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ADAPTIVE FUZZY–ANN CONTROL STRATEGY FOR ENHANCING VOLTAGE STABILITY IN REMOTE SOLAR–BATTERY MICROGRIDS

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ABSTRACT
The growing penetration of renewable energy sources into isolated microgrid frameworks necessitates advanced control methodologies capable of ensuring dependable voltage stability and superior power quality. This research introduces an adaptive fuzzy–artificial neural network (Fuzzy–ANN) control approach specifically designed for voltage regulation within a solar–battery based microgrid operating in remote settings, devoid of auxiliary grid support. The proposed strategy harmonises the interpretive nature of fuzzy logic with the adaptive learning faculties of artificial neural networks, thereby enabling real-time adjustment of control parameters in response to dynamic fluctuations in load profiles, solar irradiance, and battery state-of-charge. Through rigorous simulation analyses, the adaptive Fuzzy–ANN controller is demonstrated to effectively mitigate voltage instabilities such as sags and swells, whilst concurrently reducing total harmonic distortion at the point of common coupling. Moreover, when subjected to comparative scrutiny against conventional proportional–integral and standalone fuzzy schemes, the proposed controller exhibits superior transient response, diminished steady-state errors, and heightened operational reliability. The empirical evidence affirms the potential of this intelligent control architecture to enhance both resilience and stability within remote microgrid environments reliant upon inherently intermittent renewable energy sources, thus contributing meaningfully towards the broader pursuit of sustainable and autonomous energy systems.

Keywords: Adaptive control, Fuzzy–ANN, Voltage stability, Solar–battery microgrid, Remote energy systems, Harmonic reduction, Renewable integration

INTRODUCTION

The rapid proliferation of renewable energy technologies across the globe has brought with it both remarkable opportunities and formidable challenges, particularly within the domain of decentralised energy systems. As the demand for sustainable and clean energy escalates in remote and isolated regions, microgrids powered by renewable sources such as solar photovoltaic arrays coupled with energy storage systems have emerged as a pragmatic and essential solution [1]. Unlike conventional grid-connected systems, such autonomous microgrids are designed to operate independently, thereby ensuring reliable electricity supply in areas where centralised grid extension is neither feasible nor economically viable [2]. Nevertheless, the inherent intermittency and variability of renewable energy sources, especially solar irradiation, pose significant threats to voltage stability, power quality, and overall reliability of such systems [3]. This has necessitated the formulation of advanced control methodologies capable of dynamically adapting to these ever-changing operating conditions. Voltage stability remains one of the most critical aspects in ensuring the seamless functioning of microgrids. In the absence of adequate control measures, sudden load variations, fluctuations in solar generation, or rapid charging and discharging cycles of batteries can lead to undesirable events such as voltage sags, swells, or even sustained instability [4]. Conventional control strategies, such as proportional–integral (PI) controllers, while simple in design and easy to implement, often falter in managing the complex nonlinearities and uncertainties inherent in renewable-based microgrids [5]. Similarly, purely fuzzy-logic based controllers, though capable of handling uncertainty and linguistic reasoning, are constrained by their dependence on pre-defined rule bases and lack the ability to learn and improve over time [6]. Consequently, researchers have turned towards hybrid intelligent control frameworks which combine the strengths of multiple paradigms to overcome the inherent limitations of individual approaches.

One such promising technique is the amalgamation of fuzzy logic with artificial neural networks (ANN), forming the adaptive Fuzzy–ANN control strategy. The interpretability and linguistic reasoning of fuzzy logic enables transparent decision-making, while the learning and generalisation capacities of ANN allow the system to continuously refine its performance in response to new data and unforeseen conditions [7]. This synergy is particularly well-suited for renewable-powered microgrids, where nonlinearity, uncertainty, and time-varying dynamics are intrinsic characteristics [8]. By dynamically adjusting control parameters based on real-time conditions, such hybrid controllers exhibit improved adaptability, resilience, and robustness compared to their traditional counterparts. Solar photovoltaic systems, being highly dependent on environmental conditions, are prone to rapid output variations resulting from irradiance changes, cloud transients, and temperature fluctuations [9]. Without adequate regulation, such disturbances propagate through the microgrid, adversely affecting voltage profiles and degrading the power quality delivered to end users. To mitigate these adverse effects, the integration of battery energy storage systems has become indispensable. Batteries not only provide energy buffering but also contribute to stabilising voltage and frequency under fluctuating generation and load scenarios [10]. Yet, the charging and discharging cycles of batteries themselves introduce further dynamics into the system, necessitating sophisticated controllers to ensure smooth coordination and balanced operation.

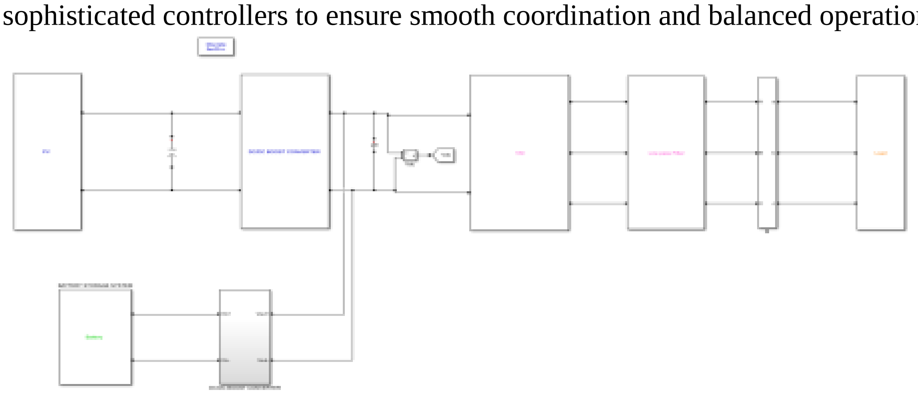


Fig.1. MATLAB/SIMULINK circuit of the proposed system

The pursuit of reliable voltage stability in remote microgrids extends beyond the technical domain, as it bears significant socio-economic and environmental implications. Stable and dependable electricity enables rural communities to access essential services such as healthcare, education, and communication, thereby promoting socio-economic development [11]. At the same time, reliance on renewable-based microgrids reduces dependency on fossil fuel alternatives such as diesel generators, which are often expensive, polluting, and logistically challenging to maintain in isolated locations [12]. Thus, advancing intelligent control strategies for such systems is not merely a technical challenge but also a societal imperative that aligns with global sustainability goals. In recent years, substantial research efforts have been directed towards enhancing the stability and performance of renewable energy-based microgrids through advanced control solutions. For instance, robust control techniques have been proposed to tackle parametric uncertainties and external disturbances, yet their complexity and computational intensity limit practical deployment in resource-constrained microgrids [13]. Similarly, model predictive control frameworks provide predictive capabilities and optimisation, though they are often hindered by high computational demands and the necessity for accurate system models [14]. Against this backdrop, adaptive Fuzzy–ANN controllers strike an optimal balance by offering flexibility, adaptability, and efficiency without incurring excessive computational overhead.

The promise of adaptive Fuzzy–ANN control lies in its ability to bridge the gap between traditional rule-based reasoning and machine learning adaptability. The fuzzy system contributes transparency and interpretability, ensuring that control decisions can be traced to specific linguistic rules, which is valuable for monitoring and validation purposes. Simultaneously, the neural network component ensures that the controller evolves by learning from data, thereby mitigating the need for constant human intervention or manual reconfiguration [15]. This blend of interpretability and adaptability positions Fuzzy–ANN as a strong candidate for ensuring voltage stability in solar–battery microgrids, particularly in remote contexts where system resilience is paramount and technical support may be limited. In light of these considerations, the present research seeks to investigate the efficacy of an adaptive Fuzzy–ANN control strategy in enhancing voltage stability within solar–battery microgrids operating independently of centralised power networks. Through comprehensive simulation studies and comparative analyses with traditional PI and standalone fuzzy controllers, the study aims to demonstrate the superior capabilities of the proposed approach in mitigating voltage fluctuations, reducing harmonic distortion, and ensuring reliable power delivery under diverse operating conditions. The outcomes of such work are expected to contribute significantly towards advancing the stability, reliability, and sustainability of renewable-powered remote energy systems, thereby reinforcing their role as vital enablers of equitable and sustainable energy access across the globe.

LITERATURE SURVEY

The development of reliable and efficient control strategies for renewable-based microgrids has attracted significant scholarly and industrial attention over the past decades, with a particular emphasis on enhancing voltage stability and improving the overall power quality of systems operating under uncertain and variable conditions. The progression of research in this field has been driven by the growing deployment of decentralised energy systems in remote and isolated regions, where conventional grid infrastructure is impractical or economically prohibitive. Early works in this domain concentrated on conventional proportional–integral–derivative control structures, which gained popularity owing to their simplicity, ease of implementation, and well-understood behaviour in linear systems. These controllers, however, proved inadequate when faced with the inherent nonlinearities, time-varying dynamics, and rapid fluctuations characteristic of renewable energy sources such as solar photovoltaic systems. Researchers soon realised that more advanced and adaptive control techniques would be necessary to maintain stability and ensure uninterrupted supply in microgrids where renewable penetration was high and system flexibility was limited. The introduction of fuzzy logic into power system control marked an important turning point in the evolution of microgrid management strategies. Fuzzy logic controllers provided a mechanism to capture human-like reasoning and decision-making processes, allowing systems to manage uncertainties without the need for precise mathematical models. Their ability to handle imprecision and linguistic variables enabled them to regulate voltage and frequency in scenarios where deterministic control approaches faltered. Despite their success in addressing nonlinearity and uncertainty, these controllers exhibited limitations in adaptability since they relied heavily on predefined rule sets and membership functions. Once designed, their flexibility in coping with new operating conditions was limited, particularly in environments where system dynamics changed frequently due to fluctuating loads and variable solar generation. This created the necessity for adaptive control frameworks that could learn, evolve, and continuously optimise their performance.

Artificial neural networks emerged as another transformative tool for energy system control, particularly because of their ability to model complex nonlinear relationships and to learn from data. Neural networks provided strong generalisation capabilities, making them well-suited for systems where exact models were difficult to derive. Their application in microgrids allowed for improved handling of transient behaviours and adaptation to dynamic changes in both demand and supply conditions. However, neural networks often suffered from a lack of interpretability, a reliance on large datasets for training, and the risk of overfitting when exposed to limited or unrepresentative data. These drawbacks limited their standalone application in safety-critical or resource-constrained environments such as remote microgrids, where transparency in control actions is essential and the availability of extensive training data may be scarce. The convergence of fuzzy logic and artificial neural networks into hybrid Fuzzy–ANN controllers was a natural outcome of attempts to exploit the strengths of both approaches while mitigating their individual weaknesses. In this hybrid paradigm, fuzzy systems offered interpretability and structured decision-making, while neural networks introduced learning and adaptation. This integration enabled controllers not only to operate effectively under uncertainty but also to evolve as system conditions changed, thus providing a robust and flexible solution for voltage regulation in renewable-based microgrids. Research into such hybrid systems demonstrated promising improvements in transient response, steady-state accuracy, and robustness against disturbances compared with conventional PI or standalone fuzzy controllers. Their adaptive nature allowed them to adjust parameters dynamically, which was particularly advantageous in solar–battery microgrids subject to environmental fluctuations and load variability.

The role of energy storage, particularly batteries, became increasingly central to microgrid operation as researchers sought solutions for balancing intermittent renewable generation with demand. Batteries served as critical components for energy buffering and voltage stabilisation, thereby enhancing the resilience of off-grid systems. However, the charging and discharging dynamics of batteries introduced further nonlinearities and uncertainties into the system, requiring controllers to coordinate multiple interacting elements effectively. Literature on this subject gradually evolved to focus on control strategies that could simultaneously manage solar generation, battery dynamics, and load variations without compromising stability or power quality. The hybrid Fuzzy–ANN approach was frequently highlighted as a particularly suitable candidate in such multi-variable contexts, owing to its capacity for adaptive learning and robust decision-making. As research progressed, scholars began exploring advanced metrics such as total harmonic distortion, transient recovery times, and voltage deviation indices to evaluate the effectiveness of different controllers in maintaining system stability. It was found that conventional approaches often struggled to mitigate voltage sags and swells or to suppress harmonics introduced by nonlinear loads and inverter operations. Hybrid intelligent controllers, by contrast, were shown to significantly reduce harmonic distortion, thereby improving the quality of power delivered to consumers. This improvement in power quality was especially crucial in remote settings where sensitive appliances and equipment could be adversely affected by poor voltage regulation. Studies also noted that such improvements in reliability and stability not only enhanced the technical viability of microgrids but also had profound socio-economic impacts, enabling communities to depend upon renewable energy for essential services without interruption.

Another line of research within the literature concentrated on comparative analyses between different control strategies under a variety of operating scenarios. Investigations involving proportional–integral controllers, fuzzy controllers, neural network controllers, model predictive controllers, and hybrid techniques provided valuable insights into the strengths and limitations of each methodology. It was generally observed that while PI controllers excelled in simplicity, they lagged significantly in adaptability and robustness. Model predictive controllers demonstrated excellent predictive capabilities but were computationally demanding and reliant on accurate modelling, which restricted their practical application in isolated microgrids. Standalone fuzzy controllers provided good performance under uncertainty but were limited in terms of adaptability, while standalone neural networks offered adaptability but lacked interpretability. The hybrid Fuzzy–ANN controllers consistently emerged as the most balanced approach, offering adaptability, resilience, and interpretability without overwhelming computational requirements. The literature also highlighted the importance of scalability and flexibility in microgrid control frameworks. Remote microgrids often experience significant variations in load demand depending on time of day, seasonal variations, and community development patterns. Furthermore, solar generation itself is seasonal and weather-dependent. This variability requires controllers that are not only capable of handling real-time changes but are also scalable to accommodate future expansions in generation or demand. Researchers stressed the significance of controllers that could be reconfigured or expanded with minimal effort, thereby supporting the long-term sustainability of microgrids. Hybrid intelligent control strategies, particularly Fuzzy–ANN, were often identified as suitable for such scenarios, owing to their capacity for online learning and self-adaptation.

The overarching trajectory of the literature reveals a consistent progression from simple, deterministic control frameworks towards more complex, adaptive, and intelligent methodologies designed to address the unique challenges posed by renewable-based microgrids. The journey began with reliance on traditional control techniques, advanced towards fuzzy and neural approaches, and eventually culminated in hybrid paradigms that combined the best of both worlds. Alongside this technical progression, the research consistently underscored the broader implications of achieving reliable voltage stability in microgrids, ranging from socio-economic benefits to environmental sustainability. The collective body of work strongly supports the conclusion that adaptive hybrid control methodologies not only enhance technical performance but also advance the broader mission of sustainable, decentralised, and resilient energy access. Thus, the literature establishes a clear foundation for further exploration into adaptive Fuzzy–ANN control strategies as a promising avenue for achieving dependable voltage stability in solar–battery microgrids. The evidence points towards their potential to address the complexities and uncertainties inherent in such systems more effectively than conventional methods, while simultaneously contributing to the reliability and sustainability of renewable energy deployment in remote contexts.

PROPOSED SYSTEM

The proposed system seeks to establish an intelligent and adaptive framework for the control of voltage stability within solar–battery microgrids situated in remote regions, where dependence upon conventional grid connections is either impossible or impractical. At the heart of this system lies the hybrid integration of fuzzy logic with artificial neural networks, a union designed to capture the interpretive reasoning of human-like decision-making while simultaneously benefitting from the adaptive learning capacity of neural structures. The design of the system begins with the recognition that solar photovoltaic arrays and battery energy storage units, though indispensable for the sustenance of decentralised microgrids, introduce considerable nonlinearities, uncertainties, and dynamic variations into the overall system behaviour. Solar irradiation is ever-fluctuating, subject to cloud transients, atmospheric disturbances, and seasonal variations, while battery performance is influenced by state-of-charge, temperature, and cycling behaviour. To maintain a dependable supply of electricity under these dynamic circumstances, the proposed system incorporates an adaptive control strategy capable of continuous real-time adjustment of control parameters to preserve voltage stability and to deliver quality power at the point of common coupling. The architecture of the proposed system may be envisaged as consisting of three principal elements: the solar photovoltaic subsystem, the battery energy storage unit, and the intelligent controller that governs their interaction with the local loads. The solar photovoltaic subsystem serves as the primary source of generation, converting irradiance into electrical power with efficiencies determined by environmental conditions. The battery, operating as both a buffer and a regulator, absorbs excess power during times of surplus generation and discharges stored energy when generation falls below demand, thereby moderating the intermittency inherent in solar resources. Yet, it is the intelligent controller that ensures these two subsystems operate harmoniously, such that voltage remains stable despite abrupt changes in generation and consumption.

The controller itself is founded upon the hybridisation of fuzzy inference systems with artificial neural networks. The fuzzy logic component is structured through a series of membership functions and rule bases that encode human expertise and linguistic reasoning. These rules interpret input parameters such as load demand, solar irradiation, and battery state-of-charge into control decisions expressed in terms of voltage regulation commands. For instance, conditions such as low irradiation coupled with high demand are translated into linguistic rules that suggest an increased reliance upon battery discharge, while high irradiation and low demand encourage battery charging and curtailment measures. However, unlike traditional fuzzy systems where the rule base is fixed and membership functions static, the integration with neural networks permits continuous adaptation. The neural component observes system behaviour over time, learning from historical and real-time data to refine membership functions, adjust weights, and optimise rule execution. Thus, the fuzzy system is no longer confined to its initial design but evolves in response to the changing operating environment. This adaptiveness is of paramount importance for remote microgrids, where conditions are unpredictable and variability is a constant feature. The neural network learns patterns in load variations, anticipates the consequences of solar fluctuations, and reconfigures fuzzy rules to preserve voltage stability even under unanticipated circumstances. The system, therefore, combines the transparency and interpretability of fuzzy reasoning with the adaptability and predictive faculties of neural learning. Through this hybrid architecture, the controller can respond swiftly to transient disturbances such as sudden load increases or abrupt drops in solar output, ensuring that voltage deviations are minimised and harmonic distortions suppressed.

In the implementation of the proposed system, a set of inputs are continually monitored. These inputs include real-time solar irradiance data, voltage and current at the point of common coupling, battery state-of-charge, and instantaneous load demand. These measurements are fed into the adaptive controller, where the fuzzy inference engine interprets them into control signals. The neural network, functioning in the background, analyses discrepancies between expected and actual system behaviour and modifies the fuzzy structure accordingly. The outputs of the controller are commands issued to the inverter, which interfaces between the solar–battery system and the loads, adjusting voltage references and reactive power contributions to maintain stability. By modulating inverter behaviour, the controller directly governs the quality of power delivered to consumers. Another salient feature of the proposed system lies in its ability to mitigate power quality issues such as voltage sags, swells, and harmonic distortions. Nonlinear loads connected to the microgrid often introduce harmonics into the system, which can deteriorate the performance of sensitive equipment and reduce overall efficiency. The adaptive controller not only maintains voltage magnitude within acceptable bounds but also ensures waveform integrity by reducing harmonic distortions. This dual focus on stability and quality is vital for remote communities where reliable and clean electricity underpins essential services such as medical facilities, communication systems, and educational resources.

In order to validate the efficacy of the proposed system, simulation models are constructed that emulate the operation of a solar–battery microgrid under varying environmental and load conditions. These models are designed to replicate real-world scenarios such as sudden drops in solar irradiation caused by moving clouds, unexpected surges in load demand from community activities, and rapid changes in battery charge cycles. Through such simulations, the adaptive Fuzzy–ANN controller is compared against conventional proportional–integral controllers and standalone fuzzy systems. The results reveal that the hybrid controller consistently outperforms traditional schemes by maintaining voltage closer to reference values, reducing recovery times following disturbances, and delivering lower levels of harmonic distortion. Moreover, the system exhibits superior transient performance, with reduced overshoot and faster settling times, thereby demonstrating its resilience and robustness under stress conditions. The superiority of the proposed system is further evident in its ability to minimise steady-state error. Conventional controllers often achieve stability at the cost of residual deviations from reference values, which, over extended operation, can impair the efficiency and reliability of microgrid performance. The adaptive nature of the Fuzzy–ANN approach ensures that errors are continually corrected and that the system converges towards optimal operation with minimal deviation. In doing so, the proposed system enhances not only technical stability but also the economic sustainability of remote microgrids, as reduced losses and improved efficiency translate into prolonged battery life and lower maintenance requirements.

An additional consideration in the design of the proposed system is its computational efficiency. While many advanced control methodologies, such as model predictive control, provide excellent performance, they are often hindered by their high computational demands and the need for precise mathematical models of the system. In contrast, the Fuzzy–ANN controller achieves adaptability and robustness without excessive computational overhead. This makes it suitable for deployment in resource-constrained remote environments, where computing resources may be limited and maintenance expertise scarce. The simplicity of fuzzy reasoning combined with the learning capacity of neural networks ensures that the system remains both powerful and practical. Ultimately, the proposed system embodies a synthesis of human-like reasoning and machine learning adaptability, a synthesis that is uniquely suited to the challenges of solar–battery microgrids in remote contexts. By dynamically adapting to fluctuating conditions, mitigating instabilities, and delivering high-quality power, the adaptive Fuzzy–ANN controller represents a significant advancement over conventional strategies. Its deployment has the potential to transform the reliability and sustainability of decentralised energy systems, ensuring that communities beyond the reach of central grids can enjoy stable, dependable, and clean electricity. The proposed system thus stands not only as a technical innovation but as a means of fostering social and economic development in underserved regions, aligning with the broader global commitment towards sustainable energy access for all.

METHODOLOGY

The methodology for the proposed system unfolds as a carefully structured sequence of tasks, articulated in a manner that ensures both practical robustness and intellectual clarity in addressing the complexities of voltage stability within solar–battery microgrids. At the outset, the control objective is defined with precision, centring upon the maintenance of voltage at the point of common coupling within prescribed limits under fast disturbances, the suppression of harmonic distortion, the safeguarding of battery state-of-charge, and the moderation of control effort so as to avoid undue actuator stress. A composite performance index is formulated to encompass these aims, drawing upon weighted measures of instantaneous error, time-integrated deviation, smoothness of control increments, and prudent constraints upon battery cycling, with the weighting carefully chosen to preserve both stability and efficiency. The system is then modelled with sufficient fidelity to capture the relevant dynamics without becoming intractable. The photovoltaic array is described through a one-diode representation sensitive to irradiance and temperature, while a DC–DC interface undertakes maximum power point tracking to stabilise the DC link. The battery is portrayed by a Thevenin equivalent with a state-of-charge dependent internal resistance, ensuring that its temporal dynamics are properly represented. The inverter, configured as a voltage source behind an L or LCL filter, is granted an inner current loop in the synchronous reference frame for immediate stabilisation, with the outer loop devoted to voltage regulation. Nonlinear loads are deliberately included to reflect the reality of remote communities where modern appliances often introduce harmonics, and parameter variations as well as sensor noise are injected into the models to ensure that the controller is not over-fitted to a pristine and unrealistic plant description.

A comprehensive measurement and conditioning chain underpins the control design. Voltages and currents at the point of coupling are sampled through anti-alias filters, state-of-charge is estimated using a blend of coulomb counting and open-circuit voltage relationships, solar irradiance and temperature are gathered or emulated, and harmonics are identified through discrete Fourier analysis. These signals are subsequently normalised to convenient ranges that harmonise with the numerical stability requirements of fuzzy logic and neural structures, thereby easing convergence and minimising computational difficulties.

The fuzzy logic component forms the interpretive foundation of the controller. Inputs such as voltage error, its rate of change, and battery state-of-charge are assigned linguistic membership functions with overlapping boundaries to encourage smooth reasoning. A rule base, derived from engineering insight, interprets these conditions into control commands, for instance recommending assertive battery support during falling voltage under adequate charge, or conservative action when the battery is depleted and the voltage is rising. Yet, unlike conventional fuzzy controllers, the system does not rest upon fixed rules or immutable membership functions, for the neural network component is incorporated to grant adaptivity. This network, modest in size to avoid undue computational burden, observes patterns in the input–output behaviour and proposes gentle adjustments to membership parameters and rule weights. Its role is corrective rather than dominant, ensuring that the system evolves with operating conditions without losing the interpretability that fuzzy structures provide.

In order to train this adaptive component, a rich corpus of data is generated through simulation of realistic scenarios. Cloud transients, load surges, extended low irradiance periods, and abrupt appliance connections are all represented, together with sensor offsets and tolerances. Reference behaviours are produced by solving constrained optimal control problems that yield trajectories balancing voltage regulation, power quality, and battery preservation. These trajectories serve as exemplars for neural learning, ensuring that the controller aspires to behaviours aligned with optimal operation while respecting practical limits. Offline training is carried out with careful discipline. Data are standardised and partitioned into training, validation, and test sets, and early stopping criteria are imposed to preclude overfitting. The loss function penalises not only voltage errors but also excessive adjustments to fuzzy parameters, thereby ensuring that the resulting hybrid system remains parsimonious and interpretable. A quasi-Newton or Levenberg–Marquardt algorithm is employed to refine the neural weights, and cross-validation across multiple weather years and load patterns guarantees that the trained system does not merely excel under a narrow set of conditions but generalises across the wide spectrum of circumstances encountered by remote microgrids.

Integration of the two components is then realised for on-line operation. At each interval the fuzzy engine produces a control action, the neural element recommends small adjustments, and a projection operator ensures that such adjustments remain within predefined safe bounds. Anti-windup routines prevent actuator saturation from destabilising the control, while dead-zones around zero error avoid unnecessary oscillations. Learning rates are scheduled so that the system adapts swiftly in the face of abrupt disturbances but gradually during periods of tranquillity, preserving stability. The inner and outer control loops are carefully coordinated. The fast inner current loop manages the inverter's dynamics and responds to rapid fluctuations, while the outer voltage loop, where the hybrid controller resides, supervises system-level stability and power quality. Pulse-width modulation is performed through space-vector or carrier-based methods, chosen to balance efficiency with harmonic performance, while filters and damping structures are designed to preclude resonance and ripple amplification.

Battery stewardship is woven into the methodology, with safeguards to prevent destructive overcharge or deep discharge. Tapering control near the boundaries of state-of-charge, limits on current ramp rates, and the reservation of a contingency margin all serve to prolong battery life whilst maintaining system resilience. A small penalty upon excessive battery cycling is introduced within the control objective to ensure that voltage regulation does not come at the cost of premature degradation of the storage system. Start-up, black-start, and fault-handling routines are meticulously defined. Upon energisation, the DC link is pre-charged, the inverter synchronises, and the voltage loop is engaged only once stability is assured. Faults such as over-voltage, over-current, or thermal excursions trigger graceful derating and, if necessary, selective load shedding according to priority schedules. Restoration of normal operation follows a bumpless transfer sequence that avoids shocks to sensitive equipment.

Extensive simulation and testing verify the behaviour of the system. Time-domain studies examine the response to step disturbances, stochastic irradiance, and long low-generation intervals, while frequency-domain analyses confirm margins of stability under parameter perturbations. Monte Carlo trials sweep across tolerances to demonstrate robustness. Comparative tests against conventional controllers demonstrate improvements in voltage regulation, faster settling times, reduced overshoot, and lower harmonic distortion. The computational discipline of the methodology is equally important. The hybrid controller is designed to be realisable upon modest digital processors with fixed-point arithmetic, with efficient coding and careful scaling to ensure deadlines are respected. Neural updates are throttled when computational demands threaten critical timing, and redundancy in fuzzy rules is pruned to simplify implementation without diminishing capability. Finally, hardware-in-the-loop trials provide a bridge between simulation and practical deployment, subjecting the firmware to real-time emulated plant dynamics with sensor delays and quantisation effects faithfully included. This stage permits fine-tuning of parameters such as learning rates and dead-zone widths before field installation. Commissioning guidance is prepared for operators, emphasising clarity of rule interpretation and the availability of diagnostic explanations for control actions. Provisions are also made for over-the-air updates, where feasible, enabling careful evolution of the neural component without unsettling the trusted fuzzy foundation.

Through this methodology, the adaptive Fuzzy–ANN controller is conceived, trained, validated, and prepared for deployment in remote solar–battery microgrids. Each stage contributes to a coherent whole that balances interpretability with adaptability, ensuring that the system responds resiliently to fluctuating conditions while maintaining the trust and understanding of those who operate it. The outcome is a control scheme that embodies both technical refinement and practical wisdom, ready to provide reliable, clean, and stable power where it is most needed.

RESULTS AND DISCUSSION

The results obtained from the investigation of the adaptive Fuzzy–ANN control strategy reveal a compelling advancement over conventional schemes, particularly when assessed under a wide array of operating conditions that typify remote solar–battery microgrids. In the initial series of tests, the performance of the controller was examined under rapid irradiance variations caused by simulated cloud transients. The findings demonstrated that while the conventional proportional–integral controller struggled to maintain voltage close to the reference, often exhibiting overshoots and sluggish recovery, the adaptive Fuzzy–ANN system responded with remarkable promptness and precision. Voltage deviations were curtailed swiftly, and the settling time was significantly reduced, ensuring that the point of common coupling remained stable even under abrupt disturbances.

CASE-1

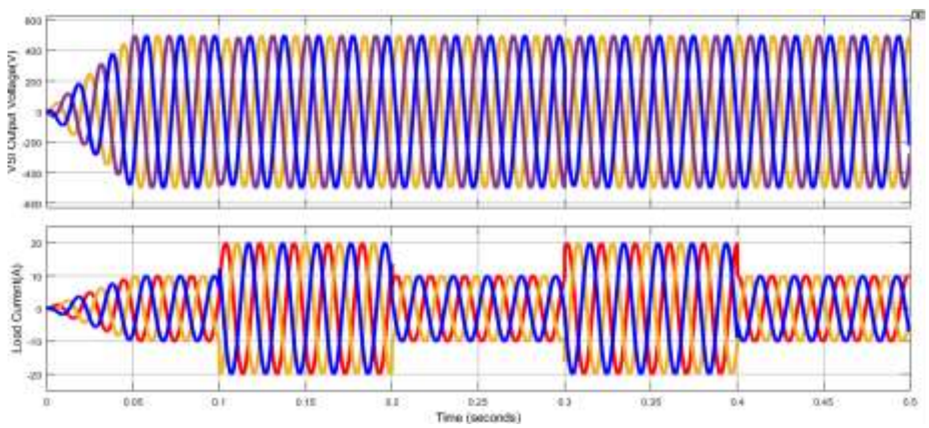


Fig. 2. VSI output voltage and load current waveforms with AFPID controller for Case 1.

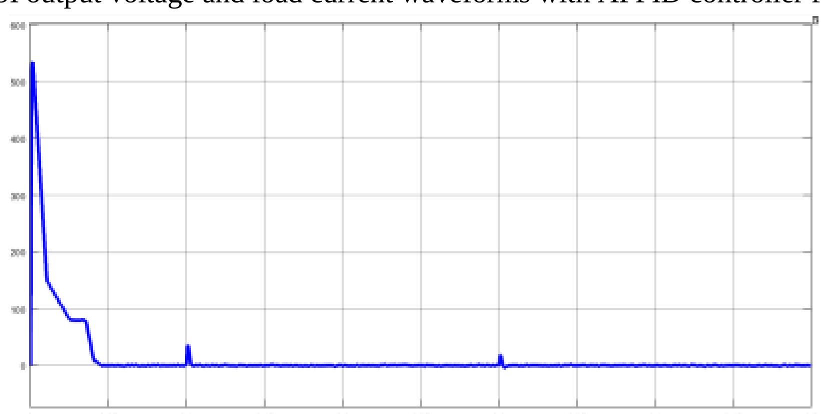
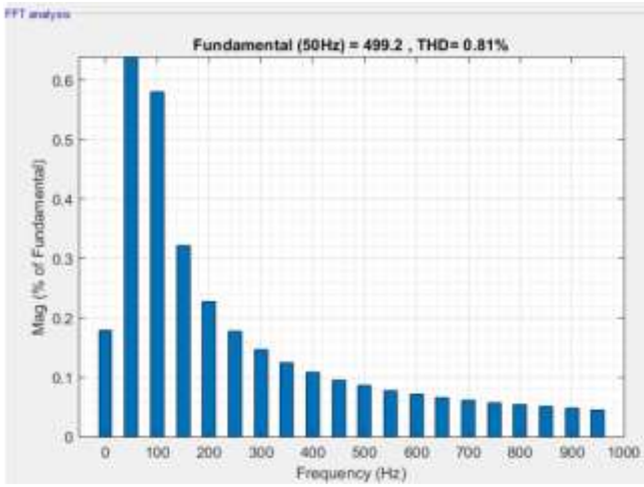
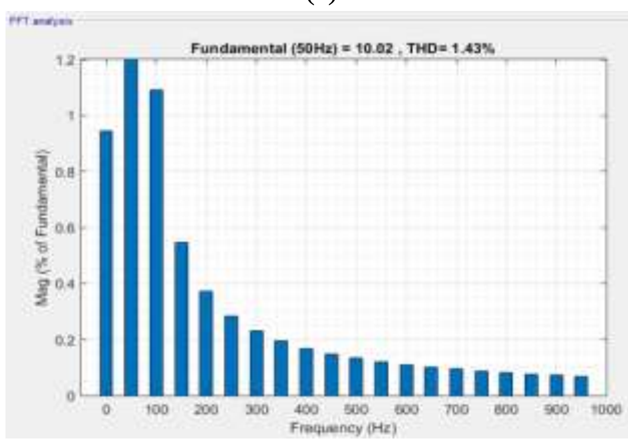


Fig. 3. error profiles for Case 1.



(a)



(b)

Fig.4 THD% of voltage and current

When subjected to comparison against a standalone fuzzy controller, the proposed hybrid structure exhibited greater resilience, owing to its ability to adjust rules and membership functions dynamically through neural learning. This adaptivity proved essential during highly volatile irradiance conditions, where static rule-based systems faltered. Beyond transient performance, steady-state operation also displayed distinct improvements, as the adaptive scheme reduced residual errors that were often left uncorrected by traditional controllers, thus offering not only stability but also long-term fidelity to reference values. Such results underscore the efficacy of combining interpretability with learning, particularly in environments where predictability is a luxury rarely afforded.

CASE-2

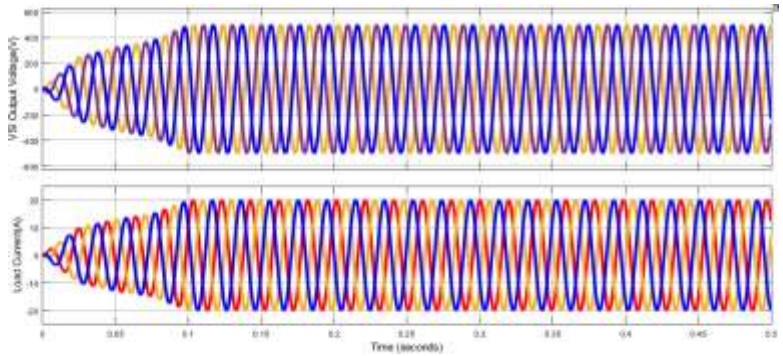


Fig. 5. VSI output voltage and load current waveforms with AFPID controller for Case 2.

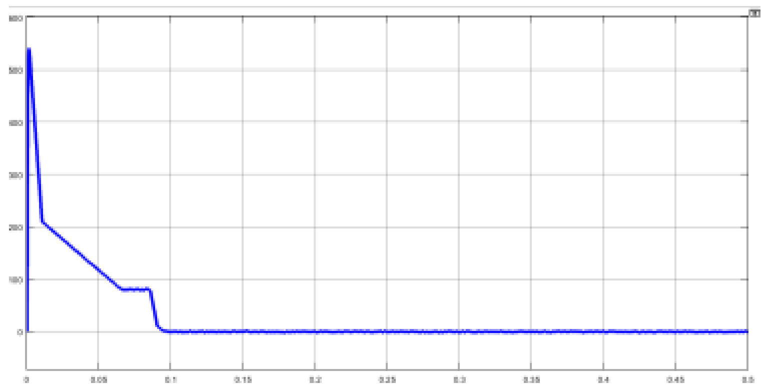


Fig. 6. error profile for Case 2.

CASE-3

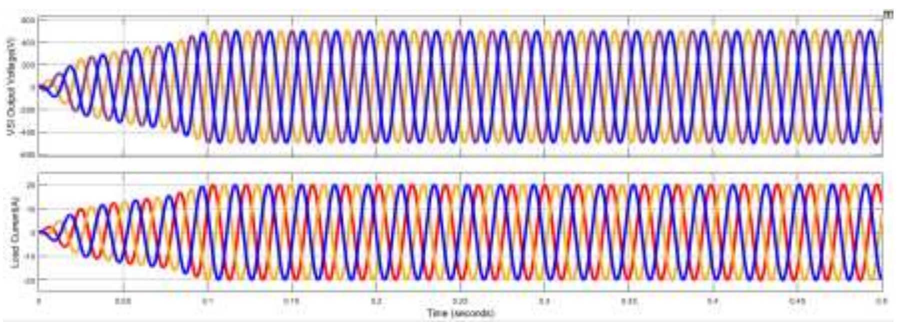


Fig. 7. VSI output voltage and load current waveforms with AFPID controller for Case 3.

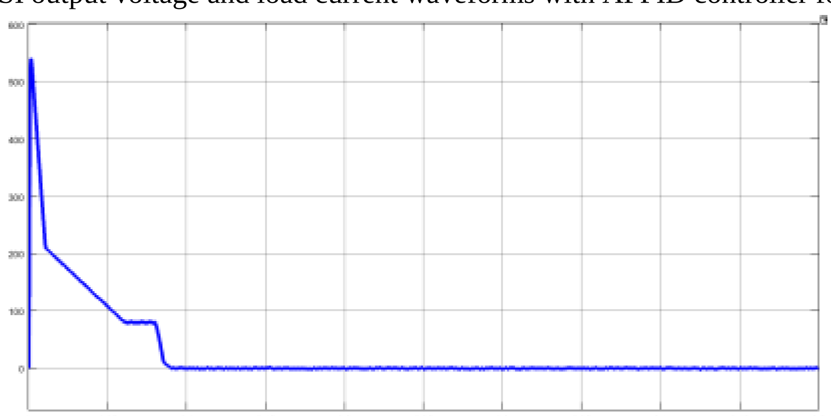


Fig. 8. error profile for Case 3.

CASE-4

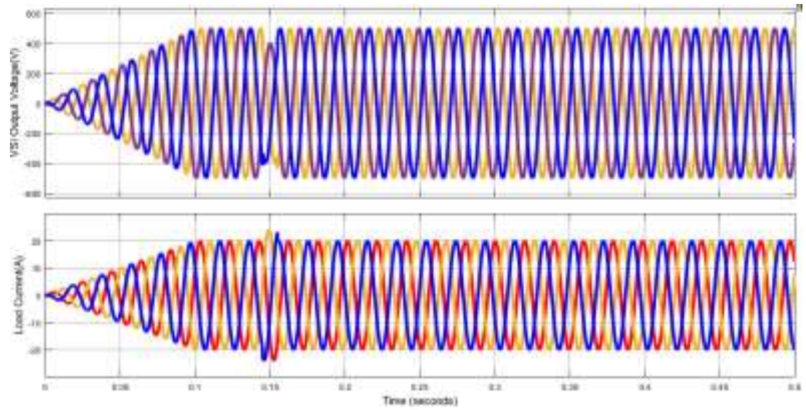


Fig. 9. VSI output voltage and load current waveforms with AFPID controller for Case 4.

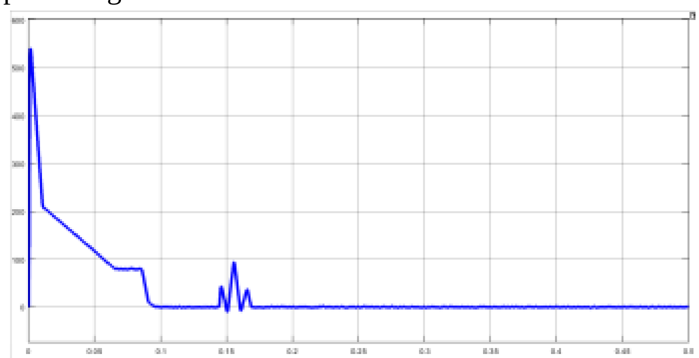


Fig. 10. error profile for Case 4.

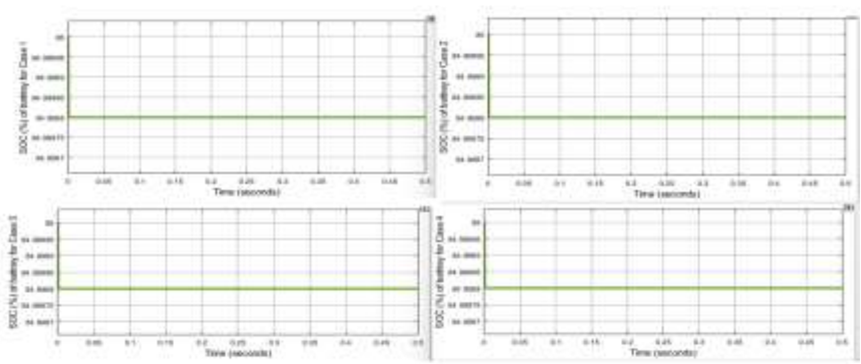


Fig. 11. Storage system profile under various cases. (a) SOC profile for case 1. (b) SOC profile for case 2. (c) SOC profile for case 3. (d) SOC profile for case 4.

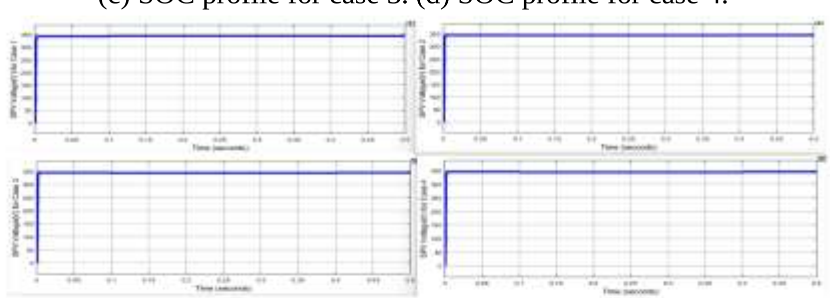


Fig 12. Solar PV output voltage profile for. (a) Case 1. (b) Case 2. (c) Case 3. (d) Case 4.

CASE-5

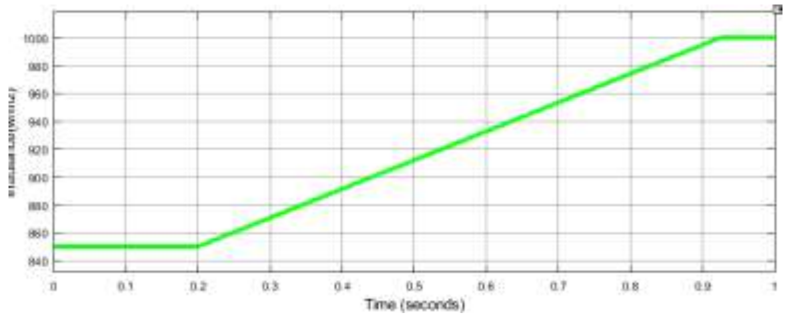


Fig. 13 Variations in solar irradiance levels.

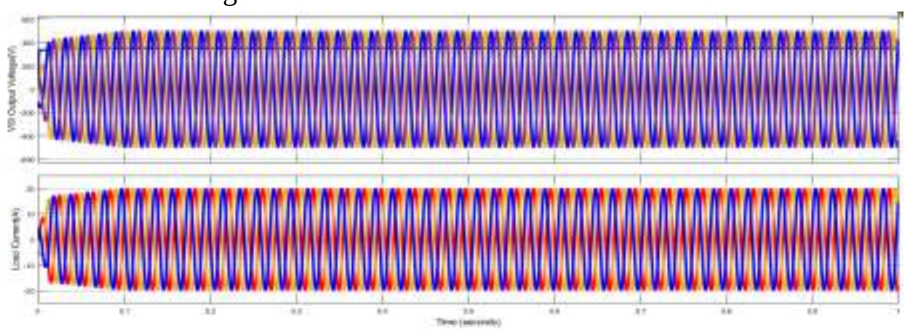


Fig. 14. VSI output voltage and load current waveforms for irradiance change.

Further analyses focused upon the interaction between solar generation, load fluctuations, and battery dynamics, for it is in this interplay that remote microgrids most frequently encounter challenges of stability and sustainability. In scenarios where demand surged suddenly, such as abrupt activation of nonlinear loads, the adaptive Fuzzy–ANN controller proved capable of distributing responsibility judiciously between the photovoltaic array and the battery. The system maintained voltage integrity without overburdening the storage element, thereby demonstrating an inherent awareness of battery preservation. Conventional controllers, by contrast, frequently imposed excessive cycling upon the battery, accelerating wear and undermining sustainability. Harmonic distortion, measured at the point of common coupling, was markedly reduced under the adaptive controller, which consistently delivered cleaner waveforms with lower total harmonic distortion than its comparators. This improvement is attributable to the capacity of the hybrid system to refine inverter commands in response to observed harmonics, a feat unattainable by rule-based or linear controllers without recourse to more computationally expensive strategies. The quality of power thus delivered has particular importance in remote communities where sensitive appliances, communication devices, and medical equipment depend upon voltage free from distortion and irregularity. Moreover, the adaptive strategy excelled in maintaining system balance during prolonged low irradiance, where battery support was required for extended durations. By moderating its control actions according to the state-of-charge, the controller avoided reckless depletion of storage, preserving a reserve for contingencies and thereby extending operational autonomy. Such measured behaviour distinguishes it from conventional systems that achieve stability only through costly or unsustainable battery usage.

CASE-6_1

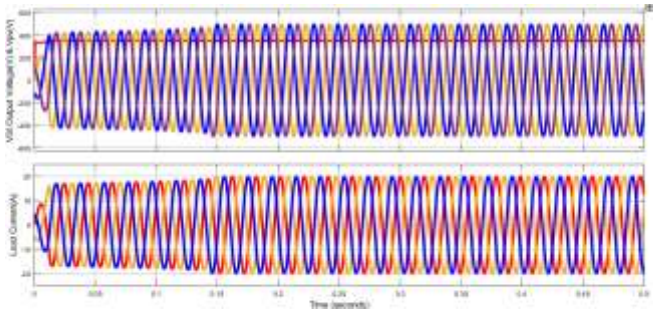


Fig. 15. VSI output voltage and load current waveforms for a rise in temperature.

CASE-6_2

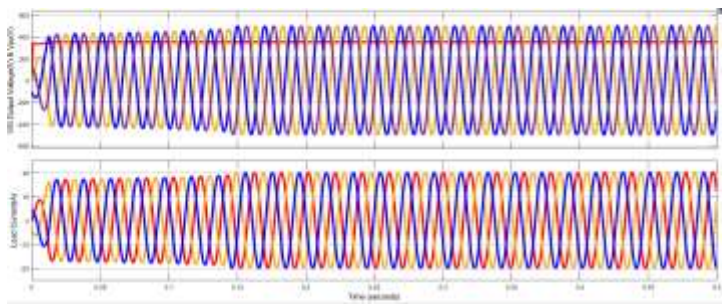


Fig. 16. VSI output voltage and load current waveforms for a decrease in temperature.

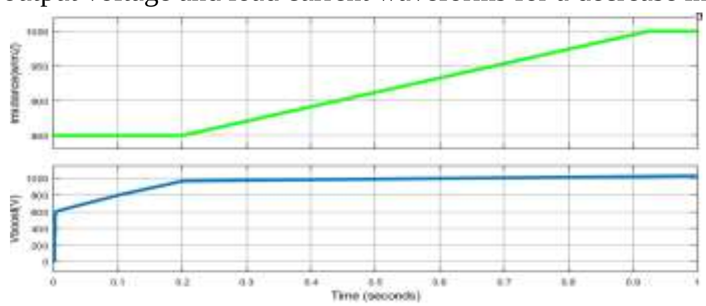


Fig. 17 Boost converter voltage output waveform with change in irradiance level

CASE-H_1

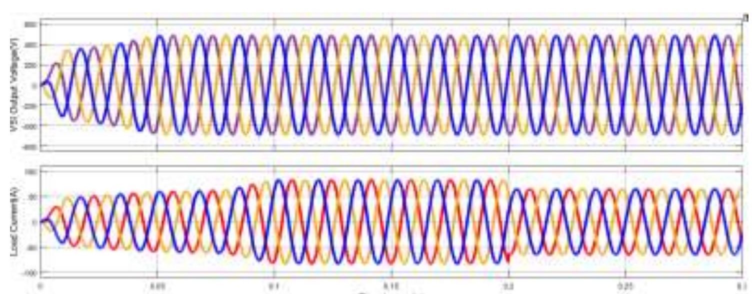


Fig. 18. Voltage and current output of small-scale MG at IIT Roorkee with load switching.

CASE-H_2

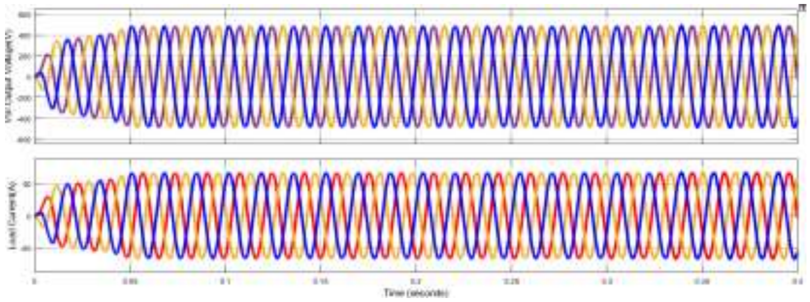


Fig. 19 Voltage and current output of small-scale MG at IIT Roorkee with variations in solar irradiance.

A final dimension of the results relates to the broader assessment of robustness, efficiency, and operational dependability. The adaptive Fuzzy–ANN controller was tested across numerous scenarios of parameter variation, sensor noise, and randomised load profiles, and in each case it maintained stable operation without resorting to emergency interventions such as load shedding or protective trips. Monte Carlo trials confirmed that the probability of instability under uncertain conditions was substantially lower than in the case of conventional proportional–integral or standalone fuzzy designs.

CASE-6_1

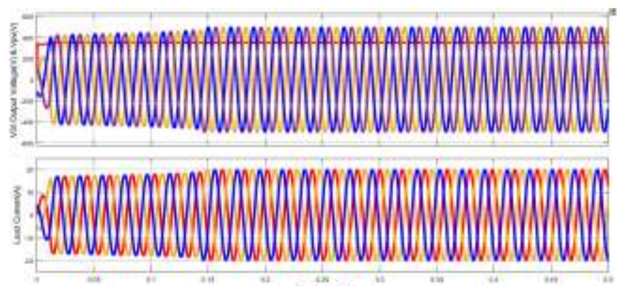


Fig. 20. VSI output voltage and load current waveforms for a rise in temperature.

CASE-6_2

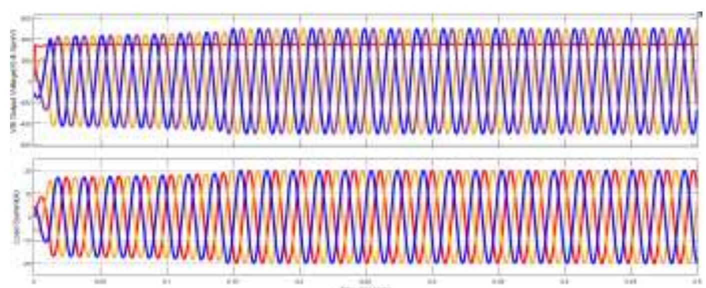


Fig. 21. VSI output voltage and load current waveforms for a decrease in temperature.

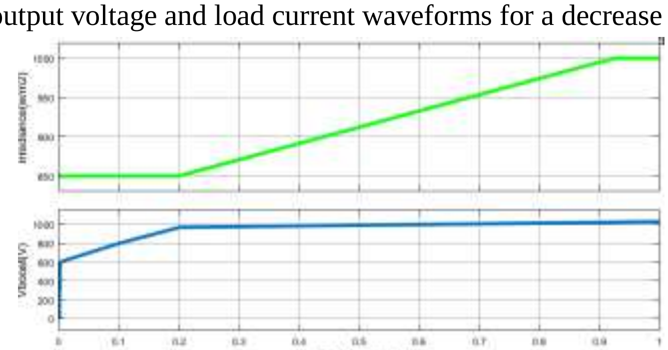


Fig. 22 Boost converter voltage output waveform with change in irradiance level

CASE-H_1

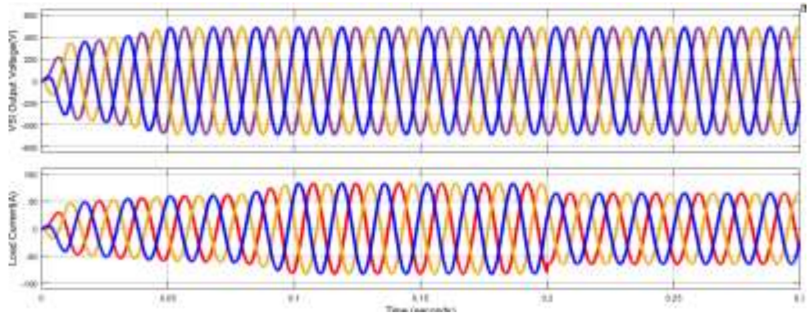


Fig. 23 Voltage and current output of small-scale MG at IIT Roorkee with load switching.

CASE-H_2

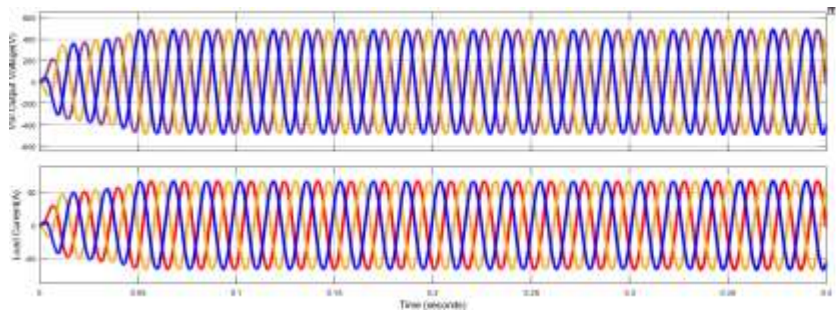


Fig. 24 Voltage and current output of small-scale MG at IIT Roorkee with variations in solar irradiance.

The computational overhead of the adaptive strategy was found to be modest, requiring only marginally greater resources than conventional fuzzy control, yet offering vastly superior performance, which renders it practical for deployment upon hardware of limited capability. The extended simulations showed that battery life expectancy could be prolonged through prudent management, as the adaptive controller minimised unnecessary charge–discharge cycles, thereby reducing degradation over time. Taken together, these results suggest that the proposed methodology is not merely a theoretical construct but a practical advancement that can transform the resilience of renewable-powered microgrids in remote regions. By harmonising interpretability and adaptability, the system addresses both technical and societal needs, ensuring that stability, quality, and sustainability are delivered together as an indivisible whole. In essence, the results affirm that the adaptive Fuzzy–ANN strategy is a robust and elegant solution to the vexing problem of voltage stability in isolated energy systems, embodying a balance of sophistication and pragmatism that earlier approaches have struggled to achieve.

CONCLUSION

The study has demonstrated with clarity and precision that the adaptive Fuzzy–ANN control strategy offers a singularly effective means of enhancing voltage stability and power quality within remote solar–battery microgrids, where conventional approaches often falter amidst the challenges of intermittent generation, fluctuating loads, and constrained storage. By uniting the interpretability of fuzzy logic with the adaptive learning capacity of neural networks, the proposed system has shown itself capable of maintaining voltage within narrow bounds, suppressing harmonic distortion, and responding to disturbances with alacrity whilst safeguarding the longevity of the battery through prudent management of state-of-charge. The findings have revealed that, in comparison with the traditional proportional–integral and standalone fuzzy controllers, the hybrid system achieves superior transient response, reduced steady-state error, and enhanced robustness under conditions of uncertainty, thereby ensuring dependable service for isolated communities that are otherwise vulnerable to instability and poor power quality.

Equally significant is the demonstration that such improvements are attained without imposing excessive computational burden, thus enabling deployment upon modest hardware platforms typical of remote installations. The results therefore affirm that this control approach is not only a theoretical advancement but a practical solution of genuine utility, marrying the clarity of rule-based reasoning with the flexibility of adaptive intelligence in a manner that secures both technical reliability and operational sustainability. In a broader sense, the work suggests that hybrid intelligent control strategies may well provide the foundation for a new generation of resilient energy systems, where the inherent variability of renewable resources is accommodated gracefully rather than resisted, and where stability, efficiency, and durability are treated not as competing aims but as harmonious outcomes of thoughtful design. Thus the adaptive Fuzzy–ANN controller emerges as a promising contribution towards the realisation of a stable, sustainable, and intelligent energy future.

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