A REVIEW ON SOFT COMPUTING APPROACHES FOR OPTIMAL ECONOMIC LOAD DISPATCH IN MICROGRIDS

Abstract

This article examines the utilization of soft computing techniques to enhance the optimization of economic load distribution within 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.

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I. 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 article provides an extensive overview of how soft computing techniques are employed to optimize the economic load allocation 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, the intention of this review is to offer guidance to researchers, power system operators, and policymakers, aiding them in making well-informed choices regarding the identification and adoption of suitable 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.

II. 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.

1. **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].

$$C_F = \sum_{K=1}^{N_G} C_I(P_I) \tag{1}$$

Where C_F – Fuel cost, N_G - Generator's Number

$C_I(P_I)$- Fuel cost and power generation of the I^{th} generator.
The $C_I(P_I)$ is defined as,

$$C_I(P_I) = (\mu_I P_I^2 + \varphi_I P_I + \omega_I) \tag{2}$$

where μ_K, φ_K and ω_K are used as cost coefficients of the I^{th} generator.

$$Min(C_I) = \sum_{I=1}^{GN_G}(\mu_I P_I^2 + \varphi_I P_I + \omega_I) \tag{3}$$

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].

$$Min\ (C_F) = \sum_{I=1}^{GN}(\mu_I P_I^2 + \varphi_I P_I + \omega_I) + abs(\delta_I \times \sin(\chi_I \times (P_I^{min} - P_I) \tag{4}$$

The operation of conventional gas or diesel generators leads to the emission of particular pollutants. From an environmental standpoint, it becomes imperative to confine these emissions within defined thresholds. Simultaneously, optimizing generator costs while minimizing emissions becomes a multi-faceted task. To address this multi-objective issue, the notion of a penalty factor is introduced. This factor serves to convert the multi-objective problem into a singular function formulation.

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

$$C_E = \sum_{I=1}^{N_G}(\zeta_I P_I^2 + \eta_I P_I + \theta_I) \tag{5}$$

Where ζ_I, η_I, and θ_I are used as coefficients of emission for I^{th} generator.

The accurate depiction of generator cost attributes considers the inherent complexity of higher-order nonlinearity. Sudden shifts in the cost function predominantly result from valve point loading (VPL), and this influence is incorporated into the main objective function. This function is subsequently subjected to supplementary nonlinear restrictions including minimum fuel requirements (MF), disallowed operational regions (POZ), start-up ramping (SR), and ramp rate limitations (RRL). The entirety of this problem formulation is classified as a static economic dispatch (ED) problem, as it customarily functions within a predetermined timeframe.

2. **Cost Function for Solar Power:** The expression representing the cost function related to solar power is detailed in reference [9].

$$C(S_P) = 547.7483 \times S_P \tag{6}$$

Where S_P is the solar power in MW.

3. **Cost Function for Wind Power:** The calculation of the cost function for wind energy is performed as follows:

$$C(W_P) = 153.3810 \times W_P \tag{7}$$

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

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

$$P_L = \sum_{I=1}^{N_G} P_I + S_P + W_P \tag{8}$$

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

III. 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.

1. **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:

   - **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.

- **Methods Rooted in Swarm Intelligence (34):** Algorithms that use swarm intelligence are inspired by the group 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).

- **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.

2. **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:

- **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. Utilizing selection, crossover, and mutation operations, GA iteratively evolve the population across consecutive generations, aiming to discover the optimal power generation schedule that achieves the dual objectives of minimizing total operational cost and adhering to demand and constraints.

- **PSO [21]:** Particle Swarm Optimization (PSO) is an optimization technique rooted in swarm intelligence, drawing inspiration from the social behaviors observed in birds flocking or fish schooling. In the context of microgrid Economic Load Dispatch (ELD), PSO emulates a population of particles, symbolizing potential solutions. Each particle refines its position by considering its individual experience and the collective experience of neighboring particles. This cooperative motion guides the particles toward the optimal power generation schedule, achieving cost minimization while satisfying operational limitations.

- **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.

- **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.

- **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.

- **The Grey Wolf Optimization (GWOA) [29-30]** is an optimization algorithm inspired by the social hierarchy and hunting patterns of grey wolves. In the context of microgrid Economic Load Dispatch (ELD), GWOA emulates the leadership and hunting strategies observed in wolf packs. This enables the algorithm to converge towards the optimal distribution of power output, aiming to minimize costs while fulfilling load demands and adhering to 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

	Genetic algorithm – Sequential Quad. Prog.	3, 6, 11, 13, 15, 20	Non linear constraints with VPLE, POZ, VF and RRL	60
	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
	Crow Search Algorithm	IEEE 37 Node feeder	Non linear constraints	61
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

	Dynamic Differential Annealed Optimization	6, 40 units	Non linear constraints with VPLE, POZ and RRL	62
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

IV. CONCLUSION

This paper offers an extensive review of recent research endeavors centered on addressing three pivotal problems: classical dispatch, dynamic dispatch, and Economic Emission Dispatch. The study delves into practical ELD challenges that encompass both convex and non convex cost functions, while accommodating the intricate nonlinear inequality constraints of modern generators.

The exploration commences from a vantage point of centralized optimization, tackling computational hurdles such as premature convergence, entrapment in local minima, convergence behaviors, and implementation time associated with diverse optimization methods. The discourse then expands to encompass various strategies for managing equality and inequality constraints in both single-objective and multi-objective ED scenarios.

Moreover, the article delivers a comprehensive survey of a wide spectrum of optimization techniques, evaluating their performance across multiple nonlinear operational constraints including Valve Point Effect (VPE), Valve-Fuel Interaction (VF), POZ, RRL, and Start-up Ramp (SR), all while benchmarked against IEEE standard test systems.

The paper deeply investigates considerations revolving around computational efficiency, communication congestion, and potential topological alterations in forthcoming power systems. What sets it apart from preceding works is its holistic coverage of advancements in centralized, decentralized, and distributed optimization approaches, presenting an intricate categorization and their practical applications within economically efficient operations of deregulated power systems.

The author emphasizes upcoming patterns obtained from the reviewed literature, highlighting the following points:

- 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.
- A comprehensive investigation into a variety of market-based approaches within deregulated environments is imperative to effectively tackle security, privacy, and economic considerations in multi-area interconnected systems.
- With the proliferation of communication-based technologies, the notion of operations management in future power systems is poised to remain interdisciplinary. The integration of these technologies into the hierarchical control level holds substantial promise.

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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