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Bell-shaped fuzzy decision tree: a novel approach for improved decision making

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Abstract

This paper addresses the challenges of economic dispatch (ED) optimization, with a particular focus on incorporating environmental constraints. Previous studies have highlighted the effectiveness of decision tree (DT) architectures in tackling these challenges. Building on this foundation, a novel approach is introduced by integrating fuzzy logic (FL) into unit limit considerations, resulting in the development of a bell-shaped fuzzy logic-based decision tree (FLDT). This innovative method leverages bell-shaped curves for efficient nonlinear assessments of cost and emission level functions, which are particularly advantageous for managing complex thermal power plants with significant nonlinearities. The incorporation of FL enhances the numerical understanding of the process, while the use of bell-shaped functions to smooth power generation boundaries leads to reduced generation costs compared to traditional methods. Furthermore, the model addresses load uncertainty by accounting for imperfect load conditions, providing optimal solutions that balance cost efficiency and uncertainty management. To validate the methodology, it was applied to a 6-unit institute of electrical and electronics engineers (IEEE) evaluation system, demonstrating substantial performance improvements over previous approaches. The study highlights the practical significance and superior performance of the bell-shaped fuzzy decision trees (BSFDT) approach in addressing ED optimization challenges.

Keywords

Economic dispatch, Fuzzy logic, Decision tree, Optimization, Bell-shaped fuzzy decision trees.

1.Introduction

The economic dispatch (ED) problem is a critical aspect of modern electricity generation, focusing on the efficient allocation of power production among various generators to meet fluctuating demand [1]. This process aims to minimize operational costs while adhering to technical constraints, ensuring both reliability and efficiency within power systems [2]. As electricity demand continues to rise, optimizing generation costs has become increasingly essential for utility companies [3]. Traditional methods used to address the ED problem, such as linear and quadratic programming, encounter significant challenges. These include their complexity, slow convergence rates, and susceptibility to local minima in nonlinear search spaces [4]. These inefficiencies affect the optimization of power generation processes, particularly in addressing valve-point effects, ramp rate constraints, and prohibited operating zones, while simultaneously tackling the urgent need to reduce greenhouse gas emissions and production costs [5, 6].

Previous research has identified several challenges associated with traditional approaches to the ED problem, including:

- Traditional optimization methods, such as linear and quadratic programming, often struggle with the complexity of the ED problem, resulting in slow convergence rates and a tendency to become trapped in local minima [7,8].
- The growing emphasis on reducing greenhouse gas emissions necessitates the incorporation of environmental constraints into the ED problem, further complicating the optimization process [9, 10].
- The nonlinear nature of the ED problem, characterized by valve-point effects, ramp rate

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constraints, and prohibited operating zones, introduces complexities that traditional methods struggle to handle effectively [11, 12].

- The computational demands of traditional techniques can be prohibitive, particularly for large-scale power systems, emphasizing the need for more efficient and scalable approaches [13, 14].

These limitations hinder the attainment of optimal solutions, emphasizing the need for an approach that effectively addresses the complexities of the ED landscape. The ED problem is characterized by various challenges that complicate traditional optimization techniques. These include complexities arising from nonlinearities, such as valve point loading effects and ramp rate constraints, which introduce irregularities that traditional methods struggle to handle effectively. Furthermore, the increasing focus on environmental sustainability necessitates the incorporation of greenhouse gas emission constraints, adding another layer of complexity to the optimization process. Additionally, the computational demands of conventional methods can be prohibitive, particularly in large-scale power systems, thereby highlighting the urgent need for more efficient and scalable solutions.

This study aims to develop a novel methodology for solving the ED problem through a bell-shaped fuzzy decision trees (BSFDT) approach, addressing both computational complexities and environmental constraints. The primary objective is to establish a framework for combined economic and emission dispatch, introducing the term 'bell-shaped fuzzy decision tree (DT) methodology' to describe a hybrid strategy that integrates fuzzy logic (FL) concepts into DT framework. This approach seeks to balance conflicting objectives in power systems, such as reducing emissions and minimizing operating costs.

The key objectives of this study are as under:

1. To develop a computationally efficient method for optimizing the ED problem, emphasizing the balance between economic resolution and computational complexity.
2. To integrate FL into the ED optimization framework, enabling the handling of both hard and soft constraints in power generation for more adaptable and robust solutions.
3. To validate the proposed BSFDT approach by applying it to a 6-unit institute of electrical and electronics engineers (IEEE) evaluation system, demonstrating its capability to address environmental constraints, reduce generation costs, and manage load uncertainties effectively.

FL is employed to address the nonlinearities and uncertainties inherent in emission dispatch and economic concerns. Fuzzy sets are used to represent inputs such as fuel price, environmental levels, and power demand. These fuzzy sets include linguistic variables like 'low,' 'medium,' and 'high.' The term 'bell-like' refers to the use of membership functions that are either Gaussian or bell-shaped, effectively illustrating the degree of membership for fuzzy parameters. These functions are particularly well-suited for modeling real-world systems with gradual state transitions. Additionally, the study examines the impact of various cost indices (e.g., b and cmin) on the total cost of electricity generation, particularly in high-demand scenarios [15]. The proposed approach enhances system efficiency while reducing computational complexity, incorporating ecological considerations and soft constraints to achieve cleaner and more cost-effective power generation.

Key contributions include identifying the optimal dispatch options through an organized, rule-based approach provided by DTs. Branching decisions are determined by the degree of participation of variables in fuzzy sets, with each node in the tree representing a potential fuzzy rule. The tree enables the decomposition of the complex dispatch problem into smaller, more manageable components. It facilitates the optimization of power generation while considering factors such as valve-point effects, ramp rate limits, and prohibited operating zones, and simultaneously minimizes environmental impacts by reducing greenhouse gas emissions (e.g., CO, SO_2, and N_2O). This technique provides an efficient and straightforward solution for early detection of optimization issues with minimal processing overhead.

Furthermore, this research introduces a novel fuzzy logic-based decision tree (FLDT) approach to address the inherent nonlinearities and uncertainties of the ED problem [16]. By incorporating FL into unit limit specifications, a more flexible framework is established, effectively handling both hard and soft constraints. This integration allows for the softening of generation boundaries, leading to lower generation costs and improved system performance, especially under varying load conditions [17].

The primary contributions of this research are the development of a straightforward and reliable technique for solving the ED problem. This approach minimizes the number of iterations needed to achieve optimal solutions while accounting for the influence of various cost indices on electricity generation costs, especially in high-demand scenarios. By incorporating FL into the optimization framework [18–23], this study introduces a more flexible and effective method for addressing both hard and soft constraints, thereby improving system performance and mitigating ecological impacts

The structure of this paper is as follows: Section 2 provides a comprehensive literature review, emphasizing the limitations of traditional methods and the advantages of innovative approaches. Section 3 details the proposed methodology. Section 4 presents the results, showcasing the performance improvements achieved through the proposed approach. Lastly, Section 5 concludes the study by summarizing the key findings and suggesting directions for future research.

2.Literature survey

The objective of ED, a critical optimization challenge in power systems, is to minimize energy production costs while adhering to system constraints such as generator limits and power demand. This concept is extended by combined economic and emission dispatch (CEED), which incorporates multiple objectives and constraints into the decision-making process, including operational flexibility, renewable energy integration, and pollution reduction [24, 25].

CEED enables the simultaneous optimization of various objectives, such as system reliability, environmental impact, and economic cost [26, 27]. This comprehensive approach aligns with modern environmental goals, making it particularly suitable for policies aimed at reducing emissions and integrating green energy. Additionally, CEED enhances the adaptability of power systems by accounting for uncertainties associated with renewable energy sources like solar and wind. Techniques incorporating stochastic or fuzzy reasoning can effectively manage such uncertainties, ensuring reliable and efficient power delivery under ambiguous conditions.

CEED also proves to be a valuable tool for modern power system operations by considering variables such as grid congestion, ancillary services, and dynamic pricing. It supports demand-response strategies and the transition to smart grids. By balancing trade-offs among fuel costs, emissions, and operational constraints, CEED ensures more efficient resource allocation. This is particularly advantageous in deregulated energy markets, where conflicting objectives among stakeholders are common.

Advanced decision-making techniques such as FL, neural networks, and evolutionary algorithms integrate seamlessly with CEED frameworks [28, 29]. For instance, fuzzy DTs with bell-shaped membership functions can effectively capture nonlinear relationships with uncertainties, thereby improving decision accuracy. The hierarchical structure of these methods helps break down complex problems into smaller, manageable sub-problems, significantly reducing computational complexity.

However, integrating multiple objectives and constraints into CEED frameworks increases computational demands. Solving multi-objective optimization problems often requires high processing power and sophisticated algorithms, which can be challenging for real-time applications. Furthermore, the accuracy of CEED frameworks heavily depends on the quality and availability of input data. Inaccurate or incomplete data, especially in systems with high renewable energy penetration, can result in suboptimal decision-making [30–32]. Implementing CEED frameworks may also require policy adjustments, additional investments in computational tools, and system upgrades, which could face regulatory or stakeholder resistance. Additionally, the performance of CEED models diminishes with the size and complexity of the system, particularly in large interconnected grids or networks with a significant share of distributed energy resources.

The BSFDT technique offers a novel solution to some of CEED's challenges, particularly in handling uncertainties and nonlinear decision-making scenarios. Bell-shaped membership functions enable smooth transitions between fuzzy states, enhancing the representation of uncertainties related to grid constraints and renewable energy generation. Moreover, the hierarchical nature of BSFDT simplifies computational complexity by decomposing large problems into smaller, manageable components.

CEED provides a robust framework for addressing the complexities of modern power systems, it also presents challenges related to data dependency, trade-off management, and computational demands [33, 34]. These challenges can be mitigated by employing advanced techniques like BSFDT, which enable more efficient and accurate decision-making in complex energy systems. The integration of CEED frameworks with cutting-edge decision-making technologies holds promise for developing resilient and sustainable power systems [35].

This opens new opportunities for BSFDT applications, which are particularly well-suited for solving unpredictable and dynamic dispatch problems [36, 37]. In ecological and environmental contexts, fuzzy DTs have demonstrated their versatility by balancing economic benefits and environmental impacts in pricing models. Traditional deterministic models often fail to handle the complex, dynamic datasets arising from the unpredictable nature of inductive load patterns in electric power systems, particularly in microgrid configurations. BSFDT has enabled the development of adaptable pricing approaches that are both cost-effective and environmentally sustainable.

Fuzzy DTs have also proven effective in other technical applications requiring resilient handling of uncertainties and nonlinear control, such as sensor design, hybrid circuit control, and Lidar-based monitoring [38]. Their adaptability is critical for real-world engineering tasks where uncertainty is a constant factor, such as perturbations in merged ED optimization. In such scenarios, precise monitoring is required, yet data is often noisy or incomplete.

The combination of fuzzy DTs with advanced machine learning models, such as neural networks, holds significant potential for developing resilient and adaptable decision-making systems. These systems can address economic and emission dispatch optimization challenges arising from nonlinear loads [39]. As fuzzy DT models continue to demonstrate their value in domains requiring complex and high-stakes decision-making—such as energy management, environmental policy, and automated controls—they are expected to become indispensable tools for contemporary control systems and decision-making frameworks [40].

3.Proposed approach

The study presents an innovative approach called BSFDT to enhance decision-making in mixed financial dispatch scenarios. Initially, the unified ED problem is defined, focusing on optimizing electricity generation across diverse energy sources to meet demand, reduce costs, and adhere to operational constraints. To maintain consistency, historical data on power usage, generation costs, fuel costs, and constraints is gathered and preprocessed [41, 42]. FL is then applied to compensate for the unpredictability and ambiguity introduced by decision-making processes. Fuzzy sets are defined for each variable input, and systems use inference with fuzzy sets to simulate the relationships between the inputs and the results. The BSFDT technique distinguishes itself by using bell-shaped membership functions that allow for better capture of nonlinear interactions and uncertainty. These functions provide smooth transitions between membership grades, increasing the precision and longevity of the DT. The BSFDT is constructed using pre-processed data and fuzzy inference methods. These methods direct the decision-making process by examining fuzzy rules to identify the optimum dispatch mechanisms for specific cases. The model's parameters are refined using optimization techniques, and its performance is validated through cross-validation methods. This demonstrates its effectiveness in enhancing strategies for combined ED guidelines. The implementation was carried out using MATLAB on a Pentium 5 (P5) machine with a central processing unit (CPU) speed of 50 MHz. Most of the findings in the proposed approach were achieved using MATLAB coding and a suitable algorithm. The fundamental steps for utilizing the BSFDT method to address a combined dispatching problem are as follows [43–45]:

3.1Objective function

The combined ED problem involves optimizing power generation while considering both economic costs and emission levels represented by Equations 1, 2 and 3, making it a dual constraint optimization task. To address the complexities of real-world power systems, the inclusion of valve point loading in the cost model becomes more advantageous. In this study, both the cost function and emission levels are transformed into cubic equations to facilitate the optimization process.

Optimize

$$F_{1i} = \sum_{i=1}^{m} f_{1i}(Pg_i) \qquad (1)$$

Where F_{1i} is defined as follows:

$$F_{1_i} = \tau_{1i} + \tau_{2i}P_{gi} + \tau_{3i}{P_{gi}}^2 + \tau_{4i}{P_{gi}}^3 + abs(\tau_{5i}sin(f_i \times (P_{min} - P_{gi})) \qquad (2)$$

Taking

τ_{1i}, τ_{2i}, …. τ_{5i} represent the fuel purchase function’s pricing coefficients that is found employing the procedures laid down below.

3.1.1Procedure for obtaining price functionality and emission level parameters for cubic cost and emission level functions

Method1:

Step 1: Use this hit-and-try approach to get a solution for the cubic equation. To solve the cubic equation P(x), set x = 0, ±1, ±2, ±3, & continue until P(a) = 0.

Step 2: After we obtain P(a) = 0, calculate the component (x – a) of P(x).

Step 3: Dividing P(x) by (x – a) to derive the quadratic equation Q(x).

Step 4: Use the quadratic equation Q(x) to find the variables (x – b) and (x – c).

Step 5: Express P(x) as the product of its factors: P(x)=(x – a)(x – b)(x – c). Solving these factors gives the roots *a*, *b*, and *c*.

Step 6: Calculate the cost of fuel, including coal, expressed in dollars per hour for a given unit:

$\lambda = b + 2cP_{gi} + 3dP_{gi}^{2}$

Where P_{gi} represents the power generation for unit i.

Step 7: Repeat Steps 1–6 to determine the cost and emissions coefficients for the system.

Method2:

Step 1: Using the hit and try strategy, try a single solution to the cubic problem. To solve the cubic equation P(x), set x = 0, ±1, ±2, ±3, & continue until P(a) = 0.

Step 2: Calculate the first root, once a is found, compute the first root using the formula:

$x_1 = a - \frac{f(a)}{f'(a)}$

Step 3: Calculate the second root, using x1 find the next root

$x_2 = x_1 - \frac{f(x1)}{f'(x1)}$

Step 4: Repeat the process to find x_3, x_4, x_5,…,x_n, until the values converge, meaning successive approximations of x become nearly equal.

Step 5: The final values of x, when convergence is achieved, represent the roots of the cubic equation a, b, c.

Step 6: The cost of fuel, including coal, is represented in dollars per hour for a specific unit as:

$\lambda = b + 2cP_{gi} + 3dP_{gi}^{2}$

Step 7: The coefficients for cost and emissions are determined by following steps 1 through 7.

Step 8: The pollution level function coefficients are determined as:

$$F_{2_i} = \tau_{6i} + \tau_{7i}P_{gi} + \tau_{8i}{P_{gi}}^{2} + \tau_{9i}{P_{gi}}^{3}$$

Where

F_{1_i}= thermal unit cost of fuel function

P_i^{min}= the ith smallest power unit

T_{6i}, τ_{7i}, τ_{8i}, τ_{9i} are the coefficients for the emission level function, calculated using the method described in Section 3.1. The cost and emission coefficients are shown in *Table 1* and *Table 2*.

Table 1 Cost and emission coefficients along with P_{gimin} and P_{gimax} limits without loss

τ_{1i}	τ_{2i}	τ_{3i}	τ_{4i}	τ_{5i}	τ_{6i}	τ_{7i}	τ_{8i}	τ_{9i}	P_{gimin}	P_{gimax}	f_i
0.0148	0.097	97.9	1405.4	453.58	0.02	1.35	200.3	222.62	90	453	0.1344
0.001	0.0173	17.34	248.8	182.45	0.0034	0.065	32.58	245.46	38	182	0.054
0.0013	0.044	15.33	677.9	135.65	0.0032	0.12	29.35	183.99	27	135	0.00002
0.000607	0.0285	24.7	1202.74	90.99	0.0033	0.0303	40.39	73.49	18	91	0.0269
0.00194	0.017	7.956	221.57	90.93	0.0032	0.0449	31.01	0.369	18	91	0.0269
0.000742	0.0211		412.61	108.94	0.0025	0.1299	40.46	1.28	22	109	0.0322

Table 2 Cost and emission coefficients along with P_{gimin} and P_{gimax} limits with loss

τ_{1i}	τ_{2i}	τ_{3i}	τ_{4i}	τ_{5i}	τ_{6i}	τ_{7i}	τ_{8i}	τ_{9i}	P_{gimin}	P_{gimax}	f_i
0.015	0.0999	99.91	1433.5	462.65	0.0211	1.377	204.6	227.07	91.43	461.74	0.137
0.00107	0.01769	17.69	253.85	136.09	0.0034	0.067	33.23	250.36	36.78	135.72	0.0551
0.0013	0.0447	15.58	688.98	137.36	0.0033	0.122	29.82	136.98	27.24	137.59	0.00008
0.000619	.0291	25.21	1266.69	92.79	0.0034	0.030	41.19	74.96	18.338	92.60	0.0275
0.0019	0.0174	3.11	225.98	92.79	0.0033	0.045	31.63	38.63	18.338	92.60	0.0275
0.00075	0.0208	15.16	420.97	111.12	0.0265	0.1325	41.28	130.62	21.96	110.9	0.032

3.1.2Algorithm for BSFDT in combined ED

```
Step 1: Start
Step 2: Select the total number of iterations as N
        While I is lower than N
        I=I+1
        Construct fuzzy learning set (FLS) (the power and cost).
        Fuzzify the technological limits.
        Calculate every objective cost.
        Fuzzyify the cost equations according to Equation 1.
```

Calculate the threshold value.
Label each load segment (LS) objective into classes C1 or C2.
Save the most effective solution of the class.
Increase solution search.

Step 3: Start Fuzzification of technical boundaries for all units, P^i

If P_{min}^i is less than or equal to the technical minimum, the new minimum is computed as follows:

$$Min^i = \delta min * P_{min}^i(\mu - 1) + P_{min}^i$$

If P_{max}^i larger than or equal to the technological maximum, the updated technical maximum is computed as follows:

$$Max^i = \delta max * P_{max}^i(1 - \mu) + P_{max}^i$$

End to all units

Step 4: Solution search intensification

Initially, FLS is created varying the powers from minimum to maximum technical values. Then Class C_1 is obtained.
Start of an intensification cycle
New P_{min}^i and P_{max}^i are found for each unit inside all objects of Class C_1 (or C_1', if it is not the first intensification cycle)
A new FLS is created thus resulting a new class C_1' and therefore, a new solution is found.
End intensification cycle

Step 5: Use the objective operation, limitations, and system models to define the economic load dispatch (ELD) problem as a computational optimization problem. This entails expressing the problem by means of decision variables, goal functions, and constraints.

Step 6: Use the specified optimization algorithm to find an ideal or near-optimal solutions to the stated ELD problem. The method iteratively adjusts the selection variables to reduce the function's value while adhering to the constraints.

Step 7: Validate the resulting solution to ensure that it meets the operational criteria of the power system. Conduct a sensitivity analysis to assess the impact of changes in input variables on the solution's accuracy and robustness. Incorporate the optimized dispatch strategy into the power system's operation and control framework. Align the approach with real-time monitoring and control mechanisms. Implement integrated control systems to enhance operational efficiency and responsiveness to dynamic fluctuations in demand and generation.

Step 8: This approach provides a comprehensive foundation for enhancing power system performance through ELD.

The steps in this method may vary based on the specific requirements and characteristics of the power system, as outlined in Section 3.1.2.

Uncertainties in input data, such as fuel prices and demand forecasts, are typically addressed in ELD models using various strategies designed to mitigate risks and enhance solution robustness under uncertainty. Common approaches include:

Scenario-based approaches: This method involves generating a set of scenarios representing different possible outcomes. By analyzing multiple scenarios, decision-makers can develop dispatch strategies that perform well under a range of possible conditions.

Robust optimization: Robust optimization techniques focus on finding solutions that remain effective under uncertain conditions by considering worst-case scenarios. Instead of optimizing for a single predicted case, the objective is to identify strategies that perform well across all possible variations while adhering to predefined constraints.

Risk-averse optimization: This approach incorporates risk metrics, such as Value-at-Risk (VaR) or Conditional Value-at-Risk (CVaR), into the optimization framework. By explicitly accounting for potential adverse effects of uncertainty, the model seeks to balance expected performance with minimizing downside risks.

Real-time adjustments: ELD models can also be designed to adapt dynamically by modifying dispatching decisions in real time as new information becomes available. This may involve employing forecasting techniques to predict future values of uncertain parameters and updating dispatch strategies accordingly.

The selection of an appropriate uncertainty management strategy depends on the specific characteristics of the problem, the availability of data, and the decision-makers' risk tolerance. Each approach has its strengths and limitations, requiring careful evaluation to determine the most suitable method for a given power system.

3.1.3Detailed explanation of the construction of Fuzzy DT and their utility within the framework of the combined dispatching problem

Fuzzy DT use FL to handle ambiguity and vagueness in data. They are widely utilized in decision-making processes where both inputs and results are not clearly defined and may be uncertain. Here is a detailed explanation of how fuzzy DTs are constructed and applied in the context of the combined dispatching problem:

Problem formulation: The combined dispatching problem involves determining how to allocate resources and schedule jobs in complex systems such as manufacturing facilities or transportation networks. This problem often includes multiple conflicting objectives, imprecise information, and unpredictable circumstances.

Data collection: The first step in constructing a fuzzy DT is gathering relevant data related to the combined dispatching problem. This data may include information on available resources, job requirements, environmental conditions, and past performance.

Fuzzification: Fuzzification is the process of converting crisp (precise) data into fuzzy sets to model vagueness and ambiguity in decision-making. For example, instead of defining temperature as exactly 25 degrees Celsius, it can be represented as a fuzzy set with membership functions such as "very hot," "warm," and "cool."

Feature selection: Next, relevant features or attributes are selected from the collected data to serve as inputs for the fuzzy DT. These attributes should include key information that influences decision-making, such as resource availability, task complexity, and environmental conditions.

Partitioning: The feature space is divided into fuzzy sets based on linguistic terms. For example, if the attribute is "resource availability," it can be categorized into fuzzy sets such as "low," "medium," and "high," based on specific criteria or expert knowledge.

Rule generation: Rules are formulated based on the fuzzy sets defined during the partitioning process. These rules establish the conditions under which specific choices or actions should be taken. For example, a rule might state: "If resource availability is high and task complexity is low, then allocate the resource immediately."

Rule evaluation: Once the rules are created, they are evaluated using fuzzy inference techniques. This involves determining the degree to which each condition satisfies the criteria based on the current input data. FL enables reasoning with imperfect and uncertain data, making it well-suited for handling the inherent ambiguity in the combined dispatching problem.

Decision-making: Resource allocation and job scheduling decisions are made based on rule evaluations. These decisions aim to optimize multiple competing objectives, such as minimizing costs, maximizing efficiency, and meeting deadlines, while considering the uncertainties and constraints inherent in the problem.

Information and modification: The fuzzy DT structure is dynamic and flexible, incorporating feedback mechanisms to continuously improve decision-making performance over time. Feedback can be obtained through monitoring system performance, collecting new data, or adjusting fuzzy sets and rules based on expert knowledge and experience.

Fuzzy DT can be integrated with other optimization techniques and decision-support tools to effectively address the combined dispatching problem. They provide a flexible and interpretable decision-making framework, allowing decision-makers to analyze, understand, and manage complex systems in uncertain environments.

Importance of BSFDT over other heuristic method

This approach has faster uncertain handling, greater interpretability, and nonlinearity handling capabilities, robustness, adaptability, hybrid methods, scalability, and composite performance properties.

Sensitivity analysis: It is used to select key parameters, choose an appropriate ELD method, construct a performance matrix, conduct experiments, and solve mathematical models in a real-time environment. This process involves a fuzzy bell-shaped membership function and the corresponding domain areas it covers.

Scalability of FLDT: The adaptability of the Fuzzy DT approach for larger and more complex power systems in ELD refers to its ability to manage increasing system complexity and scale while maintaining effectiveness and computational efficiency. Scalability is essential in ELD, which involves allocating loads among multiple generating units to meet demand at the lowest possible cost.

As power systems expand or become more complex—due to factors such as the growing integration of renewable energy sources or various operational constraints—the ELD approach must be capable of efficiently managing these challenges. FLDT approaches help describe and regulate complex systems by combining the interpretability of fuzzy reasoning with the decision-making capabilities of DT. In the context of ELD, FLDT approaches facilitate optimal generator scheduling while considering multiple factors and constraints, ensuring a balanced, cost-effective, and adaptive dispatch strategy.

The scalability of FLDT approaches in ELD depends on several key factors:

Computational complexity: As the size of the power network increases, the computational challenge of solving the ELD problem also grows. FLDT algorithms must be capable of handling this increased complexity efficiently, ensuring that computation times remain feasible even for large-scale power systems.

Model adaptability: FLDT approaches should be flexible enough to accommodate different system configurations and constraints. They should be able to integrate new data and constraints dynamically as the system evolves, without requiring extensive retraining or recalibration.

Accuracy and performance: Despite increasing system complexity, FLDT approaches should maintain high accuracy and robust performance in identifying optimal or near-optimal ELD solutions. Key considerations are production costs, transmission constraints and environmental regulation.

Interpretability: One of the advantages of FLDT approaches is their transparency, allowing operators to understand the decision-making process behind the optimization. However, as the system scales in size and complexity, maintaining interpretability becomes more challenging. Nevertheless, it remains crucial for effective decision-making and operational reliability.

Overall, the adaptability of FLDT approaches in ELD for larger or more complex electrical systems depends on their ability to efficiently handle increased computational demands, adapt to changing system conditions, maintain accuracy and performance, and remain interpretable for decision-makers. Advancements in computational techniques and method optimization can enhance the scalability of FLDT methods, enabling them to effectively address the challenges of modern power systems.

3.1.4Impact of environmental regulations and emission standards on the performance and selection of ELD methods

Environmental restrictions and emission limits significantly impact the performance and selection of ED methods in the energy sector. One of the primary considerations is cost. Environmental regulations often impose penalties or charges for exceeding emission limits. Since ED systems are designed to minimize the total cost of power generation while meeting demand, strict emission requirements necessitate incorporating the costs of emissions, including potential fines or penalties for non-compliance. This adjustment modifies the cost function used in ED optimization, requiring a balance between generation costs and regulatory expenses.

Another crucial factor is technology selection. Emission levels vary depending on the type of power generation technology used. Environmental regulations may incentivize cleaner energy sources or impose restrictions on high-emission methods, affecting the choice of dispatch strategies. ED systems must consider these regulatory factors when determining the most cost-effective combination of power generation units, ensuring both economic efficiency and compliance with emission standards.

BSFDT workflow

Step 1: Convert clear input data (such as demand, fuel costs, and emission variables) into fuzzy sets using bell-shaped membership functions.

Step 2: Develop fuzzy rules that represent the trade-offs between emission constraints and ED objectives.

Step 3: Build a DT with nodes and branches that illustrate decision pathways based on the fuzzy rules.

Step 4: Traverse the DT to determine the optimal dispatch parameters while balancing economic efficiency and emission compliance.

Step 5: Convert fuzzy outputs back into crisp values to generate actionable dispatch instructions.

3.2Optimization of power system operations

Within the context of optimizing power system operations, a crucial set of constraints includes both equality and inequality conditions that govern various aspects of the system's behavior. These constraints account for power balancing and consumption limitations, playing a pivotal role in ensuring a reliable and efficient power generation process. One of the most fundamental constraints in this category is the requirement to maintain a balance between power generation and consumption. This stipulates that the total power output of the system must precisely match the total demand placed upon it. Mathematically, this constraint can be expressed as (Equation 3 to 6):

$$P_{gi}=\mathrm{PD}+P_{loss} \quad (3)$$

$$P_{gimin} \le P_{gi} \le P_{gimax} \quad (4)$$

$$T_L=\sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j \quad (5)$$

PD = 1050MW without loss

$$P_L=\sum_{i=1}^{m}\sum_{j=1}^{m} P_{gi} B_{ij} P_{gj}+\sum_{i=1}^{m} B_{oi} P_{gi}+B_{00} \quad (6)$$

Where,

P_{gi}: Power generated by the ith generator.

PD: Total power demand of the system.

P_{loss}: Total power loss in the system, mainly due to transmission losses.

P_{gimin}: Minimum allowable power output of generator i.

P_{gimax}: Maximum allowable power output of generator i.
T_L: Total transmission line losses in the system.
P_i,P_j: Power outputs from different generating units.
B_{ij}: Loss coefficient matrix, which represents how power losses are affected by power generation at different
Locations

3.3Uncertain threshold cost

Each cost object is assigned a membership function, as illustrated in *Figure 1* and Equation 7.

$$.\mu_c = \begin{cases} (1), (c = c_\beta) \\ (b/2a), (0 \le c \le c_\beta) \\ (-b/2a), c_\beta \le c_{ovu}) \\ 0, (c \ge c_{ovu}) \end{cases} \qquad (7)$$

$$Where, c_\beta = c_{ovu} - \beta(c_{ovu} - c_{min}), 0 \le \beta \le 1$$

Where β signifies the degree of ambiguity, with $\beta = 0$ indicating firm boundaries and $\beta = 1$ representing fuzziness.
A low fuzzy threshold strategy [46, 47], which defines the minimum level of membership required for an item to be classified under C_1. The smallest cost among items in a specific LS is referred to as C_{min}, while C_{ovu} represents the ideal generating cost threshold value. Category C_1 is mathematically defined using Equation 8 as follows:

$$C_1 = \{o \in U \mid \mu_o \ge \mu_{cmin}\} \qquad (8)$$

Where o∈U: Specifies that o is an object or item that belongs to the universal set U
μ_o: Denotes the membership degree of the object o in a fuzzy set.
μ_{cmin}: Represents the minimum membership degree required for an item to be included in category C_1.

3.4Limits on generator power in fuzzy modelling

The primary purpose of this research is to assess the financial viability of controlled generation overloading and its effects on system costs. While it is widely recognized that generator overloads can be managed within specific timeframes, this paper focuses exclusively on static analysis, deliberately excluding dynamic aspects. This focus is particularly relevant in contexts such as Chile, where generator overloads are commonly employed to address active power contingencies.

The study evaluates the economic feasibility of this practice in such scenarios. By evaluating each unit's operation within controlled limits, this study investigates whether intentional overloading, either above or below power limits, can optimize system costs. The analysis focuses on the economic implications of managed generator overloads, particularly in scenarios where the supplier's income is determined by the system's marginal cost. This setup incentivizes overloading as a strategy to avoid unmet commitments and reduce reliance on potentially costly spot market purchases.

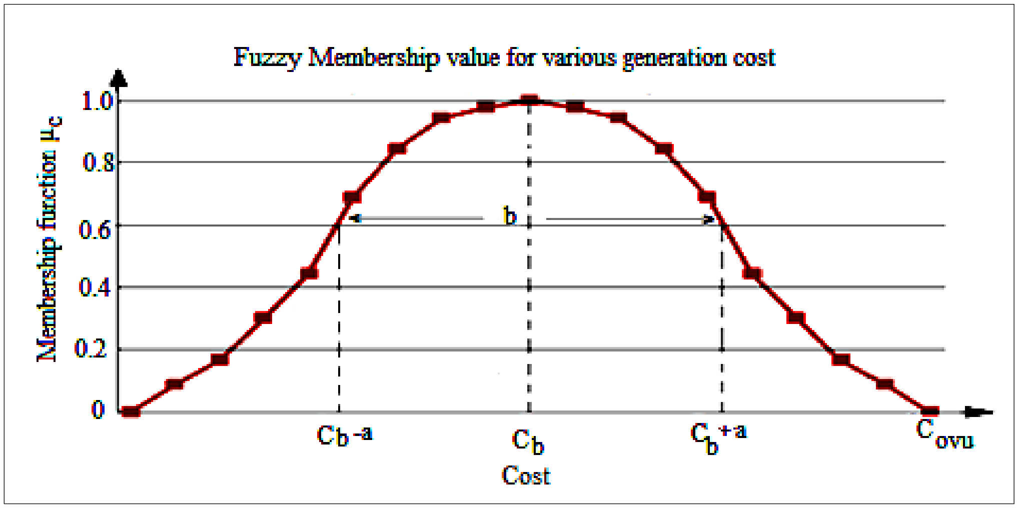

Figure 1 Variation of fuzzy membership function with real power generation cost

3.5Fuzzification of generator limits

The process involves fuzzifying the limits, as demonstrated in *Figure 2* using P_{max} as an example (a similar approach is applied for P_{min}). The unit-generated power incorporates a membership function as described in [41, 42] and is represented by Equation 9.

$$\mu_p = \begin{cases} (1), (p = p_\beta) \\ (b/2\delta_{max}), (0 \le p \le (p_\beta - \delta_{max})) \\ (-b/2\delta_{max}), (p_\beta \le p \le (p_\beta + \delta_{max})) \\ (0), (p \ge p_{ovu}) \end{cases} \qquad (9)$$

Where P is unit-generated power, percentages over P, denoted by the feasible range 0.2 <P_i, < 0.5.

μ_p indicates membership value for unit-generated power p. p_β is the central or ideal power output value where membership is maximum (equals 1). δ_{max} indicates maximum deviation allowed from p_β, b is the scaling factor used to adjust the slope of the membership function. p_{ovu} is the overload power limit beyond which membership drops to 0.

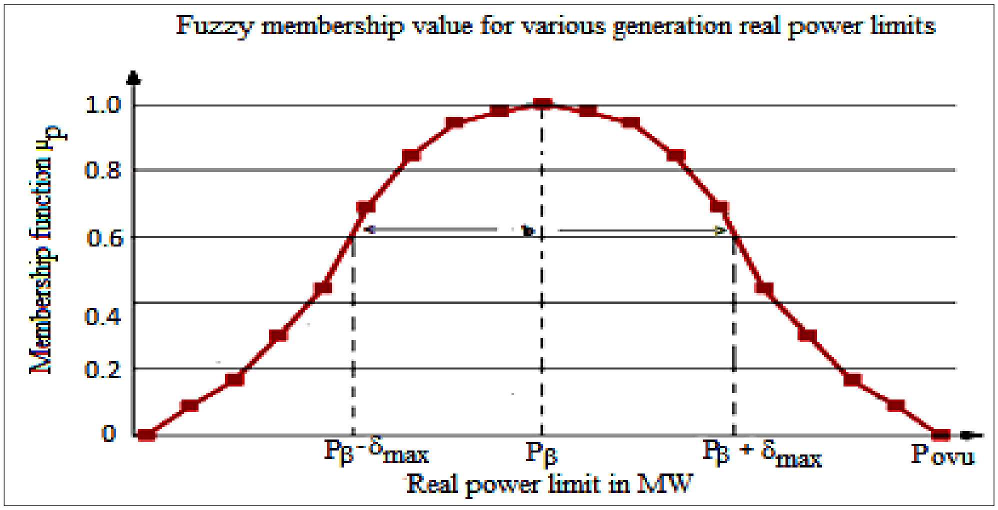

Figure 2 Variation of fuzzy membership value for different generator real power limits

3.6Fuzzy demand

The fuzzification of demand, as represented by Equation 10, ensures a higher probability of occurrence around the anticipated demand levels rather than deviating significantly from it. *Figure 3* illustrates the grouping function applied to the demand, centered on the anticipated value. The use of a triangular membership function highlights the effectiveness of this approach, balancing simplicity and precision. This method serves as a foundation for more complex and traditional formulations, which are being explored as part of ongoing research.

$$\mu_d = \begin{cases} 1, D = Dda \\ b/2\rho, 0 \le D \le Dda \\ -b/2\rho, Dda \le D \le D_{ovu} \\ 0, D \ge D_{ovu} \end{cases} \qquad (10)$$

μ_d is the membership value for the system demand D. D represents the system demand. D_{da} represents the projected or anticipated demand for a specific time period. Variance around the projected demand D_{da} is represented by ρ.

D_{ovu} shows the over-demand threshold beyond which the membership drops to zero.

In the context of power system optimization, several key considerations are crucial for effective decision-making. One notable aspect is the fuzzification of system demand, represented by D. Through this process, values are redistributed to favor levels closer to the projected demand (D_{da}), rather than those farther away. The degree of demand variation around the projected demand is indicated by a specific variable that quantifies this variation.

Another important constraint is related to ramp rates, which define the upward and downward slope rates of a generator. These ramp rates impose restrictions on how quickly a generator's output can increase or decrease. Consequently, the generator's operating limits are adjusted to align with these constraints [48–50]. The fuzzy DT technique has been devised to address these considerations, and the basic algorithm outlined below provides a clear representation of its implementation. This approach ensures that the optimization process accounts for both demand fuzzification and ramp rate constraints while maintaining operational efficiency.

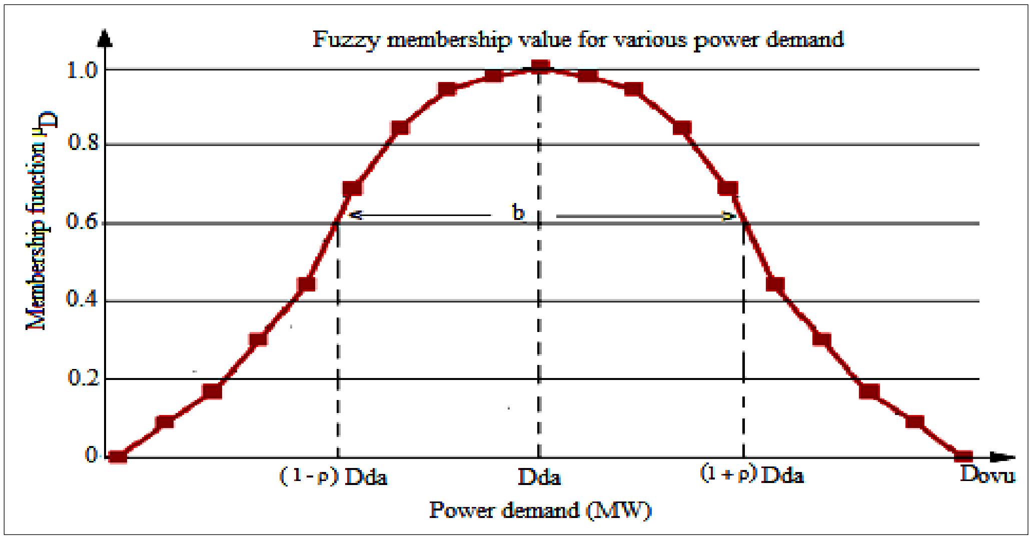

Figure 3 Variation of membership function value for different values of power demands

Implementation steps

Step 1: Start

Step 2: Define N as the total number of iterations available for optimization, which progresses according to Equation 11.

Step 3: Initialize the iteration counter I=0.

Step 4: Increment the iteration counter:
Update I=I+1 whenever I<N.

Step 5: Create a cost-effective and adaptable learning kit. Identify and remove any technological constraints.

Step 6: Calculate the target cost values for all objectives.

Step 7: Use the fuzzy cost equation. Apply Equation 1 to compute the fuzzy cost for each target.

Step 8: Determine the threshold value. Establish the threshold to evaluate the solutions.

Step 9: Evaluate the actual power generation outputs from the system.

Step 10: Categorize each LS goal. Sort the goals into Category C_1 based on membership criteria.

Step 11: Retain the best Category C_1 solution. Select the most optimal solution from Class C_1.

Step 12: Broaden the search space to identify potential improvements in subsequent iterations.

Step 13: End the process once the optimal criteria are met.

Step 14: Stop

Methodological limits of fuzzification

Start fuzzification for all units, P^i. If the minimum power price p_{min}^{i} is less than or equal to the lowest technological threshold, the following formula is applied to determine the next technical low, as represented by Equation 11. If p_{max}^{i} is greater than or equal to the current technical highest, the following formula, shown in Equation 12, is used to calculate the next technical optimum.

$$\text{Min}^i = \delta_{min} \times p_{min}^{i} (\mu - 1) + p_{min}^{i} \tag{11}$$

$$\text{If Max}^i = \delta_{max} \times p_{max}^{i} (1 - \mu) + p_{max}^{i} \tag{12}$$

Algorithm for intensifying solution lookup

The search for solutions is intensified by the following steps:

1. Initial LS formation: The LS is initially formed by modifying the power values from the lowest technical value p_{min}^{i} to the highest technical value p_{max}^{i} for each unit.
2. Acquisition of class C_1: After forming the initial LS, class C_1 is identified, representing the optimal or best class based on the criteria.
3. Cycle of intensification begins: The intensification cycle starts, wherein new p_{min}^{i} and p_{max}^{i} values are discovered for each unit across all class objects.
4. First cycle check: If this is the first cycle of intensification, a new LS is produced, leading to the creation of a new class C_i and ultimately a new solution. If it is not the first cycle, the process continues by adjusting parameters based on the intensification strategy.
5. Finish the intensification cycle: The intensification cycle ends when the desired optimization criteria are met, resulting in an improved solution.

These codes help in understanding the efficacy of the solution, but further clarification is needed to fully appreciate its advantages. Firstly, the strength of the algorithm lies in its ability to avoid local minima, consistently searching for valleys with the lowest objective function values. It navigates these valleys through the intensification procedure. Secondly, regardless of the starting point, the algorithm always converges to the optimal solution, as the threshold values themselves represent the objective costs.

Unlike other heuristic methods, this approach does not require an extensive training process, aside from calibrating the overall solution's precision, which is directly linked to the load shedding grid. The proposed algorithm offers a comprehensive solution for power system optimization. By fuzzifying demand and incorporating ramp rate constraints, it provides a robust and effective strategy. The pseudocodes provide a clear framework for system optimization, illustrating the algorithm's functionality, its ability to avoid local minima, its reliability in reaching optimal solutions, and its simple implementation. This research introduces a novel approach to power system optimization, considering both economic and technical aspects under various constraints.

The algorithm’s ability to avoid local minima is crucial, as it consistently seeks the lowest objective function values and refines the solution through the intensification process. Furthermore, it converges to the optimal solution, regardless of the initial conditions, because the threshold values represent the objective cost. One significant advantage of this approach is that, unlike many other heuristics, it requires no additional training beyond calibrating precision to the load shedding grid. *Tables 1* and *2* include cost and emission coefficients, along with P_{gmin} and P_{gmax} limits, both with and without considering losses.

4.Results and discussion

The results for determining the ED problem using the proposed approach are presented in *Tables 3* to *6*. For power demands of 1250 MW, 4000 MW, and 7000 MW, the performance of various optimization techniques is evaluated in *Tables 7*, *8*, and *9*. These techniques include the Lagrange method, particle swarm optimization (PSO) method, non-fuzzy logic-based decision tree (NFLDT) approach [51–53], and the proposed BSFDT approach. The primary performance measures for comparison include the cost per hour ($/hr) and the power loss in megawatts (MW). The results indicate that the bell-shaped FLDT method significantly impacts moderate and high-range power demands.

Using bell-shaped fuzzy decision-making in economic load distribution enhances electrical system operations, resource utilization, stability, reliability, and decision-making in uncertain and dynamic contexts. This method effectively addresses the limitations of traditional optimization techniques by integrating FL into bell-shaped membership functions, allowing for precise modeling of complex systems such as ELD. The application of FL improves the efficiency of generation resource distribution and ensures robustness against uncertainty and variations in load demand, fuel prices [46–48], and other factors, which contributes to overall power system stability.

The adaptability of bell-shaped fuzzy decision-making allows power system operators to respond effectively to fluctuating market conditions and regulatory requirements. Additionally, optimized economic load distribution reduces operational costs by minimizing fuel consumption, maintenance, and other expenses [54, 55]. The risk of incorrect economic load distribution decisions is also reduced through FL, which explicitly considers uncertainty [56]. *Figures 4*, *5*, and *6* illustrate the defuzzification of membership functions with respect to power demand and real power generation, with and without transmission loss.

Table 7 presents a comparative analysis of the 1250 MW power demand, evaluating cost and emissions across different methods. The BSFDT method achieves the lowest cost ($0.1293/hr) compared to the Lagrange ($0.1290/hr), PSO ($0.1295/hr), and NFLDT ($0.1298/hr) methods when losses are considered. Although the differences are minor, they translate into substantial cost reductions over extended periods.

For a 4000 MW power demand, *Table 8* compares the costs and power losses of various methods. The Lagrange method incurs a cost of $40,528.30/hr with a power loss of 105.53 MW, while the NFLDT method has a cost of $40,413.24/hr with a loss of 90.95 MW. The BSFDT method results in a cost of $40,446.63/hr with a power loss of 92.23 MW. The BSFDT method remains competitive, offering cost-effective results while minimizing transmission losses. *Figures 7* and *8* illustrate the variation of membership functions concerning cost, with and without transmission losses, while *Figures 9* and *10* show cost variations concerning real power generation. For a 7000 MW power demand, *Table 9* evaluates the performance of different optimization methods. The Lagrange method has a cost of $70,705.16/hr with power losses of 321.76 MW, the NFLDT method incurs a cost of $70,590.60/hr with losses of 311.97 MW, and the BSFDT method achieves a lower cost of $70,345.91/hr with losses of only 286.93 MW. The BSFDT approach demonstrates superior performance in cost reduction and loss minimization at high demand levels, significantly outperforming the Lagrange and NFLDT methods. *Figures 11* and *12* illustrate emission variations with and without transmission losses.

Table 3 Cost and emission without and with transmission loss

P_{gi} with loss	P_{gi} without Loss	Cost in \$/hr ($\times 10^{10}$) without loss for proposed method	Cost in \$/hr ($\times 10^{10}$) with loss for proposed method	Cost in \$/hr ($\times 10^{10}$) without loss for Lagrange method	Cost in \$/hr ($\times 10^{10}$) with loss for Lagrange method	Cost in \$/hr ($\times 10^{10}$) without loss for PSO method	Cost in \$/hr ($\times 10^{10}$) with loss for PSO method	Cost in \$/hr ($\times 10^{10}$) without loss for NFLDT method	Cost in\$/hr ($\times 10^{10}$) with loss for NFLDT method
94	97	0.1284	0.1293	0.1280	0.1290	0.1286	0.1295	0.1289	0.1298
152	150	0.0840	0.0902	0.0836	0.0900	0.0843	0904	0.0846	0.0907
210	200	0.5506	0.6381	0.5504	0.6379	0.5508	0.6384	0.5510	0.6385
214	212	1.1461	1.2192	1.1459	1.2190	1.1463	1.2195	1.1465	1.2196
274	268	0.4289	0.4670	0.4287	0.4668	0.4291	0.4672	0.4293	0.4675
331	323	1.3906	1.5480	1.3904	1.5478	1.3908	1.5482	1.3911	1.5484

Table 4 Comparison of cost and emissions for the proposed method with other metaheuristic methods, with and without transmission loss

P_{gi} with loss	P_{gi} without Loss	Cost in \$/hr ($\times 10^{10}$) without loss for proposed method	Cost in \$/hr ($\times 10^{10}$) with loss for proposed method	Cost in \$/hr ($\times 10^{10}$) without loss for Lagrange method	Cost in \$/hr ($\times 10^{10}$) with loss for Lagrange method	Cost in \$/hr ($\times 10^{10}$) without loss for PSO method	Cost in \$/hr ($\times 10^{10}$) with loss for PSO method	Cost in \$/hr ($\times 10^{10}$) without loss for NFLDT method	Cost in\$/hr ($\times 10^{10}$) with loss for NFLDT method
94	97	0.1284	0.1293	0.1280	0.1290	0.1286	0.1295	0.1289	0.1298
152	150	0.0840	0.0902	0.0836	0.0900	0.0843	0904	0.0846	0.0907
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331	323	1.3906	1.5480	1.3904	1.5478	1.3908	1.5482	1.3911	1.5484

Table 5 Comparison of the outcomes for a 4000 MW power demand

Power (MW)	Lagrange technique	NFLDT Technique	Bell-shaped FLDT
P1	785	785	720.81
P2	327.69	385	364.04
P3	765	765.58	695.54
P4	865	865	965
P5	835	805.03	756.42
P6	724	685	749
P7	865	861	765.30
P8	755	755.36	825.22
P9	725	725	690.60
P10	675.07	680	755
Cost ($\$\ h^{-1}$)	70705.16	70590.60	70345.91
Losses (MW)	321.76	311.97	286.93

Table 6 Comparison of outcomes for 7000 MW power demand

Power (MW)	**Lagrange Technique**	**NFLDT Technique**	**Bell-shaped FLDT**
P1	434.86	363.17	301.72
P2	128.76	160.49	197.53
P3	399.66	327.68	412.86
P4	458.99	533.19	515.49
P5	454.27	365.22	388.13
P6	344.04	424.38	415.70
P7	458.99	392.69	429.56
P8	406.94	468.42	482.29
P9	403.74	377.93	333.82
P10	615.28	677.78	610
Cost($ h^{-1})	40528.30	40413.24	40446.63
Losses(MW)	105.53	90.95	92.23

Table 7 Comparison of Cost and emissions for the proposed method with other metaheuristic methods for a power demand of 1250 MW

P_{gi} with loss	**P_{gi} without loss**	**Cost in \$/hr $(\times 10^{10})$ without loss for proposed method**	**Cost in \$/hr $(\times 10^{10})$ with loss for proposed method**	**Cost in \$/hr $(\times 10^{10})$ without loss for Lagrange method**	**Cost in \$/hr $(\times 10^{10})$ with loss for Lagrange method**	**Cost in \$/hr $(\times 10^{10})$ without loss for PSO method**	**Cost in \$/hr $(\times 10^{10})$ with loss for PSO method**	**Cost in \$/hr $(\times 10^{10})$ without loss for NFLDT method**	**Cost in \$/hr $(\times 10^{10})$ with loss for NFLDT method**
94	97	0.1284	0.1293	0.1280	0.1290	0.1286	0.1295	0.1289	0.1298
152	150	0.0840	0.0902	0.0836	0.0900	0.0843	0904	0.0846	0.0907
210	200	0.5506	0.6381	0.5504	0.6379	0.5508	0.6384	0.5510	0.6385
214	212	1.1461	1.2192	1.1459	1.2190	1.1463	1.2195	1.1465	1.2196
274	268	0.4289	0.4670	0.4287	0.4668	0.4291	0.4672	0.4293	0.4675
331	323	1.3906	1.5480	1.3904	1.5478	1.3908	1.5482	1.3911	1.5484

Table 8 Comparison of the outcomes for A 4000 MW power demand

Power (MW)	**Lagrange Technique**	**NFLDT Technique**	**Bell-shaped FLDT**
P1	434.86	363.17	301.72
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P9	403.74	377.93	333.82
P10	615.28	677.78	610
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Losses(MW)	105.53	90.95	92.23

Table 9 Comparison of outcomes for 7000 MW power demand

Power (MW)	**Lagrange Technique**	**NFLDT Technique**	**Bell-shaped FLDT**
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P3	765	765.58	695.54
P4	865	865	965
P5	835	805.03	756.42
P6	724	685	749
P7	865	861	765.30
P8	755	755.36	825.22
P9	725	725	690.60

Power (MW)	**Lagrange Technique**	**NFLDT Technique**	**Bell-shaped FLDT**
P10	675.07	680	755
Cost ($ h^{-1})	70705.16	70590.60	70345.91
Losses (MW)	321.76	311.97	286.93

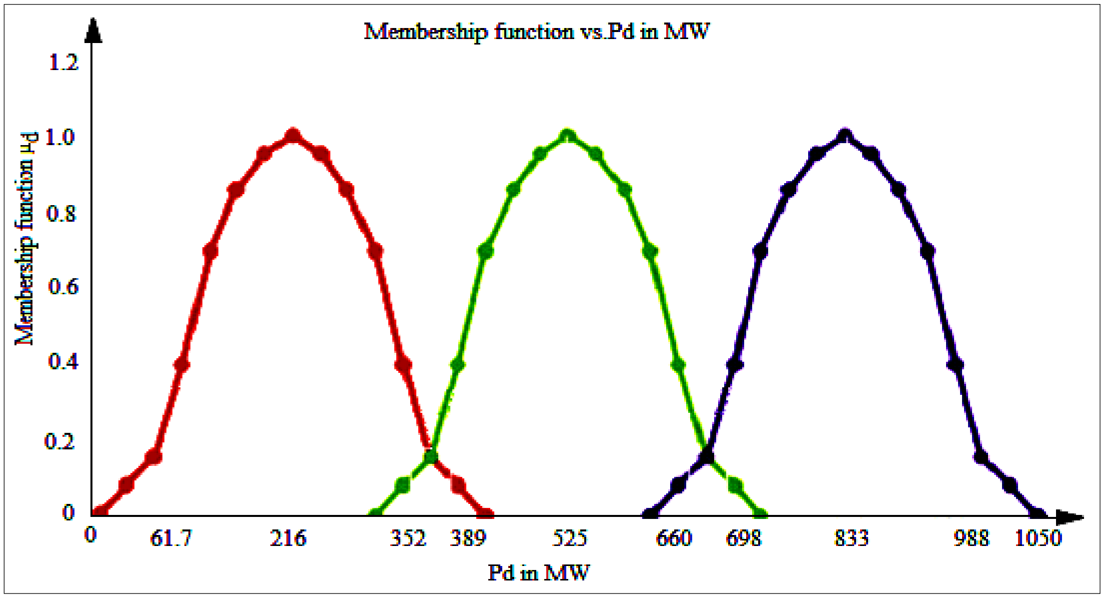

Figure 4 Defuzzification of membership function in relation to power demand

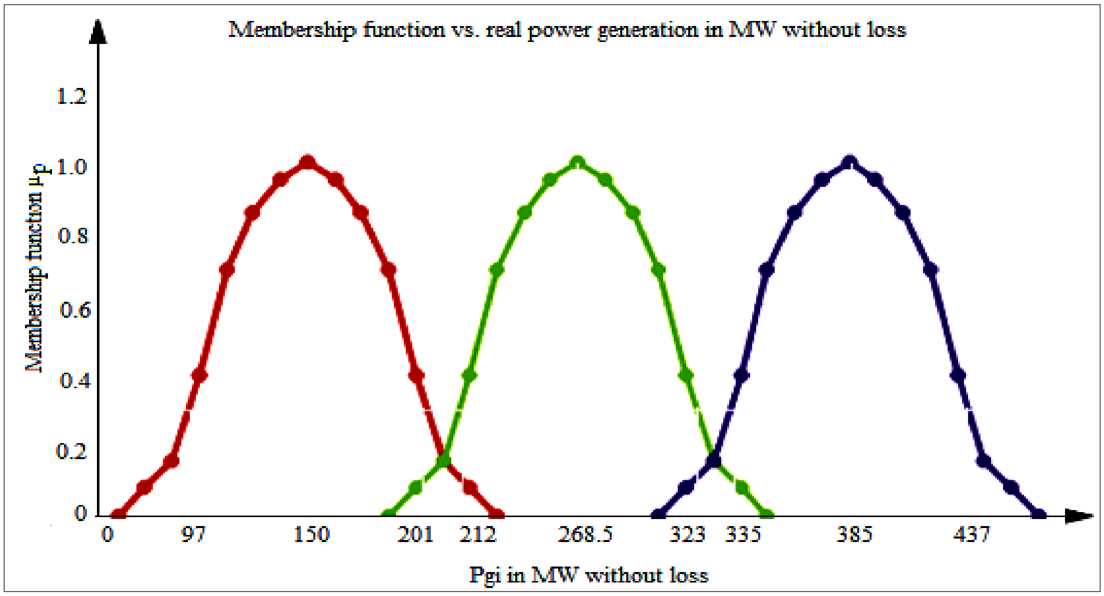

Figure 5 Defuzzification of membership function in relation to real power generation without loss

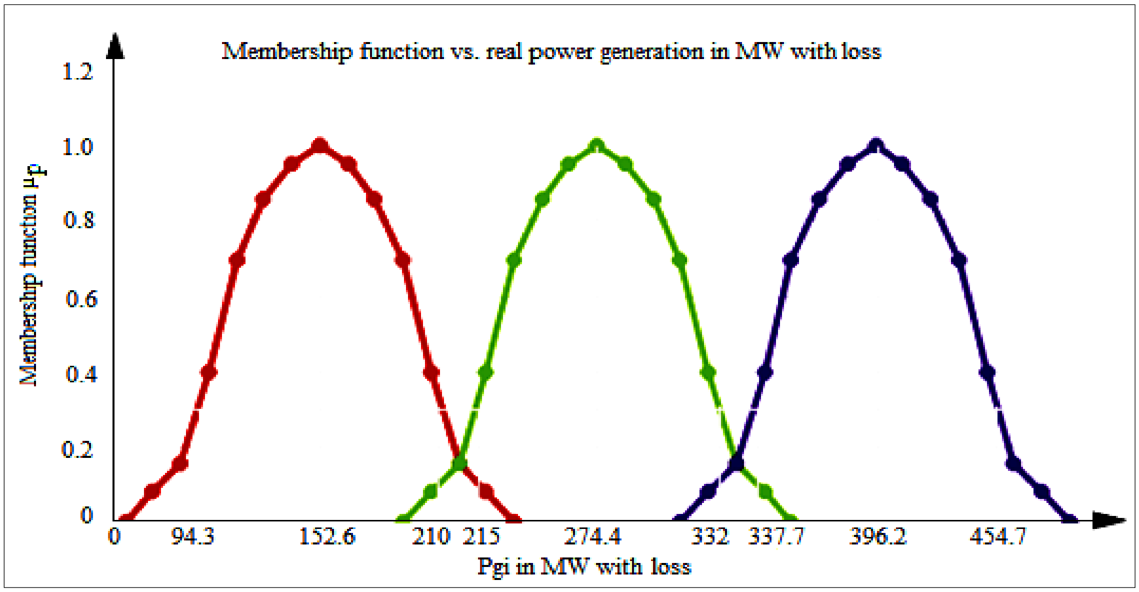

Figure 6 Defuzzification of membership function in relation to real power generation with loss

Table 7 presents a comparative analysis of the 1250 MW power demand, evaluating cost and emissions across different methods. The BSFDT method achieves the lowest cost ($0.1293/hr) compared to the Lagrange ($0.1290/hr), PSO ($0.1295/hr), and NFLDT ($0.1298/hr) methods when losses are considered. Although the differences are minor, they translate into substantial cost reductions over extended periods.

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For a 7000 MW power demand, *Table 9* evaluates the performance of different optimization methods. The Lagrange method has a cost of $70,705.16/hr with power losses of 321.76 MW, the NFLDT method incurs a cost of $70,590.60/hr with losses of 311.97 MW, and the BSFDT method achieves a lower cost of $70,345.91/hr with losses of only 286.93 MW. The BSFDT approach demonstrates superior performance in cost reduction and loss minimization at high demand levels, significantly outperforming the Lagrange and NFLDT methods. *Figures 11* and *12* illustrate emission variations with and without transmission losses.

The findings from *Tables 7* to *9* confirm that the BSFDT methodology is an effective and reliable approach for optimizing power generation across different demand levels. It consistently outperforms or competes closely with traditional methods, making it a promising solution for power system management. The method proves particularly effective at higher power demand levels, where its ability to reduce both cost and losses becomes more evident.

These results suggest that the BSFDT method should be prioritized for ED applications due to its superior balance of cost-effectiveness, stability, and adaptability. Its potential to enhance decision-making in power systems makes it a valuable option for utilities and energy management applications, offering a more sustainable and reliable approach to power generation optimization.

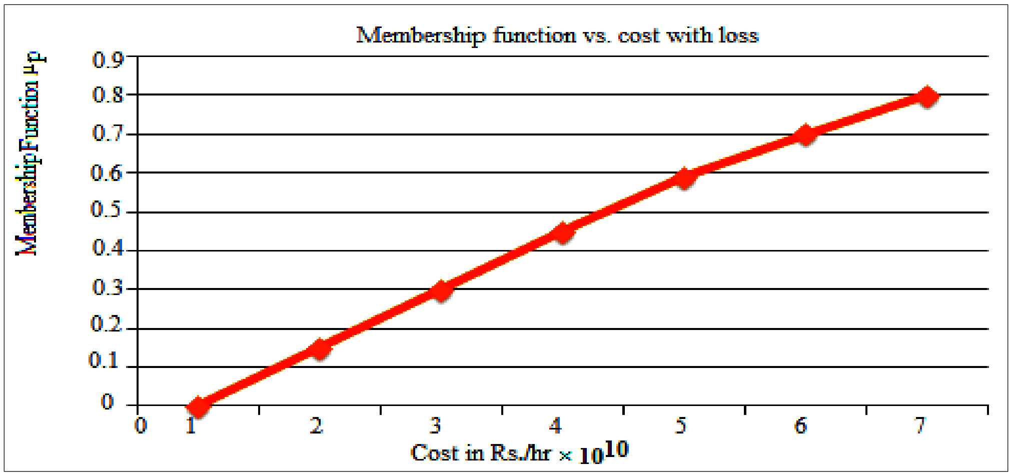

Figure 7 Variation of membership function in relation to cost with loss

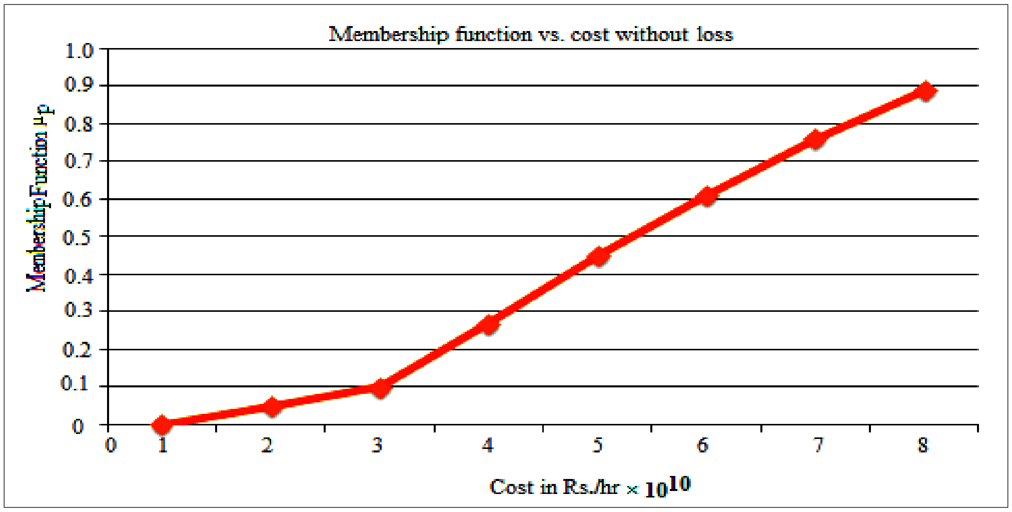

Figure 8 Variation of membership function in relation to cost without loss

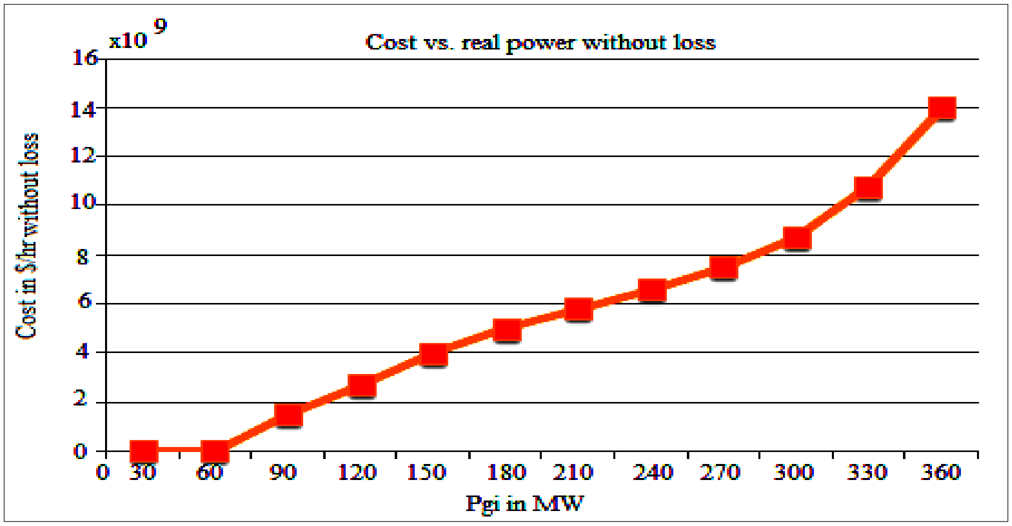

Figure 9 Cost function variation in relation to actual power generation without transmission loss

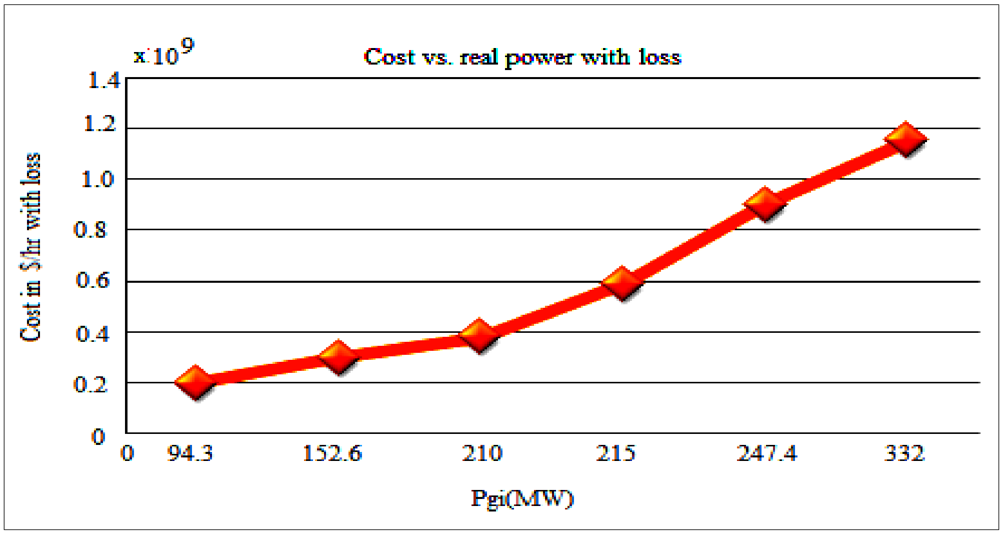

Figure 10 Cost vs. real power generation with transmission loss

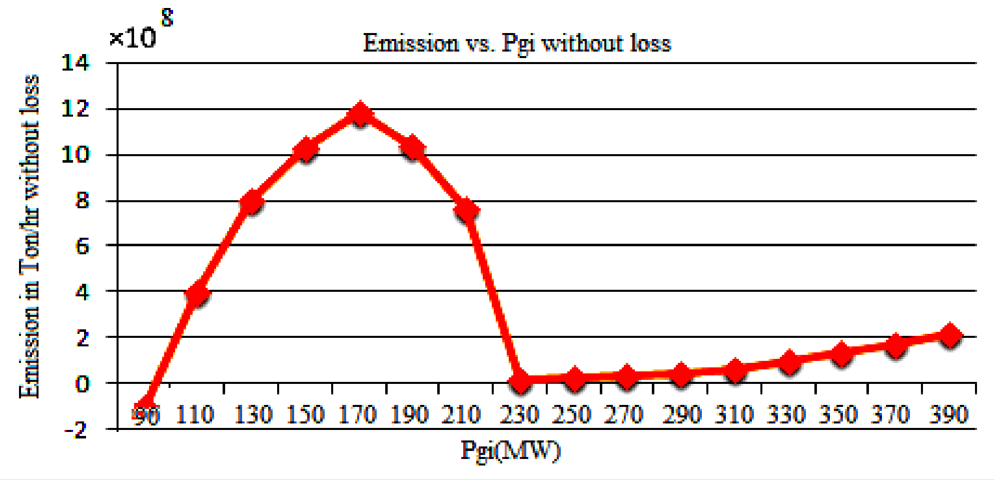

Figure 11 Variation of emission level function in relation to real power generation without transmission loss

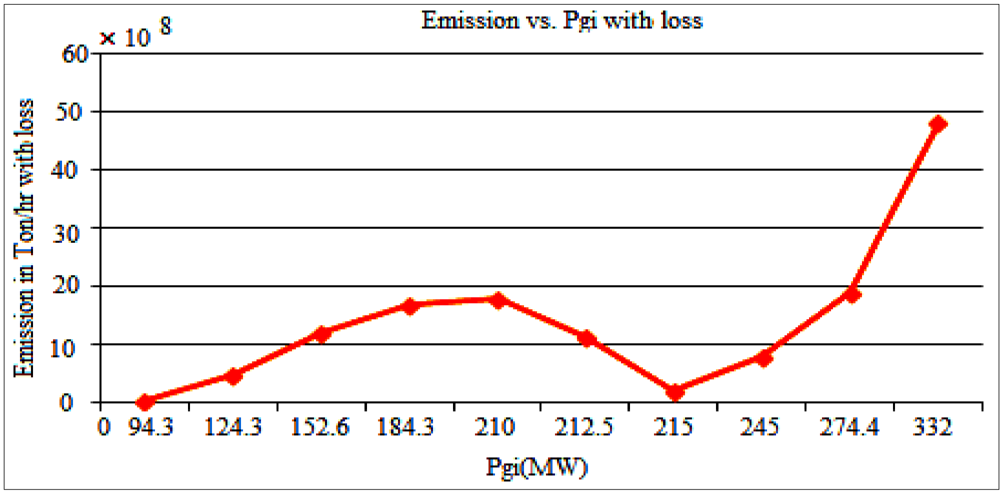

Figure 12 Variation of emission level function in relation to real power generation incorporating transmission loss

Limitations

The bell-shaped membership-based fuzzy decision-making system represents a major advancement in ELD and power system optimization. It allows for greater accuracy in decision-making, improved resource allocation, and enhanced grid stability. By capturing system constraints and preferences with greater precision, this method reduces operating costs and improves power system efficiency.

However, while this approach offers several advantages over traditional optimization methods, it also has some limitations. The effectiveness of the bell-shaped membership function depends on precise parameterization [57–59]. Any inaccuracies in defining these parameters may lead to suboptimal performance. Additionally, while this approach excels in stable conditions, its adaptability in handling real-time uncertainties and dynamic load variations may be limited. Power systems often face fluctuating demand and increasing integration of renewable energy sources, which necessitates continuous monitoring and calibration of the fuzzy decision-making model.

To fully leverage the benefits of this system, power system operators should invest in advanced data analytics and machine learning techniques to enhance parameter accuracy. Additionally, real-time monitoring systems and contingency plans should be developed to address unexpected changes in power demand. Training programs focused on the implementation and optimization of the bell-shaped approach can help system operators maximize its potential while addressing challenges associated with parameter sensitivity and real-time adaptability [60, 61].

The BSFDT approach provides a significant improvement in ELD by optimizing load distribution, reducing costs, and enhancing power system stability. Despite its reliance on precise parameterization, this approach remains a valuable tool for utilities and energy management applications. By addressing its limitations and integrating advanced optimization strategies, power system operators can ensure a more sustainable, efficient, and resilient power supply. A complete list of abbreviations is listed in *Appendix I.*

5.Conclusion and future work

This study introduces the BSFDT methodology to enhance decision-making in ED scenarios. The BSFDT method effectively addresses challenges in solving the economic dispatch problem (EDP), including improving solution quality, computational efficiency, and global search capability, through the application of FL, intensification procedures, and optimization strategies. The BSFDT approach demonstrates exceptional adaptability by utilizing bell-shaped membership functions that effectively capture nonlinear interactions and uncertainties in power systems. By integrating FL into the decision-making process, the method ensures flexibility in managing constraints and optimizes resource allocation. The inclusion of fuzzy demand modeling enhances the ability to evaluate generation costs comprehensively while addressing uncertainties in demand forecasting. The findings indicate that the BSFDT achieves significant reductions in costs and transmission losses across varying power demand levels (e.g., 1250 MW, 4000 MW, and 7000 MW). It proves particularly effective at higher power demands, where its ability to optimize resource utilization and minimize losses becomes more evident. Furthermore, the methodology incorporates environmental considerations, offering a balanced approach to achieving economic efficiency and sustainability in power system operations. The BSFDT methodology represents a notable advancement in power system optimization. By addressing real-world complexities, improving decision-making processes, and providing sustainable solutions, the approach ensures efficient, reliable, and environmentally responsible power system management. Its adaptability and scalability make it a valuable tool for modern utilities and energy management applications.

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Data availability

None.

Conflicts of interest

The authors have no conflicts of interest to declare.

Author’s contribution statement

All authors have contributed equally to this research work.

References

[1] Ahmed I, Rehan M, Basit A, Tufail M, Hong KS. Neuro-fuzzy and networks-based data driven model for multi-charging scenarios of plug-in-electric vehicles. IEEE Access. 2023; 11:87150-65.

[2] Kumar AN, Chakravarthy M, Kumar MS, Nagaraju M, Ramesha M, Gururaj B, et al. Fuzzy location algorithm for cross-country and evolving faults in

EHV transmission line. International Journal of Fuzzy Logic and Intelligent Systems. 2023; 23(2):130-9.

[3] Uddin M, Mo H, Dong D, Elsawah S, Zhu J, Guerrero JM. Microgrids: a review, outstanding issues and future trends. Energy Strategy Reviews. 2023; 49:101127.

[4] Jia Y, Ran G, Gong Y, Wang L, Xu F. Dynamic feedback tracking control for interval type-2 TS fuzzy nonlinear system based on adaptive event-triggered strategy. Neural Processing Letters. 2023; 55(2):1715-40.

[5] Hentout A, Maoudj A, Aouache M. A review of the literature on fuzzy-logic approaches for collision-free path planning of manipulator robots. Artificial Intelligence Review. 2023; 56(4):3369-444.

[6] Sun HY, Han HG, Sun J, Yang HY, Qiao JF. Security control of sampled-data T–S fuzzy systems subject to cyberattacks and successive packet losses. IEEE Transactions on Fuzzy Systems. 2022; 31(4):1178-88.

[7] Xie X, Yang F, Wan L, Xia J, Shi K. Enhanced local stabilization of constrained N-TS fuzzy systems with lighter computational burden. IEEE Transactions on Fuzzy Systems. 2022; 31(3):1064-70.

[8] Dehak A, Nguyen AT, Dequidt A, Vermeiren L, Dambrine M. Reduced-complexity LMI conditions for admissibility analysis and control design of singular nonlinear systems. IEEE Transactions on Fuzzy Systems. 2022; 31(4):1377-90.

[9] Narayanamoorthy S, Ramya L, Gunasekaran A, Kalaiselvan S, Kang D. Selection of suitable biomass conservation process techniques: a versatile approach to normal wiggly interval-valued hesitant fuzzy set using multi-criteria decision making. Complex & Intelligent Systems. 2023; 9(6):6681-95.

[10] Zhang P, Zhang Z, Gong D, Cui X. A novel normal wiggly hesitant fuzzy multi-criteria group decision making method and its application to electric vehicle charging station location. Expert Systems with Applications. 2023; 223:119876.

[11] Singh DJ, Verma NK. Interval type-3 TS fuzzy system for nonlinear aerodynamic modeling. Applied Soft Computing. 2024; 150:111097.

[12] VO TK, Nguyen XD, Ha MT, Le TK. Implement fuzzy-PID controllers for trajectory tracking of an underactuated surface vessel. International Journal of Intelligent Systems and Applications in Engineering. 2023; 11(2):126-32.

[13] Song YH, Wang GS, Wang PY, Johns AT. Environmental/economic dispatch using fuzzy logic controlled genetic algorithms. IEE Proceedings-Generation, Transmission and Distribution. 1997; 144(4):377-82.

[14] Mabrouk AB, Alanazi A, Bassfar Z, Alanazi D. New hybrid model for nonlinear systems via Takagi-Sugeno fuzzy approach. AIMS Mathematics. 2024; 9(9):23197-220.

[15] Duan Z, Ding F, Liang J, Xiang Z. Observer-based fault detection for continuous–discrete systems in TS fuzzy model. Nonlinear Analysis: Hybrid Systems. 2023; 50:101379.

[16] Sharifian Y, Abdi H. Multi-area economic dispatch problem: methods, uncertainties, and future directions. Renewable and Sustainable Energy Reviews. 2024; 191:114093.

[17] You W, Xie X, Wang H, Xia J, Stojanovic V. Relaxed model predictive control of TS fuzzy systems via a new switching-type homogeneous polynomial technique. IEEE Transactions on Fuzzy Systems. 2024; 32(8):4583-94.

[18] Xu J, Song T, Wang J. Finite-time fuzzy fault-tolerant control for nonlinear flexible spacecraft system with stochastic actuator faults. Mathematics. 2024; 12(4):1-25.

[19] Yan F, Feng S, Liu X, Feng T. Parametric dynamic distributed containment control of continuous-time linear multi-agent systems with specified convergence speed. Sensors. 2023; 23(5):1-17.

[20] Liu G, Sun J, Wang W, Hui N, Zou L, Liu C. H∞ static output feedback control for TS fuzzy systems via lyapunov functions. In 43rd Chinese control conference (CCC) 2024 (pp. 2618-23). IEEE.

[21] Yang H, Zhang S, Yu F. Admissibility analysis and controller design improvement for TS fuzzy descriptor systems. Symmetry. 2024; 16(8):1-16.

[22] Kchaou M, Regaieg MA, Jerbi H, Abbassi R, Stefanoiu D, Popescu D. Admissible control for non-linear singular systems subject to time-varying delay and actuator saturation: an interval type-2 fuzzy approach. Actuators. 2023; 12(30):1-20.

[23] Lu DH, Huang CP. Refined admissible analysis and design conditions for discrete fuzzy singular systems with multiple difference matrices. Applied Artificial Intelligence. 2023; 37(1):1-19.

[24] Li J, Piao Y. Multi-object tracking based on re-identification enhancement and associated correction. Applied Sciences. 2023; 13(17):1-16.

[25] Ravi S, Matheswaran S, Perumal U, Sivakumar S, Palvadi SK. Adaptive trust-based secure and optimal route selection algorithm for MANET using hybrid fuzzy optimization. Peer-to-Peer Networking and Applications. 2023; 16(1):22-34.

[26] Rahman S, Khan I, Dey S, Mallik A. Triple-active bridge-based dynamic power balancing solution for minimizing overdesigning in military aircraft power system. IEEE Transactions on Vehicular Technology. 2023; 73(3):3329-39.

[27] Wu J, He X, Niu Y, Huang T, Yu J. Circuit implementation of proximal projection neural networks for composite optimization problems. IEEE Transactions on Industrial Electronics. 2023; 71(2):1948-57.

[28] Shen M, Wang X, Zhu S, Wu Z, Huang T. Data-driven event-triggered adaptive dynamic programming control for nonlinear systems with input saturation. IEEE Transactions on Cybernetics. 2023; 54(2):1178-88.

[29] Massaoudi M, Abu-rub H, Ghrayeb A. Advancing lithium-ion battery health prognostics with deep learning: a review and case study. IEEE Open Journal of Industry Applications. 2024; 5:43-62.

[30] Coy JJ, Saito M, Yang P, Liu X, Hu Y. A robust ice cloud optical property model for LiDAR-based remote sensing applications. IEEE Geoscience and Remote Sensing Letters. 2023; 21:1-5.

[31] Wang D, Duan X, Yeh SH, Zou J, Song D. Calibration system and algorithm design for a soft hinged micro scanning mirror with a triaxial hall effect sensor. IEEE Robotics and Automation Letters. 2024; 9(3):2447-54.

[32] Lee SC, Hwang HS, Lee KC. Accuracy of deep learning-based integrated tooth models by merging intraoral scans and CBCT scans for 3D evaluation of root position during orthodontic treatment. Progress in Orthodontics. 2022; 23(1):1-11.

[33] Wu L, Gao H. Sliding mode control of two-dimensional systems in Roesser model. IET Control Theory & Applications. 2008; 2(4):352-64.

[34] Yang ZJ, Shibuya Y, Qin P. Distributed robust control for synchronised tracking of networked Euler–Lagrange systems. International Journal of Systems Science. 2015; 46(4):720-32.

[35] Yuan YH, Zhang QL, Zhang DQ, Chen BI. Admissible conditions of fuzzy descriptor systems based on fuzzy Lyapunov function approach. International Journal of Information and Systems Sciences. 2008; 4(2):219-32.

[36] Kunya AB, Abubakar AS, Yusuf SS. Review of economic dispatch in multi-area power system: state-of-the-art and future prospective. Electric Power Systems Research. 2023; 217:109089.

[37] Jadoun VK, Prashanth GR, Joshi SS, Narayanan K, Malik H, Márquez FP. Optimal fuzzy based economic emission dispatch of combined heat and power units using dynamically controlled whale optimization algorithm. Applied Energy. 2022; 315:1-12.

[38] Maged NA, Hasanien HM, Ebrahim EA, Tostado-véliz M, Turky RA, Jurado F. Optimal real-time implementation of fuzzy logic control strategy for performance enhancement of autonomous microgrids. International Journal of Electrical Power & Energy Systems. 2023; 151:109140.

[39] Takagi T, Sugeno M. Fuzzy identification of systems and its applications to modeling and control. IEEE Transactions on Systems, Man, and Cybernetics. 1985; 15(1):116-32.

[40] Kaloop MR, Bardhan A, Kardani N, Samui P, Hu JW, Ramzy A. Novel application of adaptive swarm intelligence techniques coupled with adaptive network-based fuzzy inference system in predicting photovoltaic power. Renewable and Sustainable Energy Reviews. 2021; 148:111315.

[41] Hasan F, Kargarian A. Topology-aware learning assisted branch and ramp constraints screening for dynamic economic dispatch. IEEE Transactions on Power Systems. 2022; 37(5):3495-505.

[42] Ramachandran M, Mirjalili S, Ramalingam MM, Gnanakkan CA, Parvathysankar DS, Sundaram A. A ranking-based fuzzy adaptive hybrid crow search algorithm for combined heat and power economic dispatch. Expert Systems with Applications. 2022; 197:116625.

[43] Gajanan LS, Kirar M, Paliwal P, Rajak N. A state-of-the-art review on modern artificial intelligence based techniques for economic load dispatch. In renewable energy and sustainable E-mobility conference 2023 (pp. 1-6). IEEE.

[44] Azeem F, Ahmad A, Gondal TM, Arshad J, Rehman AU, Eldin EM, et al. Load management and optimal sizing of special-purpose microgrids using two stage PSO-fuzzy based hybrid approach. Energies. 2022; 15(17):1-19.

[45] Xu D, Xiao J, Wang X. Environmental economic dispatch of power system based on multi-objective improved hybrid leapfrog algorithm. In 2nd international conference on electrical engineering and control science 2022 (pp. 504-10). IEEE.

[46] Marzbani F, Abdelfatah A. Economic dispatch optimization strategies and problem formulation: a comprehensive review. Energies. 2024; 17(3):1-31.

[47] Nguyen AT, Sentouh C, Popieul JC. Fuzzy steering control for autonomous vehicles under actuator saturation: design and experiments. Journal of the Franklin Institute. 2018; 355(18):9374-95.

[48] Nguyen AT, Campos V, Guerra TM, Pan J, Xie W. Takagi–sugeno fuzzy observer design for nonlinear descriptor systems with unmeasured premise variables and unknown inputs. International Journal of Robust and Nonlinear Control. 2021; 31(17):8353-72.

[49] Chen J, Sun Y, Min H, Sun F, Zhang Y. New results on static output feedback H∞ control for fuzzy singularly perturbed systems: a linear matrix inequality approach. International Journal of Robust and Nonlinear Control. 2013; 23(6):681-94.

[50] Nguyen AT, Coutinho P, Guerra TM, Palhares R, Pan J. Constrained output-feedback control for discrete-time fuzzy systems with local nonlinear models subject to state and input constraints. IEEE Transactions on Cybernetics. 2020; 51(9):4673-84.

[51] Xie XP, Yue D, Park JH. Robust fault estimation design for discrete-time nonlinear systems via a modified fuzzy fault estimation observer. ISA Transactions. 2018; 73:22-30.

[52] Kwon OM, Park MJ, Park JH, Lee SM. Stability and stabilization of TS fuzzy systems with time-varying delays via augmented Lyapunov-Krasovskii functionals. Information Sciences. 2016; 372:1-5.

[53] Wang L, Liu J, Lam HK. New results of observer design for continuous-time fuzzy systems: a switching technique. IEEE Transactions on Systems, Man, and Cybernetics: Systems. 2021; 52(9):5702-6.

[54] Gong A, Xie XP, Peng C. Enhanced observer-based state estimation of discrete-time Takagi-Sugeno fuzzy systems via a distinctive multi-instant gain-scheduling law. Journal of the Franklin Institute. 2021; 358(17):9288-306.

[55] Maharana HS, Dash SK. Comparative optimization analysis of ramp rate constriction factor based PSO and electro magnetism based PSO for economic load dispatch in electric power system. In international conference on applied machine learning 2019 (pp. 63-8). IEEE.

[56] Gachhayat SK, Dash SK. Modified sub-gradient based combined objective technique and evolutionary programming approach for economic dispatch involving valve-point loading, enhanced prohibited zones and ramp rate constraints. International Journal of Electrical and Computer Engineering. 2020; 10(5):5048-57.

[57] Chen G, Tan T, Xiang W, Guan Z, Tan H, Yu J, et al. Solving environment economic power dispatch problems by multi-objective modified seagull optimization algorithm with novel constraint treatments. IAENG International Journal of Applied Mathematics. 2023; 53(1):1-17.

[58] Gachhayat SK, Dash SK, Deo BP. Approaches for smart linear regression in a difficult quasi economic dispatch problem. International Journal of Electrical & Computer Engineering. 2023; 13(4):4752-60.

[59] Roman RC, Precup RE, Hedrea EL. Intelligent proportional controller tuned by virtual reference feedback tuning and fictitious reference iterative tuning. Procedia Computer Science. 2023; 221:86-93.

[60] Kaur A, Narang N. Multi-objective generation scheduling of integrated energy system using hybrid optimization technique. Neural Computing and Applications. 2024; 36(3):1215-36.

[61] Daqaq F, Ouassaid M, Ellaia R. A new meta-heuristic programming for multi-objective optimal power flow. Electrical Engineering. 2021; 103(2):1217-37.

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Appendix I

S. No.	Abbreviation	Description
1	BSFDT	Bell-Shaped Fuzzy Decision Trees
2	CO	Carbon Monoxide
3	CPU	Central Processing Unit
4	CVAR	Conditional Value-at-Risk
5	DT	Decision Tree
6	ED	Economic Dispatch
7	EDP	Economic Dispatch Problem
8	ELD	Economic Load Dispatch
9	FL	Fuzzy Logic
10	FLS	Fuzzy Learning Set
11	FLDT	Fuzzy Logic-Based Decision Tree
12	IC	Integrated Circuit
13	IEEE	Institute of Electrical and Electronics Engineers
14	LS	Load Segment
15	NFLDT	Non-Fuzzy Logic-Based Decision Tree
16	N_2O	Nitrous Oxide
17	P5	Pentium 5
18	PSO	Particle Swarm Optimization
19	SO_2	Sulfur Dioxide