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A comparison of Improved Nature-Inspired Algorithms for Optimal Power System Operation

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Abstract: The influencing factors associated with the efficient operation of power systems are minimum fuel cost and losses in the transmission line. Optimal Power Dispatch (OPD) problem is treated to minimize instantaneous operating cost, incremental cost, and transmission line losses considering various network operating constraint. Newly developed Nature-inspired optimization algorithms approach are proposed in this analysis with robust parameter selections. The results of most popular Genetic Algorithm (GA) and based on swarm behavior Particle Swarm Optimization (PSO) are compared with four Nature-inspired metaheuristic algorithms of Cuckoo Search (CS), Bat Algorithm (BA), Flower Pollination Algorithm (FPA), and Firefly Algorithm (FA). The quadratic cost function of power generation and penalty function to account for inequality constraints on dependent variables are added for solving OPD problem. A common algorithms evaluation parameters such as population size and generation limit are designated on an equal scale. Explicit parameters for each algorithm are tuned properly for optimal operations. The algorithms are tested on IEEE-26 and IEEE-30 system. Analysis Outcomes obtained showcase the efficiency of each algorithms parametric turning improvement.

Keywords: fuel cost; nature-inspired optimization, optimal power dispatch, parametric turning,

1. INTRODUCTION

Scheduling and operational future growths of power system networks and defining the best scenario of existing systems is the essential backbone of fully deregulated power sector as commodity enterprises. Optimal power dispatch (OPD) problem is dealing with the lowest cost of fuel and loss delivery of power produced by organizing the production cost at all power plant working on the system (Saadat, 1999). It's an optimization problem with aims to reduce total operational cost, and transmission losses, but the minimum loss problem, the economic dispatch problems are solved by optimal power flow (OPF) program. The OPD with minimum generation cost requires that the optimization algorithm calculation balance the entire power flow at the same time combining with economic dispatch problem (Wood and Wallenberg, 1996). The main purpose of optimal power dispatch is to identify the optimal set of control variables for minimization of the given objective function in our case fuel cost, incremental fuel cost and line losses while satisfying a series of system constraints over the entire dispatching period. Control variables contain discrete variables and continue variables, besides that power network composed equality constraints and inequality constraints. Therefore when regarded as an optimization problem, optimal power dispatch is complex nonlinear optimization problem that requires algorithms with the capability of exploration and exploitation for searching in global search space for optimal results. With these in mind, it's significant to explore and compare optimization algorithms for academia and industrial.

From another point of view is improving economy and security of power system are achieved by minimizing the total active power transmission losses and operate with minimum cost. Numerous classical practices such as gradient search technique, non-linear programming, mix-integer linear programming, Newton's approach, Jacobian matrix and interior point, are applied to find optimal result of non-linear OPD problems (Deeb and Shahidehpour, 1988; Grudinin, 1998; Granville, 1994; Lee et al., 1984; Narayan, 1999). Quadratic programming previously played important role in OPD approach (Nanda, 1989). Some of the previous problems are solved by a mathematical technique that takes the advantage of network run structure of the problem (Carvalho et al., 1998). Artificial intelligence approach such as an artificial neural network (ANN), chaotic krill herd algorithm (CKHA), and Fuzzy logic (FL) play a vital role in OPD problem solution with different objective function and constraints (Gutierrez-Martinez et al., 2011; Mukherjee, 2016; Ramesh, 1997). Currently, heuristic and metaheuristic based on swam, evolutionary, and nature-inspired algorithms take the center stage of OPD solutions with robustness in the optimal solution. Particle swarm optimization (POS) and hybrid PSO (Ahmet et al., 2016; AlRashidi and El-Hawary, 2009; Esmin et al., 2005; Yoshida et al., 2000), an improved particle swarm optimization algorithm using eagle strategy for optimal power dispatch is presented in (Hamza and Çetinkaya, 2017), while binary PSO is used in distribution grid network reconfiguration for loss minimization and voltage profile improvement in (Abdullahi et al., 2016). Genetic algorithms (GA), modified GA, and Adaptive GA (Devaraj, 2007; Wu et al., 1998), Cuckoo Search (CS), and Modified CS (Chetan, 2015; Nguyen, 2016; Thang, 2016), Cuckoo Search also play vital role in multi-machine power system stabilization analysis apart from OPD problem (Rangasamy, 2014). Bat Algorithm (BA) and modified BA (Biswal et al., 2013; Latif et al., 2016), Flower Pollination algorithm (FPA) and modified FPA (Kumar, 20015; Regalado, 2015), hybridization of FPA and feedforward neural network proved to be efficient in forecasting load flow in smart grid environment for security assessment (Shehu and Çetinkaya, 2018). Firefly Algorithm (FA) (Herbadji et al., 2013; Hendrawati et al., 2015; Lin et al., 2015) have been employed in solving OPD and related power system problem with satisfactory results. The economics aspect of a power dispatch optimization problem with nature-inspired algorithms are treated in (Mimoun, 2013) the idea is based on hybrid FFA and Ant Colony Optimization for a practical strategy for faster convergence, the finding proved the ability of FFA of solution search.

A Multi-objective Adaptive clonal selection (ACS) an artificial intelligence based algorithm for solving OPD with load uncertainty to minimized fuel cost, loss, and L-index are presented in (Srinivasa, 2016), non-dominated sorting procedure has been applied to preserved distributed Pareto optimal set, the procedure is verified on IEEE-30 bus system, the results are compared with related literature and found multi-objective ACS is fit to the problem solutions. In (Ahmet et al., 2016), fuel cost is reflected as a cost function four heuristic algorithms i.e. PSO, GA, ABC, and DE are employed. Valve point effect and a penalty function are added to control active power generated violations for effective fuel cost results. Finally, the authors concluded that GA possesses fast iteration speed, with minimum fuel cost for DE. CS based solution to OPD is presented in (Nguyen, 2016), the objective is to abate total fuel cost, CS is improved to combines teaching-learning based optimization to enhance the presentation of Cuckoo eggs, the technique was tested on IEEE-30 and IEEE-57 bus system. BA is proposed In (Biswal, 2013) to solve OPD problems combined cost function dispatch in 3 unit and 6 unit system, the results are matched with PSO, BA proved to have superior computational time. Regalado *et al.* (2015) presented FPA and compared with CS to solve OPD problem on IEEE-30 bus system, authors conclude FPA achieved best fuel cost and time to reach a global best result.

(Herbadji et al., 2013) applied FFA on IEEE-30 bus system, the author considers fuel cost and emission as the cost function to be minimized, the author compared the results of FA with PSO and GA are found to be in synchronization.

In this approach, multi-objective functions of fuel cost, the incremental fuel cost of each generator, and total real power loss are minimized using improved nature-inspired based optimization algorithms considering various network operating constraint, in an improved parameter setting. Penalty factor is added to account for line flow limit, bus voltages, and active generator real power violation. The objectives of this paper are to compare and investigate, test and measure the effectiveness, efficiency, and robustness of mainstream nature-inspired metaheuristic based algorithms in term of OPD best solutions, systematic convergence on power systems limits and applications, reducing operational cost and system security. The base case employed PSO and GA which are well matured and developed in power system applications especially in convergence and best solution, with newly developing CS, BA, FPA, and FA to identify robustness, and feebleness on IEEE-26 and IEEE-30 bus network. The paper is structured in five sections, section one introduction of the problems and general introduction, section two present problems formulation, while in section three summary overview of nature-inspired algorithms are reviewed, in section four test system and results are discussed, the final conclusion is presented in section five. The simulation analysis was carried out in Matlab environment.

2. PROBLEM FORMULATION

OPD is formulated to reduce fuel cost to the minimum, incremental cost and generated power loss is an optimizations problems with multi-objective function. Generally, the objective functions are express as:

$$Min.\ F = f_1 + f_2 + f_3 \tag{1}$$

Where f_1 is fuel cost function

f_2 is incremental fuel cost function

f_3 is power loss function

2.1 Fuel cost minimization

Total fuel cost function employed a quadratic convex curve function, minimum fuel cost guarantee how efficiently the power plant generators are operated.

$$f_1 = \sum_{i=1}^{ng} \gamma_i P_{gi}^2 + \beta_i\, P_{gi} + K_{pen} \tag{2}$$

Where $\gamma_i, \beta_i, \alpha_i$ are cost coefficients for generators fuel. Penalty factor K_{pen} are calculated depending if there exist possible equality or inequality constraints violation, the amount are added to fuel cost coefficient. The penalty function can transform a constrained problem into an unconstrained one. The solution which violates a constraint are punished and are regarded as infeasible solutions, thereby protecting algorithms feasible solution during the selection process, as a result, no much time is spent by the optimization algorithm looking for optimal solutions and improve the efficiency of optimization. In a situation where all the constraints are not violated the penalty factor is zero.

$$K_{pen} = \begin{cases} LF_i(P_i - P_i^+)^2\ ,\ if\ P_i > P_i^+ \\ LF_i(P_i - P_i^-)^2\ ,\ if\ P_i < P_i^- \\ \quad or \\ V_i(V_i - V_i^+)^2\ ,\ if\ V_i < V_i^+ \\ V_i(V_i - V_i^-)^2\ ,\ if\ V_i < V_i^- \\ \quad 0\ ,\ otherwise \end{cases} \tag{3}$$

2.2 Incremental fuel cost minimization

A functions parameter measuring how expensive the next generated power demand will be after generator requested supply.

$$f_2 = 2\gamma_i P_{gi} + \beta_i + K_{pen} \tag{4}$$

2.3 Active power loss

Minimum transmission losses secure and guarantee minimum cost to efficiently operate power system, the distance at which generators are located in the load center determine how much losses are inherent in the system network.

$$f_3 = \{\sum_{k=1}^{nl} g_k(V_i^2 + V_j^2 - 2V_iV_j \cos\theta_{ij})\} \quad (5)$$

2.4 Equality and Inequality constraints

Operating constraints allow the optimization to guarantee the optimal component dispatch of generation is within the allowable limit, in reality forcing the transmission system into limit violation may put the system in danger. The equality constraints are given in (6).

$$P_{gi} - P_{di} - \Re[V_i(\sum_{j=1}^{ng} Y_{ij} V_j)^*] = 0 \quad (6)$$

$$Q_{gi} - Q_{di} - \Im[V_i(\sum_{j=1}^{ng} Y_{ij} V_j)^*] = 0 \quad (7)$$

The inequality constraint of line flow of transmission line is given in (8), is the transmission capacity between bus *i* and *j*

$$LF_{ij} = \Re\{V_i[(V_i - V_j)Y_{ij} + V_{ij}^2 y_{cij}]^*\} \leq LF_{ij}^+ \quad (8)$$

The second inequality constraints associated with generators bus voltages, real and reactive power limit, shunt VAR reactive power injection, regulating transformer tap setting between lower and upper boundaries are given in (9).

$$\begin{cases} V_i^- \leq V_i \leq V_i^+ \\ P_{gi}^- \leq P_{gi} \leq P_{gi}^+ \\ Q_{gi}^- \leq Q_{gi} \leq Q_{gi}^+ \\ Q_{ci}^- \leq Q_{ci} \leq Q_{ci}^+ \\ T_i^- \leq T_i \leq T_i^+ \end{cases} \quad (9)$$

The above constraints constitute the security of the optimal dispatch operation, the nonlinearity of the constraints in optimizations necessitate applying penalty factor in the objective function, to account the violation which is also a cost.

3. NATURE-INSPIRED METAHEURISTICS OPTIMIZATION ALGORITHMS

The year 1960s and 1970s are two key periods covering the growth of evolutionary algorithms, John Holland and his associates at the University of Michigan conceptualized GA. He later considered the adaptive system which is first to applied crossover and recombination operations for demonstrating systems that lead to the development of GA (Melanie, 1995). Within year intervals, Kenneth De Jong write thesis showing the perspective and supremacy of GA for objective functions with noisy, multimodal, or even discontinuous (Holland, 1975; De Jong, 1975). Majority of classical algorithms are deterministic, in case of stochastic algorithms most types are heuristic and metaheuristic, with small differences heuristics mean finding solution by guessing of many trials, on the other hand, metaheuristic algorithms means finding advanced level solutions beyond good solutions, and these algorithms usually execute well than simple heuristics (Yang, 2014). In practice metaheuristic algorithms custom certain trade-offs of randomization and local search, Randomization offers worthy chance of algorithms deviation at local optimum trap to search on a global level (Yang, 2010). Intensification and diversification, are two key constituents of all metaheuristic optimizations programs. Diversification is to produce different output so that search space is explored on a global optimum. Intensification allowed exploiting search focus in the region of local space that a good solution is within reach (Yang and Deb, 2010). This two major component guarantee emergence of the best solutions, whereas diversification through randomization evades the best fitness confined to the local region, and this increases the diversity of solutions. Metaheuristic algorithms can be categorized as based on population and trajectory-based. In the case, of GA which is population-based since the certain set of strings are utilized; while PSO, the firefly algorithm (FFA), and cuckoo search (CS), which all use multiple agents or particles (Yang and Deb, 2009; Yang and Gandomi 2012). Some selected list of Nature-Inspired metaheuristic optimization Algorithms; PSO, GA, CS, BA, FPA, FFA, are applied on IEEE-26 and IEEE-30 bus power system, are briefly reviewed.

3.1 Particle swarm optimization PSO

PSO is first presented by Kennedy and Eberhart in 1995 (Kennedy and Eberhart, 1995), motivated by social behavior of birds flocking and fish schooling. The algorithm was established numerous analysis and simulation of many simplified works, and establish to be vigorously efficient for solving nonlinear continuous problems, and PSO is attractive because very few parameters are entailed for its applicability (Shi and Eberhart, 1999). The swarm intelligence based algorithms exploit inhabitants of particles that sail through hyperspace problem, iteration velocity of each particle are randomly adjusted best on neighborhood historical best solutions (Eberhart and Kennedy, 1995). The details overview and comprehensive survey on the power system application of PSO are presented in (Yamille et al., 2008), the paper present technical requirement such as type, particles formulation, and efficient fitness functions.

3.2 Genetic Algorithm GA

The famous and popular evolutionary algorithms are based on the mechanism of Darwin principle of evolution, natural assortment and regular genetics, (Melanie, 1995). An inhabitant's based algorithms of which search process is performed by transforming a set of individual point to another in the search space. The three genetic operator of GA is `crossover, mutation, and selection` (Yang, 2010). GA is applied in an extensive range of engineering applications with ability deal with complex problems in any directions, domain. For GA to avoid being a trap in local optima, good formulation of the fitness function and care full selection of importance parameter are necessary.

3.3 Cuckoo Search CS

The emerging CS algorithm is an optimization search algorithms formulated and developed by (Yang and Deb, 2009), their approach mimic brooding parasitic character of cuckoo species in a mixture with Levy flight of some bird and fruit flies behavior (Yang and Deb, 2009). Fittest selection and adaptation to the environment allowed the CS algorithm converge to the best optimal values. Yang and Deb described CS in three simple ways: each cuckoo lays a single egg at once randomly in a chosen nest; in a random selected best nest generation's process will continue; with the secure amount of available host nest, intruding egg can discover by the host with probability $p_a \in [0, 1]$. With following assumption nest owner usually identify the egg, there after destroy the egg or abandon the nest (Yang and Deb, 2010). CS algorithm always maintained stable distance between local and global search by p_a. Local search can be express mathematically.

$$x_i^{t+1} = x_i^t + \alpha s \otimes (p_a - \rho) \otimes (x_j^t - x_k^t) \tag{10}$$

Where $x_j^t$and x_k^t are different solutions from random the arrangement, ρ is a random number, s is a step size, and $\otimes$ is an entry wise vector product. While global search using levy walk are represented by.

$$x_i^{t+1} = x_i^t + \alpha L(s, \lambda) \tag{11}$$

And that of levy walk are given in (12)

$$L(s, \lambda) = \frac{\lambda F(\lambda) \sin\frac{\pi\lambda}{2}}{\pi} \frac{1}{s^{1+\lambda}}, \ s \gg s_0 > 0 \tag{12}$$

This algorithm can easily be fit into a power system with the fixed generator at random bus, with probability the best power be generated with minimum fuel cost and transmission losses.

3.4 Bat Algorithms BA

A nature-inspired metaheuristic BA was developed by Yang in 2010 basically on echolocation manners of bats, the echolocation fitness allowed the bat to easily prey, distinguished diverse insect and, obstructions in total darkness (Yang, 2010). For simplicity as proposed by (Yang, 2010) three idealized rule define BA are followed (Yang and Gandomi, 2012; Yang, 2010; Yang, X.S. 2011):

- Echolocation: detect and differentiate food and obstructions.
- Bats are fly with random velocity at a secure frequency with different wavelength and loudness to hunt for food.
- Bat loudness is varied in many ways from maximum to minimum.

Based on rule above virtual movement of bat are express in terms of position $y_i$and their velocity s_i with new the solution given by t time step.

$$f_i = f_m + (f_{max} - f_{min})\beta \tag{13}$$

$$s_i^{t+1} = s_i^t + (y_i^t - \boldsymbol{y}_*)f_i \tag{14}$$

$$y_i^{t+1} = y_i^t + s_i^{t+1} \tag{15}$$

Such that $\beta \in [0, 1]$ is selected from ca onstant distribution with stochastic vector properties. Here $\boldsymbol{y}_*$ is a global optimal best solution, *n* bats. With echolocation and related characters allowed BA algorithm to perfectly works in multi-objective optimization, especially in power system where darkness represent transmission distance with bat using echolocation to prey generator power delivery.

3.5 Flower Pollination Algorithm FPA

Another recent emerging nature-inspired based optimization algorithm is FPA developed by Yang in 2012, enthused by pollination process of flower, which is the transfer of pollen that is linked to natural bio habitant (Yang, 2012). Two important characters of flower pollination are abiotic and biotic, with 90 % biotic pollination and the rest abiotic require no pollinators. For FPA to solve multi-objective optimization problem such as power system dispatch a random weighted sum is added to combine a number of objectives so to become composite sole objective (Yang et al., 2013). The FPA algorithm can express in four rules for updating equations mathematically; *Rule 1* global pollination and (*Rule 3)* flower constancy is express in equation (18)

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)(g_* - x_i^t) \tag{16}$$

Where x_i^t is i solution vector x_i at iteration t, and g_* is the present best solution, γ is a scaling factor of step size control, $L(\lambda)$ is a step-size parameter. *Rule 2* and *Rule 3* both are local fertilization are express in (17).

$$x_i^{t+1} = x_i^t + \epsilon\ (x_j^t - x_k^t) \tag{17}$$

Where $x_j^t$and x_k^t are pollen from diverse flowers with similar plant species. If $x_j^t$and x_k^t are from exact species and population this become local search with $\epsilon = [0, 1]$ uniformly drawn.

Rule 4 is switching probability control between local and global pollination of value $p \in [0, 1]$.

3.6 Firefly Algorithm FA

Established by Yang in late 2007 then appeared in 2008, FA is efficient and intelligent swam centered on flashing sequence (Yang, 2010). The bioluminescence process emit flashing light, for now the exact functions of such signaling is under investigation, common knowledge of flashes application is in breeding partners attraction or food prey, it also works as guiding tool against fireflies predators, this implies optimization of FA depend on unique flashes of light (Lewis and Cratsley, 2008; Yang, 2009). In simple term FA flows three ideal rules:

- Fireflies behave in a unisex manner to attract one another.
- The direct relationship between attractiveness and brightness exist.
- The firefly brightness depends upon objective functions landscape.

The intensity I of fireflies possess a direct relationship to brightness and to the attractiveness. For best optimization to the simple scenario, firefly brightness I at a specific and precise position x is represented as $I(x) \propto (x)$, the attractiveness β vary with distance r_{ij} between firefly i and firefly j. according to inverse square law $I(r)$ varies so that becomes.

$$I(r) = \frac{I_s}{r^2} \tag{18}$$

I_s is the light source intensity, for a channel having static light absorption coefficient γ, the light intensity I diverge with the distance r. that is

$$I(r) = I_0 e^{-\gamma r}, \tag{19}$$

So I_0 is the unique light concentration at zero r to avoid the singularity at the xpression $\frac{I_s}{r^2}$, the combine effect can be approximated in (20).

$$I(r) = I_0 e^{-\gamma r^2} \tag{20}$$

Attractiveness β is directly proportional to adjacent firefly is define in equation ()

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{21}$$

The remoteness of two fireflies i and j at $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ is the rectangular space in (22), k is the k_{th} component of the three-dimensional coordinate $\boldsymbol{xi}$ of ith firefly.

$$r_{ij} = |x_i - x_j| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{22}$$

For two dimension space

$$r_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{23}$$

The drive of firefly i attracting brighter j is determined by

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2} (x_j^t - x_i^t) + \alpha \left(rand - \frac{1}{2}\right) \tag{24}$$

Where $rand$ is randomisation generator, α randomization control parameter, x_i^t is the previous value. In summary, the intensity of firefly is directly related to their brightness and to attractiveness, relative to power system the attractiveness is how the network operate efficiently at minimum fuel cost with low level losses

4. TEST SYSTEMS AND RESULTS

In this approach robustness, efficiency and feebleness of new emerging Nature-Inspired based optimization algorithm of CS, BA, FPA, and FA are compared against well-developed PSO and GA for OPD problems investigation. In our proposed approach IEEE-26 and IEEE-30 bus system are verified on, penalty function is included in case of limit violation. In the optimization procedure initials independent variable is assigned randomly to perform power flow using Newton–Raphson, and then set depended on variable automatically. The optimal solution is achieved using respective algorithm setting parameters, the procedure is shown in Fig. 1. The algorithms first initialized with random values and power flow solution is applied to those values. The constraints condition are check if a violation exists penalty function is applied. Otherwise, new random values are generated with different values. Without any violation, fuel cost and incremental fuel cost are calculated with the minimum loss for the next step. The best fitness candidate is selected, optimization algorithm operators are applied to obtained global best value for each one of the algorithms, the procedure is repeated until the maximum iteration or convergence of the algorithm is reached. Optimization common parameters controls are generation number and population size, other parameters explicitly stated, these parameter sets are obtained after several runs of course due to randomization a better result becomes worst result in some run. Population size = 60, Generation six =200,

PSO: Inertia weight = [0.4, 0.9], Acceleration factor = [2, 2].

GA: Roulette function, with scatted crossover, mutation function is a constraint, crossover fraction is positive scalar (0.8).

CS: probability of discovering nest $p_a = 0.25$ step-size scaling factor α= 0.01, Lévy exponent λ = 1.5.

BA: Loudness A= 0.9, pulse emission rate r = 0.8.

FFA: probability switch p = 0.8.

FA: absorption coefficient of light γ = 1, attractiveness β= 0.8, randomization α = 0.9.

The optimal power dispatch result for 26 bus data are presented in Table 1, and for 30 bus data are presented in Table 2. To avoid premature result interpretation, several simulations run are carrying out with fixed tuned parameters. In both cases, the total fuel cost shows a direct relationship with the total minimum loss and incremental fuel cost obtained for all the algorithms for GA in Table 1. Fuel cost (15118 \$/h), incremental fuel cost (30.186 \$/h), total losses (12.161 MW) are relatively higher than PSO, CS, BA, FPA, and FA even though GA has a minimum simulation time to approach convergence. Fig. 2 depict IEEE-26 bus fuel cost convergence curve of both the algorithms, in this scenario BA picks optimal convergence value initially (15116.966 \$/h) then the rest algorithms.

Table 2. Shows BA algorithm returning higher optimal operation fuel cost of (801.971 \$/h), incremental fuel cost (9. 861 \$/h), and total losses (9.479 MW), then PSO, GA, CS, FPA, and FA algorithms but superseded by CS algorithm intern of maximum simulation time. Fig. 3 depicted IEEE-30 bus fuel cost convergence curve, GA algorithm converge at 51 iterations and stop with optimum values of (801.844 \$/h) while the others algorithm continues to iterate to the maximum selected iteration of 200, that is why the simulation time of GA is minimum in both cases. The result from both tables there is no best algorithm with minimum real and reactive power combination, BA has the minimum slack real power of 439.565 MW, follows by GA 440.315 MW, CS 441.387 MW, and FA 441.403 MW for the case of IEEE-26. PSO, CS, and FA have minimum slack reactive power. For IEEE-30 case fluctuated combination of real and reactive power combination are observed, with BA possessing highest. The voltages profile shows in Fig. 4 for 26 bus system, and Figure 5 for 30 bus system are in tandem with voltage security of constraint for both the algorithm without violation. The figures guarantee voltage stability of our approach. The voltage range observed for 26 bus range is 0.9690 pu minimum and a maximum of 1.0250 pu. For the case of 30 bus system bus voltages stable at optimal values of 0.9957 pu to 1.0820 pu.

```
Proposed Algorithm :
Optimal_Power_Dispatch (Max_Iterations, Max_Solutions)
  Parameters List:
    Num_Iteration: generation counter;          Num_Solution: solution counter;
    Best_solution: value for best solution;     Min_Fitneess: fitness for best solution
    SOLUTIONS array that holds current generation of solutions
    Generate_Solutions():Sub-function that generate new solutions depending
                         on the optimization algorithm
    Newton_Raphson(): Sub-function that performs power flow analysis using N-R
    Violations():Sub-function that checks the constraint violations
    Optimization_Operators():Sub-function that breeds the new solutions
01  INITIALISE Num_Iteration =1; Num_Solution =1;
02  SET SOLUTIONS =Generate_Solutions();
03  LOOP WHILE Num_Iteration <= Max_Iterations
04      SET Num_Iteration= Num_Iteration+1
05      LOOP WHILE Num_Solution <= Max_Solutions
06              SET Solution= SOLUTIONS[Num_Solution]
07              RUN Newton_Raphson()
08              IF Violation()
09                      IF IS Generator_Violations
10                              Apply_Panalty()
11                              GOTO Line 15
12                      END IF
13                      GOTO Line 04
14              END IF
15              SET Fitness = objective function()
16              IF Fitness  < Min_Fitneess;
17                      SET  Min_Fitneess= Fitness
18                      Best_solution= Solution
19              END IF
20              SET Num_Solution = Num_Solution +1
21      END LOOP
22      SET SOLUTIONS =Generate_Solutions();
23      RUN  Optimization_Operators();
24  RETURN Best_solution
25  END LOOP
```

Fig. 1. Proposed pseudocode algorithms.

Table 1. IEEE-26 bus system optimized comparison results.

26 bus	PSO	GA	CS	BA	FPA	FA
P_{g1}	441.408	440.315	441.387	439.565	442.087	441.403
P_{g2}	177.229	175.325	177.267	178.159	175.289	177.248
P_{g3}	260.367	253.956	260.360	263.093	261.198	260.368
P_{g4}	134.419	131.843	134.435	129.241	135.680	134.437
P_{g5}	171.557	182.004	171.545	169.970	171.050	171.544
P_{g26}	90.130	91.718	90.099	95.015	89.819	90.111
FC ($/h)	15116.206	15118.000	15116.206	15116.799	15116.26	15116.206
IC ($/h)	30.167	30.186	30.167	30.177	30.167	30.167
TL (MW)	12.110	12.161	12.111	12.044	12.123	12.111
Time (s)	302.07	76.77	590.04	291.87	307.23	307.61

Table 2. IEEE-30 bus system optimized comparison results.

30 bus	PSO	GA	CS	BA	FPA	FA
P_{g1}	176.732	176.678	176.731	177.957	176.619	176.729
P_{g2}	48.828	48.836	48.828	48.466	49.019	48.829
P_{g3}	21.470	21.463	21.473	21.001	21.333	21.472
P_{g8}	21.643	21.681	21.650	19.621	21.971	21.650
P_{g11}	12.101	12.096	12.091	13.106	11.834	12.094
P_{g13}	12.000	12.015	12.000	12.726	12.000	12.000
FC ($/h)	801.843	801.844	801.843	801.971	801.848	801.843

30 bus	PSO	GA	CS	BA	FPA	FA
IC (\$/h)	9.615	9.616	9.612	9. 861	9.618	9.625
TL (MW)	9.376	9.372	9.376	9.479	9.377	9.376
Time (s)	261.48	67.65	527.51	288.48	262.58	264.36

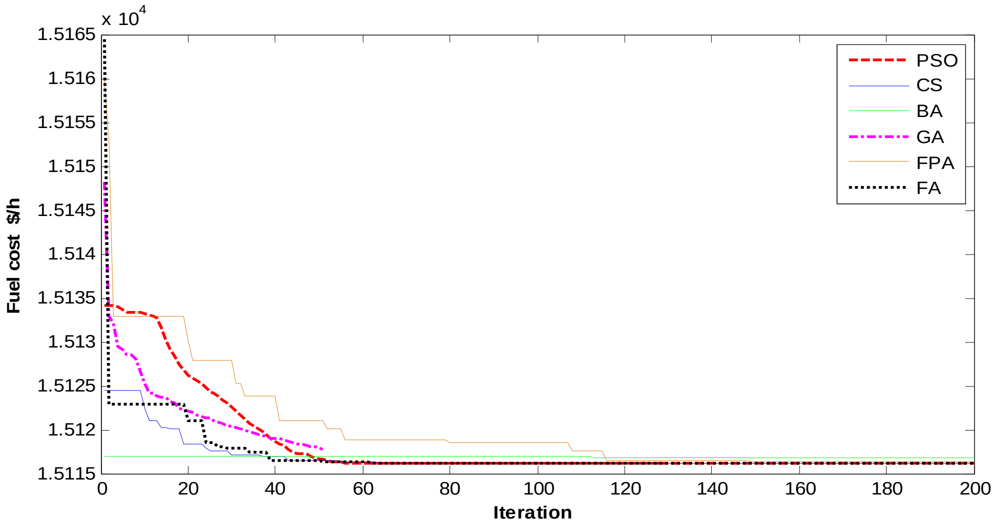

Fig. 2. Convergence curve of 26 bus fuel cost.

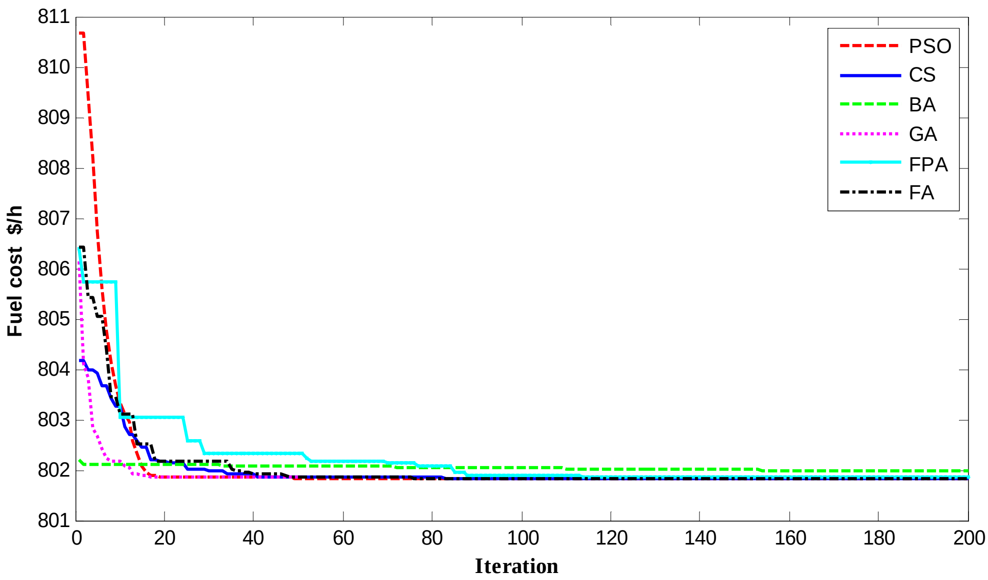

Fig. 3. Convergence curve of 30 bus fuel cost.

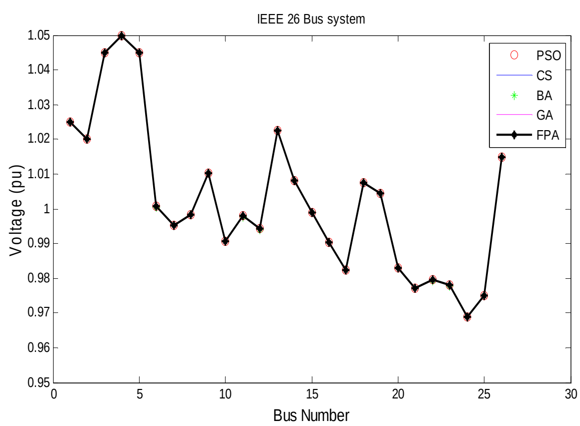

Fig. 4. Voltage profile IEEE-26 bus.

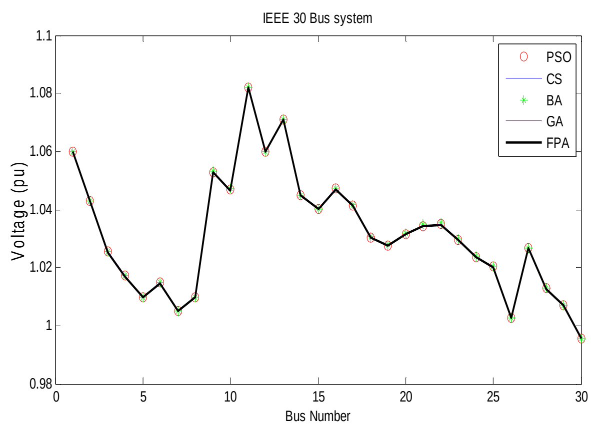

Fig. 5. Voltage profile IEEE-30 bus.

5. CONCLUSIONS

The paper investigates the ability to emerge nature-inspired based algorithm of CS, BA, FPA, and FA against well-developed metaheuristic swam intelligence PSO and evolutionary GA algorithms application for solving OPD problem. CS, BA, FPA, and FA compete favorably against PSO and GA even though with little or similar variation in objective function result. The result indicates GA has minimum iteration time due to earlier convergence, CS exhibit good result with maximum iteration time due to the utilization of Lévy process rather than random walk, while PSO, FPA, and FA maintain similar attribute of minimum cost, losses, and iteration. BA shows special attribute of earlier global convergence, this is due to key features of echolocation frequency turning, auto-zooming of solution region and couple with parameter control during iteration. The uniqueness of results among the algorithms shows a strong dedication to parametric turning capabilities. Finally, for the case of IEEE-26 bus system CS, BA, FPA, and FA perform well together with PSO in minimizing fuel cost, incremental fuel cost, and transmission losses, although GA converges first. For the case of IEEE-30 bus system, all the algorithms proved efficient in solving OPD problem with the almost similar result, but BA shows the slightly higher value of fuel cost.

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APPENDIX

Appendix A. IEEE-26 coefficient of generators unit

No	γ	β	α	P_{gi}^{-}	P_{gi}^{+}
1	0.007	7	240	100	500
2	0.0095	10	200	50	200
3	0.009	8.5	220	80	300
4	0.009	11	200	50	150
5	0.008	10.5	220	50	200
26	0.0075	12	190	50	120

Appendix B. IEEE-30 coefficient of generators unit

No	γ	β	α	P_{gi}^{-}	P_{gi}^{+}
1	0.02	2	0	50	200
2	0.0175	1.75	0	20	80
3	0.0625	1	0	15	50
8	0.00834	3.25	0	10	35
11	0.025	3	0	10	40
13	0.025	3	0	12	40

NOMENCLATURE

θ_{ij} Voltage angle difference between buses i_{th} and j_{th}
$\Re$ Component of the real part
$\Im$ Component of the imaginary part
y_{Cij} Shunt admittance between buses i_{th} and j_{th}
ng Generator number in the system
nl Transmission line number
LF_i MVA capacity of line the between buses i_{th} and j_{th}
$\boldsymbol{g_k}$ Conductance of branch k
Y_{ij} Admittance between buses i_{th} and j_{th}
V_j Voltage at bus j_{th}
V_i Voltage at bus i_{th}
V_i^- Lower voltage at bus i
V_i^+ Upper voltage at bus i
P_i Real power at bus i_{th}
P_{gi} Real output power bus i_{th}
P_{gi}^- Lower limit of real power at bus i_{th}
P_{gi}^+ Upper limit of power at bus i_{th}
P_{di} Real power at bus i
Q_{di} Reactive power at bus i
Q_{gi} Reactive output power bus i_{th}
Q_{gi}^- Minimum of reactive power limit at bus i_{th}
Q_{gi}^+ Maximum of reactive power limit at bus i_{th}
Q_{ci} Reactive power supply by shunt at bus i_{th}
Q_{ci}^- Minimum Reactive power by shunt at bus i_{th}
Q_{ci}^- Maximum Reactive power by shunt at bus i_{th}
T_i Transformers tap setting at line i_{th}
T_i^- Lower transformer tap setting
T_i^+ Upper transformer tap setting