A Review on Soft Computing Approaches for Optimal Economic Load Dispatch in Microgrids

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ABSTRACT

This paper discusses the application of soft computing methods for optimizing economic load dispatch in microgrids. Microgrids, with their distributed energy resources (DERs) and localized energy management, offer promising solutions for resilient and efficient power systems. However, the complex and dynamic nature of microgrids, along with uncertainties in renewable energy sources (RERs), challenges traditional optimization techniques. Soft computing methods, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Differential Evolution (DE), have demonstrated their ability to handle non-linear and multi-objective optimization tasks. This review explores the benefits and limitations of soft computing techniques in microgrid economic load dispatch, highlighting their potential for enhanced economic benefits, reduced carbon footprints, and improved grid stability. The study underscores the need for tailored approaches to maximize the potential of soft computing in microgrid optimization and presents valuable insights for researchers and practitioners in the field.

Keywords—Microgrid, Soft computing, Optimization, Economic Load Dispatch, Renewable energy sources, Distributed Energy Resources.

#  INTRODUCTION

 Microgrids have emerged as a promising paradigm in modern power systems, offering a decentralized and resilient approach to energy generation, distribution, and consumption [1, 2]. By integrating diverse DERs, energy storage systems, and smart control technologies, microgrids empower local communities and industrial facilities to manage their energy needs efficiently and independently, while also contributing to grid stability and sustainability [3, 4]. One of the critical challenges in microgrid operation is achieving optimal economic load dispatch (ELD), where the objective is to judiciously allocate power generation among various sources to minimize operational costs while meeting local demand and grid constraints [5-10].

Traditional optimization techniques, though valuable for certain power system applications, often face limitations when applied to microgrid ELD [11-13]. The decentralized nature of microgrids, coupled with the variability and uncertainty of renewable energy sources, calls for innovative approaches that can handle the complexity and non-linearity of this optimization problem. In recent years, soft computing methods have gained significant attention for their adaptability and effectiveness in addressing such intricate and dynamic tasks.

Soft computing methods encompass a diverse set of computational techniques inspired by nature and human-like reasoning. GA, PSO, ACO, DE, and other soft computing techniques offer unique strengths in tackling multi-objective, non-linear, and uncertain optimization problems, making them promising candidates for microgrids ELD optimization [14-18].

This paper presents a comprehensive review of the application of soft computing methods for optimizing economic load dispatch in microgrids. The objective is to provide a thorough understanding of the various soft computing techniques and their suitability for addressing the challenges posed by microgrid ELD. Each method's underlying principles, advantages, and limitations will be explored in the context of microgrid operation, shedding light on their potential contributions to enhanced economic efficiency, reduced environmental impact, and improved grid stability.

Furthermore, the review will emphasize the need for tailoring soft computing approaches to the unique characteristics of microgrids. Considering the diverse energy resources, load profiles, and operational constraints encountered in microgrids, the paper will discuss potential hybridization and customization of soft computing methods to maximize their effectiveness in solving ELD problems.

As microgrids continue to evolve and gain traction as viable energy solutions, the role of soft computing in optimizing their operation becomes increasingly significant. By providing insights into the state-of-the-art soft computing techniques for microgrid ELD, this review aims to guide researchers, power system operators, and policymakers in making informed decisions regarding the selection and implementation of appropriate optimization strategies. Ultimately, harnessing the potential of soft computing methods in microgrid ELD is crucial for realizing the full potential of these energy systems in creating sustainable, resilient, and economically efficient power networks.

# MATHEMATICAL FORMULATION OF ELD PROBLEM

 In the context of microgrids, the ELD problem involves determining the optimal allocation of power generation among diverse DERs and energy storage systems to minimize the operational cost while meeting local demand and grid constraints. The primary objective is to achieve an efficient and cost-effective power generation schedule that accounts for the intermittent and uncertain nature of renewable energy sources and varying load profiles within the microgrid.

## **Conventional Generator Cost Function**

 The primary goal of economic generator dispatch is to determine how to allocate the available load demands among the online units available for dispatch [31]. The main objectives include minimizing generator fuel costs while meeting load requirements and adhering to operational limitations. The mathematical representation of the cost function for a conventional generator can be found in reference [32].

$C\_{F}=\sum\_{K=1}^{N\_{G}}C\_{I}\left(P\_{I}\right)$ (1)

Where $C\_{F}$ – Fuel cost, NG - Generator’s Number

$C\_{I}\left(P\_{I}\right)$- Fuel cost and power generation of the Ith generator.

The $C\_{I}\left(P\_{I}\right)$ is defined as,

$C\_{I}(P\_{I})=(μ\_{I}P\_{I}^{2}+φ\_{I }P\_{I}+ω\_{I})$ (2)

where $μ\_{K}$, $φ\_{K }$and $ω\_{K}$are used as cost coefficients of the Ith generator.

$Min\left(C\_{I}\right)=\sum\_{I=1}^{GN\_{G}}(μ\_{I}P\_{I}^{2}+φ\_{I }P\_{I}+ω\_{I}) $ (3)

Valve point loading introduces complexity to the cost function of conventional generators, rendering it both non-linear and non-smooth. The formulation of the economic dispatch cost function considering valve point loading can be found in reference [33].

$Min \left(C\_{F}\right)= \sum\_{I=1}^{GN}(μ\_{I}P\_{I}^{2 }+ φ\_{I}P\_{I}+ ω\_{I})+abs(δ\_{I}×sin⁡(χ\_{I}×(P\_{I}^{min }- P\_{I })$ (4)

The functioning of traditional gas or diesel generators results in the release of specific pollutants. From an environmental perspective, it becomes essential to restrict the emissions within certain limits. The optimization of generator cost and the reduction of emissions can be tackled simultaneously as a multi-objective challenge. To address such a multi-objective problem, a concept called a penalty factor is introduced. This factor transforms the multi-objective problem into a single-function formulation.

The cumulative emission level for the given system is aggregated as follows:

$C\_{E}= \sum\_{I=1}^{N\_{G}}(ζ\_{I}P\_{I}^{2}+ η\_{I}P\_{I}+ θ\_{I})$ (5)

Where$ ζ\_{I}$, $η\_{I}, $and$θ\_{I}$ are used as coefficients of emission for Ith generator.

The precise representation of generator cost characteristics takes into account the inherent higher-order nonlinearity. The abrupt changes in the cost function primarily arise from valve point loading (VPL), and this impact is integrated into the objective function. This function is then subject to additional nonlinear constraints such as minimum fuel constraints (MF), prohibited operating zones (POZ), start-up ramping (SR), and ramp rate limits (RRL). The entirety of this problem formulation is categorized as a static economic dispatch (ED) problem, as it typically operates within a fixed time frame.

## **Cost Function for Solar power**

The expression representing the cost function related to solar power is detailed in reference [9].

$C\left(S\_{P}\right)= 547.7483 ×S\_{P}$ (6)

Where SP is the solar power in MW.

## **Cost Function for Wind power**

The calculation of the cost function for wind energy is performed as follows:

$C\left(W\_{P}\right)=153.3810 × W\_{P}$ (7)

Where the value of WP represents the wind power in megawatts.

Therefore, the power balance equality constraint is formulated as follows:

$P\_{L}= \sum\_{I=1}^{N\_{G}}P\_{I}+S\_{P}+W\_{P}$ (8)

Where PL represents the cumulative power generated by conventional generating units, SP signifies the output derived from solar sources, WP represents the output harnessed from wind sources, and PL corresponds to the total connected load within the microgrid.

# SOFT COMPUTING TECHNIQUES

 Due to the complexity, non-linearity, and uncertainty associated with microgrid operations, traditional optimization methods may not be sufficient to obtain the global optimal solution. Hence, the application of soft computing methods, such as GA, PSO, ACO, and others, becomes essential to address the challenges posed by microgrid ELD effectively. These soft computing techniques can efficiently navigate large solution spaces, consider multi-objective criteria, and adapt to the dynamic nature of microgrids, resulting in improved economic efficiency, reduced environmental impact, and enhanced grid stability.

## **Classification and application of soft computing techniques**

 Soft computing techniques can be broadly classified into three main categories based on their underlying principles and approach to problem-solving:

1. Evolutionary Algorithms (34): Evolutionary algorithms draw inspiration from the principles of natural selection and genetics. They employ the concept of evolution to iteratively improve a population of potential solutions over generations. The fittest individuals in the population are selected, undergo genetic operations (crossover and mutation), and produce offspring that inherit their traits. This process simulates the survival of the fittest and drives the population towards optimal or near-optimal solutions. Examples of evolutionary algorithms include GA, Genetic Programming (GP), and DE.

2. Swarm Intelligence-based Techniques (34): Swarm intelligence algorithms are inspired by the collective behavior of social organisms, such as ants, birds, and fish. They involve a population of agents (particles, ants, bees, etc.) that interact with one another and with their environment to find solutions to complex problems. These algorithms often use simple rules for communication and movement, leading to emergent behavior that guides the search towards the optimal solution. Examples of swarm intelligence-based techniques include PSO, ACO, and Firefly Algorithm (FF).

3. Fuzzy Systems (1): Fuzzy systems deal with uncertainty and imprecision in data and reasoning. They are based on fuzzy logic, a mathematical approach that allows variables to have partial membership in a set. Instead of crisp binary values (true/false, 0/1), fuzzy logic uses degrees of membership (between 0 and 1) to represent vague or uncertain information. Fuzzy systems can handle linguistic variables and provide more human-interpretable solutions in uncertain environments. Examples of fuzzy systems include Fuzzy Logic Controllers (FLC) and Fuzzy Rule-Based Systems.

These classifications highlight the diversity of soft computing techniques and their versatility in solving complex problems across various domains, including optimization, control, pattern recognition, data analysis, and decision-making. The choice of which technique to use depends on the specific problem requirements and characteristics, and researchers often explore hybridization and customization to tailor soft computing methods to the particular needs of a given application.

## **Application of soft computing techniques**

Soft computing techniques have been successfully applied to ELD in microgrids to optimize the power generation schedule and achieve economic efficiency while satisfying various operational constraints. Here are the details of some commonly used soft computing techniques for ELD in microgrids:

1. GA [19-20]: GA is a popular evolutionary algorithm inspired by the process of natural selection and genetics. In the context of microgrid ELD, GA starts with a population of potential solutions, where each solution represents a set of power outputs for the distributed energy resources. Through selection, crossover, and mutation operations, GA evolves the population over successive generations to find the optimal power generation schedule that minimizes the total operational cost while satisfying the demand and constraints.

2. PSO [21]: PSO is a swarm intelligence-based optimization technique inspired by the social behavior of birds flocking or fish schooling. In the microgrid ELD scenario, PSO simulates a population of particles that represent potential solutions. Each particle adjusts its position based on its own experience and the experience of its neighboring particles. This collective movement guides the particles towards the optimal power generation schedule that minimizes the cost while adhering to the operational constraints.

3. ACO [22-23]: ACO is an optimization algorithm inspired by the foraging behavior of ants. In the microgrid ELD context, artificial ants are used to explore the search space of possible power generation schedules. Ants lay down pheromone trails representing the desirability of certain solutions. Over time, these trails guide other ants to converge towards the optimal power output distribution that minimizes the cost and meets the load demand.

4. DE [24-26]: DE is a population-based optimization algorithm that employs a differential mutation strategy to generate new potential solutions. In microgrid ELD, DE iteratively improves the power output distribution by creating trial solutions based on the differences between existing solutions. The best-performing solutions are retained for further optimization, leading to the convergence towards the optimal economic load dispatch.

5. Simulated Annealing [27-28] (SA): SA is a probabilistic optimization technique inspired by the annealing process in metallurgy. It allows the algorithm to accept worse solutions with a certain probability, which helps escape local optima and explore the search space effectively. In microgrid ELD, SA finds the optimal power generation schedule by gradually reducing the acceptance probability for worse solutions as the optimization progresses.

6. Grey Wolf Optimizer [29-30] (GWO): GWO is a nature-inspired optimization algorithm based on the social hierarchy and hunting behavior of grey wolves. In microgrid ELD, GWO mimics the leadership and hunting mechanisms of wolf packs to converge towards the optimal power output distribution that minimizes the cost while meeting the load demand and system constraints.

These soft computing techniques have shown significant promise in solving the economic load dispatch problem in microgrids. They offer advantages in terms of adaptability, robustness, and ability to handle the complexities and uncertainties associated with microgrid operations. Additionally, researchers often explore hybrid approaches, combining multiple soft computing methods or integrating them with other optimization techniques, to achieve even better results and overcome potential limitations.

**Table 1: Table presents a comparative analysis to monitor various soft computing techniques**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Soft computing Technique** | **Optimization Technique** | **Test Systems** | **Constraints** | **Reference** |
| **Evolutionary algorithms(34)** | Genetic algorithm | 3 units | Non linear constraints with VPLE | 36 |
| Genetic algorithm binary | 3 units | Non linear constraints with VPLE | 37 |
| Improved genetic algorithm | 40 units | Non linear constraints with VPLE | 38 |
| Differential evolution | 13 , 15 , 40 units | Non linear constraints with VPLE, POZ, VF and RRL | 39 |
| Modified differential evolution | 13 , 15 , 40 units | Non linear constraints with VPLE, POZ, and RRL  | 40 |
| Adaptive real coded genetic algorithm | 10, 40 units | Non linear constraints with VPLE and VF | 50 |
| Shuffled differential evolution | 3, 13, 40 units | Non linear constraints with VPLE | 51 |
| Conventional genetic algorithm - multiplier updating | 3, 10, 13 units | Non linear constraints with VPLE and VF | 52 |
| Classical evolutionary programming | 3,13,40 units | Non linear constraints with VPLE | 53 |
| **Swarm Intelligence-based Techniques(34)** | Ant colony optimization | 10, 13, 40 units | Non linear constraints with VPLE and VF | 41 |
| Bacterial foraging algorithm | 13, 15, 40 units | Non linear constraints with POZ and RRL | 42 |
| Modified particle swarm optimization | 3, 10, 40 units | Non linear constraints with VPLE and VF | 43 |
| Artificial bee colony algorithm | 10, 13, 15 units | Non linear constraints with VPLE, POZ and VF | 44 |
| Quantum inspired PSO | 3, 13, 40 units | Non linear constraints with VPLE | 54 |
| New particle swarm optimization | 40 units | Non linear constraints with VPLE, POZ, VF and RRL | 55 |
| Self-Organizing Hierarchical Particle Swarm Optimization  | 3, 10,15, 40 units | Non linear constraints with VPLE, POZ and RRL | 56 |
| **Fuzzy Systems(35)** | Fuzzy Logic Controller  | 3 units | Non linear constraints | 31, 45 |
| Pareto criterion and fuzzy logic  | 6 units | Non linear constraints with POZ and RRL | 46 |
| Fuzzy Logic Controlled Genetic Algorithms  | 6 units | Non linear constraints | 47 |
| Genetic algorithm and Fuzzy logic  | 10 units | Non linear constraints with POZ and RRL | 48 |
| Fuzzy logic controlled differential evolution  | 13, 40 units | Non linear constraints with VPLE | 49 |

# CONCLUSION

 This article provides an extensive review of recent research focused on solving three critical problems: classic dispatch, dynamic dispatch, and Economic Emission Dispatch (EED). The article delves into practical ELD problems that involve both convex and nonconvex cost functions, while considering modern generators' nonlinear inequality constraints.

The exploration begins with a centralized optimization perspective, addressing computational challenges like premature convergence, local-minima entrapment, convergence characteristics, and implementation time associated with various optimization techniques. The discussion then extends to different strategies for handling equality and inequality constraints in both single-objective and multi-objective ED problems.

Furthermore, the article presents a comprehensive overview of a wide array of optimization methods, comparing their performance concerning multiple nonlinear operational constraints such as Valve Point Effect (VPE), Valve-Fuel Interaction (VF), POZ, RRL, and Start-up Ramp (SR), alongside IEEE standard test systems.

The article thoroughly investigates concerns related to computational efficiency, communication congestion, and potential topological changes in future power systems. It distinguishes itself from previous articles by comprehensively covering advancements in centralized, decentralized, and distributed optimization techniques, offering a detailed taxonomy and their applications in economically operating deregulated power systems.

The author presents future trends based on the surveyed literature, emphasizing the following points:

1. Although the classic dispatch problem has been extensively explored and improved, there is still an opportunity to employ decentralized and distributed approaches that could lead to substantial operational and decision-making transformations.

2. A thorough exploration of diverse deregulated market-based approaches is essential to address security, privacy, and economic concerns in multi-area interconnected systems.

3. Given the rise of communication-based technologies, the concept of operations management in future power systems will remain interdisciplinary. Incorporating these technologies into the hierarchical control level presents significant potential.

In summary, the article offers a comprehensive and forward-looking perspective on solving economic dispatch problems, spanning both current challenges and future prospects in the domain.

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