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A Novel Hybrid Method based on Krill Herd and Cuckoo Search for Optimal Power Flow Problem

Aboubakr Khelifi [1*], Bachir Bentouati [1], Saliha Chettih [1], Ragab A. El-Sehiemy [2]
[1] Electrical Engineering Department, LMSF Laboratory, Amar Telidji University of Laghouat, Algeria
[2] Electrical Engineering Department, Faculty of Engineering-Kafrelsheikh University, Egypt
[1] Email: a.khelifi@lagh-univ.dz; b.bentouati@lagh-univ.dz; s.chettih@lagh-univ.dz.
[2] Email: elsehiemy@eng.kfs.edu.eg;

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***Abstract*—**Solving the Optimal power flow (OPF) problem is an urgent task for power system operators. It aims at finding the control variables' optimal scheduling subjected to several operational constraints to achieve certain economic, technical and environmental benefits. The OPF problem is mathematically expressed as a nonlinear optimization problem with contradictory objectives and subordinated to both constraints of equality and inequality. In this work, a new hybrid optimization technique, that integrates the merits of cuckoo search (CS) optimizer, is proposed to ameliorate the krill herd algorithm (KHA)'s poor efficiency. The proposed hybrid CS-KHA has been expanded for solving for single and multi-objective frameworks of the OPF problem through 11 case studies. The studied cases reflect various economic, technical and environmental requirements. These cases involve the following objectives: minimization of non- smooth generating fuel cost with valve-point loading effects, emission reduction, voltage stability enhancement and voltage profile improvement. The CS-KHA presents krill updating (KU) and krill abandoning (KA) operator derived from cuckoo search (CS) amid the procedure when the krill updating in order to extraordinarily improve its adequacy and dependability managing OPF problem. The viability of these improvements is examined on IEEE 30-bus, IEEE 57-bus and IEEE 118-bus test system. The experimental results prove the greatest ability of the proposed hybrid meta-heuristic CS-KHA compared to other famous methods.

***Index Terms*—**Cuckoo search algorithm (CS); krill herd algorithm (KHA); optimal power flow (OPF); voltage stability (VS); valve-point effect; emission reduction.

I. INTRODUCTION

The problem of optimal power flow (OPF) is significated considerable attention in recent years and has based its position among the main tools for the operation and planning of recent power systems. OPF is a non-linear programming problem. The major objective is to find the correct adjustment of its control variables that optimize specific objective functions/functions while sufficient the operational constraints of equality and inequality at specified loading settings and defined system parameters [1-3].

The OPF has been applied to regulate the production of real powers, generators terminal voltages, setting of transformer taps, shunt reactors/capacitors and other control variables to improve the power system requirements by minimizing the production fuel costs, reducing the network active power losses, enhance the voltage stability and voltage profile at load buses. The previous requirements are achieved while all operational requirements are preserved within the accepted operation limitations as The voltages of load bus, the reactive power products of the generator, the network's power flows and whole other state variables in the power system within their assure and operational bounds.

In its most popular formulation, the OPF is static, a non-convex, wide-ranging optimization problem with both discontinuous and continuous control variables. Even in operating cost functions' absence of non-convex generators, prohibited operating zones (POZ) of generating units and discontinuous control variables, the OPF problem is a non-convex because of the presence of non-linear alternating current power flow equality constraints. The existence of discontinuous control variables, like transformer tap positions, phase shifters, switchable shunt devices, added more difficulty the formulation and solution of the problem.

The methods were evolving to solve OPF problem can be categorized into two types conventional and advanced optimization techniques. The traditional optimization techniques were used derivatives and gradient operators. These techniques are usually not capable to find or determine the global optimal. Several mathematical suppositions like analytic, convex and differential objective functions must be made to simplicity the problem. Nevertheless, the OPF's problem is a problem of optimization non-convex and non-smooth objective function in general. As a result, it is significant to evolve optimization methods that are effective in dominating these disadvantages and to treat this hardness effectively. The computational materials' evolution in recent decades has motivated to the development of advanced optimization methods that were so-called meta-heuristics.

These techniques can dominate many disadvantages of conventional techniques [4]. Several of these recent techniques have been applied to solve the OPF problem like: Simulated Annealing (SA) [5], Genetic Algorithm (GA) [6,7], Differential Evolution (DE) [8], Tabu Search (TS) [9], Imperialist Competitive Algorithm (ICA) [10], Particle Swarm Optimization (PSO) [11], adaptive real coded biogeography-based optimization (ARCBBO)[12], Biogeography Based Optimization (BBO) [13,14], multi-phase search algorithm [15], Gbest guided artificial bee colony algorithm(Gbest-ABC) [16], Gravitational Search Algorithm (GSA) [17] , Artificial Bee Colony (ABC) [18], Multi-objective Grey Wolf Optimizer (MOGWO)[19], black-hole-based optimization (BHBO) [20], Teaching Learning based Optimization (TLBO) [21], Sine-Cosine Optimization algorithm (SCOA) [22], Group Search Optimization (GSO) [23], hybrid algorithm of particle swarm optimizer with grey wolves(PSO-GWO) [24], quasi-oppositional teaching–learning based optimization [31]have been incorporated into it. Meanwhile, many state-of-the-art meta-heuristic techniques, like Improved Colliding Bodies Optimization (ICBO) [32], Moth Swarm Algorithm (MSA) [33], Moth-Flame Optimization (MFO) [34], cuckoo search [35], firefly algorithm [36] and Backtracking Search Optimization Algorithm (BSA) [37] Surveys of different meta-heuristics used to solve the problem of OPF are offered in[25] The applications of these methods on different size systems lead to competitive results and therefore were favorable and encouraging for more study in this trend. Furthermore, because of the objectives' contrast where various functions can be envisaged for modeling the OPF problem, of course not technique can be seen as the preferable in solving whole OPF problems. Hence, it is constantly needed to have a novel technique that can successfully solve several of the OPF problems.

Optimization is turning a area of request to analysts, particularly since a framework's the competence depends on obtaining an arrangement an order that can be acquired through suitable optimization technique. It is a method in order to discover the perfect solution next assessing the cost function that denotes the association among the system framework and its limitations. Presently, meta-heuristic algorithms are being formed in many regions for example crossbreeding, multi-objective type, binary type, preparing multi-layer perceptron and ways as Lévy flight, operator, and chaos theory. Most of these improvements happened because the deterministic and evolutionary components are used [23]. A perfect incorporation of global and local search has intensive local exploration and global exploration [25].

Krill herd method (KH) first suggested by Gandomi and Alavi in 2012 [26] and because it performs well, many optimization strategies such as chaotic theory [27, 28, 36], Flower Pollination Algorithm (FPA) [29] and colonial competitive differential evolution (CCDE)[30] have been hybridized with the fundamental KH algorithm as mutation operator with the objective of further enhancing the performance of KHA. Furthermore, to make KHA perform in the most ideal way, a parametric study has been conducted through an array of standard benchmark functions [38].

Furthermore, KHA is a new population-build swarm computation [26] in view of the Lagrangian and revolutionary conduct of krill people in wildlife for utilization and investigation in a problem of optimization. KH computation occasionally is not able to must avoid local optimum [27] and [28].

Firstly, as portrayed here, a successful hybrid Meta heuristic cuckoo search krill herd (CS-KHA) technique in light of KHA and CS is initially suggested to accelerate convergence. In CSKH, we use an essential KHA to select an encouraging solution set. Consequently, krill updating (KU) and krill abandoning (KA) operator started from CS algorithm are added to the method. The KU operator is to a decent encouraging arrangement; while KA operator is made use of further improving the investigation of the CS-KHA to substitute the worse krill's a small amount at the finale of every generation.

The performance of this approach is utilized to keep away from local optimum and obtain a worldwide ideal solution, in addition, minimal computational time to achieve the ideal solution, local minimum evasion, and quicker convergence, which produce them suitable for viable implementations for solving various constrained optimization problems. The purpose of this article is to develop an improved KHA called CS-KHA to solve OPF problem. So as to proven the evolution of the CS-KHA, its efficiencies are compared to CS, KHA and other well-known optimization methods.

The rest of article is structured in the next form: The following segment outlines the formulation of the OPF problem; meanwhile, section 3 depicts the algebraic equation of CS-KHA. Section 4 shows the simulation's results and discussion. While the finally conclusion of this paper is in section 5.

II. Formulation of optimal Power Flow (OPF)

The problem of OPF aims at finding the control variables' optimal setting through minimizing /maximizing a predefined objective function while a collection of equality and inequality constraints satisfied. OPF considering the system's operating limit, hence it can be defined like a non-linear constrained optimization problem.

$$\text{Minimize: } f\left(x,u\right) \tag{1}$$

Subject to:

$$\begin{aligned} h\left(x,u\right) &= 0 \\ g\left(x,u\right) &\leq 0 \end{aligned} \tag{2}$$

Where, u is the independent variable or control's vector, is the dependent variables or state's vector. Objective functions of OPF, g(x, u): set of inequality constraints, $h(x, u)$: set of equality constraints.

A. Control variables

The vector of power network control variables is expressed as follows [37]:

$$u = \left[P_{G_2} \cdots P_{G_{NG}}, V_{G_1} \cdots V_{G_{NG}}, Q_{C_1} \cdots Q_{C_{NC}}, T_1 \cdots T_{NT} \right] \quad (3)$$

Where, P_{G_i} is the i-th active power bus generator. Chosen from bus 1 as swing bus is represented just and any one of the generator buses can be swing bus. V_{G_i} is the voltage magnitude at i-th voltage controlled generator bus, Tj is the j-th branch transformer tap, QCk is the shunt compensation at k-th bus. NG, NC and are the generators' number, transformers and shunt VAR compensators. Any value within its range can be assumed as a control variable. Practically, transformer taps are not constant. Be that as it may, the tap settings indicated are in p.u. and outright voltage's estimation is not represented. Subsequently, for the aim of this study and to compare with previously described results, all control variables including tap settings are viewed constant for general cases of study.

B. State (dependent) variables

The power system's state variables can be expressed through vector x as:

$$x = \left[P_{G_1}, V_{L_1} .. V_{L_{NL}}, Q_{G_1} .. Q_{G_{NG}}, S_{l_1} .. S_{l_{nl}} \right] \quad (4)$$

where, P_{G_1} is the active power of generator at slack bus, Q_{G_i} is the generator's reactive power linked to bus i, is the p-th load bus's bus voltage (PQ bus) and q-th line's line loading of is specified by. NL and nl are the load buses' number and lines of transmission respectively[40].

C. Power System Constraints

As aforesaid earlier, the problem of OPF presents both operational constraints on equality and inequality. These constraints are defined as follows:

C.1. Equality constraints

In OPF, the reactive and real power equilibrium equations are represented the system constraints of equality are formulated as for all system buses:

$$P_{G_i} - P_{D_i} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \cos\left(\delta_{ij}\right) + B_{ij} \sin\left(\delta_{ij}\right) \right] = 0 \quad (5)$$

$$Q_{G_i} - Q_{D_i} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \sin\left(\delta_{ij}\right) + B_{ij} \cos\left(\delta_{ij}\right) \right] = 0 \quad (6)$$

Where, $\delta_{ij} = \delta_i - \delta_j$ is the voltage angles among bus i and bus j, NB is the buses' number, Q_{Di} and P_{Di} are reactive and real load demands. G_{ij} is the transfer conductance and B_{ij} is the susceptance among bus i and bus j, respectively.

C.2. Inequality constraints

The inequality's constraint in the OPF reflects the equipment's operating limit in the power system, and too reflects the limitation of the line and the load bus to ensure the safety of the system.

a) Generator constraints:

$$V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max} \forall i \in NG \quad (7)$$

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max} \forall i \in NG \quad (8)$$

$$Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max} \forall i \in NG \quad (9)$$

b) Transformer constraints:

$$T_j^{\min} \le T_j \le T_j^{\max} \forall j \in NT \quad (10)$$

c) Shunt compensator constraints:

$$Q_{C_k}^{\min} \le Q_{C_k} \le Q_{C_k}^{\max} \forall k \in NC \quad (11)$$

d) Security constraints:

$$V_{L_p}^{\min} \le V_{L_p} \le V_{L_p}^{\max} \forall p \in NL \quad (12)$$

$$S_{l_q} \le S_{l_q}^{\max} \forall q \in nl \quad (13)$$

The control variables in constraints of inequality are self-limiting. The technique of optimization chooses a viable value for every like variable within the determined scope. Efficient methods for dealing with constraints of inequality related to dependent or state variables.

III. Suggested Hybrid Technique

A. KH technique

The KH technique is built on the natural inspiration of conduct krill individuals' imitation in the krill population. The KH technique is motivated by krill activities like [26]: 1/The movement of other krill individuals is induced; 2/Food search activity; 3/random scattering. The optimization technique has the ability to search for an uncertain search space.

• Lagrangian model is extended to an n-dimensional decision space:

$$\frac{dX_k}{dt} = N_k + F_k + D_k \quad (14)$$

Where N_k the movement is stimulated by other members of the krill; F_k is the feeding movement and D_k is the physical diffusion of the k_{th} krill.

The movement stimulated expresses the conservation of density through every individual. The matimatical formula reflects this conduct, which is worded as follows:

$$N_k^{next} = N^{\max}\alpha_k + \omega_d N_k^{present} \tag{15}$$

$$\alpha_k = \alpha_k^{local} + \alpha_k^{target} \tag{16}$$

Wherein $N^{\max}$ is the highest stimulated velocity, ω_d indicates the inertia weight in [0, 1], N_k^{Ancient} is the preceding movement α_k^{local} and α_k^{target} indicate the local effect of the neighbor, which is the best solution of the k_{th} individual. α_k^{target} is formulated by the following equations:

$$\alpha_k^{target} = C^{best}\hat{K}_{k,best}\hat{X}_{k,best} \tag{17}$$

$$C^{best} = 2\left(r_1 + \frac{I}{I_{\max}}\right) \tag{18}$$

where, C^{best} is the krill individual's effective coefficient with the preferable fitness for the first k_{th} krill, $\hat{K}_{k,worst}$ and $\hat{K}_{k,best}$ are the worst and preferable krill's fitness value so far; is a random values' number among 0 and 1. It is used to improve exploration, I is the current iterations' number, and $I_{\max}$ is the iterations' maximum number.

Foraging activities/movements are mathematically calculated as follows:

The foraging action consists of two major parameters. Premier is the position of the food F_k^{next}, followed by the preceding experiment β_k around the position of the food.

$$F_k^{next} = V_f\beta_k + \omega_f F_k^{previous} \tag{19}$$

$$\beta_k = \beta_k^{food} + \beta_k^{best} \tag{20}$$

Where, V_f is the foraging speed, ω_f is the foraging motion's inertia weight in the field [0, 1], $F_k^{previous}$ is the final foraging movement, β_k^{food} is the food attractive and β_k^{best} is the preferable fitness's effect of each krill. Depending on the foraging speed's measured values, take as 0.02 (ms^{-1}).

$$D_k = D^{\max}\delta \tag{21}$$

$$D_k = D^{\max}\left(1 - \frac{I}{I_{\max}}\right)\delta \tag{22}$$

Wherein, $D^{\max}$ is the highest induction velocity, δ is the random direction vector [0, 1].

Lastly, the location of each krill is updated to:

$$X_k^{next} = X_k^{current} + \Delta x_k(t) \tag{23}$$

$$\Delta x(t) = N_k(t) + F_k(t) + D_k(t) \tag{24}$$

Where, t is the krill's position.

B. Cuckoo search

Through optimizing the conduct of some cuckoo species, CS is suggested that is swarm intelligence's a type technique for optimization problems. In CS, Lévy flights are consolidated that decides the cuckoo's walking steps. For simplicity in portraying CS, Yang and Deb adopted some of the idealized rules. For instance, every cuckoo is just relating to one egg; the preferable nests would be preserved and not be obliterated; the possible host nest number is unchangeable, and an egg is recognized through the host bird with a possibility. In CS, every egg in a nest shows a solution. The CS is to take use of the recently created better solutions in place of a moderately poor solution. In this research, we just looked at every nest that merely had an egg. Thus, in this research, the difference between the nest egg and solution was not identified. The CS technique can make a good harmony between a local arbitrary walk and the irregular global exploratory walk using a switching parameter. The former one can be represented as

$$X_i^{t+1} = X_i^t + \beta_s \otimes H(p_a - \varepsilon) \otimes \left(X_j^t - X_k^t\right) \tag{25}$$

Where X_j^t and X_k^t are two various solutions choice at random, H(u) is function of a Heaviside , ε is a number of random drawn from a regular distribution, and sis the step size. For the global random walk, it is combined with Lévy flights as follows:

$$X_i^{t+1} = X_i^t + \beta L(s,\lambda), L(s,\lambda) = \frac{\lambda\Gamma(\lambda)\sin\left(\frac{\pi\lambda}{2}\right)}{\pi}\frac{1}{s^{1} + \lambda}, (s, s_0 \succ 0) \tag{26}$$

Here, $\beta \succ 0$ is the scaling factor of step size.

C. Proposed Hybrid CS-KHA procedure

To ameliorate the fundamental's the search capacity KH technique; genetic techniques are added to the method [26]. Numerical outcomes when contrast with other methods displays that KH II (only added crossover operator) performed the best.

In any case, KH can sometimes find it hard to come up with better solutions to several complicated problems. Consequently, in this article, a novel meta-heuristic technique by prompting KU operator and KA operator into KH to form a recent hybrid method, named CS-KHA is used to manage an OPF problem. The introduced KU/KA operators are roused by the authoritative CS algorithm. As such, in this paper, the property of cuckoo used in CS is supplemented to the krill to create excellent krill's a sort that can play out the KU/KA operator. The contrast amongst CSKH and KH is that the KU operator as a local search tool is used to adjust the new solution for every krill rather than rand walks used as KH's part (whereas in KH II, genetic generation techniques are employed). While KA operator is used to enhance further the exploration the method's ability by replacing some nests randomly thereby constructing new solutions. By the blending of CS and KH, CSKH can investigate the new search space with standard KH technique and KA operator and exploit the population information by KU operator. The main step of KU/KA operators used in CSKH method is presented by Algorithms 1 and 2, respectively.

Algorithm 1 KU operator

Begin

Get a krill i and update its solution using Lévy flights using Equation (25).

Evaluate its quality F_i

Select a krill j randomly.

If $\left(F_i \prec F_j\right)$

Replace j with the novel solution and take the novel solution as X_{i+1}

Else

Update the position of krill using equation (22) as X_{i+1}

end if

End.

Algorithm 2 KA operator

1. Begin
2. $K = rand\left(NP, D\right) \succ p_a$.
3. $P_1 = P; P_2 = P$
4. For $i = 1$ to NP (all krill) do.
5. $step = rand * \left(Y_i - Z_i\right);$
6. $X_{new} = X_i + step \odot K\left(i, :\right);$
7. End for
8. For $i = 1$ to NP (all krill) do.
9. If $F\left(X_{new}\right) \prec F\left(X_i\right)$ then
10. $X_{new} = X_i; F\left(X_{new}\right) = F\left(X_i\right)$.
11. End if
12. End for
13. end

Firstly in the proposed method, standard KHA uses three movements to look for the best solutions and engage these movements to lead the candidate solutions for the following generation. In this, KU operator is then employed to carry out local search intensively to achieve better solutions. This operator can since it abuses the search space by Lévy flight. Towards the end of each generation, the KA operator is employed to additionally ameliorate the CS-KHA's the exploration by replacing the worse krill's a fraction (pa) .Along these lines, this component used in CS-KHA can completely extend the strong the KHA's exploration and gain overcome the absence of the KHA's weak exploitation . Above all, this technique can additional unwind the inconsistency among exploration and exploitation effectively. Furthermore, another basic change is the presentation of elitism scheme into the CSKH. Likewise, with other population-based methodologies, we employ a further focused elitism technique to hold the preferable solutions for the population. That elitism system forbids the preferable krill from existence demolished through three movements and KU/KA operator. By joining previously mentioned KU/KA operator and concentrated elitism design into unique KH technique to form a new CSKH algorithm (see Algorithm 3).

Algorithm 3 CSKH algorithm

Begin

Step 1: Initialization. Set the t =1,the population P, V_f , $D^{\max}$, and $N^{\max}$, p_a and $KEEP$.

Step 2: Fitness evaluation.

Step 3: While $t \prec$ MaxGeneration do.

Sort the population.

Store the KEEP best krill.

for $i = 1 : N_P$ (all krill) do

Perform the three motions.

Update the krill position by CU operator (see Algorithm 1).

Evaluate each krill by X_{i+1} .

end for i

Destroy the worse krill and build new ones by CA operator (see Algorithm 2).

Replace the KEEP worst krill with the KEEP best krill.

Sort the population.

$t = t + 1$.

Step 4: end while

End.

IV. Objective Functions and Studied Cases

A few contextual investigations with unique and multi-objective have been made for networks IEEE 30-bus, IEEE 57-bus and IEEE 118-bus test systems. The essential characteristics of this networks exam system are given in [33].

A. IEEE 30 Bus system results

A.1.Studied Cases

A total of 8 studies of cases were implementing in the first exam system (IEEE 30-bus exam system). The first two cases studies reduced OPF's single objective function. The rest is multi-objective optimization, which translates into a single target with a weighting factor, as in numerous past studies and recreated here. The definitions of the studied cases are expressed as follows:

Case 1: fuel cost's minimization

This is the fundamental OPF's objective function in all studies. The relationship among fuel cost ($/h) and power generation Power (MW) is generally offered by two relationships, so the target function to be is reported as:

$$f\left(x,u\right)=\sum_{i=1}^{NG} a_i+b_i P_{G_i}+c_i P_{G_i}^2 \tag{27}$$

Where a_i , b_i , c_i are the *i*-th generator's cost coefficients generating produce power. IEEE 30-bus system generators' cost coefficients can be seen in [39].

Case 2: fuel cost's minimization taking into account valve point effect

The impact of the valve point should be taken into account for further practical and exact fuel cost function's modeling. The generating units with multi-valve steam turbines display a more prominent variety in the fuel-cost functions [32]. The valve loading multi-valve steam turbines' impact is modeled as function of sinusoidal, which's the absolute value is added to the fundamental cost function. The steam plant's actual cost curve function becomes non-continuous. The aim of reducing fuel cost of generating with valve-point effect is presented by [40]:

$$f\left(x,u\right)=\sum_{i=1}^{NG}\left(a_i+b_i P_{G_i}+c_i P_{G_i}^2\right)+\left|d_i \times \sin\left(e_i \times \left(P_{G_i}^{\min}-P_{G_i}\right)\right)\right| \tag{28}$$

Where, d_i and e_i are the coefficients that show the valve-point loading effect. The factors applied for calculations are given in [37].

Case 3: Fuel cost's minimization and voltage stability enhancement

Voltage dependability issues are accepting developing consideration in power systems as network breakdown have been experienced in last because of instability of voltage. Under normal condition and in the wakw of being subjected to unsettling influence, the power system's steadiness is portrayed through its capacity to keep up whole bus voltages in suitable boundaries. A system goes into voltage instability's a condition when an unsettling influence, augmentation in load demand or variation in system term causes a dynamic and wild abatement in voltage[14]. Systems with long lines of transmission and overwhelming loading are further inclined to the problem of voltage instability. In power system, a system's enhancing voltage stability is a vital part. Each bus's *L*-index fills in as perfect power system stability's marker [42]. The index's value can be between 0 and 1, where 0 existence the no load case whereas 1 is the voltage collapse. If a power system has NL load (PQ) buses' number and NG generator (PV) buses' number , L-index Lj's value of bus *j* is can be explained as:

$$L_j=\left|1-\sum_{i=1}^{NG} F_{ji}\frac{V_i}{V_j}\right|, \text{ where } j=1,2,...,NL \tag{29}$$

and

$$F_{ji}=-\left[Y_{LL}\right]^{-1}\left[Y_{LG}\right]$$

Where, Y_{LL} and Y_{LG} sub-matrices and are gotten from YBUS system matrix next separating load (PQ) buses and generator (PV) buses as shown in (29).

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix}=\begin{bmatrix} Y_{LL} & Y_{LG} \\ Y_{GL} & Y_{GL} \end{bmatrix}\begin{bmatrix} V_L \\ V_G \end{bmatrix} \tag{30}$$

$$L_{\max}=\max\left(L_j\right) \quad j=1,2.......,NL \tag{31}$$

The indicator $L_{\max}$ varies among 0 and 1 where the minimal the indicator, the further the system stable. Thus, enhancing voltage stability can be obtained by the reducing of $L_{\max}$. Hence, the objective function can be formulated as:

$$f\left(x,u\right)=\left(\sum_{i=1}^{NG} a_i+b_i P_{G_i}+c_i P_{G_i}^2\right)+\lambda_L \times L_{\max} \tag{32}$$

Where, $L_{\max}$ is chosen weight factor's value λ_L is 100.

Case 4: Fuel cost's minimization and emission

Electrical power's generation from traditional energy's sources releases dangerous gases for the environment. The nitrogen oxides (NOx) and sulfur oxides (SOx)'s amount and emission in tones per hr (t/h) is higher with augmented in generated power (in p.u. MW) next the relationship presented in Eq. (33).

$$Emission=\sum_{i=1}^{NB}\left[\left(\alpha_i+\beta_i P_{G_i}+\gamma_i P_{G_i}^2\right)\times 0.001+\omega_i e^{\left(\mu_i P_{G_i}\right)}\right] \tag{33}$$

Where, α_i , β_i , γ_i , ω_i and μ_i are all coefficients of emission provided in [41].

Therefore, the objective function of this case is given by:

$$f\left(x,u\right)=\left(\sum_{i=1}^{NG} a_i+b_i P_{G_i}+c_i P_{G_i}^2\right)+\lambda_E \times Emission \tag{34}$$

The weight factors are chosen as = 100 in this case.

Case 5: fuel cost's minimization and voltage deviation

Deviation of voltage is voltage quality's a measure in the network. The deviation's index is too vital from the security part. The indicator is expressed as cumulative voltages deviation of whole load buses in the network from nominal unity's value. Mathematically it is formulated as:

$$VD = \left(\sum_{p=1}^{NL} \left| V_{L_p} - 1 \right| \right) \quad (35)$$

The combining fuel cost's objective function and deviation of voltage is:

$$f(x,u) = \left(\sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2 \right) + \lambda_{VD} \times VD \quad (36)$$

Where, factor of weight is give a value of 100 as in [32,33].

Case 6: Fuel cost minimization and active power loss

The power loss in system of transmission is certain because the lines have latent resistance. The active power loss to be reduced is formulated as:

$$P_{loss} = \sum_{i=1}^{nl} \sum_{j=1, j \neq i}^{nl} G_{ij} \left[V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_{ij}) \right] \quad (37)$$

A multi-objective case that aims at reducing fuel cost and active power loss simultaneously is transformed into single objective as:

$$f(x,u) = \sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2 + \lambda_p \times P_{loss} \quad (38)$$

Where, P_{loss} is the active power loss and factor's value λ_p is selection as 40.

Case 7: Fuel cost's minimization and voltage stability's enhancement

The objective function's formulation , comprising of both fuel cost taking into account the valve-point effect and voltage stability, this case's the objective function can be expressed as:

$$f(x,u) = \sum_{i=1}^{NG} \left(a_i + b_i P_i + c_i P_i^2 \right) + \left| d_i \times \left(e_i \times \sin\left(P_{gi}^{\min} - P_{gi} \right) \right) \right| + \lambda_L \times L_{\max} \quad (39)$$

The choice weight factor λL is too 100.

Case 8: fuel cost's minimization, emission, voltage deviation and losses

Four objectives are put together for this case study. Fuel cost, emission, voltage deviation and active power loss in the network are whole reduced together. The objective function is presented by:

$$f(x,u) = \left(\sum_{i=1}^{NG} a_i + b_i P_i + c_i P_i^2 \right) + \lambda_E \times Emission + \lambda_{VD} \times VD + \lambda_p \times P_{loss} \quad (40)$$

The weight factors are choice as in [33] with λ_E = 19, λ_{VD} = 21 and λ_p = 22 to balance between the objectives.

V. Results and Discussion

For optimizing's case 1 essential fuel cost, CS-KHA algorithms can produce to fuel costs of 799.0595 $/h which satisfies all the system constraints, complying to the vital constraints of inequality on generator reactive power, load bus voltage and line capacity . Amongst whole the constraints of inequality , constraint on load bus voltage was discovered to be vital as the load buses' operating voltages are sometimes establish to be close the boundaries. Using the 3-methods (CS, KHA and CS-KHA), recent studies recorded better results when compared with present study are presented in table 2. The valve-point effect is studied for case 2 to achieve at a rise in cost than in case 1 with conclusive value of 830.0981$/h, get by CS-KHA. In a nutshell, in spite of the variation in efficiency is seen between three methods, produce one or more technique's outcome used in our work are better than most of the results revealed in past literatures on the problem of OPF are presented in table 2.

Case 3 to case 8 are for OPF with multi-objective for 30-bus system. In these case studies, the joined objective function's fitness is the significant factor in ranking the different optimization techniques' outcome out. For a significant comparison, other techniques' fitness value is calculated and provided here employing the different objective functions' are weight factor. In multi-objective cases, an adjustment in weight factor e.g. elevated weight factor on fuel cost in case 3 the best values of both fuel cost and the system load buses' $Lmax$, CS-KHA gives preferable produce of 799.5625 and 0.1251 respectively, superior to the other comparable algorithms as appears in the table 2. Two objectives of cost and emission are concurrently reduced **in case 4**. Along with the fitness value, CS-KHA is at the cost and emission's least values in compared with in compared with other techniques presented in table 4.

Minimizing cost and voltage deviation (VD)'s in case 5, is achieved by CS-KHA which is the least among all other comparable techniques as appear in table 4.

In case 6 will reduce the cost and power loss. Table 3 shows' quick review that any these techniques' one or more CS, KHA and CS-KHA can give the preferable fitness values in whole the cases. Despite the fact that the preferable fitness is described by CS-KHA in case 6, a transitional value fuel cost, the forming objectives' one, is accomplished. The active power loss's other goal is the minimum when compared with other methods as appears in table 4.

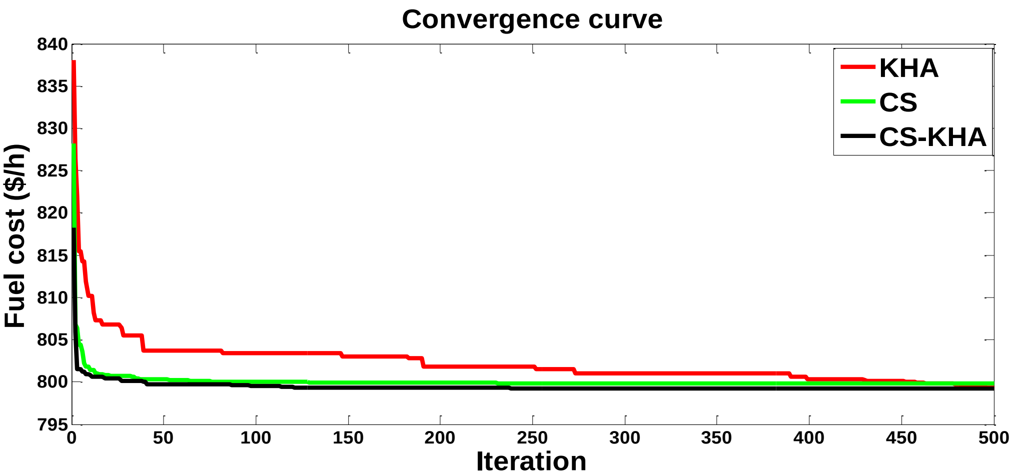


Fig.1. Convergent curves of Case 1

Table 1. The control variables' optimal settings for Cases 1-3.

	Case1			Case2			Case3		
Control variable	CS-KHA	KHA	CS	CS-KHA	KHA	CS	CS-KHA	KHA	CS
P_{G1} (MW)	177.7695	176.6985	177.0700	199.9957	199.9873	200.0000	178.3494	175.2915	178.5539
P_{G2} (MW)	48.8746	48.4488	48.8674	43.0739	42.5401	43.8734	48.2403	47.5274	48.9785
P_{G5} (MW)	21.0243	21.5532	21.3084	18.6343	19.1074	18.7891	20.5650	22.4648	21.3404
P_{G8} (MW)	21.5808	22.6989	21.0859	10.0300	10.0177	10.0000	20.3673	22.6681	21.5868
P_{G11} (MW)	10.8258	10.4866	11.8626	10.0000	10.0960	10.0000	12.7147	11.7468	10.0000
P_{G13} (MW)	12.0000	12.1911	12.0000	12.0000	12.0241	12.0000	12.0000	12.3124	12.0000
V_1(p.u)	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000
V_2(p.u)	1.0894	1.0891	1.1000	1.0854	1.0866	1.1000	1.0892	1.0937	1.0829
V_5(p.u)	1.0634	1.0631	1.0728	1.0588	1.0583	1.1000	1.0665	1.0674	1.0513
V_8(p.u)	1.0696	1.0708	1.0796	1.0665	1.0657	1.0878	1.0742	1.0825	1.0544
V_{11}(p.u)	1.1000	1.1000	1.0957	1.1000	1.0985	1.1000	1.0999	1.0999	1.1000
V_{13}(p.u)	1.1000	1.0944	1.1000	1.0975	1.0867	1.0160	1.1000	1.0982	1.1000
Qc_{10}(Mvar)	0.9873	0.7887	0	1.2012	0.3180	5.0000	4.8864	1.6654	5.0000
Qc_{12}(Mvar)	4.2959	0.8533	0	1.9153	0.1754	5.0000	0.7211	2.2254	5.0000
Qc_{15}(Mvar)	3.0959	0.0015	5.0000	0.1687	0.0254	0	0.0187	0.9965	0
Qc_{17}(Mvar)	5.0000	3.0633	5.0000	0.0310	0.0426	5.0000	0.6251	2.9405	0
Qc_{20}(Mvar)	4.4733	3.4508	3.5533	5.0000	3.3646	5.0000	0.0525	0.0173	0.8864
Qc_{21}(Mvar)	4.4607	0.4024	5.0000	0.1385	2.6324	5.0000	0.8977	0.3830	5.0000
Qc_{23}(Mvar)	0.3577	1.9594	5.0000	2.1640	0.8609	5.0000	2.4613	0.1354	0
Qc_{24}(Mvar)	5.0000	2.3827	5.0000	5.0000	1.2249	5.0000	4.0616	3.2836	5.0000
Qc_{29}(Mvar)	3.4597	2.5427	5.0000	0.0572	2.9633	5.0000	0.3548	0.8722	5.0000
$T_{6\text{-}9}$	1.0315	1.0077	0.9718	1.0763	1.0090	1.1000	0.9910	0.9888	0.9000
$T_{6\text{-}10}$	0.9073	1.0210	1.1000	0.9027	1.0357	1.1000	0.9055	0.9503	1.1000
$T_{4\text{-}12}$	0.9875	1.0364	1.1000	1.0359	1.0579	0.9000	0.9696	0.9850	1.1000
$T_{28\text{-}27}$	0.9785	0.9963	1.0194	0.9805	1.0057	1.1000	0.9417	0.9446	0.9358
Fuel cost ($/h)	**799.0595**	**799.4972**	**799.6547**	**830.0981**	**830.4199**	**833.5157**	**799.5625**	**799.8928**	**800.3034**
VD	1.7638	1.1245	1.3088	1.2223	0.8337	0.9003	1.8465	1.7461	1.4380
Lmax	0.1290	0.1357	0.1350	0.1342	0.1393	0.1487	**0.1251**	**0.1253**	**0.1268**
Emission (ton/h)	0.3685	0.3653	0.3662	0.4425	0.4423	0.4424	0.3696	0.3608	0.3708
Ploss (MW)	8.6750	8.6771	8.7944	10.3339	10.3726	11.2625	8.8367	8.6110	9.0596

Table 2. the results obtained are compared for Cases 1-3

Case 1		Case 2		Case 3		
Algorithms	Fuel cost ($/h)	Algorithms	Fuel cost ($/h)	Algorithms	Fuel cost($/h)	Lmax
CS-KHA	**799.0595**	CS-KHA	**830.0981**	CS-KHA	**799.5625**	**0.1251**
KHA	**799.497**	KHA	**830.4199**	KHA	**799.8928**	**0.1253**
CS	**799.6547**	CS	**833.5157**	CS	**800.3034**	**0.1268**
BHBO[20]	799.921	BSA [37]	830.7779	Gbest-ABC [16]	801.5821	0.1370
ARCBBO [12]	800.5159	ICBO [32]	830.4531	MSA [33]	801.2248	0.13713
BSA[37]	799.0760	CBO[32]	830.473	BSA[37]	800.3340	0.1259
MSA[33]	800.5099	ECBO[32]	830. 587	ICBO [32]	799.3277	0.1252
BBO[37]	799.1267	DE[37]	830.4425	MDE [33]	802.0991	0.13744

Table 3. the control variables' optimal settings for Cases 4-6.

	Case4			**Case5**			**Case6**		
Control variable	CS-KHA	KHA	CS	CS-KHA	KHA	CS	CS-KHA	KHA	CS
P_{G1} (MW)	112.7779	112.9464	111.7271	176.2886	176.2432	177.5324	105.5625	105.3719	102.2213
P_{G2} (MW)	59.1035	58.7161	58.4399	49.1208	48.8217	49.1973	53.9578	52.9905	56.1303
P_{G5} (MW)	28.0892	28.1822	27.3951	21.3698	21.6226	21.7154	36.9416	37.0963	37.2408
P_{G8} (MW)	34.9991	35.0000	35.0000	22.0531	22.1836	22.8823	35.0000	34.9767	35.0000
P_{G11} (MW)	26.5804	27.1184	30.0000	12.4129	12.3589	10	29.9505	29.6778	30.0000
P_{G13} (MW)	26.9020	26.6188	26.2425	12	12	12	26.3434	27.7198	27.1722
V_1(p.u)	1.1000	1.1000	1.1000	1.0387	1.0462	1.0442	1.1000	1.1000	1.1000
V_2(p.u)	1.0928	1.0924	1.1000	1.0215	1.0295	1.0278	1.0930	1.0922	1.1000
V_5(p.u)	1.0696	1.0688	1.0806	1.0092	1.0145	1.0155	1.0736	1.0695	1.0833
V_8(p.u)	1.0798	1.0800	1.1000	1.0044	1.009	1.0035	1.0824	1.0802	1.1000
V_{11}(p.u)	1.0992	1.0996	0.9000	1.0797	1.0241	1.0397	1.0997	1.0961	1.1000
V_{13}(p.u)	1.1000	1.0900	1.1000	0.9844	0.9835	0.9967	1.1000	1.1000	1.1000
Qc_{10}(Mvar)	1.1530	1.1760	5.0000	0	5	5	1.5790	3.5805	5.0000
Qc_{12}(Mvar)	3.3798	2.9034	5.0000	5	2.1588	0	3.0622	0.0852	0
Qc_{15}(Mvar)	5.0000	1.5069	5.0000	4.9985	5	0	0.1757	4.1400	0
Qc_{17}(Mvar)	3.7785	0.2768	5.0000	0	0.0767	0	5.0000	2.2509	0
Qc_{20}(Mvar)	4.1506	1.0711	5.0000	5	5	5	5.0000	2.5827	5.0000
Qc_{21}(Mvar)	1.1979	0.7196	5.0000	5	5	5	5.0000	3.6976	5.0000
Qc_{23}(Mvar)	0.0935	0.9665	5.0000	4.9587	0	5	2.9975	0.0588	4.2787
Qc_{24}(Mvar)	5.0000	0.2050	5.0000	5	5	5	5.0000	0.0048	5.0000
Qc_{29}(Mvar)	1.4504	0.3080	5.0000	0	1.6478	5	2.2077	0.1971	2.1814
T_{6-9}	1.0603	1.0374	1.0772	1.0888	1.0403	1.0596	1.0594	1.0402	1.1000
T_{6-10}	0.9000	0.9597	0.9000	0.9	0.9	0.9	0.9023	0.9182	0.9000
T_{4-12}	1.0186	1.0330	1.1000	0.9451	0.9228	0.9303	0.9945	1.0196	0.9966
T_{28-27}	0.9818	0.9857	1.1000	0.9487	0.9613	0.9797	0.9856	0.9767	0.9910
Fuel cost ($/h)	**835.3821**	**835.9164**	**839.0130**	**803.6357**	**803.6580**	**803.7306**	**853.1469**	**854.6579**	**857.3526**
VD	1.6529	1.1912	0.8867	**0.1045**	**0.1117**	**0.1066**	1.8266	1.5253	1.8731
Lmax	0.1300	0.1342	0.1487	0.1468	0.1480	0.1490	0.1288	0.1310	0.1276
Emission (ton/h)	**0.2421**	**0.2422**	**0.2404**	0.3637	0.3635	0.3677	0.2317	0.2311	0.2287
Ploss (MW)	5.0521	5.1820	5.4047	9.8452	9.8300	9.9274	**4.3558**	**4.4330**	**4.3646**

Table 4. The results obtained are compared for Cases 4-6.

Case4			**Case 5**			**Case 6**		
Algorithms	Fuel cost ($/h)	Emission (t/h)	Algorithms	Fuel cost ($/h)	VD (pu)	Algorithms	Fuel cost($/h)	Ploss(MW)
CS-KHA	**835.3821**	**0.2421**	CS-KHA	**803.6357**	**0.1045**	CS-KHA	**853.1469**	**4.3558**
KHA	**835.9164**	**0.2422**	KHA	**803.6580**	**0.1117**	KHA	**854.6579**	**4.4330**
CS	**839.0130**	**0.2404**	CS	**803.7306**	**0.1066**	CS	**857.3526**	**4.3646**
BSA [37]	835.0199	0.2425	BHBO [20]	804.5975	0.1262	FPA [33]	859.1915	4.5404
GA-MPC[41]	835.0420	0.2423	BSA [37]	803.4294	0.1147	MSA [33]	855.2706	4.7981
MOGWO [19]	833.8528	0.2451	MSA[33]	803.3125	0.1084	MFO[33]	858.5812	4.5772
NSGA-II[19]	859.849	0.3214	MFO[33]	803.7911	0.1056			
			FPA[33]	803.6638	0.13659			

Table 5. The control variables' optimal settings for Cases 7 and 8.

	Case 7			**Case 8**		
Control variable	CS-KHA	KHA	CS	CS-KHA	KHA	CS
P_{G1} (MW)	199.9573	200.0408	200.0001	122.7707	120.3378	121.4781
P_{G2} (MW)	44.0569	40.8348	47.1590	52.2425	53.9179	51.5677
P_{G5} (MW)	17.8443	18.9637	15.0000	31.2607	33.3589	30.5941
P_{G8} (MW)	10.0000	11.2088	10.0000	34.9961	35.0000	35.0000
P_{G11} (MW)	10.0028	10.5532	10.0000	26.4475	22.7272	30.0000
P_{G13} (MW)	12.0214	12.0000	12.0000	21.1133	23.4242	20.1360
V_1(p.u)	1.1000	1.1000	1.1000	1.0999	1.1000	1.1000
V_2(p.u)	1.0906	1.0880	1.1000	1.0890	1.0879	1.0887
V_5(p.u)	1.0697	1.0665	1.0747	1.0627	1.0630	1.0636
V_8(p.u)	1.0800	1.0752	1.0837	1.0718	1.0708	1.0733
V_{11}(p.u)	1.0989	1.0995	1.1000	1.0560	1.0933	1.0206
V_{13}(p.u)	1.1000	1.1000	1.1000	1.0325	1.0357	1.0562
Qc_{10}(Mvar)	0	4.8665	5.0000	2.5177	0.9657	0
Qc_{12}(Mvar)	4.8593	0.1190	0	0.1353	2.0934	0
Qc_{15}(Mvar)	3.5759	3.0433	5.0000	4.8952	1.4256	0
Qc_{17}(Mvar)	4.6437	2.8878	0	3.2609	0.0210	5.0000
Qc_{20}(Mvar)	2.5235	4.7887	0	5.0000	3.0301	5.0000
Qc_{21}(Mvar)	0.0014	4.7253	0	0.1410	2.2403	5.0000
Qc_{23}(Mvar)	4.2770	4.0181	5.0000	4.7800	0.0133	0
Qc_{24}(Mvar)	0.2174	2.1304	5.0000	0.0437	0.4552	0
Qc_{29}(Mvar)	0.6333	2.9869	0	0.5568	0.8862	5.0000
T_{6-9}	0.9844	1.0277	1.1000	1.0996	1.0405	1.1000

T_{6-10}	0.9000	0.9057	0.9000	0.9766	1.0636	0.9523
T_{4-12}	0.9658	0.9706	0.9919	1.0791	1.0482	1.1000
T_{28-27}	0.9469	0.9567	0.9472	1.0144	1.0126	1.0328
Fuel cost ($/h)	**830.5273**	**830.3209**	**831.7243**	**828.8532**	**832.1724**	**831.1796**
VD	1.9815	1.9553	1.7393	**0.4827**	**0.5205**	**0.5015**
Lmax	**0.1248**	**0.1253**	**0.1253**	0.1446	0.1440	0.1450
Emission (ton/h)	0.4426	0.4422	0.4437	**0.2537**	**0.2508**	**0.2517**
Ploss (MW)	10.4828	10.2013	10.7591	**5.4308**	**5.3660**	**5.3759**

Table 6. The results obtained are compared for Cases 7 and 8.

Case 7			**Case 8**				
Algorithms	Fuel cost($/h)	Lmax	Algorithms	Fuel cost($/h)	Ploss (MW)	VD(p.u)	Emission (ton/h)
CS-KHA	**830.5273**	**0.1248**	CS-KHA	**828.8532**	**5.4308**	**0.4827**	**0.2537**
KHA	**830.3209**	**0.1253**	KHA	**832.1724**	**5.3660**	**0.5205**	**0.2508**
CS	**831.7243**	**0.1253**	CS	**831.1796**	**5.3759**	**0.5015**	**0.2517**
BSA [37]	832.7029	0.1262	FPA [33]	835.3699	5.5153	0.49969	0.24781
			MSA [33]	830.639	5.6219	0.29385	0.25258
			MFO[33]	830.9135	5.5971	0.33164	0.2523
			MDE[33]	829.0942	6.0569	0.30347	0.2575

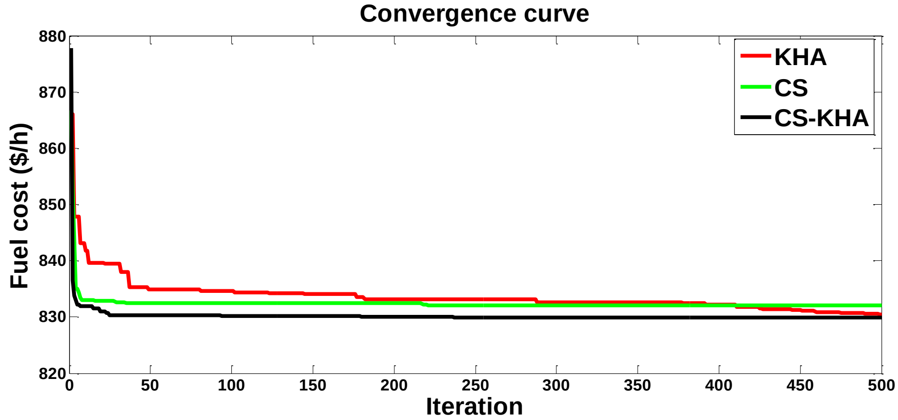


Fig.2. Convergent curves of Case 2

Important amelioration in fuel cost seen (through CS-KHA) in case 7's for multi-objective optimization where both cost considering the valve-point effect and *L*-max are minimized. Preferable to the other comparable algorithms as appears in table 6.

Cost, real power loss, emission and voltage deviation concurrently reduced four objectives are in case 8. Along with the fitness value, CS-KHA is at the cost and loss's least values in contrast with MSA [33] and FPA [33], as shown in Table 6. Graphical comparison the convergence of three proposed techniques for Case 1 and Case 2 of the objective functions related to the fuel cost is shown in Figures 1 and 2 respectively. The convergence speeds are Not distinctly various between the techniques. Be that as it may, fast and surprising convergence is seen for both KHA and CS-KHA during the search process's first phase. KHA converges to the ideal solution more consistently. Two-objective cases' convergences are given in Fig.3. (3.a and 3.b), Fig. 4. and Fig. 5. (5.a and 5.b). For clarity, only one technique's convergence achieving optimal fitness value is shown in the graph.

Comparison among CS, KHA and CS- KHA

Table 7. Shows the statistical summary of 30 runs using three proposed algorithm as the fundamental search technique for each study carried out. The columns denote the best, worst, average and standard deviation values of the objective function in every case. It is clear that no single technique is capable to issue the best mean values in whole the cases. CS-KHA is found to be superior to KHA and CS in all cases for 30-bus and 57-bus system.

A. Results of IEEE 57-bus test system

So as to exam the usability of the suggested CS-KHA technique, a greater test system is take into account in this article, which is the IEEE 57-bus test system. 57-bus system's general system data are given in [43].

CASE 9: fuel cost minimization

The goal of this case is to reduce the total generating fuel cost. Hence, this case's the objective function is presented by (27). The CS-KHA is implementation so as to get the optimal settings for this case and the gained results are presented in Table 8. In this case minimizing the fuel cost's fundamental objective produce to a value of 41660.2273 $/h by CS-KHA, the most minimal when compared with other recent studies' substantial results as seen in Table 9.

CASE 10: Fuel cost minimization and voltage deviation

The purpose of the objective function is to reduce simultaneously both fuel cost and voltage deviation. The transformed single objective function next equation (36) with weight factor λ_{VD} is chosen as 100. The results of such optimization using the suggested CS-KHA technique are given in Table 8. This table shows that the VD has been decrease from (1.5991 p.u.) to (0.6940 p.u.) compared with CASE 9. Hence, the cost has slightly augmented from (41660.2273 $/h) to (41712 $/h) compared with CASE 9.

B. *Results of IEEE 118-bus test system:*

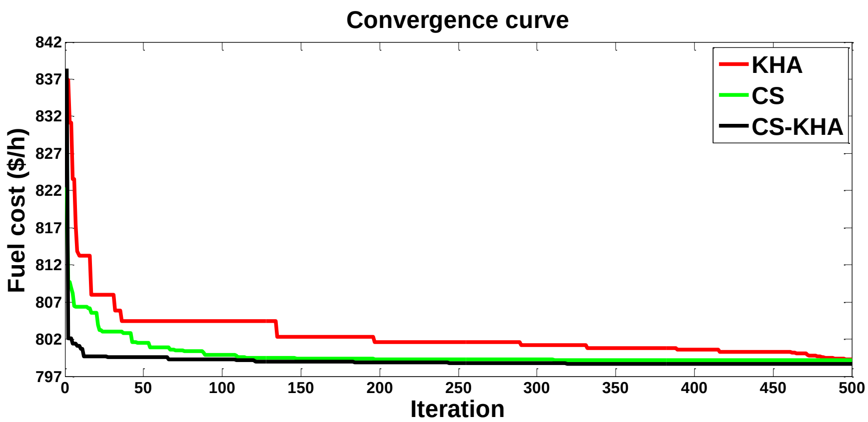
CASE 11: Fuel cost minimization

To prove performance of the suggested hybrid CS-KHA, the large-scale IEEE 118-bus system is deliberated for study goal, the essential characteristics are presented in [43]. In general, the efficiency of the proposed algorithm is excellent for variables' higher number in constrained optimization problems. Therefore, CS-KHA method is utilized to the system to decrease fuel cost. Hence, this case's objective function is presented by (27). The CS-KHA is implemented so as to get the optimal settings for this case and the gained results are presented in Table10. In this case, minimizing the fuel cost's fundamental objective produce to a value of 135260.45$/h by CS-KHA, the most minimal when compared with other recent studies' substantial results as seen in Table 11.

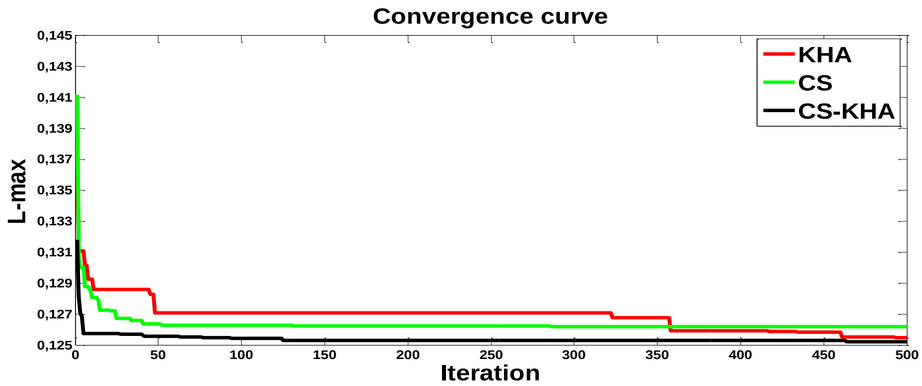
VI. Conclusion

In present study, a new Meta hybrid heuristic CSKH technique has been suggested to solve the problem of OPF. By merging the merits KU/KA operator of CS technique with the KH technique. Hence, the KH is improved and the CSKH algorithm is evaluated numerically.

The detailed expression of a new variant of KH algorithm is given, and the KU operator is adjusted dynamically in KU process. In the proposed hybrid CSKHA, a greedy option was used, often surpassing the standard CS and KH. Moreover, so as to more ameliorate the CSKH's exploration, each generation of end KA operators will be a small number of poor krill thrown away, and replaced by new randomly generated krill. The problem of OPF has been expressed as a constrained optimization problem where many objective functions have been taking into account to decrease the fuel cost, to enhance the voltage stability and to improve the voltage profile. However, non-smooth piece-wise quadratic cost objective function has been deliberated. The feasibility of the suggested CS-KHA technique for solving problems of OPF is confirm by apply three standard test power systems. The results of the simulation prove the success and robustness of the suggested method to solve problem of OPF in small and large test systems. In addition, the suggested methods in this study achieve significantly better than several other equivalent optimization techniques in obtaining solutions of OPF. Decrease in hourly operation cost has been based almost in whole the cases studied in the context of this literature. In order to add more complex objectives function when solving OPF problems, no method is the best way to solve all OPF problems. Therefore, there is always a require for a new method, capable of successfully solving as many OPF problems as possible. However, increased capability is often achieved by hybridizing method and deterministic optimization techniques. In the future, different settings of optimization techniques used in this article are chosen by trial and error to improve convergence characteristics and these settings can be optimized for improved effectiveness. Various types of sources energy, like solar cells, wind turbines can be involved in solving OPF problems.



a. Fuel cost



b. Lmax

Fig.3. Convergent curves of Cas3 (bi-objectives)

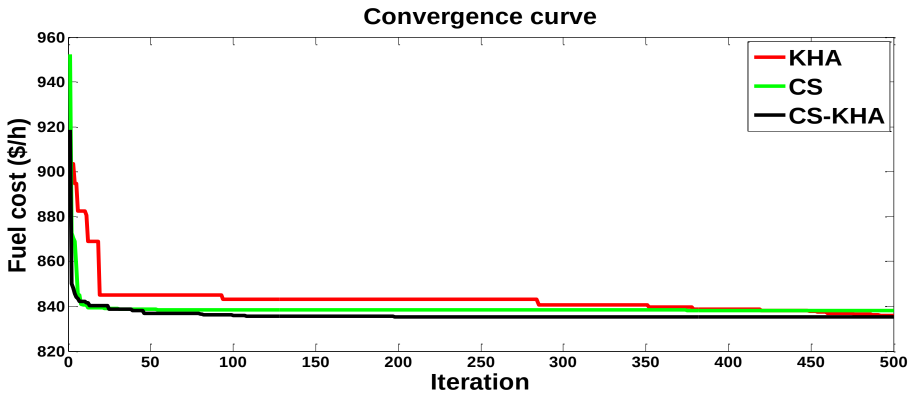
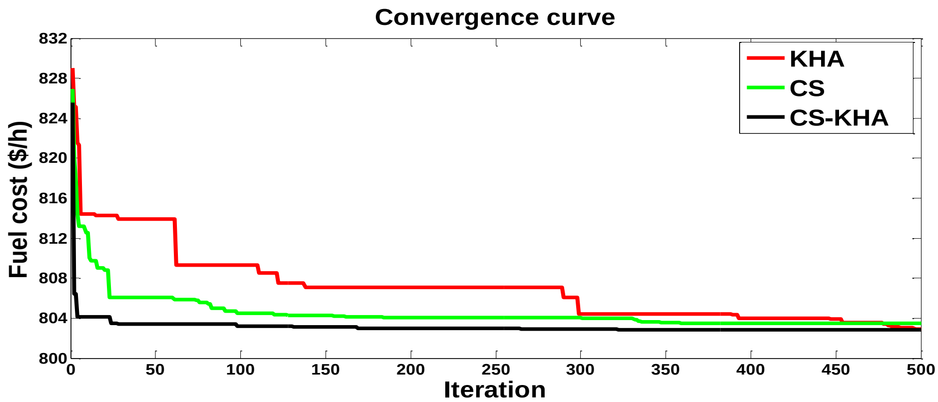
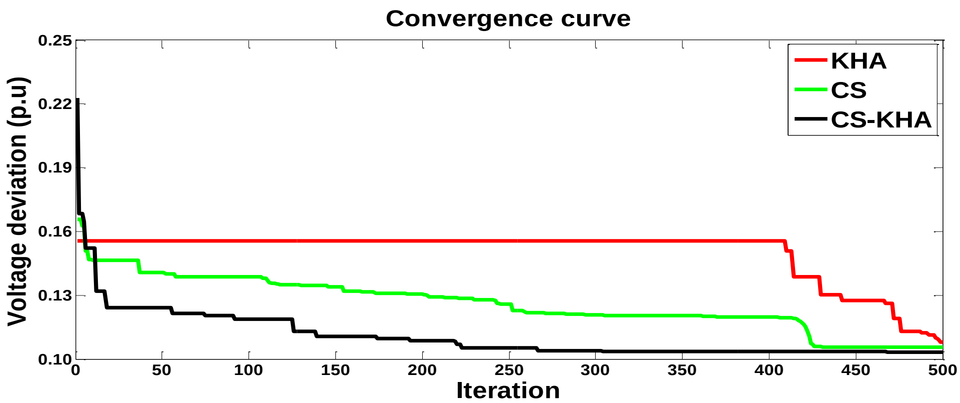


Fig.4. Convergent curves of Case 4



a. Fuel cost



b. Voltage deviation

Fig.5. Convergent curves of the objectives of Case 5

Table 7. Summary of statistical indices of the CS-KHA with CS, KHA for Cases 1-10

	CS-KHA				KHA				CS			
Case.no	**Best**	**Worst**	**Mean**	**Std dev**	**Best**	**Worst**	**Mean**	**Std dev**	**Best**	**Worst**	**Mean**	**Std dev**
Cace1	799.0595	799.4923	799.1761	0.0023	799.4972	799.9512	799.7572	0.024	799.6547	800.1054	799.9513	.0321
Case2	830.0981	830.6713	830.1625	0.019	830.4199	830.9922	830.6918	0.033	833.5157	833.9145	833.7327	0.029
Case3	799.5625	799.8921	799.7005	0.03	799.8928	800.41	800.1367	0.043	800.3034	800.9133	800.6723	0.0352
Case4	835.3821	835.8811	835.5920	0.0015	835.9164	836.5764	836.2321	0.0191	839.0130	839.7700	839.3205	0.027
Case5	803.6357	803.980	803.8100	0.023	803.6580	804.2104	803.9683	0.03202	803.7306	804.2710	803.9360	0.0331
Case6	853.1469	853.5361	853.2742	0.0026	854.6579	855.3519	854.9914	0.041	857.3526	857.9720	857.6437	0.03602
Case7	830.5273	830.9407	830.7204	0.0031	830.3209	830.9859	830.7303	0.0342	831.7243	832.1926	831.9751	0.0284
Case8	828.8532	829.2302	828.9712	0.038	832.1724	832.8743	832.5126	0.0375	831.1796	831.6991	831.4425	0.0223
Case9	41660.2273	41660.840	41660.5703	0.04	41673.5922	41674.110	41673.9078	0.051	41717.8801	41718.4713	41718.0721	0.043
Case10	41712	41712.7701	41712.3923	0.062	41705	41705. 6203	41705.274	0.0421	41791	41791.8912	41791. 4822	.037

Table 8. The control variables' optimal settings for Cases 9 and 10.

	Case 9			Case 10		
Control variable	CS-KHA	KHA	CS	CS-KHA	KHA	CS
P_{G1} (MW)	143.4297	145.0358	140.9221	140.6795	141.9955	146.9150
P_{G2} (MW)	87.0645	98.1294	77.7157	94.9802	92.1514	100.0000
P_{G3} (MW)	45.1917	47.2053	40.0000	47.1461	45.7668	40.0000
P_{G6} (MW)	67.0035	54.0795	100.0000	66.5315	78.1945	100.0000
P_{G8} (MW)	459.5789	472.6903	453.4311	460.6278	460.5117	478.9845
P_{G9} (MW)	99.7951	81.2897	100.0000	94.4812	89.2280	30.0000
P_{G12} (MW)	363.2292	367.0996	354.6953	362.1398	358.8398	371.7001
V_1(p.u)	1.0713	1.0695	1.0552	1.0206	1.0198	1.1000
V_2(p.u)	1.0746	1.0734	1.0577	1.0244	1.0253	1.1000
V_3(p.u)	1.0603	1.0611	1.0461	1.0119	1.0155	1.1000
V_6(p.u)	1.0597	1.0594	1.0654	1.0150	1.0264	1.1000
V_8(p.u)	1.0755	1.0778	1.1000	1.0384	1.0503	1.1000
V_9(p.u)	1.0710	1.0699	1.0739	1.0240	1.0329	1.1000
V_{12}(p.u)	1.0582	1.0562	1.0453	1.0040	1.0070	1.1000
Qc_{18}(Mvar)	6.8293	4.8640	20.0000	10.8442	8.0117	0
Qc_{25}(Mvar)	14.0936	16.3750	9.1658	6.4490	15.9809	15.1607
Qc_{53}(Mvar)	11.2626	17.1950	20.0000	13.4479	11.0521	20.0000
T_{4-18}	1.0432	0.9608	0.9000	0.9583	1.0192	0.9000
T_{4-18}	0.9543	1.0416	1.1000	1.0017	0.9868	1.1000
T_{21-20}	0.9981	1.0422	1.1000	0.9981	0.9773	1.1000
T_{24-25}	1.0345	1.0436	1.1000	0.9680	0.9543	0.9000
T_{24-25}	1.0039	1.0439	0.9000	0.9574	1.0740	1.1000
T_{24-26}	1.0175	1.0326	1.0668	1.0298	1.0136	1.0171
T_{7-29}	0.9975	1.0014	1.0565	0.9801	0.9951	1.0648
T_{34-32}	0.9533	0.9558	0.9000	0.9283	0.9354	0.9388
T_{11-41}	0.9016	0.9495	0.9000	0.9000	0.9001	0.9000
T_{15-45}	0.9869	0.9883	0.9795	0.9509	0.9513	1.0178
T_{14-46}	0.9832	0.9756	0.9796	0.9527	0.9606	1.1000
T_{10-51}	0.9948	0.9876	0.9951	0.9725	0.9861	1.0697
T_{13-49}	0.9579	0.9450	0.9000	0.9170	0.9177	0.9738
T_{11-43}	1.0219	0.9863	1.1000	0.9418	0.9782	1.1000
T_{40-56}	0.9860	0.9959	1.1000	1.0432	0.9771	0.9000
T_{39-57}	0.9993	0.9698	0.9869	0.9218	0.9373	1.1000
T_{9-55}	1.0120	1.0285	1.1000	1.0029	1.0128	1.1000
Fuel cost ($/h)	**41660.2273**	**41673.5922**	**41717.8801**	**41712**	**41705**	**41791**
VD	1.5991	1.6959	1.7060	**0.6940**	**0.7004**	**1.5878**
Lmax	0.2816	0.2800	0.2775	0.2931	0.2935	0.2870
Emission (ton/h)	1.3566	1.4117	1.3269	1.3554	1.3507	1.4690
Ploss (MW)	14.4929	14.7297	15.9645	15.7861	15.8877	16.8061

Table 9. The results obtained are compared for Cases 9 and10.

Case 9		Case 10		
Algorithms	Fuel cost($/h)	Algorithms	Fuel cost($/h)	VD (p.u)
CS-KHA	**41660.2273**	CS-KHA	**41712**	**0.6940**
KHA	**41673.5922**	KHA	**41705**	**0.7004**
CS	**41717.8801**	CS	**41791**	**1.5878**
MSA [33]	41673.7231	MSA [33]	41714.9851	0.67818
ICBO [32]	41697.3324	FPA [33]	41726.3758	0.69723

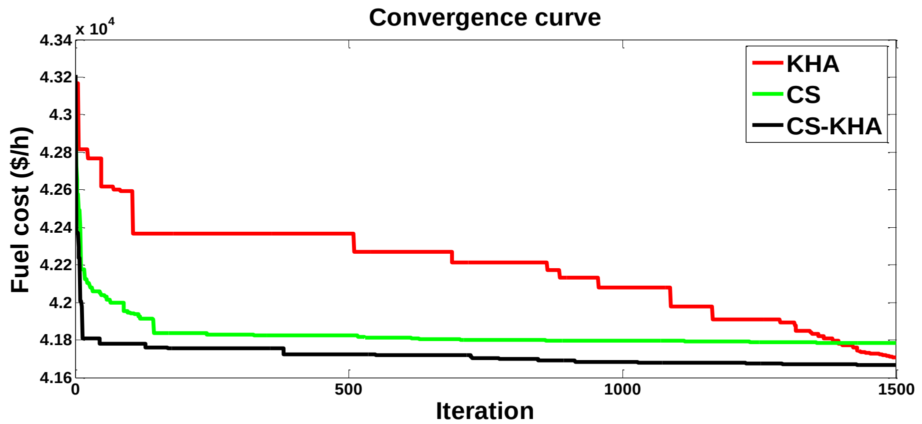


Fig.6. Convergent curves of Case 9.

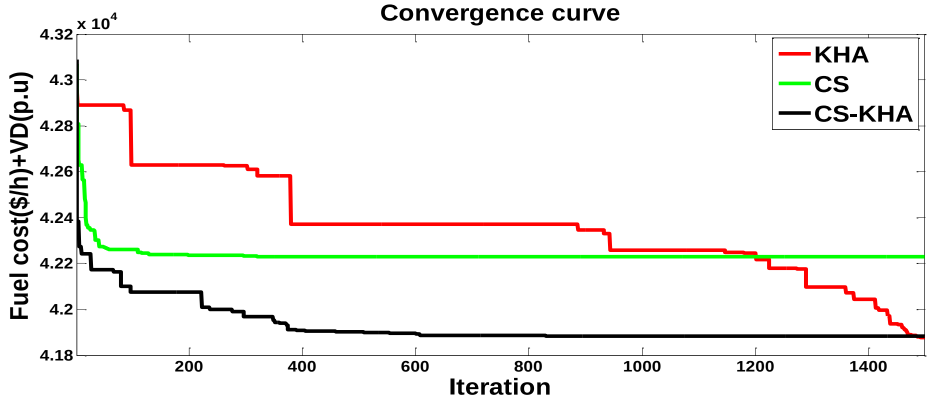


Fig.7. Convergent curves of Case 10.

Table 10. The control variables' optimal settings for case11.

Control variable	CS-KHA	KHA	CS	Control variable	CS-KHA	KHA	CS
P_{G1} (MW)	366.9132	385.4828	368.0476	V_{G1} (p.u)	1.0322	1.0169	1.0043
P_{G4} (MW)	30.0000	30.0000	40.4392	V_{G4} (p.u)	1.0515	1.0342	1.0224
P_{G6} (MW)	30.8504	30.0000	30.0056	V_{G6} (p.u)	1.0349	1.0323	1.0137
P_{G8} (MW)	30.0000	36.5892	30.5938	V_{G8} (p.u)	1.0742	1.0906	1.0714
P_{G10} (MW)	32.1926	30.0951	30.6092	V_{G10} (p.u)	1.0786	1.0965	1.0833
P_{G12} (MW)	322.0172	337.7073	298.7903	V_{G12} (p.u)	1.0353	1.0238	1.0114
P_{G15} (MW)	66.9864	67.3679	73.6602	V_{G15} (p.u)	1.0383	1.0268	1.0176
P_{G18} (MW)	34.9502	31.6466	34.1581	V_{G18} (p.u)	1.0476	1.0328	1.0167
P_{G19} (MW)	30.0126	30.1197	34.9399	V_{G19} (p.u)	1.0464	1.0356	1.0192
P_{G24} (MW)	31.2758	40.0241	32.0601	V_{G24} (p.u)	1.0571	1.0634	1.0366
P_{G25} (MW)	30.0890	30.3142	30.7494	V_{G25} (p.u)	1.0939	1.0568	1.0337
P_{G26} (MW)	152.1116	160.5087	124.9473	V_{G26} (p.u)	1.0835	1.0689	1.0860
P_{G27} (MW)	210.4531	212.1246	213.9664	V_{G27} (p.u)	1.0684	1.0325	1.0148
P_{G31} (MW)	30.0107	30.0000	32.9586	V_{G31} (p.u)	1.0559	1.0328	1.0147
P_{G32} (MW)	32.1135	32.1022	32.1000	V_{G32} (p.u)	1.0628	1.0410	1.0174
P_{G34} (MW)	30.1433	30.0000	30.0574	V_{G34} (p.u)	1.0699	1.0429	1.0476
P_{G36} (MW)	30.9994	32.3755	37.3000	V_{G36} (p.u)	1.0709	1.0615	1.0452
P_{G40} (MW)	37.2945	31.1420	39.2771	V_{G40} (p.u)	1.0584	1.0335	1.0348
P_{G42} (MW)	32.7803	40.1303	32.0453	V_{G42} (p.u)	1.0728	1.0407	1.0430
P_{G46} (MW)	30.5901	30.0504	61.3421	V_{G46} (p.u)	1.0779	1.0699	1.0825
P_{G49} (MW)	35.7090	35.7110	35.7293	V_{G49} (p.u)	1.0838	1.0856	1.0880
P_{G54} (MW)	150.1344	159.3915	147.9769	V_{G54} (p.u)	1.0743	1.0686	1.0785
P_{G55} (MW)	45.0829	45.1069	46.4248	V_{G55} (p.u)	1.0661	1.0609	1.0791
P_{G56} (MW)	30.2316	30.1951	30.0706	V_{G56} (p.u)	1.0747	1.0669	1.0783
P_{G59} (MW)	41.1021	34.2682	31.4284	V_{G59} (p.u)	1.0929	1.0880	1.0949
P_{G61} (MW)	128.9333	126.3616	116.7174	V_{G61} (p.u)	1.0857	1.0959	1.0989
P_{G62} (MW)	119.4878	104.4463	108.5139	V_{G62} (p.u)	1.0857	1.0980	1.0949
P_{G65} (MW)	30.0414	30.6740	33.8130	V_{G65} (p.u)	1.0886	1.0891	1.0524
P_{G66} (MW)	274.4206	296.6764	274.6836	V_{G66} (p.u)	1.0981	1.1000	1.0983
P_{G69} (MW)	290.2244	273.8381	285.3788	V_{G69} (p.u)	1.0819	1.0947	1.0921
P_{G70} (MW)	33.8793	31.0321	30.0310	V_{G70} (p.u)	1.0760	1.0680	1.0753

P_{G72} (MW)	30.0000	30.0000	30.5010	V_{G72} (p.u)	1.0847	1.0782	1.0618
P_{G73} (MW)	35.0183	30.0011	34.5178	V_{G73} (p.u)	1.0807	1.0823	1.0806
P_{G74} (MW)	30.0000	34.6584	30.0089	V_{G74} (p.u)	1.0614	1.0721	1.0635
P_{G76} (MW)	31.1843	30.0000	30.0515	V_{G76} (p.u)	1.0481	1.0534	1.0537
P_{G77} (MW)	30.8112	30.0330	35.3680	V_{G77} (p.u)	1.0530	1.0533	1.0694
P_{G80} (MW)	353.3451	328.0506	339.0098	V_{G80} (p.u)	1.0578	1.0871	1.0748
P_{G85} (MW)	30.4117	34.3764	30.0251	V_{G85} (p.u)	1.0698	1.0849	1.0867
P_{G87} (MW)	31.2043	31.2010	31.2000	V_{G87} (p.u)	1.0883	1.0856	1.0802
P_{G89} (MW)	373.0515	343.3753	383.0308	V_{G89} (p.u)	1.0766	1.1000	1.0966
P_{G90} (MW)	30.0217	30.0053	30.0816	V_{G90} (p.u)	1.0543	1.0908	1.0790
P_{G91} (MW)	30.1360	31.2499	33.4771	V_{G91} (p.u)	1.0621	1.0926	1.0810
P_{G92} (MW)	30.0000	31.6228	30.0239	V_{G92} (p.u)	1.0568	1.0932	1.0839
P_{G99} (MW)	31.5839	30.1290	32.1729	V_{G99} (p.u)	1.0515	1.0699	1.0605
P_{G100} (MW)	161.0126	174.5208	163.4482	V_{G100} (p.u)	1.0395	1.0786	1.0654
P_{G103} (MW)	42.2950	42.1514	42.2731	V_{G103} (p.u)	1.0212	1.0726	1.0593
P_{G104} (MW)	30.8340	31.1019	30.1950	V_{G104} (p.u)	1.0060	1.0641	1.0498
P_{G105} (MW)	30.1658	30.0082	30.0294	V_{G105} (p.u)	1.0123	1.0751	1.0472
P_{G107} (MW)	30.7389	30.1938	30.7178	V_{G107} (p.u)	0.9973	1.0717	1.0433
P_{G110} (MW)	32.0056	30.6153	30.4068	V_{G110} (p.u)	0.9894	1.0791	1.0417
P_{G111} (MW)	40.8006	40.8581	40.8015	V_{G111} (p.u)	0.9980	1.0890	1.0528
P_{G112} (MW)	30.6941	30.1776	35.3112	V_{G112} (p.u)	0.9775	1.0721	1.0298
P_{G113} (MW)	30.5556	30.1612	43.2123	V_{G113} (p.u)	1.0584	1.0584	1.0260
P_{G116} (MW)	31.5470	30.1511	30.6720	V_{G116} (p.u)	1.0928	1.1000	1.0466
Qc_{5} (Mvar)	1.0968	0.1341	0.4603	$T_{(8–5)}$	1.0269	1.0527	1.0180
Qc_{34} (Mvar)	0.0395	0.0656	7.8806	$T_{(26–25)}$	1.0551	0.9293	1.0770
Qc_{37}(Mvar)	1.7660	7.3596	2.7258	$T_{(30–17)}$	0.9923	1.0165	1.0267
Qc_{44}(Mvar)	10.4951	0.3568	0.0083	$T_{(38–37)}$	0.9561	0.9903	0.9672
Qc_{45}(Mvar)	0.0001	2.6926	1.0940	$T_{(63–59)}$	0.9402	0.9071	0.9072
Qc_{46}(Mvar)	6.3599	0.6672	17.7909	$T_{(64–61)}$	1.0339	0.9722	0.9434
Qc_{48}(Mvar)	0.3103	0.6422	0.3959	$T_{(65–66)}$	1.0317	1.0952	1.0250
Qc_{74}(Mvar)	0.5937	0.0949	12.9769	$T_{(68–69)}$	1.0046	1.0947	0.9504
Qc_{79}(Mvar)	0.4359	1.0046	1.7815	$T_{(81–80)}$	1.0284	0.9213	0.9667
Qc_{82}(Mvar)	2.6580	0	2.5440				
Qc_{83}(Mvar)	2.7523	0	2.0127	Objective functions			
Qc_{105}(Mvar)	1.1846	2.5892	10.9604	**Fuel cost ($/h)**	**135260.45**	**135400.78**	**135610.321**
Qc_{107}(Mvar)	4.1717	0.0284	4.9321	**Ploss (MW)**	**56.4548**	**58.1287**	**53.3527**
Qc_{110}(Mvar)	4.0167	0.5725	0.0614				

Table 11. The results obtained are compared for Case 11.

Case	Algorithms	Fuel cost ($/h)
	CS-KHA	135260.45
Case 11	KHA	135400.78
	CS	135610.321
	BSA [37]	135333.4743
	ABC [37]	135304.3584
	BBO [37]	135263.7289

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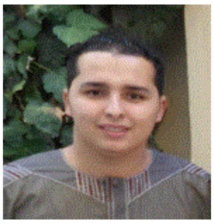
Authors' Profiles

Aboubakr Khelifi was born in Laghouat (Algeria). He received master degrees in Electrical Engineering in 2015 from Amar Telidji Laghouat, University. He is currently a PhD student at the same University. His research interests are focused on the electrical power system, optimal power flow, and optimization techniques.

E-mail address: a.khelifi@lagh-univ.dz



Bentouati Bachir was born in Laghouat, Algeria, on August 22, 1990. He received license, master and doctor degrees in Electrotechnic and Electrical Power System in 2010, 2012 and 2018 respectively from Laghouat university. His areas of research include optimal power flow, Artificial intelligence and optimization techniques.

Chettih Saliha was born on 11 may 1971 in Laghouat/Algeria. She earned his PhD degree in Electro-technology from the University of Amar Telidji. She joined the faculty of the Technology He joined the faculty of the Technology at the University of Amar Telidji, Laghouat (Algeria), in 2008 where she is currently a professor. Her research interests optimal power flow, Artificial intelligence and optimization techniques.

Ragab El- Sehiemy was born at Minoufiya, 1973. He received the B.Sc., M.Sc., and Ph.D. degrees in 1996, 2005, and 2008, respectively.

He is an Associate Professor in the Department of Electrical Engineering, Faculty of Engineering, Kafrelsheikh University, Kafr el-Sheikh, Egypt.

His research interests involve power system operation, control, and planning, applications of modern optimization techniques for variant electric power systems applications, renewable sources, and smart grid.

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