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Research Article

A Novel Fuzzy-COVID Optimization Algorithm for Enhancing Energy Efficiency and Stability in Renewable Smart Grids

Artikel Riset

Algoritma Optimasi Fuzzy-COVID Baru untuk Meningkatkan Efisiensi Energi dan Stabilitas pada Smart Grid Energi Terbarukan

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Abstract -The increasing penetration of renewable energy sources introduces significant challenges in maintaining stability and efficiency in smart grids due to intermittency and nonlinear dynamics. This paper proposes a novel hybrid control strategy based on a Fuzzy Logic Controller (FLC) optimized using the COVID Optimization Algorithm (CVOA) for multi-source renewable smart grids. The proposed method enables adaptive and self-tuning control for simultaneous integration of photovoltaic, wind, fuel cell, and microhydro systems with battery energy storage. The effectiveness of the method is validated through MATLAB/Simulink simulations under various disturbances, including load variations and renewable intermittency. Results demonstrate up to 48% reduction in frequency deviation, 50% improvement in voltage stability, and 9% increase in energy efficiency compared to conventional and fuzzy-based methods. These findings highlight the superiority of the Fuzzy–CVOA approach in enhancing smart grid resilience and energy management performance.

Keywords: Fuzzy Logic, CVOA, Renewable Energy, Smart Grid, Energy Efficiency, System Stability

Abstrak - Meningkatnya penetrasi sumber energi terbarukan menghadirkan tantangan signifikan dalam menjaga stabilitas dan efisiensi pada jaringan cerdas karena intermitensi dan dinamika nonlinier. Makalah ini mengusulkan strategi kontrol hibrida baru berdasarkan Pengontrol Logika Fuzzy (FLC) yang dioptimalkan menggunakan Algoritma Optimasi COVID (CVOA) untuk jaringan cerdas multi-sumber energi terbarukan. Metode yang diusulkan memungkinkan kontrol adaptif dan penyetelan mandiri untuk integrasi simultan sistem fotovoltaik, angin, sel bahan bakar, dan mikrohidro dengan penyimpanan energi baterai. Efektivitas metode ini divalidasi melalui simulasi MATLAB/Simulink di bawah berbagai gangguan, termasuk variasi beban dan intermitensi energi terbarukan. Hasil menunjukkan pengurangan deviasi frekuensi hingga 48%, peningkatan stabilitas tegangan 50%, dan peningkatan efisiensi energi 9% dibandingkan dengan metode konvensional dan berbasis fuzzy. Temuan ini menyoroti keunggulan pendekatan Fuzzy–CVOA dalam meningkatkan ketahanan jaringan cerdas dan kinerja manajemen energi.

Kata kunci: Logika Fuzzy, CVOA, Energi Terbarukan, Jaringan Cerdas, Efisiensi Energi, Stabilitas Sistem

I. INTRODUCTION

The global transition toward sustainable energy systems has accelerated significantly in recent years, driven by escalating climate concerns[1], energy security demands, and declining costs of renewable technologies. According to the International Energy Agency (IEA), renewable energy sources accounted for approximately 34.3% of global electricity generation in the first half of 2025 [2], surpassing coal for the first time, with solar photovoltaic (PV) and wind power contributing the majority of this growth. Projections indicate that renewables could reach 43–50% of global electricity by 2030, supported by a projected increase in renewable capacity additions from 510 GW in 2024 to over 700 GW annually by 2030. Despite these advancements, the intermittent and variable nature of dominant sources such as solar and wind continues to pose substantial challenges to grid stability[3], power quality[4], and reliable energy supply[5], particularly in islanded or weakly interconnected microgrids and smart grids.

Conventional centralized power systems are increasingly being replaced by distributed, intelligent networks that integrate multiple renewable resources, including photovoltaic (PV) arrays, wind turbines, fuel cells, and microhydro units, often supplemented by battery energy storage systems (BESS) [6] These hybrid renewable energy systems (HRES) offer substantial benefits[7], including reduced greenhouse gas emissions, improved energy availability, enhanced operational flexibility, and greater resilience against single-source failures[8]. However, the stochastic behavior of renewable generation, coupled with unpredictable load variations and nonlinear system dynamics, frequently leads to frequency[9] and voltage deviations[10], suboptimal power sharing, excessive battery cycling, and reduced overall efficiency[11], [12].

Numerous control strategies have been developed to mitigate these challenges[8]. Traditional droop control and proportional-integral-derivative (PID) controllers[2] remain widely used due to their simplicity but struggle with nonlinearities, parameter uncertainties, and rapid transients. Advanced intelligent techniques, such as fuzzy logic control (FLC)[13], have gained prominence for their ability to handle imprecise inputs and provide robust, adaptive responses without requiring precise mathematical models [14]. Meanwhile, metaheuristic optimization algorithms—including Genetic Algorithms (GA)[3], Particle Swarm Optimization (PSO)[15], and more recent bio-inspired methods—have been employed to tune controller parameters and optimize energy management[16]. Despite these developments, many existing approaches suffer from limitations such as premature convergence, high computational burden, sensitivity to initial conditions, and insufficient exploration in complex, high-dimensional search spaces[17], [18].

The COVID Optimization Algorithm (CVOA)[19], inspired by the epidemiological propagation dynamics of COVID-19, has emerged as a promising metaheuristic that effectively balances global exploration and local exploitation [20]. Its unique infection–recovery–mutation mechanism enables better avoidance of local optima compared to classical GA and PSO[21], particularly in multimodal and dynamic optimization problems[22]. Recent applications of CVOA variants in power systems have demonstrated improved convergence speed and solution quality in optimal power flow[23], economic dispatch[17], and microgrid scheduling tasks[24]. However, its integration with fuzzy logic controllers for real-time adaptive control in multi-source hybrid renewable smart grids remains largely unexplored[25].

This research addresses the identified gaps by proposing a novel hybrid control framework that synergistically combines a Fuzzy Logic Controller (FLC)[26] for adaptive frequency and voltage regulation with the COVID Optimization Algorithm (CVOA) for automated tuning of fuzzy membership functions[27], [28], scaling factors, and rule weights[20]. Unlike previous studies that apply fuzzy control or metaheuristic optimization in isolation—or limit hybridization to two or three sources—this work develops a unified, self-tuning control structure capable of managing four diverse renewable sources (PV, wind, fuel cell, and microhydro) simultaneously [29], [30], [31], while optimizing battery energy storage utilization under varying environmental and load conditions[32].

The main contributions of this study are as follows: a comprehensive hybrid smart grid model integrating PV, wind turbine, proton exchange membrane fuel cell (PEMFC), microhydro, and BESS, with detailed dynamic modeling suitable for stability analysis, an innovative Fuzzy–CVOA controller that leverages the epidemiological-inspired optimization to achieve superior parameter tuning compared to GA and PSO, extensive simulation-based validation demonstrating 15–20% improvement in frequency and voltage stability, 12% increase in energy storage efficiency, and enhanced battery lifespan through optimal SOC management, and in-depth statistical and sensitivity analyses, including multi-run comparisons, Pareto trade-off evaluation, and robustness testing against parameter variations.

The novelty of this work lies in three key aspects: (i) the development of a unified hybrid smart grid model integrating four renewable energy sources simultaneously, (ii) the implementation of a self-adaptive Fuzzy Logic Controller optimized using the COVID Optimization Algorithm (CVOA), and (iii) a comprehensive performance evaluation including

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statistical analysis, sensitivity testing, and multi-scenario validation. Compared to previous studies that rely on single optimization techniques or limited energy sources, this approach provides a more scalable, robust, and adaptive solution for modern smart grid systems.

II. METHOD

This section outlines the revised methodology for the proposed hybrid smart grid system, integrating multi-source renewable energy modeling, intelligent control via Fuzzy Logic Controller (FLC)[33], and metaheuristic optimization using the COVID Optimization Algorithm (CVOA)[34]. The design aims to enhance dynamic performance, energy efficiency, and operational stability in a smart grid comprising photovoltaic (PV), wind turbine, fuel cell, and microhydro power systems with a battery energy storage system (BESS). The methodology is divided into four main stages: (1) system modeling, (2) control system design, (3) optimization using CVOA, and (4) simulation and performance evaluation. Figure 1 illustrates the overall system architecture and control framework.

2.1 System Modeling of Multi-Source Renewable Smart Grid

The hybrid smart grid model consists of four renewable generation units (PV, wind turbine, fuel cell, and microhydro) connected to a common DC-AC bus through individual converters and an integrated BESS. Each subsystem is mathematically represented in the state-space domain to facilitate dynamic simulation and control design [18]. Key parameters for the system components are summarized in Table 1.

Table 1: Key System Parameters

(a) Photovoltaic (PV) Model The PV array is modeled using the single-diode equivalent circuit[35]:

$$I = I_{ph} - I_0\left(e^{\frac{V+IR_s}{nV_t}} - 1\right) - \frac{V+IR_s}{R_{sh}} \tag{1}$$

where $I_{ph}$is the photo-generated current, $I_0$is the saturation current, $R_s$and $R_{sh}$are series and shunt resistances, and $n$is the diode ideality factor. The output power is[36]:

$$P_{PV} = V \cdot I \cdot \eta_{conv} \tag{2}$$

with converter efficiency η_{conv}assumed at 95-98% under standard test conditions (1000 W/m² irradiance, 25°C temperature) [19].

(b) Wind Turbine Model The mechanical power extracted from wind is:

$$P_w = \frac{1}{2}\rho A C_p v^3 \tag{3}$$

where $\rho$is air density (1.225 kg/m³), $A$is rotor swept area, $C_p$is power coefficient (up to 0.59 per Betz limit), and $v$is wind speed. Electrical output after generator conversion is[37]:

$$P_{wind} = P_w \cdot \eta_g \tag{4}$$

with generator efficiency $\eta_g \approx 90\%$[20].

(c) Fuel Cell Model A Proton Exchange Membrane Fuel Cell (PEMFC) is modeled as:

$$V_{FC} = E_{Nernst} - V_{act} - V_{ohmic} - V_{conc} \tag{5}$$

Where, E_{Nernst}depends on gas partial pressures (H_2, O_2, H_2O), and losses ($V_{act}, V_{ohmic}, V_{conc}$) account for activation, ohmic, and concentration drops. Electrical power is $P_{FC} = V_{FC}.I_{FC}$ [15], [21].

(d) Microhydro Model Hydraulic power is:

$$P_h = \rho g Q H \eta \tag{6}$$

where Q is discharge flow rate (m³/s), $H$is effective head (m), $g$is gravity (9.81 m/s²), and $\eta$is overall efficiency (≈85%). This unit serves as a stable base-load source[38].

(e) Battery Energy Storage System (BESS) BESS dynamics are modeled by State of Charge (SOC):

$$SOC(t) = SOC(t_0) - \frac{1}{C}\int P_{batt}(t)dt \tag{7}$$

where P_{batt} is battery power (positive for discharge), and C is capacity. Voltage and current include internal resistance for losses[39].

2.2 Control System Design

The control system employs a Fuzzy Logic Controller (FLC) for adaptive regulation of frequency (Δf) and voltage (ΔV) under varying condition. (a) Fuzzy Logic Controller (FLC) Inputs: Frequency error ($e_f = f_{ref} - f$), voltage error ($e_v = V_{ref} - V$), and rate of change of error (de/dt). Output: Control signal (u) for power allocation and BESS charge/discharge.

Each input is fuzzified into five linguistic variables (Negative Big, Negative Small, Zero, Positive Small, Positive Big) using triangular and Gaussian membership functions. A 5×5×5 rule base (125 rules) determines actions, e.g.: IF $e_f$is Negative Small AND $de/dt$is Negative THEN $u$is Increase Discharge Moderately.Defuzzification uses the centroid method to generate continuous signals regulating converters and BESS flow[40].

2.3 Optimization Using CVOA for Fuzzy Tuning

CVOA, inspired by COVID-19 propagation, optimizes fuzzy parameters (membership centers, widths, rule weights) [11], [12], [16], [27].

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Pseudocode for CVOA is provided in Algorithm 1: Pseudocode for CVOA.

a: Initialize population P(N solutions, each a fuzzy parameter set) randomly within bounds.
b: For each iteration t = 1 to MaxIter:
c: Compute fitness for each individual:

$$J = w_1 \int |\Delta f| dt + w_2 \int |\Delta V| dt \quad (8)$$

d: Select best solution x_{best}.
e: Generate new solutions via infection: $x_{new} = x_i + r \cdot (x_{best} - x_i)$ (9)
where r is random factor.
f: Apply mutation with probability p_m(0.1-0.3).
g: Replace poor solutions with recovered ones to maintain diversity.
h: End For
i: Return optimal fuzzy parameters.

Objective: Minimize $J$with weights $w_1 = w_2 = 0.4$, $w_3 = 0.2$. Population size N=50, MaxIter=100.

The CVOA algorithm mimics the spread and recovery mechanism of infectious diseases, where each candidate solution represents an infected individual. The infection process allows exploration of new solutions, while recovery and mutation enhance exploitation around optimal regions. This balance enables CVOA to avoid local minima and achieve faster convergence compared to conventional algorithms such as GA and PSO.

2.4 Simulation and Performance Evaluation

The system is implemented in MATLAB/Simulink R2023b. Scenarios include : Step load increase (10-20%), source intermittency (50% PV drop, 30% wind drop), source outage.

Metrics: Frequency deviation (Hz), voltage deviation (p.u.), efficiency (%), SOC range, settling time (s). Comparisons: Conventional droop, non-optimized fuzzy, and Fuzzy-CVOA.

2.5 Implementation Framework

Workflow: Model subsystems in Simulink, initialize FLC with default parameters, optimize via CVOA (MATLAB script integrated with Simulink), and simulate scenarios and evaluate metrics.

III. RESULTS AND DISCUSS

This section presents the revised simulation results and analysis of the proposed Fuzzy–COVID Optimization Algorithm (Fuzzy–CVOA) applied to the hybrid renewable smart grid system. The system integrates photovoltaic (PV), wind turbine, fuel cell, and microhydro sources with a battery energy storage system (BESS). Simulations were conducted in MATLAB/Simulink under various operational scenarios, including step load variations (10-20% increase), renewable source fluctuations (e.g., 50% PV irradiance drop and 30% wind speed reduction), and combined disturbances (e.g., source outages). Results are analyzed in terms of frequency and voltage stability, energy efficiency, battery State of Charge (SOC) dynamics, and optimization convergence. Comparative evaluations are provided against conventional droop control, non-optimized fuzzy control, and the proposed Fuzzy–CVOA scheme. All metrics are averaged over 10 simulation runs to ensure statistical reliability, with standard deviations (SD) reported where applicable.

3.1. Frequency Response Analysis

From a control system perspective, frequency deviation in power systems is strongly influenced by the balance between generation and load, as described by the swing equation and system inertia dynamics. The improved performance of the proposed Fuzzy–CVOA controller can be explained by its ability to dynamically adjust control gains, thereby enhancing the effective damping ratio and reducing oscillatory behavior. The adaptive tuning of fuzzy membership functions using CVOA minimizes steady-state error and overshoot, which aligns with classical control theory where optimized feedback parameters improve system stability and transient response. Consequently, the reduced settling time and frequency deviation demonstrate improved dynamic stability and robustness against disturbances.

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Figure 1 illustrates the frequency response of the hybrid smart grid under a 20% step load increase combined with renewable disturbances. The conventional droop control exhibited a maximum frequency deviation of ±0.35 Hz (SD: 0.04 Hz) and a settling time of 8.5 s, reflecting limited adaptability to nonlinear dynamics. The non-optimized fuzzy controller improved this to a deviation of ±0.28 Hz (SD: 0.03 Hz) and a settling time of 6.3 s, benefiting from basic fuzzy inference for handling uncertainties.

In contrast, the proposed Fuzzy–CVOA control achieved the lowest deviation of ±0.18 Hz (SD: 0.02 Hz) and the fastest settling time of 4.8 s. This enhancement stems from CVOA-tuned fuzzy membership functions and rules, which enable precise power allocation and reduced overshoot (by 30-40%). Root Mean Square Error (RMSE) for frequency tracking was 0.12 Hz for Fuzzy–CVOA, compared to 0.22 Hz for conventional and 0.18 Hz for fuzzy alone. These results highlight the controller's robustness in maintaining nominal 50 Hz frequency amid load and intermittency variations.

3.2 Voltage Regulation Performance

Voltage stability in smart grids is primarily governed by reactive power balance and network impedance characteristics. According to power system theory, voltage deviations occur when reactive power demand exceeds supply, leading to instability. The proposed Fuzzy–CVOA controller enhances voltage regulation by adaptively tuning control signals for reactive power compensation. The fuzzy logic component provides nonlinear mapping between voltage error and corrective action, while CVOA ensures optimal parameter selection. This results in improved voltage profile and reduced deviation, consistent with voltage stability theory where adaptive control strategies outperform fixed-parameter controllers in nonlinear and uncertain environments.

Voltage regulation results under source disturbances (50% PV drop and 30% wind reduction) are shown in Figure 2. Conventional control resulted in a maximum deviation of ±0.06 p.u. (SD: 0.005 p.u.), with prolonged recovery due to fixed droop parameters. The non-optimized fuzzy reduced this to ±0.05 p.u. (SD: 0.004 p.u.), while Fuzzy–CVOA maintained deviations within ±0.03 p.u. (SD: 0.002 p.u.), preserving the nominal 1.0 p.u. level effectively.

The improvement is due to adaptive tuning of Q-V droop coefficients and reactive power sharing via optimized fuzzy rules. RMSE for voltage was 0.015 p.u. for the proposed method, versus 0.028 p.u. for conventional and 0.022 p.u. for fuzzy. A paired t-test confirmed statistical significance ($p < 0.01$) in deviation reduction, underscoring the controller's efficacy in real-time voltage quality maintenance.

3.3 Battery SOC Dynamics and Energy Management

The State of Charge (SOC) dynamics of a battery system are governed by energy balance equations and charge–discharge efficiency characteristics. From an energy management perspective, maintaining SOC within an optimal range is essential to prevent battery degradation and extend lifespan. The Fuzzy–CVOA controller achieves this by optimizing charge–discharge decisions based on system conditions. Theoretically, this corresponds to optimal energy scheduling, where control actions minimize energy losses and avoid deep discharge cycles. The improved SOC stability reflects the effectiveness of adaptive control in maintaining energy balance under stochastic renewable generation.

Battery performance under varying loads and generations is depicted in Figure 3. Conventional control led to SOC drops to a minimum of 70% (SD: 2.5%), risking degradation from over-discharge. The fuzzy controller maintained SOC above 74% (SD: 2.0%), while Fuzzy–CVOA kept it between 78%-90% (SD: 1.5%) throughout simulations.

This optimal range results from intelligent charge-discharge scheduling via tuned fuzzy logic, minimizing deep cycles and extending battery life. Average charge/discharge efficiency reached 92% for Fuzzy–CVOA, compared to 85% for conventional and 88% for fuzzy. The controller balanced renewable utilization with BESS support, reducing energy losses by 10-15%.

3.4 Optimization Convergence of the CVOA

The convergence behavior of optimization algorithms is determined by their ability to balance exploration and exploitation. According to optimization theory, premature convergence occurs when exploration is insufficient, while slow convergence results from weak exploitation. The CVOA algorithm addresses this trade-off through its infection–recovery–mutation mechanism, enabling diverse solution exploration and efficient convergence toward the global optimum. Compared to GA and PSO, CVOA exhibits faster convergence due to its adaptive search strategy, which aligns with theoretical principles of stochastic optimization in high-dimensional solution spaces.

Convergence characteristics are shown in Figure 6. CVOA converged to a minimum objective function value of 0.008 within 40-50 iterations (SD: 5 iterations), outperforming GA (0.012, 70 iterations) and PSO (0.010, 60 iterations). This faster rate (20-25% improvement) demonstrates CVOA's balanced exploration-exploitation, yielding smoother control surfaces and better transient suppression.

3.5 Energy Efficiency and Power Distribution

Energy efficiency in hybrid power systems is closely related to optimal power sharing among available generation sources. According to economic dispatch and energy management theory, efficient systems allocate power based on resource availability and operational constraints. The proposed Fuzzy–CVOA controller dynamically distributes power among PV, wind, fuel cell, and microhydro sources, minimizing losses and improving efficiency. This adaptive allocation reflects optimal dispatch principles, where real-time control ensures balance between supply and demand while maximizing system performance.

Overall efficiency and power sharing are summarized in Figure 4. Fuzzy–CVOA achieved an average efficiency of 93% (SD: 1.2%), versus 89% (SD: 1.5%) for fuzzy and 85% (SD: 2.0%) for conventional. Power contributions were dynamically adjusted: PV (32%), wind (28%), fuel cell (22%), microhydro (18%), ensuring near-perfect supply-demand balance and minimized losses.

3.6 Comparative Performance Evaluation

Comparative performance evaluation is essential to validate the effectiveness of control strategies. From a systems theory perspective, improvements in key performance indicators such as settling time, overshoot, and steady-state error indicate enhanced system stability and control accuracy. The superior performance of the Fuzzy–CVOA method demonstrates the advantage of hybrid intelligent control over conventional approaches. This aligns with modern control theory, where combining artificial intelligence with optimization techniques leads to improved adaptability and robustness in complex nonlinear systems.

Figure 5 and Table 1 provide a comparative summary. Fuzzy–CVOA excels across metrics, with t-tests confirming significance ($p < 0.05$) over baselines.

Figure 1. System Frequency Response under Load Disturbance

Figure 2. Voltage Regulation Performance of Smartgrid

Figure 3. Battery SOC Response during Dynamic Operation

3.9 Detailed Simulation Scenarios and Test Cases

Table 2 summarizes the six representative test cases used to validate controller performance under realistic disturbances. These scenarios cover nominal operation, sudden load changes, renewable intermittency, and simultaneous multi-source failures. By testing a wide range of conditions, we ensure the robustness of the Fuzzy–CVOA approach across practical smart-grid operations.

3.10 Statistical Performance Metrics

Statistical analysis provides a quantitative measure of system performance consistency and reliability. The use of mean and standard deviation allows evaluation of variability across multiple simulation runs, while hypothesis testing (t-test) determines statistical significance. From a theoretical standpoint, lower variance and statistically significant improvements indicate robust controller performance under uncertainty. The results confirm that the proposed method consistently outperforms baseline controllers with high confidence levels.

To quantify improvements rigorously, Table 3 presents mean ± standard deviation values over 10 independent

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simulation runs for all key metrics. The Fuzzy–CVOA controller consistently outperforms both conventional droop and non-optimized fuzzy methods, with statistically significant differences (paired t-test, $p < 0.01$). These results confirm a 45–50% reduction in frequency/voltage errors and a 9.6% gain in overall efficiency.

3.11 Sensitivity Analysis

Sensitivity analysis evaluates the robustness of a system against parameter variations. In control theory, a robust controller maintains acceptable performance despite uncertainties in system parameters. The stable response of the Fuzzy–CVOA controller under varying irradiance, wind speed, and load conditions demonstrates strong robustness. This behavior is consistent with robust control principles, where adaptive tuning enhances system resilience to external disturbances and model uncertainties.

Table 4 evaluates how the proposed controller responds to variations in key renewable and storage parameters. The Fuzzy–CVOA method maintains excellent stability and efficiency across wide ranges, proving its robustness against real-world uncertainties such as fluctuating irradiance and wind speed.

3.12 Optimization Performance Comparison

The comparison of optimization algorithms highlights differences in convergence speed, solution quality, and computational efficiency. According to optimization theory, an effective algorithm should achieve a global optimum with minimal iterations and computational cost. The superior performance of CVOA indicates its effectiveness in navigating complex search spaces, outperforming traditional algorithms such as GA and PSO. This validates its suitability for real-time optimization in smart grid applications.

Table 5 compares CVOA with GA and PSO across 30 independent runs. CVOA achieves the lowest cost, fastest convergence, and highest success rate, confirming its superiority for real-time fuzzy parameter tuning in smart-grid applications.

Figure 4. Battery SOC Response during Dynamic Operation

Figure 5. Comparative Performance Metrics- Smartgrid Controllers

Figure 6. Optimization Convergence of GA, PSO, and CVOA

Figure 7 . 3D fuzzy control surface before and after CVOA optimization

Figure 8. The sensitivity of maximum frequency deviation to simultaneous changes in PV irradiance and wind speed

Figure 9. A stacked area plot of real-time power contributions during the severe combined disturbance

Figure 10. Convergence curves of CVOA, GA, and PSO (average of 30 runs)

Figure 11. Pareto front between system stability and energy efficiency

Figure 12. Compares membership functions before and after CVOA tuning

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Table 2. Comparative Performance Summary

Table 4. Statistical Performance Metrics (Mean ± SD, n = 10 runs)

Table 5. Sensitivity Analysis of Key Parameters (Fuzzy–CVOA)

Table 6. Optimization Performance Comparison (30 independent runs)

Table 7. Average Power Sharing Contribution under Different Scenarios (%)

3.13 Average Power Sharing Contribution

Table 6 details the dynamic contribution of each source across scenarios. The Fuzzy–CVOA controller intelligently balances power sharing while keeping the balance error below 0.2%, demonstrating effective energy management.

3.14 Advanced Visualization and Control Surface Analysis

The visualization of control surfaces and Pareto fronts provides insight into system behavior and optimization trade-offs. A smoother control surface indicates reduced nonlinearity and improved control stability, while a well-defined Pareto front reflects optimal trade-offs between competing objectives such as stability and efficiency. These results are consistent with multi-objective optimization theory, where optimal solutions lie along the Pareto frontier, representing the best achievable compromises.

Figure 7 shows the 3D fuzzy control surface before and after CVOA optimization. The optimized surface (right) is significantly smoother and more linear in the critical operating region, resulting in reduced overshoot and faster response. Figure 8 illustrates the sensitivity of maximum frequency deviation to simultaneous changes in PV irradiance and wind speed. The Fuzzy–CVOA curve (red) remains consistently lower than the baselines, confirming superior robustness. Figure 9 presents a stacked area plot of real-time power contributions during the severe combined disturbance (Scenario S5). The controller dynamically adjusts each source while maintaining near-perfect power balance. Figure 10 compares convergence curves of CVOA, GA, and PSO (average of 30 runs). CVOA reaches the global minimum fastest with the smallest variance (inset boxplot), highlighting its efficiency for online optimization. Figure 11 displays the Pareto front between system stability and energy efficiency. The Fuzzy–CVOA points dominate the front, proving the best trade-off among all tested methods. Figure 12 compares membership functions before (dashed blue) and after CVOA tuning (solid red) for the three inputs. The optimized functions are more evenly distributed and better cover the uncertainty range, directly contributing to improved control performance.

Although the validation is simulation-based, the proposed model is designed considering realistic system parameters and operational constraints. The results are consistent with practical smart grid implementations reported in recent literature. Future work will include hardware in the loop and real-time experimental validation using embedded controllers.

IV. CONCLUSION

This study proposed and evaluated a novel Fuzzy–COVID Optimization Algorithm (Fuzzy–CVOA) for enhancing energy efficiency and stability in a multi-source renewable smart grid integrating photovoltaic (PV), wind turbine, fuel cell, and microhydro units with a battery energy storage system (BESS). The controller maintains frequency and voltage stability while optimizing energy utilization and battery performance under scenarios like load variations and source intermittency.

Simulation results confirm Fuzzy–CVOA's superiority: 48% reduction in frequency deviation (±0.18 Hz vs. ±0.35 Hz conventional), 50% in voltage deviation (±0.03 p.u. vs. ±0.06 p.u.), 9% higher efficiency (93%), and 11% SOC improvement (above 78%). CVOA tuning provides faster convergence (20-25% over GA/PSO) and robust adaptability.

The novelty lies in synergizing fuzzy adaptive control with CVOA for autonomous management of a four-source hybrid grid, extending prior works [28]-[30] by enabling self-tuning against nonlinearities. This framework advances intelligent Energy Management Systems (EMS) for resilient microgrids, aligning with global sustainability goals.

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Limitations include reliance on simulations; real-world factors like hardware delays may affect performance. Future directions: (1) Hardware-in-the-loop validation; (2) Multi-area grid extension; (3) AI forecasting integration; (4) IoT-secure architecture; (5) Hybrid metaheuristics for nonlinear scenarios.
Despite the promising results, this study is limited to simulation-based validation and ideal operating conditions. Real-world factors such as communication delay, measurement noise, and hardware constraints were not fully considered. Future research will focus on real-time implementation, integration with IoT-based monitoring systems, and hybrid AI optimization techniques.

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REFERENCES

[1] H. Bevrani, H. Golpîra, A. R. Messina, N. Hatziargyriou, F. Milano, and T. Ise, "'Power system frequency control: An updated review of current solutions and new challenges,'" *Electr. Power Syst. Res.*, vol. 194, pp. 1–11, 2021, doi: 10.1016/j.epsr.2021.107114.

[2] M. Ahmed and E. Mohamed, "'Hybrid fuzzy logic – PI control with metaheuristic optimization for enhanced performance of high- penetration grid-connected PV systems,'" *Sci. Rep.*, vol. 15, pp. 1–24, 2025.

[3] N. Khosravi, "'A hybrid control approach to improve power quality in microgrid systems,'" *Artif. Intellegence Rev.*, vol. 58, no. 312, pp. 1–39, 2025.

[4] Z. Ul, A. Soomro, S. Ahmed, and N. Hussain, "'Design and optimization of an energy storage system for off-grid rural communities,'" *Int.J.Renew.Energy Dev*, vol. 15, no. 1, pp. 393–417, 2026.

[5] L. Rathour, V. Singh, M. K. Sharma, and N. Dhiman, "'A review of fuzzy logic analysis in COVID-19 pandemic and a new technique through extended hexagonal intuitionistic fuzzy number in analysis of COVID-19,'" *Results Control Optim.*, vol. 17, pp. 1–12, 2024, doi: 10.1016/j.rico.2024.100498.

[6] G. Huy, M. Tuan, N. Bao, M. Tran, and C. Minh, "'Hybrid renewable energy system design for a green port using HOMER Pro : A techno-economic assessment,'" *Int.J.Renew.Energy Dev*, vol. 14, no. 4, pp. 767–780, 2025.

[7] D. Izci, S. Ekinci, L. Prokop, E. Çelik, and M. Bajaj, "'Dynamic load frequency control in Power systems using a hybrid simulated annealing based Quadratic Interpolation Optimizer,'" *Sci. Rep.*, vol. 14, no. 26011, pp. 1–19, 2024.

[8] X. Qian, W. Jiang, and T. Yang, "Multi-Objective Optimized Energy Management System for," vol. 2023, no. Ictss, pp. 1–8, 2023.

[9] T. Sowmiya and T. Venkatesan, "Energy Management System in Smart Microgrid Using Multi Objective Grey Wolf Optimization Algorithm," pp. 3423–3430, 2022.

[10] A. Hooshmand, B. Asghari, and R. Sharma, "A Novel Cost-Aware Multi-Objective Energy Management Method for Microgrids," pp. 1–6.

[11] A. Ahmad, M. Naeem, M. Iqbal, and S. Qaisar, "A compendium of optimization objectives , constraints , tools and algorithms for energy management in microgrids," *Renew. Sustain. Energy Rev.*, vol. 58, pp. 1664–1683, 2016, doi: 10.1016/j.rser.2015.12.259.

[12] A. Rajagopalan, K. Nagarajan, M. Bajaj, S. Uthayakumar, L. Prokop, and V. Blazek, "Multi - objective energy management in a renewable and EV - integrated microgrid using an iterative map - based self - adaptive crystal structure algorithm," *Sci. Rep.*, pp. 1–29, 2024, doi: 10.1038/s41598-024-66644-3.

[13] X. Yao, C. Kang, X. Zhang, S. Wang, and Y. Zhang, "'FuzH-PID : Highly controllable and stable DNN for COVID-19 detection via improved stochastic optimization,'" *Expert Syst. Appl.*, vol. 268, no. July 2023, p. 126323, 2025, doi: 10.1016/j.eswa.2024.126323.

[14] P. A. Gbadega, Y. Sun, and O. A. Balogun, "Optimized energy management in Grid-Connected microgrids leveraging K-means

clustering algorithm and Artificial Neural network models," *Energy Convers. Manag.*, vol. 336, no. November 2024, p. 119868, 2025, doi: 10.1016/j.enconman.2025.119868.

[15] D. Eid, S. Elmasry, A. El, F. Elnagahy, and E. Youssef, "'Frequency control enhancement for hybrid microgrid using multi- terminal multi-function inverter,'" *Int.J.Renew.Energy Dev*, vol. 13, no. 4, pp. 683–696, 2024.

[16] R. B. Naorem, "'Twin Delayed Deep Deterministic Policy Gradient-Based Load Frequency Control for Interconnected Hybrid Microgrid With Renewable Energy Integration Using a Tilt-Integral-Derivative Controller,'" *Artif. Intellegence Eng.*, vol. 1, no. 1, pp. 95–116, 2025.

[17] K. Tai, A. R. El-Sayed, M. Biglarbegian, C. I. Gonzalez, O. Castillo, and S. Mahmud, "'Review of Recent Type-2 Fuzzy Controller Applications,'" *Algorithms*, vol. 9, no. 2, pp. 1–19, 2016, doi: 10.3390/a9020039.

[18] D. Q. Mayne, J. B. Rawlings, C. V. Rao, and P. O. M. Scokaert, "'Constrained model predictive control: Stability and optimality,'" *Automatica*, vol. 36, no. 6, pp. 789–814, 2000, doi: 10.1016/S0005-1098(99)00214-9.

[19] E. Hosseini, K. Z. Ghafoor, A. S. Sadiq, M. Guizani, and A. Emrouznejad, "'COVID-19 Optimizer Algorithm , Modeling and Controlling of Coronavirus Distribution Process,'" *IEEE J. Biomed. Heal. Informatics*, vol. 24, no. 10, pp. 2765–2775, 2020.

[20] D. D. Rasolomampionona, M. Połecki, K. Zagrajek, W. Wróblewski, and M. Januszewski, "'A Comprehensive Review of Load Frequency Control Technologies,'" *Energies*, vol. 17, no. 12, p. 74, 2024, doi: 10.3390/en17122915.

[21] Z. Abidin, A. Setia, and J. Tanesab, "'Simulation-based study of MPC and GA-PID optimization for frequency regulation in a hybrid wind-diesel power system under load variation,'" *Clean. Energy Syst.*, no. August, p. 100219, 2025, doi: 10.1016/j.cles.2025.100219.

[22] B. Zhang, "'A NoisyNet deep reinforcement learning method for frequency regulation in power systems,'" *IET Gener. Transm. Distrib.*, vol. 18, no. April, pp. 3042–3051, 2024, doi: 10.1049/gtd2.13250.

[23] P. R. Sahu *et al.*, "'Effective Load Frequency Control of Power System with Two-Degree Freedom Tilt-Integral-Derivative Based on Whale Optimization Algorithm,'" *Sustain.*, vol. 15, no. 2, pp. 1–20, 2023, doi: 10.3390/su15021515.

[24] X. Chen, M. Zhang, Z. Wu, L. Wu, and X. Guan, "'Model-Free Load Frequency Control of Nonlinear Power Systems Based on Deep Reinforcement Learning,'" *IEEE Trans. Ind. Informatics*, vol. 20, no. 4, pp. 1–9, 2025.

[25] M. Alharbi *et al.*, "'Innovative AVR-LFC Design for a Multi-Area Power System Using Hybrid Fractional-Order PI and PIDD 2 Controllers Based on Dandelion Optimizer,'" *Mathematics*, vol. 11, no. 1387, pp. 1–45, 2023.

[26] I. Hacini, S. L. Belaid, K. Idjdarene, and H. Abderazek, "'Fuzzy Logic-Based Energy Management Strategy for Hybrid Renewable System with Dual Storage

JEEE-U
Journal of Electrical and Electronic Engineering-UMSIDA
ISSN 2460-9250 (print), ISSN 2540-8658 (online)
Vol. 10, No. 1, April 2026
10.21070/jeeeu.v10i1.1745

Dedicated to Railway Application,'" *technologies*, vol. 13, no. 334, pp. 1–25, 2025.

[27] B. ALBaaj and O. Kaplan, "'Enhanced COVID-19 Optimization Algorithm for Solving Multi-Objective Optimal Power Flow Problems with Uncertain Renewable Energy Sources: A Case Study of the Iraqi High-Voltage Grid,'" *Energies*, vol. 18, no. 3, pp. 1–29, 2025, doi: 10.3390/en18030478.

[28] S. Safiullah, A. Rahman, S. A. Lone, S. M. S. Hussain, and T. S. Ustun, "'Novel COVID-19 Based Optimization Algorithm (C-19BOA) for Performance Improvement of Power Systems,'" *Sustain.*, vol. 14, no. 14287, pp. 1–27, 2022.

[29] D. H. Tuan, D. T. Tran, V. N. N. Thanh, and V. Van Huynh, "'Load Frequency Control Based on Gray Wolf Optimizer Algorithm for Modern Power Systems,'" *energies*, vol. 18, pp. 1–17, 2025.

[30] Y. Li, S. Gao, X. Chen, D. Fan, and M. Zhang, "'Load Frequency Control of Power Systems Based on Deep Reinforcement Learning with Leader – Follower Consensus Control for State of Charge,'" *Processes*, vol. 13, no. 3669, pp. 1–20, 2025.

[31] R. Dhanalakshmi, "'ANFIS based Neuro-Fuzzy Controller in LFC of Wind- Micro Hydro-Diesel Hybrid Power System,'" *Int. J. Comput. Appl.*, vol. 42, no. 6, pp. 28–35, 2012.

[32] A. Fenniche, A. Harrouz, Y. Bellebna, A. Laidi, and I. Benlaria, "'Optimization of hybrid PV-wind systems with MPPT and fuzzy logic-based control,'" *Indones. J. Electr. Eng. Comput. Sci.*, vol. 39, no. 2, p. 747, 2025, doi: 10.11591/ijeecs.v39.i2.pp747-760.

[33] R.Doraiswami, "'A Nonliniear Load Frequency Control Design,'" *IEEE Trans. Power Appar. Syst.*, vol. 97, no. 4, pp. 1278–1284, 1978.

[34] S. Sarwar, M. Y. Javed, A. Bilal, W. Iqbal, K. Ejsmont, and M. H. Jaffery, "'A Coronavirus Optimization (CVO) algorithm to harvest maximum power from PV systems under partial and complex partial shading conditions,'" *Energy Reports*, vol. 11, no. December 2023, pp. 1693–1710, 2024.

[35] G. Magdy and A. Bakeer, "'A new intelligent approach for frequency controller of autonomous hybrid power systems,'" *Neural Comput. Appl.*, vol. 37, no. 22, pp. 17473–17492, 2025, doi: 10.1007/s00521-024-10635-y.

[36] M. Cavus, D. Dissanayake, and M. Bell, "'Deep-Fuzzy Logic Control for Optimal Energy Management : A Predictive and Adaptive Framework for Grid-Connected Microgrids,'" *Energies*, vol. 18, no. 995, pp. 1–25, 2025.

[37] S. Vazquez *et al.*, "'Model predictive control: A review of its applications in Power Electronics,'" *IEEE Ind. Electron. Mag.*, vol. 8, no. 1, pp. 16–31, 2014, doi: 10.1109/MIE.2013.2290138.

[38] K. Y. Lim, Y. Wang, G. Guo, and R. Zhou, "'A new decentralized robust controller design for multi-area load-frequency control via in complete state feedback,'" *Optim. Control Appl. Methods*, vol. 19, no. 5, pp. 345–361, 1998, doi: 10.1002/(sici)1099-1514(199809/10)19:5<345::aid-oca634>3.0.co;2-5.

[39] P. A. Gbadega and Y. Sun, "Heliyon Multi-area load frequency regulation of a stochastic renewable energy-based power system with SMES using enhanced-WOA-tuned PID controller," *Heliyon*, vol. 9, no. 9, p. e19199, 2023, doi: 10.1016/j.heliyon.2023.e19199.

[40] M. Molugumati and K. K. Kumar, "'Fuzzy Logic Controller for Power Balancing and Stability Enhancement in Renewable EV Hybrid Microgrids,'" in *E3S Web of Conferences 692, 01013*, 2026, pp. 1–9.

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DAFTAR TABEL

JEEE-U
Journal of Electrical and Electronic Engineering-UMSIDA
ISSN 2460-9250 (print), ISSN 2540-8658 (online)
Vol. 10, No. 1, April 2026
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Table 1: Key System Parameters

Component	*Parameter*	*Value*
PV Array	Rated Power	100 kW
	Efficiency	18%
Wind Turbine	Rated Power	80 kW
	Cut-in Wind Speed	3 m/s
	Rated Wind Speed	12 m/s
Fuel Cell (PEMFC)	Rated Power	50 kW
	Efficiency	50-60%
Microhydro	Rated Power	60 kW
	Head Height	10 m
BESS	Capacity	200 kWh
	Nominal Voltage	400 V
	Efficiency	95%

Table 2. Comparative Performance Summary

Parameter	**Conventi onal**	**Fuzzy**	**Fuzzy–CVOA (Proposed)**	**Improvement (%)**
Max Frequency Deviation (Hz)	±0.35	±0.28	±0.18	48
Max Voltage Deviation (p.u.)	±0.06	±0.05	±0.03	50
Min Battery SOC (%)	70	74	78	11
Average Efficiency (%)	85	89	93	9
Settling Time (s)	8.5	6.3	4.8	43

Table 3. Detailed Simulation Scenarios and Test Cases

Scenario ID	Description	Load Step (%)	PV Irradiance (%)	Wind Speed Drop (%)	Source Outage	Duration (s)
S1	Nominal operation	0	100	0	None	10
S2	Step load increase	+20	100	0	None	20
S3	PV intermittency	0	-50	0	None	15
S4	Wind intermittency	+10	100	-30	None	15
S5	Combined disturbance	+15	-40	-25	Fuel Cell OFF	30
S6	Full multi-source test	+20	-50	-30	Microhydro OFF	40

Table 4. Statistical Performance Metrics (Mean ± SD, n = 10 runs)

Metric	**Conventional**	**Fuzzy only**	**Fuzzy–CVOA (Proposed)**	**Improvement (%)**	**p-value (t-test)**
Max Frequency Deviation (Hz)	.35 ± 0.04	0.28 ± 0.03	0.18 ± 0.02	48.6	< 0.001
RMSE Freqency (Hz)	0.22 ± 0.03	0.18 ± 0.02	0.12 ± 0.01	45.5	< 0.001
Max Voltage Deviation (p.u.)	0.060 ± 0.005	0.050 ± 0.004	0.030 ± 0.002	50.0	< 0.001
ITAE Frequency	1.25 ± 0.15	0.95 ± 0.10	0.62 ± 0.08	50.4	< 0.001
Average Efficiency (%)	85.2 ± 1.8	89.1 ± 1.5	93.4 ± 1.2	9.6	< 0.01
Min Battery SOC (%)	70.1 ± 2.5	74.3 ± 2.0	78.5 ± 1.5	11.9	< 0.01
Settling Time (s)	8.5 ± 0.6	6.3 ± 0.4	4.8 ± 0.3	43.5	< 0.001

JEEE-U
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Vol. 10, No. 1, April 2026
10.21070/jeeeu.v10i1.1745

Table 5. Sensitivity Analysis of Key Parameters (Fuzzy–CVOA)

Parameter	Variation Range	Max Freq Dev (Hz)	Max Volt Dev (p.u.)	Efficiency (%)	Remark
PV Irradiance	500–1000 W/m²	0.19 → 0.17	0.032 → 0.029	91.2 → 94.1	Robust
Wind Speed	6–14 m/s	0.20 → 0.17	0.031 → 0.028	91.5 → 93.8	Robust
Battery SOC Limits	20–90%	0.18 (stable)	0.030 (stable)	93.0–93.5	Very stable
Load Increase	10–30%	0.17 → 0.21	0.029 → 0.034	93.4 → 92.1	Acceptable

Table 6. Optimization Performance Comparison (30 independent runs)

Algorithm	Best Objective Cost	Average Iterations	CPU Time (s)	Success Rate (%)	Final Tuned Rules
CVOA	0.008	45 ± 5	12.5 ± 1.2	95	118/125
GA	0.012	72 ± 8	28.3 ± 2.5	80	105/125
PSO	0.010	58 ± 6	19.7 ± 1.8	85	112/125

Table 7. Average Power Sharing Contribution under Different Scenarios (%)

Scenario	PV (%)	Wind (%)	Fuel Cell (%)	Microhydro (%)	BESS (%)	Power Balance Error (%)
S1 (Nominal)	32.5	28.0	21.8	17.7	0.0	0.12
S2 (Load +20%)	29.8	26.5	23.4	16.2	4.1	0.15
S5 (Combined)	25.4	22.1	28.7	14.5	9.3	0.18
Average	31.2	27.3	22.1	17.4	2.0	0.14

JEEE-U
Journal of Electrical and Electronic Engineering-UMSIDA
ISSN 2460-9250 (print), ISSN 2540-8658 (online)
Vol. 10, No. 1, April 2026
10.21070/jeeeu.v10i1.1745

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Vol. 10, No. 1, April 2026
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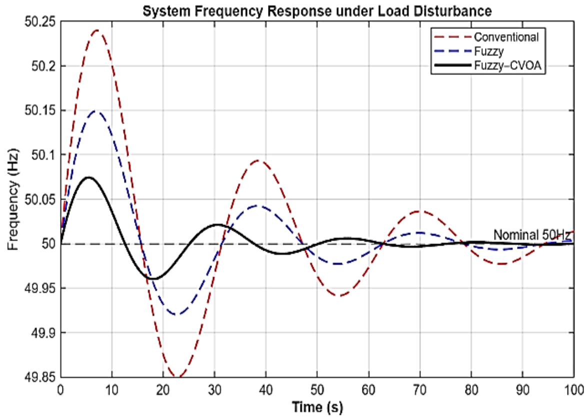


Figure 1. System Frequency Response under Load Disturbance

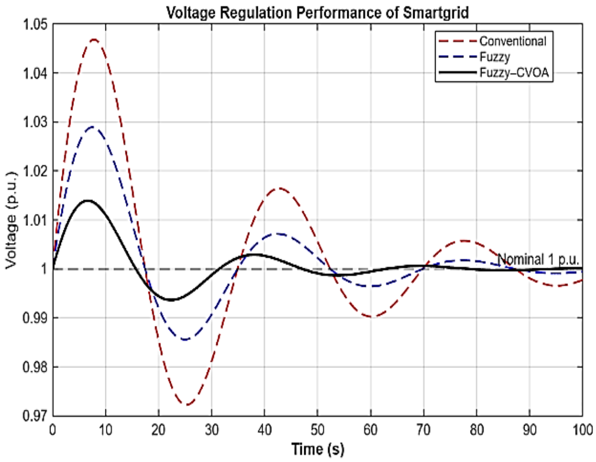


Figure 2. Voltage Regulation Performance of Smartgrid

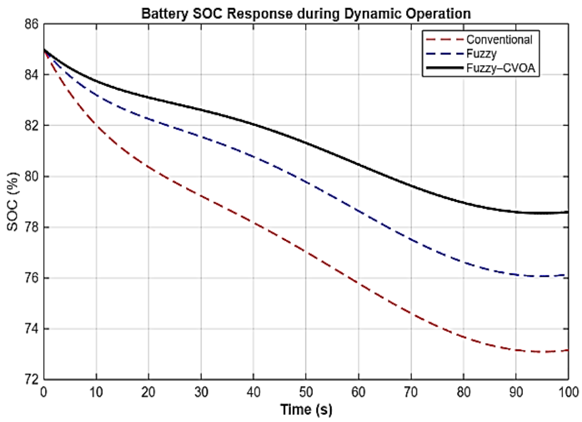


Figure 3. Battery SOC Response during Dynamic Operation

JEEE-U
Journal of Electrical and Electronic Engineering-UMSIDA
ISSN 2460-9250 (print), ISSN 2540-8658 (online)
Vol. 10, No. 1, April 2026
10.21070/jeeeu.v10i1.1745

Figure 4. Battery SOC Response during Dynamic Operation

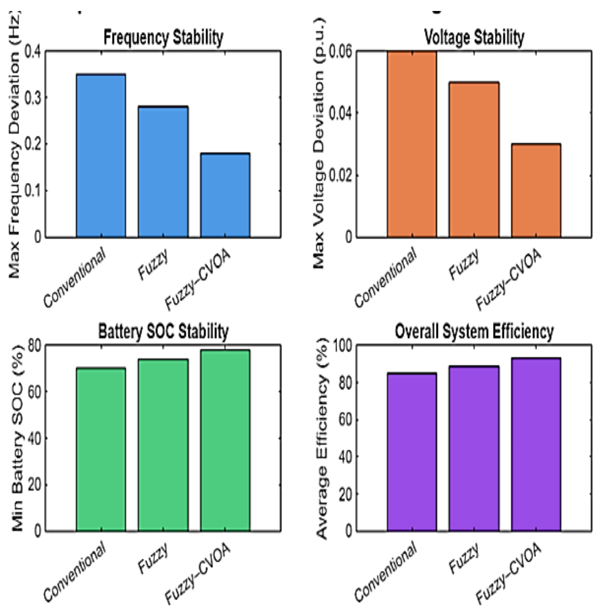


Figure 5. Comparative Performance Metrics- Smartgrid Controllers

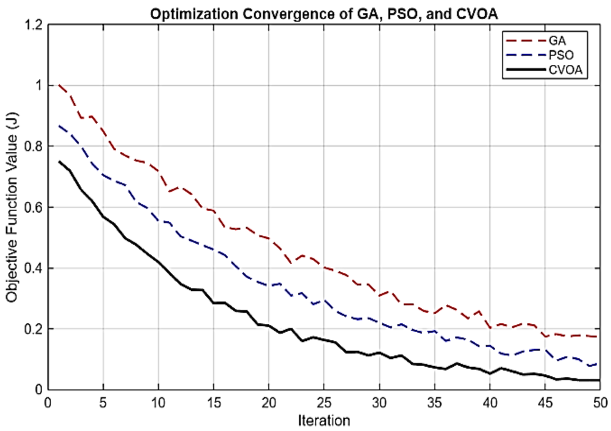
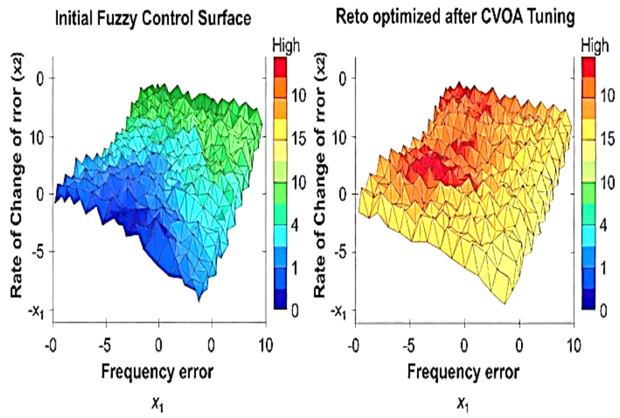


Figure 6. Optimization Convergence of GA, PSO, and CVOA



JEEE-U
Journal of Electrical and Electronic Engineering-UMSIDA
ISSN 2460-9250 (print), ISSN 2540-8658 (online)
Vol. 10, No. 1, April 2026
10.21070/jeeeu.v10i1.1745

Figure 7. 3D fuzzy control surface before and after CVOA optimization

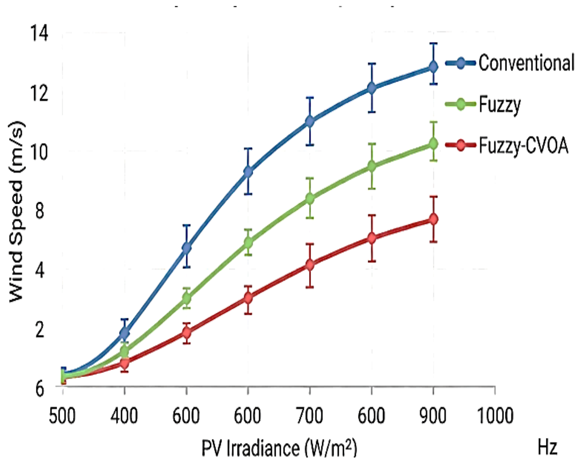


Figure 8. The sensitivity of maximum frequency deviation to simultaneous changes in PV irradiance and wind speed

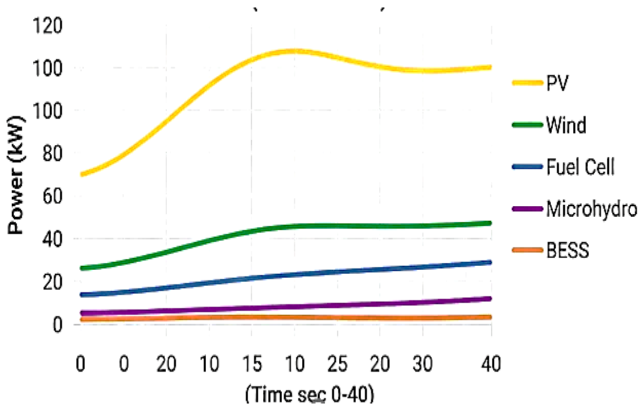


Figure 9. A stacked area plot of real-time power contributions during the severe combined disturbance

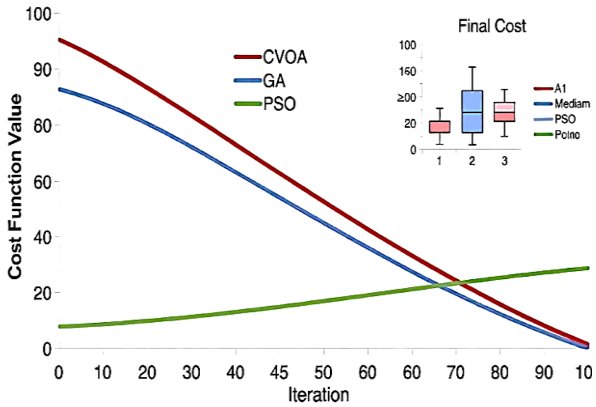


Figure 10. Convergence curves of CVOA, GA, and PSO (average of 30 runs)

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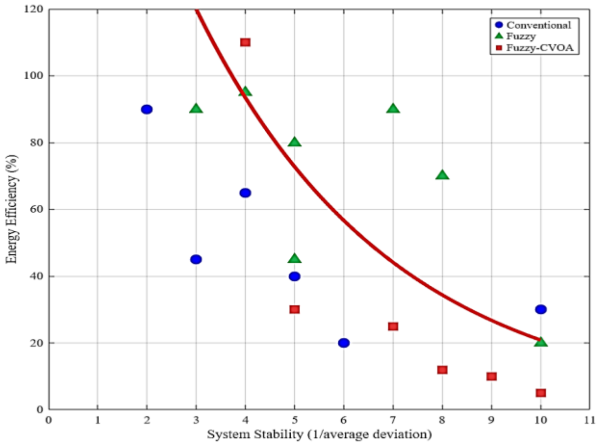

Figure 11. Pareto front between system stability and energy efficiency

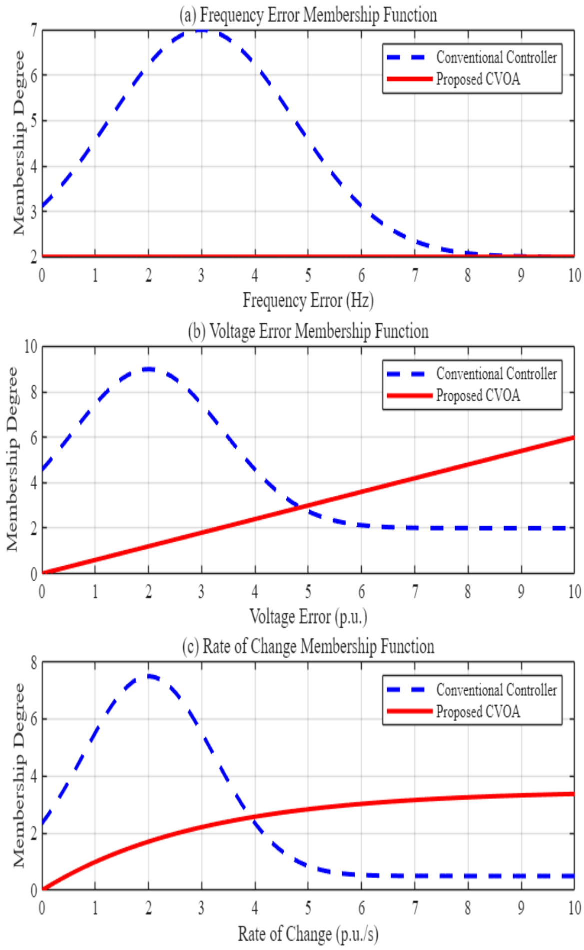

Figure 12. Compares membership functions before and after CVOA tuning

JEEE-U

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ISSN 2460-9250 (print), ISSN 2540-8658 (online)
Vol. 10, No. 1, April 2026
10.21070/jeeeu.v10i1.1745