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Application of differential evolution algorithm in static and dynamic economic or emission dispatch problem: A review

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ABSTRACT

Economic Load Dispatch (ELD) is an imperative assignment in contemporary aggressive power demand market. Dearth of power generation in all dimensions of energy resources will result escalating in generation cost wants the optimal power dispatch at minimum fuel cost. Owing to the confined optimum convergence, the predictable optimization methods are not proficient to crack such problems. Evolutionary optimization techniques are proved to be superior to the conventional techniques to solve ELD problems. Differential Evolution Algorithm (DEA) is one of the foremost and recent evolutionary techniques in modern optimization state of affairs. The application of DEA in multi directional ELD problem has been technologically summarized in this paper.

1. Introduction

The feasible and effective optimum operation of electric power dispatch plays a principal role in modern vibrant power generating sector. Economic load dispatch is a predominant member of power system operation pool for determining unit commitment, load flow and available transfer capability. The ELD having different forms like Convex Economic Dispatch (CED), Non Convex Economic Dispatch (NCED), Economic Emission Dispatch (EED), Emission constrained Economic Dispatch (ECED) and Combined Economic Emission Dispatch (CEED) under static and dynamic scenario. The major task of ELD is the availability of optimum power delivery at minimum fuel cost with associated operational constraints. From the past decades there are several predictable methods akin to Linear Programming(LP) [1,2], Non Linear Programming (NLP) [3,4], Mixed Integer Linear Programming (MILP) [5], Dynamic Programming (DP) [6], Quadratic Programming (QP) [7,8] and Network Flow Method (NFM) [9] focused in the literature are used to solve such problems. Due to the poor convergence and complexity of computational operation, the conventional techniques are not suitable to expose the effective results under handling of multi objective functions and numerous constraints. The arrival of recent heuristic optimization techniques incorporating the concept of artificial intelligence like Simulated Annealing (SA) [10,11], Tabu Search (TS) [12], Improved Tabu Search (ITS) [13], Ant Colony Optimization (ACO) [14,15] , Neural Network (NN) [16], Hopfield Neural Network (HNN) [17], Two Phase Neural Network (TPNN) [18],

Abbreviations: ACO, Ant Colony Optimization; ACSA, Ant Colony Search Algorithm; AHDEA, Adaptive Hybrid - Differential Evolution Algorithm; ALF, Augmented Lagrange Function; ALHN, Augmented Lagrange Hopfield Network; ALM, Augmented Lagrange Multiplier; APSO, Anti Predatory Particle Swarm Optimization; BBO, Biogeography-Based Optimization; BF, Bacterial Foraging; BFOA, Bacterial Foraging Optimization; CED, Convex Economic Dispatch; CEED, Combined Economic Emission Dispatch; CGA, Conventional Genetic Algorithm; CHDPSO, Combined Hybrid Differential Particle Swarm Optimization; CO_2, Carbon Dioxide; CPSO, Chaotic Particle Swarm Optimization; CRPSO, Craziness-based Particle Swarm Optimization; DEA, Differential Evolution Algorithm; DED, Dynamic Economic Dispatch; DEED, Dynamic Economic Emission Dispatch; DP, Dynamic Programming; ECED, Emission constrained Economic Dispatch; ED, Economic Dispatch; EED, Economic Emission Dispatch; ELD, Economic Load Dispatch; EP, Evolutionary Programming; EPSO, Enhanced Particle Swarm Optimization; GA, Genetic Algorithm; HDEA, Hybrid Differential Evolution Algorithm; HGA, Hybrid Genetic Algorithm; HNN, Hopfield Neural Network; IDEA, Improved Differential Evolution Algorithm; IPADEA, Interior Point Assisted Differential Evolution Algorithm; ITS, Improved Tabu Search; LP, Linear Programming; MAED, Multi Area Economic Dispatch; MDEA, Modified Differential Evolution Algorithm; MILP, Mixed Integer Linear Programming; MODEA, Multi Objective Differential Evolution Algorithm; MOEED, Multi Objective Economic Emission Dispatch; MOEEPD, Multi Objective Environmental Economic Power Dispatch; NCED, Non Convex Economic Dispatch; NFM, Network Flow Method; NLP, Non Linear Programming; NN, Neural Network; NO_X, Nitrogen Oxide; POZ, Prohibited Operating Zones; PSO, Particle Swarm Optimization; QP, Quadratic Programming; RGA, Refined Genetic Algorithm; SA, Simulated Annealing; SO_2, Sulfur Dioxide; SQP, Sequential Quadratic Programming; TPNN, Two Phase Neural Network; TS, Tabu Search; VNS, Variable Neighborhood Search; VPE, Valve Point Effect

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Table 1
Major advantages and disadvantages of key optimization methods focused in literature.

Optimization methods	Ref. No.	Advantages	Disadvantages
Linear Programming (LP)	[1,2]	• Uncomplicated and easy to understand. • Analyse the problems in more flexibility and adaptive. • Provided the quality of verdict is better.	• It is impossible to solve a number of problem having in excess of two variables in graphical method. • Unfeasible to solve non linear functions.
Dynamic Programming (DP)	[6]	• Permits to build up subordinate solutions of a large program. • Possible to reuse the partly covered subordinate solutions.	• Necessary to maintain the number of partial solutions in a track. • Not able to solve non-integer constraint based problems.
Simulated Annealing (SA)	[10,11]	• Coding is simple even for composite problems • Cost functions and arbitrary systems are easy to deal.	• There are a small number of local minima. • Requires a few other complementary methods to find an optimal solution.
Tabu Search (TS)	[12]	• Possible to apply for both continuous and discrete solution spaces. • Permits non-improving solution to be accepted so as to flee from a local optimum.	• Several parameters to be determined. • Large number of iterations is required. • Difficult to find global optimum depends on parameter settings.
Ant Colony Optimization (ACO)	[14,15]	• Intrinsic parallelism. • Well-organized for some problems similar to Travelling Salesman Problem. • Can be used in dynamic applications.	• Difficult to understand the hypothetical analysis. • More convergence time.
Genetic Algorithm (GA)	[20–22]	• Easy to solve each optimisation problem which can be explained with the chromosome encoding. • Easy to solve multiple and multi-dimensional solution problems. • It can be easily transferred to existing models and simulations. • Simple to understand.	• Variant problems cannot be solved owing to badly known fitness functions which are producing bad chromosomes. • No guarantee to find a global optimum. • Cannot assure stable optimisation response times like other artificial intelligence techniques.
Particle Swarm Optimization (PSO)	[26–30]	• Very efficient for global search optimization. • Less number of parameters. • Suitable for simultaneous process (Parallelized without difficulty). • Functioning in easier way.	• Ability of local search is weak • propensity to a premature and quick convergence in mid optimum points
Evolutionary Programming (EP)	[35–37]	• Suitable for requirement of multiple solutions. • Easy to parallel implementation	• Trial-and-error based parameter tuning • No assurance for finding optimal solutions in a limited time.

Augmented Lagrange Hopfield Network (ALHN) [19], Genetic Algorithm (GA) [20–22], Refined Genetic Algorithm (RGA) [23], Hybrid Genetic Algorithm (HGA) [24,25], Particle Swarm Optimization (PSO) [26–30], Chaotic Particle Swarm Optimization (CPSO) [31–33] , Anti Predatory Particle Swarm Optimization (APSO) [34] and Evolutionary Programming (EP) [35–37] to tackle the convergence properties, complexity of computational operation and provide the finest solution against the conventional methods. The merits, demerits and properties are quiet different in each and every method. The major advantages and disadvantages of some key optimization methods focused in this section are given in Table 1.

However, even though the meta-heuristic optimization techniques are not giving the assurance at any time determining globally optimal solutions in limited time, they frequently give a quick and logical solution. From the family of evolutionary algorithms DEA having high potential and fine standpoint solution of different optimization problems. It has been effectively applied in different types of ELD problems like various forms of DEA [44–67], Improved DEA [68–74], Modified DEA [75–79], Hybrid DEA [80–119] and Multi Objective DEA [120–130]. The objective of this paper represents a technological review about the application of multi type DEA in a variety of ELD problems. Section 2 provides an overview of DEA. The problem formulation related to ELD problem including various cost functions with equality and inequality constraints are discussed in Section 3. The various categories of DEA based ELD reviews are presented in Section 4. The conclusion about presented work is projected in Section 5.

2. Overview of DE algorithm

Storn and Price proposed a new evolutionary parallel direct search algorithm called Differential Evolution Algorithm (DEA) due to unusual type of differential operator which they appealed to make new progeny from parent chromosomes in place of conventional crossover or mutation having the properties of finding the accurate global minimum irrespective of the initial system parameter values, hasty convergence and least number of control parameters [38,39]. DEA is generally chosen for its effectiveness, ease of design and coding. DEA is using three operators named crossover, mutation and selection. The control parameters are having several optimization parameters which were to be tuned and joined together. The first entrant solutions are selected arbitrarily surrounded by the margin under starts to travel around the search space. The population is iterated refining through reproduction and selection will formulate that the algorithm tries to locate the global best solution [40]. Further development of this population based algorithm makes its suitability for global numerical optimization in multi directional ways like self (strategy) adaptation [41], neighborhood based mutation operation [42] and ensemble of mutation and crossover strategy [43].

2.1. Mutation

At the stage of mutation DEA randomly selects three distinct parameter vectors $x_{r1,m}$,$x_{r2,m}$ and $x_{r3,m}$ as of the present set $\{x_{1,m}, x_{2,m}, \ldots x_{NP,m}\}$. No one of this parameter vector ought to match with the current target vector $x_{i,m}$. The weighted distinction of any two points is then added to the third point. For each target vector $x_{i,m}(i = 1,2, \ldots NP)$, a mutant vector $M_{i,m}$ is generated according to

$$M_{i,m+1} = x_{r1,m} + F.\ (x_{r2,m} - x_{r3,m}) \tag{1}$$

where F is greater than zero is a scaling factor, and $x_{r1,m}$ is identified as the base vector. The mutation operation is replaced when the point $M_{i,m+1}$ is a non zero value.

2.2. Crossover

To raise the multiplicity of the perturbed parameter vectors, cross-