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An efficient global technique for solving the network constrained static and dynamic economic dispatch problem

Aamir NAWAZ[1,*], **Nasir SALEEM**[1], **Ehtasham MUSTAFA**[1], **Umair Ali KHAN**[2]
[1]Department of Electrical Engineering, Faculty of Engineering and Technology, Gomal University, Dera Ismail Khan, Khyber Pakhtunkhwa, Pakistan
[2]Ordnance Training School, Pakistan Navy, Pakistan Navy Base Camp, Karachi, Pakistan

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Abstract: This paper presents a new approach for solving the economic load dispatch (ELD) problem with generator constraints and transmission losses. The constrained globalized Nelder–Mead algorithm is a newly proposed algorithm for solving economic dispatch problems with and without valve-point effects. Convex and nonconvex cost functions with equality and inequality constraints are difficult to optimize. To circumvent these problems, a robust global technique is desirable. In this paper, the constrained globalized Nelder–Mead algorithm is proposed to optimize the ELD problem globally using variance variable probability. To validate the proficiency of the proposed approach, statistical studies have been accomplished for different test systems of static economic dispatch including 3-unit convex and nonconvex systems without losses, a 6-unit convex system with losses, 13-unit nonconvex systems without losses, and a 20-unit nonconvex system without losses. The proposed model proficiency is verified by applying it to dynamic economic dispatch for test systems including a 3-unit convex system with no losses and a 5-unit nonconvex system with losses. Comparison of the proposed algorithm with other optimization algorithms reported in the literature shows that the proposed algorithm is quite robust. The proposed algorithm has improved results from 0.0001% to 4.44% in different case studies.

Key words: Globalized Nelder–Mead, static and dynamic economic dispatch, convex and nonconvex problems, valve-point effects

1. Introduction

Economic load dispatch (ELD) is one of the critical steps of power system planning. Economic dispatch (ED) is a complex and nonlinear problem with equality and inequality constraints. The main objective of the ED problem is to plan the dedicated generating units' generation in such a way as to achieve minimum operating cost while satisfying all system constraints. Different optimization techniques such as the lambda iteration method [1], gradient method [2], Newton's method [3], linear programming [4], interior point method [5], and dynamic programming [6] have been used to solve the basic ED problem.

In the case of real generating systems, the input-output characteristics are nonconvex because of valve-point effects. Furthermore, there are many limitations in the control and operation of power systems due to constraints such as ramp rate limits and prohibited operating zones. Thus, in reality, the ELD problem is represented in terms of a nonconvex optimization problem with different equality and inequality constraints. In the last few years, as an alternative to the conventional mathematical approaches, different heuristic methods

*Correspondence: aamirnawaz@gu.edu.pk

have been implemented for the ELD problem, such as improved tabu search, neural networks [7], evolutionary programming [8], genetic algorithms [9], and particle swarm optimization [1,10–14].

In [1,10–14], modified particle swarm optimization (MPSO), a hybrid algorithm involving particle swarm optimization (PSO) and BFOA, a hybrid algorithm using PSO with Gaussian probability and chaotic sequences, a PSO model for solving the combined economic emission dispatch problem, and modified PSO with particle initializing technique PSO method were respectively used for solving the ED problem.

The authors of [15] proposed a new hybrid approach, differential evolution with chaotic sequences and sequential quadratic programming (DEC-SQP). The authors of [16] presented an enhanced comparison on the basis of search capability and convergence speed of DE, PSO, and improved PSO for solving multiarea economic dispatch problems. The authors of [17] presented a review of ED using the Lagrange multiplier method. The authors of [18] proposed improved bacterial foraging for solving ED problems involving renewable energy sources such as wind power. Nawaz et al., in [19], presented a new approach called the globalized Nelder–Mead algorithm for training of artificial neural networks to solve short-term load forecasting problems. The author of [20] proposed multiobjective PSO (MOPSO), which has been used for the evaluation of Pareto solutions to preserve diversity of optimization. In [21] the authors proposed a seeker optimization algorithm to solve the ED problem for convex and nonconvex systems. Yang et al., in [22], proposed a firefly algorithm (FA) for solving nonconvex ED problems.

The author of [23] presented a real and binary-coded genetic algorithm (GA) for solving the network constrained economic dispatch (NCED). In [24], Ahmed et al. presented a review on ED using different techniques including lambda iteration and gradient methods and also metaheuristic algorithms. In [25], Manoharan et al. presented evolutionary programming with Levenberg–Marquardt optimization (EPLMO) for solving multiarea ED problems.

This paper presents a new algorithm that has just been evaluated with mathematical test functions in MATLAB by Ghiasi et al. [26]. It has not been implemented in any area of power systems except short-term load forecasting [19] and other potential research areas.

2. Problem formulation

The ELD problem is a quite complex and nonlinear optimization problem. The main task of the ED problem is to minimize fuel costs while satisfying different constraints such as generator constraints, ramp rate limits, and prohibited operating zones.

2.1. Convex economic dispatch

In convex ED, the fuel cost function is formulated as a quadratic function of real power generation with no valve-point effects as given below:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{1}$$

Here, $F_i(P_i)$ is the incremental cost for the ith generating unit, i represents unit index, and a_i, b_i, and c_i represent fuel coefficients.

2.2. Nonconvex economic dispatch

In nonconvex ED, the fuel cost function is considered as a quadratic function of real power generation with valve-point effects due to steam valves and is formulated as:

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

Here, $F_i(P_i)$ is the incremental cost for the ith, generating unit considering valve-point effects, and e_i and f_i, are fuel coefficients for representing valve-point effects.

2.3. Generator units' capacity limits

Each generation unit in a power system has a certain minimum and maximum generation limit. Therefore, efficient use of generators is needed for minimal economic dispatch operation. The following equation must be satisfied while minimizing fuel cost function:

$$P_i^{\min} \leq P_i \leq P_i^{\max} \tag{3}$$

Here, $P_i^{\min}$ and $P_i^{\max}$ represent lower and higher power generation limits for the ith generating unit.

2.4. Generator ramp rate limits

In dynamic ED, the operational range of online generating units is constrained by the ramp rate limits. These limits effect the operation of the power system and an economic decision is required considering the ramp rate limits.

These possibilities are represented by inequality constraints. When generation is increased, the inequality constraint will be:

$$P_i - P_i^0 \leq UR_i \tag{4}$$

Here, P_i^0 represents the previous hour's generation of the ith generating unit and UR_i represents the up-ramp rate of the ith generating unit.

When generation is decreased, the inequality constraint will be:

$$P_i^0 - P_i \geq DR_i \tag{5}$$

Here, P_i^0 represents the previous hour's generation of the ith generating unit and DR_i represents the down-ramp rate of the ith generating unit.

Generator constraints can be modified as:

$$\max(P_i^{\min}, P_{i,t}^0 - DR_i) \leq P_{i,t} \leq \min(P_i^{\max}, P_{i,t}^0 + UR_i), \qquad t = 1, 2, 3, ..., T \tag{6}$$

Here, $P_{i,t}^0$ represents the previous hour's generation from hour t, ng represents the number of generating units, and T represents the total number of hours.

2.5. Prohibited operating zones

Steam valves or auxiliary equipment such as boilers cause vibrations in shaft bearings. This is the main reason for prohibited operating zones (POZs) in the fuel cost function. The shape of a fuel cost curve with POZs is difficult to determine, which is why avoiding operation of generating units in a POZ gives the best economic operation.

POZs divide the operating region of generating units into disjoint convex regions with minimum and maximum generating limits. The generation limits of generating units with POZs are given below:

$$\begin{array}{l} P_{i,t}^{\min} \le P_i \le P_{i,1}^{D} \\ P_{i,r-1}^{U} \le P_i \le P_{i,r}^{D} \\ P_{i,m}^{U} \le P_i \le P_{i,t}^{\max} \qquad , r = 2, 3, ..., m \end{array} \tag{7}$$

Here, i represent the unit index, m is the number of prohibited zones of the ith generating unit, and $P_{i,r}^{U}$ and $P_{i,r}^{D}$ represent the upper and lower limits of the rth prohibited operating zone of the ith generating unit.

2.6. Power balance constraint and transmission losses consideration

The power balance constraint is an equality constraint given by following equation:

$$\sum_{i=1}^{ng} P_i = P_D + P_L \tag{8}$$

Here, P_D is power demand and P_L is transmission power losses.

Transmission power loss is considered to be a quadratic function of the generating units' powers, which is given as:

$$P_L = \sum_{i=1}^{ng} \sum_{j=1}^{ng} P_i B_{ij} P_i + B_{i0} P_j + B_{00} \tag{9}$$

Here, B_{ij}, B_{i0}, and B_{00} are loss coefficients of specific test systems.

3. Overview of the Nelder–Mead algorithm

3.1. Classical Nelder–Mead algorithm

The Nelder–Mead algorithm is one of the fastest and most simple algorithms for local minimum and multidimensional optimization problems. It is different from gradient methods as it does not have to calculate derivatives. This method forms a simplex, which converges to local minima. There are three parameters that can affect convergence of the simplex, i.e. α (reflection coefficient to define reflected point distance from centroid), β (contraction coefficient), and γ (expansion coefficient).

The Nelder–Mead simplex method steps can be summarized as follows:

Step 1: Select α, β, γ, and an initial random simplex with vertices $x_0, x_1 \dots x_n$ and evaluate the function value for each vertex.

Step 2: Sort the vertices $x_0, x_1 \dots x_n$ according to function values as $f_0, f_1 \dots f_n$ in ascending order.

Step 3: Evaluate the point of reflection x_r, f_r.

Step 4: If $f_r < f_0$:

a. Evaluate the point of extension x_e, f_e.

b. If $f_e < f_0$, substitute the poorest point by the point of extension $x_n = x_e, f_n = f_e$.

c. If $f_e > f_0$, substitute the poorest point by the point of reflection $x_n = x_r, f_n = f_r$.

Step 5: If $f_r > f_0$:

a. If $f_r < f_i$, substitute the poorest point by the point of reflection $x_n = x_r, f_n = f_r$.

b. If $f_r > f_i$:

(i) If $f_r > f_n$: evaluate point of contraction x_c, f_c.

i. If $f_c > f_n$ then shrink the simplex.

ii. If $f_c < f_n$ then substitute the poorest point by contraction point $x_n = x_c, f_n = f_c$.

(ii) If $f_r < f_n$: substitute the poorest point by point of reflection $x_n = x_r, f_n = f_r$.

Step 6: If the stop criterion is not satisfied, the algorithm will continue at step 2.

3.2. Constrained Globalized Nelder–Mead (CGNM) algorithm

Global optimization can be performed by restarting a local optimizer again and again. In [27], Luersen and Le Riche proposed a probabilistic restart procedure that starts the algorithm in a region far away from previous points and local points. They utilized a multidimensional probability (MDP) density. MDP assigns probability values to points to determine points with a maximum likelihood for solution.

In [26], Ghiasi et al. proposed a new probability evaluation method, called variable variance probability (VVP). The new probability evaluation method is based on the least space to the points previously tested and is represented as:

$$\phi(x) = \frac{1}{2\pi}\left(1 - e^{-\left(\frac{d_{\min}^2}{2\sigma^2}\right)}\right) \tag{10}$$

$$d_{\min} = \min_{i=1,2,3\ldots m}\left\{d_i = \sqrt{\sum_{k=1}^{n}\left(\frac{x_{k,i} - x_k}{x_{ku} - x_{kl}}\right)}\right\} \tag{11}$$

Here, $\varphi(x)$ is the selection probability of a point x, n is the number of variables, x_i is a point already sampled, and m is the number of points already sampled. d_i is the nondimensional space between point x and point x_i.

The variance of the normal probability density, updated in each restart, is given by:

$$\sigma = \frac{1}{3\sqrt[n]{m}} \tag{12}$$

The variance for a particular pool decreases as points in that pool increase.

The variance gives points located away from the previously sampled points. In every restart, variance will do the same procedure and gives points away from previously sampled ones, which increases the chance of selection of global optima region points.

4. Economic dispatch solution using CGNM algorithm

The ED problem is a nonlinear problem and becomes more complex when equality and nonequality constraints are involved with convex and nonconvex systems. The CGNM algorithm is a quite robust technique to find the optimal solution of ED of generating units. The flowchart in the Figure briefly explains how the algorithm works.

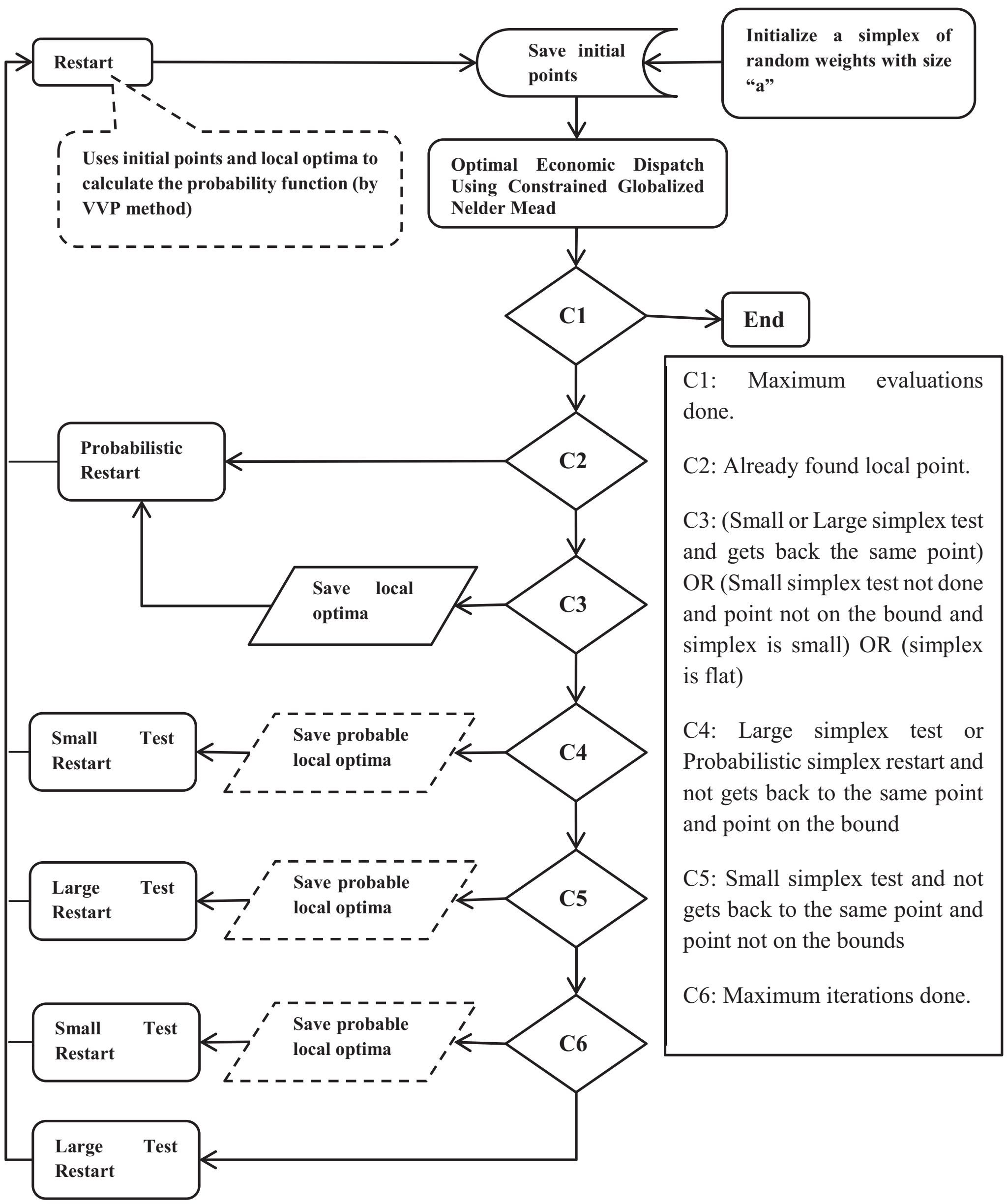

Figure. Flowchart of constrained globalized Nelder–Mead algorithm for solving economic dispatch problems.

Moreover, different parameters for the CGNM algorithm are selected in such a manner that the algorithm has to do a deeper search. Reflection, expansion, contraction, and shrink are properties associated with Nelder–Mead local search while probabilistic, small, and large tests are for global search. Table 1 gives parameter selection for the CGNM algorithm.

Table 1. Parameters selection for CGNM algorithm.

Parameters	Value
Reflection	1.0
Contraction	0.5
Expansion	2.0
Shrink	0.5
Large test simplex size	0.2
Small test simplex size	0.02
Probabilistic test simplex size	0.2

5. Case studies

Different case studies have been studied using various test systems. All statistical evaluations have been carried out on an Intel Core i5 platform, 2.50 GHz, 4 GB memory. The proposed algorithm was developed in MATLAB r2011a.

5.1. Static economic dispatch

In static ED, the optimal cost of a test system is evaluated for a single particular demand. Multiple case studies involving convex and nonconvex systems have been carried out on different test systems.

5.1.1. Convex system

5.1.1.1. Case I: 3-machine test system with no losses

In this case study, the proposed method has been implemented on a test system with 3 generating units without transmission losses. Fuel cost evaluation data for each generator were taken from [1]. The optimum solution for each unit and total cost as evaluated by the proposed CGNM method and other algorithms in the literature [1] are compared in Table 2.

Table 2. Fuel cost ($) comparison of different algorithms with proposed algorithm for all case studies.

	1.1.1.1 Fuel cost ($) for case studies				
Methods	Convex system			Nonconvex system	
	Case I	Case II	Case III	Case I	Case II
LIM [1,29]	8194.36	-	62456.64	-	-
MPSO [1]	8194.36	-	-	8234.12	-
GA [1]	8194.98	-	-	8237.6	-
IEP [1]	8194.36	-	-	8234.09	-
EP [1]	-	-	-	8234.076	-
SWT [28]	-	18721.39	-	-	-
IBFA [18]	-	18721.5		-	-
Hopfield [29]	-	-	62456.63	-	-
SA [24]	-	-	-	-	17975.39
PS [24]	-	-	-	-	18927.21
SQP [24]	-	-	-	-	19131.55
SA-SQP [24]	-	-	-	-	17998.82
PS-SQP [24]	-	-	-	-	18891.59
CGNM	8194.2646	18719.57	62451.957	8234.073	17968.1

5.1.1.2. Case II: 6-machine convex system with losses

In this case study, a system with six generating units is optimized using the proposed approach. Fuel cost data for each generating unit were given in [18,28]. The optimum solution of fuel cost for a six-unit generating system of the proposed algorithm and previous algorithm results in the literature [18,28] are presented in Table 2.

5.1.1.3. Case III: 20-machine system with losses

A test system with 20 generating units has been considered in this case. Cost coefficients and generation limits of each generating unit were taken from [29]. Comparison of the proposed algorithm has been accomplished with the lambda iteration method and Hopfield modeling [29] and is presented in Table 2.

5.1.2. Nonconvex system

5.1.2.1. Case I: 3-machine system with valve point effects

In this case study, the proposed approach is tested on a test system with 3 generator units and transmission losses. Furthermore, valve-point effects are also included, which makes this problem nonconvex. Data of generators for fuel cost evaluation were taken from [1]. A comparison of the proposed algorithm with other optimization algorithms in the literature [1] such as GA, IEP, and MPSO is given Table 2.

5.1.2.2. Case II: 13-machine system without losses

In this case, a test system with 13 generator units and valve-point effects is considered for performance evaluation of the proposed approach. Generators' data for the mentioned test system were taken from [24]. The proposed approach is compared with previous techniques in the literature [24] in Table 2.

5.2. Dynamic economic dispatch

5.2.1. Convex system

5.2.1.1. Case I: 3-machine system without losses

In this case, dynamic dispatch of a test system with 3 generating units has been tested with the proposed approach for 24-h demand data. The generators' cost data and power generation limits, POZs, previous-hour generator allocations, and up-ramp and down-ramp rate limits were given [30]. Due to these constraints, searching for the optimized cost of this test system is quite difficult. Therefore, the robustness of the algorithm can be evaluated on the basis of these problems. Comparison of the proposed approach has been done with the bacterial foraging algorithm (BFA) and improved bacterial foraging algorithm (IBFA), presented in [30], as given in Table 3.

5.2.2. Nonconvex system

5.2.2.1. Case I: 5-machine system with losses

In this case, a test system with 5 generator units and transmission losses is considered. The proposed algorithm has been implemented on this test system to optimize cost for 24-h demand. In Table 3, the proposed CGNM algorithm is compared with other techniques in the literature [17]. This comparison shows the significance of the proposed algorithm.

Table 3. Fuel cost ($) comparison of different algorithms with proposed algorithm for all case studies.

	1.1.1.2 Fuel cost ($) for case studies	
Methods	Convex system	Nonconvex system
	Case I	Case I
BFA [30]	104137.39	-
IBFA [30]	103700.89	-
PSO [17]	-	50124.00
SA [17]	-	47356.00
MSL [17]	-	49216.81
CGNM	99087.6	47285.6

6. Conclusion

This paper introduces a new CGNM algorithm to solve convex and nonconvex ED problems statically and dynamically. The CGNM algorithm, with its local and global search properties and different constraint handling features, has proved to be advantageous over many other techniques in the literature. For performance evaluation of the CGNM algorithm, different test systems for static ED have been used, such as 3-, 6-, 13-, and 20-unit test systems, and for dynamic operation, 3- and 5-generating unit test systems have been used. The CGNM algorithm has shown quite promising results for economic operation of different standard test systems. This algorithm can be further hybridized with heuristic algorithms to improve its convergence speed and get more accurate results. VVP can be replaced with some other more optimal probability methods to improve CGNM performance. As CGNM is a new algorithm, it can be applied in different optimization problems of power systems and other fields of interest for researchers.

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