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J. Electrical Systems 15-3 (2019): 375-391

JES
Journal of Electrical Systems

Regular paper

A hybrid cuckoo search and krill herd technique for solving problem of optimal power flow in power systems

In order to remedy the poor exploitation of the krill herd algorithm (KHA), a breed cuckoo search and KHA (CS-KHA) technique have been developed for the optimal power flow (OPF) problem. The proposed 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. OPF is formulated as a nonlinear optimization problem with conflicting objectives and subjected to both equality and inequality constraints. This paper looks at CSKHA for solving non-convex and non-smooth OPF problem. The viability of these enhancements is tested on standard two standard test systems called IEEE 57-bus and IEEE 118-bus with five case studies. Experimental results appear, in all cases, this proposed hybrid meta-heuristic CSKHA is more and effective than the original CS, KHA, as well as other methods in the literature.

Keywords: Optimal power flow; krill herd algorithm (KHA); cuckoo search algorithm (CS); voltage deviation; emission.

Article history: Received 30 March 2019, Accepted 25 June 2019

1. Introduction

The problem of optimal power flow (OPF) has significant and considerable attention in recent years. OPF is one of the main issues in the operation and planning power systems. OPF is mathematically formulated as static, non-convex, non-linear programming problem. The major objective is to find the correct adjustment of certain control variables that able to optimize specific objective function/s while the operational constraints at specified loading settings and defined system parameters are preserved [1-3].

In the physical point of view, the OPF aims at finding the optimal regulated control variables as production/the terminal voltages of generating units, setting of transformer taps, shunt reactors/capacitors. The target of the OPF problem is to improve the economic and technical 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 wide-range OPF optimization problem has both continuous and discontinuous 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. No doubt, the existence of

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discontinuous control variables, like transformer tap positions, phase shifters, switchable shunt devices, added more difficulty to the problem formulation as well to solution methodology.

The methods were evolving to solve OPF problem can be categorized into two types conventional and search based optimization techniques. The conventional optimization techniques were used derivatives and gradient operators. These techniques are usually not capable to determine the global optimal [1], [2]. 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 search-based optimization methods that were so-called meta-heuristics. These techniques can dominate many disadvantages of conventional techniques [3].

Several of these recent techniques have been applied to solve the OPF problem like: modified shuffle frog leaping algorithm [4], Simulated Annealing (SA) [5], Genetic Algorithm (GA) [6,7], Differential Evolution (DE) [8], Tabu Search (TS) [9], Imperialist Competitive Algorithm (ICA) [10], [42], [52] 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], particle swarm optimizer with grey wolves [24]. A survey on different meta-heuristics, that were used to solve the OPF problem are offered in [25].

Krill herd method (KH) was suggested by Gandomi and Alavi in 2012 [26] as new population-based swarm computation [26]. 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. KH computation occasionally is not able to must avoid local optimum [27] and [28]. Therefore, many optimization strategies such as chaotic theory [27], [28], Flower Pollination Algorithm (FPA) [29] and colonial competitive differential evolution (CCDE) [30] have been hybridized with KH algorithm as mutation operator to enhance 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]. In the area of multi-objective framework, several optimization techniques were developed to solve the OPF problem as quasi-oppositional teaching–learning based optimization [31], 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].

This article provides a successful hybrid meta-heuristic cuckoo search krill herd (CS-KHA) technique for solving the OPF problem. The proposed algorithms aim to accelerate the solution quality and convergence. In the proposed CS-KHA, the KHA is used 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. To prove the efficiencies of the CS-KHA compared with 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.

2. Formulation of optimal Power Flow (OPF)

The notation of OPF problem 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.

Minimize: $f\left(x,u\right)$ (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, x is the dependent variables or state's vector. $f\left(x,u\right)$ refers to the OPF objective function/s, $g(x, u)$ refers to set of inequality constraints, □(x, u): set of equality constraints.

2.1 Control variables

The vector of control variables is expressed as follows:

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

where, P_{G_i} is the i-th generator active power output. Consider bus 1 as a swing bus. V_{G_i} is the voltage magnitude at i-th voltage controlled generator bus, T_j is the j-th branch transformer tap, Q_{Ck} 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, the tap settings indicated are in p.u. and outright voltage's estimation is not represented.

2.2 State variables

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

$$x = \left[P_{G_1}, V_{L_1} \ldots V_{Lq} \ldots . V_{L_{NL}}, Q_{G_1} \ldots Q_{G_{NG}}, S_{l_1} \ldots . S_{lk} \ldots S_{l_{nl}} \right] \tag{4}$$

where, $P_{G_1}\ and\ Q_{G_1}$ are the active and reactive powers of generator at slack bus, respectively. V_{Lq} is the q-th load bus's bus voltage (PQ bus) and S_{lk} is the k-th line loading level. NL and nl are the load buses' number and lines of transmission respectively [40].

2.3 Power System Constraints

The problem of OPF has both operational equality and inequality constraints. These constraints can be defined as follows:

2.3.1 Equality constraints

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

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

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

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} and B_{ij} are the transfer conductance and susceptance among the line connected between buses i and j, respectively.

2.3.2. Inequality constraints

The inequality operational constraints of the OPF problem reflect the equipment's operating limits, the limitation of the line loading and the voltage levels at loading buses to ensure the security and power quality of the system. The control variables are self-limiting between their hard boundaries as in Eqs. (7) – (9).

a) Generator constraints:

$$V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max} \forall i \in NG \tag{7}$$

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max} \forall i \in NG \tag{8}$$

$$Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max} \forall i \in NG \tag{9}$$

1) **Transformer constraints:**

$$T_j^{\min} \le T_j \le T_j^{\max} \forall j \in NT \tag{10}$$

1) **Shunt compensator constraints:**

$$Q_{C_k}^{\min} \le Q_{C_k} \le Q_{C_k}^{\max} \forall k \in NC \tag{11}$$

d) Security constraints:

$$V_{L_p}^{\min} \le V_{L_p} \le V_{L_p}^{\max} \forall p \in NL \tag{12}$$

$$S_{l_q} \le S_{l_q}^{\max} \forall q \in nl \tag{13}$$

3. 3. Suggested hybrid technique

The proposed hybrid algorithm merges the merits of KH technique and the cuckoo search method. In this section, a description of the two merged algorithms and the proposed one is carried as follows:

3.1. KH technique

The KH technique is built on the natural inspiration of conduct krill individuals' imitation in the krill population. The KH optimization technique has the ability to search for an uncertain search space. The KH technique is motivated by krill activities like [26]:

1) The movement of other krill individuals is induced;

$$\frac{dX_k}{dt} = N_k + F_k + D_k \tag{14}$$

The induced movement is expressed by Lagrangian model which is extended to an n-dimensional decision space:

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 that is expressed as follows:

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

$$\alpha_k = \alpha_k^{local} + \alpha_k^{t\arg et} \tag{16}$$

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 $\alpha_k^{t\arg et}$ indicate the local effect of the neighbor, which is the best solution of the k_{th} individual. $\alpha_k^{t\arg et}$ is formulated by the following equations:

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

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

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.

2) Food search activity;

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. The foraging activistes/mouvements are mathematically defined as follows :

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

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

where, V_f is the foraging speed, ω_f is the foraging motion's inertia weight in [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.

3) Random scattering.

Depending on the foraging speed's measured values, the random scattering process is employed as:

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

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

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.

3.2. Cuckoo search algorithm

In CS algorithm, the Lévy flights are consolidated that decides the cuckoo's walking steps. 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 involved to take use of the recently created better solutions in place of a moderately poor solution. In this article, it is looked at every nest that merely had an egg. Thus, the difference between the nest egg and solution was not identified. The CS algorithm makes a good harmony between a local arbitrary walk and the irregular global exploratory walk using a switching parameter. The updating equation 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 eaviside, ε is a number of random drawn from a regular distribution, and β_s is 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.

3.3. Proposed procedure of the Hybrid CS-KHA

In this work, a novel meta-heuristic technique is employed by prompting KU operator and KA operator into KH algorithm. The proposed algorithm, CS-KHA, is developed to manage the optimal solution of an OPF problem. The introduced KU/KA operators are roused by the authoritative CS algorithm. So, 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 CS-KHA is presented by Algorithms 1 and 2, respectively.

Algorithm 1 **KU operator**

gin
Get a krill i and update its solution using Lévy flights using **Equation (25)**.
Evaluate its quality F_i
Select a krill j randomly.
f $\left(F_i \prec F_j\right)$
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}
nd if
nd.

Algorithm 2 **KA operator**

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

In the proposed method, standard KHA carries three movements to find the best solutions and engage these movements to lead the candidate solutions for the following generation. Then, the KU operator is employed to carry out local search intensively to achieve better solutions. This operator can concentrate the search space by Lévy flight. Towards the end of each generation, the KA operator is employed to upgrade the CS-KHA's exploration by replacing the worse krill.

This action extends the strong the KHA's exploration and overcomes the absence of the KHA's weak exploitation. Added to that, the proposed technique can unwind the inconsistency among exploration and exploitation effectively. Furthermore, another basic change called elitism scheme is incorporated into the proposed CS-KHA. Likewise, the elitism scheme is help to hold the preferable solutions for each 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 CS-KHA algorithm (see Algorithm 3).

Algorithm 3 **CS-KHA**

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.

4. Objective functions and studied cases

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

4.1. IEEE 57 Bus system results

A total of 4 cases were implementing for the IEEE 57-bus 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 cases are expressed as follows:

CASE 1: fuel cost minimization

The goal of this case is to reduce the total generating fuel cost. Hence, this objective function is presented as:

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

The CS-KHA is implemented to get the optimal settings for this case and the simulation results are presented in Table 1. In this case, minimizing the fuel costs is achieved to a 41660.2273 $/h by CS-KHA. The highest reduction in the fuel costs, compared with other recent studies that were reported in the literature, is achieved using the proposed CS-KHA as shown in Table 2.

CASE 2: Fuel cost minimization and voltage deviation

The purpose of the objective function is to reduce simultaneously both fuel cost and voltage deviation.

$$VD = \left(\sum_{p=1}^{NL} \left| V_{L_p} - 1 \right| \right) \tag{28}$$

The transformed single objective function next by combining both objectives as:

$$f(x,u) = \left(\sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2 \right) + \lambda_{VD} \times VD \tag{29}$$

With weight factor λ_{VD} which is chosen as 100. The simulation results of the proposed CS-KHA technique are given in Table 1. This table shows that the VD has been decreased from (1.5991 p.u.) to (0.6940 p.u.) compared with CASE 1. Hence, the cost has slightly augmented from (41660.2273 $/h) to (41712 $/h) compared with CASE 1.

Table 1: the optimal control variables' settings for Cases 1 and 2.

Control variable	Case 1			Case 2		
	CS-KHA	KHA	CS	CS-KHA	KHA	CS
PG1 (MW)	143.4297	145.0358	140.9221	140.6795	141.9955	146.9150
PG2 (MW)	87.0645	98.1294	77.7157	94.9802	92.1514	100.0000
PG3 (MW)	45.1917	47.2053	40.0000	47.1461	45.7668	40.0000
PG6 (MW)	67.0035	54.0795	100.0000	66.5315	78.1945	100.0000
PG8 (MW)	459.5789	472.6903	453.4311	460.6278	460.5117	478.9845
PG9 (MW)	99.7951	81.2897	100.0000	94.4812	89.2280	30.0000
PG12 (MW)	363.2292	367.0996	354.6953	362.1398	358.8398	371.7001
V1 (p.u)	1.0713	1.0695	1.0552	1.0206	1.0198	1.1000
V2 (p.u)	1.0746	1.0734	1.0577	1.0244	1.0253	1.1000
V3 (p.u)	1.0603	1.0611	1.0461	1.0119	1.0155	1.1000
V6 (p.u)	1.0597	1.0594	1.0654	1.0150	1.0264	1.1000
V8 (p.u)	1.0755	1.0778	1.1000	1.0384	1.0503	1.1000
V9 (p.u)	1.0710	1.0699	1.0739	1.0240	1.0329	1.1000
V12 (p.u)	1.0582	1.0562	1.0453	1.0040	1.0070	1.1000
Qc18(Mvar)	6.8293	4.8640	20.0000	10.8442	8.0117	0
Qc25(Mvar)	14.0936	16.3750	9.1658	6.4490	15.9809	15.1607
Qc53(Mvar)	11.2626	17.1950	20.0000	13.4479	11.0521	20.0000
T4–18	1.0432	0.9608	0.9000	0.9583	1.0192	0.9000
T4–18	0.9543	1.0416	1.1000	1.0017	0.9868	1.1000
T21–20	0.9981	1.0422	1.1000	0.9981	0.9773	1.1000
T24–25	1.0345	1.0436	1.1000	0.9680	0.9543	0.9000
T24–25	1.0039	1.0439	0.9000	0.9574	1.0740	1.1000
T24–26	1.0175	1.0326	1.0668	1.0298	1.0136	1.0171
T7–29	0.9975	1.0014	1.0565	0.9801	0.9951	1.0648
T34–32	0.9533	0.9558	0.9000	0.9283	0.9354	0.9388
T11–41	0.9016	0.9495	0.9000	0.9000	0.9001	0.9000
T15–45	0.9869	0.9883	0.9795	0.9509	0.9513	1.0178
T14–46	0.9832	0.9756	0.9796	0.9527	0.9606	1.1000
T10–51	0.9948	0.9876	0.9951	0.9725	0.9861	1.0697
T13–49	0.9579	0.9450	0.9000	0.9170	0.9177	0.9738
T11–43	1.0219	0.9863	1.1000	0.9418	0.9782	1.1000
T40–56	0.9860	0.9959	1.1000	1.0432	0.9771	0.9000
T39–57	0.9993	0.9698	0.9869	0.9218	0.9373	1.1000
T9–55	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 (pu)	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 2: Assessing CS-KHA compared with previous methods for Cases 1 and 2.

Case 1		Case 2		
Algorithms	Fuel cost($/h)	Algorithms	Fuel cost($/h)	VD (pu)
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	FPA [33]	41714.9851	0.67818
ICBO [32]	41697.3324	MSA[33]	41726.3758	0.69723
SP-DE [46]	41667.82	CSHS[51]	41707.8925	0.6947
DSA[47]	41686.82	MICA-TLA [52]	41959.18	0.5390
ARCBBO [48]	41686	ISA[53]	41,939.7706	0.9931
EADDE [49]	41713.62	EADDE [49]	42051.44	0.7882

Table 3: The control variables' optimal settings for Cases 3 and 4.

Control variable	Case 3			Case 4		
	CS-KHA	KHA	CS	CS-KHA	KHA	CS
PG1 (MW)	141.0169	149.7398	135.3757	142.7262	144.1672	144.5195
PG2 (MW)	91,12616	92,77993	42,92031	99,93954	94,75922	100
PG3 (MW)	43,7481	47,06133	40	50,42962	47,9257	40
PG6 (MW)	70,98798	74,6893	100	100	93,97267	100
PG8 (MW)	460,9236	490,6303	439,7154	423,9762	427,6062	423,8661
PG9 (MW)	100	35,61091	100	99,94481	100	100
PG12 (MW)	358,1413	376,1065	410	348,3181	356,7317	359,134
V1 (p.u)	1,069525	1,069637	1,013521	1,072837	1,073154	0,9867924
V2 (p.u)	1,071727	1,070619	1,014491	1,077189	1,076509	0,9910011
V3 (p.u)	1,060491	1,063399	1,006911	1,060709	1,063729	0,9763403
V6 (p.u)	1,061281	1,061452	1,034508	1,062784	1,065579	0,9818358
V8 (p.u)	1,080564	1,076722	1,1	1,086087	1,080184	0,9883548
V9 (p.u)	1,072581	1,071394	1,1	1,074625	1,073543	0,9737766
V12 (p.u)	1,054979	1,0591	1,03528	1,062436	1,061184	0,9691483
Qc18(Mvar)	3,388758	0	20	0,837715	0,05746264	20
Qc25(Mvar)	9,968179	8,882754	0	5,755562	2,543406	20
Qc53(Mvar)	0,6916095	3,655351	20	6,890428	2,017853	0
T4–18	0,9116748	0,954039	0,9364702	0,9305397	0,9982046	0,9
T4–18	1,046934	0,9846332	1,1	1,037653	1,008725	1,1
T21–20	0,9848523	1,051181	1,1	1,046842	1,053418	1,084211
T24–25	1,060192	0,9488512	1,026403	0,9803888	0,9671955	1,1
T24–25	0,9664268	1,045189	0,9	0,9278637	0,945062	0,9
T24–26	1,041014	1,012783	1,1	1,030378	1,019413	1,009746
T7–29	0,9893253	0,9934664	0,98973	0,9959099	0,9915116	0,9
T34–32	0,9001227	0,9001866	0,9	0,9005716	0,960261	1,1
T11–41	0,924181	0,9014515	0,9	0,9	1,040878	0,9
T15–45	0,9882288	0,990620	0,9	1,000737	0,986191	0,9
T14–46	0,9726825	0,9752828	0,9650387	0,989256	0,9781929	0,9
T10–51	0,991607	0,9934092	1,0241970	1,031124	0,9939326	0,9
T13–49	0,9188166	0,922587	0,9	0,9628982	0,9488045	0,9
T11–43	0,985097	1,008904	1,1	1,018159	0,9748567	0,9
T40–56	1,046024	1,05656	1,1	0,9555413	1,061963	0,9
T39–57	0,9570362	1,013273	0,980621	0,9433542	0,9607729	1,1
T9–55	1,034521	1,030943	1,1	1,024265	1,017888	0,9
Fuel cost ($/h)	41674.5094	41754.0879	41978.0631	41728.5873	41710.9858	41823.76550
VD (pu)	1.8715	1.8314	1.7189	1.5817	1.5474	1.6717

Lmax	0.2718	0.2713	0.2709	0.2772	0.2848	0.2956
Emission (ton/h)	1.3510	1.5090	1.3919	1.2207	1.2456	1.2458
Ploss (MW)	15.1443	15.8184	17.2116	14.5348	14.3629	16.7197

Table 4: Assessing CS-KHA compared with previous methods for Cases 3 and 4.

Case 3			Case 4		
Algorithms	Fuel cost($/h)	Lmax	Algorithms	Fuel cost($/h)	Emission
CS-KHA	**41674.5094**	**0.2718**	CS-KHA	**41728.5873**	**1.2207**
KHA	**41754.0879**	**0.2713**	KHA	**41710.9858**	**1.2456**
CS	**41978.0631**	**0.2709**	CS	**41823.76550**	**1.2458**
MSA [33]	41675.9948	0.27481	ESDE-MC [44]	42857.4869	1.2191
ICBO [32]	41694.1407	0.27918	ESDE [44]	42863.3243	1.2662
MDE [8]	41765	0.2957	ISPEA2 [50]	42444.5535	1.2904
DSA [47]	41761.22	0.2383	MOMICA [45]	41886.7982	1.4784
ESDE-EC [44]	41718.3844	0.2754	MOICA [45]	41919.7061	1.601

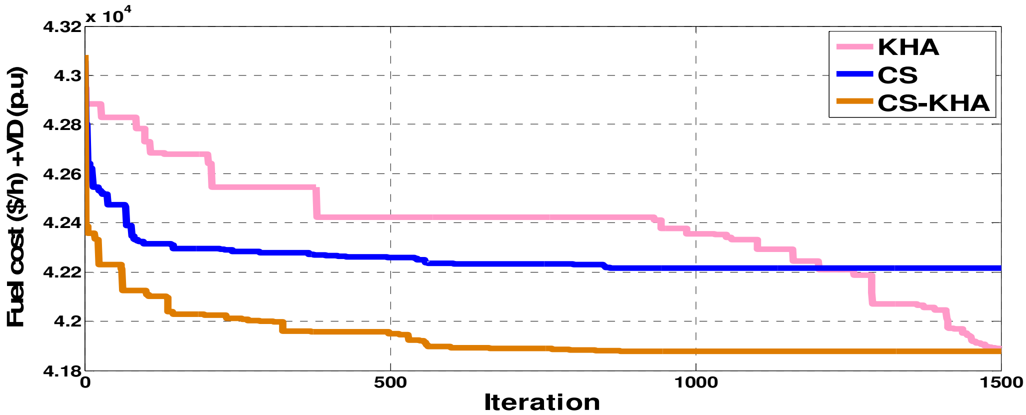

Fig. 1. Convergence curves of Case 2.

CASE 3: Fuel costs 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 wake of being subjected to unsettling influence, the power systeam's steadiness is portrayed through its capacity to keep up whole bus voltages in suitable boundaries. A system goes into voltage instability 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, 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:

$$L_j = \left| 1 - \sum_{i=1}^{NG} F_{ji} \frac{V_i}{V_j} \right|, \text{ where } j = 1, 2, \dots, NL \tag{30}$$

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 Eq. (30).

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = \begin{bmatrix} Y_{LL} & Y_{LG} \\ Y_{GL} & Y_{GL} \end{bmatrix} \begin{bmatrix} V_L \\ V_G \end{bmatrix} \tag{31}$$

$$L_{\max} = \max\left(L_j\right) \; j = 1, 2 \ldots\ldots, NL \tag{32}$$

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:

$$f\left(x, u\right) = \left(\sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2\right) + \lambda_L \times L_{\max} \tag{33}$$

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

In Case 3, the best values of both fuel cost and the system load buses' L_{max}, CS-KHA gives preferable produce of 41674.5094 and 0.2718 respectively, superior to the other comparable algorithms as appears in the Table 4.

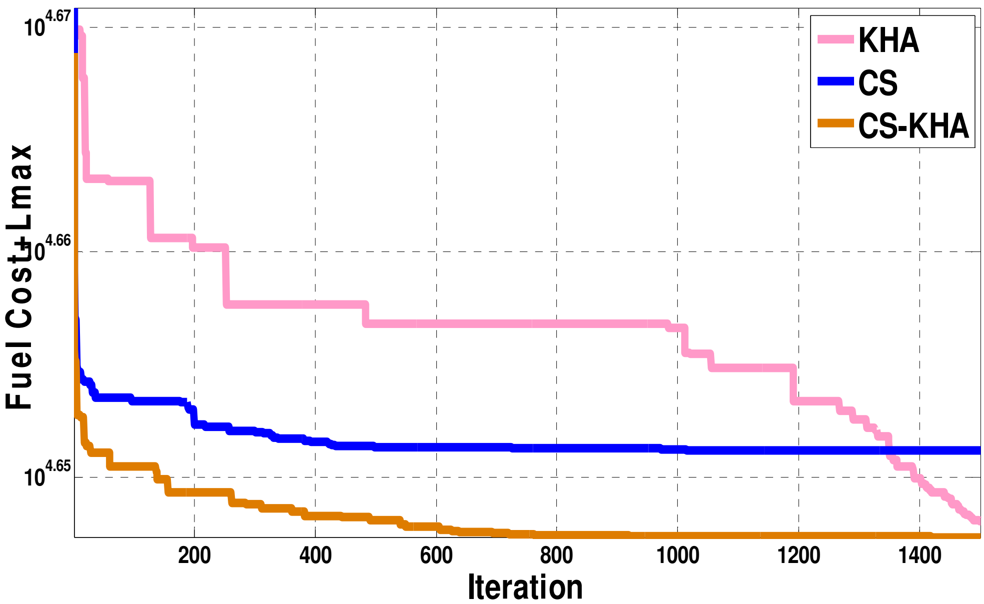

Fig. 2. Convergence curves of Case 3.

CASE 4: Fuel cost's minimization and emission

Electrical power that is generated from traditional energy sources releases dangerous gases for the environnement. The nitrogen oxides (Nox) and sulfur oxides (Sox)'s amount and emission in (ton/h) are higher than the augmented in generated power next the relationship presented in Eq. (33) as:

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

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:

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

The weight factors are chosen as 100 in this case.

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.

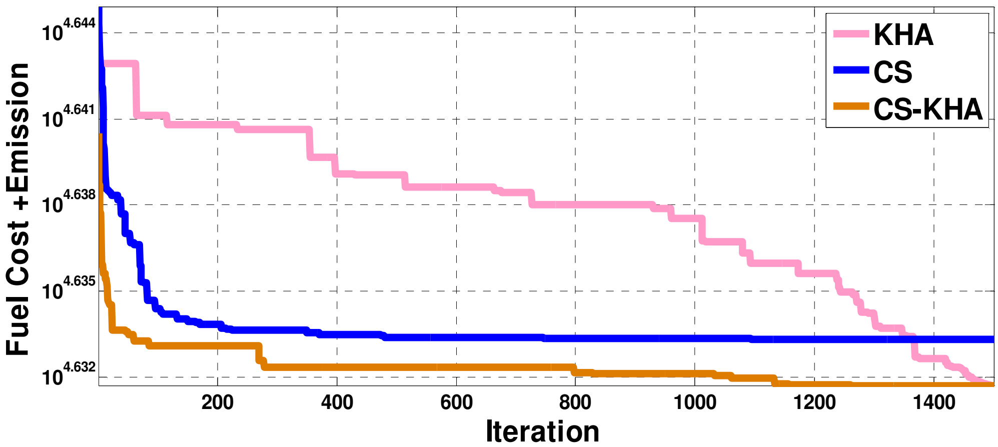

Fig. 3. Convergence rates of Case 4.

4.2. IEEE 118 Bus system results

CASE 5: 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 of the tested network are presented in [43]. The proposed CS-KHA is utilized to decrease fuel costs. The CS-KHA is implemented to get the optimal settings for this case and the gained results are presented in Table 5. 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 6.

5. Conclusion

In present study, a new meta hybrid heuristic CS-KHA has been developed to solve the OPF problem. By merging the merits KU/KA operator of CS technique with the KH technique. Hence, the KH is improved and the CS-KHA is evaluated numerically. A new variant of KH algorithm is proposed. The KU operator is dynamically adjusted in KU process. In the proposed hybrid CS-KHA, a greedy option was used, often surpassing the standard CS and KH. Moreover, so as to more ameliorate the CS-KHA'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 formulated as a constrained multi-objective optimization problem as 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 compared with several previous optimization methods.

Table 5: Simulation results for Case 5

variable	CS-KHA	KHA	CS	Variable	CS-KHA	KHA	CS	Variable	CS-KHA	KHA	CS
P_{G1} (MW)	366.91	385.482	368.047	P_{G103}(MW)	42.2950	42.1514	42.273	V_{G80}	1.0578	1.0871	1.0748
P_{G4} (MW)	30.00	30.0000	40.4392	P_{G104}(MW)	30.8340	31.1019	30.195	V_{G85}	1.0698	1.0849	1.0867
P_{G6} (MW)	30.8504	30.0000	30.0056	P_{G105}(MW)	30.1658	30.0082	30.029	V_{G87}	1.0883	1.0856	1.0802
P_{G8} (MW)	30.0000	36.5892	30.5938	P_{G107}(MW)	30.7389	30.1938	30.718	V_{G89}	1.0766	1.1000	1.0966
P_{G10}(MW)	32.1926	30.0951	30.6092	P_{G110}(MW)	32.0056	30.6153	30.407	V_{G90}	1.0543	1.0908	1.0790
P_{G12}(MW)	322.0172	337.707	298.790	P_{G111}(MW)	40.8006	40.8581	40.801	V_{G91}	1.0621	1.0926	1.0810
P_{G15}(MW)	66.9864	67.3679	73.6602	P_{G112}(MW)	30.6941	30.1776	35.311	V_{G92}	1.0568	1.0932	1.0839
P_{G18}(MW)	34.9502	31.6466	34.1581	P_{G113}(MW)	30.5556	30.1612	43.212	V_{G99}	1.0515	1.0699	1.0605
P_{G19}(MW)	30.0126	30.1197	34.9399	P_{G116}(MW)	31.5470	30.1511	30.672	V_{G100}	1.0395	1.0786	1.0654
P_{G24}(MW)	31.2758	40.0241	32.0601	V_{G1}	1.0322	1.0169	1.0043	V_{G103}	1.0212	1.0726	1.0593
P_{G25}(MW)	30.0890	30.3142	30.7494	V_{G4}	1.0515	1.0342	1.0224	V_{G104}	1.0060	1.0641	1.0498
P_{G26}(MW)	152.1116	160.508	124.947	V_{G6}	1.0349	1.0323	1.0137	V_{G105}	1.0123	1.0751	1.0472
P_{G27}(MW)	210.4531	212.124	213.966	V_{G8}	1.0742	1.0906	1.0714	V_{G107}	0.9973	1.0717	1.0433
P_{G31}(MW)	30.0107	30.0000	32.9586	V_{G10}	1.0786	1.0965	1.0833	V_{G110}	0.9894	1.0791	1.0417
P_{G32}(MW)	32.1135	32.1022	32.1000	V_{G12}	1.0353	1.0238	1.0114	V_{G111}	0.9980	1.0890	1.0528
P_{G34}(MW)	30.1433	30.0000	30.0574	V_{G15}	1.0383	1.0268	1.0176	V_{G112}	0.9775	1.0721	1.0298
P_{G36}(MW)	30.9994	32.3755	37.3000	V_{G18}	1.0476	1.0328	1.0167	V_{G113}	1.0584	1.0584	1.0260
P_{G40}(MW)	37.2945	31.1420	39.2771	V_{G19}	1.0464	1.0356	1.0192	V_{G116}	1.0928	1.1000	1.0466
P_{G42}(MW)	32.7803	40.1303	32.0453	V_{G24}	1.0571	1.0634	1.0366	Qc_5 (Mvar)	1.0968	0.1341	0.4603
P_{G46}(MW)	30.5901	30.0504	61.3421	V_{G25}	1.0939	1.0568	1.0337	Qc_{34}(Mvar)	0.0395	0.0656	7.8806
P_{G49}(MW)	35.7090	35.7110	35.7293	V_{G26}	1.0835	1.0689	1.0860	Qc_{37}(Mvar)	1.7660	7.3596	2.7258
P_{G54}(MW)	150.1344	159.391	147.976	V_{G27}	1.0684	1.0325	1.0148	Qc_{44}(Mvar)	10.4951	0.3568	0.0083
P_{G55}(MW)	45.0829	45.1069	46.4248	V_{G31}	1.0559	1.0328	1.0147	Qc_{45}(Mvar)	0.0001	2.6926	1.0940
P_{G56}(MW)	30.2316	30.1951	30.0706	V_{G32}	1.0628	1.0410	1.0174	Qc_{46}(Mvar)	6.3599	0.6672	17.7909
P_{G59}(MW)	41.1021	34.2682	31.4284	V_{G34}	1.0699	1.0429	1.0476	Qc_{48}(Mvar)	0.3103	0.6422	0.3959
P_{G61}(MW)	128.9333	126.361	116.717	V_{G36}	1.0709	1.0615	1.0452	Qc_{74}(Mvar)	0.5937	0.0949	12.9769
P_{G62}(MW)	119.4878	104.446	108.513	V_{G40}	1.0584	1.0335	1.0348	Qc_{79}(Mvar)	0.4359	1.0046	1.7815
P_{G65}(MW)	30.0414	30.6740	33.8130	V_{G42}	1.0728	1.0407	1.0430	Qc_{82}(Mvar)	2.6580	0	2.5440
P_{G66}(MW)	274.4206	296.676	274.683	V_{G46}	1.0779	1.0699	1.0825	Qc_{83}(Mvar)	2.7523	0	2.0127
P_{G69}(MW)	290.2244	273.838	285.378	V_{G49}	1.0838	1.0856	1.0880	Qc_{105}(Mvar)	1.1846	2.5892	10.9604
P_{G70}(MW)	33.8793	31.0321	30.0310	V_{G54}	1.0743	1.0686	1.0785	Qc_{107}(Mvar)	4.1717	0.0284	4.9321
P_{G72}(MW)	30.0000	30.0000	30.5010	V_{G55}	1.0661	1.0609	1.0791	Qc_{110}(Mvar)	4.0167	0.5725	0.0614
P_{G73}(MW)	35.0183	30.0011	34.5178	V_{G56}	1.0747	1.0669	1.0783	$T_{(8–5)}$	1.0269	1.0527	1.0180
P_{G74}(MW)	30.0000	34.6584	30.0089	V_{G59}	1.0929	1.0880	1.0949	$T_{(26–25)}$	1.0551	0.9293	1.0770
P_{G76}(MW)	31.1843	30.0000	30.0515	V_{G61}	1.0857	1.0959	1.0989	$T_{(30–17)}$	0.9923	1.0165	1.0267
P_{G77}(MW)	30.8112	30.0330	35.3680	V_{G62}	1.0857	1.0980	1.0949	$T_{(38–37)}$	0.9561	0.9903	0.9672
P_{G80}(MW)	353.3451	328.05	339.009	V_{G65}	1.0886	1.0891	1.0524	$T_{(63–59)}$	0.9402	0.9071	0.9072
P_{G85}(MW)	30.4117	34.3764	30.0251	V_{G66}	1.0981	1.1000	1.0983	$T_{(64–61)}$	1.0339	0.9722	0.9434
P_{G87}(MW)	31.2043	31.2010	31.2000	V_{G69}	1.0819	1.0947	1.0921	$T_{(65–66)}$	1.0317	1.0952	1.0250
P_{G89}(MW)	373.0515	343.375	383.030	V_{G70}	1.0760	1.0680	1.0753	$T_{(68–69)}$	1.0046	1.0947	0.9504
P_{G90}(MW)	30.0217	30.0053	30.0816	V_{G72}	1.0847	1.0782	1.0618	$T_{(81–80)}$	1.0284	0.9213	0.9667
P_{G91}(MW)	30.1360	31.2499	33.4771	V_{G73}	1.0807	1.0823	1.0806				
P_{G92}(MW)	30.0000	31.6228	30.0239	V_{G74}	1.0614	1.0721	1.0635	**Ploss(MW)**	**56.4548**	**58.1287**	**53.3527**
P_{G99}(MW)	31.5839	30.1290	32.1729	V_{G76}	1.0481	1.0534	1.0537	**Fuel cost ($/h)**	**135260.45**	**135400.78**	**135610.32**
P_{G100}(MW)	161.0126	174.520	163.448	V_{G77}	1.0530	1.0533	1.0694				

Table 6: Assessing CS-KHA compared with previous methods for Case 5.

Algorithm	Fuel cost($/h)	Algorithm	Fuel cost($/h)	Algorithm	Fuel cost($/h)
CS-KHA	**135260.45**	BBO [37]	135263.7289	ICBO [32]	135121.570
KHA	**135400.78**	BSA [37]	135333.4743	DE[32]	142751.1178
CS	**135610.321**	ABC [37]	135304.3584	BBO[32]	135272.1959

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