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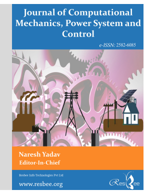

SFOA: Sun Flower Optimization Algorithm to Solve Optimal Power Flow

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Abstract: In electric power systems engineering, the set of optimization problems called cooperatively as OPF, which is the main sensibly significant as well as well-researched subfields of constrained nonlinear optimization. Moreover, OPF have the benefits of an affluent research history, novelty, and publication since its five decades ago. However, entry into OPF research is an intimidating job for the uninitiated—both because of the sheer volume of literature. In additionally, it is due to the OPF's ubiquity within the electric power systems community, which has led authors to presume an immense deal of prior knowledge that readers unknown with electric power systems may not possess. In this paper, a novel Sunflower Optimization Algorithm (SFOA) is proposed, which is enthused by the orientation of sunflower towards the sun to resolve constrained OPF problem. The proposed method is simulated to optimize the objective models namely fuel cost, voltage profile, emission, voltage stability, and active power loss. Moreover, the proposed method is compared with the conventional algorithms in the IEEE 30-bus, 57-bus, and 118-bus power systems. Finally, the simulation outcomes exhibit that the proposed method performs superior to other conventional approaches.

Keywords: Optimal Power Flow; Control Variables; Constraints; Sunflower; Optimization Algorithms

Nomenclature

Abbreviations	Descriptions
OPF	Optimal Power Flow
LP	Linear Programming
MSA	Moth Swarm Algorithm
ANN	Artificial Neural Network
GWO	Grey Wolf Optimization
GSA	Gravitational Search Algorithm
PSTs	Phase-shifting transformers
FPA	Flower Pollination Algorithm
ADMM	Alternating Direction Multiplier Method
MILP	Mixed-Integer Linear Programming
PSO	Particle Swarm Optimization algorithm
VD	Voltage Deviations
APP	Auxiliary Problem Principle
GA	Genetic Algorithm
QP	Quadratic Programming
MFO	Moth Flame Optimization
WDF	Weibull Distribution Function

1. Introduction

Nowadays, electricity demand has been increasing day by day. On the basis of the thermal power plant, the production of energy meets 70% all over the world. Hence, the cost of fuel gets increases due to the huge demand for fuel [1]. At all load conditions, the economic operation is determined to contribute power from the well effectual plant. Based on the equality constraints like reactive and active power demand, the economic dispatch highly concerns while Optimal Power Flow represents the power system constraints such as the security and the load. Moreover, the OPF is considered as an operational planning tool that has the ability to reduce the objective model without breaching any associated constraints.

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In power system operation and planning, at the present time, the OPF considered as crucial research [2]. In planning problems, OPF is extensively exploited or to locate optimal generation schedules in reactive and active power on an operational level, which reduce the operating system costs dependent on grid constraints [20].

OPF plays a significant problem to integrate electrical energy system with the wind energy generations. When processing OPF, important issues such as operating and planning energy systems occur while it is integrated into remote areas. One of the main objectives of the operating power flow is to control the fundamental dispatching procedure, demands to distribute as well as to reduce the transmission loss. Furthermore, it increases and idea in minimizing the whole generation cost as well as the requirements and the operation procedure. For the users, the unavoidable space is developed by electrical energy, an industrialist who employs the energy system and all the stockholders in the practice of energy with the assist of wind power.

Earlier, numerous researchers examined on several optimization algorithms that exhibit the different issues and how it obtain and resolved with assist for the solution of the OPF [4]. Generally, two kinds of algorithms are exploited namely traditional and intelligent algorithms in order to resolve the OPF problems. The optimal power flow solutions methods in traditional methods like LP, QP, Newton Raphson, and Gradient methods are presented in the state of the art. One of the trendy methods, APP, was exploited to parallelize the problem in OPF solution [9]. The intelligent algorithms in order to solve the OPF solutions are such as PSO [12], GA [11], ANN [14], and GWO Algorithm [13]. In recent times, the ADMM has shown high interest [10]. These aforesaid algorithms engross the multiplier updating procedure that is frequently attained by a central coordinator [21].

The main contribution of this paper is to propose a novel Sunflower Optimization Algorithm (SFOA), this algorithm is exploited to solve the OPF in the proposed system. Moreover, the proposed method is simulated to optimize the objective functions namely fuel cost, voltage profile, emission, voltage stability, and active power loss.

This paper is organized as follows: Section 2 describes the literature review section and section 3 defines the problem formulation. Section 4 describes the proposed sun flower optimization algorithm for OPF problem. Section 5 summarizes the results and discussions sections and section 6 describes the conclusion of the paper.

2. Literature Review

In 2018, Shilaja C. and Arunprasath T [1], presented a hybrid MSA-GSA algorithm, was integrated by both the GSA and MSA for power systems with Wind energy sources. For showing the irregular nature of the wind farm, the WDF was exploited. In order to solve the objective models for failing the cost of fuel for the minimized power loss, with and without wind power test cases were considered. At last, the experimentation outcomes were examined on IEEE 30-bus, 57 bus and 118 bus without and with wind power.

In 2019, Zhangliang Shen et al [2], presented a novel technique in order to expand convex relaxations of OPF issues to comprise ZIP load models representations. In order to unwind the expressions of voltage magnitude, the geometric relationships approach was exploited with the help of the reference bus' phase angle knowledge. Hence convex demonstration of ZIP load models was enabled to form the constant-current mechanism. For the OPF problem, the presented technique was exploited for quadratic convex programming relaxations, second-order cone, semi-definite.

In 2019, P. Fortenbacher and T. Demiray [3], proposed a new technique to estimate the nonlinear AC OPF into tractable QP/LP. Moreover, for power system planning as well as operation the OPF problems was exploited. In the structure of absolute value functions, a linear branch and power flow estimate was considered. A power loss estimation, which was appropriate to wrap a broader operating range, was derived. Here, the main notations were to detain the losses of power and flows of power in the full decision variable domain.

In 2019, Guido Coletta et al [4], addressed a problem in weather-based method, which was identified as a major potential facilitating technique in order to increase the system suppleness using the components of real power loadability. Nevertheless, in real operation circumstances, the consumption of this method could be acutely cooperation because of the uncertainty data effects. The investigation of reliable approaches that concentrated at managing and representing uncertainties indicates the majority of pertinent issues to resolve. Equipped with this idea, correlated and multiple uncertainties presence, this article supports the function of Affine Arithmetic in consistent resolving OPF problems on the basis of weather.

In 2018, Tao Ding et al [5], developed a PSTs technique that has the ability to regulate and reduce the total generation cost in OPF problems. By managing a small fraction of PSTs, multiple optimal solutions of PST angle modification and enhanced economy can attain under the perception. Therefore, a MILP model was presented in order to optimally decide the PSTs subset for angle modification. Finally, the simulation outcomes on numerous test systems such as large-scale systems demonstrate that the proposed method can offer enhanced economic.

In 2019, Zhifang Yang et al [6], presented a competent OPF method in order to hybridize the AC-DC grids with discrete control devices. In both AC and DC grids, a successive linear approximation technique for the power flow equations was developed. Moreover, for the converter station, the operational constraints were methodically examined. The convexity for the modeling of the VSC, the linearization of the power flow equations was presented. In order to hold the extremely nonlinear converter losses, an invented branch was augmented to the AC grid. Moreover, an iterative solving method was presented for the model of the OPF.

In 2019, Wentian Lu et al [7], developed a fully OPF decentralized method for multi-area interconnected power systems on the basis of the distributed interior-point technique. Moreover, the regional modification equations were converted into a parametric QP issue. In order to tackle the decentralized OPF problems, this technique was considered as a novel technique, as well as the convergence property of this technique was analyzed. In addition, the aforesaid decentralized technique likes the similar performance of the convergence as well as, the precision as same as the centralized interior-point technique.

In 2018, Wei Wei et al [8], worked on a novel class of OPF problems in the distribution systems. By modifying the demands, the elastic loads act in response with the real-time nodal prices. In order to identify equilibrium, a fixed point iteration method was recommended. To evaluate the convergence, a brief criterion was developed.

3. Problem Formulation

In general, an OPF is contemplated as a nonlinear and non-convex optimization issue. It is used to decrease objectives of a particular power system that subjects to numerous equality and inequality constraints. It is done by deciding the optimal control variables in order to present load settings. Eq. (1), (2), and (3) presents the objective model of OPF.

$$\mathrm{Min}: \mathrm{l}(\mathrm{y},\mathrm{v}) \tag{1}$$

$$\text{subject to}: \mathrm{m}(\mathrm{y},\mathrm{v}) = 0 \tag{2}$$

$$\mathrm{n}(\mathrm{y},\mathrm{v}) \le 0 \tag{3}$$

In eq. (1), y represents the system vector state or dependent variables, v represents the vector of independent or control variables, $l(y,v)$ represents the objective model to be reduced, $m(y,v)$ represents the equality constraints, and $n(y,v)$ indicates the inequality constraints. The state and the control variables of the OPF problem are listed below.

a) Control variables:

As eq. (4), the set of parameters that controlled by the power flow equations, are indicated with respect to the decision vector.

$$\mathrm{v} = \left[\mathrm{M}_{\mathrm{h}_2},\ldots\ldots,\mathrm{M}_{\mathrm{F}_{\mathrm{NF}}},\mathrm{U}_{\mathrm{f}_1},\ldots..\mathrm{U}_{\mathrm{f}_{\mathrm{nf}}},\mathrm{TR}_1,,,,,\mathrm{TR}_{\mathrm{NT}},\mathrm{N}_{\mathrm{C}_1},\ldots.,\mathrm{N}_{\mathrm{C}_{\mathrm{Nc}}}\right] \tag{4}$$

In eq. (4), M_h denotes the active power generator, *TR* is the transformer tap, U_f denotes the voltage magnitude generators, N_C denotes the shunt reactive power VAR compensators, N_T represents the amount of regulating transformers and N_c represents the shunt VAR compensators units, correspondingly.

b) State variables

The eq. (5) indicates the set of variables that denote the power system.

$$\mathrm{y} = \left[\mathrm{M}_{\mathrm{h}_1},\mathrm{U}_{\mathrm{f}_1},\ldots..,\mathrm{M}_{\mathrm{F}_{\mathrm{NF}}},\mathrm{N}_{\mathrm{h}_1},\ldots.,\mathrm{N}_{\mathrm{F}_{\mathrm{Nh}}},\mathrm{R}_{\mathrm{f}_{\mathrm{f}}},\ldots.\mathrm{R}_{\mathrm{f}_{\mathrm{nf}}}\right] \tag{5}$$

In eq. (5), M_{h_1} represents the generation of active power at slack-bus, U_f denotes the voltage magnitude at load bus, N_h represents the reactive power outputs of the generators, and R represents the apparent power flow, correspondingly. N_F represents the number of load buses $(M-N)$, N_h represents the generators buses $(M-U)$, and N_{nl} represents the transmission lines, correspondingly.

3.1 Constraints

The OPF problem needs to complete both inequality as well as equality constraints. As equality constraint, the power balance constraints are represented. The power system operating limits components are represented as inequality constraints.

a) Equality constraints

As eq. (6) and (7), the balance of the reactive and active power is exploited, and these constraints indicate the typical load flow equations.

$$M_{hi} - M_{di} - U_i \sum_{j=1}^{na} U_j \left[H_{ij} \cos(\Delta_i - \Delta_j) + A_{ij} \sin(\Delta_i - \Delta_j) \right] = 0 \forall i \varepsilon na \tag{6}$$

$$N_{hi} - N_{di} - U_i \sum_{j=1}^{na} U_j \left[H_{ij} \sin(\Delta_i - \Delta_j) - A_{ij} \cos(\Delta_i - \Delta_j) \right] = 0 \forall i \varepsilon na \tag{7}$$

Where, M_d indicates the demand of active load, N_d represents the demand of reactive load, na indicates the total number of buses, N_h indicates the reactive power generator, H_{ij} indicates the transfer conductance and A_{ij} represents the and susceptance among bus i and bus j, correspondingly. During the load flow procedure, these constraints are severely imposed that promises, which the optimal searched solution is possible.

b) Inequality constraints:

These constraints indicate the operation of power system limits is listed below.

(i) Constraints of generation:

In eq. (8), (9) and (10), using the upper and lower limits the real power, the voltages, and reactive power of the generators are limited for stable operation.

$$M_{hi}^{min} \le M_{hi} \le M_{hi}^{max} 0 \forall i \varepsilon NH \tag{8}$$

$$N_{hi}^{min} \le N_{hi} \le N_{hi}^{max} 0 \forall i \varepsilon NH \tag{9}$$

$$U_{hi}^{min} \le U_{hi} \le U_{hi}^{max} 0 \forall i \varepsilon NH \tag{10}$$

(ii) Constraints of Transformer

Eq. (11) states the transformers tap settings should be limited by their upper and lower limits.

$$TR_i^{min} \le TR_i \le TR_i^{max} 0 \forall i \varepsilon NTR \tag{11}$$

(iii) Security constraints:

The constraints of transmission line loadings and load buses voltage magnitudes have to be limited within their limits.

$$U_{Ai}^{min} \le U_{Ai} \le U_{Ai}^{max} 0 \forall i \varepsilon NF \tag{12}$$

$$R_{fi} \le U_{Ai}^{max} 0 \forall i \varepsilon nl \tag{13}$$

(iv) Constraints of Shunt VAR compensator

Eq. (14), the shunt VAR compensators are limited by their limits.

$$N_{ci}^{min} \le N_{ci} \le N_{ci}^{max} 0 \forall i \varepsilon NC \tag{14}$$

3.2 Handling of Constraints

The inequality constraints of dependent variables comprise magnitude of load bus voltage; generation output of real power at the slack bus, generation of reactive power output as well as line loading are integrated into the comprehensive objective model to maintain the dependent variables within their allowable limits and to refuse any impossible solution.

In eq. (15) represents the penalty function, which is described using quadratic terms [15].

$$\text{Penality} = O_M \left(M_{h1} - M_{h1}^{lim} \right)^2 + O_N \sum_{i=1}^{Nh} \left(N_{hi} - N_{hi}^{lim} \right)^2 + O_U \sum_{i=1}^{Nf} \left(U_{Ai} - U_{Ai}^{lim} \right)^2 + O_R \sum_{i=1}^{nf} \left(R_{fi} - R_{fi}^{lim} \right)^2 \tag{15}$$

In eq. (15), O_M, O_N, O_U and O_R represents the factors of penalty that possess a high positive value that is indicated as 100 excluding the load voltage (KV) is set to 100,000. In eq. (16), y^{lim} represents the debased value of the limit dependent variable y.

$$y^{lim} = \begin{cases} y^{max} \text{ if } y > y^{max} \\ y^{min} \text{ if } y > y^{min} \end{cases} \tag{16}$$

4. Proposed Sun Flower Optimization Algorithm (SFOA)

In this section, the detailed procedure of the proposed Sun Flower Optimization Algorithm (SFOA) [16] is discussed in order to solve the OPF problem.

(a) Basic Concepts:

Each and every day, the sunflower cycle remains the same, the sunflower rouse and follows the sun similar to the needles of a clock. During the night, the sunflower explores the opposing way to wait over again for their exodus next morning. In [17], a novel technique was presented on the basis of the flower pollination procedure of flowering plants taking into consideration of the biological procedure of reproduction.

(b) Mathematical Description of proposed algorithm:

In the proposed algorithm, the uncharacteristic sunflowers behavior in the search for the optimal point of reference in the direction of the sun has considered. Moreover, in a random manner, the pollination is contemplated besides the least distance among the flower i and the flower $i+1$. Each patch of the flower frequently liberates millions of pollen gametes in fact. On the other hand, presume that each sunflower merely generates one pollen gamete as well as reproduce independently for ease.

The inverse square law radiation is represented as an additional significant nature-based optimization. Here, it exhibits the radiation intensity, which is inversely proportional to the square of the distance. In proportion, the radiation intensity minimizes and so the square of the distance gets increases. If the distance gets thrice the intensity minimizes to a factor 9, and if the distance gets double, the intensity minimizes to a factor 4, and so on. In this scenario, the quantity of radiation obtained will be higher when the distance from the plant to the sun is lesser, as well as it will be inclined to steady in this surrounding area. Conversely, if the distance from the plant to the sun is higher, the quantity of heat obtained by it will be lesser. In the proposed technique, the similar steps are followed that may acquire more steps to obtain as near as probable to the global optimum (sun) [18]. After that, the quantity of heat H obtained by each plant is stated in eq. (17). Here, S indicates the source power and d_i^2 represents the distance among the current optimal and the plant i.

$$H_i = \frac{S}{4\pi d_i^2} \tag{17}$$

The sunflowers direction to the sun is represented in eq. (18). Eq. (19) is exploited to compute the step of the sunflowers on the direction m.

$$\vec{r}_i = \frac{Y^* - Y_i}{\left\| Y^* - Y \right\|}, i = 1,2,....,n_s \tag{18}$$

$$m_i = \lambda \times S_i\left(\left\| Y_i + Y_{i-1} \right\|\right) \times \left\| Y_i + Y_{i-1} \right\| \tag{19}$$

In eq. (19), λ indicates the constant value, which states a "inertial" displacement of the plants, $S_i\left(\left\| Y_i + Y_{i-1} \right\|\right)$ indicates the pollination probability, that is the sunflower i pollinates with its adjacent neighbor $i-1$ producing a new individual in an arbitrary location, which deviates consistent with each distance among the flowers i.e., individuals nearer to the sun may acquire lesser steps for a search of local modification when distant is more individuals will move usually. Also, it is essential to limit the utmost step specified by each individual, in turn not to leave out areas flat to be global least candidates. The utmost step can be defined as eq. (20), whereas Y_{max} represents upper bounds, Y_{min} represents lower bounds, N_{pop} represents a number of plants in the total population.

$$m_{max} = \left\| \frac{Y_{max} - Y_{min}}{2 \times N_{pop}} \right\| \tag{20}$$

The updating formula of the proposed method is represented in eq. (21).

$$\vec{Y}_{i+1} = \vec{Y}_i + m_i \times \vec{r}_i \tag{21}$$

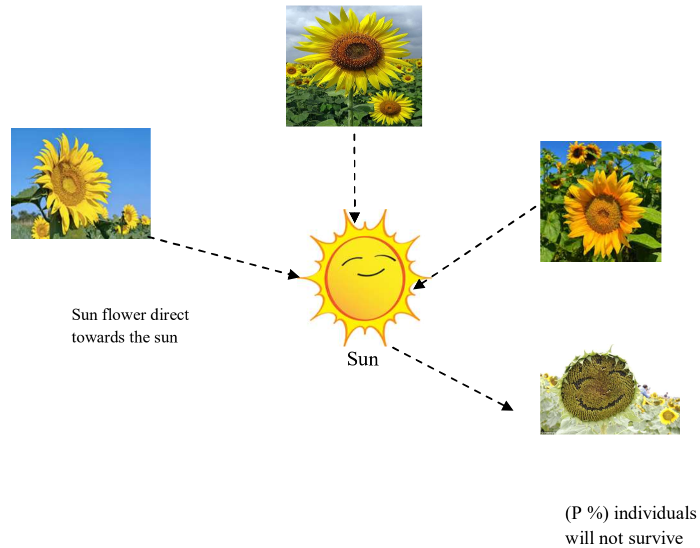

Fig. 1. *Diagrammatic representation of the proposed SFOA algorithm*

Fig. 1 demonstrates the diagrammatic representation of the proposed SFOA algorithm. The method starts with the creation of an individual's population and that might be even or random. Each individual evaluation permits assess that one will be distorted into the sun, i.e., the one with the optimal evaluation amid all. The main steps of the proposed algorithm are defined as follows:

Algorithm 1: Pseudo code of the SFOA technique	
Initialize a random population of n flowers	
In the initial population, find the sun (optimal solution r^*)	
Adjust all plant towards the sun	
while (l<Maximum days)	
	For each plant compute the adjusted vector
	Remove (p%) plants further away from the sun
	For each plant compute the step
	Optimal sunflower plants will pollinate around the sun
	New individuals will be evaluated
	Update the sun, if a new individual is a global optimal
end while	
Optimal solution found	

5. Results and Discussions

5.1Simulation Procedure

In this section, the simulation experiment of six different scenarios was done, and it was tested in the IEEE 30-bus, 57-bus, and the 118-bus systems. Here, the SFOA method was exploited as the proposed method and it was compared with the conventional algorithms such as FPA [17], PSO [12] and MFO [19].

Here, 6 different scenarios were considered to examine the complex system for both the single and multi-objective power flow. First three scenarios such as total fuel cost, emission, and active power loss were considered for single-objective model and remaining three such as fuel cost and the transmission power loss, the fuel cost and VD and L-index were considered for multi-objective power flow.

The objective model taking into consideration for the minimization of the total fuel cost of power generation is represented as the first single objective model, and it stated in eq. (22), where x_i, y_i and z_i represents the coefficient cost of i^{th} generator.

$$f_c = \left(\sum_{i=1}^{NH} x_i M_{hi}^2 + y_i M_{hi}^2 + z_i \right) + \text{Penality}(\$/h) \tag{22}$$

The objective model in order to reduce the emission level of the two significant pollution gases such as SOx and NOx for the single objective model that can be computed as using eq. (23), where α_i, β_i, δ_i and λ_i represents the coefficient cost of i^{th} generator

$$f_e = \left(\sum_{i=1}^{NH} \alpha_i M_{hi}^2 + \beta_i M_{hi}^2 + \delta_i + \phi_i e^{(\lambda_i M_{hi})} \right) + \text{Penality}(\text{ton/h}) \tag{23}$$

For a single objective model, the minimization of the active power loss for each transmission line is stated in eq. (24).

$$f_p = \sum_{i=1}^{nf} \sum_{i=1}^{nf} H_{ij} U_i^2 + U_i^2 - 2U_i U_j \cos(\Delta_i - \Delta_j) + \text{Penality}(MW) \tag{24}$$

The objective model to the minimization of the fuel cost and the transmission power loss for the multi-objective problem is stated in eq. (25).

$$\begin{aligned} f = &\left(\sum_{i=1}^{NH} x_i M_{hi}^2 + y_i M_{hi}^2 + z_i \right) + \lambda_m \sum_{i=1}^{nf} \sum_{i=1}^{nf} M_{ij} U_i^2 + U_i^2 \\ &- 2U_i U_j \cos(\Delta_i - \Delta_j) + \text{Penality} \end{aligned} \tag{25}$$

The multiple objective models to minimize the fuel cost and VD are summarized in eq. (26).

$$f = \left(\sum_{i=1}^{NH} x_i M_{hi}^2 + y_i M_{hi}^2 + z_i \right) + \lambda_{vd} \sum_{i=1}^{nf} \left| U_{F_i} - 1 \right| + \text{Penality} \tag{26}$$

The minimization of fuel cost with voltage stability indicator named L-index, which is an important objective model for power system operation and planning, summarized in eq. (27).

$$LI_i = \left| 1 - \sum_{i=1}^{NH} F_{ji} \frac{U_i}{U_j} \right| \forall j = 1,2,......, NF \tag{27}$$

5.2 IEEE 30 Bus System

This section summarizes the efficiency of the proposed method in the IEEE 30 bus system. Table 1 shows the efficacy of the proposed technique for both the single and multi-objective models. Here, the performance of the proposed technique shows better result than the conventional techniques. Table 2 shows the computation time of the proposed method and conventional techniques. Here, the proposed technique is 0.6% better than the FPA method, 0.82% better than the PSO method, and 0.54% better than the MFO method.

Table 1. *Performance analysis of the proposed and existing methods on IEEE 30 bus system*

Objective model	FPA	PSO	MFO	SFOA
Fuel cost ($/h)	723.45	745.67	763.78	711.334
P_{loss}(MW)	4.545	4.346	4.654	4.341
Emission(ton/h)	0.456	0.445	0.448	0.399
Q_{loss}(MW)	12.345	13.125	13.234	11.126
VD(p.u)	1.278	1.345	1.343	1.121
L-index	0.346	0.376	0.368	0.332

Table 2. *Computation time of the proposed and conventional algorithms on IEEE 30 bus system*

Methods	Time (s)
FPA	14.79
PSO	15.34
MFO	14.33
SFOA	13.89

5.3 IEEE 57 Bus System

This section demonstrates the performance analysis of the proposed and conventional methods on IEEE 57 Bus system. In Table 3, the objective models such as fuel cost, emission, Ploss, Qloss, VD, and L-index is exploited. The overall analysis exhibits the proposed technique is superior to the conventional techniques. Table 4 shows the computation time of both the proposed and conventional techniques. Here, the proposed technique is 10% superior to FPA, 11% superior to PSO, and 11.23% superior to MFO.

Table 3. *Performance analysis of the proposed and conventional algorithms on IEEE 57 bus system*

Objective model	FPA	PSO	MFO	SFOA
Fuel cost ($/h)	512.12	532.45	547.23	503.124
Emission(ton/h)	0.163	0.125	0.167	0.111
P_{loss}(MW)	3.236	3.153	3.248	3.043
Q_{loss}(MW)	13.267	12.674	14.128	12.435
VD(p.u)	2.345	2.432	2.536	2.225
L-index	0.143	0.236	0.278	0.124

Table 4. *Computational time of the proposed and Existing methods on IEEE 57 bus system*

Methods	Time (s)
FPA	16.12
PSO	16.90
MFO	15.12
SFOA	14.37

5.4 IEEE 118 Bus System

In this section, the effectiveness of the proposed method in IEEE 118 bus system has been demonstrated. Table 5 summarizes the efficiency of the proposed method for both the single and multi-objective models. Here, the performance of the proposed method shows enhanced result than the conventional methods. Table 6 shows the computation time of the proposed method and conventional methods. Here, the proposed method is 22% better than the FPA method, 21% better than the PSO method, and 18% better than the MFO method.

Table 5. *Performance analysis of the proposed and conventional algorithms on IEEE 118 bus system*

Objective model	FPA	PSO	MFO	SFOA
Fuel cost ($/h)	849.69	876.37	884.32	823.43
P_{loss}(MW)	5.435	5.426	5.267	5.176
Emission(ton/h)	0.284	0.256	0.278	0.232
Q_{loss}(MW)	22.324	22.126	21.672	20.324
VD(p.u)	3.256	3.237	3.267	3.154
L-index	0.732	0.716	0.745	0.705

Table 6. *Computational time of the proposed and existing methods on IEEE 118 bus system*

Methods	Time (s)
FPA	17.32
PSO	17.89
MFO	16.26
SFOA	13.43

6. Conclusion

This paper presents a novel SFOA method in order to resolve the objective models of OPF in the power system. The proposed method was compared with the conventional methods such as FPA, PSO, and MFA. It was clear that the proposed method was appropriate in order to solve the complex problems and non- smooth problems from the attained results. Finally, the comparative analysis of the proposed technique and conventional techniques proves the superiority of the proposed concept. Moreover, the proposed method is 22% better than the FPA method, 21% better than the PSO method, and 18% better than the MFO method, which shows the proposed method is possible to discover suitable and precise solutions particularly for the multi-objective optimization issues and large-scale power systems.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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