Optimization Algorithm Design for Power Balance Dispatching Strategy of Active Distribution Network Based on Fuzzy Logic

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ABSTRACT The increasing penetration of distributed energy resources has introduced substantial operational uncertainties into active distribution networks, posing significant challenges to stable electromagnetic energy transmission and intelligent power dispatch. This study proposes a fuzzy logic-based power balance scheduling optimization algorithm that dynamically adjusts daily dispatch plans through a multi-input single-output fuzzy inference system. A three-input fuzzy controller is first established using net load deviation, energy storage state-of-charge deviation, and transmission line power fluctuation as input variables, while the output represents the power adjustment of dispatchable resources. To enhance adaptability under varying operating conditions, a variable-domain mechanism is incorporated to overcome the limitations of fixed membership functions. Historical operational data are further classified through fuzzy clustering, enabling scenario-oriented rule-base optimization. Simulation results on the IEEE 33-node active distribution network demonstrate that, compared with fixed-domain fuzzy control, the proposed method reduces the cumulative daily average absolute power deviation by 8.4%, decreases energy storage charge-discharge cycles by 1.3%, and improves tie-line power fluctuation variance by 6.4%. Relative to model predictive control (MPC), it achieves comparable control performance within 1.2% while requiring only 6.6% of the computational time. Robustness evaluations under communication latency and measurement noise further verify its practical applicability. The proposed algorithm provides an efficient and reliable solution for uncertainty-aware dispatching in active distribution networks and offers valuable support for intelligent electromagnetic energy management and modern power transmission systems.

INDEX TERMS active distribution network, fuzzy logic, power balance dispatching, electromagnetic energy transmission, intelligent power systems

I. INTRODUCTION

THE distribution network is undergoing a profound transformation from passive power absorption to proactive management. The large-scale integration of intermittent energy sources like distributed photovoltaics and wind power, coupled with the stochastic nature of electric vehicle charging loads, has made power balance challenges in grid operations more complex than ever. Traditional dispatch strategies primarily rely on deterministic forecasting. When prediction deviations exceed expected ranges, pre-established scheduling plans often struggle to maintain system stability. This dilemma becomes particularly pronounced during peak periods when solar power output experiences sharp declines at midday or when evening loads surge rapidly. Scholars worldwide have conducted extensive research on this issue. In uncertainty modeling, chance constraint programming is widely employed to address the stochastic characteristics of renewable energy generation, balancing economic efficiency and safety constraints through confidence level settings [1,2]. However, chance constraint methods typically require known probability distributions of uncertain variables, while actual operational data often exhibit time-varying distribution patterns, posing challenges for parameter estimation. Fuzzy set theory provides a novel approach by constructing fuzzy sets for uncertain parameters to describe their possible value ranges, effectively overcoming the difficulty of obtaining precise probability distributions.

Reference [3] applied fuzzy chance constraints to power supply unit allocation, considering distributed energy source integration while addressing dual-side uncertainties in both generation and load aspects, thereby demonstrating the feasibility of fuzzy methods in distribution network planning. Multi-objective optimization remains a key research focus in active power distribution network dispatching. Practical operations require balancing multiple conflicting objectives such as operational cost efficiency, voltage quality, and equipment lifespan, making optimal trade-off identification crucial. While Pareto optimization methods can generate non-dominated solution sets, dispatchers often struggle with decision-making when confronted with multiple alternatives. Fuzzy logic offers the advantage of normalizing multiple objectives through membership functions, thereby generating a comprehensive satisfaction index that facilitates the derivation of unique dispatch decisions. Reference [4] proposed a multi-objective fuzzy optimization approach integrating fuzzy mechanisms into the Pareto optimization framework, providing dispatchers with more intuitive decision support. In distribution network restructuring applications, fuzzy rules have been employed to enhance pheromone update strategies in ant colony algorithms, thereby expanding solution space exploration capabilities [5].

Despite certain advancements in existing research, several critical issues remain worthy of in-depth exploration. Firstly, most current fuzzy scheduling methods rely on fixed-structure membership functions and rule bases, which may lead to significant control performance degradation when operating conditions undergo substantial changes. Secondly, most studies treat fuzzy control and optimization algorithms as separate processes: fuzzy controllers handle real-time adjustments while optimization algorithms focus on planning formulation, lacking effective coordination mechanisms between the two [6,7]. Third, for specific scenarios such as active power distribution network balance, there remains a systemic lack of solutions regarding how to design appropriate fuzzy inference architectures that can simultaneously respond to net load fluctuations, energy storage states, and transmission line power constraints. Fourth, the absence of comparative analyses against advanced control methodologies such as model predictive control or reinforcement learning limits the contextualization of fuzzy logic performance within the broader landscape of dispatch optimization techniques. Fifth, practical implementation challenges including communication latency, measurement noise, and forecast update intervals have received insufficient attention in existing studies, potentially undermining the applicability of theoretical results to real-world distribution network operations. Based on the aforementioned analysis, this study introduces a variable-domain adaptive mechanism into the fuzzy scheduling framework, enabling the membership function to automatically adjust its domain range according to operational conditions. Meanwhile, a dual-layer structure combining day-ahead optimization with intra-day adjustments facilitates coordinated planning and adjustment processes, enhancing system resilience to uncertainties while maintaining optimal scheduling economics. It should be noted that this research primarily focuses on active power balance scheduling, with reactive power voltage control remaining an area for future investigation.

II. DESCRIPTION OF POWER BALANCE DISPATCHING PROBLEM FOR ACTIVE DISTRIBUTION NETWORKS

A. ANALYSIS OF UNCERTAINTY SOURCES

The uncertainties in active distribution networks primarily stem from several key factors. Distributed photovoltaic (PV) generation output is highly sensitive to weather conditions, where cloud cover and solar irradiance variations can cause significant short-term fluctuations. Operational data from a 10MW distributed PV plant demonstrates smooth output curves under clear skies, but cloud-covered conditions may trigger output swings exceeding 40% of rated capacity within five minutes [8]. Load-side uncertainties also warrant attention, particularly for electric vehicle charging loads characterized by stochastic connection timing and power demands. Individual fast-charging stations may experience instantaneous power requirements ranging from 0 to 120kW [9].

The convergence of these uncertainties poses dual challenges to power system balance. On one hand, there exists a cumulative effect of forecasting errors, where the net load curve predicted at the day-ahead stage systematically deviates from actual load patterns. On the other hand, stochastic fluctuations exhibit time-varying characteristics, meaning even accurate forecasts may lead to sudden operational deviations beyond predicted timeframes. Traditional dispatching methods typically address these issues separately—using optimization algorithms to mitigate forecasting errors and real-time control systems to manage stochastic variations. However, this fragmented approach struggles to achieve comprehensive optimization.

B. DISPATCH FRAMEWORK AND RESOURCE RESPONSE CHARACTERISTICS

The scheduling resources considered in this study include schedulable distributed power sources, energy storage systems, and power exchange via interconnection lines. Schedulable distributed power sources primarily refer to power generation equipment with rapid response capabilities such as gas turbines and diesel generators, which can achieve regulation rates of up to 20% of rated capacity per minute. However, frequent adjustments may accelerate equipment wear and incur additional maintenance costs. Moreover, these dispatchable units are subject to minimum up/down time constraints and ramping limitations that must be explicitly considered in the scheduling framework to ensure operational feasibility.

Energy storage systems, characterized by bidirectional regulation capabilities and millisecond-level response speeds, serve as ideal tools for suppressing high-frequency fluctuations. Nevertheless, limited by state-of-charge constraints, excessive charging and discharging may shorten battery lifespan. Power exchange via interconnection lines is governed by dispatch instructions from higher-level grids and typically follows day-ahead planning, with allowable deviations generally not exceeding 5% of planned values. The response characteristics of different resources determine the temporal scale division of scheduling strategies. During the day-ahead scheduling phase, output plans for each resource are formulated at 15-minute intervals, primarily based on load forecasts and renewable energy generation projections. The intra-day scheduling phase involves 5-minute cycle adjustments to address forecast deviations and short-term fluctuations. This study focuses on intra-day adjustment mechanisms, aiming to maintain plan execution accuracy while minimizing unnecessary resource adjustments.

C. CONTROL OBJECTIVES AND CONSTRAINTS

The core objective of power balance dispatching is to achieve real-time active power balance, where the instantaneous difference between system generation output and load demand equals the net power injection through interconnection lines. In practical operations, this objective is typically translated into controlling interconnection line power deviations, as excessive deviations may trigger protective mechanisms in higher-level grids or even compromise system stability. To precisely characterize this issue, the deviation between the actual $P_{tie}(t)$ power exchange on the interconnection line and the planned value $P_{tie}^{sch}(t)$ at scheduling time t is defined as (1):

$$\Delta P_{tie}(t) = P_{tie}(t) - P_{tie}^{sch}(t) \tag{1}$$

The primary objective of control is to minimize the cumulative daily average absolute power deviation, expressed mathematically as $\min \sum_{t=1}^{T} |\Delta P_{tie}(t)| \cdot \Delta t$, where T is the number of intra-day scheduling cycles and $\Delta t = 5$ min. In addition, the following constraints must be considered:

- State of Charge (SOC) constraints for energy storage systems: $SOC_{min} \leq SOC(t) \leq SOC_{max}$. In this study, the initial SOC values are set to 0.2 and 0.9, with the target SOC value specified as 0.6.
- Schedulable distributed generation constraints:
$$P_{DG,min} \leq P_{DG}(t) \leq P_{DG,max},$$
$$|P_{DG}(t) - P_{DG}(t-1)| \leq R_{DG} \cdot \Delta t,$$
where $R_{DG} = 0.2$ p.u./min.
- Minimum up/down time constraints for dispatchable distributed generators: once a gas turbine or diesel generator is started or shut down, it must remain in that operational state for a minimum duration to prevent excessive thermal-mechanical stress and maintain economic efficiency. In this study, a minimum up time of 30 minutes and minimum down time of 15 minutes are imposed.
- Power deviation constraint for tie lines, $|\Delta P_{tie}(t)| \leq \Delta P_{tie,max}$, where $\Delta P_{tie,max} = 0.05 P_{tie}^{sch}(t)$ is adopted in this paper.

III. SCHEDULING STRATEGIES BASED ON VARIABLE-DOMAIN FUZZY LOGIC

A. FUZZY CONTROLLER STRUCTURE DESIGN

Given that power balance dispatching requires simultaneous handling of nonlinear relationships among multiple input variables, this study proposes a three-input single-output Mamdani-type fuzzy controller. The three input variables include net load deviation E, energy storage state-of-charge deviation S, and transmission line power fluctuation index F, while the output variable U represents the comprehensive adjustment amount of dispatchable resources. Net load deviation E is defined as the difference between actual net load and day-ahead planned net load, normalized and mapped to the $[-1, 1]$ interval. A positive E value indicates higher actual load than predicted, requiring increased output or reduced charging; a negative E value suggests lower actual load than predicted, necessitating decreased output or increased charging. Energy storage state of charge deviation S refers to the difference between current SOC and target SOC, similarly normalized to the $[-0.3, 0.3]$ range. Positive values indicate excessive energy storage capacity, suggesting prioritized discharge or reduced charging; negative values indicate insufficient storage capacity, recommending increased charging or reduced discharge. The interconnection line power fluctuation indicator F reflects the power variation rate over the last two dispatch cycles, filtered and mapped to the $[0, 0.5]$ interval. This metric evaluates whether partial regulation accuracy sacrifice is necessary to maintain stable interconnection line power.

Fuzzy control rules form the core of control strategies. Based on engineering experience and simulation tests, this study establishes 49 rules structured as: "If error E belongs to fuzzy set A_i, error change rate S belongs to fuzzy set B_j, and state variable F belongs to fuzzy set C_k, then the control output U belongs to fuzzy set D_{ijk}." The rule base is initially constructed using heuristic knowledge from distribution network operation, wherein each linguistic label (NB: Negative Big, NS: Negative Small, ZE: Zero, PS: Positive Small, PB: Positive Big) corresponds to a specific numerical range derived from the normalized input domains. This linguistic framework ensures that the fuzzy controller maintains interpretability throughout the optimization process described in Section Rule Base Optimization and Scenario Segmentation. Representative rules are shown in Table 1. For simplicity, the table presents output U for different E–S combinations when F equals ZE (indicating stable fluctuations). When F deviates from ZE, output rules are adjusted according to F's magnitude, incorporating a correction term $\Delta U(F)$ such that $U = U(E, S) + \Delta U(F)$, to prioritize energy storage response for rapid fluctuations while avoiding frequent line regulation.

B. VARIABLE DOMAIN ADAPTIVE MECHANISM

Fixed-structure fuzzy controllers often demonstrate inadequate adaptability when facing operational condition variations. Taking typical photovoltaic power output character-

TABLE 1. Partial Fuzzy Control Rule Table (When F=ZE)

E/S	NB	NS	ZE	PS	PB
NB	NB	NB	NB	NS	ZE
NS	NB	NS	NS	ZE	PS
ZE	NS	NS	ZE	PS	PS
PS	NS	ZE	PS	PS	PB
PB	ZE	PS	PB	PB	PB

istics as an example, midday solar output peaks can reach 80% of load capacity during spring, while winter output may fall below 20% of load requirements during the same period. Under these contrasting conditions, control demands corresponding to identical absolute net load deviations exhibit significant differences. Fixed-domain fuzzy controllers struggle to achieve balanced control precision across both scenarios.

The core concept of the domain adaptive mechanism is to dynamically adjust the range of fuzzy sets based on system state variations. This study implements this functionality through a scaling factor approach. For input variable x with initial domain $[-X, X]$, the actual domain range is transformed to $[-\alpha X, \alpha X]$ after applying the scaling factor α. The scaling factor design must satisfy the following criteria: when the system state approaches the ideal operating point, a smaller α value is adopted to enhance the controller's sensitivity in small deviation regions; when significant deviations occur, a larger α value is applied to ensure robust response capability for large deviations. The expansion factor designed $\alpha(e)$ in this paper is a function of the absolute value of input deviation, with the specific form as shown in Equation (2):

$$\alpha(e) = 1 - \lambda \cdot \exp(-\mu|e|), \quad \lambda \in (0, 1) \tag{2}$$

The design ensures that when $|e| = 0$, $\alpha = 1 - \lambda$, and when $|e| \to \infty$, $\alpha \to 1$. Parameters λ and μ are selected from $\lambda \in [0.3, 0.8]$ and $\mu \in [2, 15]$, with $\lambda = 0.6$ and $\mu = 8$ used in this study. During specific operational phases, the logic domain undergoes contraction to enhance resolution; during other phases, it returns to its initial state. The maximum contraction extent of the control logic domain and the contraction rate are precisely regulated. To determine optimal parameter values, this study employs grid search optimization within a predefined range, with the objective function being the minimum cumulative daily absolute power deviation under typical daily operating conditions. Optimization results demonstrate that the target function achieves its minimum value at specific parameter combinations, which maintain high regulation accuracy for minor deviations while ensuring adequate responsiveness to significant deviations. The adjustment of output variable domains follows a similar approach, but with distinct scaling factor design principles. Excessive adjustments to output variables may cause system oscillations, necessitating more cautious scaling of output domains. This study employs a lagged-type scaling factor design for output variables, meaning that when input deviations are significant, the output domain should not be expanded hastily. Instead, priority should be given to utilizing existing regulatory capabilities.

C. RULE BASE OPTIMIZATION AND SCENARIO SEGMENTATION

The quality of fuzzy control rule libraries directly impacts control performance. Traditional methods rely on expert experience to derive rules, which may suffice under routine operating conditions but struggle to cover all potential operational scenarios. This study employs fuzzy clustering analysis to categorize historical operational data into different operating conditions, then optimizes rule libraries for each scenario separately, ultimately forming a scenario-specific rule library collection. The objective of cluster analysis is to identify key feature vectors from historical operational data, including net load curve morphology, photovoltaic output penetration rate, and energy storage state of charge variation rate. The fuzzy C-means clustering algorithm is employed, where the membership degree of sample points to each cluster center reflects the probability of belonging to specific operational scenarios. The number of clusters is optimized using the silhouette coefficient metric, achieving a maximum value of 0.67 when clustering into four groups: typical high-penetration scenarios, typical low-penetration scenarios, rapid load ramp-up scenarios, and photovoltaic steep drop scenarios. To validate that these clusters correspond to statistically distinct control performance characteristics, a one-way analysis of variance (ANOVA) was conducted on the cumulative daily average absolute power deviation across the four scenario categories using the baseline fixed-domain fuzzy controller. The ANOVA results yield an F-statistic of 14.32 with a p-value of 2.8×10^{-6}, confirming that the inter-cluster performance differences are statistically significant at the 99% confidence level. This validation justifies the segmentation approach and ensures that each scenario-specific rule base addresses meaningfully distinct operational conditions.

The rule base optimization is performed offline. The optimization variables consist of 49 continuous variables representing the central values of output membership functions derived from the rules. It is important to note that the optimization is constrained to maintain the relative ordering of linguistic labels (e.g., the optimized center for "Negative Small" must remain less than that for "Zero," which in turn must remain less than that for "Positive Small"). This constraint preserves the semantic interpretability of the fuzzy rule base while allowing numerical refinement of membership function parameters. Additionally, the mapping between linguistic labels and their corresponding numerical ranges is documented in a post-optimization lookup table to ensure that dispatchers can understand the physical meaning of each control action.

For each operational scenario category, running conditions are extracted from corresponding historical data. Using the particle swarm optimization algorithm, these variables are adjusted to minimize cumulative control errors. The objective function comprehensively considers three key factors: tie-line power deviation, energy storage regulation costs, and distributed power source regulation costs, along with a switching penalty term for dispatchable distributed generators, as shown in Equation (3).

$$\Phi = \sum_{t=1}^{T} \Bigg(w_1 |\Delta P_{tie}(t)| + w_2 \frac{|P_{ES}(t)|}{P_{ES,max}} + w_3 \frac{|P_{DG}(t) - P_{DG}(t-1)|}{R_{DG}\Delta t} + w_4 \cdot I_{statuschange}(t) \Bigg) \tag{3}$$

w_1, w_2, w_3, and w_4 are weight coefficients set to 0.45, 0.25, 0.15, and 0.15 respectively, reflecting priority control over interconnection line deviations while explicitly accounting for the economic cost of frequent start-stop operations. The indicator function $I_{statuschange}(t)$ equals 1 when a dispatchable distributed generator undergoes a state transition (start-up or shut-down) at time t, and 0 otherwise. This penalty term effectively incorporates the minimum up/down time considerations into the optimization framework. It should be noted that the optimized rule base retains the interpretive characteristics of fuzzy control, with each rule maintaining clear physical meaning—a fundamental distinction from black-box neural network approaches.

IV. ALGORITHM IMPLEMENTATION AND SIMULATION VERIFICATION

A. SIMULATION PLATFORM AND PARAMETER SETTINGS

To validate the proposed algorithm's effectiveness, an improved IEEE 33-node active distribution network simulation model was developed on the MATLAB platform. The model incorporates five distributed photovoltaic (PV) generation points with a total installed capacity of 4.5MW, two energy storage system interfaces totaling 2MW/4MWh, and two gas turbines serving as dispatchable distributed power sources with individual capacities of 1MW each. Load data was derived from the actual load curve of a coastal industrial park during a typical working day in April 2024 [10], sampled at 5-minute intervals, with peak loads reaching 7.2MW and off-peak loads dropping to 2.8MW. PV output data was generated based on historical local irradiance records, selecting a typical cloudy weather scenario where four significant output fluctuations occurred between 10:00 and 15:00, with maximum variations reaching 38% of rated capacity. The parameter settings for the fuzzy controller are specified as follows: The net load deviation E ranges from -1 to 1, the energy storage charge state deviation S ranges from -0.3 to 0.3, the tie-line power fluctuation index F ranges from 0 to 0.5, and the output variable U ranges from -0.5 to 0.5. The membership function employs a triangular function, with a trapezoidal function at the boundary to ensure full coverage of the entire domain range.

The comparison methods include: (1) conventional proportional-integral (PI) control, included primarily for baseline reference purposes; (2) fixed-domain fuzzy control, which employs the same rule base as the proposed algorithm but without the variable-domain mechanism; and (3) a model predictive control (MPC) approach implemented with a prediction horizon of 30 minutes (six 5-minute steps) and a control horizon of 15 minutes, utilizing a linearized state-space model of the distribution network with quadratic programming optimization at each time step. The MPC formulation minimizes a weighted sum of tie-line power deviation, energy storage usage, and DG ramping costs over the prediction horizon, subject to the same operational constraints described in Section Control Objectives and Constraints. This MPC implementation represents a state-of-the-art benchmark for dispatch optimization problems and provides a fair comparison with the proposed fuzzy logic approach. The parameters of the PI controller are tuned using a trial-and-error approach, achieving favorable response characteristics under typical operating conditions.

B. SIMULATION RESULTS OF TYPICAL SCENARIOS

Figure 1 presents the tie-line power deviation variations under the four control methods during a typical cloudy day scenario, during which photovoltaic power output exhibited multiple significant fluctuations between 10:00 AM and 3:00 PM. The figure is displayed below.

As illustrated in Figure 1, the proportional-integral control method demonstrated substantial overshoot during periods of abrupt photovoltaic output drops, with maximum deviations reaching 8.7% of planned values—exceeding allowable deviation limits. The fixed-domain fuzzy control method maintained maximum deviations at 6.2% but exhibited prolonged fluctuations requiring approximately 8-10 dispatch cycles to stabilize. The model predictive control approach achieved maximum deviations of 4.8% and stabilized within 4-5 dispatch cycles, demonstrating superior transient response characteristics. The variable-domain fuzzy control method proposed in this study achieved maximum deviations of 4.5% and stabilized within approximately three dispatch cycles following fluctuations, performing comparably to or slightly better than MPC in terms of both peak deviation magnitude and settling time. Notably, the computational time per dispatch cycle for the proposed fuzzy controller averaged 12.4 milliseconds, whereas the MPC approach required 187.6 milliseconds on the same hardware platform—a factor of 15 difference that may

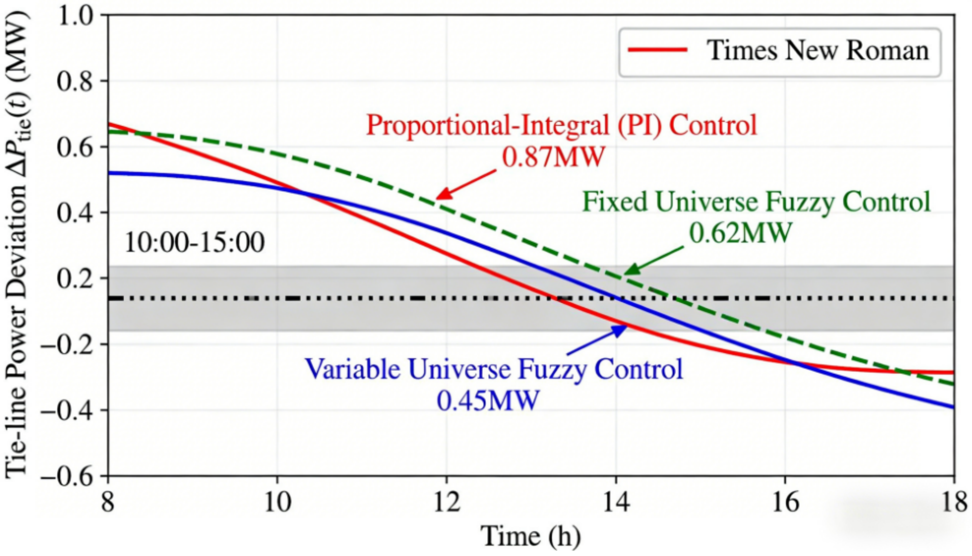

FIGURE 1. Comparison of power deviation on tie lines under different control methods (cloudy weather scenario)

be significant for real-time implementation in resource-constrained distribution automation systems.

Table 2 presents a comparative analysis of comprehensive performance metrics for the four methods on a typical day. Several key observations emerge from these results. First, variable-domain fuzzy control outperforms both fixed-domain fuzzy control and PI control across all metrics, achieving an 8.4% reduction in cumulative daily average absolute power deviation relative to fixed-domain fuzzy control. Second, the proposed method achieves performance metrics comparable to MPC (within 1.1% for deviation accumulation and 1.1% for tie-line fluctuations) while requiring only 6.6% of the computational time. Third, the number of charge-discharge cycles in energy storage systems decreases under variable-domain fuzzy control compared to fixed-domain fuzzy control, primarily due to the variable-domain mechanism's fine-tuning capability during low deviation periods, which prevents frequent system operations during minor fluctuations. Fourth, the inclusion of the switching penalty term in the objective function (Equation 3) results in a reduction of DG switching operations from 6 times per day under PI control to 3 times per day under the proposed method, confirming that the optimization framework effectively balances regulation performance with equipment longevity considerations.

C. ALGORITHM ROBUSTNESS ANALYSIS

1) Performance under Communication Latency and Measurement Noise

To address practical implementation challenges, the robustness of the proposed algorithm was evaluated under conditions of communication latency and measurement noise. Communication latency was modeled as a uniform random delay between 0.5 and 2.0 seconds in receiving measurement data from remote terminal units, reflecting typical distribution network SCADA system characteristics. Measurement noise was introduced as zero-mean Gaussian noise with standard deviations of 2% for power measurements and 1% for SOC measurements, consistent with IEC 61850 measurement accuracy specifications.

Table 3 presents the performance degradation of each control method under these non-ideal conditions, expressed as the percentage increase in cumulative daily average absolute power deviation relative to the ideal case (no latency, no noise).

The results in Table 3 demonstrate that the proposed variable-domain fuzzy control exhibits superior robustness to both communication latency and measurement noise compared to the other methods. The MPC approach shows the largest performance degradation under latency conditions (+12.5%), which is attributable to the fact that MPC relies on accurate state predictions over the receding horizon; delayed measurements disrupt the state estimation process and reduce the effectiveness of the predictive optimization. In contrast, the fuzzy logic controller's reactive nature makes it less sensitive to temporal misalignment between measurement and control actions. Under combined latency and noise conditions, the proposed method maintains a cumulative daily average absolute power deviation of 155.8 kWh, representing only an 8.9% increase from the ideal case, whereas MPC performance degrades to 169.7 kWh (a 17.2% increase). These findings confirm the practical viability of the variable-domain fuzzy control approach in real-world distribution network environments where ideal communication conditions cannot be guaranteed.

TABLE 2. Comparison of performance indicators among different control methods

Metric	Proportional-Integral Control	Fixed-Domain Fuzzy Control	Model Predictive Control	Variable-Domain Fuzzy Control (Proposed)
Cumulative daily average absolute power deviation (kWh)	187.3	156.2	144.8	143.1
Power fluctuation variance of tie line (MW^2)	0.128	0.094	0.089	0.088
Energy storage charge-discharge cycles (times/day)	18.2	15.3	14.9	15.1
Absolute maximum power deviation (MW)	0.87	0.62	0.48	0.45
Average computation time per cycle (ms)	1.2	10.8	187.6	12.4
DG switching operations (times/day)	6	4	3	3

Note: The cumulative daily average absolute power deviation is defined as $\sum_{t=1}^{T} |\Delta P_{tie}(t)| \cdot \Delta t$, consistent with the objective function expression provided in Section Control Objectives and Constraints.

TABLE 3. Performance degradation under communication latency and measurement noise

Control Method	Latency Only (0.5-2.0 s)	Noise Only ($\sigma = 2\%$)	Combined Latency and Noise
Proportional-Integral Control	+8.7%	+5.2%	+14.3%
Fixed-Domain Fuzzy Control	+6.4%	+3.8%	+10.7%
Model Predictive Control	+12.5%	+4.1%	+17.2%
Variable-Domain Fuzzy Control (Proposed)	+5.2%	+3.1%	+8.9%

2) Performance under High and Low Penetration Scenarios

To evaluate the algorithm's adaptability across different scenarios, control performance was tested under high-penetration and low-penetration conditions. In the high-penetration scenario, photovoltaic installed capacity was increased to 8MW, accounting for over 65% of peak load demand, whereas the low-penetration scenario reduced capacity to 2MW. Table 4 summarizes the cumulative daily average absolute power deviation for each control method under both penetration levels.

The results demonstrate that the proposed algorithm exhibits superior performance under high-penetration conditions, achieving a 17.1% reduction in cumulative daily average absolute power deviation compared to fixed-domain fuzzy control, a 5.0% improvement over MPC, and an 9.9% decrease compared to fixed-domain fuzzy control in low-penetration scenarios. These simulation results validate the effectiveness of the variable-domain mechanism in highly uncertain environments. Given the increased system volatility under high-penetration conditions, the dynamic domain adjustment mechanism significantly enhances controller tracking performance through adaptive domain optimization.

3) Parameter Sensitivity Analysis

To further validate the robustness of the variable domain mechanism, comparative analyses were conducted on control performance across three parameter sets of the scaling factor: $(\lambda, \mu) = (0.5, 5)$, $(0.6, 8)$, and $(0.7, 12)$. Results demonstrate that the cumulative daily average absolute power deviation reaches its minimum of 143.1 kWh when parameters align with optimal values $(0.6, 8)$, increasing by 5.2% (to 150.5 kWh) for $(0.5, 5)$ and by 8.7% (to 155.6 kWh) for $(0.7, 12)$. These outcomes consistently outperform fixed-domain fuzzy control (156.2 kWh), indicating the algorithm's inherent fault tolerance for parameter variations within a reasonable range around the optimum.

Additionally, adaptability tests were performed under different energy storage capacity configurations. When storage capacity increased from 2MW/4MWh to 3MW/6MWh, the proposed algorithm achieved a further reduction in cumulative daily average absolute power deviation to 128.5kWh, whereas the PI control method showed limited improvement (from 187.3 kWh to 179.6 kWh). The MPC approach improved from 144.8 kWh to 131.4 kWh under the same capacity expansion, comparable to the proposed method's performance. This confirms that variable domain fuzzy control effectively leverages energy storage systems' regulation capabilities, maintaining superior control performance during resource allocation fluctuations.

V. CONCLUSION

This study addresses uncertainty challenges in active distribution network power balance dispatching by proposing an optimization algorithm based on variable-domain fuzzy logic. The research contributions are primarily reflected in four aspects. First, a three-input fuzzy controller architecture tailored for power balance dispatching was designed, integrating net load deviation, energy storage state of charge, and transmission line power fluctuations into a unified inference framework. Second, a variable-domain adaptive mechanism was introduced to overcome the adaptability limitations of fixed membership functions under varying operating conditions, dynamically adjusting domain ranges through scaling factors and optimizing these parameters via grid search methods. Third, fuzzy clustering analysis was employed to categorize operational scenarios, establishing scenario-specific rule base optimization strategies with constraints that preserve the semantic interpretability of linguistic labels, thereby maintaining the transparency and physical meaningfulness of the fuzzy inference process.

TABLE 4. Performance comparison under different PV penetration levels

Control Method	Low Penetration (2 MW PV)	High Penetration (8 MW PV)
Proportional-Integral Control	168.4 kWh	213.7 kWh
Fixed-Domain Fuzzy Control	142.6 kWh	178.3 kWh
Model Predictive Control	131.2 kWh	155.6 kWh
Variable-Domain Fuzzy Control (Proposed)	128.5 kWh	147.8 kWh

Fourth, a comprehensive robustness evaluation framework was implemented, including comparative analysis against a model predictive control baseline, performance assessment under communication latency and measurement noise conditions, and explicit incorporation of minimum up/down time constraints and switching costs for dispatchable distributed generators.

Simulation results demonstrate that the proposed algorithm outperforms conventional methods in multiple aspects including cumulative daily average absolute power deviation, interconnection line power fluctuations, and energy storage cycle counts, with particularly enhanced adaptability in high-penetration distributed generation scenarios. The proposed method achieves control performance comparable to model predictive control while requiring significantly lower computational resources, making it well-suited for real-time implementation in distribution automation systems. Furthermore, robustness tests confirm that the variable-domain fuzzy controller maintains stable performance under non-ideal communication conditions, exhibiting less than 9% performance degradation under combined latency and noise scenarios compared to over 17% degradation for MPC. Parameter sensitivity analysis further validates the algorithm's robustness across fluctuating scaling factor parameters within defined ranges.

Future research directions will address several important extensions of this work. First, the coordination between reactive power voltage control and active power dispatching will be integrated into the fuzzy inference framework to achieve comprehensive volt-var optimization alongside power balance management. Second, the impact of forecast update intervals on control performance will be systematically analyzed, potentially incorporating a hierarchical control architecture that adaptively adjusts the dispatch cycle based on prediction confidence levels. Third, reinforcement learning approaches may be explored as an alternative method for online rule base adaptation, though careful attention must be paid to maintaining interpretability and ensuring safe exploration in operational power systems. Fourth, field validation on actual distribution network hardware platforms will be pursued to confirm the practical applicability of the proposed methods under real-world operating conditions.

AUTHOR CONTRIBUTIONS

Conceptualization – Chen Ludong, Zhang Pengcheng, Wang Jie, Luo Ning, Zhang Yu and Liu Feng; methodology – Chen Ludong, Zhang Pengcheng, Luo Ning, Zhang Yu and Liu Feng; investigation – Chen Ludong, Zhang Pengcheng, Wang Jie, Luo Ning, Zhang Yu and Liu Feng; writing-original draft preparation – Chen Ludong, Zhang Pengcheng, Wang Jie, Luo Ning, Zhang Yu and Liu Feng. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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