A NOVEL CONSTRAINT HANDLING APPROACH FOR METAHEURISTIC TECHNIQUES IN SOLVING ECONOMIC DISPATCH PROBLEMS

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ABSTRACT

This paper proposes a novel constraint handling strategy (CHM) based on random walk for metaheuristic techniques in solving the optimal economic dispatch (ED) problems. To implement this CHM, a Cuckoo Search (CS) algorithm has been adopted. The absolute as well as the relative performance of the resultant hybrid algorithm is experimentally investigated using a standard test case with valve point effects. Statistical parameters are used in order to evaluate the robustness of the method. The proposed methodology proves that it outperforms established methods such as particle swarm optimization and genetic algorithm methods in terms of robustness and achieving consistent results throughout all the trials in each experiment.

Keywords: power system operations, economic dispatch, constraint handling, cuckoo search, metaheuristic algorithms

1. INTRODUCTION

Economic dispatch (ED) problem is a traditional optimization problem whereby the power system utility operator uses it in order to minimize their operation costs. The objective of this mathematical modelling of the system is to optimally set the generator loadings so that their overall operating cost is minimized [1]. Earlier formulations of the problem were tackled using basic mathematical techniques such as interior point method, linear programming and many others [2]. However, those methods cannot solve the ED problem when formulated in a non-linear context which is mostly the case.

In recent times, the knowledge growth of metaheuristic methods has given an opportunity to optimize the ED problem in a more practical way than the mathematical techniques. Researchers have tried many heuristic techniques to solve the problem such as genetic algorithm (GA) [3], particle swarm optimization (PSO) [3, 4], evolutionary programming (EP) [5, 6] and others. However, literature indicates [7] that with the proper design of an efficient constraint handling mechanism (CHM), evolutionary techniques are able to solve the problem efficiently. Based on this notion, this paper proposes a novel CHM technique for metaheuristic techniques to solve the ED problems.

Recently, Xin-She Yang and Deb developed a Cuckoo Search (CS) algorithm [8]. CS is a powerful metaheuristic technique which is uniquely developed in order to solve the highly multimodal optimization problems. Since the ED is known to be a multimodal, nonlinear practical problem, this algorithm is considered a perfect match for the problem. In that regard, this paper adopts the CS algorithm to investigate the applicability of the proposed novel CHM.

In the rest of the paper, the problem formulation of the ED problem is explained in section 2.0. Section 3.0 briefly introduces CS algorithm. A customized RW-based method for solving the constraint handling mechanism of the ED problems is formulated and explained in section 4.0. Section 5.0 presents the experimental results. The paper ends with brief summary of overall concluding remarks.

2. PROBLEM FORMULATION

The economic dispatch is normally formulated as an optimization problem whereby the operating cost of all the generating plants are tried to be minimized to the extent possible. The objective of the problem can be mathematically defined by the following cost function:

$$\min F_i = \sum_{i=1}^{n} F_i\left(P_i\right) \tag{1}$$

$$F_i\left(P_i\right) = a_i P_i^2 + b_i P_i + c_i + \left| e_i \sin\left(f_i \left(P_i - P_i^{\min} \right)\right)\right| \tag{2}$$

where a_i, b_i, and c_i are the cost coefficients of the generation unit i; e_i and f_i are the valve point effect coefficients; F_i is the fuel cost of generator i and P_i is the scheduled power for generator i.

Besides, the equality constraint represented by the power balance constraint and the inequality constraint represented by the generating units power limits are mathematically formulated as shown in equations (3) and (4), respectively.

$$\sum_{i=1}^{n} P_i - P_D - P_L \tag{3}$$

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad i = 1, 2, ..., n \tag{4}$$

where $P_i^{\min}$ and $P_i^{\max}$ are the minimum and the maximum limits of the power generation unit; P_D is the total system demand; and P_L is the system loss.

3. CUCKOO SEARCH ALGORITHM

Cuckoo search (CS) algorithm was developed by Xin-She Yang and Suash Deb in 2009 [8]. The algorithm is basically built upon the theory of Cuckoos, particularly their brood parasitism characteristics in combination with the Levy flight concept. The most important thing that is related to the algorithm about the cuckoos is their aggressive breeding strategy. The reader is directed to [9] in order to obtain further information of the theoretical understanding of the algorithm.

4. DEVELOPMENT OF CONSTRAINT HANDLING MECHANISM

There are two common methods to handle the power balance constraints. Firstly, the use of heuristic techniques (used in [10, 11]) or local search methods [12], just to name only a few. Secondly, the direct use of various types of penalty factors – a very popular approach among researchers in the ED problem. However, both of these methods do not provide robust results despite having occurrences of global optimum randomly because of two reasons. The first methods suffer from low intelligence ability due to unguided efforts and the penalty factor approach is too simplistic.

However, studies with the combination of these two methods obtained better results than those that single-handedly implemented each on its own. On that basis, in our method, both are maintained. But a more intelligence is obtained by introducing random walk (RW)-based method. The RW-based methods are easily customisable to a particular problem, efficient in solving many complex problems and have extreme abilities to increase algorithmic intelligence [13].

4.1 Proposed strategy

In this strategy, the penalty factor-based objective function is used with a very small value of penalty factor. This allows the system to slightly favour the optimal results and those that are close to the limits but highly favourable. In order to eliminate these defected good solutions, an intensification-oriented strategy is adopted. This concurrently serves dual advantages. First, it solves the lack of constraint fulfilment problem. Second, it carries out localized neighbourhood search steps. The latter is considered crucial, particularly in the ED problem, due to the high multimodality with critically sensitive equality constraint particularly in operation-wise. A potential location with an equality constraint violation could be deeply explored by this random walker until it finds a local optimum that does not violate the constraint requirement.

In a random walk, new solutions are generated around a potential solution with defects using this equation:

$$x_{t+1} = x_t + s\varepsilon_t \tag{5}$$

where x_{t+1} and x_t represent new and previous solutions, respectively. The elements of ε_t are drawn from a uniform distribution with zero mean, and s is the step length of the RW.

4.2 Implementation of RW in constraint handling process

According to [9], for any application, the design of the proper step size (s) is a crucial element of the effectiveness and the suitability of the RW-based strategy. In this work, the step size is chosen in such a way that only the local neighbourhood around the solution is visited while also solving for the power balance constraint. To achieve this in the ED problem, a vector called ΔP_g is proposed as the appropriate step size. This vector contains the power mismatch of the solutions that do violate the equality constraint and it is calculated as follows:

$$\Delta P_g = \sum_{i=1}^{n} P_i - P_D - P_L \tag{6}$$

Besides, in our implementation, ε_t is set to be normal or Gaussian distribution in order to smoothly and uniformly cover all the search space. It is known that Gaussian distributions normally tend to emphasize deeply on local explorations due to their small steps [13]. The resultant updating formula for the RW used in handling the constraints is:

$$P_g^k = P_g^k + \Delta P_g \varepsilon_t \tag{7}$$

where k is the generator number visited at each iteration. The complete flowchart of this strategy is shown in **Figure-1**.

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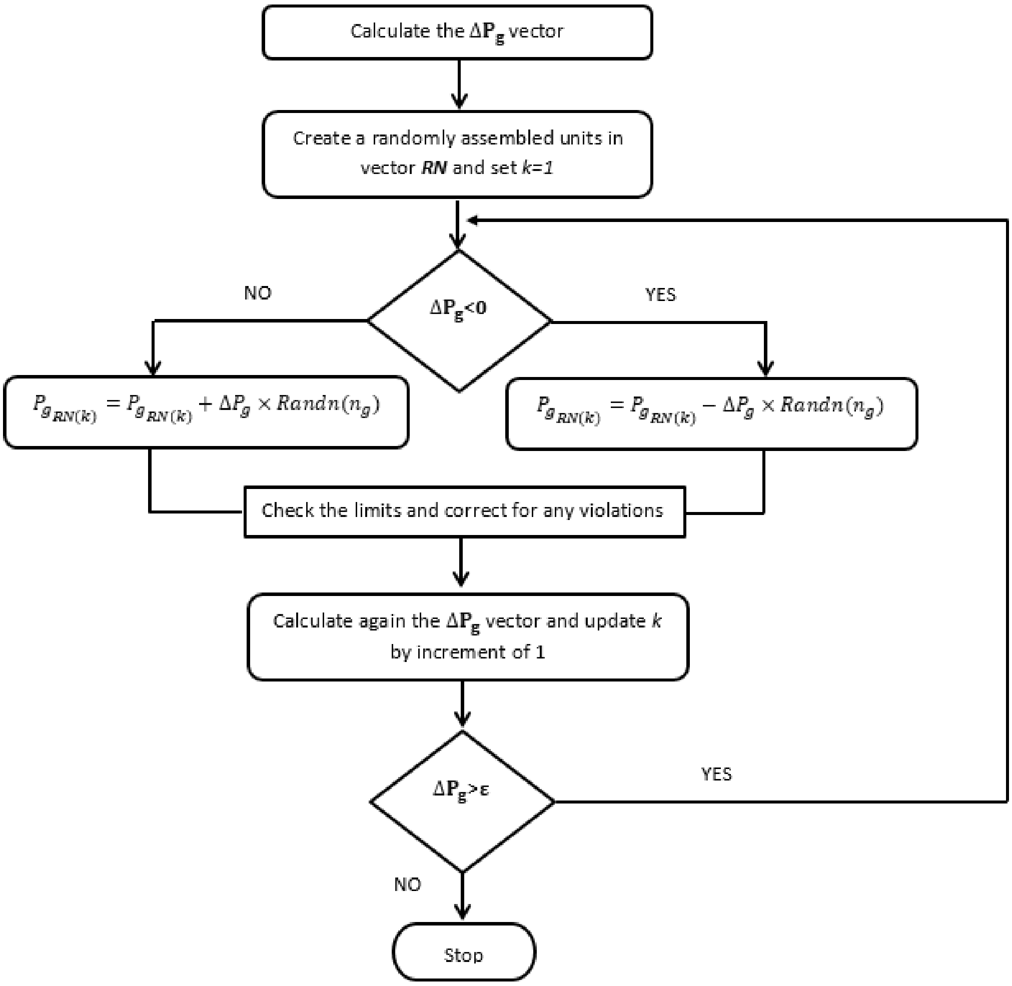

Figure-1. The flowchart of the proposed constraint handling mechanism.

5. EXPERIMENTAL RESULTS

In this paper, two different test cases were considered to test the efficiency and the effectiveness of the method. The first test case is a practical non-linear three unit system with a total load of 850 MW, and a system capacity of 1.2 GW. The cost function used includes the valve-point effects and the data is obtained from [5]. In this study, a comparative analysis between the performance of RCS and the EP variants presented in [5] is carried out. The second test case has six generating units and a total load of 1263 MW. Its generator characteristics and the overall system data are obtained from [3].

The algorithm was experimentally set using the combination of our own experience and the suggestions in the literature [9, 14-16]. In all of our implementations, the probability of discovering an alien egg was fixed to 0.3. The population size was set at 50. Similarly, the maximum iteration number was set at 8000 for all test cases. The penalty factor (PF) was set at 50. In order to test the robustness of the proposed algorithm, 100 trials were run for every test case.

5.1 Optimal results

The optimal results of each test case obtained by the proposed methodology are presented in Table 1 and 2, showing the results for the two test cases. Compared with the other results, it is evident that the RCS is able to achieve the global optimal results known for the test cases. Besides, it is worth-noting that the results do not show any residual power errors while the constraints are also smoothly fulfilled.

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Table-1. Optimal results of the CS_RW in comparison with various other literatures for case 1.

Generation	FCASO-SQP [4]	EP [6]	MPSO [7]	BSA [17]	RCS
P1 (MW)	300.266	300.26	300.27	300.27	300.2669
P2 (MW)	400.000	400	400	400	400
P3 (MW)	149.734	149.74	149.73	149.73	149.7331
$\sum P_{Demand}$ **(MW)**	850	850	850	850	850
Total cost ($/h)	8234.07	8234.07	8234.07	8234.07	8234.07

Table-2. Optimal results of the CS_RW in comparison with various other literatures for case 2.

Unit	RCS	SPSO [18]	PC_PSO [18]	SOH_PSO [18]
P1 (MW)	446.7195	442.86	445.00	446.68
P2 (MW)	171.2456	175.58	173.21	171.24
P3 (MW)	264.1356	263.04	262.86	264.13
P4 (MW)	125.1861	128.35	123,78	125.18
P5 (MW)	172.1077	172.37	172.64	172.15
P6 (MW)	83.6055	80.80	85.51	83.62
$\sum P_{Demand}$ **(MW)**	**1263.0000**	**1263.00**	**1263.00**	**1263.00**
Total Cost ($/h)	15,275.93039	**15,276.38**	**15,276.05**	**15,275.93**

5.2 Robustness and solution quality

To analyse the robustness of the proposed RCS method, two different analyses are carried out. Firstly, the performance of the algorithm in the various test cases was examined using descriptive statistical analysis. Secondly, the performance of the algorithm in comparison with the results reported in the literature [3, 5, 19] are examined. The central tendency statistical parameters are used in order to evaluate the robustness of the algorithm. Additionally, the potential economic impact of using this proposed RCS method over the other algorithms is analysed and visualized putting the significance of the algorithm in economic value.

5.2.1 Performance of RCS in various test cases

To observe how the algorithm performs in various situations and its consistency in achieving the optimal solutions, the descriptive statistical analysis of 100 different trials of each test case were carried out. The results are shown in Table-3.

Table-3. Descriptive statistical analysis of the various test cases.

Statistical analysis	3 Unit	6 Unit
Standard Error	0.0004	0.0000
Standard Deviation	0.0040	0.0000
Sample Variance	0.0000	0.0000
Range	0.0208	0.0002
Count	100	100

Looking at the Table-3, all the trial runs for the two test cases overwhelmingly showed the lowest variability in achieving the optimal costs with either negligible or zero standard deviation, standard error, sample variance and range (the difference between the maximum and the minimum cost achieved in all the trials). Comparatively, the proposed RCS has shown marginally lower capability in achieving optimal costs for the first test case in comparison with second test case. Despite the first test having lower dimensional solution space than the second test case, the method was more sensitive to the valve point effects present in the first test case. In other words, the non-linearity is more significant than the dimensionality of the systems studied for this particular method.

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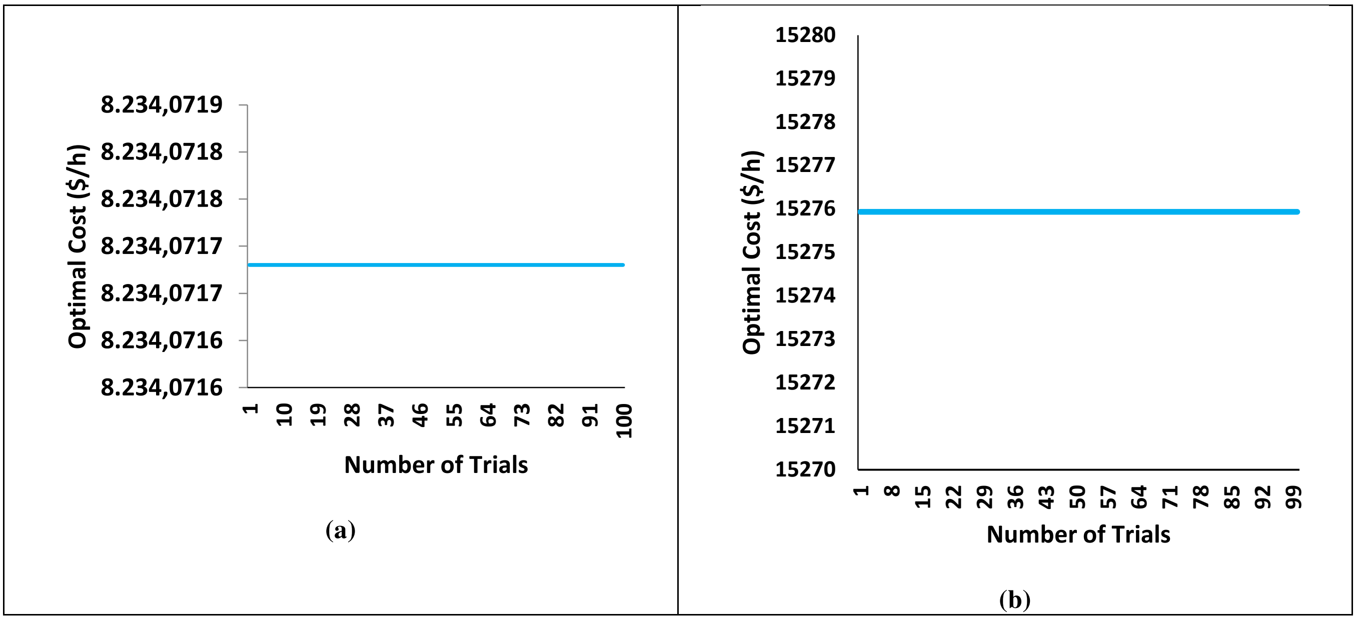

Figure-2. The behaviour of the proposed RCS in achieving optimal cost (a) test case 1 (b) test case 2.

To visualize graphically the above mentioned statistical inferences, Figure 2 (a, b) is drawn for the two cases. Looking at these figures, it is evident that the overall performance of the proposed RCS algorithm is consistent, stable and robust despite varying system complexities. This is further evidenced when the obtained results are compared with the algorithms presented in the existing literature as discussed in the following sub-section.

5.2.2 Performance of RCS in comparison with the existing methods

Here, the performance of the proposed algorithm when compared with the literature is examined. Statistical analyses for the first test case were reported in Table-4 along with the other statistics in the literature [3, 5]. The proposed algorithm's result is also listed in the last row of Table-4. Since most of the work in the literature reports the simplest parameters that indicate the central tendency of optimal results, only those parameters are chosen for comparison reasons, despite their low indication of algorithmic robustness. It is evident that RCS has the lowest statistical parameters (minimum, mean and maximum optimal costs) presented in the table.

Table-4. Statistical comparison with other methods reported in the literature for a three unit system.

Method	Min Cost	Mean Cost	Max Cost
PSO [3]	8234.072	8330.851	8421.523
PSO-CRAZY [3]	8234.072	8279.165	8382.008
RGA [3]	8234.073	8337.033	8432.157
CEP [5]	8234.07	8235.97	8241.83
FEP [5]	8234.07	8234.24	8241.78
MFEP [5]	8234.07	8234.71	8241.80
IFEP [5]	8234.07	8234.16	8234.54
RCS	8234.07173	8234.07173	8234.07173

Another way to compare the results reported in the literature with the obtained results of RCS is by using the frequency distribution charts. In this way, the consistency of the algorithm in obtaining optimal results is observed. The choice of this comparison is because of its adoption in the existing established literature. Figures-3 and 4 indicate the frequency distribution chart comparisons of RCS with three common algorithms that are implemented in the ED problems. These algorithms are evolutionary programming (EP), particle swarm optimization (PSO) and genetic algorithm (GA).

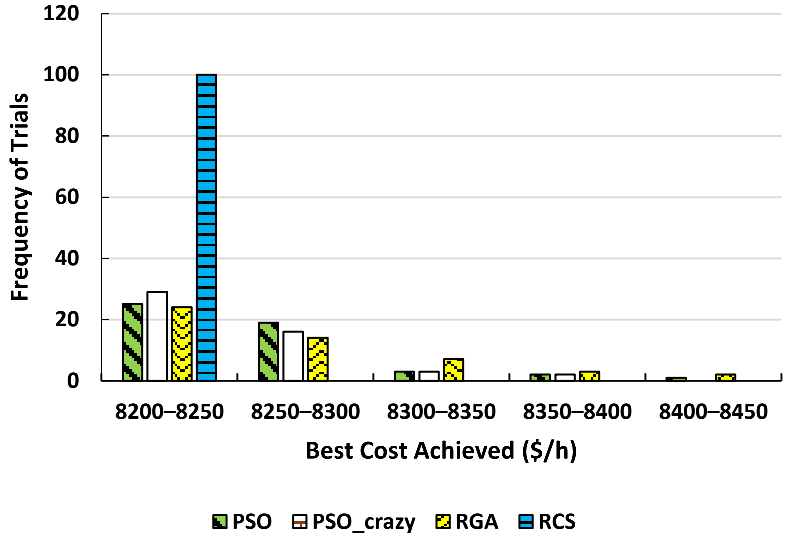

Figure-3. Frequency distribution for RCS in comparison of PSO variants and RGA.

The work of Chaturvedi *et al* [3] reports two different variants of PSO (basic PSO and PSO_CRAZY) and a single variant of GA (called RGA). The performance of RCS is excessively better than the performance of all the other three variants as shown in Figure-3. The closest algorithm in terms of robustness and solution quality is the PSO_CRAZY with only 29% of solutions achieving between 8250 $/h and 8200 $/h (a cost range of 50 $/h). It is worth-noting that RCS achieves all its trials within an optimal cost range of a negligible value with a 100% of success rate (as previously shown in Table-4).

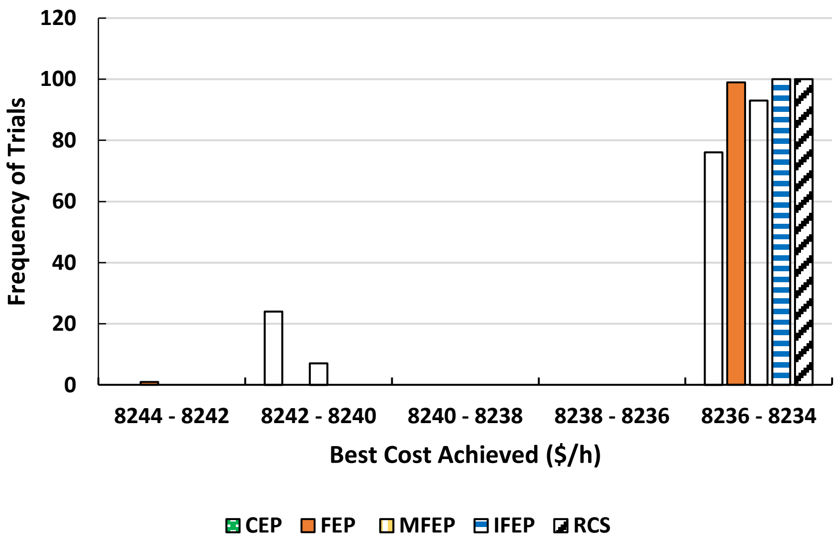

Figure-4. Relative frequency convergence using the proposed method versus other methods.

Similarly, the work of Sinha *et al* [5] presents four different variants of EP. Figure-4 indicates the comparison between the four variants of EP with RCS. Of all the four variants, only IFEP has equal performance with RCS while it outperforms the other three strategies presented in [5]. The similarity of performance between RCS and IFEP is the fact that both algorithms use statistical random variables. IFEP uses Cauchy mutation operator that enhances the EP's ability to find global optimal solutions for multimodal problems in a robust way [20].

With this comparison, one can see the solution quality and the robustness inherent to the combined effect of a powerful CS algorithm with an effective CHM for power balance constraint coupled with penalty factor operator in the objective function. This result is consistent with the original experimental results obtained by Yang and Deb [8] that CS outperforms PSO and GA in terms of success rate.

6. CONCLUSIONS

This paper proposes an efficient constraint handling mechanism for metaheuristic techniques in solving the economic dispatch problems. Cuckoo search algorithm is adopted as a metaheuristic technique in the overall methodology of the paper. The results of the method are tested on two standard IEEE test cases with three and six units. The results of the paper demonstrate the efficiency of the proposed method when implemented in the economic dispatch field. The algorithmic results of the method are compared with the results presented in the literature showing that with this CHM, the algorithm is better in terms of obtaining the solution quality and the in terms of robustness and the consistency of the results.

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