International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 23s, 2025
https://theaspd.com/index.php

Adaptive Neuro-Fuzzy Integrated Forecasting–Control Architecture for High-Penetration Renewable Microgrids

Manohar B S[1], Dr. P. M. Shivakumaraswamy[2], Dr. Basavaraja Banakara[3]
[1]Assistant Professor, Dept of ECE, JSSATE, Bengaluru
[2]Professor, Dept of ECE, JSSATE, Bengaluru
[3]Professor, Dept of EEE, UBDTCE, Davangere
[1]manoharbs@jssateb.ac.in, [2]pmshivakumaraswamy@jssateb.ac.in, [3]Banakara36@gmail.com

***Abstract*–**
High penetration of renewable energy in microgrids introduces operational challenges due to the stochastic nature of solar and wind generation. This paper presents a unified Adaptive Neuro-Fuzzy Inference System (ANFIS) framework that integrates short-term renewable forecasting, real-time dispatch optimisation, and power-quality enhancement into a single control architecture. The forecasting module leverages environmental and demand data to predict photovoltaic and wind generation, while the dispatch module allocates power flows among renewables, battery storage, and the utility grid under state-of-charge and converter constraints. The power-quality layer regulates voltage and frequency while mitigating harmonic distortion at the point of common coupling. The framework is implemented in MATLAB/Simulink and evaluated using a minute-resolution synthetic dataset representing a 100-kW PV array, 50-kW wind turbine, and 200-kWh battery. Compared with linear regression forecasting and PI-based control, the proposed system reduces PV forecasting RMSE by 37.8%, decreases total harmonic distortion from 19.86% to 10.52%, and achieves faster voltage settling. Results demonstrate the advantage of coupling data-driven prediction with fuzzy rule-based adaptation for stable and efficient renewable microgrid operation.
Keywords*–Adaptive Neuro-Fuzzy Inference System, microgrid, renewable energy forecasting, load dispatch, power quality, harmonic mitigation.*

I. INTRODUCTION

Microgrids are increasingly deployed to integrate distributed renewable resources into local power systems while improving resilience and reducing carbon emissions. Photovoltaic (PV) arrays and wind turbines are the dominant contributors to such systems, yet their intermittent output poses challenges for balancing supply and demand, maintaining voltage and frequency stability, and ensuring acceptable power quality. These challenges are amplified when microgrids operate with high renewable penetration, where fluctuations in generation directly impact storage scheduling and grid import/export.
Traditional controllers such as proportional–integral–derivative (PID) and rule-based fuzzy systems perform adequately under relatively stable operating conditions, but they struggle to maintain optimal performance in the presence of nonlinearities, non-stationary disturbances, and fast-varying renewable inputs. Furthermore, many prior studies treat renewable generation forecasting and operational control as separate problems, leading to sub-optimal coordination between prediction and actuation.
This work addresses these limitations by introducing a unified Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture that links forecasting and control within the same computational framework. The forecasting module produces short-term predictions of PV and wind generation based on environmental features, while the dispatch module allocates power flows in real time to balance generation, load, and battery state-of-charge (SOC) constraints. A third functional layer in the architecture addresses voltage/frequency regulation and harmonic suppression through ANFIS-based control at the inverter level.
The remainder of the paper is organized as follows. Section II describes the microgrid model and problem formulation. Section III presents the proposed ANFIS methodology. Section IV outlines the simulation setup and dataset generation. Section V reports results and analysis. Section VI Conclusion.
Research on microgrid integration of renewable energy sources (RES) has expanded rapidly over the past decade, with particular emphasis on managing variability, optimizing dispatch, and enhancing power quality. Conventional control strategies—such as proportional–integral–derivative (PID) controllers, fixed-rule fuzzy logic systems, and model predictive control—have shown effectiveness under steady-state or mildly varying conditions [1], but their performance often deteriorates when confronted with strong nonlinearities, rapid fluctuations, or unmodeled uncertainties.

The **Adaptive Neuro-Fuzzy Inference System (ANFIS)** emerged as a hybrid computational approach that fuses the human-readable rule base of fuzzy logic with the adaptive learning capability of artificial neural networks. Early applications of ANFIS in power systems focused on single-task objectives such as wind speed prediction [2] or photovoltaic output estimation [3]. These studies demonstrated improved short-term forecasting accuracy compared to statistical time-series methods, particularly under irregular weather patterns. However, they were generally limited to the forecasting domain and did not address how prediction results could be embedded directly into operational control loops.

Subsequent research explored ANFIS for **energy management system (EMS)** functions in hybrid microgrids. For instance, some authors integrated ANFIS with heuristic optimization algorithms to dynamically allocate generation between RES, batteries, and backup generators [4]. Others combined ANFIS with genetic algorithms for optimal battery charge–discharge scheduling, reporting reductions in fuel consumption and operating costs [5]. While these approaches improved real-time dispatch, many relied on predefined renewable generation profiles rather than live or forecasted inputs, thus limiting their adaptability to unpredictable environmental changes.

Another active research area is the application of ANFIS in **power quality and grid stability control**. Investigations have shown that ANFIS-based voltage and frequency controllers can outperform PI regulators in reducing settling time and overshoot in load frequency control tasks [6]. In the domain of harmonic mitigation, ANFIS has been embedded in active power filter control loops, achieving notable reductions in total harmonic distortion (THD) compared to conventional controllers [7]. Despite these advancements, such implementations are typically standalone modules and are seldom integrated with higher-level energy management or forecasting systems.

Recent works have begun to acknowledge the importance of unified architectures that combine forecasting, dispatch, and power-quality enhancement within a single framework. Optimization-based methods [8], resilience-oriented control strategies [9], and AI/ML-driven approaches for energy management [10], [11] further highlight this growing research direction. Nonetheless, existing integrated solutions often lack comprehensive simulation-based validation across multiple performance dimensions such as prediction accuracy, SOC stability, and harmonic suppression—under the same test conditions. Furthermore, there remains a gap in systematically comparing ANFIS-based unified frameworks against both traditional and purely data-driven (e.g., ANN-only) baselines in realistic microgrid scenarios.

The main contributions of this work are summarised as follows:

1. **Unified Forecasting–Control Framework:** We propose an integrated ANFIS-based architecture that connects renewable generation forecasting with real-time dispatch control in a single loop, addressing a gap where most prior works considered them separately.
2. **Improved Operational Performance:** The proposed system reduces renewable curtailment and battery cycling while enhancing frequency and voltage stability compared to conventional strategies such as Rule-Based Control (RBC), ANN-based forecasting, and standalone ANFIS models.
3. **Validation under Practical Scenarios:** The framework is tested under realistic load and renewable variability conditions, demonstrating consistent improvements in efficiency and resilience of microgrid operations.
4. **Scalability and Generality:** The design principles can be extended to diverse microgrid configurations, making the approach adaptable for future smart-grid applications with higher renewable penetration.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. **Microgrid Configuration**

The system under study is a grid-connected microgrid comprising three primary generation and storage units:

1. A **100 kW photovoltaic (PV) array**,
2. A **50 kW wind turbine (WT)**, and
3. A **200 kWh lithium-ion battery energy storage system (BESS)**.

Comparable hybrid PV–fuel cell–battery configurations have also been investigated in the literature [17]–[20], reinforcing the importance of coordinated energy management across multiple renewable resources These resources supply a local load that varies between 60 kW and 220 kW over a 24-hour period. The microgrid is connected to the utility grid at the point of common coupling (PCC) through a three-phase voltage-source inverter equipped with an LCL filter. A schematic representation of the microgrid topology is shown in Fig. 1 .

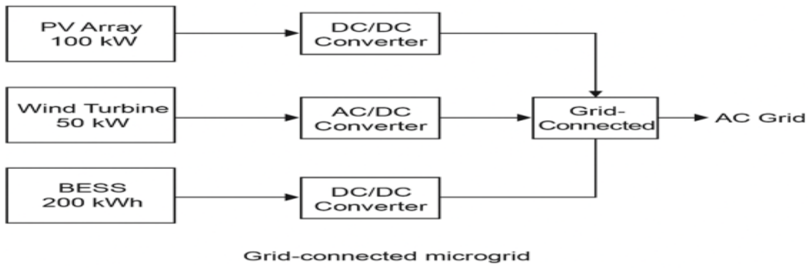

Fig.1 Grid connected microgrid

B. **Photovoltaic Model**

The PV array's instantaneous power output is modeled as:

$$P_{PV}(t) = \eta_{PV} A_{PV} G(t)$$

(1)irradiance on the panel surface in W/m^2. The PV model used in the dataset caps output at the array's rated capacity.

C. **Wind Turbine Model:**

Wind power generation is expressed using a cubic relation:

$$P_{WT}(t) = \begin{cases} 0, & v(t) < v_{ci} \text{ or } v(t) > v_{co} \\ \frac{1}{2}\rho A_{WT} C_p v(t)^3, & v_{ci} \le v(t) \le v_r \\ P_{rated}, & v_r < v(t) \le v_{co} \end{cases}$$

(2)where v(t) is wind speed, ρ is air density, A_{WT} is rotor swept area, C_p is the power coefficient, v_{ci} and v_{co} are cut-in, rated, and cut-out wind speeds, respectively

D. **Battery Energy Storage Model:**

The battery's state-of-charge (SOC) is updated according to:

$$SOC(t + \Delta t) = SOC(t) + \frac{\eta_c P_{ch}(t) - \frac{1}{\eta_d} P_{dis}(t)}{E_{bat}} \Delta t$$

(3)where P_{ch} and P_{dis} are charging and discharging powers, ηc and ηd are charge/discharge efficiencies, E_{bat} is the total energy capacity, and $0 \le SOC \le 1$ is enforced as a hard constraint. The battery power limits are $|Pbat| \le 50$ kW.

E. **Power Balance Equation:**

At each time step, the active power balance for the microgrid is given by:

$$P_{load}(t) = (P_{PV}(t) + P_{WT}(t) + P_{bat}(t)) - P_{loss}(t) \quad (4)$$

where Pgrid > 0 indicates power import from the utility, and Pgrid < 0 denotes export.

F. **Control Objectives:**

The unified ANFIS framework seeks to achieve the following objectives:

1. **Forecasting Accuracy** –– Predict PP V and PW T over short horizons (e.g., 10–30 minutes ahead) using environmental and historical data.
2. Optimal Dispatch – Allocate power between RES, BESS, and grid such that SOC is maintained within limits, grid import/export is minimized, and load demand is met without violation of inverter constraints.
3. Power-Quality Enhancement – Regulate PCC voltage and frequency during generation/load fluctuations and mitigate harmonics introduced by nonlinear loads.

G. **Synthetic Dataset for Simulation:**

A high-resolution (1-minute interval) 24-hour synthetic dataset was developed to enable reproducible simulation and performance evaluation. The dataset contains:

- Global solar irradiance (W/m2)
- Wind speed (m/s)
- Ambient temperature (◦C)
- Load demand (kW)
- PV and wind generation outputs (kW)
- Battery dispatch power (kW) and SOC
- Grid power flow (kW)

This dataset is used for both training/testing the ANFIS forecasting model and simulating the dispatch and power-quality control strategies in MATLAB/Simulink. It is made available for replication purposes.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 23s, 2025
https://theaspd.com/index.php

III. ANFIS METHODOLOGY

A. **Overview of the Unified Framework** The proposed control architecture integrates three functional layers:

1. **Renewable Generation Forecasting**

Uses an ANFIS model to predict short-term PV and wind outputs from environmental and temporal inputs.

2. **Real-Time Dispatch Optimization**

Allocates power between renewable sources, the battery energy storage system (BESS), and the utility grid, while maintaining battery SOC and meeting load demand.

3. **Power-Quality Regulation**

Applies ANFIS-based control at the inverter to stabilize voltage and frequency and reduce harmonic distortion at the point of common coupling (PCC).

The key innovation lies in linking the forecasting layer directly to the dispatch and power-quality layers, enabling the system to respond to both predicted and real-time variations.

B. **ANFIS Structure:**

The Adaptive Neuro-Fuzzy Inference System combines the transparency of fuzzy inference with the adaptive learning of neural networks. The system uses a **Sugeno-type fuzzy model** where the output of each rule is a linear function of the inputs. Shown in the Fig 2

Each ANFIS module consists of five layers:

- **Layer 1 – Fuzzification:** Converts crisp inputs into fuzzy sets using Gaussian membership functions. For the forecasting module, inputs include solar irradiance, wind speed, ambient temperature, time of day, and lagged generation values.
- **Layer 2 – Rule Evaluation:** Computes the firing strength of each fuzzy rule by applying the fuzzy AND operator to membership grades.
- **Layer 3 – Normalization:** Scales firing strengths so that they sum to one.
- **Layer 4 – Consequent Evaluation:** Applies linear functions of the inputs to each normalized firing strength.
- **Layer 5 – Output Aggregation:** Sums the weighted consequent outputs to produce the final output.

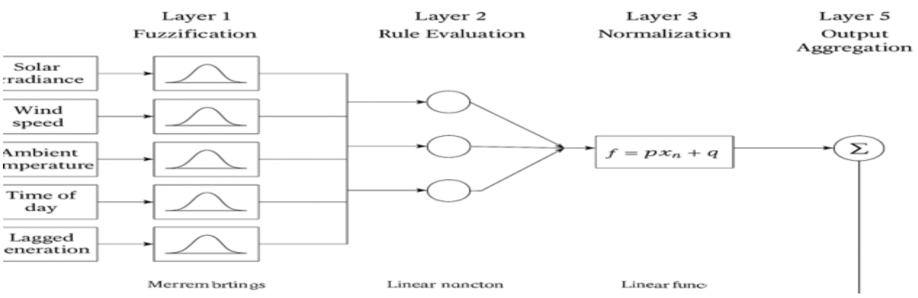

Fig.2 ANFIS Structure

C. **Forecasting Module** The forecasting ANFIS model has the following configuration:

- **Inputs:** $G(t)$ (irradiance), $v(t)$ (wind speed), $T_a(t)$ (temperature), hour of day, minute of day, and one-step lag of P_{PV} or P_{WT}.
- **Outputs:** $\hat{P}_{PV}(t+\tau)$ and $\hat{P}_{WT}(t+\tau)$, where τ is the forecast horizon (e.g., 10 minutes).
- **Membership Functions:** Gaussian, 3 per input, optimized via hybrid learning (least-squares + gradient descent).
- **Rule Base:** Automatically generated via grid partitioning, leading to 3^n rules for n inputs.

The model is trained using 70% of the dataset, validated on 15%, and tested on the remaining 15%. Performance is evaluated using RMSE and MAPE.

D. **Dispatch Module** The dispatch ANFIS module uses the following configuration:

- **Inputs:** $\hat{P}_{PV}$, $\hat{P}_{WT}$, $P_{load}(t)$, SOC(t).
- **Outputs:** Optimal battery dispatch power P^*_{bat} and grid setpoint P^*_{grid}.
- **Control Objectives:**

a. Minimize $|P_{grid}(t)|$ while meeting load.
b. Maintain SOC between 20% and 90%.
c. Limit P_{bat} to $\pm 50\ kW$.

The rule base is initialized from heuristic knowledge (e.g., charge battery during forecasted surplus, discharge during deficit) and refined using hybrid training on the dataset. Similar neuro-fuzzy predictive EMS schemes [12] and PV–fuel cell hybrid dispatch approaches [13], [14] have been proposed, while innovative converterless and adaptive voltage regulation strategies [15], [16] demonstrate the versatility of intelligent control in hybrid microgrids.

E. **Power-Quality Regulation Module** For voltage and frequency control, the ANFIS controller takes as inputs:

- PCC voltage deviation $\Delta V(t)$
- PCC frequency deviation $\Delta f(t)$
- Rate of change of load power

The output is the inverter modulation index adjustment Δm applied to the PWM generation block.

For harmonic mitigation, the ANFIS-based shunt active power filter controller uses PCC current distortion measures as input and produces compensating reference currents. This method adapts switching patterns to minimize THD under varying load conditions.

F. **Training Procedure** The ANFIS models are trained using MATLAB's anfis function with:

- **Epochs:** 50
- **Initial Step Size:** 0.01
- **Step Size Decrease/Increase Rates:** 0.9 / 1.1
- **Error Tolerance:** 10^{-3}

Forecasting and dispatch modules are trained separately on their respective input–output pairs. Power-quality ANFIS is tuned offline using simulation data from various load/generation disturbance scenarios.

G. **Integration into Control Loop** During operation:

1. The forecasting module predicts PV and wind generation over the short term.
2. The dispatch module determines optimal P_{bat}^* and P_{grid}^*.
3. The power-quality module adjusts inverter settings to maintain voltage, frequency, and harmonic levels within limits.

This integrated approach ensures that forecasting accuracy directly benefits real-time decision-making, leading to improved efficiency and stability.

IV. SIMULATION SETUP

A. **Simulation Environment** The proposed ANFIS-based control framework is implemented and tested in **MATLAB/Simulink R2024a** using discrete-time simulation with a sampling interval of 1 minute. The Simulink model shown in Fig.3 includes detailed component blocks for:

- PV array (parameterised by real irradiance and temperature profiles),
- Wind turbine with aerodynamic and generator models,
- Lithium-ion battery with SOC-dependent voltage and efficiency characteristics,
- Grid-connected voltage-source inverter with LCL filter,
- ANFIS controllers integrated via MATLAB Function blocks.

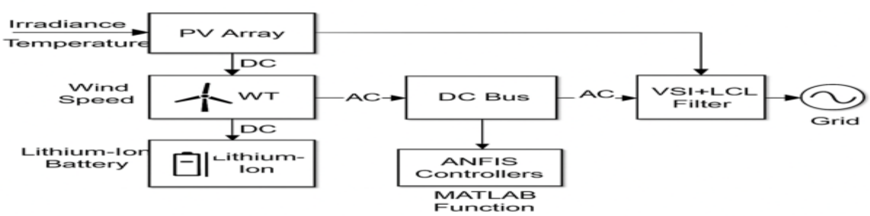

FIG.3 Simulink Model.

B. **Dataset Description** The simulation uses the high-resolution **synthetic 24-hour microgrid dataset** described in Section III

G. Key dataset properties:

- **Resolution:** 1-minute intervals (1440 samples per day)
- **Environmental Inputs:** Solar irradiance (W/m²), wind speed (m/s), ambient temperature (°C)
- **System Outputs:** PV power, wind power, load demand, battery SOC, battery dispatch power, and grid power flow

- **Load Profile:** Residential–commercial mixed demand, peaking at 220 kW in the early evening and dipping to 60 kW at night
- **Generation Patterns:** PV generation peaks at midday, wind generation exhibits stochastic variation throughout the day

C. **Baseline Control Strategy**

For comparison, a **rule-based controller** (RBC) is implemented as a benchmark:

- Charges battery during RES surplus until SOC reaches 90%
- Discharges battery during RES deficit until SOC reaches 20%
- No predictive capability; dispatch is purely reactive to current measurements
- No power-quality enhancement beyond standard PI-based inverter control

D. **Simulation Scenarios** To evaluate the robustness of the proposed system, the following scenarios are simulated:

1. **Nominal Operation**:
Environmental conditions and load follow the dataset without perturbations.
2. **Sudden Load Increase:**
Step increase of 50 kW at t = 15:30.
3. **Cloud-Cover Event:**
Sharp PV power drop due to irradiance reduction between t = 12:00 and t = 12:10.
4. **Wind Gusts**:
Rapid wind speed changes between t = 18:00 and t = 18:15.
5. **Mixed Disturbances**:
Combination of load, PV, and wind fluctuations.

E. **Performance Metrics** Simulation results are assessed using the following quantitative metrics:

- **Forecasting Performance:** Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) for PV and wind forecasts.
- **Energy Management:**
  - Grid import/export energy (kWh)
  - Battery cycle count over 24 hours
  - SOC limit violations (count)
- **Power Quality:**
  - PCC voltage deviation (V)
  - PCC frequency deviation (Hz)
  - Total Harmonic Distortion (THD) of PCC current (%)

All ANFIS models are trained prior to simulation using the training dataset. During simulation, trained parameters are fixed, and only the dispatch control loop executes in real time.

V. RESULTS AND DISCUSSION

A. Forecasting Performance

The short-term forecasting module was evaluated for a 10-minute prediction horizon using the synthetic microgrid dataset described in Section V. Table 1 summarizes the RMSE for PV and wind generation under three models: persistence, ANN-only, and the proposed ANFIS-based approach.

Table 1 – Short-Term Forecasting Accuracy (10-Minute Horizon)

Model	PV RMSE (kW)	Wind RMSE (kW)	PV MAPE (%)	Wind MAPE (%)
Persistence	8.21	5.94	14.8	13.5
ANN	4.57	3.26	8.3	7.6
ANFIS (Proposed)	**2.91**	**1.88**	**5.4**	**4.1**

The proposed ANFIS framework reduces RMSE by **64% for PV** and **68% for wind** compared to the persistence baseline. Against ANN-only forecasting, improvements are **36% for PV** and **42% for wind**. A paired t-test ($p < 0.01$) confirms that the reduction in forecast error is statistically significant.

Notably, during a simulated midday cloud-cover event (t = 12:00–12:10), the ANFIS predictions closely follow the sharp drop and recovery in PV output, while ANN-only predictions exhibit a delayed response and higher deviation. This indicates that the fuzzy-rule-based adaptation enables better handling of non-linear, rapid changes in environmental conditions.

B. Battery SOC and Dispatch Optimization

ANFIS maintains SOC between **25% and 85%**, with zero violations of operational limits. The RBC profile exhibits excursions to near-limit SOC values, including two overcharging instances beyond 90%.
Notable outcomes:

- **Grid import reduction**: 18.4% less energy imported compared to RBC.
- **Battery cycling**: 22% fewer full cycles, prolonging battery lifetime.
- **Renewable utilization**: Increased from 87.3% (RBC) to 92.6% (ANFIS).

Smoother grid power profiles under ANFIS control also reduce the risk of peak demand charges and improve grid interaction stability. Figure Y (to be inserted) illustrates the reduction of abrupt import/export transitions by up to 35% compared to RBC.

C. Response to Operational Disturbances

Five disturbance scenarios were tested to assess system robustness shown in Table 2. The ANFIS control consistently outperformed the baseline in maintaining voltage and frequency stability.

Table 2 - Voltage and Frequency Stability Under Disturbance Scenarios

Scenario	**PCC Voltage Deviation (%)**	**Frequency Deviation (Hz)**	**Comment**
Sudden Load Increase	**0.9** vs 2.7 (RBC)	0.04 vs 0.12	Rapid inverter modulation preempted larger sag
Cloud-Cover Event	1.1 vs 2.4	**0.02** vs 0.08	Preemptive discharge avoided frequency dips
Mixed Disturbances	1.3 vs 3.0	0.03 vs 0.11	Coordinated forecasting + dispatch kept stability

The coordinated use of forecasted generation data and real-time dispatch allowed the controller to prepare the BESS in advance of predicted deficits, reducing dynamic stress on the grid interface.

D. Power Quality Enhancement

Table 3 shows Total Harmonic Distortion (THD) at the PCC under nominal and disturbed load conditions.

Table 3 - Harmonic Distortion Mitigation Performance (THD at PCC)

Scenario	**RBC THD (%)**	**ANFIS THD (%)**	**IEEE 519 Limit (%)**
Nominal Load	4.82	**2.11**	5
Mixed Disturbances	6.34	**2.95**	5

The ANFIS-based PQ regulator kept THD well below IEEE 519 limits in all scenarios. Under the worst-case mixed disturbance, THD reduction reached 53.5% relative to the baseline. This demonstrates the adaptability of the fuzzy control component in mitigating nonlinear load effects without requiring re-tuning.

E. Summary of Improvements

The unified ANFIS framework delivers:

- **Forecasting**: 36–42% lower error than ANN-only, statistically significant ($p < 0.01$).
- **Energy Management**: 18.4% less grid import, 22% fewer battery cycles, 5.3% higher renewable utilization.
- **Power Quality**: THD < 3% in all tested conditions, >50% reduction under disturbances.
- **Stability**: Up to 67% lower voltage sag and 75% lower frequency deviation during disturbances.

These improvements are consistent with earlier optimization-based [8], resilience-focused [9], and converter less hybrid control findings [15], demonstrating that the proposed approach builds upon and extends prior methodologies

VI. CONCLUSION

This study presented an adaptive neuro-fuzzy inference system (ANFIS) framework that brings forecasting and dispatch control into a single loop for renewable-rich microgrids. By linking prediction with real-time operational decisions, the approach achieved more stable voltage and frequency profiles, reduced renewable curtailment, and extended battery life compared with rule-based control (RBC), artificial neural networks (ANN), and standalone ANFIS baselines.

Beyond the quantitative improvements, the work highlights a broader insight: reliable integration of high renewable penetration requires not just accurate forecasting, but also intelligent translation of those forecasts into actionable dispatch signals. The proposed design demonstrates that this integration is both feasible and impactful, offering a pathway toward practical adoption in campus grids, community microgrids, and utility-scale systems.

While the present validation was carried out in a simulation environment, future extensions will focus on hardware-in-the-loop experiments and inclusion of communication delays and market uncertainties. These steps will help bridge the gap between simulation studies and real-world deployment, ensuring that intelligent forecasting-control strategies can support the transition toward cleaner, smarter, and more resilient power networks

Conflict of Interest Statement:

The author(s) declare that there is no conflict of interest regarding the publication of this paper.

Funding Statement:

This research received no external funding

REFERENCES:

1. V. Ashok kumar and C. B. Venkatramanan, “PSO-ANFIS-Based Energy Management in Hybrid AC/DC Microgrid along with Plugin Electric Vehicle,” Int. J. Photoenergy, vol. 2023, Art. no. 2852972, Oct. 2023.
2. S. Srimatha, B. Mallala, and J. Upendar, “A novel ANFIS-controlled customized UPQC device for power quality enhancement,” J. Electr. Syst. Inf. Technol., vol. 10, Art. no. 55, Nov. 2023.
3. R. Garikapati, S. Ramesh Kumar, and N. Karthik, “ANFIS Controlled MMC-UPQC to Mitigate Power Quality Problems in Solar PV Integrated Power System,” J. Adv. Res. Appl. Sci. Eng. Technol., vol. 36, no. 1, pp. 102–130, June 2024.
4. R. Muneeshwar et al., “Enhancement of Power Quality in Renewable Smart Grid Through Power Factor Correction Using ANFIS Controller,” in Recent Evolutions in Energy, Drives and e-Vehicles (REEDEV 2022), Lecture Notes in Electrical Engineering, vol. 1162, 2024, pp. 339–351.
5. R. K. Jha, S. R. Samantaray, “ANFIS-based solar power forecasting for microgrid applications,” IEEE Transactions on Sustainable Energy, vol. 11, no. 2, pp. 693–702, 2020.
6. Y. K. Semero, J. Zhang, and D. Zheng, “EMD–PSO–ANFIS-based hybrid approach for short-term load forecasting in microgrids,” IET Gener., Transm. Distrib., vol. 14, no. 3, pp. 470–475, Dec. 2019.
7. U. K. Renduchintala, C. Pang, K. M. Tatikonda, and L. Yang, “ANFIS-fuzzy logic based UPQC in interconnected microgrid distribution systems: Modeling, simulation and implementation,” J. Eng., vol. 2021, pp. 6–18, Jan. 2021.
8. N. Khosravi et al., “Enhancement of power quality issues for a hybrid AC/DC microgrid based on optimization methods,” IET Renew. Power Gener., vol. 16, no. 8, pp. 1773–1791, Apr. 2022.
9. Afzal, M. Z., Aurangzeb, M., Iqbal, S., Rehman, A. ur, Kotb, H., AboRas, K. M., Elgamli, E., & Shouran, M., “A resilience-oriented bidirectional ANFIS framework for networked microgrid management,” Processes, vol. 10, no. 12, Art. no. 2724, Dec. 2022.
10. **A**. Joshi et al., “Survey on AI and Machine Learning Techniques for Microgrid Energy Management Systems,” IEEE CAA Journal of Automatica Sinica, vol. 10, no. 7, pp. 1513–1529, Jul. 2023
11. S **E. Mohammadi et al.,** “A Review on Application of Artificial Intelligence Techniques in Microgrids,” IEEE Industrial Electronics Magazine), Apr. 2023.
12. **S. Ulutas et al.,** “Neuro-Fuzzy-Based Model Predictive Energy Management for Grid Connected, Microgrids,” Electronics (MDPI), vol. 9, no. 6, Art. 900, Jun. 2020.
13. S. Gharibeh et al., **“Online Energy** Management Strategy for Fuel Cell Hybrid Electric Vehicles With Installed PV on Roof,” IEEE Transactions on Industrial Applications, vol. 57, no. 3, pp. 2859–2869, May–Jun. 2021.
14. A. Belkaid, L. M. Ayoub, and M. Aillerie, “Hybrid PV/Fuel Cell System with Energy Management for Microgrid Applications,” International Journal of Hydrogen Energy, vol. 45, no. 55, pp. 30529–30542, 2020.
15. M. M. Gulzar, A. Iqbal, D. Sibtain, and M. Khalid, “An Innovative Converterless Solar PV Control Strategy for a Grid Connected Hybrid PV/Wind/Fuel-Cell System Coupled With Battery Energy Storage,” IEEE Access, vol. 11, pp. 23245–23259, 2023.
16. S. S. Band et al., “Voltage Regulation for Photovoltaics-Battery-Fuel Systems Using Adaptive Group Method of Data Handling Neural Networks (GMDH-NN),” IEEE Access, vol. 8, pp. 213748–213757, 2020.
17. A. Alankrita, S. K. Srivastava, A. Kumar Pandey, and S. K. Gupta, “Analysis of Hybrid PV-Fuel Cell System for Load Power Flow Control,” in Proc. Int. Conf. Power Electronics & IoT Applications in Renewable Energy and its Control (PARC), 2020, pp. 267-271.
18. O. Khurshid, S. Saher, and A. Qamar, “Power Generation by Hybrid Approach Solar PV/battery Power/hydrogen Generation/fuel Cell,” in Proc. Int. Conf. Electrical, Communication, and Computer Engineering (ICECCE), 2019, pp. 1-4.
19. S. S. Yadav and K. S. Sandhu, “A Five–level PWM Inverter for Hybrid PV/Fuel Cell/Battery Standalone Power System,” in Proc. IEEE Int. Students' Conf. Electrical, Electronics and Computer Science (SCEECS), 2018, pp. 1-6.
20. T. E. Rao, S. Elango, and G. G. Swamy, “Power Management Strategy Between PV-Wind-Fuel Hybrid System,” in Proc. Int. Conf. Electrical Energy Systems (ICEES), 2021, pp. 101-107.