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Economic Load Dispatch in Smart Renewable Energy Grid with the Help of Advanced Soft Computing Techniques

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ABSTRACT

Economic Load Dispatch (ELD) is crucial in managing and operating renewable energy power systems by aiming to minimize overall generation costs while fulfilling demand and adhering to operational constraints. The incorporation of renewable energy sources (RES) and the development of smart grids have made ELD increasingly complex. To address these challenges, advanced soft computing methods like Genetic Algorithms (GA), Particle Swarm Optimization (PSO) and Fuzzy Logic offer promising solutions. This paper thoroughly reviews the application of these techniques in ELD within smart grids, discussing their advantages, limitations, and potential for future research. The integration of advanced technologies fuzzy systems and soft computing is crucial for effective renewable energy supply. Conceptually, a smart renewable energy grid represents the integration of information and operational technologies in the power grid, providing sustainable options to customers and enhancing security. This approach can lead to reduced power losses to improved utilization

of power.

1. Introduction

Economic load dispatch (ELD) is a crucial aspect of power system operation, addressing the need to distribute load efficiently across generating units. This task is inherently discontinuous, nonlinear, and combinatorial. Traditional ELD methods typically sum all load buses without considering the capacity of transmission lines [1] . These conventional algorithms often employ the Lagrange method and first or second-order gradients, along with dynamic programming. A relative overview of the current state of economic dispatch for renewable energy can be found in recent surveys [2]. These reviews trace the evolution of optimal dispatch back in early 1920s, when scientist first tackled the challenge of economically allocating generation and distributing load among available units[3] . Before 1930, various methods were utilized, including base load method, which involved loading the most efficient unit to its full capacity before proceeding to the next and "Best Point Loading," where units were loaded to their lowest heat rate points in descending order of efficiency.

Modern approaches to solving the economic dispatch problem with transmission capacity constraints have been documented, with direct search methods explained in detail [4]. For example, studies from 2007 discuss solving two-area power system economical dispatch problems while taking transmission capacity limitations[5] [6].

Electrical energy is vital for domestic, industrial development of country, as it can be generated centrally in large amounts and cost-effectively transmitted over long distances. Its adaptability for related applications, especially for lighting, maintenance and industrial work, makes it indispensable. The per capita consumption of electrical energy is a dependable measure of a country's development level; in 1986, this was for India in the capacity of 150 kWh, 4000 kWh for the UK, and 9000 kWh for the USA.

As we know electricity cannot be stored economically, and utilities have limited control over load fluctuations. Therefore, the power system must continuously match generator output to demand at specified voltage and frequency levels. This challenge is compounded by daily load variations, which include a steady base load, a variable component influenced by time of day, weather, season, and events, and a random component of smaller amplitude.

The load factor is the ration of the average load divided by the maximum peak load, is always less than unity. This ratio helps determine the power use n over a day, peak load along with standby capacity considerations, dictates the plant capacity required to meet demand. A high load factor indicates more efficient energy use from a given installation. Power system loads are categorized into three main sectors like domestic, commercial, and industrial. Heavy industrial loads are connected to the grid, while large industrial loads are served directly from the sub-transmission network. Industrial loads, primarily consisting of induction motors, are composite in nature. Commercial and residential loads, which are independent of frequency and consume minimal reactive power and varies throughout the day, requiring continuous availability to meet consumer demand. The peak or maximum demand within a 24-hour period represents the highest load value, and the load factor defined as average load over a period to the peak load in that period, is used to assess the generating plant's efficiency.

Load factors can be calculated for different time periods, such as a from day to year. The daily load factor is given by:

$$Daily\ Load\ factor = \frac{Average\ Load}{Peak\ Load}$$

The annual load factors is annual L.F. = $\frac{\text{Total annual energy}}{Peak\ Load} \times 8760hr$

Different classes of loads typically have varying peak loads, which contributes to an improved overall system load factor. For a power plant to operate efficiently and economically, it must maintain a high load factor. Currently, typical system load factors range between 55% and 70%.

The transition from traditional power systems to smart grids has brought new challenges in Economic Load Dispatch (ELD). Smart grids incorporate diverse renewable energy generation for infrastructure, requiring advanced methods to ensure optimal power distribution. This paper examines how advanced soft computing techniques can improve ELD processes, addressing the inherent complexities and variability of smart grids.

1.1 Novelty of Idea

This work introduces innovations in the field of smart renewable energy grids, focusing on emerging trends in Economic Load Dispatch (ELD) for smart grids through the use of advance techniques. It emphasizes the integration of machine learning and artificial intelligence, the creation of more efficient hybrid algorithms, and the enhancement of real-time optimization and decision-making capabilities. These approaches have not yet been fully utilized by researchers.

2 Method and methodology

Neural networks and fuzzy logic are nature-inspired approaches to solving complicated issues that are beyond the scope of conventional solutions. These techniques have been effectively implemented in a range of difficult real-world problems, including signal processing, image processing system control, electric machinery, communication, and robotics. Their use in power systems is well-established. Within the domain of artificial neural networks (ANNs), various types have been developed

The advanced intelligent methods utilizing different ANFIS systems have been explored. A significant use of smart grids is the development of good quality sensors and telecommunication systems, which enhance the visibility of traditional power grids. The integration of new plants into a power system or grid introduces complexities. For instance, adding wind energy to a grid presents unique challenges, as Since it has no marginal cost, it provides the least expensive power.

As a preliminary step, we propose the relative costs of energy from different available power sources, we present a method to identify the optimal option of a suitable generation source to supply a given electric load.

3.Proposed Method

The standard genetic operators are applied for unit commitment problem, finding feasible solutions can be challenging. To achieve feasible solutions within Several genetic operators are presented within a realistic computation time.

During the generation of initial populations, if populations are created randomly, it becomes difficult to produce feasible solutions. To address this, initial data found on the load curve, ensuring feasibility. For instance, many units are decommitted during periods of light load.

In the copy method, the best solution is duplicated to ensure that it is preserved for the next generation and can continue to evolve. Regarding mutation that is typically selects mutation points randomly, making it difficult to meet minimum up/down time constraints. To manage these constraints effectively, specific mutations are adopted that take these minimum up/down times into account.

3.1 Interior Structure

The proposed internal structure of each data is founded on the concept of fuzzy controller. Consequently, each agent should essentially include a fuzzifier, an inference engine, and a defuzzifier. Figure 1 illustrates the overall proposed internal architecture for the agents.

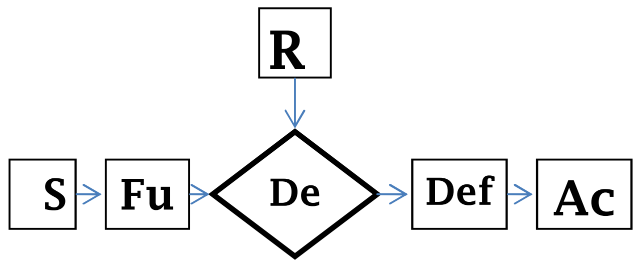

Fig.1. Proposed interior structure of a single agent

The construction of a simple fuzzy controller is shown in Figure 1. A fuzzification interface, which transforms the current values of input variables into linguistic expressions or fuzzy sets, is a component of a fuzzy controller. The fuzzy sets connected to the linguistic terms and the domains of these variables are both stored in the knowledge base. As a result, the dynamic interactions of different pieces inside the grid make modelling more complex.

The standard Optimal Power Flow (OPF) issue can be expressed as a limited optimization problem in the following way:

$$\min f(x) \quad (1)$$

$$g(x) = 0$$

$$h(x) \leq 0$$

In this formulation, f(x) is objective function and g(x) is the equality constraints, h(x) is the inequality constraints, whereas x is control variables vector. These variables include generator real power (PgP), generator voltages (Vg), transformer tap settings (T), and reactive power from VAR sources (cQc). The following objective function is introduced here:

3.1.3 Emission objective function

In Optimal Power Flow (OPF) problem formulation, the primary task is typically to minimize grid load, operational cost of fuel used to generate electricity over a specified time period, such as one hour.Each generating unit's cost is represented by a quadratic function and is assumed to be a function o nly of real power output.The total of these quadratic cost functions for every generator is the goal functi on for the power system as a whole.

Power utilities must maintain pollutant levels under the annual emission limitations established for fossil -fuel units, which results in emission control expenditures. To reduce total emissions, it is essential to minimize the three primary pollutants: nitrogen oxides (NOx), carbon dioxide (CO_2) and sulfur oxides (SOx). Based on generator real power output (PgiP_{gi}Pgi), the objective function for minimising overall emissions can be expressed as a linear equation that sums the contributions of these three pollutants.

3.1.4 Total objective function

The overall objective function simultaneously addresses both generation costs and pollution control costs. These objectives are inherently complex and often conflict with one another—for example, minimizing generation costs might lead to increased emission costs, and vice versa. Nevertheless, solutions can be found where fuel costs and emissions are integrated into a single function, using different weighting factors to balance the two aspects.

3.1.5Types of equality constraints

Making ensuring that the generation satisfies both the load demands and the transmission line losses is essential for minimizing the objective function. Power flow equations that explain the active and reactive power injections at each bus serve as a representation of the equality restrictions.

3.2 Objective Function

Total Cost

$$\text{Min } T_C = \sum_{t=1}^{T} \times \sum_{i=1}^{N} (\text{FCi}(t) + \text{SCi}(t))$$

Fuel Cost

$$\text{FCi}(t) = a_i + b_i\, P_i(t) + C_i\, P_i^2(t)$$

where, a_i, b_i, c_i are fuel cost function coefficients.

Start UP Cost

$SC_i\,(t) = \{ h\_cost: \; T_i^{0ff} \leq X_i^{off}(t) \leq H_i^{off}$

$\{ \; c\_cost: \; X_i^{off}(t) > H_i^{off}$

$H_i^{off}(t) = T_i^{0ff} + c\_s\_hour_i$

3.2.1 Constraints

System Power Balance

$$D\,(t) = \sum_{i=1}^{N} Pi(t)$$

Spinning Reserve

$$\sum_{i=1}^{N} Ii(t).P_i^{max} \geq D\,(t) + R\,(t)$$

Unit Output Limit

$$P_i^{min} \leq P_i(t) \leq P_i^{max}$$

Minimum Up-Down Time

$$\begin{cases} Ti\ 0n \leq Xion\ (t) \\ Ti\ 0ff \leq Xioff(t) \end{cases}$$

4. Soft Computing Techniques

Soft computing techniques mimic human reasoning and learning to solve complex optimization problems. This section discusses three prominent techniques: Fuzzy Logic (FL), Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). This paper provides a structured overview of the role of advanced soft computing techniques in optimizing ELD for smart grids. It underscores the potential of these methods to increase the efficiency and reliability of modern power systems, clearing the path for additional advancements in the industry

4.1 Genetic Algorithms (GA)

Genetic Algorithms are inspired by natural selection principles, operating through selection, crossover, and mutation processes to evolve solutions over generations.

- **Application in ELD**: GAs explore a wide search space and adapt to changing grid conditions, finding optimal or near-optimal solutions for ELD.
- **Advantages**: Robustness and the capacity to manage non-convex and non-linear optimization issues
- **Limitations**: Computationally intensive with slow convergence speed.

4.2 Particle Swarm Optimization (PSO)

It is basically based on the social behavior of birds flocking or fish schooling. It iteratively improves candidate solutions based on single or multi person experiences.

- **Application in ELD**: PSO effectively handles the non-linearity and high dimensionality of ELD problems in smart grids.
- **Advantages**: Simplicity, ease of implementation, and fast convergence.
- **Limitations**: Prone to local optima, performance dependent on parameter tuning.

4.3 Fuzzy Logic

Fuzzy Logic handles uncertainty and imprecision using fuzzy sets and linguistic variables.

- **Application in ELD**: Fuzzy Logic models uncertainties in load demand and generation, enabling flexible and adaptive dispatch strategies.
- **Advantages**: Ability to model complex systems and robustness to noisy data.
- **Limitations**: Requires expert knowledge to define rules and membership functions.

5. Conclusion

In the context of the high energy price, smart renewable electric grids are anticipated to offer a dependable, effective, and long-lasting solution for low-cost electricity supply electrical network. Developing such system is the part of interdisciplinary research and engineering, with a strong emphasis on intelligence and innovation in electric power engineering. Traditional expert systems based on convolution rules require hundreds of rules, while fuzzy set-based expert systems often replace many of these rules with calculations involving membership functions. This paper develops a practical understanding of electric power grids and enhance their grasp of cybersecurity.

Advanced soft computing techniques offer significant potential for addressing Economic Load Dispatch challenges in smart grids. By utilizing Genetic Algorithms, Particle Swarm Optimization, and Fuzzy Logic, it is possible to achieve more efficient, reliable, and cost-effective power distribution. Ongoing research and development are vital for unlocking the full capabilities of smart grids and securing a sustainable energy future. Future research opportunities include improving computational efficiency and scalability, addressing cybersecurity issues in smart grid ELD, and expanding the application of soft computing techniques to other areas of power system management.

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