Optimal Placement of FACTS Devices and Power Flow Solutions for a Power Network System Integrated With Stochastic Renewable Energy Resources Using New Metaheuristic Optimization Techniques.

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Abstract:

Flexible AC Transmission Systems (FACTS) and Optimal Power Flow (OPF) solutions play an important role in solving power operation problems. The volatile nature of the power generation profiles from renewable energy sources, solar, and wind systems, and determining the optimal locations and sizes of FACTS devices increase the complexity of the OPF problems in modern power network models, such as transmission power loss, power generation operation cost and voltage deviation, as a highly nonlinear-nonconvex optimization problem. Therefore, this article introduces and employs four new independent, reliable and efficient optimization algorithms inspired by nature and biological nature, namely: Slime Mould Algorithm (SMA), Artificial Ecosystem-based Optimization (AEO), Marine Predators Algorithm (MPA) and Jellyfish Search (JS), for solving both multi and single OPF objective problems for a power network incorporating FACTS and stochastic renewable energy sources. The proposed new metaheuristic optimization techniques are compared to the common and available alternatives in the literature, Particle Swarm Optimization (PSO), Moth Flame Optimization (MFO) and Grey Wolf Optimizer (GWO), using IEEE 30- bus test system. To consider and address the challenges of the OPF in modern power network models, the proposed optimization techniques tested under different operation cases such as increasing in the load, with and without FCTAS and renewable energy sources, different renewable energy sources locations on the network. The result showed that the MPA,SMA,JS and AEO algorithms are more effective solvers for the OPF problems cases compared to the PSO, GWO and MFO algorithms. For example, the AEO obtained 0.0844 p.u in case of minimizing the voltage deviation compared to 0.1155 p.u for PSO, which means that the AEO algorithm improved the voltage deviation term by 27% compared to the PSO algorithm.

Keywords: Optimal power flow (OPF); Flexible AC Transmission Systems (FACTS); metaheuristic optimization algorithms; renewable energy sources.

1. Introduction

1.1. Background

Nowadays, the contribution of renewable energy sources such as wind and Photovoltaics (PV) systems in the power structure is presented as the main power sources alternatives to face the yearly growth in electricity demand due to rising population and a solution to the power system quality [1, 2]. In addition, the interest in renewable energy sources increased because of the decreasing installation and operation costs for the renewable energy systems and the high international concerns about environmental problems [2,3]. However, considering renewable energy sources in the power generation dispatch problems is turned to be a crucial matter due to the volatile behavior of these resources [1,3]. Recently, OPF including renewable energy and fossil fuel power sources is presented as a fundamental single or multi-optimization problem to determine the optimal power-flow and

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generations by solving an objective function such as minimizing power losses, energy generation cost, gas emission and voltage deviation [4,5]. Furthermore, controlling the voltage magnitude and active and reactive power injections have become more challenging due to the volatile behavior of renewable energy sources in the power network. The traditional solutions for these power quality problems such as under load tap changing transformers and load shedding are limited with low operational efficiency and less compatibility due to the network and transformers tap operation constrainers [6]. In addition, reactive power injection techniques are very slow to handle sudden demand changes or the volatile behavior of renewable energy sources. Therefore, power electronic technologies and Flexible AC Transmission System (FACTS) devices can be a significant solution for controlling voltage and reactive power problems in power network under dynamic state [7]. FACTS and OPF management solutions aim to improve the power quality at the network by maintaining the voltage stability and provide cost effective and environmentally friendly power supply solutions [8,9]. In the literature, the OPF studies for a power network integrated with FACTS have mainly solved OPF without considering renewable generation sources or used only one deterministic renewable generation profile (wind or PV) [10,11] and without taking into account the stochastic behavior of these sources to solve single objective function OPF problem. Therefore, unlike the previous research [8-12], this article will focus on developing a realistic power flow model for a power network integrated with FACTS with single and multi-objective functions which treating the stochastic behavior of renewable generation profiles, wind and PV sources, . In addition, this paper will investigate the impact of renewable generation locations and increasing load demand on the network performances.

1.1. Literature review

In literature, various optimization methods are utilized to solve the OPF problem with or without renewable energy sources. Generally, there are three main categories of optimization methods: mathematical, heuristic and metaheuristic algorithms. The mathematical optimization methods in particular linear and quadratic programming, interior point, and Newton-based methods have been mainly used to solve single objective OPF problem [13,14]. However, these mathematical optimization methods [13,14] are limited due to the sensitivity to initial estimates and leading by the non-continuity and non-derivability of the objective function, which helps to trap the solution at local optimal. The mathematical approaches suffered during solving multi-objective OPF problems, due to the limitation of solving nonlinear functions or complex problems. Therefore, mathematical approaches showed low performance in solving OPF problems for modern power networks equipped with renewable energy sources [4,15]. An alternative optimization method, heuristic algorithms such as swarm intelligence and support vector machines, for mathematical methods is presented in [16,17]. The heuristic algorithms are easy to develop without requiring a re-programming for including new OPF constraints. However, the heuristic algorithms converge and trap in the local solution with high computational cost on solving OPF problems [1,6]. The developing and employing recent optimization algorithms are also a consideration of this paper, limited studies consider the benefit of using metaheuristic optimization methods. The combination of the previous two optimization methods (mathematical and heuristic) is called metaheuristic. This optimization approach is an approximation optimization method, which can be used to solve complex OPF problems with and without renewable energy sources [1, 6]. For example, MFO [14], GWO [16], PSO [17,18], Moth Swarm Optimization (MSO) [19], Teaching-Learning-Based Optimization (TLBO) [3], Golden Ratio Optimization Method (GROM) [3], evolutionary algorithms [20,21] Adaptive Differential Evolution (SHADE) [22] have been developed to solve single and multiple objective function problem for a power network system with or without renewable energy sources. As discussed in Section

1.1, FACTS devices play a significant role in modern power networks such as reducing the power losses and generation costs and improving the voltage stability by controlling transmission lines parameters (series and shunt impedance, and phase angle). However, considering FACTS devices in the OPF problems increases the complexity of the OPF problem difficulties of achieving the optimal solution. In the literature, heuristic and metaheuristic optimization methods used to solve single-objective OPF problems. For example, PSO [7,8,23], TLBO [24], Fuzzy Harmony Search Algorithm (FHSA) [25] and Symbiotic Organisms Search (SOS) [26] algorithms are employed to solve OPF problem integrated with FACTS. However, the literature in [23–26] is targeted at solving single objective function OPF problems and which mainly power generation cost or gas emission. The studies in [27,28] worked on solving single and multi-objective function OPF problems by assuming the perfect future knowledge for the renewable energy sources, which is unrealistic due to the non-smooth nature of renewable energy sources. Furthermore, the hybrid optimization algorithms suffered during solving multi-objective functions due to the complexity and the high computational cost of the hybrid algorithms [27,28]. In general, the studies on solving OPF problems for a network integrated with renewable energy and FACTS using metaheuristic optimization methods [29] are sparse in the literature and no studies present the impact of renewable energy resources (wind and PV) on the network and optimization methods performance or compare different new metaheuristic optimization methods.

Recently, Biswas et al. [22] solved OPF by Success History-based Adaptive Differential Evolution (SHADE) algorithm for IEEE-30 bus system integrated with wind power and FACTS. However, , Biswas et al. aimed to solve single and multi objective function OPF problems for two main cases power generation cost and power loss, without considering other OPF problems such as minimizing the voltage level deviation problem. The FACTS and the high uncertainty level of wind power generation have a significant impact on the voltage level deviation, which discussed in this paper. Furthermore, Biswas et al. [22] is only employed the wind power generations units in fixed location as renewable energy sources in the power network without taking into account the PV generation units as one of main renewable energy resources. In our article, the volatile nature of both the PV and wind power generation systems are considered which increased the complexity of the OPF problems and determining the optimal locations and sizes of FACTS devices. In addition, the impact of renewable energy resources (PV and wind) locations and increasing the level of load demand on the optimization algorithms and power network performance are investigated in this paper. Biswas et al. [22] similar to other works [24, 25] employed only one of the recent optimization method and comparted to common methods, however, in this article four new methods (SMA, AEO, MPA and JS) are used to solve complex OPF and FACTS problems and compared them to common optimization method. In general, the OPF solutions of power network equipped with FACTS have mainly solved in the literature [7,8] without considering renewable generation sources in the power grid or used only one deterministic renewable generation profile (wind or PV) [12,22] without taking into account the stochastic behavior of these sources to solve single and multi-objective function OPF problem. Therefore, this work aims to develop new metaheuristic optimization algorithms for improving the power network performance by solving both multi and single objective function OPF problems for a modern power network integrated with FACT devices and considering the stochastic behavior of renewable energy sources, wind and PV systems. In addition, the impact of increasing the load demand and the location of renewable energy sources on the OPF is presented by taking into account the non-convex and highly complex optimization problem nature. The current literature has begun to investigate the benefits of treating the uncertainty of renewable energy sources to increase the power network power flow efficiency [3]. Probabilistic estimation techniques are employed in [1-3] to generate the wind and PV profiles considering the uncertainty in the generation of renewable energy sources. Challenges in predicting the stochastic nature of the renewable energy sources for a power network equipped with FACT devices increase the difficulties of optimality solving OPF problems. In this paper, the stochasticity of renewable energy sources will be treated by creating a realistic model compared to the literature-based probabilistic estimation techniques (Weibull and lognormal). In addition, the new metaheuristic optimization algorithms in this article, namely: MPA [30], JS [31], SMA [32] and AEO [33] are employed and used to decrease the impact of the uncertainty term due to the renewable energy sources and FACTS on the power network performance for a given OPF single and multi cost objective functions. The new metaheuristic optimization techniques are required less adjustable parameters compared to other metaheuristic techniques [30-33], which means that these techniques are easier to be developed and implemented with a lower computational cost. This helps these new algorithms to be the potential for solving OPF problems compared to common optimization methods in the literature.

In general, the new metaheuristic optimization techniques algorithms are bio-inspired algorithm (MPA and JS) and nature-inspired algorithm (SMA and AEO) [30-33] developed based on the intelligent movements and activities in nature. These new optimization algorithms aim to provide highly efficient algorithms for solving complex actual engineering problems. The performance of newly proposed optimization algorithms is compared and evaluated throughout benchmark test functions and different actual engineering problems [30-33]. The new proposed metaheuristic optimization techniques performance results show a powerful ability to achieve a global solution and outperformed over twenty well-studied and new metaheuristics algorithms such as PSO, Genetic Algorithm (GA) and TLBO. Therefore, the MPA, JS, SMA and AEO algorithms can be beneficial for solving complex power flow problems (single and multi-objective functions) for a power network system integrated with stochastic renewable energy resources and FACTS Devices. Adequate new optimization models for power network applications integrated with stochastic renewable energy resources have a worldwide interest due to the significant benefits of reducing gas emission, energy losses and generation cost. To the author's knowledge, there are no works on solving OPF and energy optimization problems have used and employed the new proposed metaheuristic optimization techniques in this paper (MPA, JS, SMA and AEO) and considering the impact of the volatile nature of renewable energy resources and their locations, FACT devices and increasing the load demand on the power network performance. Furthermore, this paper introduces a comprehensive analysis of the literature utilizing the most common, powerful and recent metaheuristic algorithms, PSO, MFO and GWO [14, 18].

1.2. Contributions

In this work, the new proposed metaheuristic optimization techniques have been presented and employed for a power network integrated with stochastic renewable energy resources and FACTS devices. The renewable energy resource profiles (PV and wind) are generated based on the stochastic probability prediction model. To the author's knowledge, the new proposed metaheuristic optimization techniques in this paper (MPA, JS, SMA and AEO) have not used on solving OPF and energy optimization problems, unlike the previous studies [14-18, 23-29] that only used and applied one optimization method and comparted to common methods. In addition, the new proposed techniques in this paper are compared to a common and powerful metaheuristic optimization method, PSO, and other common methods from literature in solving different OPF problems and under different power operation scenarios. The newly proposed metaheuristic algorithms have been designed to minimize generation cost, power losses and voltage deviation on IEEE 30-bus power network. Furthermore, this paper aims to fill the gap in the literature by investigating the impact of renewable energy resource locations and increasing the level of load demand on the optimization algorithms and power network performance. The contributions of this article are summarized as follows:

i. New metaheuristic optimization techniques (MPA, JS, SMA and AEO) are developed and employed to solve OPF problems (single and multi-objective function) considering FACT devices and the volatile behavior of renewable energy resources by using a probabilistic estimation model.

ii. Unlike the previous studies [23-29], these papers aim to develop a realistic power network model integrated with stochastic renewable energy resources and FACTS devices. Furthermore, a comparison analysis for the metaheuristic optimization techniques on solving single and multi-objective functions for power networks equipped with or without FACTS and renewable energy resources.

iii. A comparison analysis for new metaheuristic optimization techniques on different scenarios and investigating the impact of renewable energy resources locations and increasing the level of load demand on the optimization algorithms and power network performance.

1.3. Outline of paper

The remaining parts of this study are structured as follows: Section 2 detail and present the OPF problems formulation, the probability prediction models for renewable energy resources and FACTS devices. The new proposed metaheuristic optimization techniques are described in Section 3. Finally, the simulation results, comparisons and discussions are elaborated in Section 4. The summary of this work and conclusions are given in Section 5.

2. OPF Problem Description: mathematical formulation and modeling.

The main target of developing OPF problem for a power network is finding the optimal generation mix under a predefined objective function and number of constraints. However, the OPF problems for a power network equipped with renewable energy resources and FACTS devices are complex, nonlinear and non-convex optimization problems. In this paper, the most important objective functions, single and multi-objective functions, are presented and developed for OPF problems [3, 7, 13]. The single and multi-objective functions for the OPF have been divided into 4 main cases. These objective functions are solved for a power network (30-bus IEEE) equipped with renewable energy resources and FACTS devices under a number of constraints including equality and inequality limitations, as it will be introduced in subsections 2.1 and 2.2. In subsection 2.3, the probabilistic estimation model for renewable energy resources (PV and wind) is developed and presented. The multi-objective function is formulated in this work as summations for the single objective functions. The single and multi-objective functions of OPF are expressed as follows:

- Case 1: minimizing the power losses.

The power transmission losses for the proposed power network model, P_{los}, for all types of generation units is given by [3, 13-15] as

$$P_{los} = \sum_{n=1}^{N} C_n\left(V_i^{\,2} + V_j^{\,2} - 2V_iV_j\ \cos\left(\theta_i - \theta_j\right)\right), \tag{1}$$

where P_{los} is the total of power transmission losses over all buses and lines in the power network, N is the total number of lines and buses, V_i and V_j are the voltages magnitudes between bus i and bus j of branch n, θ_i and θ_j are the voltage angles between bus i and bus j of branch n and C_n is the conductance of branch n.

- Case 2: minimizing the generation cost.

The generation cost of all committed units for the proposed power network model, P_{cost} , is given using a common quadratic function that is presented in [3, 24, 28] as

$$P_{cost} = \sum_{g=1}^{G} \lambda_g + \delta_g\, P_g + \varphi_g {P_g}^2, \tag{2}$$

where P_{cost} is the total generation cost of all committed units (G), P_g the power generated from unit (g), the cost coefficients for the generation unit (g) are λ_g , δ_g and φ_g.

- Case 3: minimizing the voltage level deviation.

The voltage deviation, V_{dev}, is one of the most common terms to evaluate the quality of the power networks. The V_{dev} is defined as the summation of the voltage deviations between the actual voltage at each load bus in the system, V_d and the rated voltage, which equal to 1.0 per unit, for all buses, *D*, as shown in Equation (3) [3,20].

$$V_{dev} = \sum_{d=1}^{D} |V_l - 1| \tag{3}$$

- Case 4: minimizing the power losses, generation cost and voltage deviation.

In order to evaluate the proposed new metaheuristic optimization techniques on different level of complexity for the OPF cost function, Case 4 merges three single cost functions into a multi cost function. In Equation (4), the generation cost, power losses and voltage deviation functions (Case 1 to 3) are emerged as multi cost function in Case 4, as

$$\begin{aligned} K_{all} = \left(\vartheta_P \sum_{n=1}^{N} C_n\left({V_i}^2 + {V_j}^2 - 2V_iV_j\ \cos\left(\theta_i - \theta_j\right)\right)\right) + \left(\vartheta_f \sum_{g=1}^{G} \lambda_g + \delta_g\, P_g + \varphi_g {P_g}^2\right) \\ + \left(\vartheta_{VD} \sum_{d=1}^{D} |V_l - 1|\right). \end{aligned} \tag{4}$$

In Equation (4), the ϑ_P, ϑ_f , ϑ_{VD} are the weight factors for power losses, generation cost and voltage deviation indexes and they are assumed to be equal 22, 1 and 21 , respectively, as common and optimal values for the proposed power network [3, 24,28]. In general, the weighted sum strategy, Equation 4, is one of the most popular multi objective functions strategies. This strategy has been used in this paper, which required converting the objective problems into a scalar problem through scaling operation and then adding a weighted sum of all the objectives. In order to recover the original values of the objective function, its required to reverse the scaling. Equation (4) presented the multi objective function form as common and standard equation for the proposed power network [3, 24,28].

2.1 FACTS device modeling

Flexible AC Transmission Systems (FACTS) devices as power electronic converters aim to increase the power transfer capability and give more flexibility and speed to control the power flow by controlling the various parameters in transmission line circuits [7,23-26]. In general, many types of FACTS device controllers are developed and used to increase the overall power network efficiency [7]. In this work, the common types of FACTS devices are employed, which are: shunt controllers (SVC) and series controllers (TCSC and TCPS). For more details and comprehensive information about the type of FACTS controllers, interested readers are directed to [7,34-36]. The significance of integrating FACTS devices in the power network depends on the location and sizing of the FACTS devices and coordination between them. In this paper, the optimal location and sizing of FACTS devices have been determined based on achieving the maximum improvement at each cost function (Cases 1 to 4). The proposed new metaheuristic optimization techniques in this paper are employed to solve OPF with FACT devices considering the FACTS rating presented in Table 1 [7,34-36].

Table 1: The FACTS operation rating.

Description	**Operation rating**	
	Min	**Max**
Compensation by TCSC	0%	50%
Angle of phase shifter (TCPS)	$-5°$	5°
SVC can either absorb (negative) or deliver (positive) reactive power up (MVAr)	-10	10

2.2 The power network constraints

In a power network, the OPF problems are limited to a number of constraints, which are usually related to the physical limitations for the network equipment and the operating conditions such as frequency, current and voltage. These constraints are basically divided into equality and inequality constraints.

- Equality Constraints for OPF problem:

The equality constraints are typically described as the power flow between the generation and consumer sides in a network. The total active and reactive power, $\sum_{g=1}^{G} P_g$, and, $\sum_{g}^{G} Q_g$, are described by Equations (5) and (6), respectively, for all available thermal and renewable energy resources generations units [1,3, 13-20] as

$$\sum_{g=1}^{G} P_g = P_L + P_{los}, \tag{5}$$

$$\sum_{g=1}^{G} Q_g = Q_L + Q_{los}, \tag{6}$$

where P_L and Q_L are the active and reactive of load demand (consumer sides), G is the total number of generation units, P_g and Q_g are the total active and reactive generated from generation unit g, P_{los} and Q_{los} are the total active and reactive power loss over all buses and lines in the network, respectively. Furthermore, the power flow constraints at the level of single generation unit in the power network can be described as follow [3]:

$$P_g - P_{L_g} = V_g \sum_{n=1}^{N} V_n\big(C_{gn}\cos\theta_{gn} + B_{gn}\sin\theta_{gn}\big), \tag{7}$$

$$Q_g - Q_{L_g} = V_g \sum_{n=1}^{N} V_n\big(C_{gn}\sin\theta_{gn} + B_{gn}\cos\theta_{gn}\big), \tag{8}$$

where the P_{L_g} and Q_{L_g} are the active and reactive load connected to the generation unit g, *N* is the total number of buses, V_g and V_n are the voltage magnitudes at buses g and n, C_{nq} is the conductance between buses g and n, B_{gn} is the transfer susceptance for buses g and n, θ_{gn} is the variance of voltage angle for buses g and n.

- Inequality Constraints for OPF problem:

Generally, the power network operates under a number of limitations related to the physical network equipment and the operating conditions such as frequency, current and voltage. These limitations are mainly inequality constraints and can be described as following [1,3]:

- Power generation limitations.

$$V_g^{\min} \le V_g \le V_g^{\max}, \tag{9}$$

$$P_g^{\min} \le P_g \le P_g^{\max}, \tag{10}$$

$$Q_g^{\min} \le Q_g \le Q_g^{\max}, \tag{11}$$

where $V_g^{\min}$ and $V_g^{\max}$ are the minimum and maximum voltage magnitude at unit g, $P_g^{\min}$ and $Q_g^{\min}$ are the minimum active and reactive power at unit g, $P_g^{\max}$ and $Q_g^{\max}$ are the maximum active and reactive power generation at unit g, respectively.

- The tap setting limitation at power transformer.

$$TS_r^{\min} \le TS_r \le TS_r^{max}, \tag{12}$$

where the TS is the tap setting of power transformers for regulating tap $r = 1,2,\ldots,R$ and R is the number of taps, $TS_r^{\min}$ and $TS_r^{\max}$ are the minimum and maximum tap setting limitation, respectively.

- The voltages level limitations

$$v_l^{\min} \le v_l \le v_l^{\max}, l = 1,2,\ldots,\mathrm{L}, \tag{13}$$

where v_l is the magnitude of voltage at bus *l*, L is the total number of buses, $v_l^{\min}$ and $v_l^{\max}$, are the minimum and maximum voltages at the load bus *l*.

- The transmission loading limitations

$$D_m \le D_m^{\max}, \ m = 1,2,\ldots,\mathrm{M}, \tag{14}$$

where the D_m is the loading magnitude at transmission line *m*, M is the total number of transmission lines and $D_m^{\max}$ is the maximum loading at line *m*.

- Handling inequality constraints

In this paper, the external penalties function is applied to handle inequality constraints and decline any infeasible solutions [2, 3]. The penalty function in Equation (15) aims to add penalties on any infeasible solutions, which will help to keep the dependent variables within the values of the constraints during solving the optimization problem as an iterative searching process. In addition, the OPF cost functions (Cases 1 to 4) can be converted using a penalized cost function into an unconstrained optimization problem. The penalized objective function for the inequality constraints is defined as [3,13]:

$$F_{penalty} = H_P\left(P_1 - P_1^{\lim}\right)^2 + H_Q\sum_{g=1}^{G}\left(Q_g - Q_g^{\,lim}\right)^2 + H_V\sum_{l=1}^{L}\left(v_l - v_l^{\,lim}\right)^2 + \ H_D\sum_{m=1}^{M}\left(D_m - D_m^{\,lim}\right)^2, \tag{15}$$

where H_P, H_Q, H_V and H_D are the external penalties factors and they are assumed to be 100, 100, 100, and 100,000, respectively as in [1-3], P_1 is the active power magnitude at the slack bus, $P_1^{\lim}$ is the limit value of P_1, $Q_g^{\,lim}$ is the reactive power limit at Q_g, v_l is the voltage at bus *l*, $v_l^{\,lim}$ is the voltage limit value at bus *l*, the limit value of the transmission line loading D_m is $D_m^{\,lim}$.

2.3 The estimation model for renewable energy sources

Nowadays, renewable energy resources have a significant impact on power networks and markets. Therefore, renewable energy resources need to be employed in power network models to improve the reliability and quality of the networks [1,3]. However, renewable energy resources are naturally stochastic and depended on the weather conditions [37, 38]. This increase the challenging of accurately estimating the renewable energy resources and optimality solving OPF problem. To effectively, solve OPF for power networks with renewable energy resources, a probabilistic predicting model for the renewable energy resources profiles is essential instead of assuming accurate profiles or deterministic forecast profiles. The probabilistic predicting model aims to deal with the uncertainties in renewable energy resources profiles, in order to improve the performance of solving the OPF problem. In this paper, the IEEE 30-bus power network model equipped with wind and PV energy sources within different location scenarios is addressed. The wind and PV power generations have estimated using probabilistic algorithms (Weibull and lognormal). In the power network model, to give the priority to available renewable energy resources to be firstly fed to the power network than the rest of the thermal source units, the wind and PV generation profiles are utilized as negative load values [1-3]. In addition, this helps to reduce the total load demand, generation cost and power losses of the thermal units.

2.3.1 PV generation units

The power output of PV generation units are guided by weather condition such as the solar irradiance and clouds. Therefore, the power profile of PV units can be descried as stochastic and volatile, especially during unclear sky conditions. In general, solar irradiance, S, can be described by lognormal probability distribution function, L (S), as common and standard model [3,37] to present the solar irradiance as random variable, as presented in Equation (16) [3,37]:

$$L(S) = \frac{1}{S\sigma\sqrt{2\pi}}\exp\left(\frac{-(\ln S - \mu)^2}{2\sigma^2}\right), S\ > 0, \tag{16}$$

where μ is the mean and σ is the standard deviation of the lognormal probability function. The PV system works on converting the solar irradiance, S, to electrical power, P(S), by using Equation (17), based using the probabilistic estimating in Equation (16) [3,38].

$$\mathrm{P}(S) = \begin{cases} P_{nom}\dfrac{S^2}{S_{st}S_c}, & for \quad 0 < S < S_c \\ P_{nom}\dfrac{S}{S_{st}}, & for \qquad S \geq S_c, \end{cases} \tag{16}$$

where the nominal power output of the PV unit is P_{nom} , S_{st} is the standard solar irradiance, S_c is the irradiance critical point. Furthermore, the total generation cost for PV units is calculated as presented in [3,37,38].

2.3.2 Wind Power Units

The output of wind power units are guided by wind speed as one main variable. Therefore, the power profile of wind power units can be descried as stochastic quantity. In general, wind speed, W, can be described by Weibull probability distribution function, V (W), to present it as random variable, as presented in [3]:

$$V(W) = \frac{d}{K}\left(\frac{W}{K}\right)^{d-1} e^{-\left(\frac{W}{K}\right)^{d}}, \tag{19}$$

where W is the wind speed, K is the scale factor of the Weibull function, and d is the dimensionless shape factor. The wind unit works on converting the kinetic energy at wind to electrical power by using Equation (19), based using the probabilistic estimating of the wind speed in Equation (19) [3,37].

$$V_P(W) = \begin{cases} 0, & W < W_{in}\ and\ W > W_{out} \\ V_{nom}\left(\dfrac{W - W_{in}}{W_r - W_{in}}\right), & W_{in} \leq W \leq W_r \\ V_{nom}, & W_r < W \leq W_{out}, \end{cases} \tag{19}$$

where V_{nom} is the nominal power value of the wind unit,W_r, W_{in} and W_{out} are the rated, cut-in and cut-out wind speed, respectively, for the proposed wind generation unit. In this paper, the generation cost of wind power generation units is calculated as presented in [3,37,38].

3. Proposed method: New metaheuristic optimization algorithms

In this article, the new metaheuristic optimization algorithms MPA, JS, SMA and AEO [30-33] are adapted and employed to solve OPF problems and handle the high uncertainty level in the power network due to equipping the renewable energy sources and FACT devices. In general, the new metaheuristic optimization techniques designed to handle stochastic, volatile and complex optimization problems [30-33]. In addition, the new algorithms are easier to developed and implement with lower computational cost, where they required less adjustable parameters compared to other metaheuristic techniques [30-34]. Therefore, the proposed new metaheuristic optimization algorithms can be beneficial for solving complex power flow problems (single and multi-objective functions) for a power network system integrated with stochastic renewable energy resources and FACTS Devices. Adequate new optimization models for power network applications have a worldwide interest due to the significant benefits of reducing gas emission, energy losses and generation cost. To the author's knowledge, there are no works on solving OPF and energy optimization problems that have used the MPA, JS, SMA and AEO algorithms and considering the impact of the volatile nature of renewable energy resources or FACT devices. Furthermore, this paper introduces a comprehensive analysis of the literature utilizing one of the most powerful, common and recent metaheuristic algorithms, PSO, MFO and GWO [14,16-18]. The simulation models for all proposed metaheuristic optimization algorithms have been implemented based on optimal parameters and the details will be presented within Section 4.1.

3.1.1 MPA and JS algorithms

In 2020, new bio-inspired metaheuristic optimization algorithms called Marine Predators Algorithm (MPA) and Jellyfish Search (JS) have been introduced by Faramarzi et al. [30] and Chou and Truong [31], respectively. Firstly, the main aim of MPA is to introduce an alternate metaheuristic algorithm for handling stochastic optimization problems. The basic idea of MPA is inspired by the intelligent activities and movements of ocean predators to creating widespread foraging strategies [30]. The MPA follows the unique ocean predator's movements, Lévy and Brownian movements, in line with an optimal rate policy for the attacking interaction between predator and prey [30]. The MPA algorithm for solving stochastic and complex optimization problems is summarized and described through main three phases in Figure 1. In the first optimization phase, the search domain in initial iterations is determined based on the Brownian motion for the prey. The search domain in the first stage is are uniformly distributed, where the Brownian motion helps preys to separately explore their neighborhood and lead to good searching of the domain. In this first step, the distance between predator and prey will be assumed relatively large. Then, the new searching position is evaluated using the fitness function and the new searching position is replaced by the previous position if it is more fitted. The fitted positions in MPA algorithm are inspired by the prey movement for abundant food areas, which including also saving procedures for the new and old positions. Here, phase two of MPA optimization starts, where predators start looking for foraging while the prey also looking for food. Therefore, half of the domain population is in charge of predators looking for prey in Brownian motion and the other half is for prey which switches to Lévy strategy. The Lévy strategy aims to effectively search in neighborhood area and in case there is, no solution (food) will take a long jump, which helps to avoid the trip with a locally optimal solution. Here, the two searching strategies (predator and prey locations) will become close to each other, as the final optimization stage. In this stage, the predator will switch from Brownian to Lévy strategy to follow the prey movement and be more effective neighborhood searching. Furthermore, a convergence factor will be used in this stage to help predators to limit the search areas and non-promising regions of the domain, which will help to minimize the computational complexity (time search effort) and achieve the global solution.

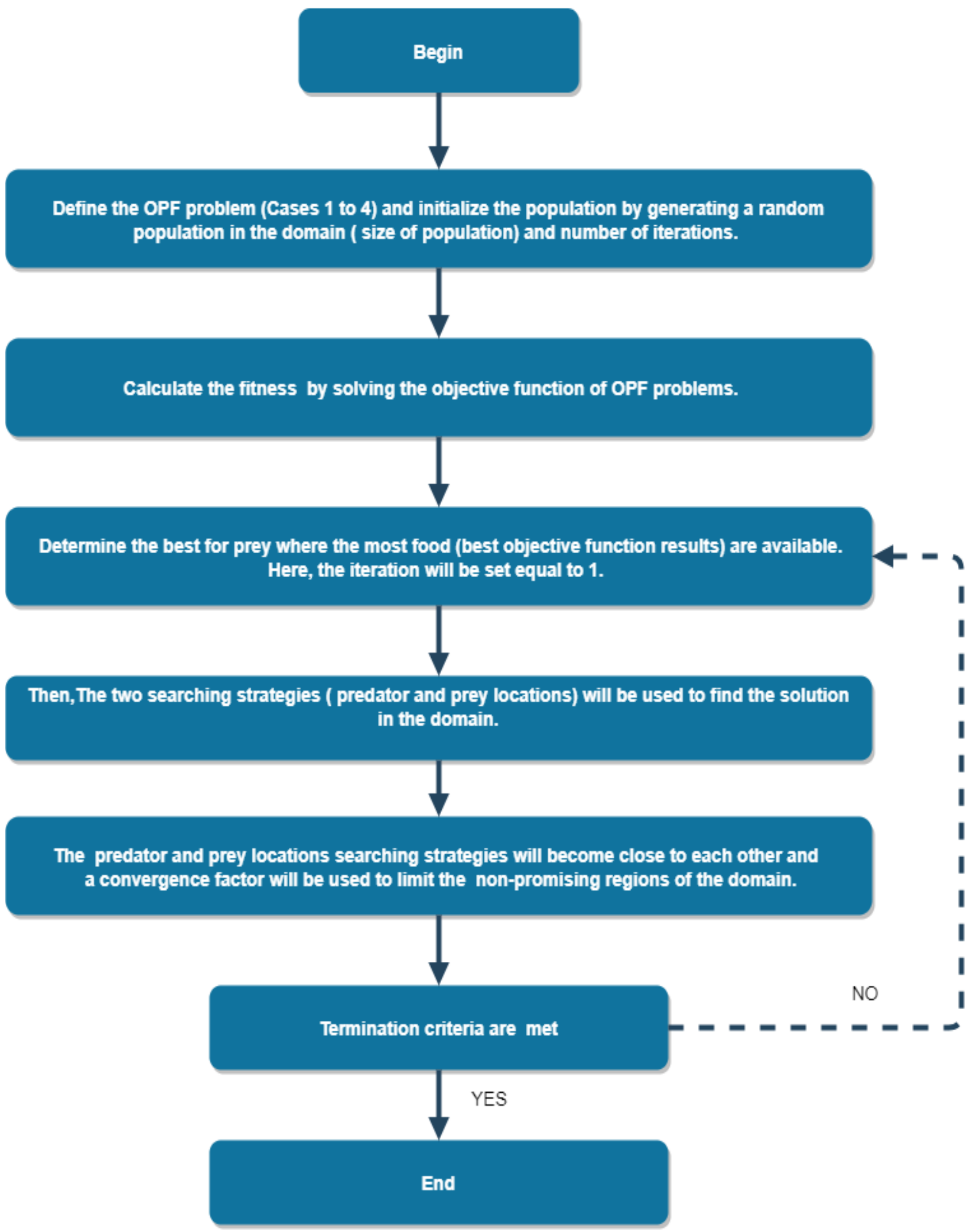


Fig. 1. The Marine Predators Algorithm (MPA) procedures.

In another algorithm, the behavior of jellyfish in the ocean is motivated [31] to develop a novel metaheuristic algorithm called artificial Jellyfish Search (JS). The JS optimization is used the jellyfish nature movements from the ocean current motions, the swarm motions. Furthermore, a time control mechanism is employed to switch between these movements and achieve convergences. The JS optimization algorithm can be described by three main Jellyfish movement rules, which close to MPA algorithm.

- Jellyfish movements in the ocean aims to search for food and the best movement's location where the more quantity of food is available.
- Finding the high quantity of food is determined based on an objective function.
- Jellyfish moves with the ocean current or the swarm, and time control mechanism works on switching between them to find best food location (solving the objective function).

The artificial Jellyfish Search (JS) algorithm for solving complex and stochastic optimization problems is summarized below:

Step 1 Define the objective and initialize the population: this step aims to select the cost function for the proposed problem, OPF in our work, set the search space and size of population and number of iterations. Furthermore, in this step, a random population in the domain will be generated.

Step 2 Calculate the quantity of food (the cost function value for OPF problems) by solving the objective function and determine the best location where most of the food (best objective function result) is available. Here, the iteration will be set equal to 1.

Step 3 Searching steps (time control mechanism): at each iteration, a time control function as a random value between 0 to 1 is compared to a constant time value. This process aims to regulate the jellyfish movement between ocean current and swarm motions. In case the time control function value is larger than the set constant time, the ocean current moves will be followed otherwise the swarm motions will be followed to select the new position.

Step 4 Recalculate the quantity of food (cost function value) by solving the objective function at the new position and determine the best location where most of the food (best objective function result) is available. Here, the iteration will be updated.

Step 5: Repeat steps 2–4 until the maximum iterations number, which is the stop criterion here.

3.1.2 SMA and AEO algorithms

New nature-inspired metaheuristic optimization algorithms called Slime Mould Algorithm (SMA) and Artificial Ecosystem-based Optimization (AEO) have been introduced in 2019 by Li *et al.* [32] and Zhao *et al.* [33], respectively. Firstly, the proposed SMA aims to introduce an alternate metaheuristic algorithm for solving complex and stochastic optimization problems based on the life cycle of SMA and its morphological changes in foraging. The SMA algorithm for solving stochastic optimization problems is summarized in Table 2.

Table 2: The Slime Mould Algorithm (SMA) algorithm procedures.

Step	Description
1	Initialize the population: set the search space and size of population and number of iterations. Furthermore, in this step a random population in the domain will be generated.
2	Define the objective (cost function of OPF) and Initialize the first slime mould positions. Here, the iteration will be set equal to 1
3	Calculate the the fitness of all SM positions by solving the objective function and determine the best location where the best fitness.
4	Searching where the high quantity of food (the cost function value) connected to the SM, at each iteration. This process aims to regulate the SM movement towards the best cost function values. Then, the update positions is selected and the fitness value is calculated.
5	Repeat steps 2–4 until the maximum iterations number, which is the the stop criterion here.

In another algorithm, the flow of energy in an ecosystem is motivated [33] to develop a novel metaheuristic algorithm called artificial ecosystem-based optimization (AEO). AEO algorithm high ability in solving complex problems with less convergence rate and computational costs. The AEO optimization uses three behavior levels of living organisms, which are production, consumption, and decomposition. The AEO optimization algorithm can be described by following energy movement's rules in an ecosystem:

- The ecosystem is the population search area, which includes the following living organisms: producer, consumer, and decomposer.
- The population (ecosystem) will only include one producer and one decomposer as an individual in the population.

- The rest of the individuals in the population will be consumers (carnivore, herbivore, or omnivore).
- Each of the individual in a population will have an energy level. This energy level will be evaluated by using cost function (fitness value), where the higher fitness value pointed to higher energy level.

The AEO algorithm for solving complex and stochastic optimization problems is summarized below:

Step 1 Initialize the population of an ecosystem: this step aims to select the cost function for the proposed problem, set the search space and size of population and number of iterations.

Step 2 Identify the objective cost function (fitness function) and calculate the best fitness (solution) for initial populations by solving the objective function.

Step 3 Searching steps: at each iteration, a mimics food (cost function) searching process is applied, where each consumer may eat (search move) a random producer, or consumer with a lower level of energy or both. This process is a random walk searching steps aims to effectively explore the search space with neighborhood and long-run movements close to JS algorithm, which help to the global optimum and avoid local ones.

Step 4 Update the position of each individual for the producer, consumer, and decomposer and then recalculate the fitness by solving the objective function at the new positions and determine the best available solution. Here, the iteration will be updated.

Step 5: Repeat steps 2–4 until the maximum iterations number, which is the stop criterion here.

4. Results and discussion

In order to examine and validate the performance of the proposed new metaheuristic optimization algorithms, an IEEE 30-bus with renewable energy resources and FACT devices has been used. Firstly, the description of case studies is presented; then, the proposed optimization algorithms evaluated and tested under different network operation scenarios and for different OPF problems (single and multi-objective functions). Throughout this section, the proposed new metaheuristic optimization techniques (MPA, JS, SMA and AEO) are comparable to the common heuristics optimization algorithms from the literature, specifically: PSO, MFO and GWO [14,16-18].

4.1 The power network system: Case studies

The IEEE 30 power network is obtained from [3,37,38] as a reference network model, as described in Table 3, with 6 thermal generation units, 30 buses, 41 branches, 24 control variables and load equal to 100 MVA single swing bus which is bus 1.

Table 3: The main characteristics of IEEE 30-bus system.

Characteristics	**Value**
Thermal generations	Located at buses number 1, 2, 5, 8, 11 and 13.
Load voltage	0.95–1.05 p.u
Generator voltage	0.95–1.1 p.u
Transformers with tap changer	Located at buses number 11,12,15 and 36; varying the voltage from 0.9 to 1.1 p.u
Swing bus	Bus 1
Active and reactive demand	2.834 p.u and 1.262 p.u
Limits of voltage automatic regulator	0- 0.5 p.u

This reference network model is adjusted by incorporating two-variable PV and wind generation units. The PV and wind systems are presented in Section 2.3 and the model's data is presented in Tables 4 [3]. Throughout this section, the results of the proposed optimization algorithms will be compared for specific power network models based on the following configurations:

- The IEEE 30-bus system –(1): The IEEE 30-bus system is modified in this model by adding PV and wind generation units at bus 24 and 28, respectively, and replacing the thermal generation units at buses 5 and 13 with PV units and replacing the thermal generation at bus 11 by wind system, as presented in Figure 2.
- The IEEE 30-bus system –(2): to explore the impact of the PV and wind generation units on the performance of the power network and proposed optimization algorithms, the IEEE 30-bus system is modified by adding PV and wind units at buses 17 and 25, respectively, and replacing thermal generation at buses 5 and 13 by PV units and at bus 5 by wind unit at bus 11.

In this paper, to investigate and evaluate the impact of incorporating FACT devices to the power network system on the optimization algorithm performance and solving the OPF problems, the proposed IEEE 30-bus systems (1) and (2) are modified by inserting FACT devices. The optimal location and sizing of FACTS devices have been founded based on achieving the maximum improvement at each cost function.

The proposed IEEE power network models (1) and (2) are used to formulate the single and multi-objective functions for the OPF problem, as presented in Section 2. Table 5 presents the coefficients of the proposed cost function for the OPF in Section 2 [3]. In order to solve the cost functions in Section 2 and achieve the best optimal solution, the parameters of the proposed new metaheuristic optimization techniques (MPA, JS, SMA and AEO) need to be first selected. In general, the optimization algorithm's performance relies on different factors such as the optimization solver parameters, the OPF complexity, the problem constraints and the availability of the data [3.30-33]. Furthermore, each optimization algorithms has a number of advantages and drawbacks and there is no optimization solver that can be suitable for all engineering problems. Therefore, we evaluated and compared different new metaheuristic optimization algorithms. The parameters of the proposed new metaheuristic optimization algorithms are selected and verified by using empirical tests based on previous studies model data. In this article, the proposed optimization algorithms are simulated over a wide range of values for each parameter and the optimal value for each parameter (i.e., which achieves the best solution) is selected. Table 6 presents the range and the optimal values of the main parameters for each metaheuristic optimization algorithms. In this work, the simulation models for the proposed metaheuristic optimization algorithms have been developed on MATLAB 2016 using 2.8-GHz i7 PC with 16 GB of RAM.

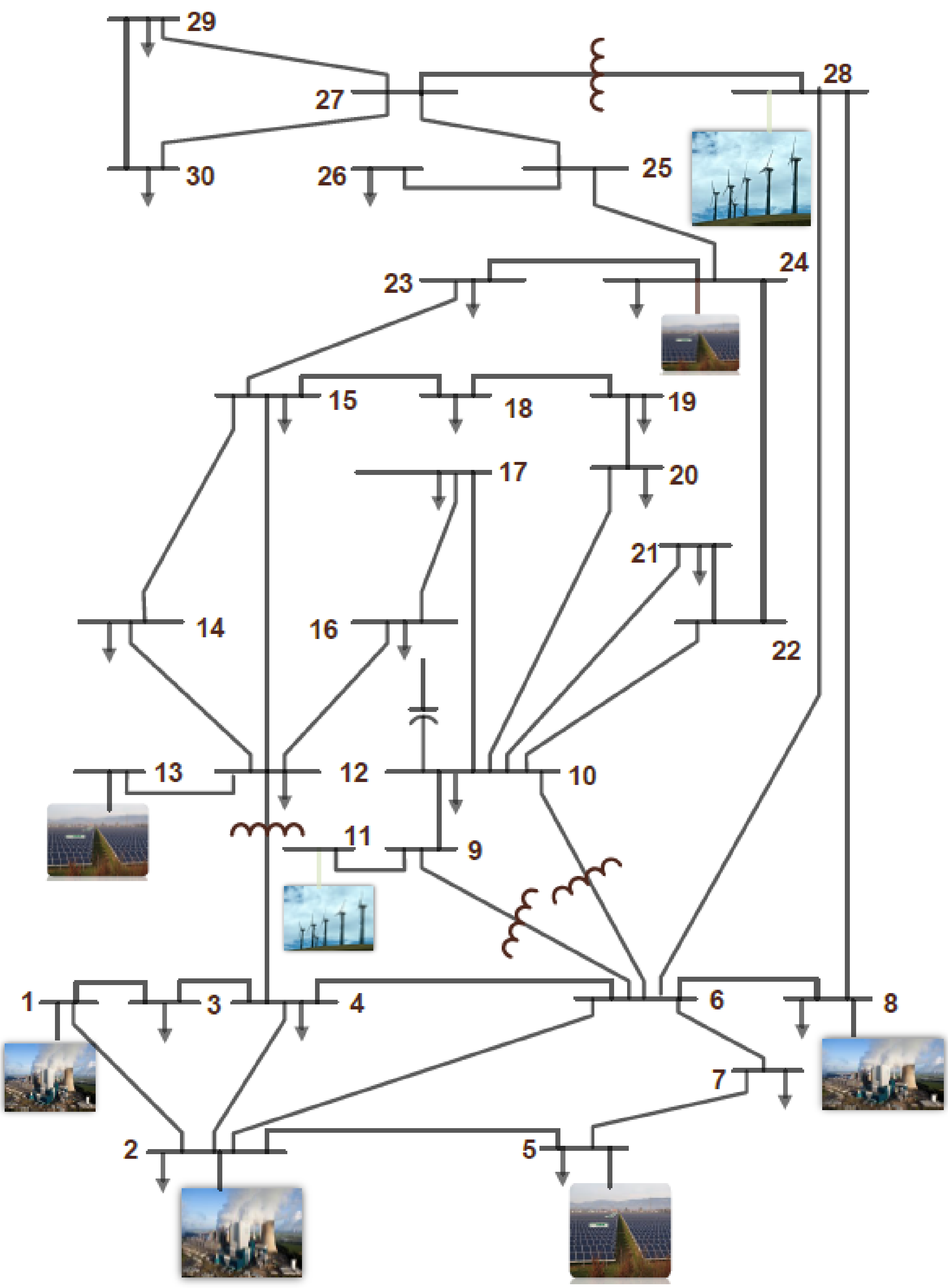


Fig. 2. The proposed IEEE 30-bus system – (1).

Table 4: The PV and wind systems data.

Wind system.									
Unit	Bus Modified 1	Bus Modified 2	No. of turbines	V_{nom}	K	d	W_{in} (m/s)	W_{out} (m/s)	W_r (m/s)
1	11	11	10	2	9	1.65	4	25	13
2	28	17	12	2	10	1.7	4	25	13
PV system.									
Unit	Bus Modified 1	Bus Modified 2	P_{nom} (MW)	S_{st} (W/m²)	S_c	μ	σ		
1	5	5	25	800	120	6	0.6		
2	13	13	30	800	200	6	0.6		
3	24	25	30	800	170	6	0.6		

Table 5: The generation operational cost coefficients.

The generation cost coefficients				
Generator	bus	λ_g	δ_g	φ_g
1	1	0	2	0.00375
2	2	0	1.75	0.0175
4	8	0	3.25	0.00834

Table 6: The proposed new metaheuristic optimization optimization parameters.

Algorithm	Parameters	Values	Testing Range
PSO [7,8,23]	Coefficient of inertia	Decreasing from 0.9 to 0.4 (linearly)	----
	Search agents number	50	25-100
	Maximum iteration number	100	50-200
	Coefficient of acceleration	1 and 2	
MFO [14]	Size of population	50	25-100
	Maximum iteration number	100	50-200
GWO [16]	Size of population	50	25-100
	Maximum iteration number	100	50-200
MPA [30]	Size of population	50	25-100
	Maximum iteration number	100	50-200
JS [31]	Size of population	50	25-100
	Maximum iteration number	100	50-200
SMA [32]	Maximum iteration number	100	25-100
	Size of population	50	50-200
AEO [33]	Maximum number of iterations	100	50-200
	Size of population	50	25-100

4.2 OPF problems results with single and multi objective function

This section aims to present the performance of the proposed metaheuristic optimization algorithms using IEEE 30-bus system – (1) for all objective function cases, as presented in Section 2. The objective function values for each metaheuristic optimization solver are used to compare the results, where the transmission network loss, generation cost and voltage deviation are given in MW, $/h and p.u, respectively. In Figure 3, the proposed new metaheuristic optimization algorithms outperformed the PSO, GWO and MFO algorithms, as a common and new algorithms in the literature, in all OPF cases. In addition, the result showed that the AEO algorithm outperformed all other metaheuristic optimization algorithms for Cases 1 and 2 with the minimum cost function value. For example, the AEO obtained 752 $/h in case 2 compared to 778 $/h and 765 $/h for PSO and SMA, respectively. However, the SMA outperforms the AEO algorithm and all other metaheuristic optimization algorithms in Case 3 by achieving the lower cost function equal to 0.123689 p.u. The SMA and MPA algorithms have obtained close results for the multi-objective function problem (Cases 4). In Case 4, the AEO algorithm handled multi-function in a better way and outperformed other algorithms and achieved the lower cost function value equal to 1109.49.

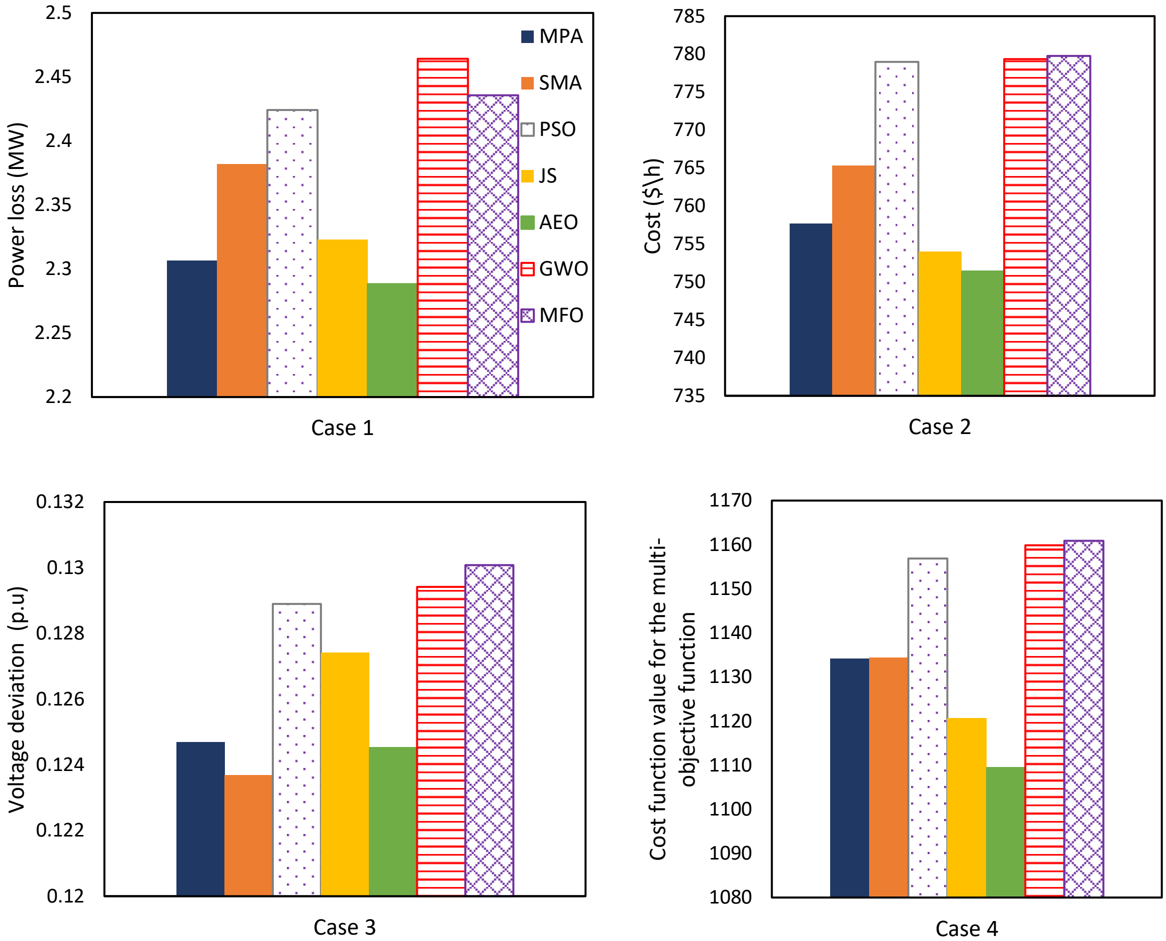


Fig. 3: Results of the proposed metaheuristic optimization algorithms for IEEE 30-bus system – (1).

In order to investigate how the proposed optimizations algorithm converges, the convergence curves for all cases are presented in Figure 4. The convergence curves aim to introduce the relationship between the number of model iterations and the value of the cost function. Figure 4 shows that the AEO algorithm has the smoother and most speedy convergence curve compared to the other proposed metaheuristic optimization algorithms, where the AEO reached the optimal values for all cases with the less number of iterations. This presented the AEO algorithm as the most efficient algorithm in terms of lower computational cost and higher efficiency in CPU utilization.

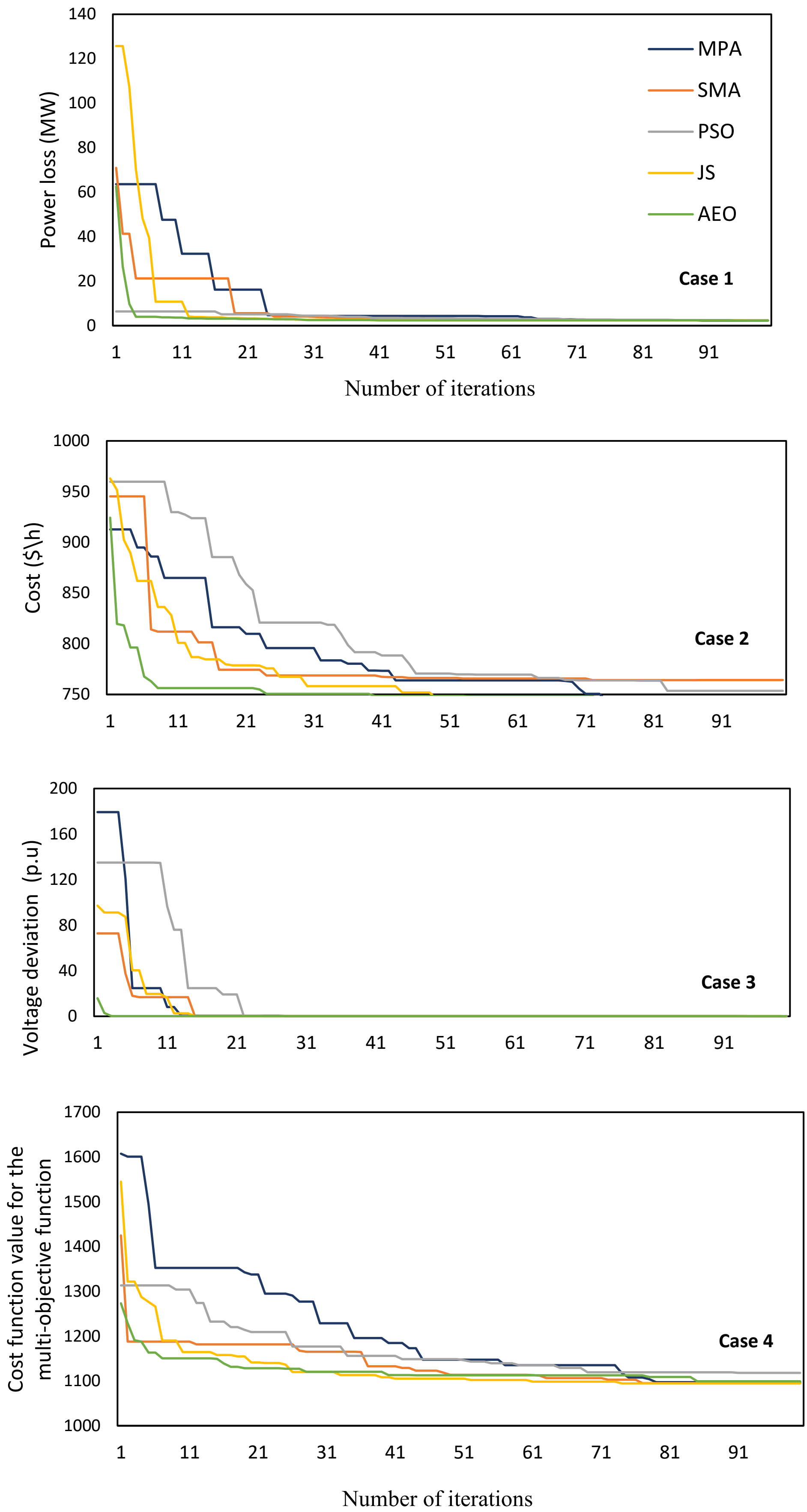


Fig. 4. Convergence curves of the proposed metaheuristic optimization models for IEEE 30-bus system – (1).

4.2.1 The impact of Renewable energy sources locations on the OPF problem

In order to introduce and investigate the impact of the renewable energy source locations on the OPF solvers, the IEEE 30-bus system– (1) has been used in this section. In the previous section, the AEO outperformed all other algorithms for Cases 1,2 and 4 for the IEEE 30-bus system– (1). Table 7 presents the results of the proposed metaheuristic optimization models for the IEEE 30-bus system – (1) and IEEE 30-bus system – (2) for all cases. The metaheuristic optimization results in Table 7 indicate that the renewable energy sources and their locations have a significant impact on the optimization solver performance and OPF solutions. In Table 7, the proposed new metaheuristic optimization algorithms outperformed the PSO, GWO and MFO algorithms, as a common and new algorithms in the literature, in all operation scenarios. The results also show that there is a difficulty for a specific metaheuristic optimization to a suitable and optimal solver for all case and operation generation scenarios. For example, the AEO algorithm in case 1 for the IEEE 30-bus system– (1) with 2.288 MW outperformed all other algorithms but for the IEEE 30-bus system– (2) was not the case and the MPA algorithm achieved the lower losses result with 2.5 MW.

Table 7: Results of the proposed metaheuristic optimization models for (A) the IEEE 30-bus system – (1) and (B) the IEEE 30-bus system – (2) for all cases.

	Case 1		**Case 2**		**Case 3**		**Case 4**	
	(A)	**(B)**	**(A)**	**(B)**	**(A)**	**(B)**	**(A)**	**(B)**
MPA	2.306	**2.500**	757.663	767.532	0.1246	0.1389	1134.19	**1121.98**
SMA	2.381	2.621	765.360	767.991	**0.1236**	0.1398	1134.41	1146.68
PSO	2.424	2.635	778.975	764.061	0.1288	0.1335	1156.86	1143.22
JS	2.322	2.570	754.027	**758.408**	0.1274	0.1408	1120.66	1138.76
AEO	**2.288**	2.535	**752.468**	767.306	0.1245	**0.1314**	**1109.49**	1140.63
GWO	2.464	2.681	779.360	768.968	0.1294	0.1410	1159.89	1151.68
MFO	2.435	2.659	779.745	767.561	0.1300	0.1409	1160.86	1142.53

4.3 FACT devices results

To explore the impact of incorporating FACT devices to the power networks on the power network and OPF problems solvers performance, FACT devices have been added to the IEEE 30-bus system – (1) and IEEE 30-bus system – (2). In this paper, the optimal location and sizing of FACTS devices have been determined based on achieving the maximum improvement at each cost function. The proposed new metaheuristic algorithms results by using IEEE 30-bus model – (1) are presented in Figure 5 and compared to the results from IEEE 30-bus model – (2) in Table 8. The result of the IEEE 30-bus system - (1) with FACT devices showed that the proposed new metaheuristic optimization algorithms (MPA,SMA,JS,AEO) are more effective solvers for the OPF problems cases compared to the PSO, GWO and MFO algorithms. In Figure 5, the AEO algorithm outperformed all other metaheuristic optimization algorithms for all OPF cases. For example, the AEO obtained 0.0844 p.u in case 3 compared to 0.1155 p.u for PSO, which means that the AEO algorithm improved the voltage deviation term by 27% compared to the PSO algorithm. The AEO and JS algorithms have obtained close results for all OPF cases. In Case 4, the PSO algorithm was not able to handle the multi-functions in and complexity compared to other algorithms, where it achieved the higher cost function value.

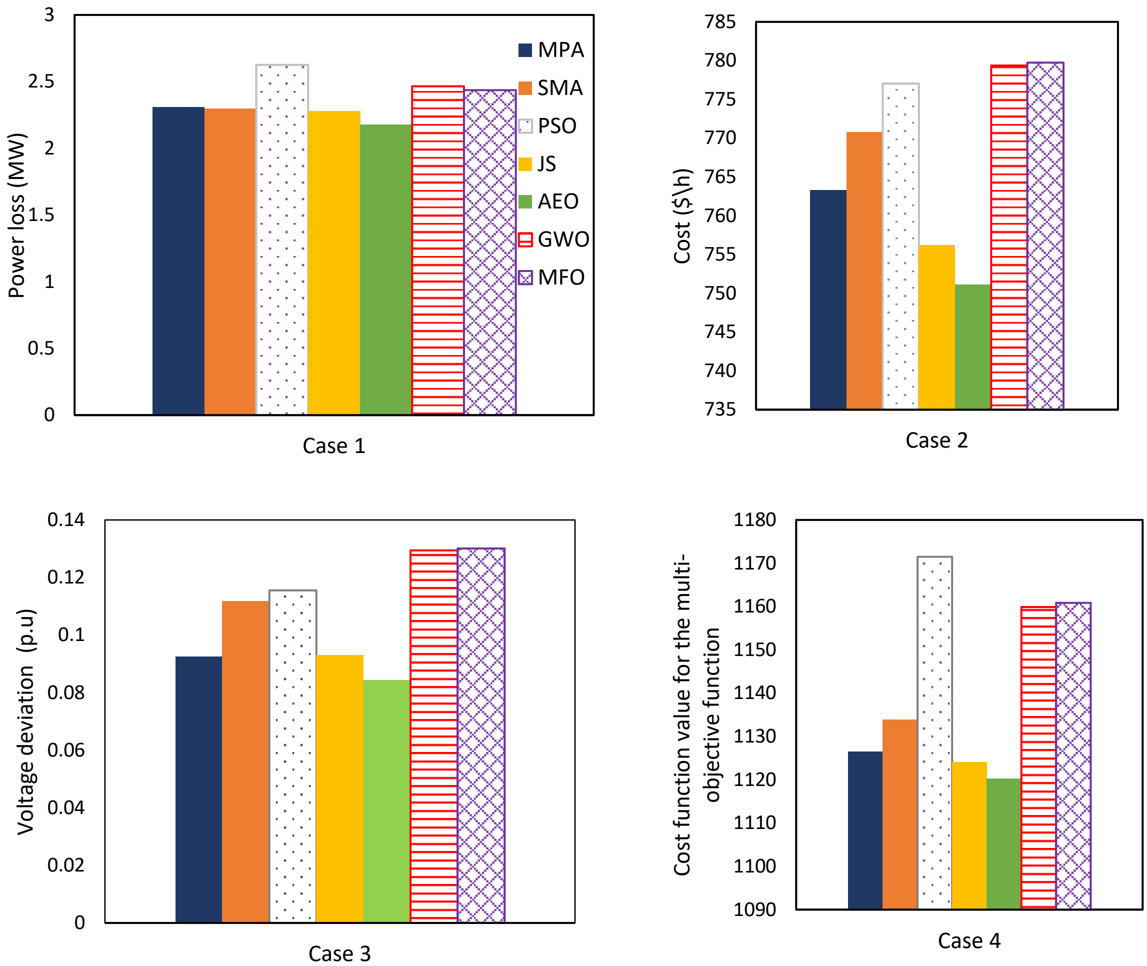


Fig. 5. Results of the proposed metaheuristic algorithms for IEEE 30-bus system - (1) with FACT devices.

In order to present the efficiency in CPU utilization for the proposed metaheuristic optimizations algorithms, Figure 6 shows the convergence curves for IEEE 30-bus system – (1) with FACT for all cases. Figure 6 shows that the AEO algorithm is the most efficient algorithm in term of lower computational cost and higher efficiency in CPU utilization, where the AEO curve was the smoother and most speedy compared to the other proposed metaheuristic optimization algorithms and achieved the optimal values for all cases with the less number of iterations.

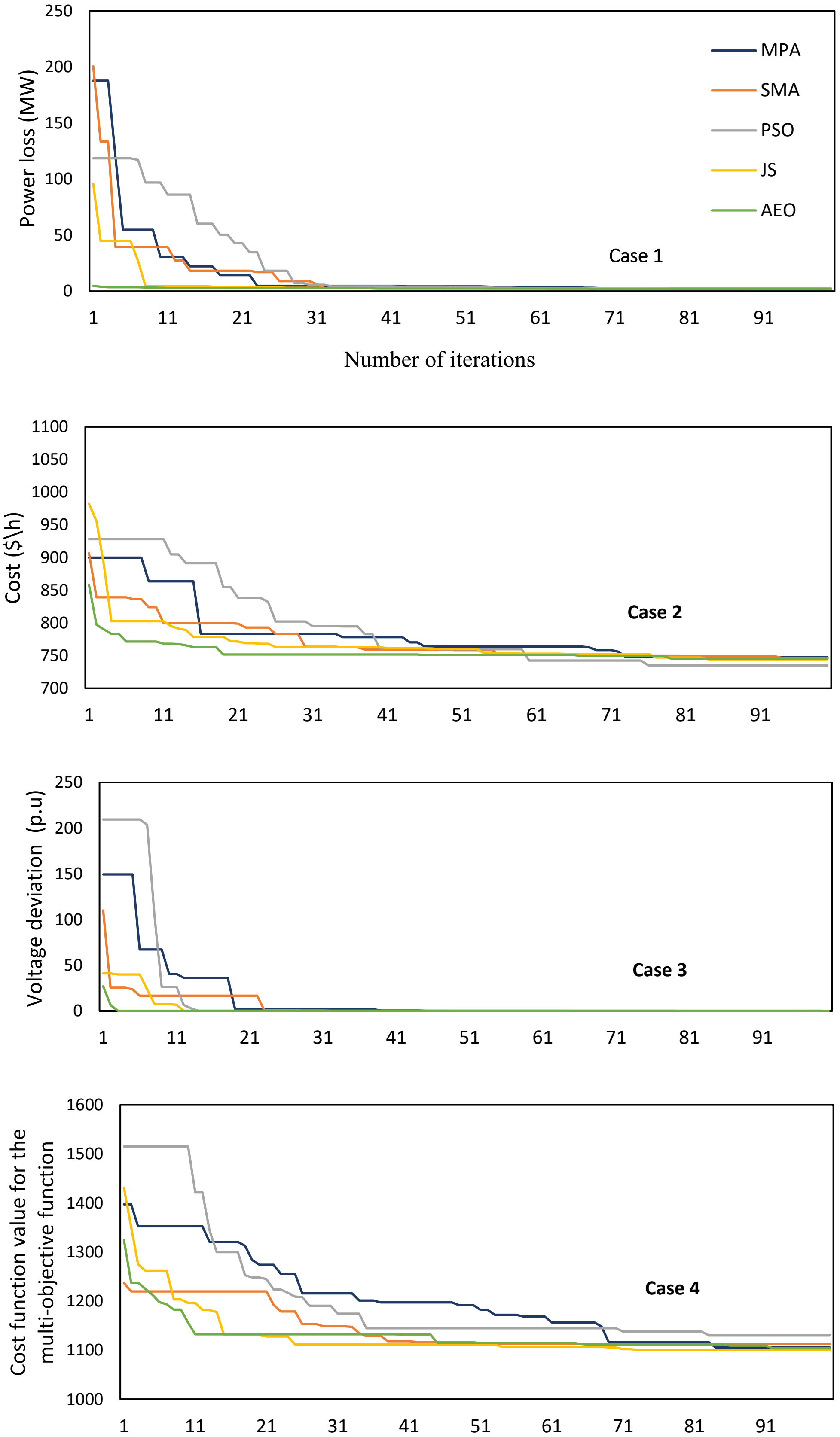


Fig. 6. Convergence curves of the proposed metaheuristic optimization models for IEEE 30-bus system – (1) with FACT.

4.3.1 The impact of Renewable energy sources locations and FACT devices on the OPF problem

In this subsection, firstly we will investigate the impact of the renewable energy sources locations on the OPF solvers, the IEEE 30-bus system– (1) equipped with FACT devices. Then, the results will discuss the impact of adding FACT devices into the power network. In the previous section, the AEO outperformed all other algorithms for all OPF cases for the IEEE 30-bus system– (1) with FACT devices. Table 8 presents the results of the proposed metaheuristic optimization models for the IEEE 30-bus system – (1) with FACT and IEEE 30-bus system – (2) with FACT for all cases. The proposed MPA,SMA,JS and AEO algorithms introduced as more effective solvers for the OPF problems cases compared to the PSO, GWO and MFO algorithms, as shown in Table 8. In the power networks (1) and (2) with FACT devices, the AEO outperformed all other optimization (MPA, SMA, PSO and JS) by decreasing the cost function, for example the cost function reduced by 6.1%, 6.0%, 20.7% and 4.7%, respectively, for Case 1 OPF problem using network– (1). This indicates that the location of renewable energy sources locations on the power network with FACT devices has a limited impact on the optimization algorithm compared to the power network without FACT devices as presented in Section 4.2.1. However, the AEO and the other proposed optimization algorithm results for the IEEE 30-bus system – (2) with FACT has been increased compared to the IEEE 30-bus system – (1) with FACT, for example the cost functions values obtained by AEO for Case 1 to 4 increased by 10.5%, 0.07%, 3.2% and 0.3%, respectively. Table 9 presents the results of the proposed metaheuristic optimization models for the IEEE 30-bus system – (1) with and without FACT devices for all cases. The metaheuristic optimization results in Table 8 indicate that adding FACT devices to the network will have a significant impact on the OPF solutions in all cases. The results also showed that the power network with FACT devices achieved better and lower cost function values for all cases except case 4 (multi functions) compared to network without FACTS. This is mainly related due to the increase in the complexity of the system and cost functions by adding FACTS and solving multi cost function. As result, adding FACT devices to the network improved the voltage profile, decreased power losses, generation cost and consequently increased stability the power network operation condition.

Table 8: Results of the proposed metaheuristic optimization models for (A) the IEEE 30-bus system – (1) with FACT and (B) the IEEE 30-bus system – (2) with FACT for all cases.

	Case 1		Case 2		Case 3		Case 4	
	(A)	**(B)**	**(A)**	**(B)**	**(A)**	**(B)**	**(A)**	**(B)**
MPA	2.307	2.757	763.339	764.094	0.0924	0.1084	1126.462	1140.011
SMA	2.300	2.554	770.772	749.549	0.1117	0.0970	1133.841	1149.381
PSO	2.626	2.898	777.041	780.591	0.1155	0.1045	1171.485	1153.269
JS	2.278	2.587	756.213	755.658	0.0930	0.1096	1124.101	1132.627
AEO	**2.176**	**2.404**	**751.130**	**751.625**	**0.0844**	**0.0871**	**1120.285**	**1123.203**
GWO	2.672	2.9351	783.041	783.576	0.1187	0.1084	1180.565	1147.011
MFO	2.626	2.6437	779.453	781.609	0.1159	0.1098	1186.537	1153.381

Table 9: Results of the proposed metaheuristic optimization models for (A) the IEEE 30-bus system – (1) **without** FACT and (B) the IEEE 30-bus system – (1) **with** FACT for all cases.

	Case 1		Case 2		Case 3		Case 4	
	(A)	**(B)**	**(A)**	**(B)**	**(A)**	**(A)**	**(A)**	**(B)**
MAP	2.306	2.307	757.663	763.339	0.1246	0.0924	1134.19	1126.462
SMA	2.381	2.300	765.360	770.772	**0.1236**	0.1117	1134.41	1133.841
PSO	2.424	2.626	778.975	777.041	0.1288	0.1155	1156.86	1171.485
JS	2.322	2.278	754.027	756.213	0.1274	0.0930	1120.66	1124.101
AEO	**2.288**	**2.176**	**752.468**	**751.130**	0.1245	**0.0844**	**1109.49**	**1120.285**
GWO	2.464	2.672	779.360	783.041	0.1294	0.1187	1159.89	1180.565
MFO	2.435	2.626	779.7459	779.453	0.1300	0.1159	1160.86	1186.537

4.3.2 The FACT devices settings and locations

In this paper, the common types of FACTS devices are employed, which are: shunt controllers (SVC) and series controllers (TCSC and TCPS) to increase the power transfer capability and the overall power network efficiency. The significance of integrating FACTS devices in the power network depends on the location and sizing of the FACTS devices and coordination between them. Therefore, the optimal location and sizing of FACTS devices have been founded based on achieving the maximum improvement at each cost function (Cases 1 to 4) using the proposed new metaheuristic optimization techniques, as shown in Tables 10 and 11. Table 10 presents an example for the placement and ratings details for all FACT devices in the IEEE 30-bus system –(1). The results in Table 10 presented the optimal location, L, at the network (bus for SVC and line for TCSC and TCPS) and the magnitude, M, of FACT devices and the objective function value, O.F, for two optimal power flow problems, voltage deviation (case 3) and power losses (Case 1), with load 100% and 120%. In Table 10, the impact of the renewable energy sources locations on the placement of FACT devices and the OPF solvers is presented. Table 11 presents the results of the optimal location, L, at the network (line/Bus number) and the magnitude, M, of FACT devices the IEEE 30-bus system– (1) and 2 with 120% load using the proposed metaheuristic optimization models for the multi-objective function (Case 4). Overall, the proposed metaheuristic optimization models determined the placement and ratings for the FACT device, which help the OPF to achieve the minimum value cost function for each case or operation scenario. This leads to conclude that there is no fixed and best location for FACT devices suitable for all operation and OPF cases.

Table 10: Results the optimal location, L, at the network (bus for SVC and line for TCSC and TCPS) and the magnitude, M, of FACT devices the IEEE 30-bus system– (1) with 100% and 120% load using of the proposed metaheuristic optimization models for cases 1 and 3.

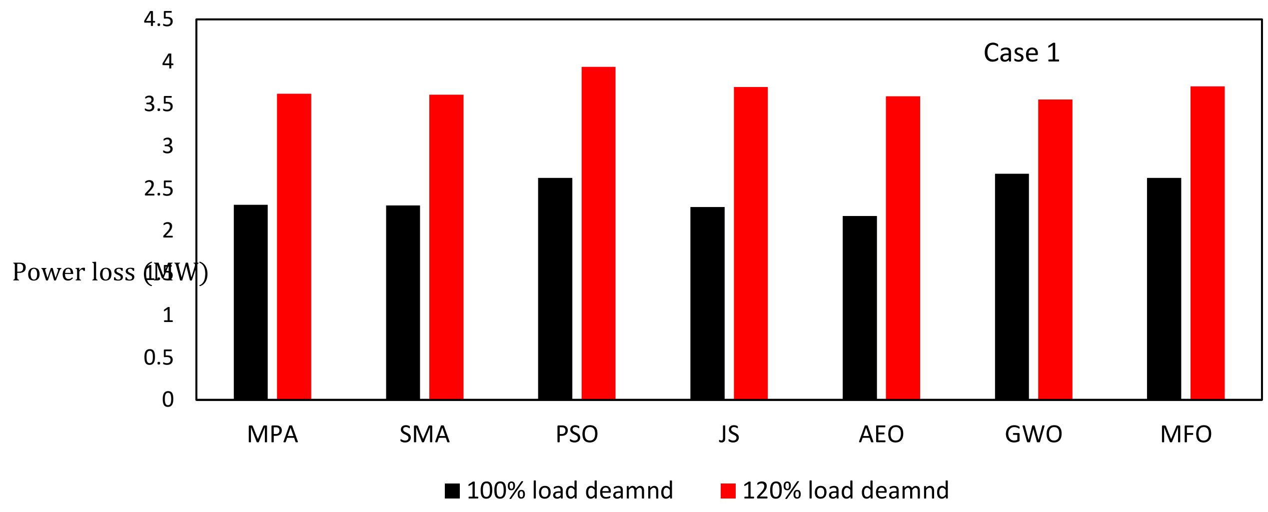
		SVC				TCSC				TCPS				O.F value
Load	Techniques	L	M	L	M	L	M	L	M	L	M	L	M	**Case 3**
100%	MPA	19	7.601	15	6.786	26	0.227	41	0.498	22	2.836	20	0.092	0.09248
	SMA	9	1.967	20	3.074	11	0.282	22	0.316	27	0.122	33	3.775	0.11179
	PSO	19	9.698	3	-9.524	23	0.377	34	0.500	1	-2.763	1	-5.000	0.11556
	JS	17	2.925	19	9.204	26	0.238	34	0.342	29	0.447	15	1.487	0.09300
	AEO	22	5.494	19	9.993	23	0.345	26	0.114	26	-0.681	20	-1.468	0.08443
														Case 1
100%	MPA	13	1.130	21	9.250	13	0.197	39	0.292	7	-4.989	41	-0.333	2.30747
	SMA	19	2.313	24	2.278	23	0.305	30	0.244	33	1.634	29	1.592	2.30030
	PSO	21	10.00	27	8.927	35	0.422	8	0.006	28	1.589	41	-1.597	2.62646
	JS	21	3.796	19	1.849	32	0.259	22	0.259	25	0.590	20	1.154	2.27883
	AEO	19	7.663	17	9.369	33	0.442	14	0.173	17	3.562	24	-3.846	2.17632
														Case 3
120%	MPA	3	-9.82	19	9.999	8	0.289	10	0.495	30	-0.013	9	-2.138	0.10721
	SMA	19	8.397	30	3.918	24	0.485	28	0.310	34	-1.513	20	0.002	0.10162
	PSO	19	10.00	3	7.085	34	0.015	30	0.004	16	-3.119	1	5.000	0.13403
	JS	22	1.568	19	9.884	36	0.307	37	0.293	26	-0.135	24	-1.184	0.11855
	AEO	20	4.488	19	6.228	8	0.096	29	0.211	11	1.855	33	-2.955	0.10669
														Case 1
120%	MPA	16	0.783	21	10.000	35	0.225	24	0.255	18	2.063	35	0.884	3.62043
	SMA	28	3.993	27	5.540	9	0.033	19	0.124	31	2.342	13	0.469	3.60788
	PSO	3	8.132	4	10.000	1	0.497	1	0.000	6	4.165	30	3.170	3.93822
	JS	20	6.684	23	2.423	25	0.279	33	0.317	26	0.227	26	2.237	3.69841
	AEO	18	-1.82	19	4.764	33	0.241	8	0.133	24	1.508	16	-1.476	3.58927

Table 11: Results the optimal location, L, at the network (bus for SVC and line for TCSC and TCPS) and the magnitude, M, of FACT devices the IEEE 30-bus system– (1) and 2 with 120% load using of the proposed metaheuristic optimization models for case 4.

Load	Techniques	SVC				TCSC				TCPS				O.F value
		L	M	L	M	L	M	L	M	L	M	L	M	**Case 4**
IEEE 30-bus system– (1)	MPA	8	5.129	22	-3.881	13	0.002	23	0.038	38	1.030	35	-0.341	1126.4629
	SMA	17	2.524	19	2.610	27	0.371	27	0.317	34	1.603	23	1.288	1133.8412
	PSO	12	-2.060	12	5.101	21	0.411	35	0.500	29	5.000	36	0.387	1171.4858
	JS	13	1.234	19	4.456	26	0.233	28	0.270	20	1.128	28	0.419	1124.1010
	AEO	9	-1.180	16	6.997	11	0.217	12	0.231	24	-1.946	33	0.286	1120.2850
IEEE 30-bus system– (2)	MPA	22	-5.504	8	4.227	24	0.279	35	0.422	28	0.144	37	0.069	1140.0112
	SMA	19	3.660	3	9.915	1	0.414	23	0.210	8	1.927	18	0.180	1149.3819
	PSO	4	6.650	17	9.423	40	0.348	37	0.235	1	-4.265	1	-4.312	1153.2694
	JS	14	0.961	16	3.689	23	0.218	21	0.199	16	1.475	23	1.389	1132.6270
	AEO	15	9.905	13	-2.243	18	0.447	19	0.186	6	-0.651	34	2.60	1123.2038

4.4 Power network stability **:** *Increase demand results*

Every year, the electricity energy consumption is significantly increasing worldwide due to the moving towards using electrical vehicles, increasing of using electricity heating and air conditioning at homes and growing population. This increased the stress on the existing networks, energy suppliers and network operators. To explore the impact of the proposed metaheuristic optimization algorithms on the power network stability, the proposed algorithms are tested on IEEE 30-bus system - (1) with FACT devices and 20% load increasing for OPF cases 1 and 3. Figure 7 indicates that the increase in electricity energy consumption has a significant impact on the OPF solutions. The proposed optimization algorithms results (objective function values) for 120% load demand has been increased for all algorithms compared to the power network with 100% load demand, except only for the SMA algorithm in Case 3. As an example, the objective function value obtained by the JS algorithm for case 1 was dramatically increased from 2.278 MW with 100% load demand to 3.698 MW for the 120% load demand scenario. In Case 3, the impact of increasing the load demand on the optimization solver results was limited compared to Case 1. This mainly due to that the power loss term (Case 1) is linked to the increment in the power consumption (current), while this increment have a lower impact on voltage deviation (Case 3). Furthermore, the proposed MPA,SMA,JS and AEO algorithms have the ability to handle the demand increasing compared to the PSO, GWO and MFO algorithms, as shown in Figure 7.



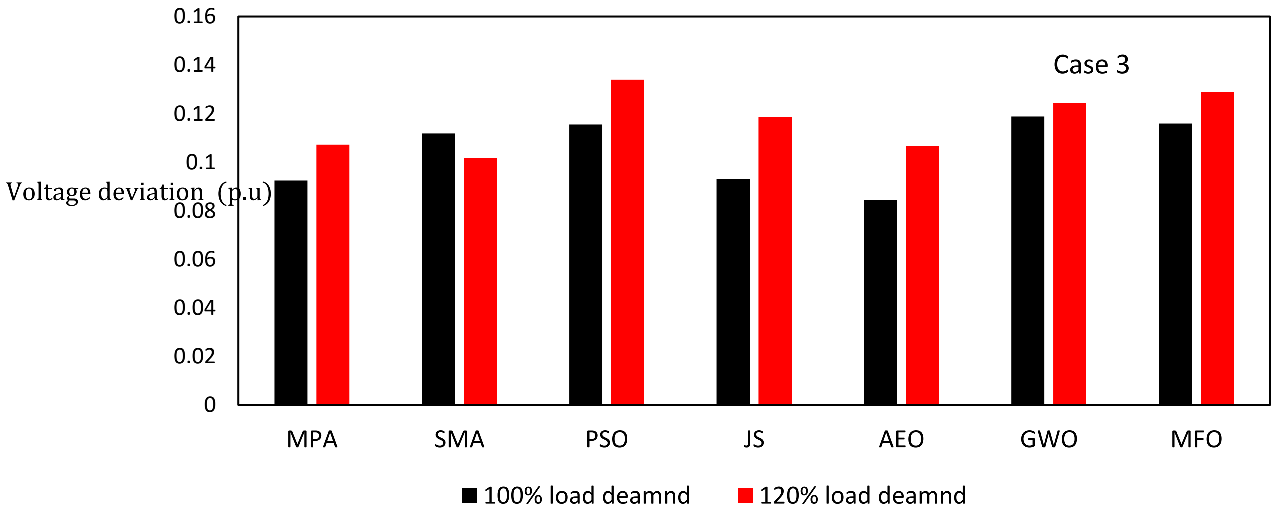


Fig. 7. Results of the proposed metaheuristic algorithms for IEEE 30-bus system - (1) with FACT devices and 100% and 120% load demand for Case 1 and Case 3.

4.5 Statistical analysis for the proposed metaheuristic optimization algorithms

In the previous sections, the proposed new metaheuristic optimization algorithms results were presented for different power network scenarios and OPF problem cases. This section aims to provide further analysis and evidence on the performance of the proposed metaheuristic optimization algorithms were used to solve Case 1 and Case 4 problems for IEEE 30-bus system - (1) with FACT model over 30 runs of simulations. Table 12 presents the statistical analysis which includes the minimum and maximum values of the cost function (Case1 and 4), median and standard deviation for all methods. The results show that the AEO is the most effective metaheuristic optimization algorithm compared to other algorithms where it achieved the lower value of cost function in both cases 1 and 4 for the minimum, maximum and median values. For example, the median value for the AEO algorithm in Case 2 was 777 $/h in case 2 and 1137 in case 4 compared to 798 $/h and 1193 for the PSO algorithm.

In this work, the results analysis for the proposed new metaheuristic optimization algorithms (MPA, SMA, JS, AEO) for different OPF problems (single and multi cost functions) showed a high ability to handle simple and complex problem and cost functions compared to the PSO, GWO and MFO algorithms. Furthermore, the proposed methods have been tested under different network scenarios (different renewable energy reassures locations and with and without FACTS) and they showed high performance compared to PSO, which mean more capability to solve complex operation scenarios. Table 13 presents the proposed new metaheuristic optimization algorithms (MPA, SMA, JS, AEO) results for IEEE 30-bus system – (1) with FACT for case 4 as example. In Table 13, the PG, V and T are the optimal values for the generators active power, the generator voltage magnitude and the tap changer voltage, respectively. The next step after having successful and more effective solvers for the OPF problems is in to implement the proposed models in real power system (physical system). This implementation will required a central control system in the power generation operator center. This central control system needs to be connected via high efficient communication way with the respective generating units. In addition, the forecasted load demand is feed to the central control system, where the control system will analysis the data and calculated the optimal values for each generating units within the real time sensing. The implementation of the optimal control model will be part of our future work.

Table 12: An example of the statistical analysis for the metaheuristic optimization algorithms.

IEEE 30-bus system - (1) with FACT (Case 2)				
	Minimum	**Maximum**	**Median**	**Standard deviation**
MPA	764.0944212	827.6935279	778.1959756	17.52491818
SMA	749.5494199	814.2483846	790.0545993	19.30104853
PSO	780.5919434	816.002263	798.3366146	10.41263946
JS	755.658667	804.0993203	782.9635723	14.65774005
AEO	**751.625188**	**799.5335415**	**777.7425605**	12.91117797
GWO	783.041372	832.4576209	798.2466997	16.3903049
MFO	779.4530062	831.4342224	785.3670284	16.74506701
IEEE 30-bus system - (1) with FACT (Case 4)				
	Minimum	**Maximum**	**Median**	**Standard deviation**
MPA	1126.462918	1163.607485	1151.974092	13.01650462
SMA	1133.841221	1166.586344	1147.253348	10.21013379
PSO	1171.485865	1218.246118	1193.230814	14.52953599
JS	1124.101015	1172.156689	1138.665991	14.52826773
AEO	**1120.285054**	**1162.130096**	**1137.830899**	14.13981913
GWO	1180.565865	1216.903826	1196.755997	11.09601208
MFO	1186.537627	1227.246118	1196.740404	13.45301569

Table 13: Results of the proposed new metaheuristic optimization algorithms (MPA, SMA, JS, AEO) for IEEE 30-bus system – (1) with FACT over Case 4.

Parameters	Min	Max	AEO	JS	SMA	MPA	PSO	GWO	MFO
PG2 (MW)	20	80	60.91590074	61.75439726	59.1589857	50.66387545	53.0141836	69.95356678	58.0882959
PG5 (MW)	15	50	38.86379597	35.09899276	38.13127567	47.46714526	42.34352238	15.0012478	49.88826941
PG8 (MW)	10	35	31.02593299	27.51352351	18.25423341	34.33809228	29.71446607	35.0102357	10.00471378
PG11 (MW)	10	30	19.24021631	25.62443086	24.07287831	29.06903483	29.46654127	30.011785	30.0054231
PG13 (MW)	10	40	29.06308837	28.41005394	32.11575496	25.71477374	30.91206419	34.42460375	39.9820039
PG24 (MW)	10	40	31.08996052	29.15786141	25.09889601	23.06182076	34.43814828	14.43228539	10.0011789
PG30 (MW)	10	40	23.28022569	25.96990342	25.17768462	25.80002554	29.85067365	27.00338789	27.30842714
V1 (p.u.)	0.95	1.1	1.027171101	1.05620988	1.067212132	1.031378457	1.037852309	1.10078521	1.033414137
V2 (p.u.)	0.95	1.1	1.021959573	1.046154317	1.06587831	1.012041209	1.017129991	1.081552392	1.009320154
V5 (p.u.)	0.95	1.1	0.996665931	1.013067307	1.03182639	0.99431944	0.976508666	1.016130962	0.973710352
V8 (p.u.)	0.95	1.1	1.004713358	1.032821269	1.047164574	1.006129423	0.957250041	1.029020865	0.95010047
V11 (p.u.)	0.95	1.1	1.041945288	1.053985009	1.001603553	1.065567198	0.982000793	0.985809577	1.042131812
V13 (p.u.)	0.95	1.1	1.043220276	1.029773296	1.003870344	1.024509111	1.024986989	1.033621204	1.018703925
V24 (p.u.)	0.95	1.1	1.019101157	1.027296875	1.007721629	1.006897391	1.03595268	1.01463105	1.007281203
V30 (p.u.)	0.95	1.1	1.001708492	1.030688211	1.048237654	1.004723209	0.960408344	1.03924616	0.962066795
T11 (p.u.)	0.9	1.1	0.972353335	1.041330495	1.038901981	0.984948871	0.900147	1.099999997	0.90016977
T12 (p.u.)	0.9	1.1	1.000748841	1.005308415	0.993247369	0.94239339	0.90232755	0.910539756	0.917339616
T15 (p.u.)	0.9	1.1	1.032562343	1.001704502	1.002087402	0.947895542	0.901590	0.90100852	0.900402839
T36 (p.u.)	0.9	1.1	0.973470462	0.994348396	1.003857876	0.953914139	0.902273908	0.969580494	0.946880002
Objective function			1109.49	1120.66	1134.41	1134.19	1156.86	1159.89	1160.86

5. Conclusions

In this work, new metaheuristic optimization algorithms have been developed and employed to find the optimal placement and ratings for the FACT device in line with solving different OPF problems. The OPF problems for IEEE 30-bus equipped with renewable energy sources (wind and PV) and FACTS have been formulated as single and multi-objective functions through four cases considering the power line loss, power generation cost and voltage deviation. In this article, a probabilistic estimation model developed as a realistic model to generate the wind and PV power generation profiles. Then, new optimal solvers (MPA, SMA, JS, AEO) have been used to improve the power grid quality by determining the optimal location and size of FACT devices to achieve cost-effective and environmentally friendly power supply solutions. In the result and discussion section, the new metaheuristic optimization algorithms have been evaluated and compared to common and powerful algorithms, PSO, GWO and MFO. The results show that the AEO is the most effective metaheuristic optimization algorithm compared to other algorithms where it achieved the lower value of cost functions due to the high ability of solving complex OPF problems with less convergence rate and computational costs. For example, the AEO outperformed MPA, SMA, PSO and JS algorithms by decreasing the cost function around 6.1%, 6.0%, 20.7% and 4.7%, respectively, for Case 1 OPF problem using network–(1). The proposed new metaheuristic optimization algorithms have been developed and compared in this work to provide the network operator and the decisionmaker different suitable optimization solvers by considering different operation cases such as increasing the load demand, with and without FACTS and renewable energy sources, different renewable energy sources locations on the network. The implementation of proposed new metaheuristic optimization algorithms in real power systems and including energy storage systems with different PV system model in the power network will be part of our future work.

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