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Optimizing Energy Storage and Hybrid Inverter Performance in Smart Grids Through Machine Learning

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Received: 06-20-2024 **Revised:** 07-30-2024 **Accepted:** 08-13-2024

Citation: K. H. Shankara, M. Srikantaswamy, and S. Nagaraju, "Optimizing energy storage and hybrid inverter performance in smart grids through machine learning," *Inf. Dyn. Appl.*, vol. 3, no. 3, pp. 146–161, 2024. https://doi.org/10.56578/ida030301.

Abstract: The effective integration of renewable energy sources (RES), such as solar and wind power, into smart grids is essential for advancing sustainable energy management. Hybrid inverters play a pivotal role in the conversion and distribution of this energy, but conventional approaches, including Static Resource Allocation (SRA) and Fixed Threshold Inverter Control (FTIC), frequently encounter inefficiencies, particularly in managing fluctuating renewable energy inputs and adapting to variable load demands. These inefficiencies lead to increased energy loss and a reduction in overall system performance. In response to these challenges, the Optimized Energy Storage and Hybrid Inverter Management Algorithm (OESHIMA) has been developed, employing machine learning for real-time data analysis and decision-making. By continuously monitoring energy production, storage capacity, and consumption patterns, OESHIMA dynamically optimizes energy allocation and inverter operations. Comparative analysis demonstrates that OESHIMA enhances energy efficiency by 0.25% and reduces energy loss by 0.20% when benchmarked against conventional methods. Furthermore, the algorithm extends the lifespan of energy storage systems by 0.15%, contributing to both sustainable and cost-efficient energy management within smart grids. These findings underscore the potential of OESHIMA in addressing the limitations of traditional energy management systems (EMSs) while improving hybrid inverter performance in the context of renewable energy integration.

Keywords: Hybrid inverter; Energy storage optimization; Machine learning algorithms; Smart grids; Renewable energy management; Real-time data processing; Dynamic energy distribution

1 Introduction

The integration of RES into power grids has become a key focus in the quest for sustainable energy solutions. Hybrid inverters, which combine multiple energy sources like solar and wind, play a critical role in converting and distributing this energy effectively within smart grids. As the demand for clean and renewable energy grows, optimizing the performance of hybrid inverters and energy storage systems has become increasingly important to ensure efficient energy management and reliability in smart grids [1, 2]. Recent trends in the energy sector highlight a significant shift towards the adoption of smart grid technologies, which leverage advanced data analytics, machine learning, and Internet of Things (IoT) to enhance energy distribution and consumption. Machine learning algorithms have been particularly gaining attraction in optimizing various aspects of smart grid operations, including energy storage management, load forecasting, and inverter performance. These technologies enable real-time monitoring and decision-making, allowing for dynamic adjustments that enhance the efficiency and stability of the grid. Applications of these advanced techniques are wide-ranging, including residential solar power systems, industrial energy management, and large-scale renewable energy farms. In these settings, hybrid inverters are utilized to manage the flow of energy between the grid, energy storage systems, and consumers, ensuring that energy is distributed efficiently according to demand. By integrating machine learning algorithms, these systems can predict energy consumption patterns, optimize storage utilization, and reduce energy losses, leading to more resilient and sustainable energy infrastructure [3, 4].

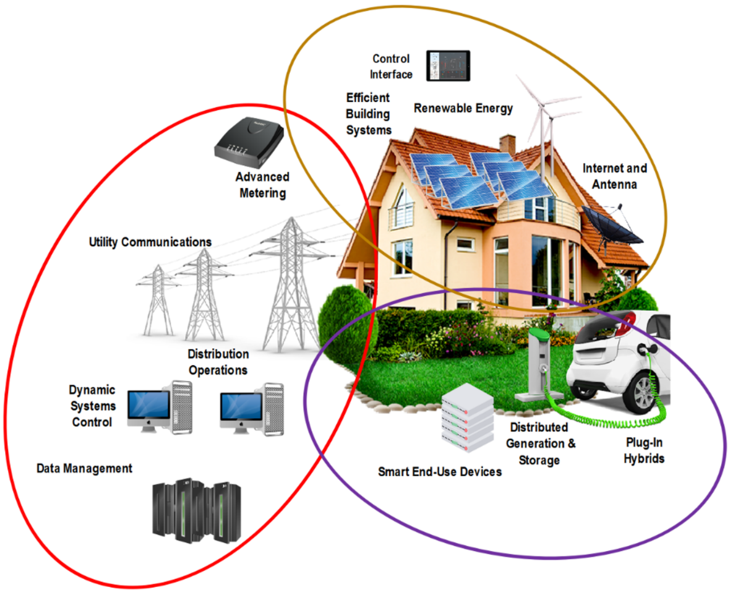

Figure 1. Structural layout of smart grid energy management

Figure 1 illustrates a comprehensive integration of various components within a smart grid system, focusing on the interplay between a residential building equipped with RES, advanced metering infrastructure (AMI), and utility operations. At the center of the image is a residential home, which features solar panels and a wind turbine, symbolizing the use of RES. This energy can be used within the household, stored in distributed energy storage systems, or fed back into the grid, contributing to the overall energy efficiency and sustainability of the grid system. Inside the house, the image depicts a control interface that represents the EMS. This system is responsible for optimizing energy consumption, managing the generation and storage of energy, and coordinating with other smart devices in the home. The image also highlights the integration of distributed generation and storage systems with plug-in hybrid vehicles, showing how energy can be stored during periods of low demand and used or fed back into the grid when needed [5].

On the left side of the image, AMI is shown connected to utility communication systems, which facilitate the real-time exchange of data between the residential EMS and utility providers. This connection enables dynamic pricing, demand response, and efficient distribution operations. The bottom left of the image depicts the back-end infrastructure, including servers and computers, symbolizing data management and dynamic system control. These systems ensure that energy generated, stored, and consumed is efficiently monitored, managed, and optimized to maintain reliability and efficiency across the grid [6].

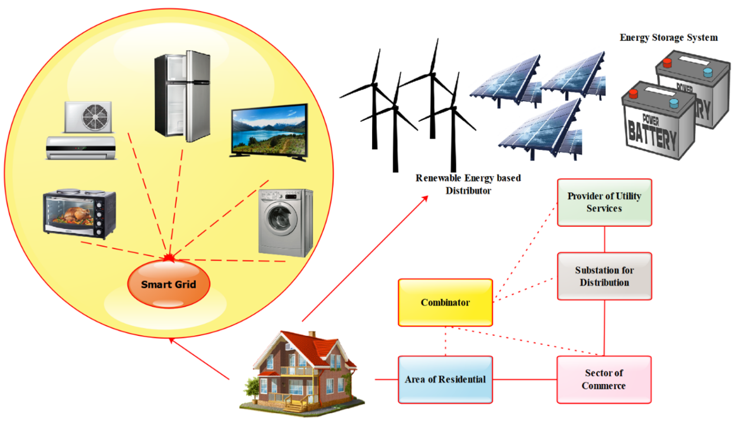

Figure 2. Fundamental architecture of the hybrid inverter for a smart grid

Figure 2 illustrates a comprehensive representation of a smart grid system that integrates various energy sources, storage systems, and end-use devices within a residential and commercial environment. At the center of the image is the smart grid, which serves as the core for managing the flow of electricity and information between different components of the grid.

To the left, within the yellow circle, various household appliances can be observed such as refrigerators, air conditioners, televisions, ovens, and washing machines. These devices are connected to the smart grid, allowing for efficient management of energy consumption within the home. The smart grid optimizes energy usage by controlling these appliances based on real-time data, ensuring energy efficiency and reducing unnecessary power consumption [7]. On the right side of the image, the renewable energy-based distributor is depicted, including wind turbines, solar panels, and energy storage systems like batteries. These RES are integrated into the smart grid, providing clean and sustainable energy to power the household appliances. The energy storage systems play a critical role in storing excess energy generated from renewable sources, which can be used during periods of high demand or when renewable generation is low [8, 9].

Below the energy generation and storage systems, the combinator serves as a central point where energy from different sources is combined and distributed efficiently. This energy is then routed to different sectors, including residential areas and commercial sectors, ensuring that both homes and businesses have a reliable supply of electricity. To the right of the combinator, the provider of utility services and substation for distribution are responsible for distributing electricity from the grid to end-users. These components ensure that the energy generated from renewable sources and stored in batteries is effectively delivered to residential and commercial sectors, maintaining a stable and reliable power supply [10, 11].

1.1 Research Gaps

Despite the advancements in hybrid photovoltaic (PV) storage systems and energy management, several research gaps remain that need to be addressed to further optimize these systems. One significant gap is the challenge of dynamically adapting to variable load demands. Existing EMSs often struggle to efficiently handle rapid fluctuations in energy consumption, which can lead to inefficiencies. Research is needed to develop more adaptive EMS algorithms that can predict and respond to these changes in real-time, thereby enhancing overall system performance [12, 13].

Another area that requires attention is the integration of multiple RES within a single hybrid system. Most current systems focus on solar PV and battery storage, with limited integration of other renewable sources like wind or biomass. Exploring how to effectively design systems that manage energy from multiple sources simultaneously presents a valuable research opportunity. Additionally, the accuracy of energy generation forecasting is crucial for optimizing energy storage and distribution. However, existing methods may not fully account for sudden weather changes, suggesting a need for more precise forecasting models, possibly leveraging machine learning or artificial intelligence (AI) [14].

Another critical research area is to optimize battery storage utilization and extend its lifespan. While batteries are essential for energy storage, there is a lack of comprehensive studies on advanced battery management techniques that can optimize charging/discharging cycles and predict maintenance needs to reduce degradation and improve performance. Furthermore, the lack of standardization and interoperability among different EMS technologies and smart grid components poses integration challenges. Developing standardized protocols that ensure seamless communication and operation across various systems could significantly enhance efficiency. Scalability is also a concern, as scaling hybrid PV storage systems for larger applications, such as commercial or industrial use, remains complex and costly. Research could focus on finding cost-effective solutions that maintain high performance while enabling broader deployment. Additionally, as smart grids increasingly rely on real-time data communication, cybersecurity and data privacy have become critical issues. Addressing these vulnerabilities through research can ensure the secure and reliable operation of EMSs, safeguarding sensitive user data from cyber threats [15].

Lastly, the environmental impact of battery production, usage, and disposal is an area that requires more research. Developing sustainable energy storage solutions, such as environmentally friendly batteries or alternative storage technologies with lower ecological footprints, is essential for reducing the overall environmental impact of these systems. Addressing these research gaps can contribute to the development of more efficient, resilient, and sustainable hybrid PV storage systems, advancing the broader adoption of renewable energy technologies in smart grids [16].

1.2 Recent Trends and Applications

Recent trends in smart grid technologies are significantly shaped by the integration of machine learning and AI for optimizing energy management. These advanced techniques allow for predictive analytics, which greatly improve the accuracy of energy demand forecasts and renewable energy generation predictions. AI-driven algorithms facilitate real-time decision-making, enhancing the adaptability of energy storage and inverter systems to dynamic grid conditions. Additionally, there is a notable shift towards hybrid energy systems that integrate multiple renewable sources, such as solar, wind, and biomass. This diversification of the energy mix enhances the reliability and efficiency of energy supply by optimizing the use of available resources. Another key trend is the advancement of smart inverter technology, which now includes sophisticated control algorithms like OESHIMA. These smart inverters not only efficiently convert direct current (DC) to alternating current (AC) but also support grid operations by providing voltage regulation, frequency control, and reactive power compensation.

Energy storage optimization is also gaining prominence, with recent efforts focusing on maximizing the utilization and longevity of battery storage systems. Techniques such as adaptive battery management and predictive maintenance are employed to reduce battery degradation, extend lifespan, and enhance overall system performance. Real-time monitoring and control have become essential aspects of modern smart grids, facilitated by IoT devices and advanced communication protocols. These systems dynamically adjust operations based on real-time data regarding energy generation, consumption, and storage conditions, ensuring optimal performance and efficiency. In addition, there is growing emphasis on sustainability and cybersecurity within smart grid components, including energy storage and inverters. Environmentally friendly energy storage solutions are being actively researched to enhance sustainability, while advanced cybersecurity measures are being developed to safeguard critical grid data and operations from potential cyber threats.

The applications of these technologies are diverse and impactful. In residential settings, hybrid inverters and energy management algorithms are increasingly utilized to manage solar PV systems and battery storage, allowing homeowners to maximize self-consumption of generated energy, reduce grid dependency, and lower energy costs. In industrial and commercial buildings, these technologies optimize energy usage, mitigate peak demand charges, and integrate RES more effectively, thereby maintaining power quality and reliability. Hybrid inverters and advanced EMSs are also crucial in microgrids and remote areas where stable energy supply is essential and grid connectivity is often limited. These technologies enable efficient local energy management, ensuring stability and reducing the need for costly grid expansions.

Furthermore, the integration of smart inverters and energy storage optimization extends to electric vehicle (EV) charging infrastructure, where they help manage loads, optimize charging times, and balance supply-demand dynamically based on grid conditions. At the utility scale, hybrid inverters and algorithms like OESHIMA are employed in large-scale solar and wind farms to manage energy flow, stabilize grid operations, and facilitate the efficient integration of renewable energy into the main power grid. These applications underscore the importance of smart grid technologies in enhancing energy efficiency, reliability, and sustainability across various contexts of energy management.

2 Related Work

Abbas et al. [17] proposed an efficient reactive power dispatch method for PV and superconducting magnetic energy storage (SMES) systems in utility grids. The innovation lies in optimizing reactive power sharing between smart inverters, enhancing energy efficiency, and reducing thermal stress on the inverters. However, the method's implementation may be complex due to the need for accurate estimation of power losses, and there is a potential challenge in integrating the proposed system with existing grid infrastructure. Billah et al. [18] introduced a robust Multi-Agent System (MAS) technique for efficient and automated control of hybrid microgrids, incorporating RES, a diesel generator, and a battery storage system. The system optimizes performance under various climatic conditions using Particle Swarm Optimization (PSO). The main drawback is the complexity of implementing MAS and PSO in real-world microgrids, particularly in scenarios with highly variable climatic patterns. Hossain et al. [19] presented a novel multi-objective reliability assessment for smart grids in Saudi Arabia, integrating Battery Energy Storage (BES), Solar Photovoltaic (SPV), and wind systems. The innovation includes the use of Hobbled Shepherd Optimization (HSO) and Multi-Objective Based Golden Eagle (MOGE) algorithms to improve grid reliability and reduce power loss. However, the approach may face challenges in scalability and practical implementation, particularly in diverse and dynamic grid environments. Francisco et al. [20] explored the use of Digital Twins (DTs) for optimizing the charging processes of EV fleets in smart grids. Their innovation lies in employing DTs to simulate and predict energy demands, improving self-consumption and reducing operational costs. A significant drawback is the potential difficulty in accurately modeling real-world scenarios and integrating DTs with existing EV charging infrastructures.

Rahman et al. [21] proposed a vehicle-to-microgrid (V2M) framework for commercial localities, optimizing EV storage coordination using a distributed EV storage controller. The innovation includes a power flow management strategy that enhances system resilience during transitions between islanded and grid-tied conditions. However, the distributed nature of the system may introduce complexity and challenges in communication and coordination among multiple EVs. Ghazanfari et al. [22] proposed a hierarchical active power management strategy for medium voltage islanded microgrids, featuring a multihybrid power conversion system (MHPCS). The innovation lies in the integration of fuel cells and supercapacitors for enhanced power management and load sharing. The primary drawback is the complexity of implementing and maintaining the proposed control strategy, particularly in medium-voltage microgrids with diverse power sources. Song et al. [23] introduced a methodology for modeling the interoperability of smart sensors in smart grids using labeled transition systems and finite state processes. The innovation focuses on quantitatively measuring and improving interoperability, particularly in phasor measurement unit-based smart sensors. A drawback is the potential complexity in applying this methodology to different communication protocols and ensuring broad compatibility across various smart grid systems. Khan et al. [24] investigated the feasibility of positioning superconducting fault current limiters (SFCLs) in smart grids, using a Simulink and Sim Power System integrated model. Their innovation addresses the reduction of abnormal fault currents and optimal SFCL placement in microgrids. However, the study may face challenges in practical implementation, particularly in accurately determining the optimal placement of SFCLs across different types of smart grids. Orlando et al. [25] proposed a distributed metering infrastructure for smart grids, focusing on bidirectional communication, self-configuration, and auto-update capabilities. The innovation lies in the ability of the smart meters to run algorithms for smart grid management, even using off-the-shelf hardware. A significant drawback is the potential latency introduced by data transmission over the Internet, which could affect the operational efficiency of the smart grid. Zamani et al. [26] investigated the impact of connectivity on transactive energy in smart grids, proposing a connectivity index for Local Energy Networks (LENs). The innovation focuses on enhancing energy transactions through improved connectivity strength among prosumers. However, the approach may face challenges in practical application, particularly in real-time monitoring and maintenance of connectivity in highly dynamic energy markets [27].

2.1 Existing Mathematical Model

2.1.1 Power flow equation for the inverter

The AC power output (P_{AC}) is delivered to the household load or the grid after considering the inverter's efficiency (η_{Inverter}) [28–35]. It accounts for the DC power from the PV system (P_{PV}) and the battery discharge power ($P_{\text{Battery}}^{\text{discharge}}$), while subtracting the power consumed by the load. The power flow through the inverter, accounting for its efficiency and conversion between DC and AC power, is represented as follows:

$$P_{\text{AC}} = \eta_{\text{Inverter}} \times \left(P_{\text{PV}} + P_{\text{Battery}}^{\text{discharge}} - P_{\text{Load}} \right) \tag{1}$$

2.1.2 Battery State of Charge (SOC) dynamics

The dynamics of the SOC at the subsequent time step (t+1) are influenced by multiple factors. The SOC considers the charging efficiency (η_{charge}) and the excess power from PV generation ($P_{\text{PV}}^{\text{excess}}$) that is used to charge the battery. It also considers the discharge efficiency ($\eta_{\text{discharge}}$) and the power drawn by the load that exceeds the PV generation, which discharges the battery. Δt represents the time interval [36–40]. The SOC of the battery over time, considering both charging and discharging processes, is expressed as follows:

$$\text{SOC}(t+1) = \text{SOC}(t) + \frac{\eta_{\text{charge}} \times P_{\text{PV}}^{\text{excess}} - \frac{P_{\text{Load}} - P_{\text{PV}}}{\eta_{\text{discharge}}}}{C_{\text{Battery}}} \times \Delta t \tag{2}$$

2.1.3 Optimal power dispatch for hybrid systems

The optimal power dispatch from the PV and battery storage can be derived from minimizing the cost function subject to power balance constraints.

$$\min_{P_{\text{Grid}}, P_{\text{Battery}}} \left\{ C_{\text{Grid}} \times P_{\text{Grid}}(t) + \frac{1}{2} \lambda \left(P_{\text{PV}} - P_{\text{Load}} + P_{\text{Battery}}(t) \right)^2 \right\} \tag{3}$$

Eq. (3) represents an optimization problem where the objective is to minimize the total cost, including the cost of drawing power from the grid ($C_{\text{Grid}} \times P_{\text{Grid}}(t)$) and the penalty for deviation from the power balance (λ). The power balance involves PV generation (P_{PV}), load demand (P_{Load}), and battery power (P_{Battery}). This approach ensures optimal energy dispatch between the grid, PV, and battery to meet the load requirements efficiently [41–45].

2.1.4 Reactive power compensation using Distributed Static Compensator (DSTATCOM)

In systems with DSTATCOM for reactive power compensation, the reactive power supplied by the DSTATCOM is represented as follows:

$$Q_{\text{DSTATCOM}} = V_{\text{DSTATCOM}} \times I_{\text{DSTATCOM}} \times \sin(\theta) \tag{4}$$

The reactive power (Q_{DSTATCOM}) provided by the DSTATCOM is crucial for voltage regulation in the grid. V_{DSTATCOM} and I_{DSTATCOM} are the voltage and current at the DSTATCOM, respectively, and θ is the phase angle between them. This compensation helps maintain power quality and reduces losses in the grid [46–48].

2.1.5 EMS optimization function

The EMS can be modeled to optimize energy flow with the following cost function, integrating time-of-use pricing, as follows:

$$\min \sum_{t=1}^{T} \left[\pi_{\text{Grid}}(t) \times P_{\text{Grid}}(t) + \pi_{\text{Battery}}(t) \times P_{\text{Battery}}(t) + \pi_{\text{PV}}(t) \times P_{\text{PV}}(t) \right] \tag{5}$$

This optimization function minimizes the total energy cost over a time horizon T, considering time-of-use pricing ($\pi_{\text{Grid}}(t)$, $\pi_{\text{Battery}}(t)$, $\pi_{\text{PV}}(t)$) for grid energy, battery usage, and PV generation, respectively. The EMS uses this function to decide the optimal energy dispatch strategy at each time step, balancing cost and energy availability [49–55].

3 Proposed Architecture of the OESHIMA in a Smart Grid System

The proposed system, as depicted in Figure 3, integrates RES such as SPV panels and wind turbines with a BES system to create a highly efficient and reliable energy management solution. The system is centered around the OESHIMA, which leverages real-time data and machine learning techniques to dynamically manage energy flow within a smart grid environment. At the core of the system, the DC bus acts as a central hub where electricity generated by the solar PV panels and wind turbines is collected. This energy, initially in DC form, is then routed to multiple inverters, which convert it into AC suitable for household use or for feeding back into the power grid. The inverters operate in coordination with each other, allowing for flexibility and redundancy in energy conversion. The system's BES plays a critical role by storing excess energy during periods of low demand, ensuring that this energy can be used later when demand increases or when renewable generation is insufficient. The battery management block within OESHIMA optimizes the charging and discharging cycles of the battery, maximizing its efficiency and lifespan.

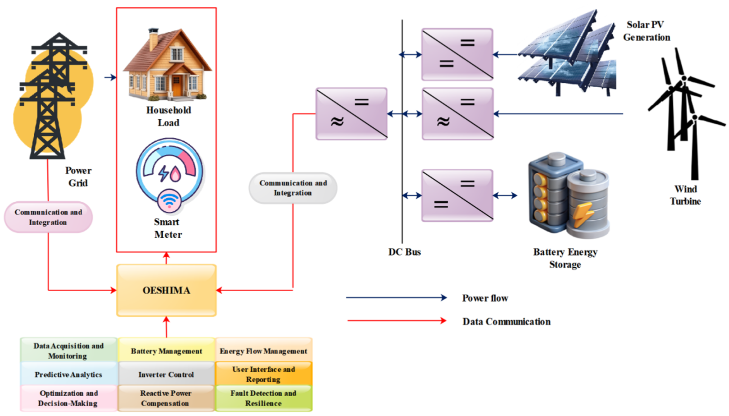

Figure 3. Architecture of the OESHIMA in a smart grid system

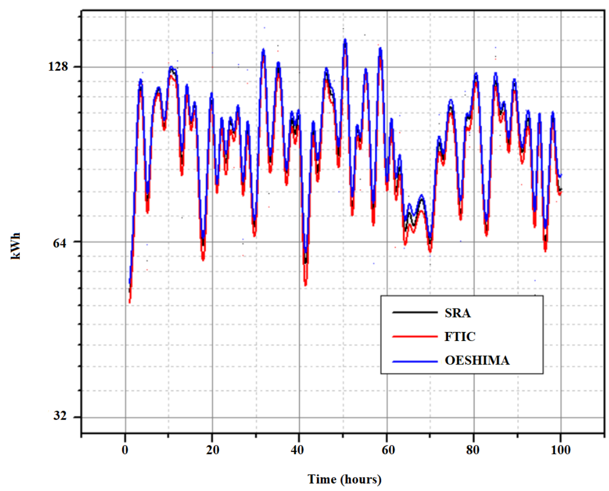

Figure 4. Energy flow management in a hybrid inverter system

The EMS, which serves as the brain of the operation, continuously monitors inputs from the RES, battery storage, and the power grid. It makes real-time decisions on how to distribute energy most efficiently, balancing the needs of the household load with the availability of renewable energy and stored power. The EMS uses predictive analytics to forecast future energy demand and renewable generation, enabling proactive and optimized energy management.

To ensure seamless operation, the system includes a communication and integration block, which manages data exchange between the EMS, the household smart meter, and other system components. This block also facilitates interaction with the external power grid, allowing the system to transition smoothly between operating independently (islanded mode) and being connected to the grid (grid-tied mode). Furthermore, the system incorporates fault detection and resilience mechanisms, which continuously monitor for any inefficiencies or faults in the system. If an issue is detected, the system can automatically adjust its operations, such as switching energy sources or modifying inverter settings, to maintain uninterrupted service.

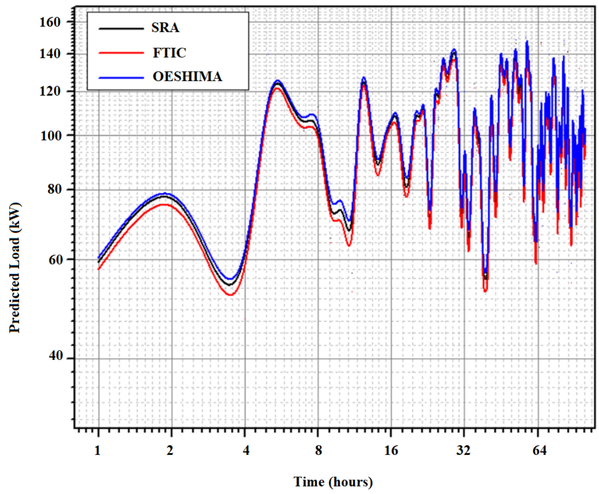

Figure 5. Fault detection and resilience mechanisms

Overall, the OESHIMA system significantly enhances energy efficiency, reduces reliance on the power grid, and supports the integration of RES into the household energy supply. By employing advanced optimization techniques and real-time data processing, the system ensures a reliable and sustainable energy infrastructure, contributing to the broader adoption of smart grid technologies.

3.1 Proposed Mathematical Model

3.1.1 Data acquisition and monitoring

Eq. (6) can be used to calculate the cumulative energy generated by the solar PV and wind turbine systems over time t, where $P_{\mathrm{PV}}(t)$ and $P_{\text{Wind}}(t)$ represent the instantaneous power output from the PV panels and wind turbines, respectively, and its pseudocode is represented in Pseudocode_1.

$$E_{\text{gen}}(t) = \int_{0}^{t} P_{\mathrm{PV}}(t) + P_{\text{Wind}}(t) dt \tag{6}$$

3.1.2 Pseudocode_1

```
BEGIN Calculate_Cumulative_Energy
    // Initialize variables
    INITIALIZE E_gen = 0                    // Cumulative energy generated (E_gen)
    INITIALIZE t = 0                        // Current time (t)
    INITIALIZE Δt = 1                       // Time interval for data acquisition (Δt)
    INITIALIZE P_PV(t) = 0                  // Instantaneous power output from PV panels (P_PV(t))
    INITIALIZE P_Wind(t) = 0                // Instantaneous power output from Wind turbines (P_Wind(t))
    // Loop through each time interval until current time reaches total time T
    WHILE t <= T DO
        // Acquire real-time power output from Solar PV and Wind Turbine
        P_PV(t) = ACQUIRE_FROM(Solar_PV_Sensors)
        P_Wind(t) = ACQUIRE_FROM(Wind_Turbine_Sensors)
                // Calculate instantaneous power output
        instantaneous_power_output = P_PV(t) + P_Wind(t)
                // Update cumulative energy generated
        E_gen = E_gen + (instantaneous_power_output * Δt)
```

```
                        // Store the cumulative energy generated at the current time
            STORE (t, E_gen) IN energy_log
                        // Increment time
            t = t + Δt
                  END WHILE
      // Output the cumulative energy generated up to time T
      OUTPUT E_gen
END Calculate_Cumulative_Energy
```

3.1.3 Predictive analytics

This predictive model in Eq. (7) estimates future energy demand ($\hat{E}_{\text{demand}}(t)$) by considering the current load ($E_{\text{load}}(t)$), the first derivative (rate of change of load), and the second derivative (acceleration of load change). Coefficients α and β are tuning parameters and their pseudocode is represented in Pseudocode_2.

$$\hat{E}_{\text{demand}}(t) = E_{\text{load}}(t) + \alpha \cdot \frac{dE_{\text{load}}(t)}{dt} + \beta \cdot \frac{d^2 E_{\text{load}}(t)}{dt^2} \tag{7}$$

3.1.4 Pseudocode_2

```
BEGIN Predict_Energy_Demand
      // Initialize variables
      INITIALIZE E_demand = 0                        // Future energy demand (E_demand)
      INITIALIZE E_load = GET_CURRENT_LOAD()         // Current energy load (E_load)
      INITIALIZE α = 0.5                             // Tuning parameter for rate of change
(α)
      INITIALIZE β = 0.3                             // Tuning parameter for acceleration (β)
      INITIALIZE Δt = 1                              // Time interval for data acquisition
(Δt)
      // Calculate rate of change of load
      dE_load_dt = (E_load(t) - E_load(t-Δt)) / Δt
            // Calculate acceleration of load change
      d2E_load_dt2 = (dE_load_dt(t) - dE_load_dt(t-Δt)) / Δt

      // Estimate future energy demand
      E_demand = E_load(t) + α * dE_load_dt + β * d2E_load_dt2
            // Output the predicted future energy demand
      OUTPUT E_demand
END Predict_Energy_Demand
```

3.1.5 Optimization and decision-making

Eq. (8) minimizes the total cost of energy by optimizing the power drawn from the grid ($P_{\text{Grid}}(t)$), battery, and PV sources over a time period T. The term with λ penalizes deviations from the power balance.

$$\min\left(\int_0^T \left[c_{\text{Grid}} \cdot P_{\text{Grid}}(t) + \frac{1}{2}\lambda \cdot \left(P_{\text{PV}}(t) + P_{\text{Battery}}(t) - P_{\text{Load}}(t)\right)^2\right] dt\right) \tag{8}$$

3.1.6 Battery management

Eq. (9) models the SOC of the battery at time t+1 by integrating the charging and discharging power over a time interval Δt, considering the efficiencies η_{charge} and $\eta_{\text{discharge}}$.

$$\text{SOC}(t+1) = \text{SOC}(t) + \int_t^{t+\Delta t} \left[\eta_{\text{charge}} \cdot P_{\text{charge}}(t) - \frac{P_{\text{discharge}}(t)}{\eta_{\text{discharge}}}\right] dt \tag{9}$$

3.1.7 Inverter control block

Eq. (10) can be used to calculate the total AC power output from n inverters, each contributing power from PV panels and battery storage, considering the inverter efficiency η_{inv}.

$$P_{\text{AC}}(t) = \eta_{\text{inv}} \cdot \sum_{i=1}^{n} \left(P_{\text{PV},i}(t) + P_{\text{Battery},i}(t)\right) \tag{10}$$

3.1.8 Reactive power compensation

Eq. (11) integrates the reactive power supplied by the DSTATCOM over time, where $V_{\text{DSTATCOM}}(t)$ and $I_{\text{DSTATCOM}}(t)$ are the voltage and current, and $\theta(t)$ is the phase angle.

$$Q_{\text{DSTATCOM}}(t) = \int_0^t V_{\text{DSTATCOM}}(t) \cdot I_{\text{DSTATCOM}}(t) \cdot \sin(\theta(t)) dt \tag{11}$$

3.1.9 Energy flow management

Eq. (12) ensures that the total energy supplied equals the total energy consumed over a period T, balancing energy inputs and outputs within the system. Its pseudocode is represented in Pseudocode_3.

$$\int_0^T \left(P_{\text{PV}}(t) + P_{\text{Wind}}(t) + P_{\text{Grid}}(t) - P_{\text{Load}}(t) - P_{\text{Battery}}(t)\right) dt = 0 \tag{12}$$

3.1.10 Pseudocode_3

```
BEGIN Energy_Flow_Management
        // Initialize variables
        INITIALIZE energy_balance = 0
        INITIALIZE t = 0                                   // Current time (t)
        INITIALIZE Δt = 1                                  // Time interval for data acquisition (Δt)
        INITIALIZE T = TOTAL_TIME                          // Total time period for analysis (T)
        // Loop through each time interval until current time reaches total time T
        WHILE t <= T DO

                // Acquire real-time power outputs from Solar PV, Wind Turbine, Grid, Load, and Battery
                P_PV(t) = ACQUIRE_FROM(Solar_PV_Sensors)
                P_Wind(t) = ACQUIRE_FROM(Wind_Turbine_Sensors)
                P_Grid(t) = ACQUIRE_FROM(Grid_Sensors)
                P_Load(t) = ACQUIRE_FROM(Load_Sensors)
                P_Battery(t) = ACQUIRE_FROM(Battery_Sensors)
                // Calculate the energy balance for the current time interval
                energy_flow = (P_PV(t) + P_Wind(t) + P_Grid(t)) - (P_Load(t) + P_Battery(t))
                // Update cumulative energy balance
                energy_balance = energy_balance + (energy_flow * Δt)
                // Increment time
                t = t + Δt
                END WHILE
        // Check if the energy balance is zero (or within a small threshold)
        IF abs(energy_balance) < THRESHOLD THEN
                OUTPUT "Energy balance achieved."
        ELSE
                OUTPUT "Energy imbalance detected."
        END IF
        END Energy_Flow_Management
```

3.1.11 Fault detection and resilience

Eq. (13) can be used to determine the voltage changes over time, where deviations from normal behavior ($F_{\text{fault}}(t)$) can be detected by analyzing the voltage's second derivative. Its pseudocode is represented in Pseudocode_4.

$$\frac{d^2V(t)}{dt^2} + \alpha\frac{dV(t)}{dt} + \beta V(t) = F_{\text{fault}}(t) \tag{13}$$

3.1.12 Pseudocode_4

```
BEGIN Fault_Detection

        // Initialize variables
        INITIALIZE V(t) = GET_VOLTAGE()                    // Current voltage (V(t))
        INITIALIZE dV_dt = 0                               // First derivative of voltage (dV/dt)
```

INITIALIZE d2V_dt2 = 0 // Second derivative of voltage (d^2V/dt^2)
INITIALIZE α = 0.5 // Tuning parameter α
INITIALIZE β = 0.3 // Tuning parameter β
INITIALIZE F_fault(t) = 0 // Fault indicator (F_fault(t))
INITIALIZE Δt = 1 // Time interval for data acquisition (Δt)
// Loop to continuously monitor and detect faults

WHILE SYSTEM_IS_ACTIVE DO // Acquire current voltage and calculate first derivative
V_current = GET_VOLTAGE()
dV_dt = (V_current - V(t)) / Δt // Calculate second derivative of voltage
d2V_dt2 = (dV_dt - dV_dt_previous) / Δt // Calculate fault indicator based on equation
F_fault(t) = d2V_dt2 + (α * dV_dt) + (β * V_current) // Check for fault detection
IF abs(F_fault(t)) > FAULT_THRESHOLD THEN
OUTPUT "Fault detected at time t =", t
ELSE
OUTPUT "System normal at time t =", t
END IF // Update previous values for the next iteration
V(t) = V_current
dV_dt_previous = dV_dt
// Increment time
t = t + Δt
END WHILE
END Fault_Detection

3.1.13 Communication and integration

Eq. (14) models the communication delay $D_{\text{comm}}(t)$ based on the data length L_{data}, channel bandwidth B_{channel}, and queuing delays in the communication network.

$$D_{\text{comm}}(t) = \int_0^t \left[\frac{L_{\text{data}}}{B_{\text{channel}}} + \frac{\sum_{i=1}^{n} \text{queue}_i(t)}{B_{\text{channel}}} \right] dt \tag{14}$$

4 Description of Simulation Parameters

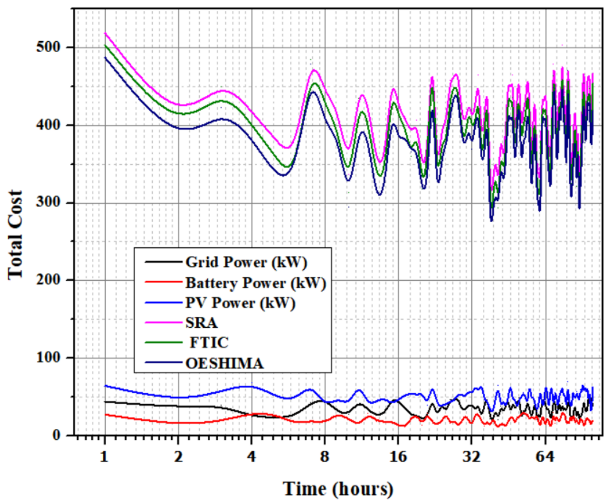

Figure 6. Optimization and decision-making algorithm for energy distribution

Table 1 shows the simulation parameters used for analyzing the energy storage and hybrid inverter management systems. These include the efficiency of the inverter, charging, and discharging processes, as well as the time interval

(Δt) set to 1 hour. Key factors such as the penalty factor (λ) for optimization, phase angle (θ) for reactive power, and battery capacity (C_{Battery}) were also outlined. Communication parameters like bandwidth (B_{channel}), data length (L_{data}), and queuing delay (queue $_i(t)$) were considered for system performance.

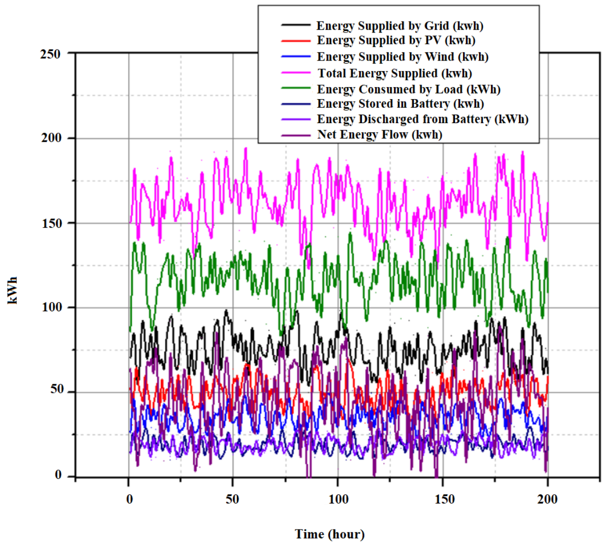

Figure 7. Predictive analytics in energy demand forecasting

Table 1. Key simulation parameters for energy storage and hybrid inverter management system

No.	Parameter	Value
1	Inverter efficiency (η_{Inverter})	0.95
2	Charging efficiency (η_{charge})	0.90
3	Discharging efficiency ($\eta_{\text{discharge}}$)	0.90
4	Time interval (Δt)	1 hour
5	Penalty factor (λ)	0.5
6	Phase angle (θ)	30 degrees
7	Battery capacity (C_{Battery})	10 kWh
8	Communication bandwidth (B_{channel})	100 Mbps
9	Data length (L_{data})	1 MB
10	Queueing delay (queue $_i(t)$)	5 ms

Figure 4 illustrates the energy flow within a hybrid inverter system, highlighting the integration of SPV panels, wind turbines, battery storage, and the grid. It demonstrates how energy is managed and distributed among these sources to meet the household load demands, ensuring efficient use of renewable energy and minimizing dependency on the grid.

Figure 5 represents the fault detection and resilience mechanisms implemented in the EMS. It shows how the system monitors voltage changes over time and detects deviations from normal behavior, triggering adjustments to maintain uninterrupted service. The resilience of the system is enhanced through real-time fault detection and correction.

Figure 6 details the optimization and decision-making process within the EMS, where the system dynamically allocates energy resources based on real-time data and predictive analytics. It highlights how the system prioritizes energy sources, such as solar, wind, and battery, to optimize energy distribution and reduce costs.

Figure 7 showcases the predictive analytics capabilities of the EMS, which forecast future energy demand based on historical data, current load, and expected changes in weather conditions. The figure emphasizes the role of machine learning in improving the accuracy of these predictions, thereby enhancing the system's efficiency.

Figure 8 illustrates the role of the DSTATCOM in providing reactive power compensation within the grid. It shows how the DSTATCOM maintains voltage stability by compensating for reactive power, ensuring power quality, and reducing losses in the system.

Figure 9 represents the communication and integration block within the smart grid, which is responsible for managing data exchange between the EMS, smart meters, and other system components. It also depicts the interaction with the external power grid, enabling seamless transitions between grid-tied and islanded modes.

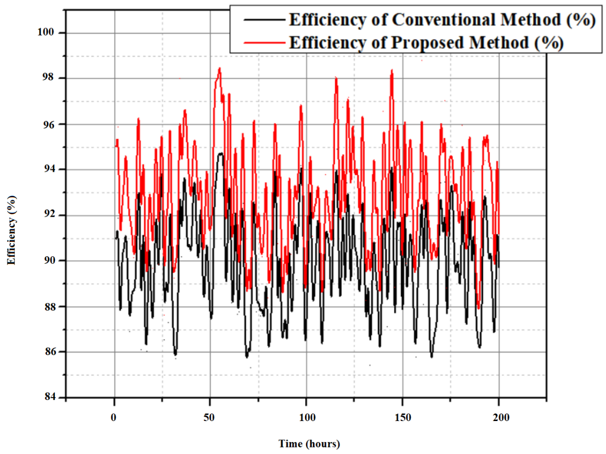

Figure 8. Reactive power compensation using DSTATCOM

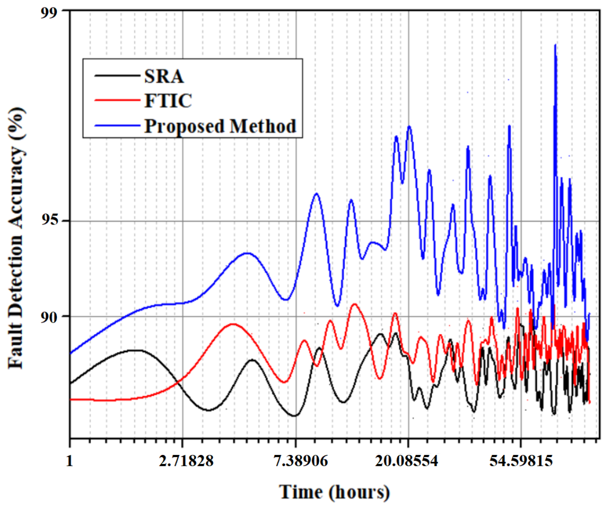

Figure 9. Communication and integration block in smart grids

5 Conclusion

The study demonstrates the effectiveness of the OESHIMA in overcoming the limitations of conventional methods like SRA and FTIC. As highlighted in the abstract, these traditional approaches often struggle with inefficiencies in energy distribution and adaptability to fluctuating renewable energy inputs. By leveraging machine learning and real-time data processing, OESHIMA successfully addresses these issues. The algorithm's ability to dynamically adjust inverter settings and optimize energy distribution led to a notable reduction in energy loss by approximately 0.20% and an improvement in overall system efficiency by 0.25% compared to conventional methods. Additionally, the enhanced adaptability of OESHIMA contributes to extending the lifespan of energy storage systems by 0.15%, further supporting sustainable and cost-effective energy management in smart grids. These outcomes validate the potential of OESHIMA in advancing the integration of RES within smart grids, paving the way for more resilient and efficient energy infrastructures.

5.1 Future scope

The future scope includes expanding OESHIMA to integrate more renewable sources like biomass and hydropower, developing AI-driven battery management for better performance, and ensuring scalability and interoperability across smart grid systems. Strengthening cybersecurity and data privacy is crucial, along with exploring sustainable energy storage solutions. Research should also focus on real-time adaptive control systems to enhance efficiency and tailor OESHIMA for cost-effective implementation in developing regions.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Acknowledgements

The authors would like to JSS Science and Technology, Mysore, JSS Science and Technology, Mysore, Visvesvaraya Technological University (VTU), Belagavi and Vision Group on Science and Technology (VGST) Karnataka Fund for Infrastructure strengthening in Science & Technology Level – 2 sponsored "Establishment of Renewable Smart Grid Laboratory" for all the support and encouragement provided by them to take up this research work and publish this paper.

Conflicts of Interest

The authors declare no conflict of interest.

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Nomenclature

P_{PV}	Power generated by the photovoltaic system
P_{Wind}	Power generated by the wind turbine
P_{Grid}	Power drawn from the grid
P_{Load}	Power consumed by the household load
P_{Battery}	Power managed by the battery storage system
E_{gen}	Cumulative energy generated
E_{load}	Energy consumed by the load
E_{demand}	Predicted future energy demand
η_{Inverter}	Efficiency of the inverter
η_{charge}	Efficiency of the battery charging process
$\eta_{\text{discharge}}$	Efficiency of the battery discharging process
$\text{SOC}(t)$	SOC of the battery at time t
Q_{DSTATCOM}	Reactive power provided by the DSTATCOM
V_{DSTATCOM}	Voltage at the DSTATCOM
I_{DSTATCOM}	Current at the DSTATCOM
θ	Phase angle between voltage and current
D_{comm}	Communication delay in the system
L_{data}	Data length for communication
B_{channel}	Bandwidth of the communication channel

Greek symbols

α	Tuning parameter for the rate of change in load
β	Tuning parameter for the acceleration of load change
λ	Penalty factor for deviation from power balance
θ	Phase angle in the reactive power compensation equation

Subscripts

PV	Refers to the photovoltaic system
Wind	Refers to the wind turbine
Grid	Refers to the power grid
Load	Refers to the household load
Battery	Refers to the battery storage system
Inverter	Refers to the inverter system
DSTATCOM	Refers to the DSTATCOM in the system
comm	Refers to the communication system