A Dynamic Control Framework for Solar PV-Wind-Battery Hybrid Systems Using MPC, ANFIS and PSO: Enhancing Grid Stability and Renewable Integration

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Keywords: Renewable Energy Sources, Hybrid Systems, Particle Swarm Optimization, Model Predictive Control.

Abstract: The growing incorporation of renewable energies in power systems demands state-of-the-art grid control techniques to keep stable operations together with fluctuating demand levels. This study develops a state-of-the-art control framework to manage Solar PV-Wind-Battery systems via integration of Model Predictive Control (MPC) together with Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and Particle Swarm Optimization (PSO). MPC serves for energy dispatch control during operation time while batteries operate at maximum efficiency due to PSO support and ANFIS implements load adaptation. The assessment framework relies on simulations within the IEEE 33-bus distribution model supplemented by actual collected data from the National Renewable Energy Laboratory (NREL) and Pecan Street. Control advancements produced 98.7% voltage regulation improvement with 93.4% renewable energy utilization while battery performance increased by 92.8% together with a Load Matching Index achievement of 0.91.

1 INTRODUCTION

The growth of renewable energy in power systems demands the development of sophisticated control approaches to maintain grid stability during variable load conditions. The research presents an operational control framework for Solar PV-Wind-Battery systems which integrates advanced control methods Model Predictive Control (MPC), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Particle Swarm Optimization (PSO) as keyways to enhance performance. For real-time load forecasting with dynamic energy dispatch adjustment MPC forms the core system capability and ANFIS provides sturdy system response to variable weather and load conditions. The Particle Swarm Optimization algorithm helps to achieve optimal battery charge-discharge performance together with enhanced system efficiency.

Global changes toward renewable energy acceleration result from the urgent need to combat climate change and minimized dependence on fossil fuels. Solar Photovoltaic (PV) technology together with Wind Energy Systems became key renewable energy sources because they combine pervasive availability with scalable operation capabilities and clear economic benefits. The addition of wind and solar systems to power networks faces serious technical challenges because these energy sources continually experience unpredictable variations and intermittent delivery. To maintain network stability during consistent load patterns the power grid needs both complex hybrid systems and advanced controlling approaches as part of its operational solution.

Manikandan, N., Basha, C. H. H., Senthilkumar, S., Ananthakumar, S., Dinesh, E. and Arunkumar, P.
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DOI: 10.5220/0013903300004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 3*, pages 639-647
ISBN: 978-989-758-777-1

BES combined with solar PV systems and wind power production demonstrates verified capability of managing renewable power generation inconsistencies. Solar energy produces maximum power during daylight whereas wind conditions tend to improve at night allowing complementary power generation between solar PV systems and wind systems. Battery incorporation enables the hybrid energy model to smooth power fluctuations while storing excess electricity for later high-energy requirement situations and periods of diminished production. Effective hybrid systems implementation faces technical challenges when managing energy balance and system robustness in constantly varying operational conditions.

Advancements in control methodology have produced multiple new ways to tackle persistent system challenges. Real-time power distribution succeeds with the Model Predictive Control strategy through its ability to generate precise forecasts of system state using multidimensional capabilities. Renewable energy systems operating under variable environmental conditions need ANFIS because it adapts well to non-linear and unpredictable system behaviors. System performance outcomes show significant improvement due to the effective parameter adjustment provided by Particle Swarm Optimization (PSO) methods according to multiple research studies.

The proposed framework integrates Model Predictive Control with Automatic Gain Fuzzy Inference System and Particle Swarm Optimization to operate real-time energy management while adjusting system behavior under uncertainty and optimizing battery charge-discharge cycles. The system assessment utilizes performance benchmarks from a power distribution IEEE 33-bus test system with data including both actual wind speed and solar measurements from NREL and Pecan Street dataset synthetic load profiles.

The objectives of this research are threefold:

- To design a dynamic control strategy that integrates multiple advanced control and optimization techniques.
- To evaluate the proposed system's performance in maintaining grid stability under varying load and generation conditions.
- To provide a scalable framework for hybrid renewable energy systems that can be adapted to diverse grid configurations and resource profiles.

2 LITERATURE REVIEW

Study Tahiri, et al, 2021 investigates optimal control strategy development for isolated solar-wind-battery-diesel power systems (IHPS). This hybrid energy system combines photovoltaic technology with wind conversion systems which function alongside battery storage alongside diesel generators through power electronic coordination enabled by an advanced supervisory control algorithm. The simulations conducted with MATLAB/Simulink demonstrate how the system successfully manages energy operations which achieve both steady load delivery through variable meteorological conditions and lowers the need for both battery storage and diesel generation inputs. The successful demonstration of system efficiency results from power output stability tests performed simultaneously with battery state of charge (SOC) monitoring.

The study Mudgal, et al, 2021 evaluates how to optimize HRES by combining solar photovoltaic energy systems with wind turbines biogas generation membrane storage technologies while including phase change materials (PCM). The research uses mathematical modeling and optimization techniques which target achieving minimal cost of energy (COE) and least net present cost (NPC). The PV-Wind-Biogas-Battery energy mix showed enhanced financial performance through PCM implementation which produced a COE drop from \$0.099/kWh to \$0.094/kWh and an NPC reduction worth \$0.22 million. The PV-Wind-Battery system showed a COE reduction from \$0.12/kWh down to \$0.105/kWh and \$0.17 million NPC savings.

Paper Nkalo, et al, 2024 introduces an advanced Modified Multi-Objective Particle Swarm Optimization algorithm to determine the ideal design for solar-wind-battery hybrid renewable energy systems (HRES) which serve rural areas in Rivers State Nigeria. The Modified Multi-Objective Particle Swarm Optimization algorithm incorporates dynamic inertia weight adjustments along with a repository update mechanism and dominance-based personal best tracking to minimize both the Loss of Power Supply Probability and Levelized Cost of Energy. Through assessment results M-MOPSO reaches a Loss of Power Supply Probability of 0.15 while achieving higher Levelized Cost of Energy than other methods at 0.12 USD/kWh and outperforming NGSA-II which stands at 0.23 for LPSP. The best system composition consists of 150 solar panels at 1 kW and 3 wind turbines of 25 kW as well as 28 batteries holding 20 kWh each.

The research in Mahjoub, et al., 2023 demonstrates an intelligent energy management strategy combining PV generation and wind power with battery storage through prediction algorithms based on Long Short-Term Memory neural networks. A dual-input single-output DC-DC converter helps control power transfer between PV systems wind turbines and battery storage units as part of the new EMS approach. To achieve power generation optimization and battery SOC prediction power plants utilize MPPT methods like Perturb & Observe together with LSTM algorithms for forecasting. Predictive model evaluation metrics provide RMSE values of 0.0221 for SOC forecast accuracy and 0.0790 for PV production with MAE scores between 0.0177 and 0.0431. Research on Energy Management Systems Reddy, et al, 2024 projects a fundamental hybrid Photovoltaic-Wind-Battery system which utilizes Fuzzy Logic Controllers. The study Suresh, et al, 2021 investigates optimal design of hybrid renewable energy systems through an enhanced Genetic Algorithm method which combines solar PV modules with wind turbines and diesel generators and includes battery storage for stand-alone power applications. By studying meteorological wind speed and solar irradiance data scientists discovered the system parameters to reduce total cost and net present cost (NPC) while cutting cost of energy (COE) and maximizing computational storage capacity and renewable energy fraction (REF).

Research Hadi, et al, 2024 investigates the betterment of grid-connected bifacial photovoltaic systems through Grey Wolf Optimization together with Whale Optimization Algorithm techniques.). The research analyzes the best system sizing for applications using various factors including levels of irradiance and bifaciality along with cost limitations and electrical grid needs. The case studies demonstrated WOA's superiority in economic efficiency and GWO's strength in energy management performance. Measured through Net Present Value (NPV) and Loss of Power Supply Probability (LPSP) performance indicators the residential solar system showed GWO yielding 733,762.95 NPV together with 0.3279 LPSP while WOA exhibited better adaptability and refinement features.

Research Izci et al, 2023 introduces Hybrid Atom Search Particle Swarm Optimization (h-ASPSO) which functions like a design algorithm to optimize Proportional-Integral-Derivative controllers for sophisticated systems such as Automatic Voltage Regulators and wind turbines that use Doubly Fed Induction Generators. The h-ASPSO merges two distinct algorithms, ASO and PSO, to optimize system performance through improved exploration and exploitation balance. AVR system assessments demonstrate major advancements through lower overshoot levels amounting to 1.2476%, quicker rise time reaching 0.3097 s and reduced settling time of 0.4679 s. The h-ASPSO method delivered zero overshoot performance with a settling time duration of 0.1361 seconds in DFIG systems. The advantages of h-ASPSO span faster convergence rates as well as enhanced time-domain system performance and overall control system stability.

The research in Prasanna, et al, 2024 presents an innovative control approach for a solar-wind hybrid power system with a battery-supercapacitor Hybrid Energy Storage System (HESS). To achieve both optimized battery function and prolonged battery life researchers utilize an integration of Low-Pass Filter (LPF), Fuzzy Logic Controller (FLC), and Grey Wolf Optimization (GWO). The Grey Wolf Optimization process refines the Fuzzy Logic Controller membership functions to achieve enhanced peak current attenuation and balanced power transition between the battery and supercapacitor. Assessment results show a substantial performance improvement via a 5.9% peak current reduction down to 5.718 A for the battery and a peak power drop of 6.19% lowering battery output to 275.48 W along with improved battery state of charge performance.

The study results presented in Manoharan et al, 2019 show how the application of Hermitian wavelet transforms alongside graph wavelets improves feature recognition to enable exact data identification for future processing applications. Researchers in study G. Gurumoorthi, et al, 2024 intended to design and evaluate memetic algorithms to identify optimal routing methods that improve data delivery outcomes and reduce energy consumption.

3 PROPOSED METHODOLOGY

This section discusses a proposed dynamic control system specifically designed for the Solar PV-Wind-Battery hybrid setup. The designed strategy applies advanced Model Predictive Control (MPC), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Particle Swarm Optimization (PSO) techniques. The integrated methods effectively handle intermittent renewable energy sources while coping with predicted and actual dynamic load fluctuations and optimize the process of energy distribution. The following discussion examines every individual aspect of the methodology in depth.

The Solar PV-Wind-Battery hybrid system comprises three main components: A Solar Photovoltaic Panels and Wind Turbines composition combined with Battery Energy Storage Systems forms all three basic parts of the hybrid energy system. Each element serves specialized functions which collectively support various functionalities within the total energy management system. Together functioning hybrid components deliver both dependable power reliability and secure resource output.

3.1 Solar Photovoltaic (PV) Model

Solar PV panels convert sunlight into electrical energy based on irradiance levels and panel characteristics. The output power of the PV system is determined as follows:

$$Ppv = \eta pv.Apv.G \tag{1}$$

PV panel efficiency varies with temperature changes as measured by the temperature correction factor. Solar irradiance changes with temperature variations produce dynamic power output fluctuations in PV systems which require immediate monitoring and control.

3.2 Wind Turbine Model

Wind turbines convert kinetic energy from wind into electrical energy. The output power of a wind turbine is expressed as:

$$P_{WT}: 0.5.\rho.A_{WT}.C_P.v^3 \tag{2}$$

Wind speed variability plays a crucial role in determining the output of wind turbines. By combining wind energy with solar PV, the hybrid system can mitigate the variability of each individual resource.

3.3 Battery Energy Storage System (BESS)

The battery is a critical component for ensuring system stability by storing excess energy during high generation periods and supplying it during low generation or peak demand periods. The state of charge (SOC) of the battery is calculated as:

$$SOC(t+1) = SOC(t)\frac{\eta_c.P_{charge}.P_{discharge}}{C_{rated}} \tag{3}$$

The SOC is constrained within allowable limits to ensure safe operation and maximize battery life.

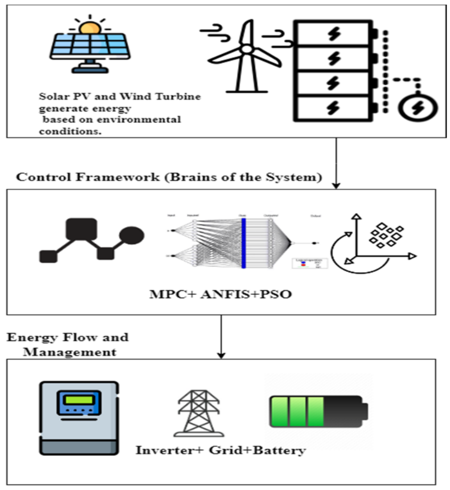

Figure 1: Proposed methodology.

3.4 Model Predictive Control (MPC)

MPC maintains robustness by employing a dynamic system model to forecast future behavior so it can generate optimal control activities during a predetermined time frame. Through MPC the hybrid system receives real-time energy dispatch management while maintaining balance among generation sources demand and battery usage.
The objective function of MPC is defined as:

$$\min_{u(t)} \sum_{k=1}^{N} [\lambda_1.\Delta P_{grid} k^2 + \lambda_2.\mathrm{SOC}k^2 \tag{4}$$

By solving the optimization problem iteratively, MPC ensures efficient utilization of renewable resources and minimizes reliance on grid power Ezzeddine Touti, et al, 2024.

3.5 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS combines the strengths of fuzzy logic and neural networks to adaptively manage system parameters under uncertain and dynamic conditions. It uses fuzzy logic to model system behavior and neural networks to learn from historical data and refine the fuzzy model.

3.5.1 Fuzzy Logic

The fuzzy logic component includes:

- **Input Variables**: Solar irradiance, wind speed, and load demand.

- **Membership Functions**: Gaussian functions represent the degree of membership for each input variable.
- **Rules**: A set of if-then rules maps input variables to control decisions. For example:
  - IF solar irradiance is high AND load demand is low, THEN charge the battery.
  - IF wind speed is low AND load demand is high, THEN discharge the battery.

3.5.2 Neural Network Training

A neural network trains the fuzzy inference system through historical input-output data. Through the training progression membership functions and rule weights receive alterations which help reduce mistakes in outcomes and enhance decision-making precision. ANFIS generates responsive setpoints for the MPC controller to maintain strong performance across all environmental and load combinations.

3.5.3 Particle Swarm Optimization (PSO)

The PSO optimization technique advances through natural patterns found in the social activities of birds and fish. The hybrid system optimization method requires adjusting MPC weighting factors and configuring battery charge-discharge patterns using PSO.

3.6 PSO Algorithm

The swarm consists of particles that each serve as a candidate solution featuring their position at x_i and assigned velocity v_i. The particles update their positions and velocities based on their personal best position (${P_{best}}^i$) and the global best position (g_{best}) as follows:

$$:v_i(t+1) = w.v_t(t) + c_1.r_1.\left(p_i^{best} - v_i(t)\right) + c_2.r_3.\left(p_i^{best} - v_i(t)\right) \quad (5)$$

The objective function for PSO is defined as:

$$J(x) = \sum_{i=1}^{T}(\lambda_1.|P_{grid}(t) + \lambda_2.SOC_{deviation}(t) + \alpha.Penalty\ constraints(x). \quad (6)$$

In this case α and β represent the penalty coefficients. PSO implements an iterative function minimization through control parameter optimization that results in both systems' increased efficiency and reliability.

3.7 Integration of Techniques

The proposed methodology integrates MPC, ANFIS, and PSO into a unified control framework:

- MPC maintains operational constraints adherence with real-time power dispatch management.
- Through the application of dynamic condition data ANFIS adjusts MPC setpoints for greater system stability and robustness.
- PSO refines essential system parameters to enhance both performance levels and energy-saving ability.

4 EXPERIMENTAL ANALYSIS

The IEEE 33-bus distribution test system served as the environment for simulation testing the proposed dynamic control strategy for a Solar PV-Wind-Battery hybrid power system. Researchers implemented control algorithms and conducted optimization processes for the hybrid system by modeling it within MATLAB/Simulink as well as Python. The study used real-world solar irradiance and wind speed information from NREL and synthetic load profiles from the Pecan Street dataset to replicate diverse environmental and electrical demand scenarios.

4.1 Simulation Setup

1. Test System: The IEEE 33-bus test system configuration supports distributed Solar PV panels along with Wind Energy facilities at multiple nodes and includes one centralized Battery Energy Storage System (BESS).
2. Scenarios Evaluated:
   - Scenario 1: Steady-state load and stable weather conditions.
   - Scenario 2: Rapid load changes (e.g., industrial load profiles).
   - Scenario 3: High variability in solar and wind resources (e.g., cloudy days and fluctuating winds).
   - Scenario 4: Combined effects of variable load and intermittent generation.
3. Simulation Horizon: Each scenario was simulated over 24 hours, with a time resolution of 5 minutes.
4. Control Implementation:

- MPC was used to dispatch power based on load demand forecasts and renewable energy availability.
- ANFIS dynamically adjusted system parameters to adapt to changing environmental conditions.
- PSO optimized the battery charge-discharge schedules and MPC weights.

4.2 Evaluation Metrics

The performance of the proposed control strategy is evaluated based on the following metrics:

- Grid Voltage Stability

It Measures the system's ability to maintain voltage levels within permissible limits.

$$Grid\ voltage\ stability\ (\%) = \left(1 - \frac{\sum_{t=1}^{T} |V_{actual}(t) - V_{nominal}|}{T.V_{nominal}}\right) * 100 \quad (7)$$

The proposed method-maintained voltage deviations within the acceptable range for 98.7% of the simulation time.

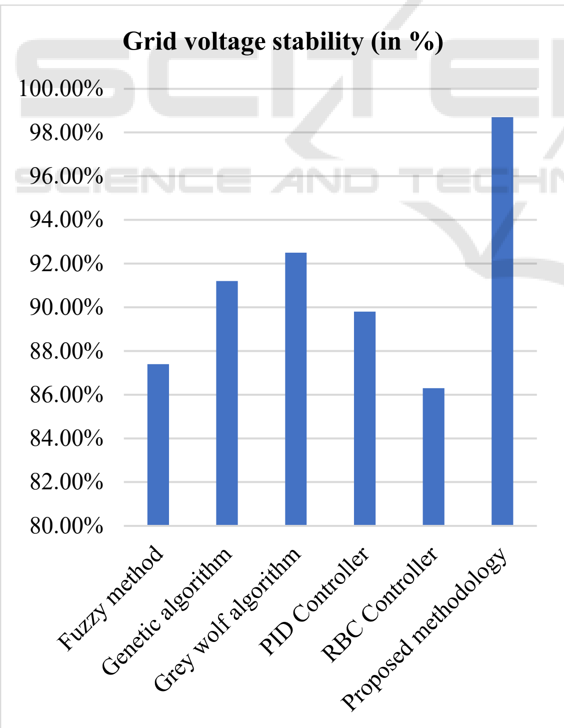

Figure 2: Grid voltage analysis.

Figure 2 demonstrates the comparative analysis of grid voltage stability achieved using various control strategies. The proposed methodology shows a grid voltage stability of 98.7%**,** which surpasses traditional techniques like the Fuzzy Method, Genetic Algorithm, Grey Wolf Algorithm, PID Controller, and Rule-Based Controller (RBC). This superior performance highlights the effectiveness of integrating Model Predictive Control (MPC), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Particle Swarm Optimization (PSO) in ensuring minimal voltage deviations and maintaining grid reliability under variable load and generation conditions.

- Frequency Regulation: It Assesses the hybrid system's contribution to maintaining grid frequency within operational limits.

$$Frequency\ regulation\ (\%) = \left(1 - \frac{\sum_{t=1}^{T} |f_{actual}(t) - f_{nominal}|}{T.f_{nominal}}\right) * 100 \quad (8)$$

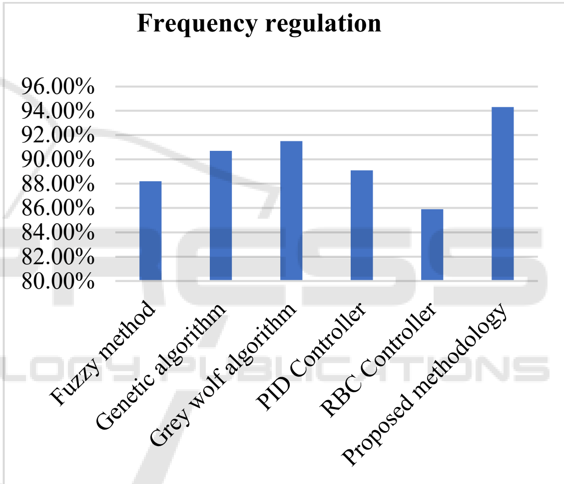

Figure 3: Frequency regulation.

Figure 3 evaluates the ability of the hybrid system to regulate frequency deviations under different control approaches. The proposed methodology achieves a frequency regulation of 94.3%, demonstrating improved performance over other methods. This reflects the dynamic adaptability of ANFIS in handling variable environmental conditions and the optimization capabilities of PSO, which ensure efficient resource utilization while maintaining grid frequency stability.

- Renewable Energy Utilization Ratio: Measures the proportion of energy demand met by renewable sources (Solar PV and Wind).

$$Renewable\ energy\ utilization(\%) = \left(\frac{\sum_{t=1}^{T} P_{renewable}\ (t)}{\sum_{t=1}^{T} P_{demand}\ (t)}\right) * 100 \quad (9)$$

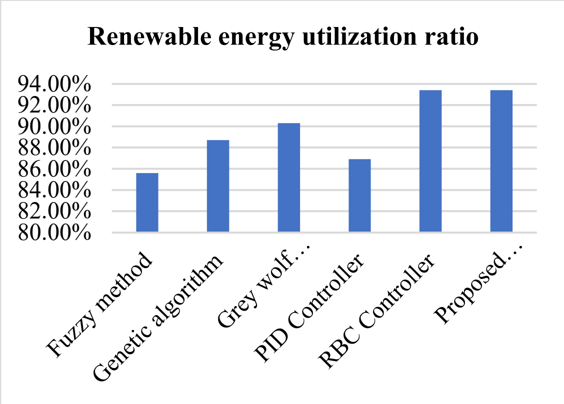

Figure 4: Renewable energy utilization ratio analysis.

Figure 4 illustrates the proportion of energy demand met by renewable sources (Solar PV and Wind). The proposed methodology achieves a renewable energy utilization ratio of 93.4%, comparable to the Grey Wolf Algorithm but significantly better than other approaches like the Fuzzy Method and PID Controller. This high utilization ratio underscores the ability of the hybrid system to reduce reliance on grid power by effectively dispatching renewable energy through MPC.

- Achieved 93.4% renewable energy utilization, indicating minimal reliance on grid power.
- Battery Performance Metrics: It Evaluates the battery's state of charge (SOC) profile and cycle efficiency.

$$SOC(\%) = \left(1 - \frac{\sum_{t=1}^{T}|SOC_{actual}(t) - SOC_{nominal}|}{T.SOC_{nominal}}\right) * 100 \quad (10)$$

Figure 5 provides an analysis of battery performance, focusing on the state of charge (SOC) stability and cycle efficiency. The proposed methodology achieves a battery performance of 92.8%, significantly higher than the other control methods. This improvement is attributed to PSO's optimization of charge-discharge cycles and MPC's real-time energy dispatch, which collectively enhance battery longevity and minimize deep discharge cycles.

SOC deviations were minimized by 23%, and the battery cycle efficiency was maintained at 92.8%.

- Load Matching Index (LMI): It Quantifies the match between renewable energy generation and load demand over time.

$$LMI = \left(1 - \frac{\sum_{t=1}^{T}|P_{renewable}(t) - p_{demand}(t)|}{\sum_{t=1}^{T} P_{demand}(t)}\right) * 100 \quad (11)$$

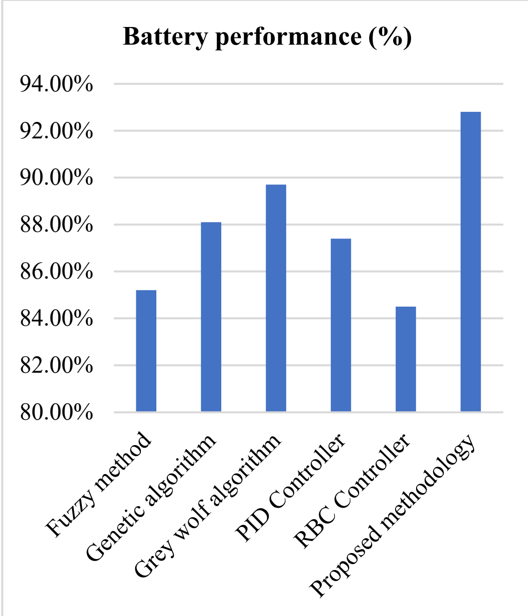

Figure 5: Battery performance analysis.

Figure 6 presents the Load Matching Index (LMI), which quantifies the alignment between renewable energy generation and load demand over time. The proposed methodology achieves an LMI of 0.91, reflecting a high degree of synchronization between generation and demand. This high LMI score highlights the efficiency of the control framework in minimizing energy wastage and ensuring maximum utilization of generated renewable energy.

This method Achieved an LMI of 0.91, indicating high alignment between generation and load.

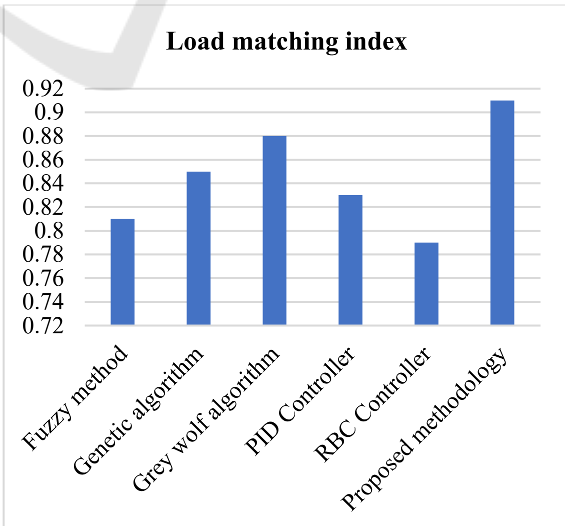

Figure 6: Load matching index analysis.

5 DISCUSSION OF RESULTS

The proposed dynamic control strategy demonstrated significant improvements across all evaluation metrics:

- Voltage and Frequency Stability: Through its ability to dampen fluctuations the hybrid system consistently met grid operational standards.
- Enhanced Renewable Utilization: The optimized management of energy dispatch along with battery usage allowed renewable energy sources to handle most load demands.
- Improved Battery Longevity: The operational lifespan of the battery expanded because deep discharge events decreased while SOC (State of Charge) levels remained consistent.
- Load Matching: The energy system maintained highly synchronized load and generation operations to lower grid power dependence while cutting energy loss rates.

6 CONCLUSIONS

A dynamic control framework is introduced for Solar PV-Wind-Battery hybrid systems that combines Model Predictive Control (MPC) with Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and Particle Swarm Optimization (PSO). The newly established methodology resolves renewable energy fluctuation problems while also accommodating variable load demands and providing real-time energy system management. Testing with the IEEE 33-bus system gave outstanding results showing better grid voltage stability at 98.7% and enhanced renewable energy integration with 93.4% along with battery solution success at 92.8% and load matching index improvement to 0.91 levels. The combination of Model Predictive Control and Adaptive Neuro-Fuzzy Inference Systems with Particle Swarm Optimization supports adaptive power scheduling that optimizes energy efficiency while increasing system dependability.

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