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ECONOMIC LOAD DISPATCH USING PARTICLE SWARM OPTIMIZATION

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Abstract - **"In the contemporary era, reducing operational expenses and carbon footprints has become a fundamental necessity for global ecological preservation. For decades, fossil fuel reserves have been extensively exploited for electricity production, creating a critical need to align rising consumer energy demands with resource efficiency. To mitigate the ongoing conventional energy crisis, the Economic Load Dispatch (ELD) framework has been a focal point of investigation. This study introduces a sophisticated stochastic optimization model that employs a hybrid Particle Swarm Optimization (PSO) methodology to address the complexities of constrained power dispatch. The analysis confirms that the integration of the PSO algorithm successfully fulfills energy requirements at an optimal generation cost while significantly lowering transmission inefficiencies."**

1. Introduction

In the contemporary landscape, research is centered on small-scale thermal power generation systems where the primary objective is ensuring a consistent and dependable energy supply to fulfill rising consumer needs through an optimal generation schedule. Due to the surge in energy requirements and fuel prices, production expenses have escalated, which eventually impacts the end-user community. Consequently, another vital goal of optimizing energy generation and distribution is to achieve a significant reduction in overall fuel expenditures and transmission line inefficiencies.

Economic Dispatch (ED) is designed to identify the most efficient scheduling for thermal units to minimize fuel costs while adhering to various operational and grid network limits. The fuel cost functions of generators are naturally nonlinear and often show discontinuities because of prohibited operating zones (POZs). Furthermore, the valve-point loading effect introduces non-convex characteristics with several local minima, posing a major challenge in reaching the global

optimum for high-dimensional ED tasks. As a result, ED remains a complex, multi-constraint optimization problem with continuous decision variables. Traditional mathematical approaches, such as Lagrange relaxation or gradient methods, are typically inadequate for such non-convex problems, leading to the adoption of advanced metaheuristic techniques like genetic algorithms (GAs), biogeography-based optimization (BBO), and ant colony optimization (ACO). These modern search strategies have demonstrated high potential in locating global or near-global solutions, though they can be computationally intensive for massive power networks.

Particle Swarm Optimization (PSO) offers distinct benefits over other metaheuristic methods, particularly regarding its simplicity, rapid convergence, and structural robustness. It is capable of reaching global or near-global optima regardless of cost function discontinuities. The efficacy of PSO in managing non-smooth ELD problems is well-documented. Nevertheless, PSO performance is highly sensitive to parameter tuning and can suffer from premature convergence or getting trapped in local optima. Being a population-based strategy, particle movement in PSO is controlled by inertia and two stochastic acceleration factors: cognitive and social components. To improve the exploration and diversity of the search process, the elements influencing particle velocity must be systematically regulated and managed to balance search capabilities."

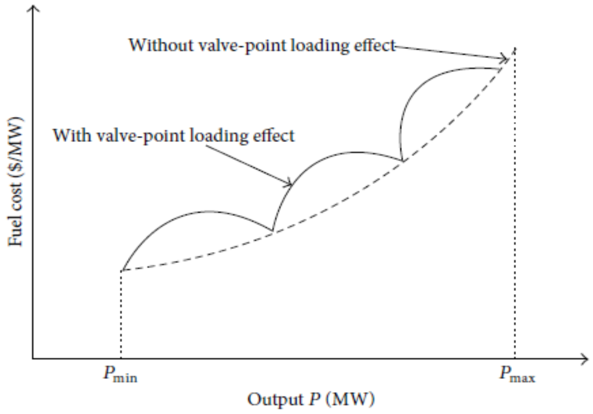


FIGURE 1: Fuel cost function with and without valve-point loading effect.

2. PROBLEM FORMULATION

The generator cost function is modeled as a quadratic equation, provided that valve-point loading impacts are overlooked. However, large-scale turbine generators are generally equipped with multiple fuel admission valves that function sequentially to accommodate higher generation levels. The activation of these valves leads to rapid throttling losses, causing a sharp increase in the incremental heat rate. This valve-point phenomenon creates ripples within the heat-rate curves, which subsequently introduces non-convexity into the generator's fuel cost profile, as illustrated in Figure 1. To accurately represent the influence of valve-point loading, a sinusoidal component is integrated into the cost function. Consequently, the modified objective function for the non-convex Economic Dispatch problem, which accounts for these advances in electrical engineering, can be formulated as follows:"

$$\text{Minimize } F(P_{Gi}) = \sum_{i=1}^{N_G} \left(a_i + b_i P_{Gi} + c_i P_{Gi}^2\right) + \left|e_i \sin\left(f_i \left(P_{Gi\min} - P_{Gi}\right)\right)\right|$$

$$\sum_{i=1}^{N_G} P_i = PD + \sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{N_G} P_{Gi} B_{i0} + B_{00},$$

where a_i, b_i, and c_i are the cost coefficients of the ith generator, e_i and f_i are the valve-point effect coefficients, P_{Gi} is the real power output of the ith generator, and N_G is the number of generating units in the system.

Subject to the following constraints:

(1) *Power Balance Constraint*

The total power generation of all generators must be equal to the sum of total power demand plus the network power loss. The network power loss can be evaluated using B-coefficient loss formula. There fore,the generator power balance equation may be stated as follows:

where B_{ij} is the transmission loss coefficient i =1, 2, . . . , N_G and j = 1, 2, . . . , N_G, B_{i0} is the ith element of the loss coefficient vector. B_{00} is the loss coefficient constant.

(2) *Generator Constraint.*

For stable operation, power output of each generator is restricted within its minimum and maximum limits. The generator power limits are expressed as follows:

Prohibited operating zones lead to discontinuities in the input output relation of generators. Prohibited zones divide the operating region between minimum and maximum generation limits into disjoint convex sub regions. The generation limits for the I th unit with j number of

(3) *Prohibited Operating Zones.*

prohibited zones can be expressed as follows:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}.$$

where superscripts L and U stand for the lower and upper limit of prohibited operating zones of generators. $NGPZ$ and $NPZi$ denote the total number of generators with prohibited zones and the total number of prohibited zones for the ith generator, respectively.

3. HYBRID PSO-ACO APROACH

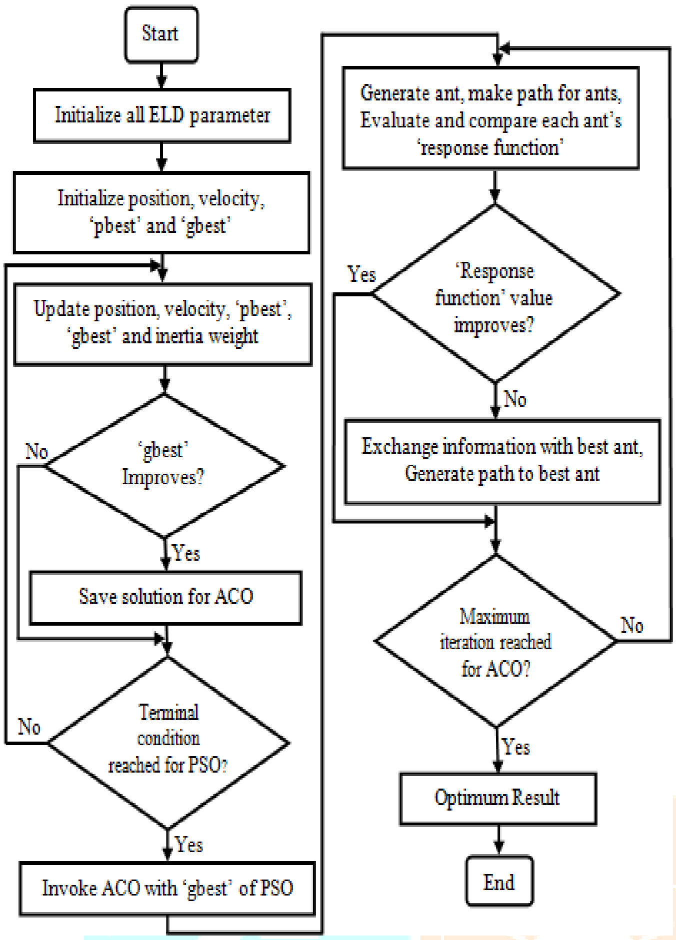
$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi,1}^{L},$$

$$P_{Gi,j-1}^{U} \le P_{Gi} \le P_{Gi,j}^{L},$$

$$P_{Gi,N_{PZi}}^{U} \le P_{Gi} \le P_{Gi}^{\max};$$

$$i \in \{1, 2, \ldots, N_{GPZ}\},\ j \in \{2, 3, \ldots, N_{PZi}\}$$

PSO is a population-centric heuristic search framework that replicates the collective behavior of swarms to identify the optimal solution for complex optimization tasks. Within the PSO mechanism, particles execute parallel explorations of the search space by continuously adjusting their velocity and coordinates. During each iteration, the algorithm monitors two critical parameters: 'pbest,' representing the individual peak performance of a particle, and 'gbest,' which denotes the overall superior value achieved by the entire group. Complementing this, ACO is a swarm-driven methodology inspired by the foraging strategy of ant colonies, where members identify the most direct route to a food source. Although every ant explores a distinct path, the colony arrives at more efficient solutions by communicating via 'pheromone' trails. Consequently, much like an actual ant, the ACO framework systematically constructs and refines solutions by traversing various nodes within a neighborhood graph. While PSO is favored for Economic Load Dispatch due to its structural flexibility and rapid convergence, it can occasionally produce suboptimal outcomes when particles over-concentrate at the 'gbest' point. Conversely, ACO is recognized for its exceptional local search capabilities near global optima. When integrated, the hybrid PSO-ACO approach provides a more effective equilibrium between global exploration and local exploitation.



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