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Integrated Cuckoo-Evolutionary Programming-Based Technique Incorporating Distribution Generation for Economic Dispatch in Power System

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Abstract

In electricity generation, optimizing operational costs remains a primary concern for power systems. Economic Dispatch (ED) has been extensively explored in the power system domain; however, the impact of compensating devices, such as Distributed Generation (DG), has not been thoroughly investigated and requires further study to enhance system efficiency. This paper introduces an integrated cuckoo-evolutionary programming-based technique, referred to as CSA-EP, which incorporates DG into the ED problem. The CSA-EP technique combines the Cuckoo Search Algorithm (CSA) with Evolutionary Programming (EP) to optimize generation costs. The proposed method aims to identify the optimal power output for all generators in the system, minimizing overall generation costs. The proposed system was tested on the IEEE 30-Bus Reliability Test System (RTS) in solving the ED problem. In comparison to CSA and EP, the CSA-EP optimization technique demonstrated superior performance. Specifically, CSA-EP achieved a minimized cost of $2649.4932 per hour under base case conditions, whereas CSA alone yielded $5167.0848 per hour, and EP resulted in $3010.9971 per hour. In Case 1, IC-EP further demonstrated its effectiveness by achieving a minimized cost of $2649.4932 per hour, in contrast to $5529.7107 per hour for CSA and $4209.5214 per hour for EP. These results underscore the superior efficacy of the CSA-EP approach in minimizing generation costs.

1. Introduction

Due to the continuous increase in demand, current study focuses on the efficient operation and planning of power systems. Increased usage and reduction of natural and fossil fuels environmental issues which are economically friendly should be included in the current perspective [1,2]. Among the most critical problems that appear in the power system complication is economic dispatch (ED) problem [3-5]. ED is a fundamental problem that seeks to find the ideal power generation to match with the interest while pleasing all the systems constraints [6]. Due to the understanding of environmental factors, society needs sufficient and secure electricity at the cheapest price possible. There are two types of economic dispatch problems in power systems, which are dynamic economic dispatch and static economic dispatch problems as reported in [7]. The purpose of this work is to minimize the generation cost. Moreover, in fossil fuel fired plants, the cost of power generation is exorbitant, and optimum dispatch saves a huge amount of money. A few classical methods such as gradient method, base point participation factor, lambda iteration, Lagrange multiplier and lastly, Newton's method can clarify ED problem the assumption that the incremental cost curves of the generating units are monotonically increasing piecewise-linear functions [8]. However, large steam turbines have several steam intake valves that add non-convexity to the fuel cost function of the generating units. Classical approaches based on calculus failed to solve these types of problems successfully and leading to thread solutions that produce enormous financial losses over time. In this respect, there are many other stochastic search algorithms such as GA (Genetic Algorithms), SA (Simulated Annealing), ACO (Ant Colony Optimization), PSO (Particle Swarm Optimization), DE (Differential Evolution), BFA (Bacterial Foraging Algorithm), AIS (Artificial Immune System), BBO (Biogeography-Based-Optimization), Cuckoo Search Algorithm (CSA) and Evolutionary Programming (EP) have been applied successfully to solve complex ED in power system incorporating DG [9-10].

Newly, different hybridization and modification of GA, PSO, DE methods like PSO-SQP (Particle Swarm Optimization-Sequential Quadratic Programming) [11], IFEP (Improved Fast Evolutionary Programming) [12], IGA (improved genetic algorithm) [13], DEC-SQP (chaotic differential evolution and sequential quadratic programming) [14] have also been used to solve issues on ED. Other significant techniques are like NPSO-LRS (new particle swarm optimization-local random search) [15], SOH-PSO (Self Organizing Hierarchical-Particle Swarm Optimization) [16], and ICA-PSO (Improved Coordinated Aggregation-based Particle Swarm Optimization) [17]. The newly hybrid differential evolution with biogeography-based optimization [18-19] have also been proposed for solving ED problem in searching for better quality solution. But these methods contain many controllable parameters which may not be properly selected. This phenomenon has led to computational burden which could be problematic to power system community. Therefore, this study focuses on the integrated cuckoo-evolutionary programming-based technique incorporating distribution generation for economic dispatch in power system. The aim of this study is to develop a new optimization technique to solve ED in power system with the presence of DG. This technique is abbreviated as CSA-EP which integrates the operator of Cuckoo Search algorithm (CSA) into the evolutionary programming (EP) algorithm. CSA-EP is applied to address the ED problems with the objective to achieve minimal cost of generation. Besides, the comparative studies are conducted with respect to the traditional EP and CSA to confirm it superiority in achieving the minimal cost of generation in ED when implemented on a chosen IEEE reliability test system (RTS) model.

2. Research Method

2.1 Economic Dispatch Problem

The ED can be formulated as a problem for nonlinear constrained optimization. The objective function FT, total cost of N committed generators of ED for economic dispatch with quadratic function cost function and transmission loss can be written as:

$$FT = \sum_{i=1}^{N} F_i(P_i) = \sum_{i=1}^{N} a_i + b_i P_i + c_i P_i \tag{1}$$

Where Fi(Pi) is the *ith* generator's cost function and is generally expressed as a quadratic polynomial: a_i, b_i and c_i are the cost coefficients of *ith* generator: N is the number of generators committed to; Pi is the power output of *ith* generator [20].

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2.2 Distributed Generation

Distributed Generation (DG) generally indicates a near-load power plants, some kilowatts to dozens of megawatts, which ecologically appeared to be reliable. DGs are now commonly accepted across the globe [21]. Generally, DG operation needs to be connected to the power grid as a compensation effort to save costs and achieve stability of the system. There are 4 categories of DG with regards to active and reactive power support to the system. The first category is DG Type-1 where this DG will supply real power to the system. This DG type provides real/active electricity, P such as solar PV or battery. Micro turbine is categorized as the second DG type (Type-2) which provides just reactive power, Q like synchronous compensator to the system. For DG Type-3, DG can provide either active and reactive power such as PV device based on inverter voltage source, double-fed wind turbine powered induction generator and biomass generators powered on synchronous machines. On the other hand, DG Type-4 generates active power control and using reactive power such as wind turbine powered induction generator. DG is specified based on the rating of generation source, including micro-DG (1W-5kW), small DG (5kW-5MW), medium DG (5MW-50MW) and large DG (50MW-300MW). Normally DG is installed with approximately 10MW or less.

2.3 Optimization techniques

This section describes optimization techniques implemented in this study. Evolutionary Programming (EP) and Cuckoo Search Algorithm (CSA) are two important optimization techniques for optimizing the Distributed Generation (DG).

2.3.1 Evolutionary Programming (EP)

EP has been known as an established optimization technique with its simple algorithm. To obtain an ideal (minimum) solution, it is necessary to pay a great price in terms of task and time. EP has been known as a reliable optimization technique in power system optimization effort. However, EP is experienced to have limited capability where its solution normally stuck at the local optima. In this study, it is taken as the benchmarked technique. Fig. 1 shows the mechanics of EP. In general, there are 4 main operators implemented in EP which are initialization, mutation, combination and tournament selection. The details explanation of these steps will be explained below [22]:

• Initialization

First and foremost, random number variables will be generated to represent the control parameters which optimize the fitness equation [23]. The objective function is to minimize or maximize the fitness equation. In this study, the objective function is to minimize the fitness equation. All the random number that has been generated will be used to assign the real power generated in the system. There are three main variables which are loc(location), xD_g (DG size) and xP_g (PG size), where each of them consists of five variables.

• Mutation/Creation of offspring

Mutation is a process by which parents are converted into offsprings or children. These offsprings are bred based on the Gaussian mutation technique provided by equation in (2).

$$X_{i+mj} = X_{i+m,j} + N\left(0, \beta\left(X_{jmax} + X_{jmin}\right)\right)\left(\frac{f_i}{f_{mx}}\right) \tag{2}$$

Where;
$X_{i+m,j}$ = mutated parents (offsprings)
$X_{i,j}$ = parents
N = Gaussian random variable with mean μ and variance γ2
β = mutation scale, 0<β<1
X_{jmax} = maximum random number for every variable
X_{jmin} = minimum random number for every variable
f_i = fitness for ith random number
f_{max} = maximum fitness

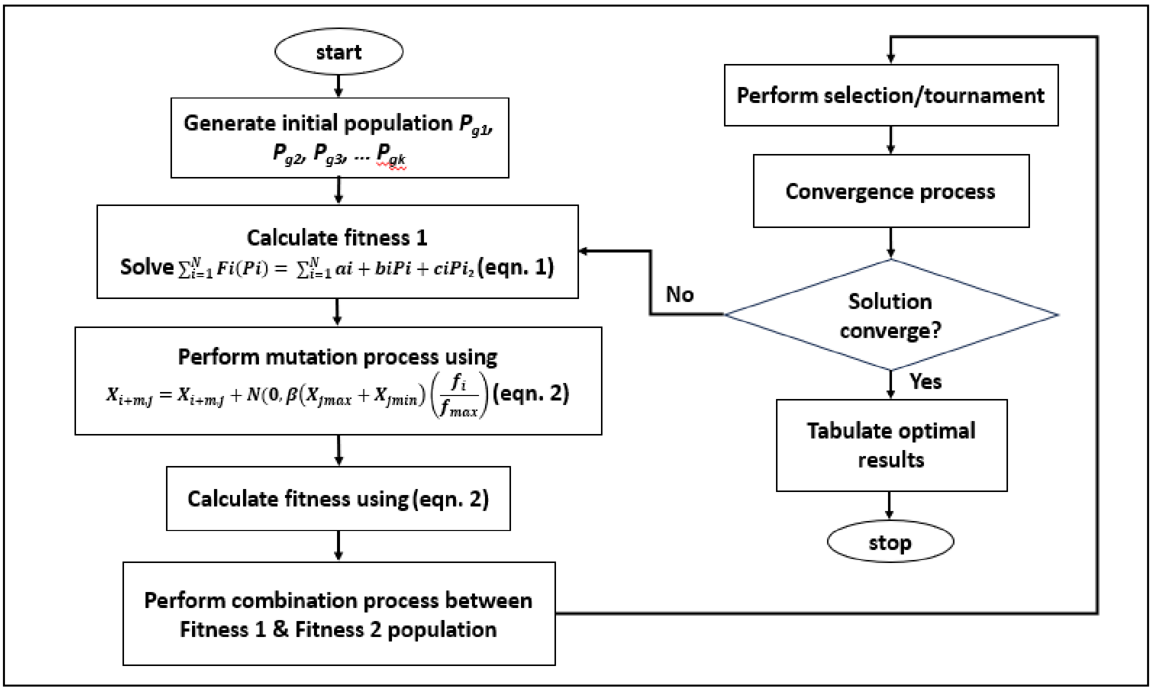

Fig. 1 *General flowchart for evolutionary programming*

• Tournament/Selection

When the process of mutation has been performed, parents and offspring will be combined with their respective fitness values, making the matrix size of the combined population equal to [2nx m], where n is the size of population or number of rows, and m is the number of variables. To transcribe the top candidates for the next generation, the combined population is then subject to the tournament. The tournament method can be done in two ways, known as pair-wise comparison or priority strategy techniques. Since the objective of the analysis is to minimize the total cost of operation, the combined population will be sorted with regards to the fitness values in ascending order. The first half of the sorted population is transcribed for the next generation in the next evolution process.

• Convergence test

In order to achieve the optimum solution, the stopping criterion determines the convergence of the optimization process. The criterion of convergence is given in (3). If the convergence criterion is not reached, it will repeat the entire process.

$$Fitness_{max} - Fitness_{min} \leq 0.0001 \tag{3}$$

2.3.2 Cuckoo Search Algorithm (CSA)

Cuckoo Search Algorithm (CSA) is a population-based method similar to other meta-heuristic methods. Normally there are two main operations in the structure of CSA which are direct search on Levy flights and a random search based on the probability for a host bird to discover an alien egg in its nest [24-26]. However, in this analysis the method that will be used is by using EP algorithm when generating new solution instead of Levy flights. In CSA, with the combination of two operations, it is a more efficient search approach than other meta-heuristic search techniques for complex and large-scale optimization [27-29]. In CSA method, each nest represents a solution, and a population of nest is used for finding the best solution to the problem. The flowchart of CSA is shown in Fig. 2. The main steps of CSA method are described below.

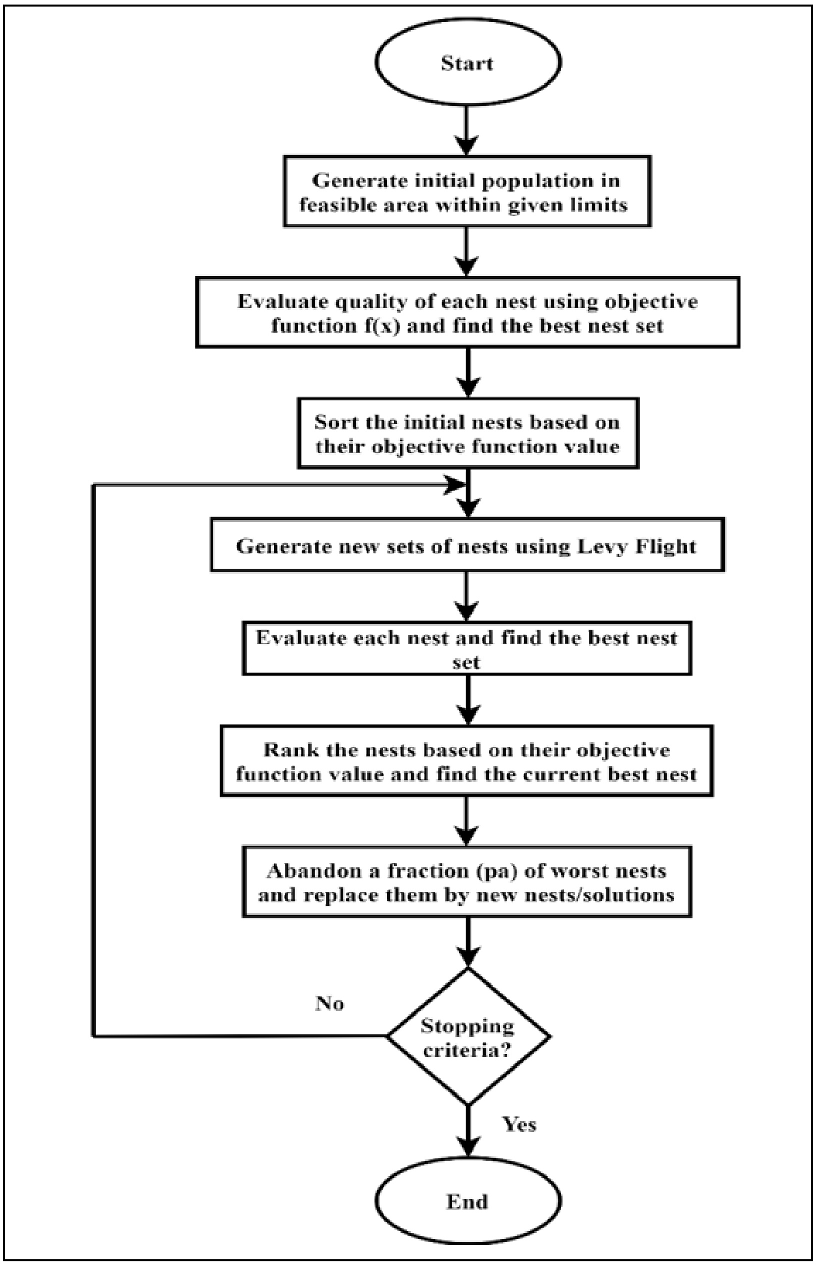

Fig. 2 *Flowchart for CSA*

• Initialization

A group of Np host nests is defined; X= [X1, X2, …, XNP]T meaning that all nest X_i= [Pi1, Pi2, …, Pij, …, PiN] described as units output power. The unit output power is computerized by:

$$P_{ij} = P_j min + rand_1 * P_j max - P_j min \quad (4)$$

Where rand1 is a consistently assigned random number between 1 and 0.

• Generation of new solution via EP

The new solution is calculated based on the method of EP where the process of EP has been described previously up until the convergence test. The newly obtained solution should be satisfied according to its lower and upper limits.

• Alien egg discovery and randomization

The process in finding alien egg in a host bird's nest with the circumstance of pa likewise give an advanced solution that is very identical to the Levy flights problems. The result is:

$$X_i^{dis} = Xbest_i + K\,x\,\Delta X_i^{dis} \tag{5}$$

For which K is the latest coefficient, based on a host bird's probability of discovering an alien egg in its nest:

$$K = \begin{cases} 1 \; if \;\; rand_3 < P_a \\ 0 \; otherwise \end{cases} \tag{6}$$

This increased value ΔX_i^{dis} determined by

$$\Delta X_i^{dis} = rand_3\, x\left[rand_{p1}\left(Xbest_i\right) - rand_{p2}\left(Xbest_i\right)\right] \tag{7}$$

Where $randi_3$ the shared inconsistent number in [0,1]. $randp_1(Xbest_i)$ and $randp_2(Xbest_i)$ the inconsistent confusion for positions of nests in $Xbest_i$.

• Stopping criterion

Stopping criterion for the optimization process is determined by the difference between the maximum fitness and the minimum fitness to be less than 0.0001. Nevertheless, it can also be stop based on the maximum preset iteration number.

2.3.3 Proposed Integrated Cuckoo-Evolutionary Programming (CSA-EP)

In this study, the IEEE-30 bus reliability system (RTS) is taken as the test specimen. It represents a simple approximation of the American Electric Power system as it was in December 1961 [30]. This proposed Integrated Cuckoo-Evolutionary Programming (CSA-EP) is based on the two methods as mentioned before. The flowchart of the proposed CSA-EP is shown in Fig. 3. The first step is the general initial population randomly where in this step all of the variables are generated, such as loc (location), xD_g (DG size) and xP_g (PG size). There are 5 variables for each of them. Then, start to find the value of FT by using the formula below:

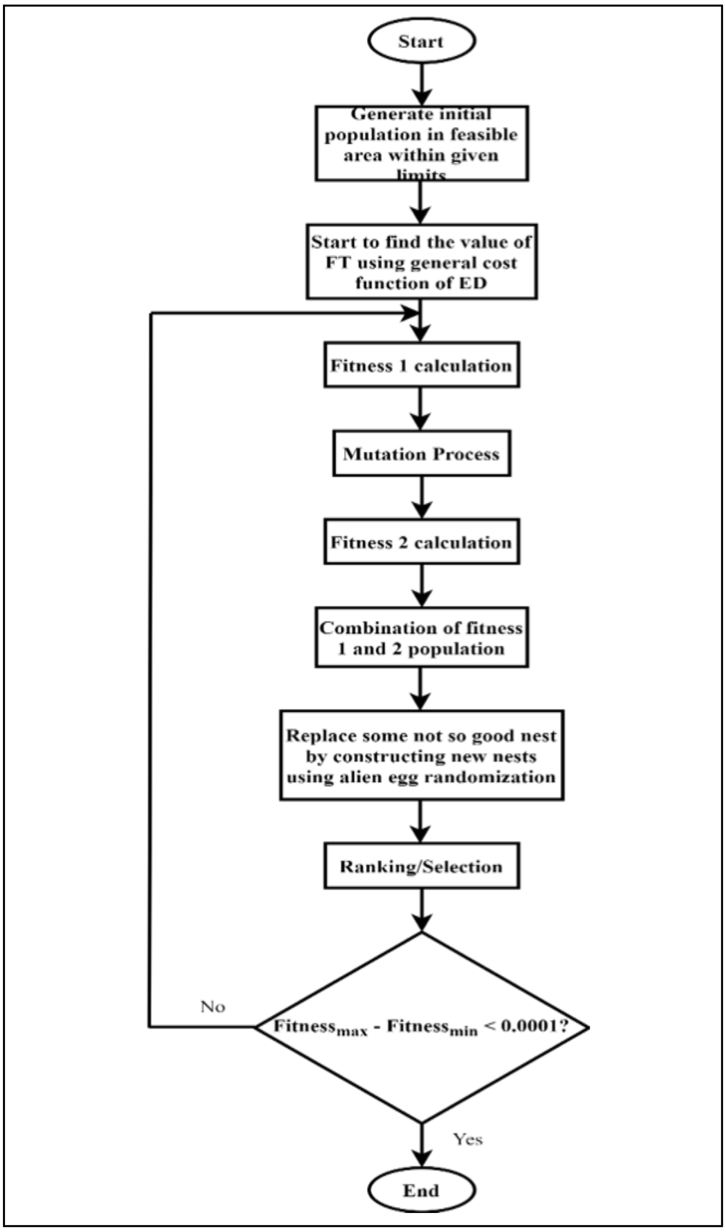

Fig. 3 *Flowchart of CSA-EP*

$$FT = \sum_{i=1}^{0} F_i\left(X_{pgi}\right) = \sum_{i=1}^{0} a_i + b_i X_{pgi} + c_i X_{pgi}^{\ 2} \tag{8}$$

Where Xpgi is the value of the solution or the nests. Then proceed with Mutation process where the initial populations (parents) are converted into offspring. These offsprings are developed on the basis of the Gaussian mutation technique provided equation (2). Then proceed with the Alien egg discovery and randomization where the process is the same with CSA but with EP variables. It is solved using equation (5).

3. Results and Discussion

The proposed Cuckoo Search Algorithm-Evolutionary Programming (CSA-EP) has been applied to solve ED problems in power system incorporating DG. The source code has been written in MATLAB R2018. Table 1 tabulates the results for optimal solution solved using CSA-EP when validated in IEEE 30-Bus RTS model. DG rating that has been applied is approximately 10MW or less.

From the table, Buses 25, 15, 24, 15 and 19 are the locations for DG installation with the corresponding sizing of 13.5468 MW, 7.7976 MW, -0.1834 MW and 9.2906 MW as indicated in the table. From all the so individuals each location and sizing show identical value or close each other, indicating that the optimal solution has been achieved.

Table 1 *Results for optimal solution for DG location and sizing solved using CSA-EP*

Iter No	*Loc 1*	*Loc 2*	*Loc 3*	*Loc 4*	DG_1 (MW)	DG_2 (MW)	DG_3 (MW)	DG_4 (MW)
1	25	15	24	19	13.5468	7.7976	-0.1834	9.2906
2	25	15	24	19	13.5440	7.7976	-0.1834	9.2906
3	25	15	24	19	13.5450	7.7976	-0.1834	9.2906
4	25	15	24	19	13.5478	7.7976	-0.1831	9.2905
5	25	15	24	19	13.5411	7.7976	-0.1835	9.2906
6	25	15	24	19	13.5422	7.7976	-0.1834	9.2906
7	25	15	24	19	13.5465	7.7976	-0.1834	9.2906
8	25	15	24	19	13.5450	7.7976	-0.1834	9.2906
9	25	15	24	19	13.5479	7.7976	-0.1834	9.2906
10	25	15	24	19	13.5445	7.7976	-0.1843	9.2905
11	25	15	24	19	13.5448	7.7976	-0.1830	9.2905
12	25	15	24	19	13.5450	7.7976	-0.1832	9.2905
13	25	15	24	19	20.9298	7.7976	-0.1831	9.2905
14	25	15	24	19	13.0551	7.7976	-0.1831	9.2905
15	25	15	24	19	13.5488	7.7976	-0.1831	9.2905
16	25	15	24	19	13.5400	7.7976	-0.1838	9.2905
17	25	15	24	19	13.5411	7.7976	-0.1837	9.2905
18	25	15	24	19	13.5472	7.7976	-0.1831	9.2905
19	25	15	24	19	5.6263	7.7976	-0.1832	9.2905
20	25	15	24	19	13.5439	7.7976	-0.1832	9.2905

It shows that the best minimum cost is at 4918.4313$/h. To achieve this, the amount of real power to be generated by the generators are: PG2 = 3.7877 MW, PG5 = -0.1732 MW, PG8 = 21.250 MW and PG13 = 0.1291 MW. The average values for minimum voltage obtained is between 0.95 until 1.00 which is very good whereas the values for power loss is below 25MW. Fig. 4 shows the minimum cost value for FT.

Table 2 *Best values for DG sizing, PG sizing, minimum cost, minimum voltage and power loss for 30-bus system*

DG_5 (MW)	PG_2 (MW)	PG_5 (MW)	PG_8 (MW)	PG_{13} (MW)	Min Cost ($/h)	Min Voltage	Power Loss (MW)
28.5922	3.7877	-0.1732	21.2540	0.1291	4918.4313	1.0033	10.0737
28.2176	3.7877	-0.2267	21.2540	0.1485	4918.5194	1.0034	10.0911
28.5884	3.7877	-0.2264	21.2540	0.1485	4918.5198	0.9831	21.5965
-36.9185	3.7877	-0.1787	21.2540	0.1491	4918.5478	0.9983	16.9662
14.4528	3.7877	-0.1735	21.2540	0.1480	4918.5875	1.0040	10.7196
14.4583	3.7877	-0.1734	21.2540	0.1480	4918.5876	0.9851	18.9881
9.8637	3.7877	-0.1730	21.2540	0.1483	4918.5915	1.0041	11.0205
9.8692	3.7877	-0.1730	21.2540	0.1483	4918.5916	0.9856	18.2639
28.5976	3.7877	-0.1732	21.2540	0.1485	4918.5931	0.9831	21.5898
0.6514	3.7877	-0.1784	21.2545	0.1297	4918.6082	1.0043	11.7692
31.0024	3.7877	-0.1786	21.2548	0.1287	4918.7368	1.0032	10.0053
27.4051	3.7877	-0.1786	21.2548	0.1287	4918.7369	0.9833	21.3508
-31.2368	3.7877	-0.1783	21.2545	0.1491	4918.7775	0.9990	15.3250
-7.0695	3.7877	-0.1783	21.2545	0.1491	4918.7776	0.9867	15.9779
-7.0602	3.7877	-0.1783	21.2545	0.1491	4918.7777	0.9863	16.0586
-12.4964	3.7877	-0.2336	21.2551	0.1295	4918.8073	1.0042	13.1856
-12.4909	3.7877	-0.2336	21.2551	0.1295	4918.8074	0.9864	15.5070
-7.0681	3.7877	-0.2069	21.2551	0.1283	4918.8237	0.9863	16.0639
-4.3356	3.7877	-0.1757	21.2551	0.1242	4918.8385	1.0006	12.9487
22.2123	3.7877	-0.1803	21.2551	0.1287	4918.8664	1.0037	10.3148

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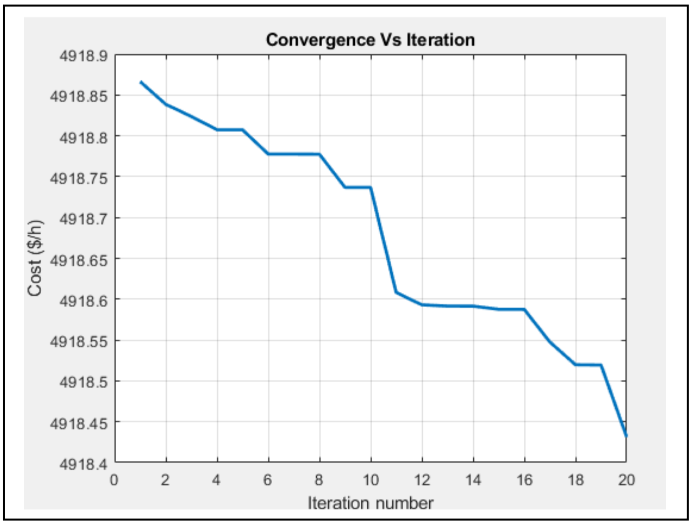

Fig. 4 *Minimum cost value for FT*

In this study, twelve different control variables (Loc 1, Loc 2, Loc 3, Loc 4 & DG1 size, DG2 size, DG3 size, DG4 size) while PG consists of four variables (PG2, PG5, PG8 and PG13). For PG, it is the power generated by all the chosen generators in the system to achieve the minimum cost of generation with the presence of DG.

Table 3 tabulates the results for comparative studies solved using EP, CSA and proposed CSA-EP at base case condition. The minimum cost achieved by CSA-EP is 2649.4932$/h; while EP and CSA methods achieved 3010.9971$/h and 5167.0848$/h respectively. Apparently, the proposed CSA-EP managed to achieve the lowest cost implying its superiority over EP and CSA. This can also be proven by the results shown in Fig. 5. CSA-EP exhibits the lowest profile indicating its strength over EP and CSA.

Table 3 *Results for optimal DG installation and economic dispatch in IEEE-30 bus RTS for base case*

Optimization Techniques	EP	CSA	CSA-EP
Loc 1	18	25	18
Loc 2	18	15	18
Loc 3	21	24	21
Loc 4	23	15	23
Loc 5	26	19	27
DG_1 *size*	4.1164	6.2520	4.9574
DG_2 *size*	8.4104	7.7986	8.4117
DG_3 *size*	2.6891	0.8064	2.6901
DG_4 *size*	4.1507	9.2898	6.1907
DG_5 *size*	5.3690	7.7541	6.4061
P_{G2}	2.0753	3.7782	2.0953
P_{G5}	-17.0500	-5.1612	-0.0517
P_{G8}	2.4545	21.2537	1.9738
P_{G13}	-1.4012	3.1829	-1.2820
Min Voltage	0.9976	1.0007	0.9381
Power Loss (MW)	17.0186	12.1318	14.8620
Cost ($/h)	3010.9971	5167.0848	2649.4932

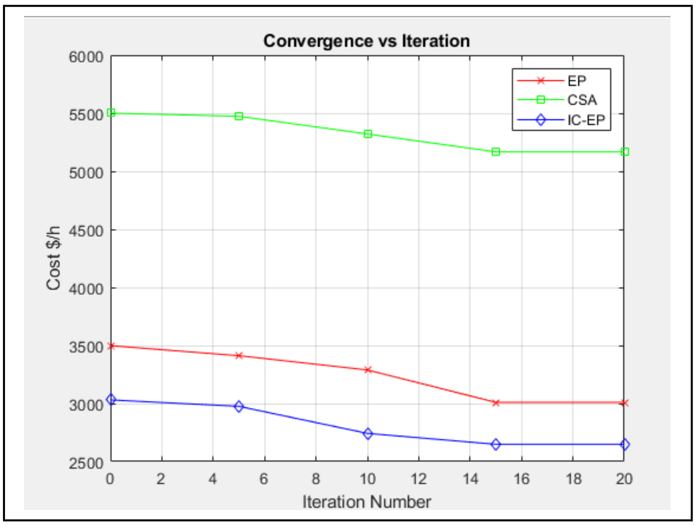

Fig. 5 *Minimum cost value for EP, CSA and CSA-EP for base case*

For the power losses, the tabulated data in Table 3 shows that the CSA method produced the least power losses worth 12.1318MW while for CSA-EP, it produced 14.8620MW losses. The difference for power losses between CSA and CSA-EP is 2.7302MW, thus it is suggested that power losses for CSA-EP is still acceptable. The result also revealed that the EP produces the highest power losses at 17.0186MW. Furthermore, this is insignificant change observed for minimum voltage for all methods with EP achieved voltage value of 0.9976 p.u., CSA gives 1.0007 p.u. and CSA-EP achieved the lowest value worth 0.9381 p.u. Results for other properties can be referred to in the same table.

The results for comparative studies for Case 1, solved using all the techniques are tabulated in Table 4. From the table, the real and reactive load in this case is P_d = 10 MW and Q_d = 10Mvar subjected to buses 10, 14, 20 and 26 implemented on IEEE-30 bus RTS.

Table 4 *Results for optimal DG installation and economic dispatch in IEEE-30 bus RTS for case 1*

Optimization Techniques	EP	CSA	CSA-EP
Loc 1	18	16	18
Loc 2	15	23	18
Loc 3	21	15	21
Loc 4	23	19	23
Loc 5	27	13	27
DG1 size	4.1204	1.2997	4.9581
DG2 size	8.4149	2.4548	8.4213
DG3 size	2.6930	7.6077	2.7102
DG4 size	4.1536	3.9510	6.2212
DG5 size	5.3725	1.7562	6.4123
PG2	2.1090	-18.5897	2.1031
PG5	-17.0233	19.2729	-0.0612
PG8	2.4817	-0.8871	1.9823
PG13	-1.3907	0.2251	-1.2901
Min Voltage	0.8449	0.8379	0.9423
Power Loss (MW)	25.1911	25.4732	18.2673
Cost ($/h)	4209.5214	5529.7107	3653.3476

From Table 4 the results for optimal DG installation and economic dispatch in IEEE-30 bus (RTS) in case 1 with P_d = 10 MW and Q_d = 10 Mvar. For the minimum cost generated, EP generated the minimum cost at 4209.5214$/h and CSA gives 5529.7107$/h but the most optimal minimum cost is generated by CSA-EP where it achieves 3653.3476$/h. Apparently, CSA-EP achieves the lowest cost as compared to others. When comparing the cost of CSA-EP in case 1 with the base case, there is an increment of 37.89% when the load is being injected at P_d

= 10 MW and Q_d = 10 Mvar. This can be referred to Fig. 6 where it shows the difference in terms of minimum cost where the value for CSA-EP is the lowest again. For the power losses, all methods show higher power loss values as compared to the base case. For case 1, the power loss for EP is 25.1911 MW whilst CSA gives 25.4732 MW. There is not much difference between them but, for CSA-EP, there is starting to have a certain gap when the power losses at CSA-EP is only at 18.2673MW.

For the minimum voltage, both EP and CSA produced 0.8449 p.u. and 0.8379 p.u. respectively while the values recorded for CSA-EP is slightly higher at 0.9423 p.u.. It can be observed that when the load is increased, the values for the variable such as min cost, power loss and minimum voltage experienced an increment when compared to the base case condition. The profiles for minimum cost value using all the techniques are illustrated in Fig. 6. Again, CSA-EP exhibits the lowest loss profile indicating its superiority over EP and CSA.

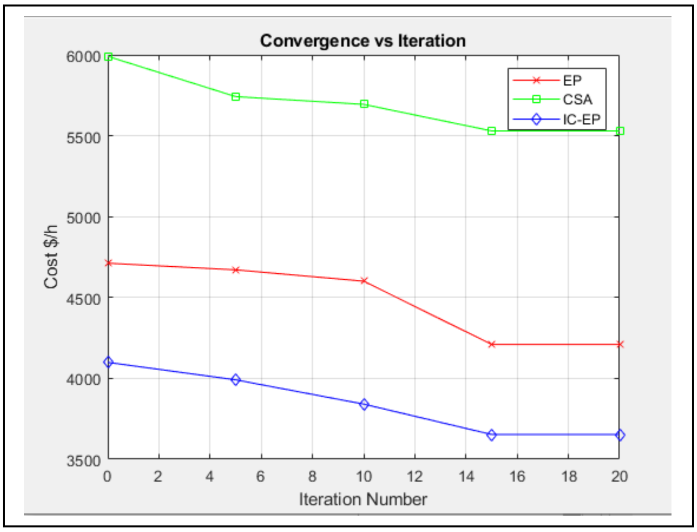

Fig. 6 *Minimum cost value for EP, CSA and CSA-EP for case 1*

4. Conclusion

This paper has presented the integrated cuckoo-evolutionary programming-based technique Incorporating distribution generation for economic dispatch in power system. The proposed CSA-EP technique integrates the operator of Cuckoo Search algorithm (CSA) into the evolutionary programming (EP) algorithm. The proposed CSA-EP exhibits the best result as compared with EP and CSA when implemented on IEEE 30-Bus RTS model. Further study can utilize the proposed optimization engine for solving similar problems in larger systems.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Ahmad Faris Hakim Ahmad Azri, Ismail Musirin;* ***data collection:*** *Ahmad Faris Hakim Ahmad Azri, Ismail Musirin;* ***analysis and interpretation of results:*** *Nor Azwan Mohamed Kamari, Azlina Abdullah, Vinothini Kasinathan, Habibah Zulkefle;* ***draft manuscript preparation:*** *Habibah Zulkefle, Mazliza Abdul Halim. All authors reviewed the results and approved the final version of the manuscript.*

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