function of the OPF has two extra costs, penalty cost and reserve cost. The penalty cost is added to formulate the underestimation of the produced power from the WPGs and SPGs, while the reserve cost is added to formulate the case of overestimation. Moreover, to decrease CO₂ emissions from TPGs, a direct carbon tax is added to the objective function in some cases. The uncertainty of load demand represents also another challenge for the OPF that must be taken into consideration while solving it. In this study, the uncertainty of load demand is represented by the normal PDF. Simulation results of ESMA for solving the OPF are compared with the results of the conventional SMA and two further optimization methods. The simulation results obtained in this research show that ESMA is more effective in finding the optimal solution of the OPF problem with regard to minimizing the total power cost and the convergence of solution.

Keywords: optimal power flow; slime mould algorithm; renewable energy sources; uncertainty

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1. Introduction

Optimal power flow (OPF) has been a crucial tool for power systems' operation in an efficient and secured way since its inception in 1962 by Carpentier [1]. OPF is employed for many objectives in power system such as minimizing total generation cost, reducing CO₂ emissions, minimizing power losses, and maintaining voltage stability, as well as maintaining the optimal settings of control variables. This process is commonly constrained by set of restrictions which have to be satisfied, such as power generator capability, bus voltage, transmission line capacity, and any other technical constraints. Conventional OPF problem deals with fossil fuels power stations. When the penetration level of solar photovoltaic (PV) and wind power into the grid increases, it is necessary to study OPF problem taking into consideration the uncertain nature of these sources. In addition to

the uncertainty in generation side, there is also uncertainty in the load side that can occur due to several factors such as the induction of electric vehicles [2,3]. Without taking this uncertainty into our consideration, realized load values will differ from the forecast values of load demand, and consequently, the planned operational state through the OPF might be non-optimal.

In the literature, different methods have been provided to model renewable energy sources (RESs) and load demand uncertainties. G-best guided artificial bee colony is provided in [4] to enhance OPF results that are verified in the past literature with similar experimental conditions. In [5], the authors proposed a modified bacteria foraging algorithm to find the best solution of OPF problem that incorporates with a mixture model for thermal power, wind power, and static synchronous compensator (STATCOM). In [6], the authors studied the OPF problem with and without wind power using the particle swarm optimization algorithm, and the Weibull distribution function was used to model the uncertain wind power generation. Reference [7] provided an OPF problem with comprehensive modeling of uncertainty in solar and wind power depending on a combination between success history-based adaptation of differential evolution and the superiority of feasible solution (SF) that is a methodology for handling constraints. The authors in [8] provided a full review of the OPF problem in its diverse formulas. OPF with traditional sources, RESs, and energy storage systems was studied. In [9], a genetic algorithm, the two-point estimation method, and Monte Carlo simulation were applied to solve the OPF problem including RESs and an energy storage system, and the uncertain nature of wind, solar, and load demand was handled by a new strategy. In [10], the authors presented a novel heap optimization algorithm (HOA) to find the optimal solution of the power flow. HOA-based OPF methodology is flexible and applicable compared with that achieved by using the genetic algorithm. A security constrained OPF (SCOPF) problem was studied in [11] incorporating wind energy and responsive demands. Gaussian distribution and Beta distribution were chosen for modeling the load demand and wind power, respectively. The authors assume operating costs, emission, and security indices as single and multi-objective functions. In [12], the OPF problem was studied incorporating several flexible AC transmission system (FACTS) devices with uncertain wind power and uncertain load demand. The uncertain output power of RESs and load demand are handled in [13] by providing uncertainty probability distribution to optimize the conventional generation. In [14], the authors developed an OPF model with stochastic wind power depending on the Lévy coyote optimization algorithm.

The Slime mould algorithm (SMA) is used in many research studies to solve the OPF problem and the economic dispatch. Like many metaheuristic optimization algorithms, SMA suffers from premature convergence during solving complex nonlinear problems. It also suffers from the insufficient precision of optimization and slow optimization speed, which may lead to easily falling into a local optima [15–18].

In this paper, an enhanced slime mould algorithm (ESMA) is proposed to overcome the drawbacks of the original SMA for solving the OPF problem. The ESMA is proposed by modifying the original SMA based on the neighborhood dimension learning (NDL) search strategy. The validity of the ESMA was tested experimentally through 23 benchmark functions. It was compared with the original (SMA) [19] and three other recent optimization algorithms, including the colony predation algorithm (CPA) [20], the aquila optimizer (AO) [21], and Runge Kutta (RUN) algorithm [22]. A modified IEEE 30-bus system incorporating one SPG and two WPGs was used for testing the validity of the proposed algorithm in reaching the optimal solution for OPF problem with uncertain renewable energy sources (RESs), variable load demand and ramp rate effect of TPGs, in addition to some theoretical cases. Two other optimization algorithms: black widow optimization algorithm (BWOA) [23], and moth swarm algorithm (MSA) [24], in addition to SMA [19] were applied for solving the OPF problem with the same conditions to verify the validity of ESMA comparing to other algorithms. The remaining sections of this research are organized as follows: Section 2 presents the mathematical modeling and

the associated system constraints that are applied on the objective functions of the OPF problem. Then, Section 3 provides the modeling of the uncertain output of WPG and SPG. Section 4 presents the ESMA to solve the OPF problem incorporating the uncertain RESs. In Section 5, simulation results are provided including several practical case studies with the four applied algorithms. Finally, conclusions of this paper are presented in Section 6.

2. Problem Formulation

TPGs have constant power outputs, while WPGs and SPG have variable power outputs that must be balanced with the aid of the energy mix of all involved generators and the reserve power, thus the total power cost consists of the operation costs for all the involved power generators, penalty cost, and reserve cost. In this subsection, the cost models of all power generators involved in the objective function of the OPF is performed as follows.

2.1. Cost Model of TPGs

Fossil fuel is used to operate TPGs. Equation (1) shows how to calculate the fossil fuel cost (\$/h) of all TPGs.

$$C_{FF} = \sum_{i=1}^{N_{TPG}} a_i + b_i P_{TPG,i} + c_i P_{TPG,i}^2 \quad (1)$$

The valve-point loading has an impact on the total fuel cost, so taking it into consideration will give more realistic and precise cost as shown in (2).

$$C_{FF} = \sum_{i=1}^{N_{TPG}} a_i + b_i P_{TPG,i} + c_i P_{TPG,i}^2 + \left| d_i * \sin \left(e_i * \left(P_{TPG,i}^{min} - P_{TPG,i} \right) \right) \right| \quad (2)$$

All coefficients of cost and emission for the TPGs that are used in cost calculations are recorded in Table 1.

Table 1. Cost and emission Coefficients for TPGs [25].

Gen.	Bus	a	B	c	d	e	α	β	γ	ω	μ	P_{TPGi}^0 (MW)	Dr_i (MW)	Ur_i (MW)
TPG1	1	0	2	0.00375	18	0.037	4.091	−5.554	6.49	0.0002	6.667	99.211	20	15
TPG2	2	0	1.75	0.0175	16	0.038	2.543	−6.047	5.638	0.0005	3.333	80	15	10
TPG3	8	0	3.25	0.00834	12	0.045	5.326	−3.55	3.38	0.002	2	20	8	4

2.2. Direct Power Cost of SPG and WPGs

When private parties have the ownership of SPG or WPG, independent system operators (ISO) will pay an amount of money proportional to the contractually scheduled output powers.

In this concept, the direct cost of wind power produced from the j th WPG in proportion to its scheduled power has been provided in (3).

$$C_{dw,j} = P_{sw,j} * h_j \quad (3)$$

Following the same method, the direct cost of the k th SPG can be modelled by

$$C_{ds,k} = P_{ssl,k} * g_k \quad (4)$$

2.3. Cost Assessment for Uncertain Wind Power Output

One of the most challenging characteristics of wind energy is its intermittent output, so two situations might arise. The first one happens if the actual output power from the WPG is lower than the anticipated power output. This means that there is an overestimation of the output of WPGs. In this case, ISO uses the spinning power reserved for maintaining the reliability of the supplied power to its consumers.

To overcome this situation, reserve cost is need to committee reserve power units. This cost can be determined for the j th WPG as follows:

$$C_{rw,j}(P_{ws,j} - P_{wav,j}) = K_{rw,j}(P_{ws,j} - P_{wav,j}) = K_{rw,j} \int_0^{P_{ws,j}} (P_{ws,j} - P_{w,j}) \times f_w(P_{w,j}) dP_{w,j} \quad (5)$$

The other situation happens if the actual output of the WPG has a value greater than expected. This means that there is an underestimation in the output power. Then, there will be a remaining power that will be dissipated if there is not any possibility to decrease the output of TPGs. In this regard, ISO should pay a penalty cost according to the rest power. This cost can be determined for the j th WPG by

$$C_{pw,j}(P_{wav,j} - P_{ws,j}) = K_{pw,j}(P_{wav,j} - P_{ws,j}) = K_{pw,j} \int_{P_{ws,j}}^{P_{wav,j}} (P_{w,j} - P_{ws,j}) \times f_w(P_{w,j}) dP_{w,j} \quad (6)$$

2.4. Cost Assessment for Uncertain Solar PV Power

Solar output power has also intermittent and uncertain nature, so the same concept followed to deal with underestimation and overestimation scenarios of output power of WPGs will be followed with solar energy. In this work, solar radiation will follow lognormal probability density functions (PDF) [26], which differs from the Weibull PDF followed by wind power.

Thus, for making calculations simpler, the models of penalty cost and reserve cost are designed in a similar concept used in [27].

Section 3 provides more details for stochastic wind and solar power calculation.

For the k th SPG, the reserve cost is given as follows:

$$\begin{aligned} C_{rs,k}(P_{ss,k} - P_{sav,k}) &= K_{rs,k}(P_{ss,k} - P_{sav,k}) \\ &= K_{rs,k} \times f_s(P_{sav,k} < P_{ss,k}) \times [(P_{ss,k} - \text{Ex}(P_{sav,k} < P_{ss,k}))] \end{aligned} \quad (7)$$

Equation (8) shows the formulation of the penalty cost corresponding to the k th SPG.

$$\begin{aligned} C_{ps,k}(P_{sav,k} - P_{ss,k}) &= K_{ps,k}(P_{sav,k} - P_{ss,k}) \\ &= K_{ps,k} \times f_s(P_{sav,k} > P_{ss,k}) \times [(\text{Ex}(P_{sav,k} > P_{ss,k}) - P_{ss,k})] \end{aligned} \quad (8)$$

2.5. Emissions and Carbon Tax

Producing electricity through burning fossil fuels is one of the most emitting sources of greenhouse gases into the surrounding environment. Emissions are determined in (t/h) as follows:

$$E = \sum_{i=1}^{N_{TPG}} [(\alpha_i + \beta_i P_{TPG,i} + \gamma_i P_{TPG,i}^2) \times 0.01 + \omega_i e^{(\mu_i P_{TPG,i})}] \quad (9)$$

The emission coefficients values of the TPGs provided in Table 1 are the same as in [25] with only small modification in the value of μ of the TPG connected at bus 1.

Due to the dangerous effects associated with climate change phenomena, regulators in many countries tend to set severe rules on power sectors to diminish the carbon emission (carbon footprint) [28] by applying a carbon tax which is one of the most useful methods for pushing investors towards renewable energy projects. The emission cost (\$/h) is determined by

$$C_E = C_{tax} E \quad (10)$$

2.6. Objective Functions of the OPF

The objective function (F1) of the OPF include all the previously presented cost models from (2) to (8). F1 neglects the cost of emissions, while another objective function (F2) is proposed with considering the cost of emissions to study its impact on the generation scheduling. F2 is expressed with the same cost models used in F1 in addition to the cost of emissions provided in (9) and (10).

Hence, the objective is to minimize F1 shown in (11):

$$F1 = C_{FF}(P_{TPG}) + \sum_{j=1}^{N_{WPG}} [h_j P_{ws,j} + K_{rw,j} (P_{ws,j} - P_{wav,j}) + K_{pw,j} (P_{wav,j} - P_{ws,j})] \\ + \sum_{k=1}^{N_{SPG}} [g_k P_{ss,k} + (P_{ss,k} - P_{sav,k}) + K_{ps,k} (P_{slav,k} - P_{ssl,k})] \quad (11)$$

To minimize F2 that is formulated as follows:

$$F2 = F1 + C_{tax}E \quad (12)$$

Both system equality and inequality constraints are imposed on the above mentioned OPF objective functions as shown below:

2.6.1. Equality Constraints

To provide an active and reactive power balance in the system, equality constraints should be applied for the system. Equality means that these active and reactive powers should be equivalent to summation of total load and total power loss in the network. Consequently, equality constraints have been given as follows [7]:

$$P_{Gi} = P_{Di} + V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_{ij}) + B_{ij} \sin(\delta_{ij})] \quad \forall i \in NB \quad (13)$$

$$Q_{Gi} = Q_{Di} + V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\delta_{ij}) - B_{ij} \cos(\delta_{ij})] \quad \forall i \in NB \quad (14)$$

2.6.2. Inequality Constraints

Equipment and components existing in any power system operate within operating limits which are called inequality constraints. These constraints can be expressed as follows:

1. Constraints of Generators:

Equations (15)–(17) represent the limits of active power generation for TPGs, WPGs, and SPGs, respectively.

$$P_{TPG,i}^{\min} \leq P_{TPG,i} \leq P_{TPG,i}^{\max}, \quad i = 1, \dots, N_{TPG} \quad (15)$$

$$P_{ws,j}^{\min} \leq P_{ws,j} \leq P_{ws,j}^{\max}, \quad j = 1, \dots, N_{WPG} \quad (16)$$

$$P_{ssl,k}^{\min} \leq P_{ssl,k} \leq P_{ssl,k}^{\max}, \quad k = 1, \dots, N_{SPG} \quad (17)$$

Reactive power limits of all generators are showed by (18) to (20) with the same arrangement in the previous active power limits equations.

$$Q_{TPG,i}^{\min} \leq Q_{TPG,i} \leq Q_{TPG,i}^{\max}, \quad i = 1, \dots, N_{TPG} \quad (18)$$

$$Q_{ws,j}^{\min} \leq Q_{ws,j} \leq Q_{ws,j}^{\max}, \quad j = 1, \dots, N_{WPG} \quad (19)$$

$$Q_{ssl,k}^{\min} \leq Q_{ssl,k} \leq Q_{ssl,k}^{\max}, \quad k = 1, \dots, N_{SPG} \quad (20)$$

Equation (21) shows the constraints applied on generator buses voltage.

$$V_{Gi}^{\min} \leq V_{Gi} \leq V_{Gi}^{\max}, \quad i = 1, \dots, N_G \quad (21)$$

2. Security constraints:

The voltage limits applied to load buses are shown by (22), while (23) gives the capacity constraints of transmission lines.

$$V_{Lp}^{\min} \leq V_{Lp} \leq V_{Lp}^{\max}, \quad p = 1, \dots, N_B \quad (22)$$

$$S_{L_q} \leq S_{L_q}^{\max}, q = 1, \dots, N_L \quad (23)$$

The active power losses (P_{loss}) in transmission lines and voltage deviation (V_d) represent also essential parameters when studying OPF problem. It is not allowable to avoid the active power loss in transmission lines because of their inherent resistances. P_{loss} of the grid is given by

$$P_{\text{loss}} = \sum_{i=1}^{NL} \sum_{j \neq i}^{NL} \left(G_{ij} \times [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_{ij})] \right) \quad (24)$$

Equation (25) refers to the voltage deviation (V_d) which indicates how much load buses voltages, in a power system, deviate from a nominal voltage value which usually is 1 p.u. V_d gives a sign for the voltage quality of the power system.

$$V_d = \sum_{p=1}^{N_L} |V_{Lp} - 1| \quad (25)$$

3. TPGs Ramp Rate Constraints:

In practical conditions, the produced power from a thermal power generator should follow ramp rates because of the physical limitations of thermal generators. This means that to rise the generated power from a thermal generator, it follows the up-ramp rate. In contrast, to reduce the generated power, it follows the down-ramp rate. In this regard, the limits of ramp rate can be formed as follows:

$$\max(P_{TPG,i}^{\min}, P_{TPG,i}^0 - Dr_i) \leq P_{TPG,i} \leq \min(P_{TPG,i}^{\max}, P_{TPG,i}^0 + Ur_i), i = 1, \dots, N_{TPG} \quad (26)$$

The constraints of ramp-rate in OPF study are formulated as following:

$$P_{TPG,i} - P_{TPG,i}^0 \leq Ur_i, \quad \text{if generation increases}$$

$$P_{TPG,i}^0 - P_{TPG,i} \leq Dr_i, \quad \text{if generation decreases}$$

It is worth pointing out that the presence of ramp-rate limits will increase the cost of generation due to changing the new operating points of TPGs from their original operating points without ramp rate constraints. The new limits of a TPG with limits of ramp-rate should not outdo the limits ($P_{TPG,i}^{\text{low}}$) and ($P_{TPG,i}^{\text{high}}$) which are provided in (27) and (28), respectively.

$$P_{TPG,i}^{\text{low}} = \max(P_{TPG,i}^{\min}, P_{TPG,i}^0 - Dr_i) \quad (27)$$

$$P_{TPG,i}^{\text{high}} = \min(P_{TPG,i}^{\max}, P_{TPG,i}^0 + Ur_i) \quad (28)$$

3. Stochastic Solar Power, Wind Power, and Models of Uncertainty

This Weibull PDF is followed by wind speed distribution for calculations of mean power of wind turbines as presented in [5,27]. The probability (f_{v_w}) of wind speed (v_w) in (m/s) based on Weibull PDF has been provided as follows:

$$f_{v_w}(v_w) = \left(\frac{k}{c}\right) + \left(\frac{v_w}{c}\right)^{(k-1)} e^{-\left(\frac{v_w}{c}\right)^k} \text{ for } 0 < v_w < \infty \quad (29)$$

In (30), the mean of Weibull PDF is defined as follows:

$$M_{wbl} = c * \Gamma_w(1 + k^{-1}) \quad (30)$$

where, Γ_w indicates gamma function which is defined as

$$\Gamma_w(x) = \int_0^\infty e^{-t} t^{x-1} dt \quad (31)$$

In this study, the IEEE-30 bus system is modified via replacing two TPGs at bus 5 and bus 11 with two WPGs in addition to replacing TPG at bus 13 with SPG, as shown in Figure 1. Other system characteristics are provided in Table 2. The selected values of Weibull scale (c) and shape (k) parameters are mentioned in Table 3. Weibull fitting and distributions of wind frequency are provided in Figure 2. They are obtained through Monte Carlo simulation running with 8000 iterations [7].

Figure 1. Modified IEEE-30 bus power system.

Table 2. Characteristics of the modified IEEE-30 bus system [7].

Item	Number	Details
Buses	30	[29]
Branches	41	[29]
TPGs (TPG1, TPG2, and TPG3)	3	Connected at bus 1 (swing), bus 2, and bus 8
WPGs (WPG1 and WPG2)	2	Connected at bus 5 and bus 11
SPG	1	Connected at bus 13
Control variables	11	The scheduled output power of: TPG2, TPG3, WPG1, WPG2, SPG, and generator buses voltages (6 generators)
Connected load	-	283.4 MW, 126.2 MVAR
Allowable voltage range for load buses	24	[0.95–1.05] p.u.

Table 3. Weibull and lognormal PDF Parameters for WPGs and SPG.

WPG	No. of Turbines	WPGs			SPG		
		Rated Power (P_{wr})	Weibull PDF Parameters	Weibull Mean, M_{wbl}	Rated Power, P_{sr}	Lognormal PDF Parameters	Lognormal Mean, M_{logn}
1 (at bus 5)	25	75 MW	$k = 2, c = 9$	$v = 7.976$ (m/s)			
2 (at bus 11)	20	60 MW	$k = 2, c = 10$	$v = 8.862$ (m/s)	50 MW (at bus 13)	$\delta = 0.6, \mu = 6$	$I = 483$ (W/m ²)

Figure 2. Wind speed distribution for WPGs, (a) WPG1 at bus 5 ($c = 9, k = 2$) and (b) WPG2 at bus 11 ($c = 10, k = 2$).

Standard [30] regulates the design requirements of wind turbines and determines wind turbine class IA which is the highest turbulent and proper for operating at the maximum annual average wind speed of 10 m/s at hub height. Parameters of wind farm scale (c) and shape (k), have been chosen sensibly in order to keep the mean of Weibull PDF at a maximum value nearby 10. This will help in reaching both diverse and realistic geographic places for the two WPGs.

The output power from the SPG is in a direct relationship with the irradiance (I) that tracks lognormal PDF [26]. The solar irradiance probability f_I with standard deviation (σ) and mean (μ), is determined by

$$f_I(I) = \frac{1}{I\sigma\sqrt{2\pi}} \exp\left\{-\frac{(\ln x - \mu)^2}{2\sigma^2}\right\} \text{ for } I > 0 \quad (32)$$

Equation (33) presents the mean parameter of the lognormal PDF ($M_{\log n}$).

$$M_{\log n} = \exp\left(\mu + \frac{\sigma^2}{2}\right) \quad (33)$$

The distribution of frequency and lognormal probability for the solar irradiance obtained by running Monte-Carlo simulation with a sample size of 8000 iterations are shown in Figure 3. The selected values of lognormal PDF parameters are provided in Table 3.

Figure 3. Solar irradiance distribution for SPG ($\sigma \mu = 6$).

3.1. Models of Solar and Wind Powers

As previously demonstrated, there are two WPGs in the new IEEE-30 bus power system. WPG 1 is linked to bus 5, and its cumulative active power is 75 MW. WPG 2 is linked to bus 11, and its cumulative active power equals 60 MW.

The output power of a wind turbine (P_w) depends on the speed of wind (v_w) as described below [7]:

$$P_w(v_w) = \begin{cases} 0 & \text{for } v_w < v_{in,w} \text{ and } v_w > v_{out,w} \\ P_{wr} \left(\frac{v_w - v_{in,w}}{v_{r,w} - v_{in,w}} \right)^3 & \text{for } v_{in,w} \leq v_w \leq v_{r,w} \\ P_{wr} & \text{for } v_{r,w} \leq v_w \leq v_{out,w} \end{cases} \quad (34)$$

Enercon E82-E4, which is a product datasheet of wind turbine, states the different speeds of a wind turbine with rated power 3 MW as follows: $v_{in,w} = 3$ m/s, $v_{out,w} = 25$ m/s, and $v_{r,w} = 16$ m/s.

Likewise, the output power of SPG, depending on solar irradiance (I), as stated below [31]:

$$P_s(I) = \begin{cases} P_{sr} \left(\frac{I^2}{I_{std}^2 R_c} \right) & \text{for } 0 < I < R_c \\ P_{sr} \left(\frac{I}{I_{std}} \right) & \text{for } I \geq R_c \end{cases} \quad (35)$$

3.2. Probability Calculation of Wind Power

The output power of WPG, according to (34), has a discrete nature in certain wind speed regions. The value of power output will be zero when the value of v_w is below $v_{in,w}$ and above $v_{out,w}$, while the wind turbine will produce the rated value P_{wr} when the value of v_w is between $v_{r,w}$ and $v_{out,w}$. For the illustrated discrete zones, the probabilities of wind turbine output power are provided by [32]:

$$f_w(P_w)\{P_w = 0\} = 1 - \exp\left[-\left(\frac{v_{in,w}}{c}\right)^k\right] + \exp\left[-\left(\frac{v_{out,w}}{c}\right)^k\right] \quad (36)$$

$$f_w(P_w)\{P_w = P_{wr}\} = \exp\left[-\left(\frac{v_{r,w}}{c}\right)^k\right] - \exp\left[-\left(\frac{v_{out,w}}{c}\right)^k\right] \quad (37)$$

The wind turbine has a continuous output power between $v_{in,w}$ and $v_{r,w}$. Thus, for the continuous zone, the probabilities of wind turbine output power are provided by [33]

$$f_w(P_w) = \frac{k(v_{r,w} - v_{in,w})}{c^k * P_{wr}} \left[v_{in,w} + \frac{P_w}{P_{wr}} (v_{r,w} - v_{in,w}) \right]^{k-1} \times \exp\left[-\left(\frac{v_{in,w} + \frac{P_w}{P_{wr}} (v_{r,w} - v_{in,w})}{c}\right)^k\right] \quad (38)$$

3.3. Over/Underestimation Cost of Solar Power

The SPG produces a power that has a stochastic nature. Figure 4 verifies this nature, and it also defines the scheduled output power of the SPG to be transferred to the grid through the dotted line. It is important to notice that the scheduled power of SPG is an inconstant value, thus the owner of the SPG and the ISO should sign a jointly power agreement. Equations (39) and (40) are developed for calculating the cost of under- and overestimation ($C_{sp,k}$, $C_{sr,k}$) in the output power of the SPG, respectively.

$$C_{sp,k}(P_{sav} - P_{ss}) = K_{ps}(P_{sav} - P_{ss}) = K_{ps} \sum_{n=1}^{N_s^+} [P_{sn+} - P_{ss}] * f_{sn+} \quad (39)$$

$$C_{sr,k}(P_{ss} - P_{sav}) = K_{rs}(P_{ss} - P_{sav}) = K_{rs} \sum_{n=1}^{N_s^-} [P_{ss} - P_{sn-}] * f_{sn-} \quad (40)$$

where P_{sn+} and P_{sn-} indicate the surplus and shortage powers which lie on the left and right half plane of schedule power P_{ss} in Figure 4, respectively. Similarly, f_{sn+} and f_{sn-} represent relative frequencies of the happening of P_{sn+} and P_{sn-} . While N_s^+ and N_s^- are the numbers of discrete bins lie on the right and left plane of P_{ss} for the generation of PDF, respectively.

Figure 4. Real power (MW) distribution for SPG at bus 13.

4. Optimization Algorithm

4.1. Original SMA

The slime mould optimization algorithm is developed in [19]. It generally denotes the physarum polycephalum and it has been named by this name because its first classification was under category of fungus [34].

The mathematical model of SMA is as follows [19]:

4.1.1. Food Approach

Based on the smell in the surrounding air, slime mould can approach food [19]. Equations (41)–(44) is provided to imitate the contraction method:

$$\overrightarrow{X(t+1)} = \begin{cases} \overrightarrow{X_b(t)} + \overrightarrow{vb} \times (\overrightarrow{W} \times \overrightarrow{X_A(t)} - \overrightarrow{X_B(t)}), & r < p \\ \overrightarrow{vc} \times \overrightarrow{X(t)}, & r \geq p \end{cases} \quad (41)$$

$$\overrightarrow{vb} = [-a, a] \quad (42)$$

$$a = \operatorname{arctanh}\left(-\left(\frac{t}{\max_iter}\right) + 1\right) \quad (43)$$

$$p = \tanh|S(i) - DF| \quad (44)$$

The slime mould weight ($\overrightarrow{W}$) is calculated as follows:

$$\overrightarrow{W(\text{SmellIndex}(i))} = \begin{cases} 1 + r * \log\left(\frac{bF-S(i)}{bF-wF} + 1\right), & \text{condition} \\ 1 - r * \log\left(\frac{bF-S(i)}{bF-wF} + 1\right), & \text{others} \end{cases} \quad (45)$$

$$\text{SmellIndex} = \text{sort}(S) \quad (46)$$

In (45), condition means that $S(i)$ ranks the first half of population.

4.1.2. Wrap Food

The mathematical approach followed by slime mould for updating its location is as follows:

$$\overrightarrow{W(\text{SmellIndex}(i))} = \begin{cases} 1 + r * \log\left(\frac{bF-S(i)}{bF-wF} + 1\right), & \text{condition} \\ 1 - r * \log\left(\frac{bF-S(i)}{bF-wF} + 1\right), & \text{others} \end{cases} \quad (47)$$

4.1.3. Grabble Food

This mathematical approach means that if the concentration of food is high, the weight close to the region is bigger. On the other hand, if the concentration of food is little, the weight close to the region will decrease and hence it decides to turn to explore other areas.

$\overrightarrow{vb}$ represents a vector that has random values oscillates in the range of $[-a, a]$ and gradually accesses zero with the iterations increment. Values of $\overrightarrow{vc}$ have been taken in the range of $[-1, 1]$ and eventually tend towards zero. Synergistic interaction that takes place between $\overrightarrow{vb}$ and $\overrightarrow{vc}$ provides a simulation for the selective behavior of slime mould. It will keep distributing organic material for exploring other regions, even if it found a better food source, trying to find a food source with higher quality instead of using all of it in one source.

4.2. Proposed ESMA

The ESMA is developed by the neighborhood dimension learning (NDL) search strategy to improve the search abilities of the ESMA and to make the exploration-exploitation more balanced [35]. In this strategy, firstly, a radius (R_i^t) is defined by Euclidean distance (D_i) between the current location of X_i^t and the candidate location $X_{i_SMA}^{t+1}$ from the following equation:

$$R_i^t = \|X_i^t - X_{i_SMA}^{t+1}\| \quad (48)$$

Then, the neighbors of X_i^t denoted by N_i^t is formed by (49) considered to R_i^t :

$$N_i^t = \{X_j^t | D_i(X_i^t, X_j^t) \leq R_i^t, X_j^t \in \text{Pop}\} \quad (49)$$

As soon as the neighborhood of X_i^t is formed, multi neighbors learning are performed using this equation:

$$X_{i_NDL}^{t+1} = X_{i,d}^t + \text{rand} \times (X_{n,d}^t - X_{r,d}^t) \quad (50)$$

where d-th dimension of $X_{i_NDL}^{t+1}$ is computed by the d-th dimension of a random of neighbor $X_{n,d}^t$ chosen from N_i^t , and a random position $X_{r,d}^t$ from the population of slime mould.

Finally, selecting the best position is given using (51).

$$X_i^{t+1} = \begin{cases} X_{i_SMA}^{t+1}, & \text{if } f(X_{i_SMA}^{t+1}) < f(X_{i_NDL}^{t+1}) \\ X_{i_NDL}^{t+1}, & \text{otherwise} \end{cases} \quad (51)$$

The flow chart of ESMA is shown in Figure 5.

Figure 5. ESMA flow chart.

5. Results

5.1. Performance of the Proposed ESMA Algorithm

In this subsection, the effectiveness and performance of the proposed ESMA algorithm are evaluated on many benchmark functions including the best values, mean values, worst values, and standard deviation (STD) for the solutions obtained by the ESMA technique, the original SMA algorithm, and the three recent optimization algorithms, including CPA, AO, and RUN. The results of the proposed ESMA algorithm are compared with these well known optimization algorithms. These algorithms have been performed in 20 independent runs. The maximum number of iterations for each run is 200 and the population size is 50. All simulations were executed using MATLAB R2016a on a laptop including Core i5-4210U CPU@2.40 GHz of speed, and 8 GB of RAM. Figure 6 illustrates the qualitative metrics using ESMA algorithm for 11 benchmark functions including 2D views of the functions, search history, average fitness history, and convergence curve.

Figure 6. Cont.

Figure 6. Qualitative metrics of 11 benchmark functions: 2D views of the functions, search history, average fitness history, and convergence curve using ESMA algorithm. (a) F1; (b) F2; (c) F4; (d) F5; (e) F7; (f) F9; (g) F12; (h) F15; (i) F16; (j) F18; (k) F21.

The statistical results of the proposed ESMA algorithm, the original SMA algorithm, and three recent algorithms when applied for unimodal benchmark functions, multimodal benchmark functions, and composite benchmark functions are presented in Tables 4–6, respectively. The best values were achieved with the proposed ESMA, SMA, CPA, AO, and RUN algorithms shown in bold. It is obviously seen that the ESMA algorithm reaches to the best solution for many benchmark functions. The convergence curves of all algorithms

for the unimodal benchmark functions are shown in Figure 7 while the boxplots for these techniques for this type of functions are displayed in Figure 8. In addition, Figure 9 shows the convergence curves of these algorithms for the multimodal benchmark functions while Figure 10 presents the boxplots for each algorithm for these functions. Finally, the convergence curves of all algorithms for the composite benchmark functions are displayed in Figure 11 while the boxplots for all algorithms for this type of benchmark functions are presented Figure 12. From these figures, it is clearly seen that the proposed ESMA technique reaches a stable point for all functions and the boxplots of the ESMA technique are very narrow for most functions compared to the other well known techniques.

Table 4. The statistical results of unimodal benchmark functions using the proposed ESMA algorithm and other recent algorithms ¹.

Function		ESMA	SMA	CPA	AO	RUN
F1	Best	0.00	1.8×10^{-293}	6.5×10^{-190}	7.15×10^{-76}	9.07×10^{-86}
	Worst	5.4×10^{-295}	1.1×10^{-156}	1.41×10^{-70}	4.17×10^{-57}	1×10^{-75}
	Mean	2.7×10^{-296}	5.3×10^{-158}	7.07×10^{-72}	2.09×10^{-58}	5.02×10^{-77}
	Std	0.00	2.4×10^{-157}	3.16×10^{-71}	9.33×10^{-58}	2.24×10^{-76}
F2	Best	7.4×10^{-162}	2.9×10^{-132}	4.8×10^{-106}	1.3×10^{-36}	1.04×10^{-47}
	Worst	1.9×10^{-148}	1.02×10^{-64}	1.07×10^{-14}	9.5×10^{-32}	2.3×10^{-42}
	Mean	1.8×10^{-149}	5.1×10^{-66}	5.36×10^{-16}	1.37×10^{-32}	1.87×10^{-43}
	Std	5.1×10^{-149}	2.28×10^{-65}	2.4×10^{-15}	3.28×10^{-32}	5.35×10^{-43}
F3	Best	0.00	1.1×10^{-254}	2.2×10^{-186}	3.39×10^{-71}	5.75×10^{-77}
	Worst	2.1×10^{-298}	1.4×10^{-140}	2.51×10^{-26}	1.58×10^{-62}	4.54×10^{-61}
	Mean	1.8×10^{-299}	6.8×10^{-142}	1.26×10^{-27}	1.28×10^{-63}	2.33×10^{-62}
	Std	0.00	3×10^{-141}	5.61×10^{-27}	3.7×10^{-63}	1.01×10^{-61}
F4	Best	8.9×10^{-159}	5.7×10^{-137}	3.78×10^{-97}	8.91×10^{-40}	1.35×10^{-42}
	Worst	3.8×10^{-146}	9.02×10^{-51}	3.54×10^{-19}	1.67×10^{-31}	4.16×10^{-34}
	Mean	1.9×10^{-147}	4.51×10^{-52}	1.77×10^{-20}	1.26×10^{-32}	2.09×10^{-35}
	Std	8.5×10^{-147}	2.02×10^{-51}	7.93×10^{-20}	4.05×10^{-32}	9.3×10^{-35}
F5	Best	26.08305	25.34758	28.12882	24.13219	23.34961
	Worst	28.94341	28.98832	28.88188	29.26575	26.52757
	Mean	28.24751	28.57338	28.53022	26.85075	24.73586
	Std	0.854929	0.807162	0.196671	1.924605	0.832917
F6	Best	0.205897	0.01122	0.000936	1.61×10^{-8}	7.23×10^{-9}
	Worst	4.076296	3.74817	1.069296	0.000556	2.24×10^{-8}
	Mean	1.054545	0.810915	0.293309	0.000145	1.19×10^{-8}
	Std	0.980102	0.967813	0.368271	0.000182	3.7×10^{-9}
F7	Best	3.22×10^{-5}	1.84×10^{-5}	3.23×10^{-5}	6.04×10^{-6}	3.74×10^{-5}
	Worst	0.003883	0.00744	0.009786	0.000818	0.000865
	Mean	0.001199	0.001253	0.00206	0.00021	0.00042
	Std	0.001113	0.00176	0.002655	0.000197	0.000268

¹ The best values obtained are in bold.

Table 5. The statistical Results of multimodal benchmark functions using the proposed ESMA algorithm and other recent algorithms ¹.

Function		ESMA	SMA	CPA	AO	RUN
F8	Best	−1850.29	− 1909.03	− 1909.03	−1901.64	−1660.17
	Worst	− 1460.88	−941.222	−841.176	−718.461	−1397.78
	Mean	−1653.2	− 1854.84	−1665.13	−1061.31	−1580.75
	Std	102.5683	215.5892	266.4826	353.9877	78.84949
F9	Best	0.00	0.00	0.00	0.00	0.00
	Worst	0.00	0.00	0.00	0.00	0.00
	Mean	0.00	0.00	0.00	0.00	0.00
	Std	0.00	0.00	0.00	0.00	0.00

Table 5. Cont.

Function		ESMA	SMA	CPA	AO	RUN
F10	Best	8.88×10^{-16}	8.88×10^{-16}	8.88×10^{-16}	8.88×10^{-16}	8.88×10^{-16}
	Worst	8.88×10^{-16}	8.88×10^{-16}	1.87×10^{-14}	8.88×10^{-16}	8.88×10^{-16}
	Mean	8.88×10^{-16}	8.88×10^{-16}	1.78×10^{-15}	8.88×10^{-16}	8.88×10^{-16}
	Std	0.00	0.00	0.00	3.97×10^{-15}	0.00
F11	Best	0.00	0.00	0.00	0.00	0.00
	Worst	0.00	0.00	0.00	0.00	0.00
	Mean	0.00	0.00	0.00	0.00	0.00
	Std	0.00	0.00	0.00	0.00	0.00
F12	Best	0.019339	0.000221	3.04×10^{-5}	1.05×10^{-10}	2.99×10^{-9}
	Worst	0.224734	0.883664	0.073697	5.46×10^{-6}	1.57×10^{-8}
	Mean	0.055819	0.053203	0.012284	6.23×10^{-7}	6.93×10^{-9}
	Std	0.046062	0.195804	0.01766	1.2×10^{-6}	3.43×10^{-9}
F13	Best	0.997042	0.007141	0.003875	1.82×10^{-7}	4.07×10^{-8}
	Worst	−1850.29	−1909.03	−1909.03	−1901.64	−1660.17
	Mean	−1460.88	−941.222	−841.176	−718.461	−1397.78
	Std	−1653.2	−1854.84	−1665.13	−1061.31	−1580.75

¹ The best values obtained are in bold.Table 6. The statistical results of composite benchmark functions using the proposed ESMA algorithm and other recent algorithms ¹.

Function		ESMA	SMA	CPA	AO	RUN
F14	Best	0.998004	0.998004	0.998004	0.998004	0.998004
	Worst	7.873993	12.67051	12.67051	12.67051	10.76318
	Mean	2.528537	2.517909	2.953424	2.573682	2.081493
	Std	2.107136	3.145931	3.84665	2.574285	2.241941
F15	Best	0.00	1.1×10^{-254}	2.2×10^{-186}	0.000325	0.000307
	Worst	2.1×10^{-298}	1.4×10^{-140}	2.51×10^{-26}	0.001155	0.001223
	Mean	1.8×10^{-299}	6.8×10^{-142}	1.26×10^{-27}	0.00053	0.00072
	Std	0.00	3×10^{-141}	5.61×10^{-27}	0.00018	0.000467
F16	Best	−1.03163	−1.03163	−1.03163	−1.03163	−1.03163
	Worst	−1.03161	−1.03013	−1.03163	−1.02995	−1.03163
	Mean	−1.03163	−1.03155	−1.03163	−1.03104	−1.03163
	Std	4.12×10^{-6}	0.000335	9.56×10^{-10}	0.000547	8.13×10^{-12}
F17	Best	0.397887	0.397887	0.397887	0.397893	0.397887
	Worst	0.397887	0.397894	0.399219	0.399082	0.397887
	Mean	0.397887	0.397889	0.397954	0.398149	0.397887
	Std	2.12×10^{-10}	1.94×10^{-6}	0.000298	0.000274	4.27×10^{-12}
F18	Best	3	3	3	3.00648	3
	Worst	3	30.00163	30	3.100674	3
	Mean	3	7.050142	4.663726	3.042457	3
	Std	2.37×10^{-14}	9.89173	6.125915	0.02737	5.41×10^{-13}
F19	Best	−0.30048	−0.30048	−0.30048	−0.30048	−0.30048
	Worst	−0.30048	−0.30048	−0.30038	−0.30048	−0.30048
	Mean	−0.30048	−0.30048	−0.30047	−0.30048	−0.30048
	Std	1.14×10^{-16}	1.14×10^{-16}	2.19×10^{-5}	1.14×10^{-16}	1.14×10^{-16}
F20	Best	−3.322	−3.32198	−3.322	−3.2947	−3.322
	Worst	−3.2031	−0.19258	−3.14355	−2.67041	−3.20309
	Mean	−3.28612	−3.06081	−3.29758	−3.1067	−3.28038
	Std	0.055765	0.747204	0.050586	0.143442	0.058183
F21	Best	−10.1532	−10.1531	−5.0552	−10.1527	−10.1532
	Worst	−5.05074	−5.05489	−4.20446	−10.1019	−5.0552
	Mean	−5.81968	−8.87754	−5.00614	−10.1365	−8.3689
	Std	1.867737	2.25068	0.190098	0.016429	2.494761
F22	Best	−10.4029	−10.4029	−5.08767	−10.4028	−10.4029
	Worst	−5.0865	−5.12737	−4.97896	−10.3216	−5.08767
	Mean	−6.94796	−9.8648	−5.08015	−10.3889	−9.07412
	Std	2.601126	1.620212	0.025303	0.019955	2.36137
F23	Best	−10.5364	−10.5363	−10.5364	−10.5362	−10.5364
	Worst	−4.63728	−5.12744	−4.82737	−10.4701	−5.12848
	Mean	−6.7263	−9.99261	−5.6062	−10.5212	−9.18443
	Std	2.561402	1.655735	1.540624	0.019921	2.402536

¹ The best values obtained are in bold.

Figure 7. The convergence curve of all algorithms for seven unimodal benchmark functions. (a) F1; (b) F2; (c) F3; (d) F4; (e) F5; (f) F6; (g) F7.

Figure 8. Boxplots for all algorithms for seven unimodal benchmark functions. (a) F1; (b) F2; (c) F3; (d) F4; (e) F5; (f) F6; (g) F7.

Figure 9. The convergence curves of all algorithms for six multi-modal benchmark functions. (a) F8; (b) F9; (c) F10; (d) F11; (e) F12; (f) F13.

Figure 10. Boxplots for all algorithms for some of multi-modal benchmark functions. (a) F8; (b) F10; (c) F12; (d) F13.

Figure 11. The convergence curves of all algorithms for ten composite benchmark functions. (a) F14; (b) F15; (c) F16; (d) F17; (e) F18; (f) F19; (g) F20; (h) F21; (i) F22; (j) F23.

5.2. Real-World Application

In this subsection, several case studies are implemented on the modified IEEE-30 bus power system to solve the OPF problem. The results of applying the enhanced ESMA for all cases are provided and explained. Conventional SMA and two different optimization algorithms, BWOA and MSA, are also applied to confirm the validity of ESMA.

The case studies are organized as follows: Cases 1 and 2 are dedicated to minimizing the total generation cost without and with carbon tax respectively, Cases 3 and 4 are performed for studying the impact of reserve and penalty cost variation on the optimized cost respectively, Case 5 is implemented for studying of ramp rate effect of TPGs, and finally, Case 6 is performed for studying the impact of load demand uncertainties.

Figure 12. Boxplots for all algorithms for ten composite benchmark functions. (a) F14; (b) F15; (c) F16; (d) F17; (e) F18; (f) F19; (g) F20; (h) F21; (i) F22; (j) F23.

The simulation of optimization techniques is performed based on MATLAB using a computer with the following properties: Intel® Core™ i3-380M Processor 3M Cache, 2.53 GHz and 4 GB RAM.

In every case, the objective function reaches its optimum value after running the algorithm 5 times, and a maximum of 1000 iterations are set as the ending criteria of the algorithms. The settings of control variables are also listed.

5.2.1. Case 1: Minimization of Generation Cost

This case is performed to optimize scheduled output powers from all different types of energy sources used in the modified power system to reach the possible minimum value of the total power cost based on (11).

Figure 13 provides the convergences of applied OPF optimization techniques. The optimally obtained results of overall cost, control variables, reactive powers, and other parameters have been provided in Table 7.

Figure 13. Characteristics of convergence for different algorithms (Case 1).

Table 7. Case 1 simulation results.

Control Variables	Min.	Max.	ESMA	SMA	BWOA	MSA
P_{TG1} (MW)	50	140	134.9143078	134.9126665	134.9318602	134.9080709
P_{TG2} (MW)	20	80	27.68805837	28.41701	30.52148	29.91749
P_{TG3} (MW)	10	35	10.01257102	10	10.02768	41.42875
$P_{ws,1}$ (MW)	0	75	43.57823017	43.97604	43.11587	10.15632
$P_{ws,2}$ (MW)	0	60	37.45089	36.74404	37.82475	37.68851
P_{ss} (MW)	0	50	35.5275	35.11807	33.36969	35.20921
V_1 (p.u.)	0.95	1.1	1.069956	1.072577	1.069029	1.071379
V_2 (p.u.)	0.95	1.1	1.056832	1.057642	1.099901	1.057197
V_5 (p.u.)	0.95	1.1	1.033471	1.037017	1.095503	1.079234
V_8 (p.u.)	0.95	1.1	1.088021	1.040221	1.02164	1.075681
V_{11} (p.u.)	0.95	1.1	1.097041	1.097474	1.00625	1.07746
V_{13} (p.u.)	0.95	1.1	1.052377	1.048536	1.067481	1.047355
Q_{TG1} (MVar)	−20	150	−6.58886	−1.73162	−20	−3.94493
Q_{TG2} (MVar)	−20	60	16.43639	12.89954	60	7.538948
Q_{TG3} (MVar)	−15	40	40	35.9758	15.65167	40
$Q_{ws,1}$ (MVar)	−30	35	21.18113	24.64654	35	35
$Q_{ws,2}$ (MVar)	−25	30	29.5482	30	2.883899	22.88516
Q_{ss} (MVar)	−20	25	16.47241	15.1557	25	15.4901
Total power cost (\$/h)			781.9375819	781.9580658	784.3423563	782.4230422
Emissions (t/h)			1.762973771	1.76261913	1.764219911	1.76173491
Carbon tax, C_{tax} (\$/h)			0	0	0	0
P_{loss} (MW)			5.771556781	5.76783193	6.401297765	5.908352008
V_d (p.u.)			0.458684989	0.451488019	0.53484521	0.443429768

The voltage of i th bus is denoted by V_i in Table 7. The effectiveness of ESMA is very clear from the simulation results of case 1. Comparing to the conventional SMA and other performed optimization techniques for OPF, ESMA has a fast convergence and better solution quality. Among all applied algorithms, ESMA achieved the minimum total power cost of **781.9376 \$/h**.

5.2.2. Case 2: Total Power Cost Minimization with Carbon Tax

The objective of this case is to minimize the total power cost, with imposing a fixed carbon tax (C_{tax}) on the thermal power generators because of their CO_2 emissions according to (12). The forced C_{tax} is supposed to be 20 (\$/ton) [7]. Increasing the penetration level of wind and solar energy into the power grid is expected with forcing the carbon tax; this conception obviously appears in the simulation results. Similarly to Case 1, a comparison between the convergence of ESMA and other performed algorithms is provided through

Figure 14, and the optimally obtained results of overall cost, control variables, reactive powers, and other parameters have been provided in Table 8.

Figure 14. Characteristics of convergence for different algorithms (Case 2).

Table 8. Case 2 simulation results.

Control Variables	Min.	Max.	ESMA	SMA	BWOA	MSA
P_{TG1} (MW)	50	140	123.4182597	123.558571	123.9385776	123.0458701
P_{TG2} (MW)	20	80	32.8988	32.70381	31.55832	31.94699
P_{TG3} (MW)	10	35	10.00018	10	10.02575	10.00019
$P_{ws,1}$ (MW)	0	75	45.87829	46.01788	43.52164	45.40579
$P_{ws,2}$ (MW)	0	60	38.84621	38.76592	38.18338	38.19805
P_{ss} (MW)	0	50	37.63186	37.63258	41.63565	40.09511
V_1 (p.u.)	0.95	1.1	1.070554	1.069455	1.076582	1.067868
V_2 (p.u.)	0.95	1.1	1.057246	1.056339	1.060155	1.055309
V_5 (p.u.)	0.95	1.1	1.036466	1.034248	1.033567	1.031957
V_8 (p.u.)	0.95	1.1	1.040751	1.082863	1.031061	1.040321
V_{11} (p.u.)	0.95	1.1	1.099149	1.1	1.07291	1.099459
V_{13} (p.u.)	0.95	1.1	1.053391	1.053591	1.056897	1.1
Q_{TG1} (MVar)	−20	150	−3.04826	−4.14907	6.942384	−6.10507
Q_{TG2} (MVar)	−20	60	12.62003	12.03468	18.60405	12.98216
Q_{TG3} (MVar)	−15	40	35.90165	40	24.44273	34.59923
$Q_{ws,1}$ (MVar)	−30	35	23.35533	21.07284	22.66046	19.91761
$Q_{ws,2}$ (MVar)	−25	30	30	30	22.74522	29.40543
Q_{ss} (MVar)	−20	25	16.83568	16.72546	20.55141	25
Total power cost (\$/h)			810.3557515	810.3738858	812.0366457	810.8842547
Emissions (t/h)			0.88593426	0.893157637	0.913174063	0.867357442
Carbon tax, C_{tax} (\$/h)			20	20	20	20
P_{loss} (MW)			5.273603276	5.278762466	5.463313439	5.291996546
V_d (p.u.)			0.464133712	0.467254932	0.450579985	0.538738367

The minimum value of total power cost achieved by ESMA is **810.3558 \$/h** which means that ESMA outdoes SMA and all other used techniques with regard to total power cost minimization and the convergence of the solution.

Load buses voltages have an important role in OPF study. Therefore, it is essential to deal with the constraints of load buses voltages. Operating voltages of all load buses in the IEEE-30 bus system must be within the range [0.95–1.05] p.u.

In this concern, Figure 15 provides voltage profiles of load buses for Case 1 and Case 2. It is clear from Figure 15 that all voltages of load buses are inside limits after finishing the optimization process of the two cases.

Figure 15. Profile voltages of Load buses for Cases 1 and 2.

5.2.3. Case 3: Impact of Reserve Cost Variation on the Optimized Cost

This case is applied to study and analyze the impact of variation of reserve cost coefficient on various optimized costs. All relevant parameters were kept as those used in Case 1 except reserve cost coefficients. In this case, SPG and WPGs have reserve cost coefficients started from $K_{rs} = K_{rw,1} = K_{rw,2} = Rc = 3$ (Case 1) to $K_{rs} = K_{rw,1} = K_{rw,2} = Rc = 4$ until $Rc = 6$ with an increase of 1, and their penalty cost coefficients are $K_{ps} = K_{pw,1} = K_{pw,2} = Pc = 1.5$ as the same values used in Case 1. The optimally scheduled powers of all generators are shown in Figure 16. To make Figure 16 clearer, Case 3a denotes $Rc = 4$, Case 3b denotes $Rc = 5$, while Case 3c denotes $Rc = 6$. The optimally scheduled powers from WPGs and SPG decrease with the increase in reserve cost coefficient as reducing the scheduled power requests a smaller quantity from the spinning reserve. When there is a shortage of output power from WPGs or SPG, TPGs compensate it. Therefore, the cost of TPGs rises as noticed from the cost profile of TPGs in Figure 17 while the costs of WPGs and SPG decreases gradually to a certain amount. In total, the entire cost of the produced power rises with the rise in the reserve cost coefficient.

Figure 16. Impact of reserve cost coefficient (Rc) variation on the optimally scheduled active powers.

5.2.4. Case 4: Impact of Penalty Cost Variation on the Optimized Cost

The effect of varying the penalty cost coefficient on various optimized costs is studied and analyzed in this case. All relevant parameters were kept as those used for Case 1 except the penalty cost coefficients. In this case, SPG and WPGs have coefficients of penalty cost started from $K_{ps} = K_{pw,1} = K_{pw,2} = Pc = 1.5$ (Case 1) to $Pc = 4$ (Case 4a), $Pc = 5$ (Case 4b), and $Pc = 6$ (Case 4c), while reserve cost coefficients remain unchanged from Case 1, $K_{rs} = K_{rw,1} = K_{rw,2} = Rc = 3$. Figure 18 illustrates the optimally scheduled power from all generators.

Figure 17. Impact of Rc variation on costs of all generators.

Figure 18. Impact of penalty cost coefficient (Pc) variation on the optimally scheduled active power.

If the penalty cost coefficient rises, the scheduled output powers of WPGs and SPG will increase because the rise in the scheduled output power will help to decrease the penalty cost in case of wind speed or solar irradiance has a high value. This concept is unlike the concept in the previous case because the raises in the scheduled output powers do not sound identical for all RESs due to the extremely non-linear relationships between PDFs and penalty or reserve cost of RESs. From Figure 19, a progressive increment in WPGs cost and a minor fluctuation in the SPG cost are observed. It is also noticed that the cost of TPGs is approximately constant in addition to a steady growth in total power cost.

Figure 19. Impact of Pc variation on costs of all generators.

All generator buses voltages for Cases 3 and 4 are presented in Figure 20. It is noticed that all generator buses voltages lie on the specified range of p.u. voltage (0.95–1.1). The

generators' reactive powers are also illustrated in Figure 21. The reactive power limits mentioned in Table 7 indicate that TPG3 and WPG2 reached their reactive power capability maximum limits for many cases. Accordingly, considering the reactive power constraints when performing any optimization technique is very important.

Figure 20. Generator buses voltages (Cases 3 and 4).

Figure 21. Scheduled reactive powers for all generators (Cases 3 and 4).

5.2.5. Case 5: The Impact of Considering Ramp-Rate Limits of TPGs

The impact of considering ramp rate limits of TPGs while minimizing the total power cost based on (11) is studied and analyzed in this case. The produced power at the preceding hour for TPGs and their limits of ramp-rate are provided in Table 1 [36].

Table 9 provides the optimal results of this case such as total power cost, control variables, reactive powers, and other important parameters.

Figure 22 provides the convergences of the different applied techniques in Case 5.

Table 9. Case 5 simulation results (considering the effect of ramp rate).

Control Variables	Min.	Max.	ESMA	SMA	BWOA	MSA
P_{TG1} (MW)	79.211	114.211	92.16880318	92.44231076	90.18995958	91.32417994
P_{TG2} (MW)	65	80	65.00002	65	65	65
P_{TG3} (MW)	12	24	12	12	12.26708	12
$P_{ws,1}$ (MW)	0	75	44.16894	43.88145	43.08437	44.17037
$P_{ws,2}$ (MW)	0	60	37.37163	37.4186	37.35422	37.33551
P_{ss} (MW)	0	50	37.31031	37.29943	40.20372	38.24819
V_1 (p.u.)	0.95	1.1	1.067626	1.066194	1.065552	1.063945
V_2 (p.u.)	0.95	1.1	1.058474	1.0575	1.00708	1.055106
V_5 (p.u.)	0.95	1.1	1.036813	1.036672	1.071627	1.1
V_8 (p.u.)	0.95	1.1	1.041757	1.041546	1.051095	1.095858
V_{11} (p.u.)	0.95	1.1	1.099689	1.099994	1.094939	1.079155
V_{13} (p.u.)	0.95	1.1	1.058374	1.067352	1.098482	1.095742
Q_{TG1} (MVar)	−20	150	−3.79857	−5.54952	6.587242	−6.53175
Q_{TG2} (MVar)	−20	60	10.15416	9.34017	−20	−2.01028
Q_{TG3} (MVar)	−15	40	35.62043	34.85711	40	40
$Q_{ws,1}$ (MVar)	−30	35	23.13793	23.5976	35	35
$Q_{ws,2}$ (MVar)	−25	30	29.97999	29.61801	27.06355	21.56442
Q_{ss} (MVar)	−20	25	18.33159	21.65564	25	25
Total power cost (\$/h)			804.5476	804.5697852	805.1313475	804.8074077
Emissions (t/h)			0.20445652	0.206348589	0.191626873	0.198813008
P_{loss} (MW)			4.619704547	4.641789739	4.699343938	4.678246985
V_d (p.u.)			0.485876946	0.518261166	0.54920658	0.517553778

Figure 22. Solution convergence of different algorithms (Case 5).

The impact of the ramp rate limits of the TPGs is clear from the Case 5 simulation results. If we look at the results of Case 5 in Table 9 and the results of Case 1 in Table 7, we can find that the total power cost is increased as expected as a result of changing the new operating points of TPGs from their original operating points without ramp rate constraints. The effectiveness of ESMA is very clear from the simulation results of Case 5. Compared to the conventional SMA and other applied optimization algorithms, ESMA has the fastest convergence and the best solution quality. The minimum overall power cost achieved using the ESMA is 804.5476 \$/h. Thus, ESMA outperforms SMA and all other performed techniques with regard to total power cost minimization and the convergence of solutions for this practical case. There is no violation in system constraints after performing the OPF study as shown in Table 9.

Figure 23 shows also the voltage profile of load buses in Case 5. It is noticed that all voltages of load buses are inside the predefined limits.

Figure 23. Profile of PQ buses voltages (Case 5).

5.2.6. Case 6: The Impact of Load Demand Uncertainties

In Case 6, another realistic situation of load demand variation is provided. The load demand uncertainty has been modeled by the normal PDF [37]. A level-based procedure is executed to accomplish the process of optimization during some different levels (scenarios) of the power system load.

The uncertainty of the load using the normal PDF with standard deviation (σ_d) = 10 and mean (μ_d) = 70 is illustrated in Figure 24. There are four-color areas in Figure 24. These areas denote the four considered levels of load demand (P_d).

Figure 24. Representation of load uncertainty by normal PDF ($\mu_d = 70$, and $\sigma_d = 10$).

The occurring probability of the i -th level of load demand ($\Delta_{sc,i}$) is depicted below [12]:

$$\Delta_{sc,i} = \int_{P_{d,i}^{low}}^{P_{d,i}^{high}} \frac{1}{\sigma_d \sqrt{2\pi}} \exp \left[-\frac{(P_d - \mu_d)^2}{2\sigma_d^2} \right] dP_d \quad (52)$$

Equation (51) determines the mean of the i -th level of load demand ($P_{D,i}$).

$$P_{D,i} = \frac{1}{\Delta_{sc,i}} \int_{P_{d,i}^{low}}^{P_{d,i}^{high}} \left(\frac{1}{\sigma_d \sqrt{2\pi}} \exp \left[-\frac{(P_d - \mu_d)^2}{2\sigma_d^2} \right] \right) dP_d \quad (53)$$

The calculated values of the four means, as a percentage of nominal loading, and the four probabilities for the four loading levels are recorded in Table 10. For each scenario, the four performed algorithms try to optimally minimize the total power cost based on (11). In each loading scenario, the scheduled powers of all the system generators are optimized.

Table 10. Probabilities and means of loading levels [12].

Loading Levels (L)	%Loading, P_d (Mean)	Level Probability, Δ_{sc}
L1	54.749	0.15866
L2	65.401	0.34134
L3	74.599	0.34134
L4	85.251	0.15866

For simplicity, only the results of loading levels 1 and 3 (L1 and L3) are recorded in Tables 11 and 12. It is clear from the results of Case 6 that the operation cost and power losses of the system under realistic loading levels are justifiably lesser than their values under theoretical conditions in Case 1. Figure 25 illustrates that ESMA outdoes all other performed methods with regard to overall power cost minimization and the convergence of solution. The voltage profiles of load buses for different loading levels for the ESMA are plotted in Figure 26. The values of voltage and system variables are recorded in Tables 11 and 12. These values show that all system constraints are satisfied.

Figure 25. Solution convergence for various algorithms (Case 6). **Figure 26.** Profiles of load buses voltages for all system loading levels (Case 6).

Table 11. Case 6 simulation results (L1).

Control Variables	Min.	Max.	ESMA	SMA	BWOA	MSA
P _{TG1} (MW)	50	140	50	50.00162628	50.00110622	50
P _{TG2} (MW)	20	80	20.01171	20.00039	20.01272	20.00006
P _{TG3} (MW)	10	35	10.01082	10.00013	10.02353	26.8289
P _{ws,1} (MW)	0	75	28.15856	28.14932	27.77365	10.00017
P _{ws,2} (MW)	0	60	24.33794	24.42657	24.38182	22.7425
P _{ss} (MW)	0	50	23.80816	23.76047	24.22643	26.88557
V ₁ (p.u.)	0.95	1.1	1.053932	1.039198	1.022464	1.032892
V ₂ (p.u.)	0.95	1.1	1.050299	1.033567	1.022308	1.024873
V ₅ (p.u.)	0.95	1.1	1.043892	1.018211	1.021484	1.016617
V ₈ (p.u.)	0.95	1.1	1.045135	1.025042	1.022508	1.02046
V ₁₁ (p.u.)	0.95	1.1	1.067695	1.066508	1.065401	1.070566
V ₁₃ (p.u.)	0.95	1.1	1.043551	1.033307	1.021062	1.099479
Q _{TG1} (MVar)	−20	150	−10.0862	−5.23151	−19.4103	−3.53245
Q _{TG2} (MVar)	−20	60	0.380669	2.905193	−0.16671	−12.781
Q _{TG3} (MVar)	−15	40	17.16212	12.39216	19.25725	9.219822
Q _{ws,1} (MVar)	−30	35	12.689	4.636251	16.49788	6.093273
Q _{ws,2} (MVar)	−25	30	13.09423	18.31955	19.9989	18.19375
Q _{ss} (MVar)	−20	25	6.054028	8.00693	5.814833	25
Total power cost (\$/h)			410.3294562	410.3686027	410.7465692	411.4454656
Emissions (t/h)			0.104010026	0.104028661	0.104018561	0.104026511
P _{loss} (MW)			1.145097577	1.180840787	1.261597597	1.296340501
V _d (p.u.)			0.65909623	0.337539839	0.240641881	0.508944469

Table 12. Case 6 simulation results (L3).

Control Variables	Min.	Max.	ESMA	SMA	BWOA	MSA
P _{TG1} (MW)	50	140	94.72947881	94.79720263	91.11355617	92.34923281
P _{TG2} (MW)	20	80	20.00008	20.00044	20	20.0001
P _{TG3} (MW)	10	35	10.0001	10	10	10.00009
P _{ws,1} (MW)	0	75	32.34282	32.20228	33.97687	32.9448
P _{ws,2} (MW)	0	60	27.78931	27.92108	28.72745	28.27017
P _{ss} (MW)	0	50	29.52108	29.5243	30.53354	30.87101
V ₁ (p.u.)	0.95	1.1	1.064273	1.067498	1.061448	1.066858
V ₂ (p.u.)	0.95	1.1	1.053301	0.973881	1.049094	0.950696
V ₅ (p.u.)	0.95	1.1	1.03721	1.038962	1.040377	1.1
V ₈ (p.u.)	0.95	1.1	1.041313	1.042134	1.079471	1.039051
V ₁₁ (p.u.)	0.95	1.1	1.097061	1.098575	1.031874	1.084509
V ₁₃ (p.u.)	0.95	1.1	1.050823	1.045943	1.070388	1.048776
Q _{TG1} (MVar)	−20	150	ESMA	SMA	BWOA	MSA
Q _{TG2} (MVar)	−20	60	−3.8362	13.44399	−2.14165	8.865571
Q _{TG3} (MVar)	−15	40	3.995005	−20	−8.97172	−20
Q _{ws,1} (MVar)	−30	35	20.7829	23.94863	40	15.9741
Q _{ws,2} (MVar)	−25	30	15.0575	19.74814	19.21955	35
Q _{ss} (MVar)	−20	25	25.63449	26.5095	2.694168	21.59284
Total power cost (\$/h)			10.81905	9.157136	20.92825	10.8832
Emissions (t/h)			576.2737229	576.4366891	576.8699631	576.6928804
Carbon tax, C _{tax} (\$/h)			0.226220505	0.226766724	0.200169215	0.208418926
V _d (p.u.)			2.970382594	3.032800323	2.938923514	3.022914078

6. Conclusions

This research provided an enhanced slime mould algorithm to solve optimally the OPF problem. The performance of the proposed algorithm has been evaluated using 23 benchmark test functions and has been compared with the conventional SMA and three recent optimization algorithms: CPA, AO, and RUN. The results of the proposed

ESMA algorithm are compared with these well-known optimization algorithms. The ESMA algorithm reached the best solution for many benchmark functions.

Consequently, the ESMA was used to solve the OPF problem in the IEEE-30 bus power system that modified to include stochastic solar and wind energy sources. The uncertain outputs of solar and wind energy sources were modelled through lognormal and Weibull PDFs, respectively.

The total cost of power produced from all power generators was optimally minimized in two different case studies; one of them neglected the carbon emission and the other considered it. The effect of varying the reserve and penalty cost coefficients of SPG and WPGs on the total power cost were also analyzed.

The impacts of considering ramp rate limits of TPGs and uncertain load demand have been studied to observe the validity of ESMA under more practical cases.

To test ESMA validity in real world applications, conventional SMA and two other optimization techniques, BWOA and MSA, were performed for the adjusted IEEE-30 bus system at the same system conditions. Simulation results obtained by the ESMA in each case study were compared with the results obtained by other applied algorithms.

Simulation results of all case studies prove the effectiveness of ESMA for solving of OPF problem with maintaining the system constraints inside the limits that have been set by the ISO. ESMA outperforms the conventional SMA and other optimization algorithms in terms of total power cost minimization and the convergence of problem solution under the practical and theoretical cases.

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Nomenclature

C_{FF}	The fossil fuel cost
a_i, b_i , and c_i	Coefficients of cost for the i th TPG
$P_{TPG,i}$	Output power from the i th TPG
N_{TPG}	The number of TPGs in the power system
d_i and e_i	Coefficients of valve-point loading
$P_{TPG,i}^{min}$	The minimum power of i th TPG
$C_{dw,j}$	The direct cost of wind power produced from the j th WPG
$P_{ws,j}$	Scheduled output power from the j th WPG
h_j	The direct cost coefficient of the j th WPG

$C_{ds,k}$	The direct cost of the kth SPG
$P_{ss,k}$	Scheduled output power from the kth SPG
g_k	The coefficient of direct cost associated with the kth SPG
$C_{rw,j}$	The reserve cost for the jth WPG
$P_{wav,j}$	The available power of the jth WPG
$K_{rw,j}$	Coefficient of reserve cost for the jth WPG
$P_{wav,j}$	Available output power from the jth WPG
$f_w(P_{w,j})$	The Weibull PDF of the jth WPG output power
$C_{pw,j}$	Penalty cost for the jth WPG
$K_{pw,j}$	Coefficient of penalty cost for the jth WPG
$P_{wr,j}$	The rated output power of the jth WPG
$C_{rs,k}$	The reserve cost for the kth SPG
$P_{sav,k}$	Available output power from the kth SPG
$K_{rs,k}$	Coefficient of reserve cost for the kth SPG
$f_s(P_{sav,k} < P_{ss,k})$	The shortage occurrence probability of solar power
$Ex(P_{sav,k} < P_{ss,k})$	The expectation of being the output of SPG below the $P_{ss,k}$
$K_{ps,k}$	Coefficient of penalty cost of the kth SPG
$f_s(P_{sav,k} > P_{ss,k})$	The surplus occurrence probability of solar power
$Ex(P_{sav,k} > P_{ss,k})$	The expectation of being the output of SPG above the $P_{ss,k}$
$\alpha_i, \beta_i, \gamma_i, \omega_i$, and μ_i	The coefficients of emissions from the ith TPG
C_E	The emission cost
C_{tax}	Carbon tax
E	Emissions (ton/h)
P_{TGi}^0	Output power from the ith TPG at previous hour
Dr_i, Ur_i	Limits of down and up ramp-rate for the ith TPG
N_{SPG} and N_{WPG}	The number of SPGs and WPGs existing in the modified power system, respectively
NB	The total number of grid buses
$\delta_{ij} = (\delta_i - \delta_j)$	The difference between voltage angles of bus i and bus j
P_{Gi} and Q_{Gi}	The active and reactive components of the generated power at bus i, respectively
P_{Di} and Q_{Di}	The active and reactive components of load demand at bus i, respectively
G_{ij} and B_{ij}	The conductance and susceptance between bus i and bus j, respectively
N_G	The total number of generators in the system
N_B	The total number of load buses
N_L	The total number of system transmission lines
k and c	Shape and scale factors of Weibull PDF, respectively
V_d	Voltage deviation
I	Solar irradiance (W/m^2)
$v_{in,w}, v_{out,w}, v_{r,w}$	The cut-in, cut-out, and rated wind speeds of the wind turbine, respectively
P_{wr}	The rated power of wind turbine
I_{std}	The solar irradiance in a standard environment ($800 W/m^2$)
R_c	Specific irradiance amount ($120 W/m^2$)
P_{sr}	The rated power of SPG
$\vec{vc}$	Value reduces linearly from one to zero
T	The t-th iteration
$\vec{X}_b$	The individual position that has the most focus on smell found currently
$\vec{X}$	The slime mould position
$\vec{X}_A$ and $\vec{X}_B$	Two individuals selected randomly from the whole population
$S(i)$	The fitness value of $\vec{X}$, $i \in 1, 2, 3, \dots, n$
R	Random value in range $[0, 1]$
bF and wF	The best and worst fitness obtained in the present iteration
SmellIndex	The sequence of sorting the values of fitness function
UB and LB	The upper and lower boundaries of the search space, respectively
Rand	The random value varies from 0 to 1
Z	Parameter between $[0, 0.1]$
$P_{d,i}^{high}$ and $P_{d,i}^{low}$	The high and low limits of i-th level of load demand, respectively

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