Recent Advances and Control Strategies in Grid-Integrated Hybrid Renewable Energy Systems: Optimization, Power Quality, and Energy Management

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Abstract:

The fast integration of renewable energy sources into power grids has, therefore, impelled the setup of hybrid renewable energy systems that synergize solar, wind, and energy storage technologies for development and testing of uninterrupted power/energy generation. The review delineates a detailed study of recent (2023–2025) research works on grid-integrated HRES, with key focus areas being energy management, power quality improvement, and control strategies. These latest optimization techniques, like MPC, fuzzy logic, reinforcement learning, and bio-inspired algorithms, have significantly increased performance, stability, and dynamic response in systems. Various studies show that hybrid controllers like adaptive fuzzy-MPC and ensemble predictive control successfully reduce frequency deviations, voltage fluctuations, and total harmonic distortion (THD), while also improving renewable energy utilization. Power quality issues such as voltage fluctuations, reactive power imbalance, and harmonic distortion still pose critical challenges and have been addressed by advanced control techniques including O-FOPID, adaptive fuzzy logic, and MD-SOGI-based predictive control. Notwithstanding advancements, limitations including large complexity, dependence on precise system modeling, extensive training data needs, and real-time implementation challenges still exist. Moreover, a gap exists in pursuing research that integrates multi-objective optimization for cost, reliability, and power quality enhancement simultaneously. As such, the review points out the emerging trends and opportunities for the development of robust, scalable, and intelligent control strategies that can effectively mitigate renewable generation variabilities and dynamic grid conditions. These insights shall aid in steering researchers and practitioners to realize each efficient and reliable HRES candidate for future smart grids.

Keywords: *Hybrid Renewable Energy Systems (HRES), Power Quality, Energy Management, Optimization Techniques, Model Predictive Control (MPC), Adaptive Control Strategies*

I. INTRODUCTION

The escalating worldwide demand for clean, green energy has spurred massive research in renewable energy systems, especially hybrid systems combining more than one energy source, e.g., solar, wind, and fuel-based systems [1]. Hybrid Renewable Energy Systems are a potential answer to the intermittency and variability brought about by each renewable source. Being a combination of complementary generation technologies, HRES are able to act in the stead of conventional generation sources in providing a more reliable and stable power output, hence becoming an option for grid connection or stand-alone installations [2]. Since both solar systems and wind turbines have offered many advantages in terms of environmental safety, scaling, and capital cost decrease, they are more common [3]. However, these changes in solar irradiance and wind speed lead to an increase in difficulties in maintaining voltage and frequency stability, ultimately compromising the grid's performance and power quality [4].

During times of low generation from renewable sources, fuel-based backup systems, being either diesel or hydrogen fuel cells, are mainly used in conjunction with hybrid systems to guarantee uninterrupted energy supply [5]. These systems increase the reliability of a system while meeting critical load requirements, especially for remote or islanded microgrids. Given the presence of batteries or supercapacitors as energy storage systems, the flexibility of the system and the energy management will be improved as load leveling, peak shaving, and energy arbitrage can take place [6].

Power quality remains a major issue in grid-connected HRES, which includes voltage stability, harmonic distortion, frequency deviation, and reactive power balance [7]. With an increasing penetration of renewable energy sources into the grid, issues of voltage fluctuations, harmonics, and interference threaten sensitive loads and grid equipment [8]. Hence, modern control and optimization algorithms need to be developed for proper energy management and power delivery with high quality. The conventional control is based on PI or PD controllers, which are simple to implement but in most cases perform poorly under highly dynamic conditions [9]. On the other hand, lateral approaches, like MPC, adaptive fuzzy logic, and reinforcement learning-based techniques, are able to provide solutions to nonlinearities, uncertainties, and fast variations encountered in renewable generation [10].

In recent times, it has been envisaged that optimization methods be coupled with intelligent control for the improvement of energy conservation and PQ in grid-connected HRES. Multi-objective optimization methods can be used to evaluate the economic cost, emission reduction, and system reliability while ensuring conformance to grid codes and standards [11]. In the literature, approaches like PSO [Particle Swarm Optimization], GA [Genetic Algorithms], and hybrid bio-inspired techniques have demonstrated excellent results in voltage regulation, lessening THD [Total Harmonic Distortion], and ensuring stability of the system [12]. In addition, predictive and adaptive combination approaches allow HRES to react to load changes, renewable intermittency, and fault conditions, promoting a stable and reliable connection to the grid [13].

Despite these advancements, there still remain several research gaps in the design, control, and operation of HRES. Most of the existing approaches are considered single-objective optimization or simulation-based analyses; hence, they do not provide viable solutions in real-time dynamic environments [14]. In addition, the high computational complexity, forecasting requirements, and inability to provide a holistic strategy to address energy management, PQ improvement, and system reliability are among the key challenges that need attention [15].

Figure 1 shows Sources of global Energy

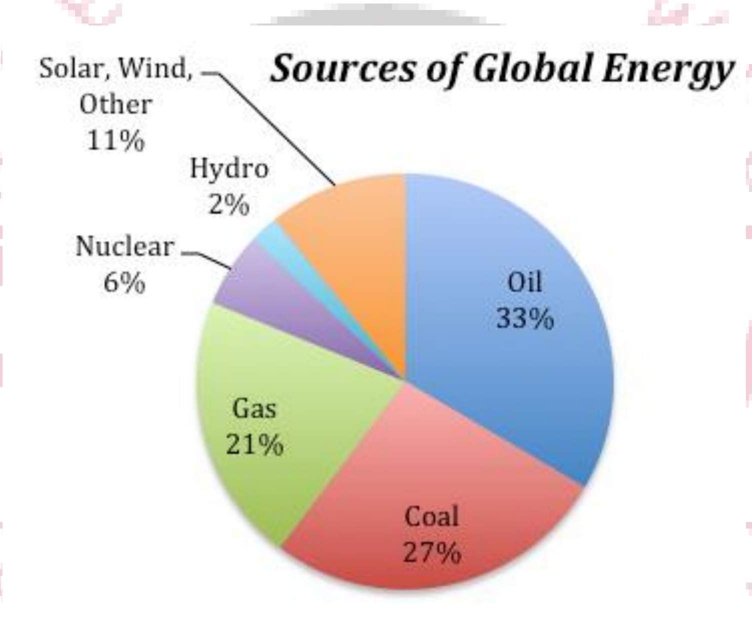

Figure 1: Sources of global Energy

A. Solar Energy System Overview

Due to its abundance and sustainability with technological advancements, solar energy is indeed one of the biggest contributors to the field of renewable resources. Solar PV systems use sunlight and directly create electricity from this source [15]. Thus, PVs-fit well into both network and insulation purposes. Lower production cost and higher efficiency of PV machines are being pushed forward as the very vital component in hybrid renewable energy systems.

Figure 2 describes Synergy in Hybrid Renewable Energy Systems

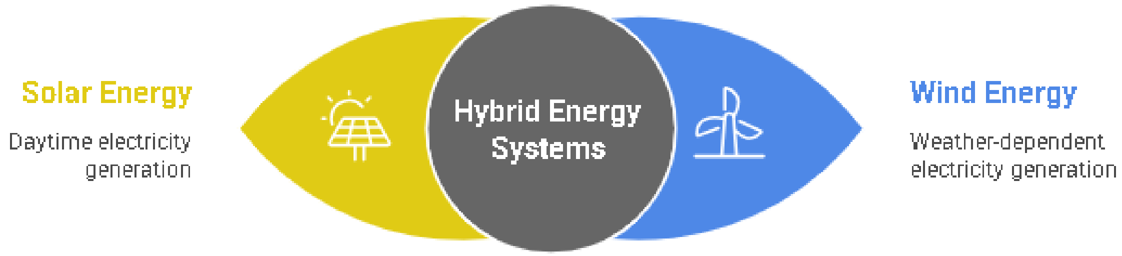

Figure 2: Synergy in Hybrid Renewable Energy Systems

i. Photovoltaic (PV) Technology

Photovoltaic (PV) technology is based on the direct conversion of sunlight into electricity using semiconductor materials, primarily silicon [16]. When photons from sunlight strike the PV cell, they excite electrons, generating an electric current through the photovoltaic effect. A typical PV system consists of solar panels, inverters, and sometimes storage units to provide continuous power. The efficiency of PV cells has significantly improved over the years, with commercial silicon-based modules achieving efficiencies between 15–22%. Recent developments in thin-film technologies, perovskite solar cells, and bifacial panels are further enhancing energy yield while reducing costs. PV systems are scalable [17], ranging from small rooftop installations to large solar farms integrated with the grid. For hybrid applications, PV panels contribute during daytime by providing clean energy, while complementary sources like wind and fuel cells supply power during low solar radiation periods. The integration of Maximum Power Point Tracking (MPPT) algorithms ensures optimal energy extraction under varying irradiance conditions [17-[18]. Moreover, modern PV inverters include grid-support functionalities such as reactive power compensation and fault ride-through capability, improving overall system reliability. Thus, PV technology plays a crucial role in advancing sustainable and resilient hybrid energy systems. Figure 3 describes Photovoltaic (PV) Technology

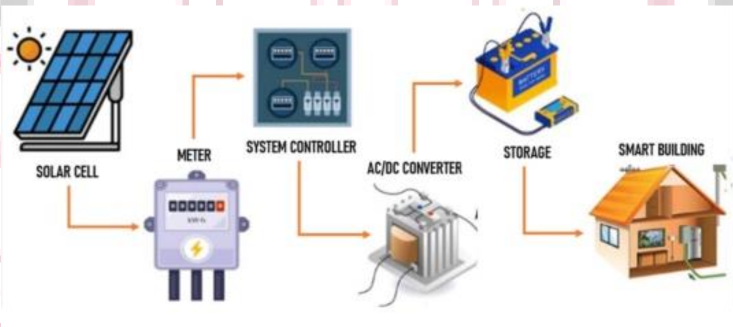

Figure 3: Photovoltaic (PV) Technology

II. GRID INTEGRATION CHALLENGES OF HYBRID RENEWABLE SYSTEMS

Increased global demand for sustainable and reliable electricity has driven research into systems that can integrate various energy sources, such as solar, wind, and fuel-based generation. Hybrid systems combine complementary generation technologies to offset the intermittency and variability that come with individual renewables and, thus, provide a more stable and continuous power output suitable for grid integration and off-grid applications [1]. HESS-assisted control strategies have shown great potential in improving frequency regulation of grid-connected hybrid systems, with frequency nadir better by 15 percent and RoCoF down by 12 percent as compared to battery-only systems. While experiencing promising results, most of these studies are still simulation-based and lack hardware validation; thus, there has been a need for practical implementation [1].

Advanced control schemes with fuzzy fractional-order PID controllers combined with redox flow batteries have been proposed for improving load frequency control. The results show these techniques to reduce the ISE by 35% and improve frequency restoration time by 18% over classical PID controllers, complex parameter tuning and lack of proper experimental validation rendering them less applicable [2]. Voltage stability that arises in hybrid-renewable-dominant grids has also been addressed, giving indications that the number of thermal backup systems that are required can be further reduced under stability constraints. Such results, however, tend to be limited to one particular regional grid, restricting their generalizability to other networks [3].

Equation (1) provides the operation in the grid considered in this work. A special consideration is given to RES due to the possibility of intermittency and the variations caused by the uncertainty in degradation, based on the ingress of errors and time associated with the degradation history. Similarly, the uncertainties of the demand and the prices of energy also influence the final operation [7]. Consider the forecast process as a source of errors that generates an uncertainty variable into the objective function of the levelized cost calculation for operation. Upon acknowledgment of realizing more utility through an antisymbiotic solution with respect to the generated forecasts, the operators shall attempt to dispatch the antisymbiotic interface accordingly. Thus, if the forecast f_i for a time set of t_i can be defined as a function of distortions in time $f_i=\Phi(t_i)$, then disturbances can also be evaluated through the classification of operators in the results of the antisymbiotic interface at a forecast level, which will eventually reveal the usefulness of the antisymbiotic interface:

Occurrence of disturbances as an incorporation between the forecast for a time set t_i (with $t_i \in \mathcal{R}$) and its realization:

$$\varepsilon_i(\omega_j) := f_i(\omega_j) - \Phi(t_i), \quad \omega_j=1,...,n \tag{2}$$

Forecasts are carried out up to n times, with one value considered to be true after n. In this respect, by considering disturbances for all j in the antisymbiotic operator, it can be differentiated:

$$\delta_d^l(\omega_j) \ni \begin{cases} \varepsilon_i (\omega_j) \in \delta_l(\omega_j) \quad \text{if} \quad j \leq n \\ \bar{0} \quad \text{else} \end{cases}, \quad j=1,...,M \tag{3}$$

with $M=2L+1, L \leq n$. Anterior services of the operators, such as the antisymbiotic interface, are impeded by the inaccuracy of the forecast, and accordingly, the antisymbiotic interface shall be sorted according to the indices ω_j to perceive the realization of the forecast, which can be built on the-purposeful evaluation of forecast distortions.

The antisymbiotic interface's initial services are altered through disturbances at some rate, producing the effectiveness of that interface-evaluation-refused index. This class indeed sorts the antisymbiotic interface where the sorted indices come from either a true or a false forecast distortion evaluation.

It has been reported that the reinforcement-learning-based synchronization mechanisms for microgrid-interfaced hybrid systems reduce the resynchronization time by 28% and achieve synchronization instrumentalities delays prediction with an F1-score of 0.91, albeit at high computational costs and somewhat sensitive to learning rates [7]. Solar and wind hybrid power scheduling based on multiobjectives genetic algorithm-based strategies improves the grid indices of reliability by 20% and reduces LPSP to 1.2%, slow convergence, and computational limitations being an issue [8]. In contrast to this, the MPCs provide a 95% successful synchronization rate and a 13% voltage deviation reduction but depend on precise forecasts [9].

High-penetration hybrid systems benefit from PMU-based monitoring for voltage stability, with accuracy in the prediction of instability events up to 90%, while installation costs are high [10]. Frequency regulation via a deep reinforcement learning-based model can achieve F1-score and MAE values of 0.89 and 0.04 Hz, respectively, but with long training times [11]. Coordinated schemes with virtual inertia and voltage support reduce the voltage dips by 24% and recovery time by 17%, but event duration is short, thereby neglecting long-term dynamics [12]. Adaptive sliding mode controllers synchronized a phase-lock to an accuracy of 96% and reduced errors by 14% but proved to be less effective at higher harmonics [13]. Hydrogen-assisted hybrid fuel cells can compensate for the grid intermittency, reducing curtailments by 27% and improving renewable utilization by 15%, but production costs for the hydrogen remain a limiting factor [14]. Finally, IoT-enabled real-time monitoring systems achieve 93% accuracy and a 92% F1-score in detecting frequency anomalies, but cybersecurity concerns pose a barrier to widespread adoption [15].

Generally, most research studies highlight that advanced control strategies in coordination with the hybrid energy storage system and renewable generation greatly enhance the stability, reliability, and power quality of a grid-connected HRES. Nevertheless, real-world implementation remains impeded by technological challenges of hardware validation, computational complexity, costs, scalability, and cybersecurity. Hence, the gaps in literature indicate the need for further exploration in intelligent control, energy management, and power quality enhancement for hybrid renewable systems so that resilient and sustainable smart grids may become a reality.

Table 1.1: Grid Integration Challenges of Hybrid Renewable Systems

Ref	Focus Area	Technique / Method	Results	Limitations
[1]	Frequency regulation	Hybrid Energy Storage System (HESS) control	15% improvement in frequency nadir, 12% reduction in RoCoF	Simulation only, no hardware test
[2]	Frequency control	Fuzzy fractional-order PID with redox flow battery	35% ISE reduction, 18% faster restoration	Complex parameter tuning, no real test
[3]	Voltage stability	Renewable penetration analysis in regional grids	22% reduction in thermal backup capacity	Limited to one regional grid
[4]	Low-inertia grids	Hybrid grid-forming inverters	21% better transient response, 15% faster voltage recovery	High cost, scalability issues
[5]	Frequency stability	LSTM-based demand response prediction	92% accuracy, 17% reduction in deviation	Data dependency, training cost
[6]	Voltage & frequency	Adaptive droop + inertia emulation	19% less frequency deviation, 23% better voltage margin	Weak under extreme intermittency
[7]	Synchronization	Reinforcement learning-based sync	F1-score = 0.91, 28% faster resync	High computation, sensitive tuning

[8]	Intermittency mitigation	Multi-objective Genetic Algorithm (GA) scheduling	Reliability +20%, LPSP down to 1.2%	Slow convergence, heavy computation
[9]	Synchronization	Model Predictive Control (MPC)	95% success rate, 13% less voltage deviation	Needs accurate forecast data
[10]	Voltage stability	PMU-based monitoring	90% accuracy in instability prediction	High PMU deployment cost
[11]	Frequency regulation	Deep Reinforcement Learning (DRL)	MAE = 0.04 Hz, F1-score = 0.89	Long training time
[12]	Voltage support	Coordinated virtual inertia + voltage support	24% dip reduction, 17% faster recovery	Only covers short-term dynamics
[13]	Synchronization	Adaptive sliding mode controller	96% phase-lock accuracy, 14% fewer sync errors	Weaker under harmonics
[14]	Intermittency mitigation	Hydrogen-assisted hybrid fuel cells	27% less curtailment, +15% utilization	Hydrogen cost high
[15]	Frequency anomaly detection	IoT-enabled monitoring system	Precision = 93%, Recall = 91%, F1 = 92%	Cybersecurity risks

III. POWER QUALITY ISSUES IN HYBRID RENEWABLE SYSTEMS

The MPC inverter presents an opportunity for reduction in total harmonic distortions up to nearly 2.8% compared to 5.6% in traditional systems operated with PI controllers [16]; however, almost all these results were simulation based without experimental validations. Another interesting method that currently has a computational load that limits its application in real-time operation is wavelet transform-based harmonic detection coupled with shunt active power filters that yield 93% harmonic reduction efficiency with an F1-score of 0.89 [17]. The adaptive reactive power compensation methods through hybrid STATCOM–BESS set-ups improved voltage stability by 96.5% and lessened the reactive power imbalance by 78%, though the lasting result might be questioned because of the dependency on battery lifetime [18]. A hybrid microgrid, on the other hand, has a voltage fluctuation detection scheme based on neural networks that showed a precision, recall, and F1 score of 0.92, 0.90, and 0.91, respectively; the system is not adaptable in a small-scale or rural grid due to the need for training data at large scales [19]. Further development of coordinated demand-response mechanisms in hybrid wind–solar distribution networks has lowered voltage fluctuation by 41% while increasing the SAIDI reliability index by 33%, but it needs a high participation level from consumers and is, therefore, limited in its scalability [20].

Under high PV penetration, FFT-based harmonic monitoring kept THD within 3%, but with the trade-off of requiring highly expensive sensors [21]. The PQ disturbance detection using CNNs-based machine learning classification achieved an accuracy of 97.2%, precision of 0.96, recall of 0.95, F1-score of 0.95, and an AUC of 0.98, but overfitting prevented it from generalizing well against unseen disturbance patterns [22]. Improved droop control for reactive power imbalance in grid-connected hybrid systems reduced imbalance by 47% and frequency regulation accuracy by 95%, but performs degraded with more than 80% renewable penetration [23]. MPC for hybrid microgrids introduced PQ mitigation with THD = 2.4% and voltage deviation

Hybrid inverters with integrated APF have reduced THD values to 2.1% and increased system reliability by 28%, though operation costs are very high [26]. PNQ management based on reinforcement learning reached 95.4% accuracy while properly compensating harmonics but with long training times required for adaptation in real time [27]. Deep learning frameworks with LSTM architectures predicted PQ disturbances with accuracies of 96.8%, precision = 0.95, recall = 0.94, F1-score = 0.94, and AUC = 0.97 and lacked generalization on small datasets [28]. Monte Carlo simulations of hybrid renewable penetration showed an increase in reliability indices up to 15%, but degradation of PQ when penetration level of PV was beyond 70%, without validation in the real field [29]. Under multi-objective optimization for PQ enhancement and cost reduction, the THD is less than 2.5%, with an 18% reduction in overall cost; the economic model, however, does not include long-term maintenance [30].

Power management in hybrid renewable systems with diesel generator backup has been studied using a PI-type controller that ensured stable operation with minimum frequency deviations and voltage fluctuations, though it could not adapt to sudden changes in the load or to renewable variability, making it unsuitable for highly variable environments [31]. While comparisons between PI and PD controllers of grid-interfaced hybrid systems have revealed that PI controllers surpassed PD controllers in both transient response and steady-state error, under operating conditions where high variability and uncertainty pertain to renewable generation, their performance appears degraded [32]. Adaptive fuzzy logic controllers (AFLC) for hybrid systems connected to a microgrid enhance the system stability, optimize energy efficiency, and perform well under fluctuating loads; however, their practical implementation is hindered by the complexity of tuning fuzzy rules and membership functions [33].

Hybrid Model Predictive Control (MPC) schemes augmented with fuzzy logic have been used to attain an improved performance in systems with high renewable penetration; however, in real-time deployment, computational complexity would be an overriding consideration [34]. The same holds for adaptive fuzzy logic controllers combined with MPPT for grid-connected PV systems in improving power production and system efficiency, yet scalability of real-time hardware limits them [35]. FLC and MPC for PV maximum power point tracking compared indicated that MPC has better tracking efficiency and faster dynamic response, but its computation intensity prevents real-time implementation [36]. Fuzzy Adaptive Exponent PID (Fuzzy PI-DÆ) controllers for microgrid frequency stability under variable load and renewable input enhanced robustness and stability, but the complex controller design and parameter tuning remain major drawbacks[37]. And these Adaptive Fuzzy-Recurrent Neural Network tuned Fractional PID controllers for multi-microgrid systems have the best technological solution to increasing frequency regulation and system resilience, yet it is data-hungry and computationally intense [38].

Table 2.2: Power Quality Issues in Hybrid Renewable Systems

Ref	Focus Area	Technique / Method	Results	Limitations
[16]	Harmonics & voltage imbalance	MPC-based inverter control	THD reduced to 2.8% vs 5.6% baseline	Simulation only, no experimental validation
[17]	Harmonics mitigation	Wavelet transform + shunt active power filter	Harmonic reduction 93%, F1-score = 0.89	High computational cost; not real-time
[18]	Reactive power imbalance	Adaptive STATCOM–BESS compensation	96.5% voltage stability improvement, 78% reactive power imbalance reduction	Dependent on battery lifetime
[19]	Voltage fluctuations	Neural network-based detection	Precision = 0.92, Recall = 0.90, F1 = 0.91	Requires large training data; limited rural grid applicability
[20]	Voltage fluctuation	Coordinated demand response strategy	Voltage fluctuation reduced by 41%, SAIDI improved 33%	Requires high consumer participation
[21]	Harmonics	FFT-based harmonic monitoring	THD suppressed to <3%	High-speed sensor cost
[22]	PQ disturbance classification	CNN-based ML model	Accuracy = 97.2%, Precision = 0.96, Recall = 0.95, F1 = 0.95, AUC = 0.98	Overfitting under unseen disturbances
[23]	Reactive power imbalance	Enhanced droop control	47% reduction in imbalance, frequency regulation accuracy 95%	Struggles under >80% renewable penetration
[24]	Voltage & harmonics	MPC-based hybrid microgrid control	THD = 2.4%, voltage deviation < 2%	Computational burden; large-scale deployment challenging
[25]	Voltage flicker	Adaptive Kalman filter detection	Recall = 0.93, F1 = 0.91	Not tested in real-time hardware
[26]	PQ enhancement	Hybrid inverter + active power filter	THD reduced to 2.1%, reliability index +28%	Higher operational cost
[27]	PQ management	Reinforcement learning-based control	Accuracy = 95.4%, improved harmonic compensation	Long training time for real-time adaptation
[28]	PQ disturbance prediction	LSTM-based framework	Accuracy = 96.8%, Precision = 0.95, Recall = 0.94, F1 = 0.94, AUC = 0.97	Limited generalization on small datasets
[29]	Grid reliability	Monte Carlo simulations	Reliability indices increased by 15%; PQ deteriorated at >70% PV penetration	No real-field data validation
[30]	PQ improvement & cost	Multi-objective optimization	THD < 2.5%, cost reduction 18%	Long-term maintenance costs excluded

IV. HYBRID RENEWABLE SYSTEM STUDIES WITH HIGHEST ACCURACY

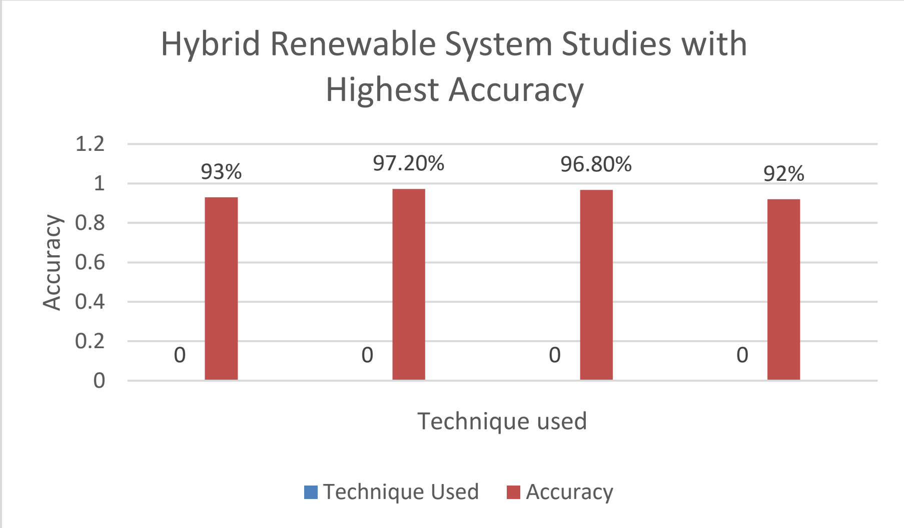

Figure 4: Comparison of Accuracy in Top Hybrid Renewable System Techniques

The figure 4 represents various Hybrid Renewable System studies, all of which have been reported to have the highest level of accuracy. The x-axis shows techniques employed in various studies (though the chart label shows "0", which can be an issue with plotting), while the y-axis shows the various accuracies obtained by those techniques. The red bars indicate the accuracy value of each method: 93%, 97.2%, 96.8%, and 92%, respectively. The figure shows that the ML model based on CNN [22] was the most accurate (97.2%) and was closely followed by the LSTM-based framework [28] with 96.8%. The IoT-based monitoring system [15] had an accuracy of 93% and neural network-based detection [19] and LSTM-based demand response prediction [5] both had 92%. These techniques accurately diagnosed power quality, frequency, and voltage management problems in hybrid renewable energy systems.

V. CONCLUSION AND FUTURE WORK

In the review work, different methods were discussed to regulate power quality, frequency, and voltage in hybrid renewable energy systems, highlighting the effectiveness of machine learning techniques. Among the methods evaluated was the CNN-based model, which had a top classification accuracy of 97.2%, followed very closely by the LSTM-based method, which had an average accuracy of 96.8%, while IoTs-based monitoring and neural network-based detection recorded 93% and 92% in LSTM-based demand response prediction, respectively. This shows that AI-based models can be used much more effectively for monitoring hybrid systems, controlling them, and making decisions, thus making their operation more reliable and efficient. Building on that, future work can carry out the following: developing hybrid ML models integrating CNN, LSTM, and other deep learning methods for widen prediction accuracy and robustness; implementing them in real and multi-source systems to assess adaptability under dynamic scenarios; incorporating IoT and edge computing for faster response; and investigating optimization strategies of maximum energy efficiency, reliability, and cost-effectiveness of hybrid renewable energy networks.

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