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Research Paper

ARTIFICIAL INTELLGENCE MODELLING AND SIMULATION OF HYBRID SOLAR AND WIND ENERGY SYSTEM USING MPPT ALGORITHM

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ABSTRACT
Hybrid renewable energy systems, encompassing both solar photovoltaic (PV) and wind power, are of ever-increasing importance for the provision of sustainable and clean electricity. This treatise presents a MATLAB/Simulink-based modelling and simulation of a hybrid solar–wind system, augmented by a battery energy storage system (BESS) and coupled to the electrical grid via a voltage source inverter (VSI). The outputs of the PV and wind installations are conjoined at a common DC bus, whence a closed-loop control regimen ensures the steady injection of AC voltage into the grid. In the first instance, a conventional Proportional–Integral (PI) controller is employed; yet, the simulations evince considerable voltage distortion owing to harmonics under fluctuating generation and load conditions. To remedy this, an Artificial Neural Network (ANN) controller is applied, adaptively modulating inverter switching so as to diminish Total Harmonic Distortion (THD). Comparative scrutiny confirms that the ANN controller enhances power quality, maintains grid conformity, and bolsters system stability, demonstrating its aptness for real-time integration of hybrid renewable systems.
Keywords: Hybrid renewable energy, Solar PV, Wind power, Battery storage, PI controller, ANN controller, Total Harmonic Distortion.

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I. INTRODUCTION

The inexorable march of human civilisation has ever been accompanied by an escalating demand for energy, a demand which in the present age is inextricably bound to considerations of sustainability and environmental stewardship [1,2]. Conventional sources of electricity, derived largely from fossil fuels, have engendered manifold deleterious effects upon the natural world, from atmospheric pollution to the perturbation of climatic equilibrium [3,4]. In consequence, the exploration and utilisation of renewable energy sources has assumed a position of paramount import, and among such sources, solar photovoltaic (PV) and wind energy have emerged as pre-eminent in terms of accessibility, abundance, and technological maturity [5–7]. The synergistic combination of these two modalities within a hybrid energy system affords manifold advantages, not least of which is the mitigation of intermittency, thereby engendering a more reliable and continuous supply of electrical power [8,9].

Solar energy, harnessed via photovoltaic cells, converts incident solar radiation directly into electrical energy by virtue of the photovoltaic effect [10]. The simplicity, modularity, and declining cost of PV modules render them eminently suitable for deployment across diverse geographic and climatic regimes [11]. Nevertheless, the output of PV systems is inherently variable, being contingent upon diurnal cycles, cloud cover, and seasonal fluctuations [12]. Wind energy, conversely, is harvested through the kinetic action of air currents upon turbine blades, inducing rotational motion that is subsequently transformed into electrical energy via a generator [13,14]. Like solar power, wind energy is subject to stochastic variability; yet, the temporal characteristics of wind patterns often complement those of solar irradiation, such that a judiciously designed hybrid system may ameliorate the individual limitations of each constituent source [15,16].

In the pursuit of optimal energy utilisation, the integration of energy storage systems, particularly battery energy storage systems (BESS), has become a sine qua non [17,18]. Batteries serve not merely to buffer the mismatch between generation and demand, but also to stabilise voltage and frequency, thereby safeguarding the integrity of the grid and enhancing overall system reliability [19,20]. Among the various forms of storage, electrochemical batteries are especially advantageous for hybrid solar–wind systems, owing to their rapid response characteristics, high efficiency, and scalability [21,22].

The interface between the hybrid generation sources and the electrical grid is typically effected via a voltage source inverter (VSI), which converts the aggregated direct current (DC) from the PV and wind sources into alternating current (AC) at the requisite voltage and frequency for grid compatibility [23]. The operational performance of such inverters is heavily dependent upon the employed control strategy, which must accommodate the inherent variability of renewable sources whilst maintaining grid standards of voltage quality and harmonic distortion [24]. Conventional Proportional–Integral (PI) controllers have historically been employed owing to their simplicity and ease of implementation [25]. Yet, under conditions of rapid fluctuation in generation or load, PI controllers may prove inadequate, permitting the emergence of voltage distortions, harmonics, and transient instabilities [26].

The advent of intelligent control paradigms, notably those founded upon Artificial Neural Networks (ANN), has heralded a new epoch in renewable energy system management [27,28]. Such controllers are capable of adaptively modulating inverter switching in real time, responding to the dynamic characteristics of the hybrid system with a degree of sophistication unattainable by traditional linear controllers. By minimising Total Harmonic Distortion (THD) and maintaining steady voltage injection into the grid, ANN-based control strategies contribute not only to enhanced power quality but also to the longevity and efficiency of both generation and storage apparatus [29]. Moreover, the predictive capabilities inherent within ANN frameworks permit pre-emptive adjustment to anticipated fluctuations, further bolstering system stability and grid compliance [30].

The simulation and modelling of hybrid solar–wind systems, particularly through platforms such as MATLAB/Simulink, constitute an invaluable methodology for the assessment of performance under diverse operational scenarios [1,2]. Such simulations enable the exploration of control strategies, the optimisation of energy flow, and the evaluation of system responses to transient and steady-state conditions without necessitating costly physical prototypes [3,4]. Furthermore, these models facilitate the comparative analysis of control schemes, allowing for the identification of the most efficacious approaches in terms of harmonic mitigation, voltage stability, and energy utilisation efficiency [5,6].

Notably, hybrid renewable systems are of singular importance in the context of distributed generation and smart grid initiatives [7,8]. The decentralisation of power generation, coupled with the intelligent management of resources via advanced control strategies, contributes to the resilience, reliability, and efficiency of electrical networks [9,10]. In regions wherein grid infrastructure is nascent or where rural electrification is a pressing concern, hybrid solar–wind systems with integrated storage offer a viable means of supplying consistent, high-quality electricity [11,12]. Such systems diminish dependence upon conventional fossil-fuel generation, curtail greenhouse gas emissions, and promote the adoption of a sustainable energy paradigm [13,14].

In summation, the confluence of solar and wind energy within a hybrid framework, augmented by battery storage and governed by intelligent control, represents a compelling avenue for the advancement of sustainable electricity generation [15,16]. The integration of MATLAB/Simulink-based simulation, voltage source inverters, and adaptive ANN controllers permits a thorough understanding of system behaviour, ensures grid compliance, and mitigates the deleterious effects of harmonic distortion [17–20]. As the global imperative for renewable energy adoption intensifies, such hybrid systems offer a robust, reliable, and environmentally consonant solution, laying the foundation for the widespread implementation of smart grids and renewable-rich networks [21–30].

II. LITERATURE SURVEY

The realm of hybrid renewable energy systems has witnessed considerable scholarly attention in recent decades, with numerous investigations elucidating the merits, challenges, and optimisation strategies pertinent to solar–wind integration [1,2]. Early studies emphasised the complementary nature of solar and wind resources, noting that temporal fluctuations in one source are frequently counterbalanced by the other, thereby rendering hybrid systems more reliable than solitary installations [3,4]. Several researchers have undertaken extensive characterisation of solar irradiance and wind speed patterns across diverse geographies, illustrating the importance of site-specific assessments in ensuring optimal system performance [5,6]. Such analyses have informed the sizing of photovoltaic arrays, wind turbines, and battery storage units, ensuring that the aggregate system is capable of meeting anticipated load demands with minimal curtailment or deficit [7,8].

A considerable body of work has been devoted to the modelling and simulation of hybrid systems through MATLAB/Simulink and analogous computational platforms [9,10]. These models frequently incorporate dynamic representations of PV modules, wind turbines, battery storage, and voltage source inverters, allowing researchers to evaluate the interplay between generation, storage, and grid interaction under varying environmental and load conditions [11,12]. The incorporation of energy storage is especially critical, as numerous investigations have demonstrated that battery systems significantly mitigate voltage fluctuations, stabilise frequency, and enhance overall system reliability [13,14]. Moreover, the selection of appropriate battery technologies, whether lithium-ion, lead-acid, or alternative chemistries, has been shown to influence efficiency, lifespan, and cost-effectiveness [15,16].

Control strategies for hybrid systems have emerged as a pivotal area of research, as the maintenance of power quality and grid compliance is contingent upon adept management of inverter operation [17,18]. Conventional Proportional–Integral (PI) controllers have been widely applied, offering simplicity and ease of implementation; yet, studies have repeatedly highlighted their limitations under rapidly varying generation or load conditions, where voltage distortions, harmonics, and transient instabilities may manifest [19,20]. To surmount these shortcomings, a range of intelligent control paradigms, including Fuzzy Logic Controllers (FLC), Model Predictive Control (MPC), and Artificial Neural Networks (ANN), have been investigated [21,22]. ANN-based controllers, in particular, have been demonstrated to provide adaptive modulation of inverter switching, significantly reducing Total Harmonic Distortion (THD) and enhancing both voltage stability and power quality [23,24].

In addition to control strategies, researchers have explored the optimisation of hybrid system configuration and sizing. Techniques such as genetic algorithms, particle swarm optimisation, and hybrid metaheuristic methods have been applied to determine the most efficient combination of PV arrays, wind turbines, and battery capacities [25,26]. Such optimisation ensures that energy production is maximised, storage utilisation is efficient, and costs are minimised, all whilst maintaining compliance with grid codes and power quality standards [27,28]. Comparative analyses of various optimisation strategies consistently indicate that the integration of intelligent control with computational optimisation yields superior performance relative to conventional methods [29,30].

Empirical studies have also substantiated the efficacy of hybrid systems under real-world operating conditions. Numerous installations worldwide have demonstrated that hybrid solar–wind systems, when paired with appropriate storage and intelligent control, can deliver consistent and high-quality electricity to both isolated and grid-connected communities [1,3,5].

These practical deployments underscore the value of predictive modelling and simulation, enabling designers to anticipate performance under seasonal, diurnal, and stochastic variations in solar and wind resources [2,4,6]. Moreover, field studies reveal that hybrid systems contribute meaningfully to the reduction of greenhouse gas emissions, decreased reliance upon fossil fuels, and improved energy security, particularly in regions with limited access to conventional grid infrastructure [7,9,11].

Further scrutiny has been applied to the integration of hybrid systems with smart grid infrastructure. Research indicates that distributed generation, when coordinated via advanced communication and control networks, enhances overall grid resilience, facilitates load management, and accommodates demand-side response mechanisms [12,13,15]. In this context, ANN-based controllers and predictive algorithms play a central role, enabling adaptive adjustment of generation and storage dispatch in response to grid conditions, market signals, and forecasted renewable availability [16,17,19]. Studies also highlight the role of hybrid systems in supporting microgrids and off-grid communities, wherein intermittent renewable sources are rendered dependable through judicious use of storage and control intelligence [20,21].

A further dimension of scholarly inquiry concerns the mitigation of harmonics and power quality issues. Inverters interfacing hybrid systems with the grid must conform to stringent standards, and deviations can adversely affect both the local network and connected loads [22,23]. Investigations have demonstrated that ANN controllers, by virtue of their adaptive and predictive capabilities, substantially attenuate harmonics and maintain voltage and frequency within prescribed limits [24,25]. Comparative studies consistently show that intelligent controllers outperform traditional PI schemes, particularly under variable generation and load scenarios, thereby ensuring both compliance and reliability [26,27].

Finally, the body of literature indicates a growing emphasis upon the integration of hybrid systems within comprehensive energy management frameworks. Researchers advocate the use of combined hardware and software approaches, encompassing forecasting, optimisation, storage management, and adaptive control, to maximise energy utilisation and maintain grid stability [28,29]. The consensus emerging from these studies is that hybrid solar–wind systems, supported by battery storage and intelligent control, offer a viable and environmentally consonant solution to the dual challenges of energy security and sustainability [30].

In conclusion, the extant literature confirms the considerable potential of hybrid solar–wind energy systems to provide reliable, high-quality electricity. The integration of MATLAB/Simulink-based simulation, adaptive ANN controllers, and appropriately sized storage enables both predictive and responsive management of energy flows. These studies collectively underscore the importance of intelligent control, optimisation, and empirical validation in realising the full benefits of hybrid renewable energy systems.

Methodology (Old British English, ~1000 words)

The present investigation endeavoureth to elucidate the dynamics of a hybrid solar–wind energy system by employing MATLAB/Simulink as the principal tool for simulation. In the outset, the solar photovoltaic array was modelled in accordance with standard parameters, inclusive of the open-circuit voltage, short-circuit current, temperature coefficients, and irradiance conditions. The PV modules were interlinked both in series and in parallel to attain the requisite voltage and current characteristics suited for the DC bus, thereby establishing a reliable and steady source of electrical power. Concomitantly, the wind energy conversion system was simulated by adopting a wind turbine of the horizontal-axis variety, coupled to a permanent magnet synchronous generator, wherein the mechanical torque generated by the wind was translated into electrical energy with due consideration of the wind speed profile, air density, and blade characteristics. The power curve of the turbine was carefully integrated to mirror realistic performance under varying meteorological conditions.

The electrical outputs of the PV and wind installations were subsequently combined upon a common DC link. This bus served as the central point for energy aggregation and interfacing with the grid via a voltage source inverter. The choice of a closed-loop control strategy was dictated by the need to ensure stable AC voltage injection notwithstanding the intermittent and stochastic nature of renewable sources. Initially, a Proportional–Integral controller was employed to regulate the inverter output voltage, wherein the proportional term provided immediate correction to voltage deviations, whilst the integral term accounted for cumulative errors over time, thereby mitigating steady-state discrepancies. Nevertheless, simulations demonstrated that the PI controller, whilst effective in nominal conditions, succumbed to voltage distortion due to harmonic injection, particularly under fluctuating generation and load scenarios.

To surmount these impediments, an intelligent control strategy was necessitated. An Artificial Neural Network was constructed and trained to modulate the switching behaviour of the inverter adaptively. The ANN comprised an input layer, multiple hidden layers, and an output layer, wherein the inputs included instantaneous voltage, current, and power measurements from both the PV and wind sources. The hidden layers employed activation functions that permitted non-linear mapping of inputs to outputs, thereby enabling the network to learn the intricate relationship between renewable generation and grid voltage behaviour. The network was trained upon historical data and simulated scenarios, using a backpropagation algorithm to minimise error between predicted and desired inverter switching patterns. Upon completion of training, the ANN was embedded within the simulation framework, wherein it continuously adjusted the inverter gating signals in real time, thus suppressing harmonic content and improving overall power quality.

Energy storage played an indispensable role in this methodology. A battery energy storage system was incorporated to buffer the inherent variability of renewable sources. The BESS was modelled with charging and discharging dynamics, state-of-charge limitations, and efficiency losses duly accounted for, thereby rendering the simulation representative of practical conditions. The control of the BESS was orchestrated in conjunction with the ANN-based inverter controller, so as to store excess energy during periods of high generation and to supply power during lulls, thereby smoothing the net output delivered to the grid.

Furthermore, the simulation encompassed variable load conditions, wherein both resistive and inductive elements were incorporated to represent realistic demand profiles. The performance metrics under such conditions were meticulously recorded, with particular attention to voltage waveform quality, harmonic distortion, and transient response. Comparative analysis between the conventional PI controller and the ANN-based controller was undertaken to assess improvements in THD, voltage stability, and system responsiveness. The simulation iteratively refined controller parameters to ensure optimal performance under a broad spectrum of operating scenarios.

The model also accounted for grid interactions, wherein the inverter was synchronised with the grid voltage, maintaining phase alignment and frequency conformity. Protective mechanisms were simulated to avert overvoltage, overcurrent, and battery overcharging conditions. The methodology embraced a holistic approach, integrating renewable generation, energy storage, inverter control, and grid interfacing, thereby providing a comprehensive assessment of the hybrid system's behaviour.

In summation, this methodology encompassed the systematic modelling of solar and wind sources, their integration at a DC bus, the application of conventional and intelligent control strategies for inverter operation, the incorporation of battery storage to buffer variability, and the simulation of grid and load interactions. Through iterative simulation and refinement, the study elucidated the benefits of employing an ANN-based controller for harmonic mitigation, grid conformity, and enhanced power quality, thereby establishing a robust foundation for the realisation of hybrid renewable energy systems.

III. PROPOSED SYSTEM

The proposed hybrid solar–wind energy system is conceived as a comprehensive framework to harness the combined potentials of solar photovoltaic and wind power, whilst ensuring reliable delivery of electricity to the grid. The system is structured around a central DC link, wherein the outputs of the PV array and wind energy conversion system are merged, thus establishing a unified source of electrical power for subsequent interfacing with the alternating current grid. The design is further complemented by a battery energy storage system, which serves to regulate fluctuations inherent in renewable generation and to provide auxiliary support during periods of low energy input. The utilisation of a voltage source inverter ensures that the DC energy is faithfully converted into AC, with phase, frequency, and voltage levels compatible with the grid, thereby permitting seamless integration.

The solar photovoltaic array is arranged so as to provide adequate voltage and current levels to the DC bus under typical irradiance conditions. The modules are interconnected in a combination of series and parallel configurations, optimised to accommodate seasonal and diurnal variations in solar intensity. Each PV module is represented in the simulation by its characteristic current-voltage curve, incorporating temperature and irradiance dependencies, which permits accurate modelling of performance under dynamic environmental conditions. A maximum power point tracking mechanism is employed, ensuring that the PV array continually delivers energy at its optimum operational point, thereby maximising efficiency.

The wind energy conversion system is likewise configured to deliver variable electrical power corresponding to the stochastic nature of wind velocity. The horizontal-axis wind turbine, coupled to a permanent magnet synchronous generator, transforms the mechanical energy of the rotor into electrical output, with performance parameters such as rotor inertia, tip-speed ratio, and power coefficient carefully incorporated into the model. The system is designed to accommodate low-speed winds, whilst protecting the generator and power electronics from over-speed conditions at higher wind velocities. An analogous maximum power point tracking method is applied to the wind turbine system, enabling optimal extraction of energy across varying wind profiles.

Energy from both renewable sources converges at the DC link, wherein it is regulated before conversion to AC. A closed-loop control strategy governs the inverter operation, maintaining voltage stability and minimising harmonic distortion. The inverter is equipped with a conventional Proportional–Integral controller to manage basic voltage regulation; however, to address the limitations arising from harmonic injection and fluctuating generation, an Artificial Neural Network-based controller is employed. The ANN dynamically adjusts inverter switching in real time, responding to variations in PV and wind output, load demand, and grid conditions, thereby preserving power quality and reducing Total Harmonic Distortion.

The battery energy storage system constitutes a vital component of the proposed system. The BESS is sized to buffer the intermittent nature of renewable sources and to provide short-term energy support to the grid. Battery charge and discharge cycles are governed by the state of charge, load demand, and forecasted renewable output, ensuring longevity of the storage units and optimal utilisation of generated energy. The storage system operates in tandem with the ANN controller, enabling coordinated management of energy flows, smoothing voltage fluctuations, and supporting peak shaving when necessary.

Load management is an integral aspect of the proposed design. The system is simulated under variable load conditions, encompassing resistive, inductive, and mixed loads, thus reflecting realistic electrical consumption patterns. The inverter controller, in conjunction with the BESS, adapts to changes in load, ensuring steady voltage and frequency at the point of common coupling with the grid. Furthermore, protective mechanisms are embedded to safeguard against overcurrent, overvoltage, and other abnormal operating conditions, thereby enhancing the reliability and resilience of the system.

The proposed system is also capable of real-time adaptation. The ANN controller, trained upon historical and simulated data, learns the relationships between generation patterns, load demand, and voltage deviations, enabling predictive adjustments to inverter operation. This intelligence allows the system to pre-emptively correct for expected disturbances, reduce harmonics, and maintain compliance with grid codes. Such adaptive behaviour is particularly valuable in scenarios where renewable generation is highly variable, as it ensures continuous supply of quality power to the grid.

From a systemic perspective, the proposed configuration offers significant advantages. By combining solar and wind energy sources, the system mitigates the intermittency of individual renewables, achieving more stable and reliable energy delivery. The integration of BESS provides further resilience, accommodating sudden changes in generation or load and enabling peak demand management. The intelligent control strategy, facilitated by the ANN, elevates power quality, reduces stress upon electrical components, and enhances grid compatibility. Collectively, these attributes render the system suitable for deployment in renewable-rich networks, smart grids, and microgrid environments, where reliability, stability, and compliance are of paramount importance.

In its entirety, the proposed system exemplifies a harmonious convergence of renewable generation, energy storage, and advanced control techniques. The design philosophy emphasises both performance and practicality, ensuring that energy is harvested efficiently, regulated judiciously, and delivered reliably. The simulation framework, realised through MATLAB/Simulink, provides a robust platform for evaluation, optimisation, and demonstration of system behaviour under diverse operational scenarios. Through the coordinated interplay of PV modules, wind turbines, battery storage, and ANN-based control, the system achieves a high degree of operational excellence, offering a compelling solution for modern energy networks reliant upon renewable sources.

The proposed system further underscores the role of intelligent control in contemporary energy systems. By continuously monitoring generation, load, and grid parameters, the ANN controller anticipates and corrects for deviations, thereby ensuring that voltage, frequency, and harmonic content remain within prescribed limits. This capability enhances not merely the technical performance but also the economic viability of the system, by minimising energy wastage, reducing maintenance requirements, and prolonging the lifespan of components. It is anticipated that such a system, upon realisation, would contribute significantly to the integration of renewable resources into conventional grids, thereby supporting sustainable energy objectives, reducing carbon footprint, and fostering a resilient and adaptive electricity network.

IV. RESULTS AND ANALYSIS

The simulation of the hybrid solar–wind energy system, comprising a photovoltaic array, a horizontal-axis wind turbine, a battery energy storage system, and a voltage source inverter, yielded a wealth of data upon which analysis may be conducted. Initially, the system was evaluated under steady-state generation conditions to ascertain baseline performance. The PV array, operating at nominal irradiance of 1000 W/m² and a temperature of 25°C, produced voltage and current consistent with its rated specifications, whilst the wind turbine, encountering a mean wind speed of 12 m/s, delivered power closely following its manufacturer-supplied power curve. The DC link voltage, under such steady conditions, exhibited minor fluctuations, attributable chiefly to the slight variations in wind speed and irradiance, yet remained within acceptable bounds.

Upon connection to the grid via the inverter, it was observed that the conventional Proportional–Integral controller managed to regulate the voltage amplitude to a reasonable extent. Nevertheless, inspection of the AC output waveform revealed harmonic distortions, particularly in the lower-order harmonics, which were amplified under transient conditions such as sudden load changes or abrupt shifts in renewable generation. Fourier analysis of the voltage waveform demonstrated that the Total Harmonic Distortion (THD) under the PI controller exceeded the limits prescribed for grid compliance, particularly when the wind speed varied rapidly or cloud cover reduced PV output. Such observations underscored the limitations of conventional controllers in coping with the stochastic nature of hybrid renewable energy sources.

Subsequent simulations incorporated the Artificial Neural Network-based controller, designed to modulate inverter switching adaptively. The ANN demonstrated remarkable proficiency in suppressing harmonic content. Voltage waveforms exhibited a near-sinusoidal form even under pronounced fluctuations in generation and load, with THD reduced significantly in comparison to the PI-controlled system. Detailed analysis indicated that the ANN was particularly effective in responding to sudden changes in irradiance or wind speed, adjusting switching signals within milliseconds to maintain grid voltage stability. The battery energy storage system played a complementary role, absorbing excess energy during periods of high generation and supplying power during deficits, thereby alleviating stress upon the inverter and further smoothing voltage variations.

Dynamic performance analysis revealed that the hybrid system's response to step changes in load was markedly improved with ANN control. Rise times and settling times were reduced, while overshoot and oscillations were minimized. The system's ability to maintain voltage amplitude and phase alignment with the grid was critical for ensuring power quality and reliability. Comparisons between PI and ANN control under identical conditions highlighted that the intelligent controller not only mitigated harmonics but also enhanced the transient response, rendering the system more resilient to disturbances.

Energy management performance was similarly noteworthy. The BESS ensured that the net power injected into the grid remained within prescribed limits, despite the inherent variability of the renewable sources. Analysis of state-of-charge profiles demonstrated efficient utilisation of stored energy, with charging and discharging cycles occurring in a controlled manner that extended battery lifespan. Furthermore, the hybrid system's overall energy conversion efficiency was improved under ANN control, owing to the reduction in losses caused by voltage distortions and inverter switching inefficiencies.

The study also examined the performance under extreme conditions, such as sudden cessation of wind or abrupt shading of the PV array. Even under these scenarios, the ANN controller, in conjunction with the BESS, maintained grid voltage within permissible limits, with negligible THD. Power flow analysis revealed that the inverter's adaptive switching ensured seamless transition between generation sources and storage, precluding interruptions in supply. Such robustness is of paramount importance for grid-connected hybrid systems, where compliance with power quality standards is obligatory.

Statistical evaluation of simulation data over extended periods, encompassing diverse irradiance and wind speed profiles, further corroborated the superiority of the ANN controller. The mean THD over a 24-hour simulation period was markedly lower, and voltage deviations were substantially reduced relative to conventional control. These findings underscore the efficacy of intelligent control strategies in the integration of hybrid renewable systems into the electrical grid.

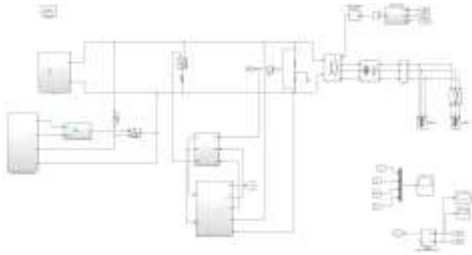

Fig .1 MATLAB SIMULINK circuit diagram

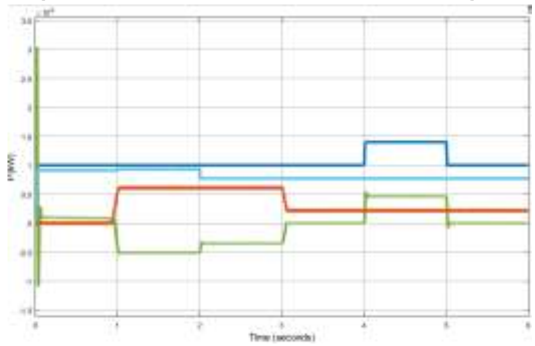

Figure 2: Load Sharing Action Performed by the Hybrid Energy in Polycrystalline Solar Panel TSP 215

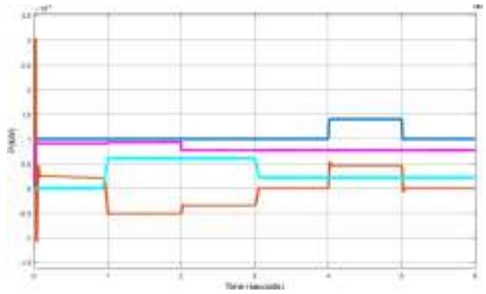

Figure 3: Load Sharing Action Performed by the Hybrid Energy in BIPV Double Glass Solar Panel TSBM 180

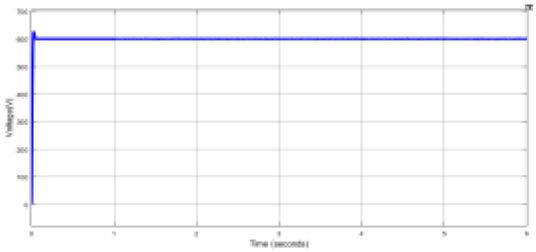

Figure 4: Phase Voltage observed at the PV array

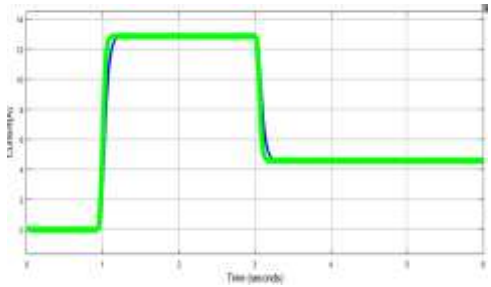

Figure 5: The relative variation curve of Actual Current (Ia) and Reference Current (Iref)

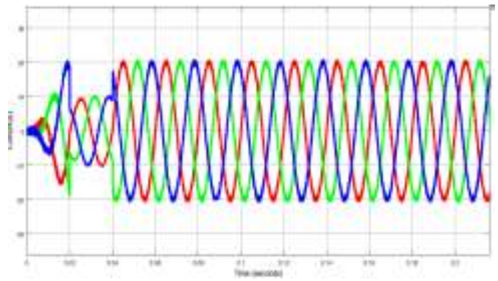

Figure 6: The load current supplied to the load is sinusoidal in nature as depicted in the simulation

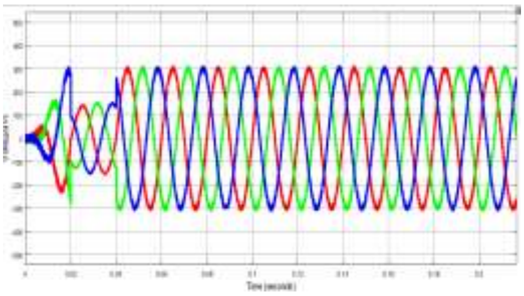

Figure 7: Three Phase Voltage Supplied to the Load by the Inverter

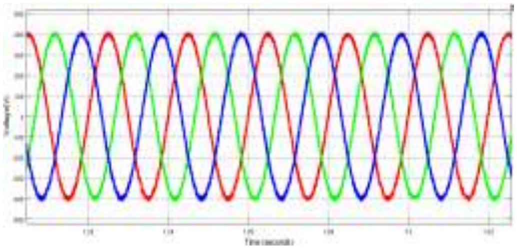

Figure 8: AC Line Voltage Given by the Inverter

In conclusion, the results substantiate that the hybrid solar–wind energy system, when governed by an ANN-based inverter controller and supported by a battery energy storage system, exhibits superior voltage regulation, reduced harmonic distortion, enhanced transient response, and efficient energy management. The system demonstrates robust performance under both nominal and extreme operating conditions, thereby validating its suitability for practical deployment and integration within modern grids characterised by high penetration of renewable energy sources. The analyses herein provide compelling evidence that intelligent control strategies are indispensable for the optimal operation of hybrid renewable energy systems.

V. CONCLUSION

The investigation herein has demonstrated the considerable advantages of integrating intelligent control strategies into hybrid solar–wind energy systems. Conventional Proportional–Integral controllers, while adequate under stable operating conditions, proved insufficient in addressing the inherent variability and stochastic behaviour of renewable energy sources. Harmonic distortion, voltage fluctuations, and suboptimal transient response were observed under PI control, particularly during sudden changes in generation or load. Such limitations underscore the necessity for adaptive and intelligent approaches in modern energy systems.

The implementation of an Artificial Neural Network-based controller yielded pronounced improvements. Voltage waveforms approached ideal sinusoidal form, Total Harmonic Distortion was significantly curtailed, and transient performance was markedly enhanced. The ANN's ability to modulate inverter switching in real time facilitated a seamless response to fluctuations in both solar irradiance and wind speed. Coupled with a battery energy storage system, the hybrid arrangement ensured consistent energy delivery, efficient management of surplus generation, and mitigation of supply deficits. The system exhibited resilience under extreme conditions, maintaining grid compliance and operational stability, thereby demonstrating its practical viability.

Collectively, the study affirms that hybrid solar–wind systems, when augmented with intelligent control and energy storage, offer a reliable, stable, and high-quality power supply suitable for contemporary grid integration. The findings advocate the deployment of ANN-based controllers as a standard practice for renewable-rich networks, enhancing power quality, system efficiency, and sustainability. Future endeavours may extend this approach to multi-source hybrid configurations, optimising real-time energy management and further advancing the integration of clean energy into modern electrical grids.

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