

# MACHINE LEARNING-ENABLED HYBRID INVERTERS FOR RENEWABLE ENERGY INTEGRATION IN SMART GRIDS: A REVIEW

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## ABSTRACT

The increasing integration of solar photovoltaic (PV) and wind energy into smart grids requires efficient power conversion, energy storage and adaptive energy-management strategies. Hybrid inverters provide an important interface for coordinating renewable generation, battery storage, local loads and grid interaction, while machine learning (ML) offers data-driven approaches for improving system operation. This review examines the applications of ML in renewable-energy forecasting, energy management, inverter control, storage coordination and power-quality improvement, with particular attention to PV–wind–battery hybrid inverter systems. The reviewed literature indicates that ML has been widely applied to individual functions such as solar forecasting, PV inverter control, energy optimisation, storage management and fault monitoring, but comparatively fewer studies integrate these functions within a common hybrid-inverter framework. An illustrative ANN-based supervisory control case is also discussed to demonstrate the potential of coordinated ML-based operation. The review identifies key research gaps related to integrated system design, real-time coordination, experimental validation and consistent performance evaluation. Overall, ML-based supervisory control shows potential for improving renewable-energy utilisation, grid interaction, power quality and hybrid-inverter performance.

**Keywords:** Hybrid Inverter, Smart Grid, Machine Learning, Artificial Neural Network, Renewable Energy Integration, Energy Management, Battery Energy Storage, Power Quality.

## 1. INTRODUCTION

A key characteristic of the development of modern electricity systems is the shift from fossil-fuel generation to generation by solar and wind energy [1]. Renewables can be utilized as distributed generation and can be integrated into grid-based power systems; however, they cannot be guaranteed because they rely on environmental factors. The output of PV cells depends on the solar irradiance and operating temperature, while the wind generation depends on the wind speed [2]. Renewable energy is not always available when it is most needed, which poses power balance, voltage stability and reliable grid interaction challenges.

Smart grids address these challenges by integrating advanced sensing, communication, power-electronic and control technologies to enable flexible coordination of generation, storage, load, and grid resources [3]. There are two factors particularly relevant. Energy-storage systems can capture excess renewable energy supplies and feed energy back into the electrical grid when renewable energy supplies are not available [4]; power-electronic inverters serve as the gateway between renewable energy supplies, AC loads, and the AC grid. The performance of the inverter such as the DC-link voltage regulation, power loss, harmonic distortion, synchronisation and exchange of power with the grid directly influences the overall system performance [5].

Traditional control methods that rely on static parameters or thresholds can work well for specific conditions, but don't necessarily flex when multiple renewable energy sources, battery status, and load demand are changing at the same time [6]. A data-driven approach is machine learning (ML) which learns the relationships between operating variables and the desired control response. In the field of smart grids, ML has been used in smart grid forecasting, smart grid optimization, smart grid control and smart grid intelligent decision making [7]. The studies have been carried out in various layers of RENs, such as prediction of renewable resources, monitoring of converter condition etc., but in few application areas.

### 1.1. Objectives of the Review

The following are the objectives of the review:

- To review the applications of machine learning in renewable-energy forecasting, energy management, inverter control, storage coordination and power-quality improvement.
- To examine the integration of PV, wind, battery storage and hybrid inverters in smart-grid systems and identify major research gaps.

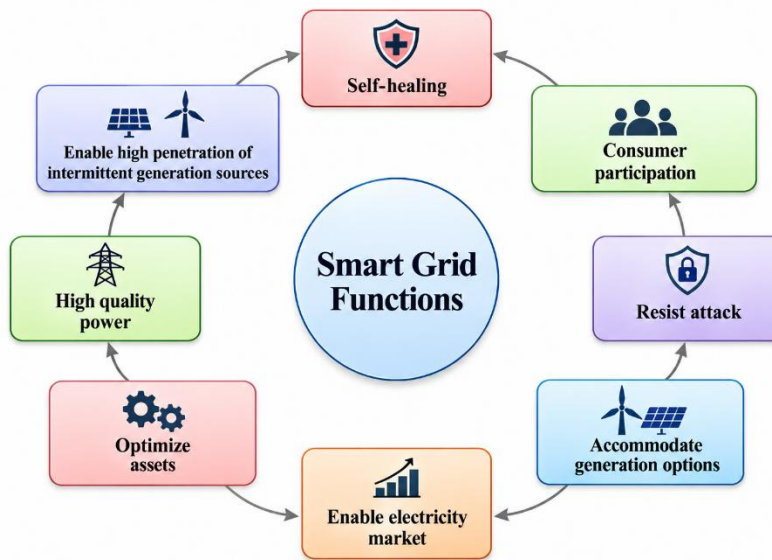
- To assess the potential of ML-based supervisory control for improving renewable utilisation, grid interaction, power quality and inverter performance.

## 2. RENEWABLE ENERGY INTEGRATION AND HYBRID SYSTEM ARCHITECTURE

For smart grids to integrate renewable energy, there needs to be a coordinated management of energy storage, power conversion and electricity demand [8]. PV–wind–battery hybrid systems offer an appropriate system architecture for integrating complementary renewable energy sources and storage together with grid support. In this section, the major challenges related to integration and the operating structure of hybrid renewable-energy systems with intelligent inverters are discussed.

### 2.1. Integration Challenges in Smart Grids

Solar PV and wind energy are two of the crucial renewable energy sources being looked at for smart-grid applications.



**Figure 1:** Smart Grid Functions [9]

Both can be deployed as distributed generation systems that can meet their local needs and lessen reliance on the conventional grid generation. However, their outputs are not guaranteed and the resulting mismatch between renewable power available and load demand must be addressed on an ongoing basis. If the renewable energy generation is greater than the load the excess can be used for battery charging or if the battery capacity is exceeded the excess can be exported to the grid [10]. If the renewable generation is not enough, the battery may be used to discharge to meet the demand, and the rest of the demand can be met by importing it from the grid.

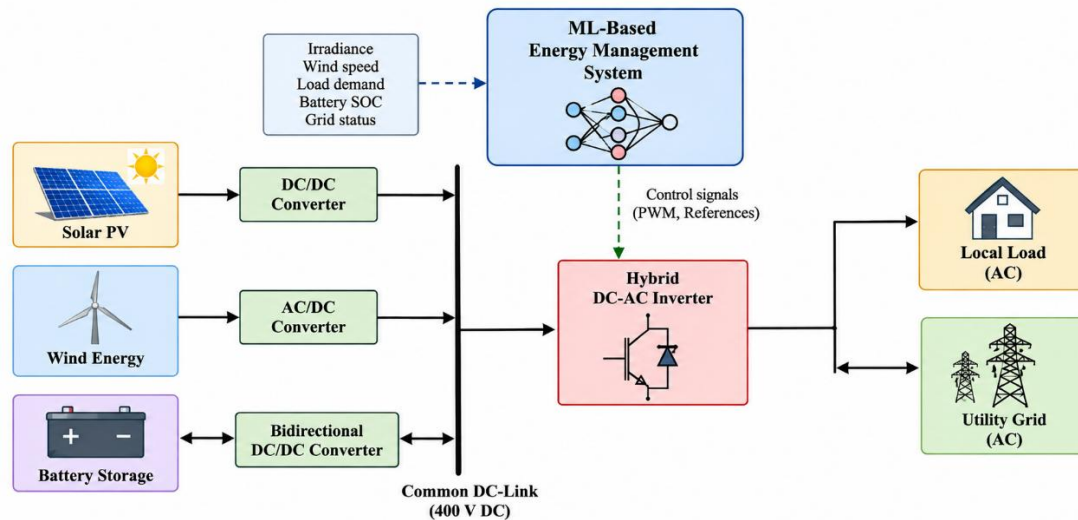
These are all factors that an energy-management system needs to take into account when sizing the renewable energy generation, the load demand, the battery state of charge (SOC) and grid requirements. The effectiveness of renewable integration is then dependent on both the generation sources and coordination of storage and power-conversion equipment and the grid. Intelligent energy-management methods can help this coordination with varying generation and demand.

### 2.2. Hybrid PV–Wind–Battery–Grid Configurations

Hybrid renewable-energy system: A combination of two or more energy sources and storage and power-conversion components that are arranged in a coordinated manner to provide an electricity supply [11]. PV and wind generation can be used together, which means that the energy produced can be generated from alternative renewable resources and can increase the availability of renewable energy as compared to dependence on a single energy source. In the literature, several configurations are studied, such as PV/wind microgrids, grid-connected PV–wind–battery systems, PV–wind systems for electric-vehicle charging stations and hybrid systems that incorporate weather-forecast information.

The general structure of PV–wind–battery–grid is formed by a PV array and a wind turbine which are connected to the same DC-link via proper power-conversion stages, and the battery is connected to the DC-link via a

bidirectional converter. A hybrid DC-AC inverter will provide the local load as well as power exchange with the utility grid at the point of common coupling (PCC). The overall architecture of the ML based PV–wind–battery hybrid inverter system is shown in Figure 2, which comprises of renewable sources, battery storage, common DC-link, hybrid inverter, grid interface and ANN based energy-management layer.

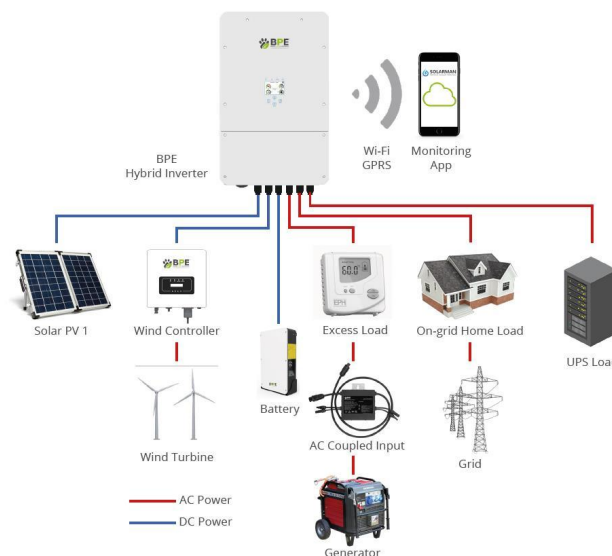


**Figure 2:** Architecture of an ML-based PV–wind–battery hybrid inverter system [12]

The four parts of the system to consider are: Renewable generation, Battery storage, Battery consumption and battery grid trading. The first power usage step is to meet the load with renewable energy when enough renewable energy is generated. Excess energy can be stored in the battery or sent back to the grid, while renewable energy generation falls short of demand, the battery can provide electricity and support the grid. As the operating requirements of each component can be affected by changes in the other, it is necessary to have a coordinated energy management in order to ensure a stable and efficient operation of the entire system.

### 3. HYBRID INVERTER TECHNOLOGY AND POWER QUALITY

The main power-conversion interface between the DC side renewable energy system and the AC side load and utility grid is the hybrid inverter [13]. It is based on the coordinated power conversion, voltage regulation, grid synchronisation and power quality management. In this section, the main functional parts of hybrid inverters and the important performance parameters of operation are discussed.



**Figure 3:** Functioning of Hybrid Inverter [14]

The hybrid inverter takes power from the PV system, wind system and battery and switches it to controlled AC power on the common DC-link. Its main functional stages are: DC-link, switching bridge, pulse-width modulation (PWM) for producing switching signals, grid synchronisation and an output filter between the inverter and the point of common coupling (PCC) to remove switching-frequency components.

Stability of the DC link voltage is important, especially as the demand from the load goes up or down, or renewable energy is generated. Very high variations of the DC link can have an impact on the quality and stability of the AC output. When the PV system is connected to the grid, the inverter should be synchronised with the grid's frequency and phase. This need is growing more and more as the use of power-electronic interfaces in renewable energy systems grows. The use of machine-learning based approaches has therefore been investigated for the application of virtual inertia and dynamic control to enhance the response of grid connected renewable systems.

Another main issue is power quality as the inverter switching may add harmonic elements to the AC wave. Intelligent MPPT and multilevel-inverter techniques can be used to enhance the extraction of renewable energy and to reduce the harmonic distortion under changing operating conditions [15]. Predictive methods can also be used to estimate the harmonic characteristics and assist in taking proactive steps in power-quality management. Power-electronic converters link renewable energy sources to the electrical network and are also of interest for their condition of operation for system reliability. The monitoring methods based on the ML can help in the detection of abnormal converter conditions and may help with timely maintenance and/or control actions.

Typical performance indicators for the hybrid inverter are the DC link voltage deviation, total harmonic distortion (THD), power loss, efficiency, utilisation of renewable energy, exchange and response of power with the grid, and response time. They are all indicators of different aspects of electrical quality, energy conversion performance and response of energy control.

#### **4. MACHINE LEARNING IN RENEWABLE ENERGY MANAGEMENT AND CONTROL**

Machine learning is utilized in various aspects of renewable-energy systems, such as forecasting, energy management, inverter control, storage coordination and system monitoring. The applications could be broadly classified based on the primary job that ML is used to do.

##### **4.1. Forecasting of Renewable Generation**

The weather conditions have a high impact on PV and wind generation, so it has a significant impact on energy balancing and scheduling [16]. History of generation and weather data can be used to make predictions of future renewable generation using ML models to help with operational planning.

Solar forecasting using hybrid ML models and AE-LSTM approaches have been used. Other methods concentrate on improving grid stability and forecasting the renewable supply in off-grid hybrid systems. Hybrid system design and energy-management decisions can also be assisted by the use of ML-based weather forecasting. But forecasting is largely mainly information and a separate decision-making layer is needed to turn predictions into real-time power-flow control.

##### **4.2. Energy Management and Optimisation**

ML can directly aid in energy-management decisions by figuring out where the available energy should go: renewable energy, battery storage, local loads, or the utility grid. This is especially helpful in the presence of continuous changes in the renewable generation and load demand [17].

Hybrid-inverter and storage coordination, PV–wind–battery management, EV-charging systems and smart-grid energy optimisation are examples of application areas for ML-based approaches. Other studies have used deep learning for renewable integration, and for microgrid operation. Overall, these approaches demonstrate that ML can help enhance adaptive energy allocation, with many of them being application-specific and without direct coordination in detailed hybrid-inverter operation.

##### **4.3. Intelligent Inverter Control & Power Quality**

Inverter-control layer, ML is being increasingly used to enhance the electrical performance and converter response under varying conditions [18]. PV/wind microgrid, grid-connected PV, reactive-power management and voltage improvement are the applications of AI and ANN based approaches.

Other smart technologies are related to MPPT, multilevel conversion, virtual inertia and prediction of harmonics. The applications here illustrate the promise of ML in the renewable-energy extraction and power delivery ranges of

the grid. Many of the studies are, however, still limited to PV based systems and do not take into account the coordination of wind generation and battery storage and grid exchange.

#### 4.4. Storage Management, Reliability and Monitoring

Energy Storage is a means to match the fluctuations in renewable energy and load. ML can assist in making battery charging and discharging decisions whilst taking into account operating conditions of the system.

Another application in the area of hybrid-storage coordination and fault prediction and converter monitoring used ML. These can enhance system awareness and reliability. In contrast, most studies on storage management and fault detection and monitoring have been conducted in isolation from renewable generation, inverter control and grid exchange in a single real-time management system.

### 5. CRITICAL DISCUSSION OF THE REVIEWED LITERATURE

The literature reviewed indicates that ML is being used for renewable-energy forecasting, energy management, coordinating energy storage, controlling the inverter and improving power quality. However, such functions are not studied together in a single framework of integrated hybrid-inverter system. A summary of selected studies related to ML-based renewable energy and hybrid inverter systems is given in Table 1.

**Table 1:** Critical Review of Selected Studies

| Reference            | Focus                                 | ML Application               | Key Contribution                                         | Limitation                                      |
|----------------------|---------------------------------------|------------------------------|----------------------------------------------------------|-------------------------------------------------|
| Kiasari et al. [19]  | Renewable integration and smart grids | ML and energy storage        | Reviews ML and storage for renewable integration         | Broad review; no specific inverter architecture |
| Shankara et al. [20] | Hybrid inverter and storage           | ML-based energy management   | Optimises storage and hybrid-inverter operation          | Limited coordination of wind, load and grid     |
| Yao et al. [21]      | Smart-grid efficiency                 | ML-based energy efficiency   | Reviews ML for energy-efficient smart grids              | Does not focus on an integrated hybrid inverter |
| Haque & Malik [22]   | Renewable energy in smart cities      | ML-based management          | Examines ML applications in smart-city renewable systems | Limited inverter-level analysis                 |
| Sakthi et al. [23]   | PV–wind hybridisation                 | ML-based analysis            | Examines PV and wind renewable integration               | Limited battery and supervisory control         |
| Zulu et al. [24]     | PV/wind power quality                 | AI, inverter control and ANN | Improves inverter control and power quality              | Further storage and grid coordination required  |

The studies indicate three main limitations. First, many people only look at PV or at a wide range of renewable-energy applications, and only consider wind, battery storage and grid exchange at the same time for a small number. Second, there are several studies that focus on a single function (optimisation, energy efficiency or power quality) and not on real-time coordination of the whole power flow. Thirdly, general review papers give some insights but don't address a certain integrated hybrid-inverter architecture.

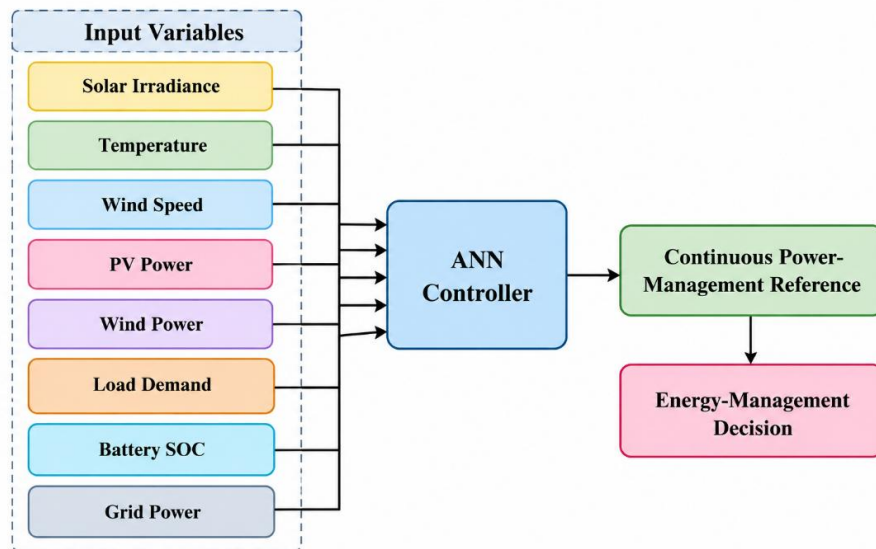
The overall literature reflects an increased use of ML in adaptive control and management of renewable energy, and in inverter control. However, there is potential for a supervisory ML framework that can control the operation of the battery, local load, inverter control and interaction with the grid while controlling renewable generation.

### 6. ANN-BASED SUPERVISORY CONTROL OF A HYBRID INVERTER

A Simulink simulation case for a combined renewable-energy system is used to illustrate the integrated approach to ML, discussed in the review. The case is a blend of renewable energy generation, battery storage, inverter operation, and interaction with the grid under a supervisory energy-management system based on ANN [25].

The system consists of a 5-kW PV source, 3-kW wind source and 10-kWh battery with an initial state of charge (SOC) of 55%. All these components are linked together using a common 400-V DC-link and an 8-kW hybrid inverter with 10kHz switching frequency. The inverter is connected to a 230/400-V, 50-Hz utility grid. The

supervisory energy-management part is an ANN. It has eight inputs including solar irradiance, temperature, wind speed, PV power, wind power, load demand, battery SOC and grid power. The ANNs-based energy-management model is shown in figure 4 along with the interaction between the hybrid inverter system.



**Figure 4:** Structure of the ANN-based energy-management model [26]

The ANN returns a reference voltage for power management, not a power management string of charges, discharges or grid commands. The reference is then used by the inverter-control layer to create the desired control signals. A “conventional” PI-controlled configuration with the same main system parameters is taken as a reference configuration.

During the simulation, PV output increased from 0.95 kW at 200 W/m<sup>2</sup> to 4.85 kW at 1000 W/m<sup>2</sup>, while wind output increased from 0.45 kW at 4 m/s to 2.85 kW at 12 m/s. The battery acted as a buffer to clean up excess electricity when renewable energy production outpaced consumption, and to compensate for electricity generation shortfalls. The grid was able to provide support for renewable generation and battery support when needed [27].

Under low generation conditions, there was a 78.9% utilization of renewable energy, which rose to 90.2% for medium generation and 94.7% for high generation conditions. The ANN reproduced the reference power-management signal with an MAE of 0.083 kW, RMSE of 0.110 kW, R<sup>2</sup> of 0.982 and prediction accuracy of 97.8%. The reference was generated by the ANN in 12ms. This value is the prediction time spent by the ANN and differs from the overall inverter response time which is 18-ms.

The ML proposed configuration demonstrated better results on the reported performance indicators than the conventional PI configuration in the given simulation settings. It also maintained a high efficiency under low, medium and high load and under variable loads, at 97.0% with high renewable energy generation.

The results show how an ANN based supervisory layer can help to coordinate the operation of renewable generation, battery and grid interaction and give a reference to the inverter control. The results, however, are applicable only to the specific MATLAB/Simulink simulation (which is given as a 10-second simulation, and also to the operating conditions that are given). These are therefore a simulation-based assessment and not hardware or grid validation. Extensive experimentation would be necessary to evaluate the performance of the proposed method in the presence of realistic hardware limitations, measurement noise, communication delay and varying grid characteristics.

## 7. RESEARCH GAPS, CHALLENGES AND FUTURE DIRECTIONS

The review reveals a significant gap in the small integration of renewable generation, energy storage, and ML-based energy management and hybrid-inverter control all into one smart-grid framework. Previous research has made progress in the aspects of solar forecasting, PV inverter control, storage management, harmonic prediction, and microgrid optimisation, but these are not necessarily integrated with PV, wind generation, local load, battery storage, and grid interaction [29]. Another blind spot is insufficient direct control of the inverter by the ML based supervisory energy management system. Future systems, using ANN or other ML systems, can take into account

renewable generation, load demand, battery SOC and grid conditions, and continuously send inputs to the inverter-control layer.

There are also a number of issues to be addressed. Most of the reported results are simulation based, and actual implementation and validation in real grid is needed. Future research is required to investigate the performance of ML-based controllers compared to conventional controllers under the same conditions using consistent benchmarks like renewable use, grid exchange, stability of the DC link, THD, power loss, efficiency and response time [30]. Energy management can also be combined with reliability monitoring, fault prediction and power quality prediction. Integrated ML-based hybrid-inverter architectures can be further verified in various applications, including EV charging, alternative energy storage systems and off-grid applications to explore their adaptability and generalisation.

## 8. CONCLUSION

This review analysed 30 papers related to the use of ML in smart grid renewable energy management and control, focusing on hybrid inverters. The literature clearly indicates that ML can be applied for enhanced forecasting, energy allocation, inverter control, power quality, storage coordination and fault awareness, as well as can solve some limitations of fixed-parameter or threshold-based control. However, most studies only cover one function or just one energy source, and few combine PV, wind, battery storage, inverter operation and energy exchange with the grid into a single smart energy management approach. The illustrative simulation case shows that an ANN-based supervisory controller can improve the utilization of renewables, decrease the grid import, DC-link deviation, THD and power loss compared to PI control, and increases efficiency and response time. The results obtained are based on simulation, and future research should focus on experimental validation, on the other hand, energy management in combination with power-quality and reliability functions, as well as on consistent performance reporting, so that the different approaches can be fairly compared.

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