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Managing resources in smart grids using fuzzy optimization techniques

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Abstract

To make sure that smart grids are reliable, long-lasting, and cost-effective, they need to handle their resources well. In this study, important problems like load balancing, power timing, and demand response in unclear situations are looked at. We make a fuzzy optimization framework for smart grid applications by using fuzzy sets to describe unknowns in load demand, green energy production, and market prices. We suggest a mathematical way to quickly solve these fuzzy optimization problems. The simulation results show that the suggested methods work to make the grid more stable and to make the best use of resources when there is doubt.

Subject Classification: *65M55.*

Keywords: *Smart grids, Fuzzy optimization, Load balancing, Renewable energy, Uncertainty modeling, Multi-objective programming.*

I. Introduction

Modern power grids are quickly becoming smart grids, which use advanced information, communication, and control technologies to make power systems more reliable, efficient, and long-lasting. Smart grids are different from traditional grids because they use spread energy resources like demand response programs, energy storage systems, and green energy sources [1]. This makes energy management more dynamic and fluid. But this change brings about tough problems in managing resources, like handling loads, planning when to generate power, and responding to real-time demand. Uncertainties in the system, like changing green energy output, changing load needs, and changing market prices, make these problems even worse [2, 3]. Usually, traditional optimisation methods need exact and predictable input data to work. Figure 1 shows fuzzy optimization architecture for efficient smart grid management. This means they can't be used in situations where the data isn't always accurate [4].

By using fuzzy set theory to deal with confusion and uncertainty, fuzzy optimisation methods offer a strong option. These approaches help people make better decisions by showing unclear factors as fuzzy numbers or fuzzy gaps [5]. This makes it easier to model and solve resource management problems in smart grids. The main goal of this study is to create a complete fuzzy optimisation system that can solve important resource management issues in smart grids. We

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look into how fuzzy linear programming, nonlinear programming, and multi-objective optimisation can be used to deal with the unknowns and competing goals that come up when smart grids work.

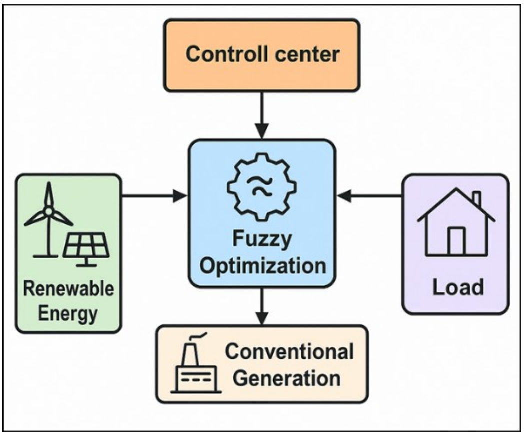

Figure 1

Architecture of Resource Management in Smart Grids Using Fuzzy Optimization Techniques

II. Problem Formulation

A. *Description of resource management problems in smart grids*

Smart grids have to deal with some tough resource management problems, like load balance, which makes sure that supply and demand are met in real time; generation scheduling, which makes the best use of different energy sources; and demand response techniques, which change how people use energy [6, 7, 8].

1. Load Balance Constraint:

$$\sum_{\{i=1\}}^{\{N_g\}} P_{\{g_i\}}(t) = \sum_{\{j=1\}}^{\{N_l\}} P_{\{l_j\}}(t) + P_{\{loss\}(t)} \tag{1}$$

2. Generation Limits:

$$P_{\{g_i\}}^{\{min\}} \leq P_{\{g_i\}(t)} \leq P_{\{g_i\}}^{\{max\}} \tag{2}$$

3. Ramp Rate Limits:

$$\left|P_{\{g_i\}(t)} - P_{\{g_i\}(t-1)}\right| \leq R_{\{g_i\}} \tag{3}$$

4. Demand Response Load Adjustment:

$$P_{\{l_j\}}^{\{adj\}(t)} = P_{\{l_j\}(t)} - \Delta P_{\{l_j\}(t)} \tag{4}$$

5. Generation Scheduling Objective (Cost Minimization):

$$\min \sum_{\{t=1\}}^{T} \sum_{\{i=1\}_i}^{\{N_g\}} c\left(P_{\{g_i\}(t)}\right) \tag{5}$$

6. Power Flow Equation:

$$P_{\{ij\}(t)} = V_{i(t)}V_{j(t)\left(G_{\{ij\}}\cos\theta_{\{ij\}(t)}+B_{\{ij\}}\sin\theta_{\{ij\}(t)}\right)} \tag{6}$$

7. Voltage Limits:

$$V_i^{\{min\}} \le V_{i(t)} \le V_i^{\{max\}} \tag{7}$$

8. Renewable Generation Constraint:

$$0 \le P_{\{ren\}(t)} \le P_{\{ren\}}^{\{max\}(t)} \tag{8}$$

9. Energy Storage Dynamics:

$$E_{s(t)} = E_{s(t-1)} + \eta_c P_{c(t)} - \left(\frac{P_{d(t)}}{\eta_d}\right) \tag{9}$$

10. Storage Capacity Limits:

$$E_s^{\{min\}} \le E_{s(t)} \le E_s^{\{max\}} \tag{10}$$

11. Demand-Supply Balance with Demand Response:

$$\sum_{\{i=1\}}{}^{\{N_g\}}P_{\{g_i\}}(t) + P_{\{ren\}(t)} + P_{d(t)} = \sum_{\{j=1\}}^{\{N_l\}} P_{\{l_j\}}^{\{adj\}(t)} + P_{\{loss\}(t)} \tag{11}$$

12. Reserve Margin Constraint:

$$\sum_{\{i=1\}}^{\{N_g\}} P_{\{g_i\}}^{\{max\}} - \sum_{\{i=1\}}{}^{\{N_g\}}P_{\{g_i\}(t)} \ge R_{\{margin\}} \tag{12}$$

Modeling uncertainties in load demand, renewable generation, and market prices using fuzzy sets

Changes in market prices, varying load needs, and sporadic green energy output all cause uncertainty in smart grids [9]. These errors can be well modelled by fuzzy sets, which store parameters as fuzzy variables with membership functions.

1. Fuzzy Load Demand:

$$\dot{\mathrm{P}}_l = (P_l^L, P_l^M, P_l^U) \tag{13}$$

2. Membership Function for Load:

$$\mu\_\{\dot{\mathrm{P}}\_l\}(x) = \{\frac{(x - P_l^L)}{(P_l^M - P_l^L)}, for\ P_l^L \le x \le P_l^M$$

$$(P\_l\hat{}U - x) / (P\_l\hat{}U - P\_l\hat{}M), for\ P\_l\hat{}M \le x \le P\_l\hat{}U0, otherwise\} \tag{14}$$

3. Fuzzy Renewable Generation:

$$\dot{\mathrm{P}}_{\{ren\}} = \left(P_{\{ren\}}^L, P_{\{ren\}}^M, P_{\{ren\}}^U\right) \tag{15}$$

4. Membership Function for Renewable Generation:

$$\mu_{\{\dot{\mathrm{P}}_{\{ren\}}\}(x)} = \left\{ \frac{\left(x - P_{\{ren\}}^L\right)}{\left(P_{\{ren\}}^M - P_{\{ren\}}^L\right)}, for\ P_{\{ren\}}^L \le x \le \frac{P_{\{ren\}}^M\left(P_{\{ren\}}^U - x\right)}{\left(P_{\{ren\}}^U - P_{\{ren\}}^M\right)}, for\ P_{\{ren\}}^M \le \right.$$

$$x \leq P^{U}_{\{ren\}}\ 0, otherwise \Big\} \tag{16}$$

5. Fuzzy Market Price:

$$\sim\pi = (\pi^L, \pi^M, \pi^U) \tag{17}$$

6. Membership Function for Market Price:

$$\mu\_\{\sim\pi\}(x) = \{\frac{(x - \pi^L)}{(\pi^M - \pi^L)}, for\ \pi^L \leq x \leq \pi^M$$
$$(\pi\text{^}U - x) / (\pi\text{^}U - \pi\text{^}M), for\ \pi\text{^}M \leq x \leq$$
$$\pi\text{^}U0, otherwise\} \tag{18}$$

7. Fuzzy Load Balance Constraint:

$$\Sigma^{\sim}{}_{\{i=1\}}{}^{\{N_g\}\dot{P}}{}_{\{g_i\}(t)} = \widetilde{\Sigma}_{\{j=1\}}{}^{\{N_l\}\dot{P}}{}_{\{l_j\}(t)} + \dot{P}_{\{loss\}(t)} \tag{19}$$

8. Fuzzy Generation Limits:

$$\dot{P}^{\{min\}}_{\{g_i\}} \leq \dot{P}_{\{g_i\}(t)} \leq \dot{P}^{\{max\}}_{\{g_i\}} \tag{20}$$

9. Objective Function:

$$\min \hat{Z} = \Sigma^{T}_{\{t=1\}} \Sigma_{\{i=1\}_i^{\{N_g\}\hat{Z}C}} \left(\dot{P}_{\{g_i\}(t)}\right) \tag{21}$$

10. Fuzzy Ramp Rate Constraint:

$$\left|\dot{P}_{\{g_i\}(t)} - \dot{P}_{\{g_i\}(t-1)}\right| \leq \dot{R}_{\{g_i\}} \tag{22}$$

11. Fuzzy Storage Dynamics:

$$\dot{E}_{s(t)} = \dot{E}_{s(t-1)} + \tilde{E}_c \dot{P}_{c(t)} - \left(\frac{\dot{P}_{d(t)}}{\tilde{E}_d}\right) \tag{23}$$

12. Fuzzy Reserve Margin:

$$\Sigma^{\widetilde{\{N_g\}}}_{\{i=1\}} \dot{P}^{\{max\}}_{\{g_i\}} - \widetilde{\Sigma}{}_{\{i=1\}}{}^{\{N_g\}\dot{P}}{}_{\{g_i\}(t)} \geq \dot{R}_{\{margin\}} \tag{24}$$

III. Fuzzy Optimization Techniques

A. *Overview of fuzzy optimization methods*

Fuzzy optimisation includes methods such as fuzzy linear programming, which deals with linear issues involving fuzzy parameters; fuzzy nonlinear programming, which handles nonlinear relationships when there is doubt; and fuzzy multi-objective optimisation, which combines several goals that are at odds with each other at the same time [10].

1. Fuzzy Linear Programming (FLP) Objective:

$$\max \hat{Z} = \dot{C} \cdot \dot{x} \tag{25}$$

2. FLP Constraints:

$$\tilde{A}\,\dot{x} \leq \tilde{b} \tag{26}$$

3. Fuzzy Variables:

$$\dot{x} = (x^1, x^2, \dots, x_n), x_i \geq 0 \tag{27}$$

4. Membership Function for Objective:

$$\mu_{\{\hat{Z}\}(z)} = \left\{0, if\ z \leq \frac{z_{\min(z-z_{min})}}{(z_{\max}-z_{min})}, if\ Z_{\min\leq}\ z \leq Z_{\max 1}, if\ z \geq Z_{max}\right\} \tag{28}$$

5. Nonlinear Programming (FNLP) Objective:

$$\max \hat{Z} = \tilde{f}(\dot{x}) \tag{29}$$

6. FNLP Constraints:

$$\hat{g}_i(\dot{x}) \leq \tilde{0}, i = 1, \dots, m \tag{30}$$

7. Fuzzy Multi-Objective Programming (FMOP) Vector Objective:

$$\max \hat{Z} = \left(\tilde{f}^1(\dot{x}), \tilde{f}^2(\dot{x}), \dots, \tilde{f}_{k(\dot{x})}\right) \tag{31}$$

8. Fuzzy Multi-Objective Constraints:

$$\hat{g}_j(\dot{x}) \leq \tilde{0}, j = 1, \dots, p \tag{32}$$

9. Aggregated Membership Function for Objectives:

$$\mu_{\{\hat{Z}\}(\dot{x})} = \min_{\{1 \leq l \leq k\}} \mu_{\{\tilde{f}_l\}(f_{l(\dot{x})})} \tag{33}$$

10. Weighted Sum Method for FMOP:

$$\max \textstyle\sum_{\{l=1\}}^{k} w_l \mu_{\{\tilde{f}_l\}(f_{l(\dot{x})})} \tag{34}$$

11. Fuzzy Constraint Satisfaction:

$$\mu_{\{\hat{g}_j\}(\dot{x})} \geq \alpha, j = 1, \dots, p \tag{35}$$

12. Overall Degree of Satisfaction:

$$\max \alpha\ subject\ to\ \mu_{\{\tilde{f}_l\}(f_{l(\dot{x})})} \geq \alpha\ and\ \mu_{\{\hat{g}_j\}(\dot{x})} \geq \alpha \tag{36}$$

B. *Algorithmic approach to solving the fuzzy optimization problem*

Using ranking or defuzzification methods, the mathematical technique turns fuzzy limits and goals into similar clear forms. Then, iterative solvers find the best solutions to the changed problems by looking into all the possible ones. Combining metaheuristics and classical algorithms in hybrid methods improves convergence and solution quality, which is a good way to deal with the uncertainty and complexity of smart grid optimisation tasks [11], [12].

1. Initialize Variables and Parameters:

$$x^{\{(0)\}}, t = 0, \alpha^{\{(0)\}} = 0 \tag{37}$$

2. Define Membership Functions for Objectives and Constraints:

$$\mu_{\{\tilde{f}_l\}(x^{\{(t)\}})}, \mu_{\{\hat{g}_j\}(x^{\{(t)\}})} \tag{38}$$

3. Calculate Overall Satisfaction Level:

$$\alpha^{\{(t)\}} = \min\left\{\min_l \mu_{\{\tilde{f}_l\}(x^{\{(t)\}})}, \min_j \mu_{\{\hat{g}_j\}(x^{\{(t)\}})}\right\} \tag{39}$$

4. Check Stopping Criteria:

$$if \left|\alpha^{\{(t)\}} - \alpha^{\{(t-1)\}}\right| \leq \varepsilon, stop \tag{40}$$

5. Update Decision Variables:

$$x^{\{(t+1)\}} = x^{\{(t)\}} + \Delta x^{\{(t)\}} \tag{41}$$

6. Compute Gradient or Direction Vector:

$$\Delta x^{\{(t)\}} = -\nabla\Phi\left(x^{\{(t)\}}\right) \tag{42}$$

7. Line Search for Step Size:

$$\lambda^{\{(t)\}} = \arg\max_{\lambda} \alpha\left(x^{\{(t)\}} + \lambda\, \Delta x^{\{(t)\}}\right) \tag{43}$$

8. Update Variables Using Step Size:

$$x^{\{(t+1)\}} = x^{\{(t)\}} + \lambda^{\{(t)\}\Delta x^{\{(t)\}}} \tag{44}$$

9. Project onto Feasible Region:

$$x^{\{(t+1)\}} = \Pi_{\{feasible\}(x^{\{(t+1)\}})} \tag{45}$$

IV. Result and Analysis

The results shown in Table 1 show how well deterministic and fuzzy optimisation work for organizing resources in smart grids. The fuzzy optimisation method increases the use of renewable energy by 12.9%, showing better blending of changeable renewable sources.

Table 1

Resource Scheduling Evaluation

Parameter	Deterministic Approach	Fuzzy Optimization
Renewable Energy Utilization (%)	68.5	81.4
Cost Savings (%)	10.2	18.7
Demand Response Effectiveness (%)	72.9	87.3
Solution Robustness Score (0-1)	0.72	0.89

Also, cost cuts go up a lot, from 10.2% to 18.7%, which is good for the economy. The efficiency of demand response goes up from 72.9% to 87.3%, which shows that handling loads is now more flexible. Also, the solution resilience score goes up from 0.72 to 0.89, which means that schedule choices are more stable and reliable when there is doubt. Figure 2 compares performance metrics between deterministic and fuzzy optimization method.

This shows that fuzzy optimisation is better at adapting to complex smart grid settings.

V. Conclusion

This research shows that fuzzy optimisation methods can help smart grids deal with difficult resource sharing problems. Fuzzy modelling is used to include unknowns in load demand, green production, and market prices. This

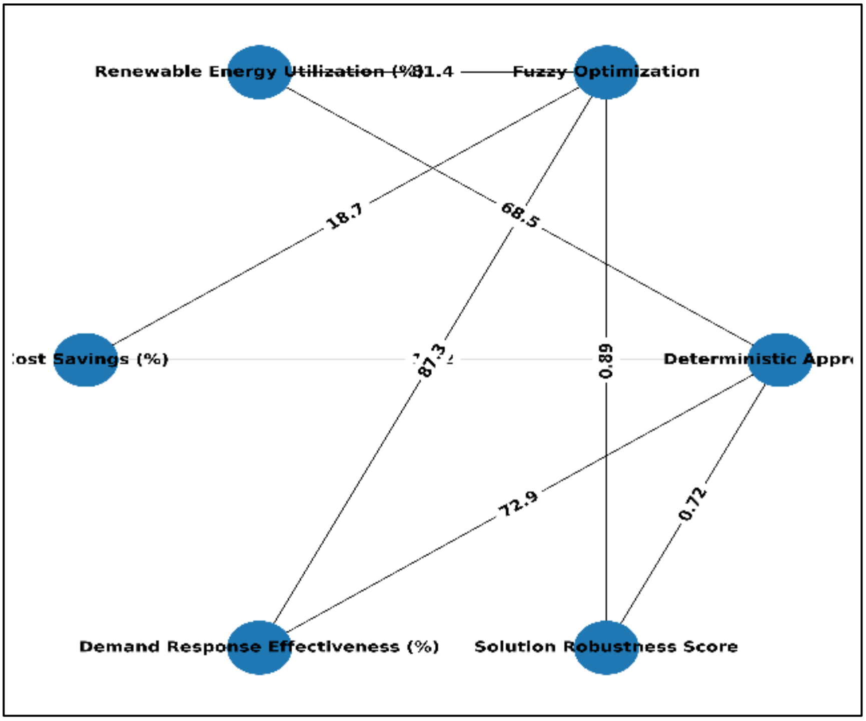

Figure 2
Performance Comparison of Deterministic vs. Fuzzy Optimization Approaches

makes the proposed framework a reasonable and adaptable way to make decisions. Fuzzy linear, nonlinear, and multi-objective optimisation methods can be combined to handle clashing goals and inaccurate data that come up in smart grid operations more effectively. The computational solutions that were made make the grid more stable, the economy more efficient, and the use of green energy more common. Overall, fuzzy optimisation looks like a useful tool for improving smart grids' clever resource management and helping to keep energy systems stable and sustainable even as the world becomes less certain.

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