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Machine Learning-Driven Multi-Objective Energy Management and Optimal Power Flow of Grid-Connected Photovoltaic–Battery Energy Storage Systems for Enhanced Grid Resilience and Renewable Energy Integration

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Abstract

Grid-connected photovoltaic-battery energy storage systems face a persistent operational problem because variable photovoltaic generation, fluctuating electricity demand, battery state-of-charge and degradation constraints, and network power-flow requirements must be coordinated simultaneously, while existing research has frequently examined forecasting, battery scheduling, optimization, optimal power flow, and grid resilience as separate functions. This study aimed to quantitatively evaluate how machine learning-based predictive energy management, multi-objective energy optimization, intelligent battery energy storage management, and machine learning-assisted optimal power flow contribute to Grid Resilience and Renewable Energy Integration Performance in selected grid-connected PV-BESS case environments. A quantitative, cross-sectional, case-study-based design was employed, using purposive sampling and a structured five-point Likert-scale questionnaire administered to technically experienced professionals associated with power systems, renewable energy, battery storage, grid operations, energy management, and machine learning. Of 330 questionnaires distributed, 305 were returned and 296 usable responses were retained, yielding an 89.7% usable response rate. Data analysis incorporated reliability testing, descriptive statistics, Pearson correlation, and multiple regression modeling. The overall instrument demonstrated strong reliability, with Cronbach's alpha of .93. Descriptively, Grid Resilience and Renewable Energy Integration Performance Recorded $M = 4.18$, $SD = 0.54$, while Multi-Objective Energy Optimization achieved the highest independent-variable mean of $M = 4.16$, $SD = 0.55$. All four predictors were positively and significantly related to performance: MLPEM, $r = .68$; MOO, $r = .72$; IBESS, $r = .70$; and MLOPF, $r = .75$, all $p < .001$. The regression model explained 69.4% of the variance in performance, $R^2 = .694$, Adjusted $R^2 = .690$, $F(4, 291) = 165.02$, $p < .001$. MLOPF emerged as the strongest predictor, $\beta = .31$, followed by MOO, $\beta = .28$, IBESS, $\beta = .24$, and MLPEM, $\beta = .22$. These findings imply that utilities, renewable-energy developers, and grid operators can strengthen resilient renewable-energy integration by coordinating predictive intelligence, multi-objective optimization, intelligent storage control, and network-aware power-flow management as an integrated operational architecture rather than isolated technological capabilities.

Keywords

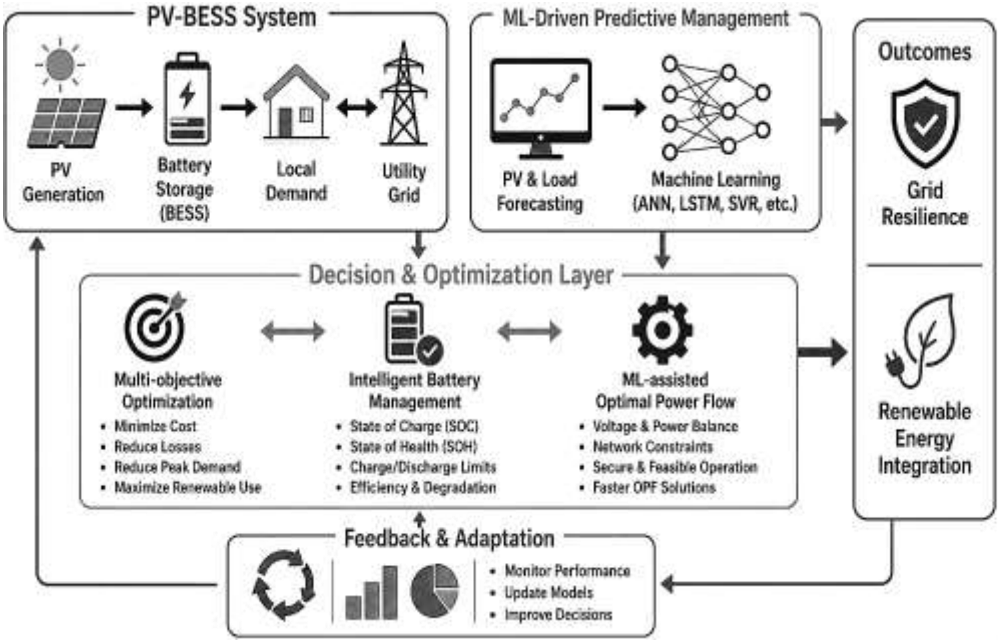
Machine Learning; Photovoltaic-Battery Energy Storage Systems; Multi-Objective Energy Optimization; Optimal Power Flow; Grid Resilience;

INTRODUCTION

Machine learning (ML) refers to a family of computational techniques through which algorithms identify patterns, estimate relationships, generate predictions, and support decision making from data without requiring every operational rule to be explicitly programmed. Within electrical power systems, ML has increasingly been applied to forecasting, system-state estimation, adaptive control, resource dispatch, and optimization problems characterized by nonlinear relationships, uncertainty, and rapidly changing operating conditions. A photovoltaic (PV) system converts incident solar radiation into electrical energy, while a battery energy storage system (BESS) stores electrical energy electrochemically and releases it according to demand, electricity price, system requirements, battery constraints, and network operating conditions. A grid-connected photovoltaic-battery energy storage system therefore represents an integrated configuration in which PV generation, battery storage, local electrical demand, power-electronic converters, control mechanisms, and the utility grid exchange electricity through coordinated operation. Microgrids and distributed-energy-resource architectures have established the technical foundation for this form of coordinated electricity management by integrating distributed generation, controllable loads, and storage resources within interconnected networks (Guerrero et al., 2011; Hatziargyriou et al., 2007). Energy management refers to the supervisory process through which available energy resources are scheduled, controlled, and dispatched, whereas optimal power flow (OPF) determines appropriate operating values for controllable network variables while satisfying power-balance equations, voltage requirements, generation limits, transmission or distribution constraints, and other engineering conditions. Predictive power-management strategies have demonstrated the importance of coordinating photovoltaic generation and battery storage to regulate grid exchange and optimize system operation (Olivares et al., 2014; Riffonneau et al., 2011). The international significance of PV-BESS operation has increased as electricity systems have incorporated larger amounts of decentralized and variable renewable generation. Battery storage can increase local consumption of photovoltaic electricity, shift energy between operating periods, reduce peak grid demand, and improve the controllability of renewable generation (Hoppmann et al., 2014; Luthander et al., 2015). Energy-storage technologies also contribute to balancing renewable generation, managing network constraints, providing operational flexibility, and supplying multiple grid-support services (Luo et al., 2015; Zakeri & Syri, 2015). Within this technical context, ML-driven energy management combines predictive data analytics with operational decision processes to coordinate PV production, battery behavior, electricity demand, and grid power exchange under multiple technical and economic constraints.

A major challenge in grid-connected PV-BESS operation arises from the intermittent, variable, and partially uncertain characteristics of photovoltaic generation and electricity demand. Solar electricity production changes according to irradiance, cloud cover, ambient temperature, panel characteristics, seasonal conditions, and geographic location, creating significant variations in available renewable generation across different time intervals. Accurate PV forecasting has therefore become an important component of energy management because forecast information supports the scheduling of battery charging, battery discharging, load supply, grid imports, and grid exports. Extensive research on photovoltaic forecasting has documented the application of statistical, physical, artificial intelligence, and hybrid methods for estimating solar generation across different forecasting horizons (Antonanzas et al., 2016; Yang et al., 2018). Machine-learning approaches have gained particular relevance because they can capture nonlinear relationships among meteorological measurements, historical PV production, temporal patterns, and operational conditions that may be difficult to represent through predetermined mathematical equations (Abdel-Nasser & Mahmoud, 2019; Voyant et al., 2017). Long short-term memory networks, artificial neural networks, support vector methods, ensemble algorithms, and other learning architectures can therefore form the predictive component of intelligent energy-management systems. Prediction alone, however, cannot ensure effective PV-BESS operation because battery scheduling must remain consistent with electrochemical and operational constraints. State of charge represents the amount of available battery energy relative to usable capacity, while state of health reflects degradation and the remaining performance capability of the battery. Accurate assessment of these parameters is essential for determining whether a battery should charge, discharge, remain idle, preserve reserve energy, or participate in grid-support activities (Berecibar et al., 2016; Hannan et al., 2017). Battery-management decisions must also account for charging limits, discharging limits, depth of discharge, round-trip efficiency, battery cycling, temperature, degradation, and usable capacity. Research on commercial PV-battery systems has demonstrated that battery sizing and scheduling directly influence photovoltaic self-consumption and the operational performance of integrated systems. Recent research on battery management has similarly emphasized the continuing importance of reliable state-of-charge estimation for maintaining safe and efficient battery operation (Hussein, 2024). Consequently, machine learning-based predictive energy management and intelligent battery energy storage management represent related but analytically distinct capabilities within grid-connected PV-BESS systems, with the former focusing on anticipating changing system conditions and the latter translating operational information into technically feasible charging and discharging decisions.

Figure 1: ML-Driven PV-BESS Energy Management Framework for Grid Resilience and Renewable Energy Integration



Energy management within photovoltaic-battery systems is inherently multi-objective because individual control decisions frequently influence several technical, economic, environmental, and operational performance criteria simultaneously. Multi-objective energy optimization refers to the systematic identification of operating solutions that balance two or more competing objectives instead of optimizing a single criterion in isolation. Relevant objectives in grid-connected PV-BESS environments may include electricity-cost minimization, reduction of power losses, peak-demand reduction, maximization of renewable-energy utilization, emission reduction, battery-degradation control, voltage-quality improvement, and minimization of unnecessary energy exchange with the utility grid. These objectives frequently interact. Maximizing immediate photovoltaic self-consumption may reduce available battery reserve for high-price periods, while aggressive battery discharge may lower short-term grid purchases but increase battery degradation. Multi-objective optimization is therefore required to identify operating decisions that balance conflicting priorities within established technical constraints. Research on microgrid energy management has demonstrated the application of multi-objective optimization to simultaneous economic and environmental objectives, including operating-cost and emission reduction (Aghajani & Ghadimi, 2018). Other research has incorporated uncertainty associated with renewable-energy production and electricity demand into multi-objective microgrid scheduling problems, illustrating the importance of stochastic operating conditions in optimization-based energy management (Ahmed et al., 2021). Machine learning has expanded these optimization approaches by enabling control systems to adjust decisions according to changing system states. Reinforcement learning is particularly relevant because it allows an intelligent agent to associate observations such as PV generation, battery state of charge, electricity demand, tariffs, and grid conditions with control actions and accumulated performance rewards. Reinforcement-learning-based scheduling has been applied to grid-connected solar PV-battery microgrids to coordinate battery operation, grid transactions, electricity costs, and battery wear (Muriithi & Chowdhury, 2021; Tonay, 2026). Deep reinforcement learning has also been investigated for microgrid environments containing storage, distributed generation, flexible electricity demand, and dynamic pricing structures (Nakabi & Toivanen, 2021; Shamsul, 2026). More recent grid-connected PV-battery research has evaluated deep reinforcement-learning strategies under varying photovoltaic penetration levels, battery capacities, and electricity-price structures, emphasizing the relevance of adaptive data-driven control to PV-BESS scheduling (Chen et al., 2024; Khatun, 2026). Battery losses have also been integrated directly into deep reinforcement-learning energy-management models, allowing scheduling policies to account more realistically for nonlinear storage behavior (Dominguez-Barbero et al., 2024; Rony & Md, 2026). Multi-objective energy optimization can consequently be viewed as the decision layer through which economic, technical, environmental, and battery-related objectives are balanced, while machine-learning techniques provide adaptive mechanisms for modifying operational decisions according to continuously changing system conditions.

Optimal power flow constitutes another critical component of intelligent PV-BESS management because energy-management decisions must remain consistent with the physical operating constraints of the electrical network. OPF is an optimization process that identifies suitable values for controllable power-system variables while satisfying electrical power-flow relationships, voltage limits, generator restrictions, network-capacity limits, power-balance requirements, and operational-security conditions. Alternating-current optimal power flow is particularly challenging because it contains nonlinear and nonconvex equations associated with voltage magnitude, voltage angle, active power, and reactive power. The integration of photovoltaic generation and battery storage adds further complexity because renewable-energy output varies over time and battery charging or discharging introduces additional controllable power injections. Coordinated predictive power-flow management has been applied directly to grid-connected photovoltaic systems with batteries, demonstrating that battery scheduling can be linked with network power-flow objectives and grid-interaction requirements (Sadia, 2026; Riffonneau et al., 2011). As networks incorporate increasing volumes of renewable and distributed resources, repeated OPF calculations may become computationally demanding when numerous operating scenarios and uncertain variables must be evaluated. Machine learning-assisted OPF addresses this difficulty by learning relationships between power-system inputs and optimized operating solutions, estimating appropriate dispatch points, predicting active constraints, or generating initial solutions that can accelerate numerical optimization. Deep-neural-network approaches have been used to approximate security-constrained DC optimal power flow, showing that learned mappings between demand conditions and generation decisions can significantly reduce computational effort while maintaining high-quality solutions (Nishat, 2026; Pan et al., 2021). Machine-learning methods have also been investigated extensively for alternating-current OPF, including neural networks, reinforcement learning, active-set prediction, surrogate modeling, and hybrid learning-optimization approaches (Jiang et al., 2024; Murad, 2026). Scalability has become an important concern because AC-OPF problems may contain large numbers of decision variables and constraints. Compact optimization-learning techniques have therefore been developed to reduce the dimensionality of AC-OPF outputs before prediction, improving the efficiency of data-driven solution methods (Shamima, 2026; Park et al., 2024). Graph-based learning has also been applied because power systems possess an explicit network topology that can be represented naturally as nodes and electrical connections. Graph neural networks combined with deep reinforcement learning have been used to generate initial estimates for AC-OPF solvers by incorporating structural information from the electricity network into the learning process (Deihim et al., 2024; Badrul, 2026). Within the present research context, ML-assisted OPF is therefore treated separately from predictive energy management because predictive management focuses primarily on anticipating and scheduling energy-resource behavior, whereas ML-assisted OPF focuses on obtaining network-feasible and optimized power-flow decisions under electrical constraints.

Grid resilience and renewable energy integration provide the central performance context through which the combined operation of machine learning, multi-objective optimization, intelligent battery management, and optimal power flow can be quantitatively examined. Grid resilience generally refers to the capability of an electrical system to recognize potentially disruptive conditions, withstand disturbances, adapt its operating configuration, maintain critical electricity service, and restore acceptable performance following significant system disruption. Resilience differs conceptually from conventional reliability because resilience places stronger emphasis on system response to severe, uncertain, and potentially high-impact disturbances. Quantitative resilience research has demonstrated that component fragility, probabilistic disturbance impacts, network configuration, and adaptive operational measures influence the magnitude and duration of power-system disruptions (Chowdhury, 2026; Panteli et al., 2017). Renewable energy integration refers to the ability of an electrical network to accommodate, utilize, and control variable renewable generation while maintaining power balance, acceptable voltage conditions, network security, and adequate operational flexibility. Very high levels of variable renewable generation create substantial requirements for system flexibility, advanced control, energy storage, coordinated dispatch, and responsive power-system operation (Kroposki et al., 2017; Pervaz, 2026). Grid-connected PV-BESS configurations directly connect renewable integration with resilience because battery storage can separate the timing of photovoltaic electricity generation from immediate electricity consumption, absorb excess solar generation, provide controllable active-power support, reduce renewable curtailment, and maintain stored energy that can support load during unfavorable operating conditions. Multi-objective microgrid studies have also demonstrated that coordinated use of clean-energy resources, storage systems, and flexible devices can address network losses, voltage deviations, operational costs, and other system-performance criteria simultaneously (Kaium, 2026; Moradi et al., 2023). Existing research nevertheless often examines solar forecasting, battery scheduling, reinforcement learning, economic dispatch, multi-objective optimization, optimal power flow, and resilience as separate analytical problems. PV-battery studies frequently emphasize economic operation, self-consumption, storage sizing, or individual control algorithms, while grid-resilience research often addresses network-level disturbance response without simultaneously evaluating the predictive, storage-management, optimization, and OPF capabilities of PV-BESS systems. This separation creates a specific empirical problem regarding how machine learning-based predictive energy management, multi-objective energy optimization, intelligent battery energy storage management, and machine learning-assisted optimal power flow relate to grid resilience and renewable energy integration performance when considered within a unified quantitative framework. The present study therefore adopts a quantitative, cross-sectional, case-study-based design using a five-point Likert scale to measure these constructs and employs descriptive statistics, Pearson correlation analysis, and multiple regression modeling to examine their individual and combined statistical relationships with grid resilience and renewable energy integration performance.

Background of the Study

The increasing penetration of renewable energy resources into modern power systems has transformed the way electricity is generated, stored, managed, and delivered. Among renewable technologies, photovoltaic energy has become one of the most widely adopted resources because of its modularity, declining installation costs, and suitability for both centralized and distributed applications. However, photovoltaic generation is inherently intermittent because its output depends on solar irradiance, weather conditions, temperature, and time of day. This variability can create mismatches between electricity production and demand, introduce voltage fluctuations, increase reverse power flow, and complicate real-time grid balancing. Battery energy storage systems have therefore become an important complementary technology because they can absorb excess photovoltaic electricity, release stored energy during periods of high demand or reduced solar generation, support peak shaving, regulate grid exchange, and improve the utilization of locally generated renewable electricity. The coordinated operation of photovoltaic generation and battery storage requires an advanced energy-management system capable of balancing multiple technical and economic objectives at the same time. Traditional rule-based and deterministic control methods may not always respond efficiently to highly variable operating conditions, uncertain generation, changing electricity demand, dynamic electricity prices, and battery constraints. Machine learning provides a data-driven mechanism for forecasting photovoltaic generation, predicting electricity demand, estimating system states, identifying operational patterns, and supporting adaptive control decisions. At the same time, multi-objective energy optimization enables an energy-management system to consider several goals simultaneously, such as minimizing operating cost, reducing power losses, improving renewable energy utilization, reducing peak demand, protecting battery health, and maintaining grid stability. Optimal power flow further ensures that energy-dispatch decisions comply with voltage, active-power, reactive-power, line-capacity, and network-security requirements. The integration of machine learning with energy management and optimal power flow therefore creates a coordinated decision framework for managing grid-connected photovoltaic-battery energy storage systems. Within such systems, predictive intelligence, battery flexibility, multi-objective optimization, and network-aware power-flow control can be examined together as important operational capabilities associated with grid resilience and renewable energy integration.

Problem Statement

Grid-connected photovoltaic-battery energy storage systems are increasingly used to improve renewable energy utilization and provide greater flexibility in modern electricity networks, yet their effective operation remains technically complex because several uncertain and competing conditions must be managed simultaneously. Photovoltaic production varies continuously with environmental conditions, electricity demand changes across operating periods, batteries have state-of-charge and degradation constraints, and distribution networks must remain within acceptable voltage and power-flow limits. Conventional energy-management approaches are often based on fixed schedules, predefined control rules, or optimization models that depend heavily on accurate input assumptions. Such approaches may become less effective when actual operating conditions change rapidly or when large volumes of uncertain renewable generation are connected to the grid. The challenge is not limited to forecasting photovoltaic production or controlling battery charging in isolation. Effective PV-BESS operation requires coordinated decisions involving renewable generation forecasting, load prediction, battery scheduling, economic objectives, power losses, grid imports and exports, network constraints, voltage stability, and resilience requirements. Existing approaches frequently address these functions separately, which can create fragmented decision processes in which an improvement in one objective may reduce performance in another. For example, aggressive battery discharge may reduce grid purchases but accelerate battery degradation, while maximizing immediate photovoltaic self-consumption may reduce stored reserve energy that could be needed during peak demand or network disturbances. Machine learning can potentially improve predictive and adaptive control, while multi-objective optimization and machine learning-assisted optimal power flow can coordinate system-wide decisions. However, there remains a need for an integrated quantitative assessment of how machine learning-based predictive energy management, multi-objective energy optimization, intelligent battery energy storage management, and machine learning-assisted optimal power flow collectively relate to grid resilience and renewable energy integration performance. This research addresses that problem by examining these capabilities within grid-connected PV-BESS case environments through measurable constructs and statistical relationships.

Objectives of the Study

The principal objective of this study is to quantitatively evaluate how machine learning-driven operational capabilities contribute to the performance of grid-connected photovoltaic-battery energy storage systems in relation to grid resilience and renewable energy integration. More specifically, the study seeks to assess the extent to which machine learning-based predictive energy management is applied to anticipate photovoltaic generation, electricity demand, electricity-price conditions, and other relevant operational variables that influence energy scheduling. It also aims to evaluate multi-objective energy optimization as a mechanism for balancing competing technical, economic, environmental, and battery-related objectives within integrated PV-BESS operation. A further objective is to assess intelligent battery energy storage management in terms of state-of-charge control, charging and discharging coordination, battery-health protection, peak-demand management, and the provision of stored energy for grid-support functions. In addition, the study seeks to determine the role of machine learning-assisted optimal power flow in improving power-flow decisions, voltage conditions, active- and reactive-power allocation, congestion management, and overall network-feasible operation. The research also aims to measure the level of grid resilience and renewable energy integration performance achieved within the selected case-study environments. Beyond evaluating the individual study constructs, the research intends to determine the strength and direction of the statistical relationships between each independent variable and the dependent variable through Pearson correlation analysis. Multiple regression modeling will then be used to determine the individual predictive contribution of machine learning-based predictive energy management, multi-objective energy optimization, intelligent battery energy storage management, and machine learning-assisted optimal power flow to grid resilience and renewable energy integration performance. The overall objective is therefore to establish an integrated empirical model capable of showing whether these machine learning-enabled and optimization-based capabilities operate as significant explanatory factors of resilient and renewable-intensive PV-BESS performance.

Research Hypotheses

The hypotheses of this study are developed from the proposed relationships among the four explanatory constructs and the dependent construct of grid resilience and renewable energy integration performance. The first hypothesis proposes that machine learning-based predictive energy management has a significant positive effect on grid resilience and renewable energy integration performance because improved anticipation of photovoltaic generation, electricity demand, grid conditions, and operational requirements can support more informed energy scheduling decisions. The second hypothesis proposes that multi-objective energy optimization has a significant positive effect on grid resilience and renewable energy integration performance because the simultaneous management of operating cost, renewable-energy utilization, power losses, peak demand, battery conditions, and other objectives can improve the overall coordination of PV-BESS resources. The third hypothesis proposes that intelligent battery energy storage management has a significant positive effect on grid resilience and renewable energy integration performance because effective state-of-charge control, charging and discharging decisions, battery-health management, and energy reserve allocation can increase the flexibility and availability of stored energy. The fourth hypothesis proposes that machine learning-assisted optimal power flow has a significant positive effect on grid resilience and renewable energy integration performance because intelligent network-aware optimization can improve voltage conditions, active- and reactive-power allocation, grid losses, and operating feasibility. Finally, the fifth hypothesis proposes that machine learning-based predictive energy management, multi-objective energy optimization, intelligent battery energy storage management, and machine learning-assisted optimal power flow collectively have a significant positive effect on grid resilience and renewable energy integration performance. The hypotheses are therefore stated as follows: H1, machine learning-based predictive energy management significantly and positively influences grid resilience and renewable energy integration performance; H2, multi-objective energy optimization significantly and positively influences grid resilience and renewable energy integration performance; H3, intelligent battery energy storage management significantly and positively influences grid resilience and renewable energy integration performance; H4, machine learning-assisted optimal power flow significantly and positively influences grid resilience and renewable energy integration performance; and H5, the four independent variables collectively exert a significant positive influence on grid resilience and renewable energy integration performance.

Significance of the Research

i. Significance for Power-System and Grid Operators: This study is significant for grid operators because it examines how predictive energy management, battery flexibility, multi-objective optimization, and optimal power flow can be coordinated within grid-connected PV-BESS environments. The results can provide a structured understanding of the operational capabilities associated with maintaining reliable grid interaction while accommodating variable photovoltaic generation.

ii. Significance for Renewable-Energy Developers: The research is important for photovoltaic developers and renewable-energy project managers because it evaluates operational factors that affect renewable-energy utilization, storage coordination, grid exchange, and system performance. This can help identify which intelligent-management capabilities deserve greater attention when PV and battery systems are designed or operated as integrated resources.

iii. Significance for Battery Energy Storage Management: The study provides specific attention to intelligent battery energy storage management as an independent operational capability. This is significant because battery performance depends not only on installed capacity but also on charging, discharging, state-of-charge control, reserve management, and degradation-aware scheduling.

iv. Significance for Machine-Learning Applications in Energy Systems: The research contributes to understanding machine learning as an operational decision-support capability rather than only as a forecasting tool. By examining predictive energy management and machine learning-assisted optimal power flow separately, the study provides a more detailed view of how data-driven techniques can support different layers of energy-system operation.

v. Significance for Multi-Objective Energy Management: The study is significant because it recognizes that PV-BESS operation involves several interacting objectives. Evaluating multi-objective energy optimization allows technical, economic, renewable-energy, and battery-related goals to be considered within the same empirical framework.

vi. Significance for Academic Research: The study provides a quantitative, cross-sectional, case-study-based framework that integrates four explanatory constructs with a single dependent performance construct. The use of reliability testing, descriptive statistics, Pearson correlation, and multiple regression provides a systematic structure for empirically testing relationships that are often investigated separately in technical simulation studies.

vii. Significance for Energy Planning and Policy: The research can also support energy planners and decision makers by providing evidence about the operational capabilities associated with resilient grid-connected renewable-energy systems. Understanding the relationships among machine learning, battery management, optimization, power flow, resilience, and renewable integration can assist in evaluating technology priorities within increasingly decentralized electricity systems.

LITERATURE REVIEW

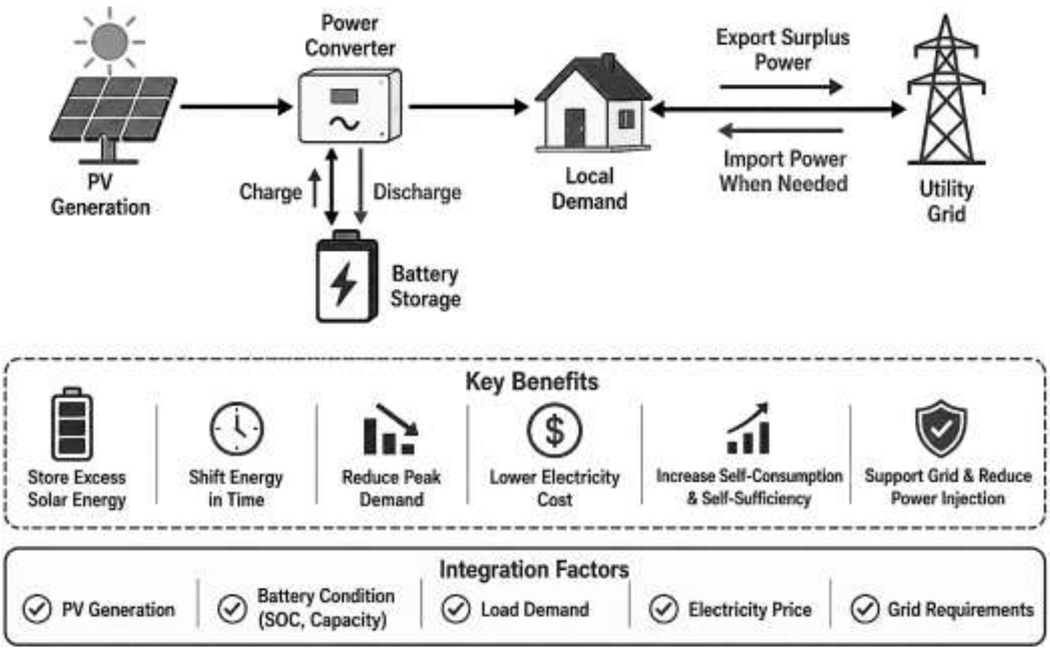
The literature concerning machine learning-driven energy management and optimal power flow in grid-connected photovoltaic-battery energy storage systems spans several closely connected areas of power-system engineering, renewable-energy integration, artificial intelligence, energy storage, optimization, and grid resilience. Grid-connected PV-BESS systems combine variable photovoltaic generation with controllable battery storage and utility-grid interaction, creating an operational environment in which generation, consumption, storage, and network conditions must be coordinated continuously. Previous research has examined photovoltaic forecasting as a means of reducing uncertainty associated with solar generation, while machine-learning methods have been used to capture nonlinear relationships among irradiance, temperature, historical generation, electricity demand, and other system variables. A parallel body of literature has focused on battery energy storage management, particularly state-of-charge estimation, state-of-health assessment, charging and discharging schedules, degradation, efficiency, and battery participation in grid-support services. Multi-objective optimization studies have investigated how energy-management systems can balance several competing goals, including operating-cost reduction, renewable-energy utilization, peak-demand mitigation, power-loss reduction, emission control, and battery lifetime preservation. Optimal power flow research has addressed the physical feasibility of power-system operation by optimizing active power, reactive power, voltage, and network flows subject to engineering constraints, while more recent machine-learning-assisted approaches have sought to reduce the computational burden of repeated OPF calculations. Another major literature stream concerns grid resilience, system flexibility, reliability, disturbance response, and the ability of electricity networks to integrate high levels of variable renewable generation. These research domains are strongly interconnected, yet they are often examined independently. A comprehensive review is therefore required to synthesize the literature on grid-connected PV-BESS systems, machine learning-based predictive energy management, multi-objective optimization, intelligent battery management, machine learning-assisted optimal power flow, grid resilience, theoretical foundations, and the conceptual relationships underlying the present quantitative study.

Grid-Connected Photovoltaic-Battery Energy Storage Systems

Grid-connected photovoltaic-battery energy storage systems represent an increasingly important configuration within distributed electricity networks because they combine renewable electricity generation, electrochemical storage, local demand, and utility-grid interaction within a coordinated operating structure. In a conventional grid-connected photovoltaic installation, electricity generated by the PV array is first supplied to local loads, while surplus production may be exported to the utility network and electricity deficits are covered through grid imports. The addition of battery storage modifies this relationship because excess photovoltaic electricity can be retained locally and discharged when solar generation becomes insufficient or electricity demand increases. This arrangement creates greater temporal flexibility between renewable production and consumption and enables system operators or consumers to determine when locally generated electricity should be consumed, stored, exported, or supplemented by grid electricity. Battery capacity and photovoltaic-system size are therefore fundamental design variables because inappropriate sizing can produce excessive capital expenditure, underutilized storage, unnecessary grid exchange, or insufficient renewable-energy utilization. Simulation-based research on residential PV-battery systems has shown that the relationship between photovoltaic capacity and battery capacity determines self-consumption, system economics, and the extent to which electricity demand can be supplied from locally generated solar energy (Debasish, 2021; Weniger et al., 2014). Grid connection also distinguishes PV-BESS installations from stand-alone renewable systems because the utility network remains an additional source and destination of electricity. This enables the battery to perform several functions beyond simple backup storage, including load shifting, peak-demand management, energy arbitrage, management of photovoltaic surplus, and regulation of power exchanged with the external network. The integration challenge consequently involves more than connecting two technologies. It requires continuous coordination among photovoltaic production, battery state of charge, load demand, converter operation, electricity tariffs, and grid requirements. Demand-side energy-management research has demonstrated that grid-connected PV-battery systems can schedule power flows to reduce electricity costs while maintaining energy balance and respecting constraints related to solar production and battery capacity (Abdur & Iftekhar, 2021; Wu et al., 2015). These characteristics establish PV-BESS as an integrated renewable-energy platform in which storage provides operational flexibility that directly affects the manner in which intermittent photovoltaic generation is absorbed and utilized within grid-connected electrical systems.

Renewable energy integration within grid-connected PV-BESS systems is strongly influenced by the temporal mismatch between photovoltaic generation and electricity consumption. Solar generation normally reaches its highest-level during daylight hours, while residential, commercial, and industrial electricity demands may peak during different periods. Without storage, a significant proportion of photovoltaic electricity can therefore be exported when local consumption is low, while grid electricity must later be imported when solar output falls. Battery storage reduces this mismatch by shifting energy from periods of surplus generation to periods of greater demand, thereby increasing photovoltaic self-consumption and self-sufficiency. Effective integration, however, requires the storage system to be planned and operated according to changing weather, electricity prices, demand patterns, battery specifications, and required reliability. Optimization-based planning research has demonstrated that investment decisions, system sizing, and operational scheduling should be treated as interconnected problems because an economically suitable battery capacity may depend on how the storage device is scheduled during actual system operation (Debasish, 2022; Khalilpour & Vassallo, 2016). This interaction is particularly important for renewable-energy integration because maximizing battery capacity alone does not necessarily maximize system performance. Oversized batteries can remain partly unused, while undersized batteries may be unable to absorb substantial photovoltaic surpluses or supply sufficient stored energy during high-demand periods. Operational strategy therefore becomes as important as installed storage capacity. Grid-connected PV-BESS operation must determine appropriate charging and discharging periods while considering battery efficiency, cycling behavior, state-of-charge limits, power ratings, photovoltaic availability, load requirements, and permitted grid exchange. The grid itself may also experience operational difficulties when large quantities of distributed photovoltaic generation are exported simultaneously. Reverse power flow can contribute to voltage-rise problems in distribution feeders, particularly during periods of high solar production and low local demand. Coordinated battery scheduling can reduce these problems by absorbing photovoltaic generation that would otherwise be injected into the grid. Research on grid-supporting PV systems has shown that battery scheduling can simultaneously address economic operating objectives and limit excessive grid power injection, illustrating the direct relationship between storage operation and distribution-network support (Ashfaq & Mohammad, 2022; Ranaweera & Midtgard, 2016). Renewable-energy integration in PV-BESS systems therefore depends on coordinated sizing, scheduling, local consumption, and grid-support behavior rather than photovoltaic penetration alone.

Figure 2: Grid-Connected PV-Battery Energy Storage System for Renewable Energy Integration



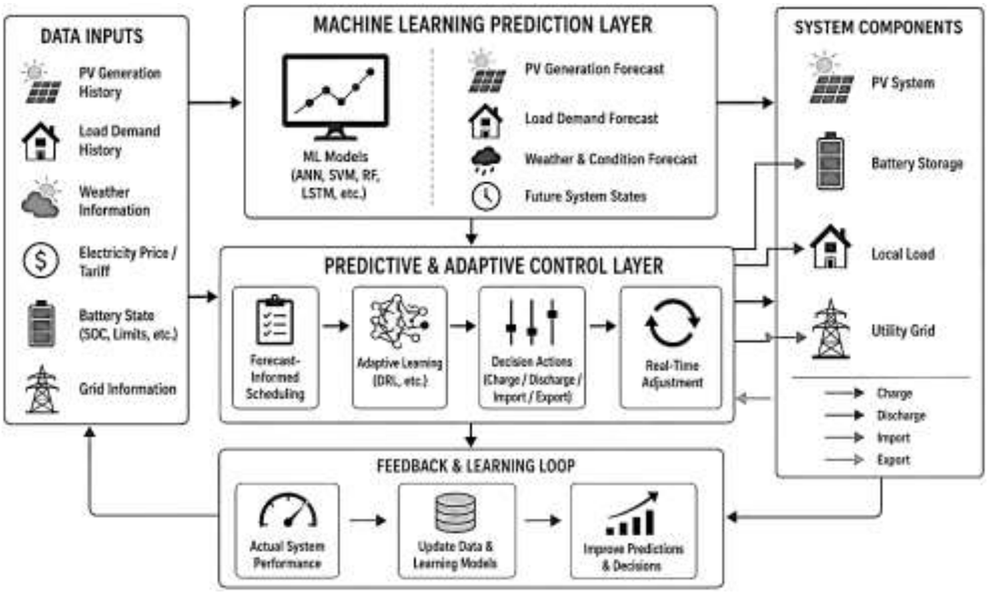
The contribution of PV-BESS to renewable-energy integration can also be understood through the interaction among self-consumption, self-sufficiency, grid dependency, and battery utilization. Self-consumption represents the proportion of photovoltaic electricity that is consumed locally rather than exported to the grid, while self-sufficiency describes the proportion of local electricity demand supplied by the photovoltaic and storage system. These indicators are related but not identical because a household or organization can achieve high self-consumption with a relatively small photovoltaic installation while still relying heavily on grid electricity, or achieve higher self-sufficiency through larger photovoltaic and battery capacities while exporting some surplus generation. Battery storage increases the ability to shift photovoltaic electricity from production periods to later consumption periods, but the scale of improvement is influenced by demand profile, climatic conditions, PV capacity, battery size, storage efficiency, and operating strategy. Large-scale statistical assessment of solar home battery systems across European household conditions has demonstrated that increasing photovoltaic and battery capacities raises self-consumption and self-sufficiency only within practical limits, while very high levels of energy independence can require substantial system oversizing (Sheak & Risha, 2022; Quoilin et al., 2016). This finding is important for grid-connected systems because complete electrical independence is not necessarily the primary objective of renewable-energy integration. Grid connection allows photovoltaic-battery installations to exchange electricity with the network when this is technically or economically appropriate, while storage can moderate the timing and magnitude of those exchanges. The resulting system can therefore function as a flexible distributed-energy resource rather than merely as a local generation unit. From a power-system perspective, coordinated PV-BESS operation can reduce peak imports, absorb midday photovoltaic surpluses, decrease abrupt variations in grid exchange, and provide controllable energy during periods when renewable generation is unavailable. These functions depend on accurate measurement of photovoltaic production, load demand, battery conditions, and grid interaction, together with an energy-management mechanism capable of determining appropriate operating actions. The literature consequently establishes grid-connected PV-BESS architecture as a multidimensional integration problem involving system configuration, battery utilization, renewable-energy capture, demand matching, and controlled grid exchange, providing the technical foundation for examining predictive energy management, intelligent storage operation, multi-objective optimization, and optimal power flow within the broader framework of this study.

Machine Learning in PV-BESS Systems

Machine learning-based predictive energy management in grid-connected photovoltaic-battery energy storage systems is centered on the ability to anticipate uncertain operating conditions before control actions are taken. The predictive layer of an energy management system converts historical and real-time measurements into estimates of photovoltaic generation, electricity demand, weather-dependent variability, and operational states that determine how energy should be allocated among local loads, battery storage, and the utility grid. For photovoltaic systems, forecasting accuracy is important because solar output changes rapidly under variable cloud conditions and forecast errors can influence battery charging schedules, grid imports, export levels, and reserve availability. Short-term photovoltaic forecasting has therefore been approached through classification and pattern-recognition methods that distinguish weather conditions before estimating expected power production. Support vector machine-based weather-status recognition has shown how solar-irradiance features can categorize operating conditions and improve short-term PV forecasting models, illustrating the value of machine learning for transforming meteorological variability into actionable power estimates (Rashedul & Kaium, 2022; Wang et al., 2015). Nonparametric learning has also been applied to photovoltaic forecasting through quantile regression forests, which can use numerical weather predictions together with measured plant output without requiring a fixed parametric representation of the PV conversion process (Almeida et al., 2015; Chowdhury & Tonay, 2022). These approaches are relevant to predictive energy management because a PV-BESS controller must decide how much energy can reasonably be expected from the photovoltaic array before determining charging, discharging, import, or export actions. Prediction thus functions as an information layer rather than an isolated analytical task. When forecasts are incorporated into supervisory control, the energy management system can anticipate renewable surplus, demand peaks, or insufficient solar generation and prepare the battery accordingly. The quality of predictive information affects the timing and feasibility of storage and grid-interaction decisions, making machine learning-based forecasting a foundational component of intelligent PV-BESS energy management across changing operating conditions.

Predictive energy management becomes more complex when photovoltaic forecasts are combined with electricity-demand forecasts, tariff information, battery constraints, and real-time deviations from expected operating conditions. In a grid-connected PV-BESS, the controller must reconcile predicted solar production with anticipated load while preserving sufficient battery capacity and respecting charging and discharging limits. Forecast-informed dispatch provides a way to convert prediction into operational schedules. Research on photovoltaic-battery dispatch has demonstrated that solar and load forecasts can be embedded in an optimization routine to establish battery-discharge targets for reducing peak demand, while forecast errors can be managed through repeated adjustment of the dispatch schedule as actual conditions become known (Hanna et al., 2014; Hossan, 2022). This type of control highlights an important characteristic of predictive energy management: the initial schedule is not static, because forecast information can be updated and corrective decisions can be taken when actual PV production or demand differs from expectations. Machine learning adds further adaptability by learning decision policies from repeated interactions with uncertain system states. Deep reinforcement learning has been applied to real-time energy purchasing in storage-integrated photovoltaic systems where solar generation, electricity demand, market prices, and nonlinear battery behavior jointly affect the control problem. By mapping observed system conditions to charging, discharging, and grid-purchase actions, reinforcement-learning agents can support adaptive decisions without solving a complete conventional optimization model (Kolodziejczyk et al., 2021; Kaniz, 2022). This capability is relevant when electricity prices, demand, and renewable output vary simultaneously. Predictive management must combine anticipatory information with responsive control. Forecasts provide estimates of what is likely to occur, while adaptive learning mechanisms determine how the system should react when those estimates interact with actual battery and grid conditions. The integration of these functions allows predictive energy management to move beyond generation forecasting and become a coordinated decision process linking data, uncertainty, scheduling, and real-time operation.

Figure 3: Machine Learning-Based Predictive Energy Management Framework for Grid-Connected PV-BESS Systems



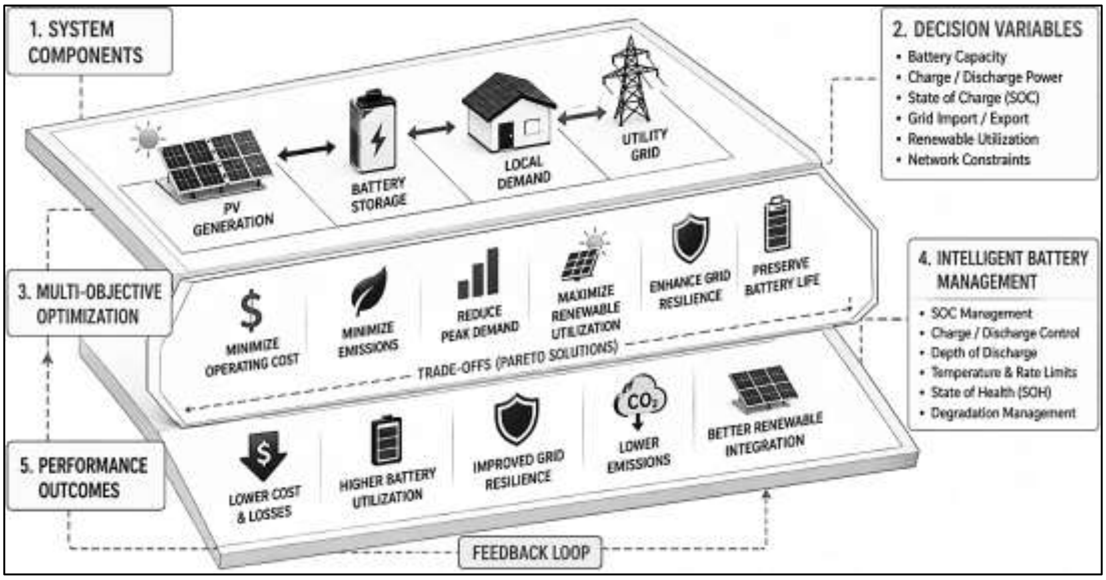
Machine learning-based predictive energy management also integrates forecasting and control within a common data-driven architecture rather than treating them as independent stages. In such an architecture, PV production, facility demand, electricity prices, weather information, battery state variables, and control actions can be used jointly to estimate system conditions and determine subsequent decisions. Deep learning is suitable for this arrangement because sequential neural-network structures can capture temporal dependencies in load and renewable-generation data, while reinforcement learning can translate predicted or observed states into operational actions. PV-battery research has combined load forecasting with deep reinforcement learning in a home energy management system, using convolutional and long short-term memory networks to strengthen demand prediction and reinforcement-learning agents to control battery operation under objectives related to electricity cost and photovoltaic self-consumption (Nishat & Kaniz, 2022; Real et al., 2024). This integration demonstrates how predictive energy management can link forecasting accuracy with the operational value of stored renewable energy. For the present study, machine learning-based predictive energy management can be conceptualized as a multidimensional technical capability. It includes prediction of photovoltaic output and electricity demand, recognition of changing system conditions, incorporation of tariff or grid information, forecast-informed scheduling, and adaptive revision of energy decisions. Within a cross-sectional case-study design, these capabilities can be measured in practice through respondents' assessments of how machine learning supports prediction, scheduling, and real-time coordination in PV-BESS environments. Two systems may contain similar photovoltaic and battery capacities while differing in the sophistication of their predictive control. A system that forecasts renewable generation but does not integrate forecasts into battery or grid decisions exhibits a lower level of predictive energy-management capability than one in which prediction continuously informs dispatch. The construct captures the extent to which machine learning converts uncertain operational data into anticipatory and adaptive energy-management decisions across the interconnected PV, battery, load, and grid components.

Multi-Objective Energy Optimization

Multi-objective energy optimization in grid-connected photovoltaic-battery energy storage systems is concerned with coordinating several competing technical, economic, environmental, and operational objectives within a single decision structure. Unlike single-objective scheduling, which may prioritize only electricity cost or renewable-energy utilization, multi-objective management recognizes that improving one performance criterion can adversely affect another. A strategy that aggressively discharges the battery during high-price periods may reduce purchased electricity but increase cycling-related degradation, while a strategy that preserves battery life may leave more photovoltaic surplus available for export or curtailment. The optimization problem therefore includes decision variables associated with battery capacity, charging and discharging power, state of charge, grid import and export, renewable-energy utilization, and network operating constraints. In grid-connected microgrids, battery sizing can be formulated as a multi-objective problem because storage capacity affects daily operating cost, emissions, system flexibility, and the extent to which variable renewable resources can be accommodated. A combined particle swarm optimization and TOPSIS framework has demonstrated that battery sizing decisions can be evaluated through explicit trade-offs between competing objectives rather than through a single economic criterion (Parashar et al., 2019; Shaiful et al., 2022). This perspective is particularly relevant to PV-BESS systems because the battery operates as both an energy-shifting device and a constrained asset whose value depends on when, how deeply, and how frequently it is used. Multi-objective optimization consequently provides a mechanism for identifying balanced operating points among cost reduction, renewable-energy absorption, peak-demand mitigation, emission reduction, and storage preservation. Pareto-based solutions are important because they represent alternative operating combinations in which improvement in one objective cannot occur without deterioration in another. For intelligent energy management, the optimization task is therefore not simply to find the lowest-cost schedule, but to determine operational compromises that respect battery limitations while supporting efficient interaction among photovoltaic generation, local demand, storage, and the utility grid and performance.

Intelligent battery energy storage management extends multi-objective optimization by incorporating the physical behavior and ageing characteristics of the storage device into scheduling and sizing decisions. Battery performance is governed by state of charge, depth of discharge, charging and discharging rates, round-trip efficiency, temperature, usable capacity, and state of health, all of which influence the feasible operating range of a PV-BESS system. Storage optimization that ignores degradation can select schedules that appear economically attractive but impose excessive cycling or high stress on the battery, increasing replacement requirements and reducing system value. Degradation-aware sizing research has therefore treated ageing as an explicit component of renewable-energy integration, showing that optimal battery capacity should depend on the required power profile, cycle depth, C-rate, calendar ageing, and the fraction of battery life consumed by repeated operation (Mohammad, 2023; Torre et al., 2019). The importance of degradation modelling also extends to daily energy management. Comparative analysis of battery ageing models in a grid-connected DC microgrid has shown that simplified degradation representations can materially change the calculated state-of-charge trajectory, operating cost, and dispatch schedule, demonstrating that battery models are not neutral elements within optimization (Debasish, 2023; Wang et al., 2020). Intelligent battery management must consequently coordinate energy objectives with preservation of the storage asset. In a grid-connected PV-BESS, this means selecting charging and discharging actions that absorb solar surplus, serve demand, maintain reserve availability, and avoid electrochemical stress. Battery intelligence also requires the energy-management system to recognize that identical amounts of discharged energy can impose different levels of degradation depending on depth of discharge, temperature, power rate, and cycling pattern. Incorporating these factors into optimization allows the battery to be treated as a dynamic resource with changing health rather than as an ideal energy container with fixed efficiency and unlimited cycling capability, strengthening the technical realism of PV-BESS management.

Figure 4: Multi-Objective Energy Optimization and Intelligent Battery Energy Storage Management in PV-BESS Systems



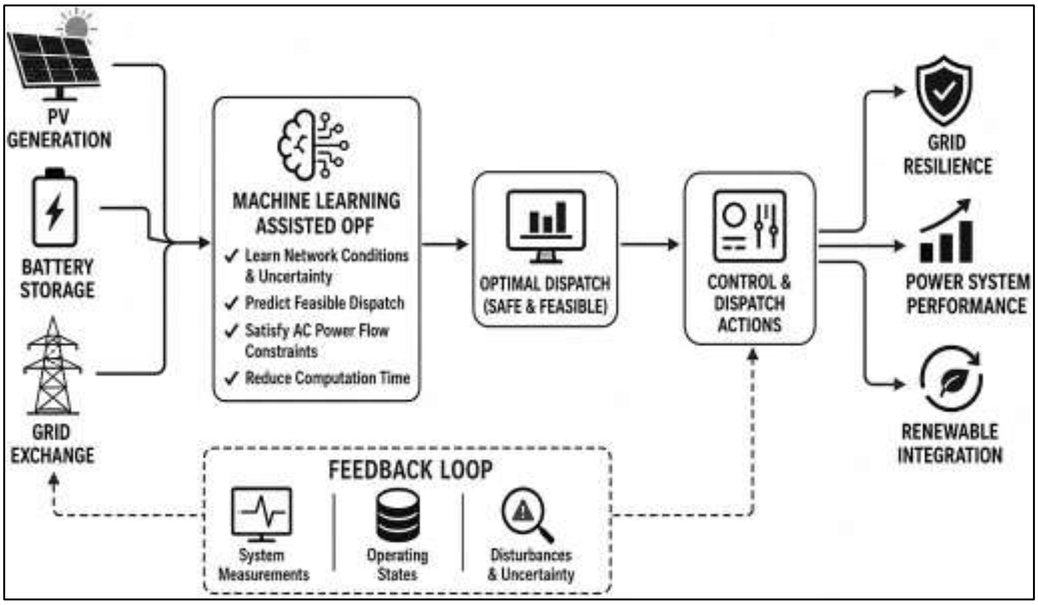
Integrating multi-objective optimization with battery-aware energy management matters when PV-BESS systems are required to balance economic performance, renewable-energy utilization, grid-support objectives, and storage longevity simultaneously. Grid-connected hybrid PV-battery optimization has demonstrated that annualized cost, greenhouse-gas emissions, peak-to-average grid-energy ratios, outage conditions, and battery degradation can be included within a common system-design problem, allowing decision makers to examine how alternative configurations redistribute performance across criteria (Kaium, 2023; Tikkiwal et al., 2021). Such formulations illustrate why intelligent battery management should not be isolated from broader energy optimization. The battery is the principal flexible resource connecting daytime photovoltaic production with later demand, yet every charging or discharging action alters the present energy balance and the remaining capability of the storage system. A well-structured optimization process must consider the value obtained from battery use against the physical cost of degradation. Recent research has treated state of health as an additional performance indicator for selecting among Pareto-optimal energy-system schedules, demonstrating that solutions with similar economic or environmental performance can impose different effects on battery condition (Jin et al., 2024; Pervaz, 2023). For this research, multi-objective energy optimization and intelligent battery energy storage management are treated as related but distinguishable capabilities. Multi-objective energy optimization represents the system-level ability to balance cost, losses, peak demand, renewable utilization, emissions, and competing goals, whereas intelligent battery management represents the storage-specific ability to regulate state of charge, charging and discharging, reserve levels, cycling intensity, and degradation within those decisions. Their interaction is central to grid-connected PV-BESS operation because optimization determines what the integrated energy system seeks to achieve, while battery management defines how much flexibility can be supplied without violating technical limits or accelerating storage deterioration. Measuring these capabilities separately allows the study to examine whether stronger optimization and battery-management practices are associated with higher levels of grid resilience and renewable energy integration performance.

Machine Learning-Assisted and Power-System Performance

Machine learning-assisted optimal power flow has emerged as an important analytical approach for managing increasingly complex power networks in which renewable generation, battery storage, variable demand, and inverter-interfaced resources must be coordinated under strict electrical constraints. Optimal power flow traditionally determines the operating values of controllable system variables that minimize an objective such as generation cost, network loss, or voltage deviation while satisfying active-power balance, reactive-power balance, generator limits, voltage limits, thermal line ratings, and other network constraints. The alternating-current formulation is particularly demanding because its nonlinear and nonconvex structure can require iterative numerical procedures that become computationally expensive as system size and operating uncertainty increase. In grid-connected photovoltaic-battery energy storage systems, this complexity is intensified because photovoltaic injections vary with weather, batteries can function as both loads and sources, and power exchange with the utility network changes according to demand, state of charge, and operational objectives. Machine learning can support OPF by learning mappings between network conditions and high-quality operating solutions, thereby reducing the time required to generate dispatch decisions. Constraint-guided deep neural networks have been developed to classify feasible and infeasible AC-OPF conditions, predict operating solutions, and use output normalization and post-processing procedures to improve compliance with generator and network limits (Lotfi & Pirnia, 2022; Chowdhury, 2023). A related development is the incorporation of physical power-flow equations directly into neural-network training. Physics-informed neural networks can use engineering knowledge to reduce dependence on very large labeled datasets while decreasing constraint violations and preserving the quality of predicted AC-OPF solutions (Badrul & Mominul, 2023; Nellikkath & Chatzivasileiadis, 2022). These approaches show that ML-assisted OPF is not merely a computational shortcut, because effective learning models must preserve the electrical feasibility, security requirements, and operating limits that determine whether a predicted dispatch can be safely implemented in an actual grid-connected PV-BESS environment across diverse real-world grid operating scenarios.

The importance of ML-assisted OPF becomes greater when renewable-energy uncertainty is incorporated into real-time power-system operation. Photovoltaic output can change rapidly, while electricity demand, local generation, battery charging, and battery discharging introduce uncertainty into nodal power injections. Deterministic operating points may therefore become unsuitable when actual conditions depart from the values assumed during optimization. Stochastic optimal power flow addresses this problem by representing uncertainty explicitly and seeking operating policies that remain technically acceptable across a range of possible conditions. Deep neural-network policies have been proposed for stochastic AC-OPF in which the learning model predicts generator dispatch in response to uncertain load and renewable injections while chance constraints and primal-dual training mechanisms are used to maintain operating limits (Gupta et al., 2022; Nishat, 2023). Such methods are relevant to grid-connected PV-BESS systems because the battery can provide a flexible response to forecast deviations, voltage conditions, renewable fluctuations, and changing grid requirements. The resulting operational performance is connected to resilience because rapid and feasible redispatch can help preserve electricity supply when the network experiences abnormal or disrupted conditions. Distributed PV and battery storage can also contribute directly to resilience when they are organized through coordinated microgrid structures. Networked microgrid research has shown that rooftop photovoltaic generation and battery energy storage can support distribution systems during natural-disaster scenarios by supplying power during outages, improving bus-voltage conditions, and reducing the number of customers affected by interruptions (Ashrafuzzaman, 2024; Galvan et al., 2020). These findings indicate that resilient performance depends on more than the physical presence of renewable generation and storage. It also depends on whether distributed resources can be scheduled, dispatched, and reconfigured in accordance with network constraints. ML-assisted OPF therefore provides a mechanism for linking the flexibility of PV-BESS resources with secure network operation by identifying feasible power-flow decisions under changing operating states, uncertainty, and disturbance conditions.

Figure 5: Machine Learning-Assisted Optimal Power Flow, Grid Resilience, and Power-System Performance



Grid resilience provides a criterion for evaluating whether machine learning-assisted energy and power-flow management improves the capacity of PV-BESS-supported networks to sustain service during disruptive events. A resilient electricity system should be able to recognize adverse operating conditions, absorb or withstand disturbance effects, adapt available resources, maintain priority loads, and restore stable operation after the event. In systems, these capabilities depend on generation, storage, controls, communications, network configuration, and operating decisions across system components. Microgrid resilience research has emphasized that physical threats, cyber vulnerabilities, local generation, storage availability, control infrastructure, and mitigation strategies must be assessed together because a microgrid can provide backup and flexible operation only when its own technical and communication functions remain capable of supporting critical loads (Debasish, 2024; Mishra et al., 2020). For grid-connected PV-BESS systems, this perspective positions optimal power flow as an operational link between renewable-energy availability and resilient network performance. Machine learning can accelerate the identification of suitable control actions, while AC-OPF constraints ensure that those actions remain compatible with voltage, power balance, generation, and line-flow requirements. Battery storage contributes controllability because charging can absorb photovoltaic surplus and discharging can support local demand or critical buses when grid conditions deteriorate. The combination of predictive intelligence, storage flexibility, and network-constrained optimization can therefore be assessed through observable performance dimensions such as rapid power-flow adjustment, voltage stabilization, reduction of overloaded conditions, continuity of electricity supply, efficient utilization of renewable energy, and adaptive response to disturbances. Within the present quantitative study, machine learning-assisted optimal power flow is consequently treated as a distinct explanatory capability rather than as a purely mathematical algorithm. Its measurement concerns the extent to which data-driven methods support feasible and network-aware operating decisions, while grid resilience and renewable-energy integration performance represent the broader system outcomes associated with coordinated PV generation, battery storage, and grid interaction.

Theoretical Framework

Dynamic Capabilities Theory provides an appropriate theoretical foundation for this study because grid-connected photovoltaic-battery energy storage systems operate in conditions characterized by variability, uncertainty, continuous information exchange, and the need for repeated operational adaptation. Dynamic capabilities describe the capacity to integrate, develop, deploy, and reconfigure competencies and resources in response to changing environments. The framework is commonly organized around three interrelated processes: sensing, seizing, and reconfiguring. Sensing concerns identifying changes, opportunities, risks, and relevant information; seizing concerns selecting and implementing appropriate responses; and reconfiguring concerns adjusting available resources and operational arrangements when environmental conditions change (Rahman, 2024; Teece, 2007). These processes correspond closely with the technological capabilities examined in this research. Machine learning-based predictive energy management represents the sensing dimension because forecasting algorithms process photovoltaic production, electricity demand, weather conditions, electricity prices, battery information, and grid variables to recognize probable system states before operational decisions are made. Multi-objective energy optimization represents an important part of the seizing dimension because it converts available information into decisions that balance electricity cost, renewable utilization, power losses, peak demand, battery preservation, and other operational objectives. Intelligent battery energy storage management also supports seizing by determining when stored electricity should be absorbed, retained, discharged, or reserved according to system conditions. Machine learning-assisted optimal power flow represents the reconfiguring dimension because it adjusts active and reactive power allocations, battery-grid interaction, voltage conditions, and network operating points when power-system conditions change. Dynamic capabilities should not be interpreted as isolated resources because their value depends on coordinated deployment and adjustment under environmental change, while different interpretations of the theory emphasize both organizational routines and higher-order capabilities for modifying resource configurations (Kaium, 2024; Peteraf et al., 2013). Within the technical setting of this research, the underlying theoretical structure can be represented through the relationship DC = f (S, Se, R), where DC represents dynamic capability, S represents sensing, Se represents seizing, and R represents reconfiguring. For the PV-BESS context, sensing is operationalized primarily through ML-based prediction, seizing through multi-objective optimization and intelligent battery control, and reconfiguring through ML-assisted OPF and adaptive energy dispatch.

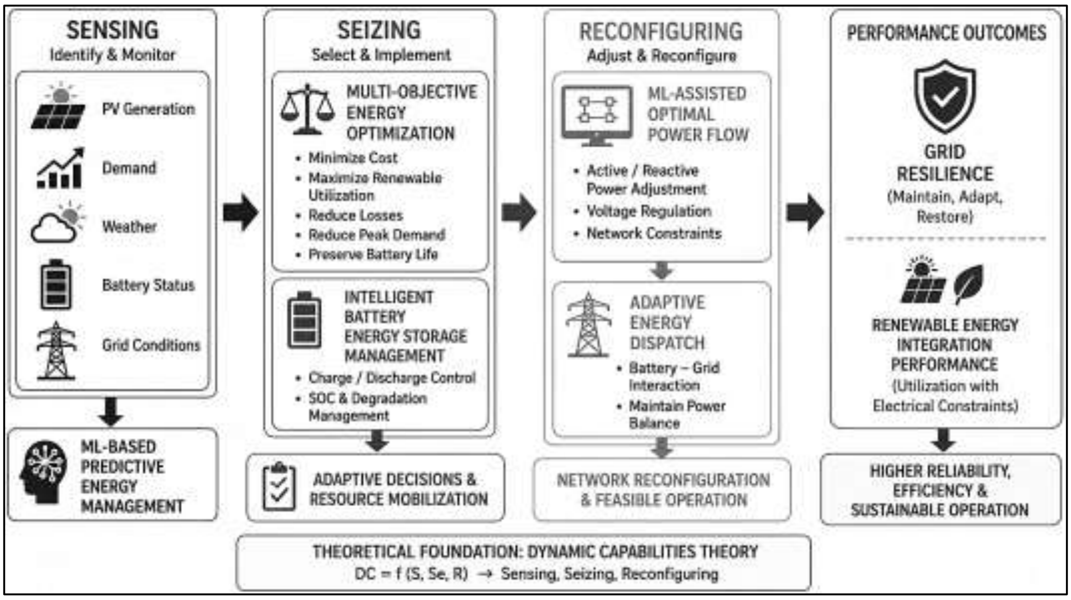
$$DC = f\,(S, Se, R)$$

The relevance of Dynamic Capabilities Theory becomes stronger when these capabilities are connected with measurable system performance rather than treated as abstract technological characteristics. Dynamic capability research indicates that the possession of adaptive processes does not automatically produce superior performance because the effectiveness of those capabilities depends on their alignment with organizational structures, environmental conditions, decision processes, and the resources being transformed (Shakhawat & Md, 2024; Wilden et al., 2013). An equivalent logic can be applied to grid-connected PV-BESS operation. Merely installing machine-learning software, photovoltaic capacity, or battery storage does not establish effective adaptive energy management. The system must transform data into predictions, predictions into coordinated decisions, decisions into feasible storage actions, and storage actions into network-compatible power-flow adjustments. Electrical-energy digitalization research has similarly demonstrated that sensing, seizing, and transforming capabilities are relevant to energy providers operating in increasingly digitalized environments characterized by distributed renewable resources, data-intensive services, and changing grid structures (Idries et al., 2022; Nishat & Jahanara, 2024). In the present study, this theoretical sequence allows the four independent variables to be treated as complementary adaptive capabilities rather than unrelated technical functions. Machine learning-based predictive energy management senses variation in renewable production and electricity demand. Multi-objective energy optimization seizes available operational opportunities by selecting solutions among competing objectives. Intelligent battery energy storage management mobilizes flexible stored energy while respecting state-of-charge, state-of-health, charging, discharging, and degradation constraints. Machine learning-assisted optimal power flow reconfigures network operating conditions by identifying feasible distributions of active and reactive power. The theoretical expectation is that stronger development of these capabilities will be associated with stronger grid resilience and renewable energy integration performance. This relationship is expressed through the central empirical model maintained throughout the study: GRRI_i = beta_0 + beta_1 MLPEM_i + beta_2 MOO_i + beta_3 IBESS_i + beta_4 MLOPF_i + epsilon_i, where GRRI_i represents Grid Resilience and Renewable Energy Integration Performance for observation i, MLPEM_i represents Machine Learning-Based Predictive Energy Management, MOO_i represents Multi-Objective Energy Optimization, IBESS_i represents Intelligent Battery Energy Storage Management, MLOPF_i represents Machine Learning-Assisted Optimal Power Flow, beta_0 is the regression constant, beta_1 to beta_4 represent the estimated effects of the explanatory constructs, and epsilon_i represents unexplained variation.

$$GRRI_i = \beta_0 + \beta_1 MLPEM_i + \beta_2 MOO_i + \beta_3 IBESS_i + \beta_4 MLOPF_i + \varepsilon_i$$

Dynamic Capabilities Theory also provides a coherent explanation for why adaptation is particularly important in renewable-intensive electricity systems. Photovoltaic generation, electrical demand, battery availability, electricity prices, and network conditions are not permanently fixed, meaning that operational resources must repeatedly be reassessed and reconfigured. Research examining transitions toward renewable-energy activities has shown that sensing, seizing, and reconfiguring operate as interconnected capabilities through which organizations identify renewable opportunities, mobilize knowledge and resources, and transform established operating arrangements (Hermundsdottir et al., 2024; Tonay et al., 2024).

Figure 6: Dynamic Capabilities Theory for Intelligent and Adaptive Energy Management in Grid-Connected PV-BESS Systems



In a grid-connected PV-BESS, an analogous adaptive sequence occurs at the operational level. The system first senses a potential condition, such as predicted photovoltaic surplus, increased evening demand, low battery reserve, voltage variation, or a disturbance affecting network operation. It then seizes the available response through an optimization decision, such as storing surplus electricity, limiting grid import, preserving battery energy, reducing peak demand, or changing the preferred energy-dispatch schedule. Finally, it reconfigures resource operation through battery charging or discharging and network-feasible power-flow adjustment. This sequence provides the theoretical mechanism connecting the study's independent and dependent variables. Grid resilience reflects the ability to maintain, adapt, and restore acceptable operating performance under changing or disruptive conditions, while renewable energy integration reflects the ability to accommodate and utilize variable photovoltaic generation without compromising electrical constraints. The four explanatory capabilities can therefore be interpreted as operational manifestations of dynamic capability: MLPEM provides anticipatory sensing, MOO provides multi-criteria decision selection, IBESS provides flexible resource mobilization, and MLOPF provides network-level operational reconfiguration. The regression equation adopted in this framework enables these theoretical relationships to be tested quantitatively using the cross-sectional case-study data. Positive and statistically significant coefficients for beta_1, beta_2, beta_3, and beta_4 would support the hypothesized association between stronger adaptive capabilities and higher GRRI performance, while the coefficient of determination, R^2, will indicate how much observed variation in GRRI is collectively accounted for by the four capability constructs.

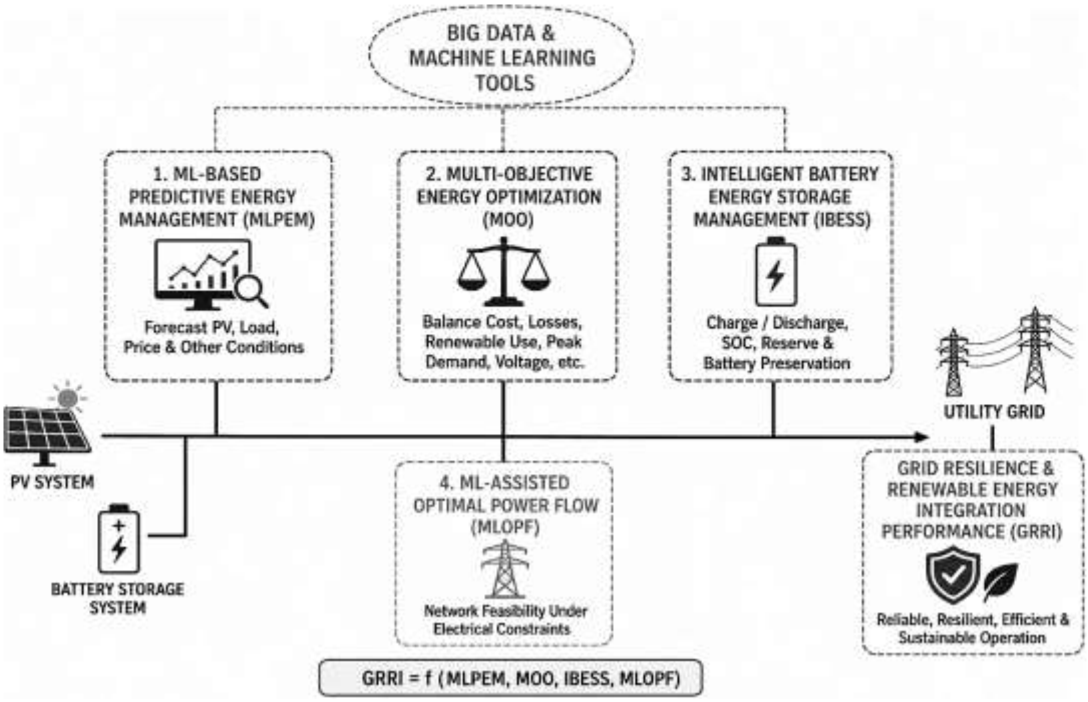
Conceptual Framework

The conceptual framework of this study integrates machine learning-based predictive energy management, multi-objective energy optimization, intelligent battery energy storage management, and machine learning-assisted optimal power flow as four complementary explanatory capabilities affecting Grid Resilience and Renewable Energy Integration Performance in grid-connected photovoltaic-battery energy storage systems. The framework is based on the premise that PV-BESS performance cannot be represented adequately by a single technical function because effective operation depends simultaneously on prediction, optimization, storage flexibility, and network-feasible power-flow control. Grid-connected PV-battery planning literature identifies energy-management strategy, technical constraints, pricing structures, system sizing, and optimization objectives as interconnected determinants of overall system performance, confirming that planning and operation should be considered within a coordinated framework rather than as isolated design choices (Khezri et al., 2022; Uddin & Risha, 2024). Within the present model, Machine Learning-Based Predictive Energy Management (MLPEM) represents the capability to anticipate photovoltaic generation, load demand, electricity-price conditions, and other operational states; Multi-Objective Energy Optimization (MOO) represents the ability to balance competing economic, technical, environmental, and renewable-energy objectives; Intelligent Battery Energy Storage Management (IBESS) represents the ability to coordinate charging, discharging, state of charge, reserve availability, and battery preservation; and Machine Learning-Assisted Optimal Power Flow (MLOPF) represents the capability to generate network-aware operating decisions under voltage, power-balance, congestion, and line-flow constraints. Evidence from low-voltage distribution systems indicates that deep-learning-based PV forecasting combined with battery control can reduce congestion and overvoltage problems while improving PV hosting capability, directly illustrating how prediction and storage coordination can influence renewable integration at the network level (Debasish, 2025a; Shabbir et al., 2024). The conceptual relationship can therefore be expressed as GRRI = f(MLPEM, MOO, IBESS, MLOPF), where GRRI denotes Grid Resilience and Renewable Energy Integration Performance and the four explanatory variables represent distinct but mutually reinforcing operational capabilities. This integrated structure allows the study to examine each capability without ignoring system-level coordination.

$$GRRI = f(MLPEM, MOO, IBESS, MLOPF)$$

The framework further assumes that the four independent constructs contribute to GRRI through different but interconnected operational mechanisms. MLPEM reduces informational uncertainty by converting historical and real-time data into forecasts that improve anticipation of renewable availability, demand conditions, electricity prices, and relevant system states. MOO then transforms these forecasts and operating requirements into decisions that balance several objectives, including energy-loss reduction, electricity-cost control, renewable-energy utilization, voltage performance, peak-demand management, and reduction of unnecessary grid purchases. Recent microgrid optimization research has demonstrated the practical compatibility of machine-learning forecasting, battery storage, and fuzzy multi-objective optimization within a distribution-network environment, where forecasted meteorological and load information was incorporated with storage decisions to address energy losses, voltage deviations, and purchased-power costs simultaneously (Debasish, 2025b; Duan et al., 2024). IBESS adds temporal and operational flexibility by controlling when electricity is stored, retained, or released, thereby connecting predicted conditions and optimization objectives with actual energy availability. MLOPF provides the network-feasibility layer by determining how these resource-management decisions interact with electrical constraints and network power-flow requirements. Grid resilience is incorporated into the dependent construct because renewable generation and battery storage can provide operational support during disruptions when they are appropriately sized, positioned, and coordinated. Multi-objective network-planning research combining renewable resources, BESS capacity, system costs, demand response, and resilience indicators has demonstrated that battery deployment can materially affect both economic and performance-related dimensions of grid resilience (Jannatul, 2025; Shafiei et al., 2024). For empirical testing, the conceptual framework is translated into the multiple-regression model GRRI_i = beta_0 + beta_1 MLPEM_i + beta_2 MOO_i + beta_3 IBESS_i + beta_4 MLOPF_i + epsilon_i, where beta_0 represents the regression intercept, beta_1 through beta_4 represent the unique predictive effects of the four independent constructs, and epsilon_i represents unexplained variation in GRRI.

Figure 7: Conceptual Framework of ML-Driven PV-BESS Optimization and Grid Resilience



This formulation creates direct statistical correspondence between the conceptual framework, research hypotheses, questionnaire constructs, and planned quantitative analysis. It also permits hypothesis testing at both individual-predictor and collective-model levels within one consistent analytical specification for the overall study.

$$GRRI_i = \beta_0 + \beta_1 MLPEM_i + \beta_2 MOO_i + \beta_3 IBESS_i + \beta_4 MLOPF_i + \varepsilon_i$$

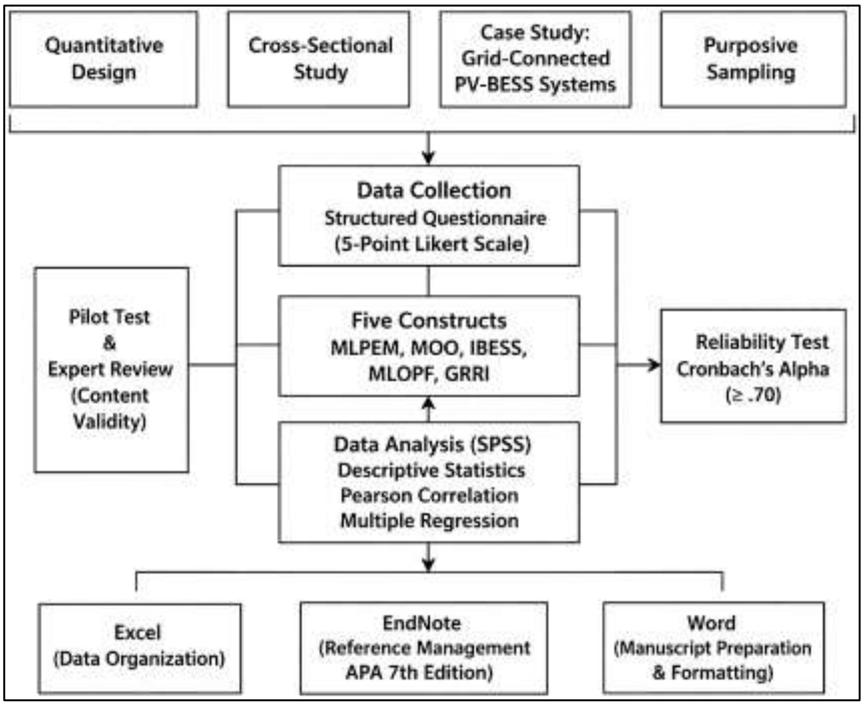
The final structure of the conceptual framework treats grid resilience and renewable energy integration as an integrated performance outcome because the operational objectives of a grid-connected PV-BESS frequently overlap. Increasing renewable-energy utilization may require the battery to absorb photovoltaic surplus during periods of high solar production, while resilience requirements may require a portion of stored electricity to remain available for outages, disturbances, peak-demand periods, or other stressed network conditions. These requirements can create trade-offs between immediate economic flexibility and preparedness for unexpected system disruptions. Research on PV-battery-equipped buildings has demonstrated that scheduling strategies can explicitly balance flexibility and resilience by incorporating outage-risk information into battery state-of-charge decisions, showing that storage allocation influences both normal-operation efficiency and the ability to maintain electricity service during disruptions (Liang et al., 2024; Rahman, 2025). Accordingly, GRRI is defined in this research as the perceived system capability to accommodate and efficiently utilize photovoltaic energy while maintaining flexible, stable, disturbance-responsive, reliable, and network-compatible operation. The conceptual framework predicts positive direct relationships between the four independent constructs and GRRI. H1 predicts beta_1 > 0, H2 predicts beta_2 > 0, H3 predicts beta_3 > 0, and H4 predicts beta_4 > 0. The collective relationship underlying H5 is represented through R^2 > 0, F_model > 0, and p < .05, where R^2 represents the proportion of variation in GRRI explained collectively by MLPEM, MOO, IBESS, and MLOPF, while the overall F-test determines whether the regression model provides statistically significant explanatory power. The conceptual framework therefore aligns directly with Likert-scale measurement, descriptive statistics, Pearson correlation analysis, and multiple regression modeling. Its operational sequence assumes that predictive intelligence strengthens awareness of changing system conditions, multi-objective optimization evaluates competing operational priorities, intelligent storage management supplies temporal energy flexibility, and ML-assisted OPF converts those decisions into network-feasible power-system operation. Grid-connected PV-BESS planning research supports treating resilience, grid dependency, technical constraints, optimization criteria, and energy management as interconnected system considerations rather than independent design elements (Khezri et al., 2022; Arif Uz et al., 2025), while integrated machine-learning and multi-objective models demonstrate the value of coordinating forecast information with storage and network objectives (Duan et al., 2024; Kaium, 2025). The resulting framework provides the structure for determining which capability has the strongest statistical relationship with resilient renewable-energy integration across the selected PV-BESS case environments as designed.

$$H_1: \beta_1 > 0 \quad H_2: \beta_2 > 0 \quad H_3: \beta_3 > 0 \quad H_4: \beta_4 > 0$$
$$H_5: R^2 > 0, F\_model > 0, p < .05$$

METHODS

This study has adopted a quantitative, cross-sectional, case-study-based research design to examine the relationships among machine learning-based predictive energy management, multi-objective energy optimization, intelligent battery energy storage management, machine learning-assisted optimal power flow, and grid resilience and renewable energy integration performance in grid-connected photovoltaic-battery energy storage systems. The case-study context has included selected grid-connected PV-BESS environments in which renewable generation, battery storage, energy management, and grid-interaction practices have been relevant to system operation. The study population has consisted of power-system engineers, electrical engineers, renewable-energy specialists, battery-storage professionals, grid operators, energy managers, smart-grid specialists, and machine-learning professionals with relevant experience in PV-BESS or intelligent energy systems. The professional respondent has been treated as the primary unit of analysis. A purposive sampling strategy has been used to select respondents who have possessed adequate technical knowledge and practical exposure to the investigated systems. Data have been collected through a structured questionnaire administered using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The instrument has been designed around five constructs: MLPEM, MOO, IBESS, MLOPF, and GRRI. A pilot test has been conducted before the main survey to identify ambiguous items and improve questionnaire clarity. Content validity has been assessed through expert review, while construct consistency and internal reliability have been evaluated using Cronbach's alpha, with values of .70 or above considered acceptable. The collected data have been screened, coded, and analyzed using IBM SPSS Statistics. Descriptive statistics, Pearson correlation analysis, and multiple regression modeling have been applied to test the research objectives and hypotheses. Microsoft Excel has been used for preliminary data organization, while EndNote has been used to organize references and maintain APA 7th edition citation consistency throughout the research, and Microsoft Word has been used for manuscript preparation and final formatting.

Figure 8: Research Methodology



DATA ANALYSIS AND PRESENTATION

Questionnaire Distribution and Respondent Profile

Table 1: Questionnaire Distribution and Respondent Profile

Category	Classification	Frequency (n)	Percentage (%)
Questionnaire Status	Distributed	330	100.0
	Returned	305	92.4
	Incomplete/Excluded	9	2.7
	Usable Responses	296	89.7
Professional Role	Power/Electrical Engineer	82	27.7
	Renewable Energy/PV Specialist	61	20.6
	Battery/Energy Storage Specialist	47	15.9
	Grid/Utility Professional	42	14.2
	Energy Manager	34	11.5
	ML/Smart-Grid Specialist	30	10.1
Professional Experience	1-5 years	74	25.0
	6-10 years	89	30.1
	11-15 years	71	24.0
	More than 15 years	62	20.9

The questionnaire distribution and respondent-profile results have established a sufficiently broad empirical foundation for evaluating machine learning-driven energy management and optimal power flow in grid-connected photovoltaic-battery energy storage systems. Of the 330 questionnaires that have been distributed, 305 have been returned, representing a gross response rate of 92.4%. Following data screening, nine questionnaires have been excluded because they have contained incomplete or unusable responses, left 296 valid questionnaires and produced a usable response rate of 89.7%. This response level has provided an adequate quantitative dataset for descriptive statistics, reliability testing, correlation analysis, and multiple regression modeling. The professional composition has also demonstrated relevant technical diversity. Power and electrical engineers have represented the largest group at 27.7%, followed by renewable-energy and PV specialists at 20.6%, battery and energy-storage specialists at 15.9%, grid and utility professionals at 14.2%, energy managers at 11.5%, and machine-learning or smart-grid specialists at 10.1%. The distribution has therefore incorporated respondents with direct knowledge of photovoltaic generation, battery operation, grid interaction, optimization, and data-driven energy management. Experience levels have been similarly distributed, with 30.1% having six to ten years of professional experience, 25.0% having one to five years, 24.0% having eleven to fifteen years, and 20.9% having more than fifteen years. The respondent characteristics have strengthened the case-study context because the unit of analysis has consisted of technically informed professionals rather than general electricity consumers. From the perspective of Dynamic Capabilities Theory, this professional composition has been particularly relevant because sensing, seizing, and reconfiguring capabilities have required knowledge of operational data, resource allocation, storage flexibility, and network control. The respondent profile has therefore supported the study's objective of quantitatively assessing adaptive ML-driven PV-BESS capabilities within technically relevant operational environments.

Reliability and Descriptive Statistics of the Study Constructs

Table 2: Reliability and Descriptive Statistics of the Study Constructs

Construct	Code	Items	Alpha	Mean	SD	Rating
Machine Learning-Based Predictive Energy Management	MLPEM	5	.88	4.11	0.58	High
Multi-Objective Energy Optimization	MOO	5	.89	4.16	0.55	High
Intelligent Battery Energy Storage Management	IBESS	5	.84	4.08	0.61	High
Machine Learning-Assisted Optimal Power Flow	MLOPF	5	.91	4.13	0.57	High
Grid Resilience and Renewable Energy Integration Performance	GRRI	5	.90	4.18	0.54	High
Overall Instrument		25	.93	4.13	0.57	High

Likert interpretation: 1.00-1.80 = Very Low, 1.81-2.60 = Low, 2.61-3.40 = Moderate, 3.41-4.20 = High, 4.21-5.00 = Very High.

The reliability and descriptive analysis have confirmed that the measurement instrument has achieved strong internal consistency and that respondents have evaluated all five study constructs positively. Cronbach's alpha values have ranged from .84 for Intelligent Battery Energy Storage Management to .91 for Machine Learning-Assisted Optimal Power Flow, while the overall 25-item instrument has achieved alpha = .93. All coefficients have therefore exceeded the commonly accepted .70 threshold, demonstrating that the items within each construct have measured sufficiently consistent dimensions of the underlying variables. The descriptive results have also shown that all constructs have fallen within the high range of the five-point Likert scale. Grid Resilience and Renewable Energy Integration Performance has obtained the highest overall mean, $M = 4.18$, $SD = 0.54$, indicating that respondents have perceived strong system capability in renewable utilization, operational flexibility, disturbance response, and grid-support performance. Multi-Objective Energy Optimization has recorded the highest independent-variable mean, M = 4.16, SD = 0.55, followed by Machine Learning-Assisted Optimal Power Flow, M = 4.13, SD = 0.57, Machine Learning-Based Predictive Energy Management, M = 4.11, SD = 0.58, and Intelligent Battery Energy Storage Management, M = 4.08, SD = 0.61. The relatively small standard deviations have suggested reasonable agreement among respondents. These findings have fulfilled the descriptive objective of assessing the level of implementation of the four explanatory capabilities and the dependent performance construct. The results have also aligned with Dynamic Capabilities Theory. MLPEM has represented sensing capability, MOO and IBESS have represented the seizing and resource-mobilization dimensions, and MLOPF has represented operational reconfiguration. Their uniformly high scores have indicated that the examined PV-BESS environments have exhibited a coordinated adaptive capability structure rather than isolated technological functionality.

Machine Learning-Based Predictive Energy Management Performance

Table 3: Machine Learning-Based Predictive Energy Management Performance

MLPEM Item	Mean	SD	Interpretation
ML-based forecasting has improved prediction of photovoltaic generation	4.15	0.57	High
ML-based forecasting has improved electricity-demand prediction	4.12	0.59	High
Predictive analytics has supported electricity-price and grid-condition assessment	4.08	0.61	High
Forecast information has been incorporated into battery and energy scheduling	4.11	0.56	High
ML-based predictive systems have supported adaptive real-time dispatch decisions	4.09	0.60	High
Overall MLPEM	4.11	0.58	High

The results for Machine Learning-Based Predictive Energy Management have demonstrated that respondents have perceived a high level of predictive intelligence within the investigated grid-connected PV-BESS environments. The highest-rated item has concerned the improvement of photovoltaic-generation prediction through machine learning, with M = 4.15 and SD = 0.57. This result has suggested that ML-enabled systems have been particularly useful for anticipating variable solar production, which has represented a central source of uncertainty in photovoltaic energy management. Electricity-demand prediction has also received a high evaluation, M = 4.12, SD = 0.59, indicating that predictive systems have supported the anticipation of changing consumption patterns. The incorporation of forecast information into battery and energy scheduling has recorded M = 4.11, SD = 0.56, demonstrating that forecasting has not been perceived merely as an analytical activity but has been connected with operational decision making. Adaptive real-time dispatch has achieved M = 4.09, SD = 0.60, while electricity-price and grid-condition assessment has obtained M = 4.08, SD = 0.61. The overall MLPEM mean of 4.11 with SD = 0.58 has confirmed a high level of implementation. These findings have fulfilled the research objective concerned with assessing machine learning-based predictive energy management in grid-connected PV-BESS systems. From the Dynamic Capabilities Theory perspective, MLPEM has represented the sensing capability because it has enabled the energy-management system to detect and anticipate changes in PV generation, load demand, electricity prices, and grid conditions. Strong sensing capability has been necessary before optimization and resource reconfiguration have occurred. The high item-level means have therefore provided descriptive evidence that the investigated systems have developed an anticipatory informational layer capable of supporting subsequent battery scheduling, multi-objective decisions, and optimal power-flow adjustments. This descriptive evidence has also provided an empirical foundation for testing H1 in the inferential analysis.

Multi-Objective Energy Optimization Performance

The Multi-Objective Energy Optimization results have indicated that the investigated systems have achieved a high level of capability in balancing competing operational objectives. The highest-rated statement has concerned electricity operating-cost minimization, M = 4.20, SD = 0.52, showing that respondents have strongly recognized economic optimization as an established component of PV-BESS energy management. Increased utilization of available photovoltaic energy has recorded M = 4.18, SD = 0.54, while reduction of peak demand and unnecessary grid purchases has achieved M = 4.17, SD = 0.55. These values have demonstrated that optimization has extended beyond cost reduction and has addressed the timing and utilization of renewable electricity. Reduction of power losses and efficient energy allocation has received M = 4.14, SD = 0.57. The balancing of economic, technical, environmental, and battery-related objectives has produced the lowest item mean within the construct, but its value of M = 4.11, SD = 0.58 has remained firmly within the high range. The composite MOO score of M = 4.16, SD = 0.55 has been the highest among all independent variables. This finding has fulfilled the objective of evaluating the extent to which multi-objective optimization has been used to coordinate several PV-BESS operating requirements simultaneously. The result has also aligned closely with the seizing dimension of Dynamic Capabilities Theory. After ML-based sensing has identified relevant changes in generation, demand, prices, and network conditions, multi-objective optimization has represented the capability through which the system has selected an appropriate response among competing alternatives. The high scores have suggested that the examined environments have not optimized isolated outcomes alone but have increasingly coordinated economic efficiency, renewable utilization, grid dependence, and technical performance. This descriptive evidence has supported the theoretical expectation underlying H2 that stronger MOO capability would be positively related to Grid Resilience and Renewable Energy Integration Performance.

Table 4: Multi-Objective Energy Optimization Performance

MOO Item	Mean	SD	Interpretation
Optimization has minimized electricity operating costs	4.20	0.52	High
Optimization has increased utilization of available photovoltaic energy	4.18	0.54	High
Optimization has reduced peak demand and unnecessary grid purchases	4.17	0.55	High
Optimization has reduced power losses and supported efficient energy allocation	4.14	0.57	High
Optimization has balanced economic, technical, environmental, and battery-related objectives	4.11	0.58	High
Overall MOO	4.16	0.55	High

Intelligent Battery Energy Storage Management Performance

The Intelligent Battery Energy Storage Management results have demonstrated a consistently high level of battery-management capability across the investigated PV-BESS cases. State-of-charge monitoring and optimization has received the highest evaluation, M = 4.12, SD = 0.58, suggesting that battery availability has been actively considered when energy-management decisions have been made. Coordination of charging schedules with photovoltaic availability has followed closely at M = 4.10, SD = 0.60, indicating that the storage systems have been used to capture renewable electricity during periods of favorable PV production. Discharging decisions associated with peak demand and grid requirements have recorded M = 4.08, SD = 0.62. Battery degradation and state-of-health consideration has achieved M = 4.06, SD = 0.63, while maintenance of stored energy reserves for operational flexibility and disturbance support has recorded M = 4.04, SD = 0.64. Although this last item has produced the lowest mean within the construct, it has remained within the high interpretation range.

Table 5: Intelligent Battery Energy Storage Management Performance

IBESS Item	Mean	SD	Interpretation
Battery state of charge has been effectively monitored and optimized	4.12	0.58	High
Charging schedules have been coordinated with photovoltaic availability	4.10	0.60	High
Discharging decisions have supported peak demand and grid requirements	4.08	0.62	High
Battery operation has considered degradation and state-of-health conditions	4.06	0.63	High
Stored energy reserves have been maintained for flexibility and disturbance support	4.04	0.64	High
Overall IBESS	4.08	0.61	High

The overall IBESS score has been M = 4.08, SD = 0.61, confirming substantial implementation of intelligent battery-management practices. These findings have fulfilled the objective of determining the extent to which battery charging, discharging, state of charge, battery preservation, and reserve management have been coordinated intelligently. Within Dynamic Capabilities Theory, IBESS has represented a resource-mobilization component of the seizing process because stored energy has functioned as a flexible resource that has been activated according to predicted and observed system conditions. The results have suggested that the battery has not been treated simply as installed capacity but has been actively managed as a strategic operational resource. This has been important for renewable integration because storage has absorbed temporal mismatches between PV generation and load demand, while it has also supported resilience by retaining energy that can be mobilized under stressed conditions. The high descriptive performance has provided the empirical basis for testing H3.

Machine Learning-Assisted Optimal Power Flow Performance

Table 6: Machine Learning-Assisted Optimal Power Flow Performance

MLOPF Item	Mean	SD	Interpretation
ML-assisted OPF has improved real-time power-flow optimization	4.18	0.53	High
ML-assisted OPF has supported acceptable voltage profiles	4.15	0.55	High
ML-assisted OPF has improved active and reactive power allocation	4.13	0.57	High
ML-assisted OPF has reduced network congestion and power losses	4.11	0.59	High

MLOPF Item	Mean	SD	Interpretation
ML-assisted OPF has accelerated network-feasible operating decisions	4.08	0.61	High
Overall MLOPF	4.13	0.57	High

Machine Learning-Assisted Optimal Power Flow has achieved a high overall performance level, with a composite mean of M = 4.13 and SD = 0.57. The highest-rated item has been improvement in real-time power-flow optimization, M = 4.18, SD = 0.53, demonstrating that respondents have perceived machine learning as particularly valuable for supporting repeated and responsive OPF decisions. Maintenance of acceptable voltage profiles has recorded M = 4.15, SD = 0.55, while improvement in active- and reactive-power allocation has achieved M = 4.13, SD = 0.57. These results have indicated that ML-assisted OPF has been associated not only with computational efficiency but also with operational conditions directly related to power-system stability and feasibility. Reduction of network congestion and power losses has obtained M = 4.11, SD = 0.59, and acceleration of network-feasible operating decisions has recorded M = 4.08, SD = 0.61. All five indicators have therefore remained within the high Likert range. The findings have fulfilled the research objective of examining the role of ML-assisted OPF in grid-connected PV-BESS operation. They have also established MLOPF as one of the strongest-performing independent constructs in the descriptive analysis. Through the Dynamic Capabilities Theory framework, MLOPF has represented the reconfiguring dimension because it has concerned the continuous adjustment of network operating points as generation, storage, demand, and grid conditions have changed. The sensing information generated through MLPEM and the decisions selected through MOO and IBESS have required network-feasible implementation, and MLOPF has provided that operational reconfiguration layer. The high scores for voltage management, power allocation, congestion reduction, and real-time optimization have therefore reflected a strong capacity to translate adaptive intelligence into technically feasible electrical operation. This pattern has provided descriptive support for the theoretical expectation underlying H4 and has anticipated the stronger inferential relationship subsequently identified between MLOPF and GRRI.

Grid Resilience and Renewable Energy Integration Performance

Table 7: Grid Resilience and Renewable Energy Integration Performance

GRRI Item	Mean	SD	Interpretation
PV-BESS operation has improved the ability to maintain supply during changing grid conditions	4.22	0.51	Very High
The system has improved utilization of available photovoltaic energy	4.20	0.52	High
PV-BESS coordination has strengthened operational flexibility and disturbance response	4.19	0.54	High
The system has reduced unnecessary renewable-energy curtailment and grid dependence	4.16	0.56	High
Coordinated operation has supported voltage stability and recovery capability	4.13	0.58	High
Overall GRRI	4.18	0.54	High

Grid Resilience and Renewable Energy Integration Performance has recorded the highest composite mean of all study constructs, M = 4.18, SD = 0.54, demonstrating that respondents have perceived a strong level of system-level performance across the investigated PV-BESS cases. The ability to maintain electricity supply under changing grid conditions has received the highest individual score, M = 4.22, SD = 0.51, placing this indicator within the very high interpretation range. Improved utilization of available photovoltaic electricity has followed at M = 4.20, SD = 0.52, suggesting that coordinated PV-BESS operation has enabled a large proportion of renewable generation to be productively integrated into energy use and grid interaction. Operational flexibility and disturbance response has achieved M = 4.19, SD = 0.54, while reduced renewable curtailment and grid dependence has recorded M = 4.16, SD = 0.56. Voltage stability and recovery capability has obtained M = 4.13, SD = 0.58, which has also remained strongly positive. These results have fulfilled the objective of assessing the dependent performance construct and have indicated that resilience and renewable integration have developed together rather than as unrelated outcomes. From the Dynamic Capabilities Theory perspective, GRRI has represented the realized performance associated with successful sensing, seizing, resource mobilization, and reconfiguration. Predictive energy management has identified emerging system conditions, multi-objective optimization has selected balanced responses, intelligent battery management has mobilized storage flexibility, and ML-assisted OPF has reconfigured network operation. The high GRRI score has therefore been theoretically consistent with the high levels recorded for each explanatory construct. Importantly, the descriptive findings alone have not established causal or predictive relationships, but they have shown that the dependent construct has exhibited sufficiently strong and variable measurement for subsequent inferential analysis. The correlation and regression tests in Section 4.8 have consequently been used to determine whether the high levels of the four independent capabilities have been statistically associated with the observed level of grid resilience and renewable energy integration.

Correlation, Multiple Regression, and Hypothesis Testing

The correlation, regression, and hypothesis-testing results have provided direct inferential evidence for the relationships proposed in the conceptual and theoretical frameworks. Pearson correlation analysis has shown that all four independent variables have been positively and significantly associated with Grid Resilience and Renewable Energy Integration Performance. Machine Learning-Based Predictive Energy Management has correlated with GRRI at $r = .68$, $p < .001$, indicating a strong positive relationship and supporting the expectation that improved sensing and prediction have been associated with stronger system performance. Multi-Objective Energy Optimization has produced $r = .72$, $p < .001$, while Intelligent Battery Energy Storage Management has produced $r = .70$, $p < .001$. Machine Learning-Assisted Optimal Power Flow has shown the strongest bivariate relationship with GRRI, $r = .75$, $p < .001$. Multiple regression analysis has further demonstrated that the four predictors have collectively explained 69.4% of the variance in GRRI, R^2 = .694, with Adjusted R^2 = .690. The overall model has been statistically significant, $F(4, 291) = 165.02$, $p < .001$, thereby supporting H5. At the individual predictor level, MLOPF has produced the strongest standardized regression effect, beta = .31, t = 7.08, $p < .001$, followed by MOO, beta = .28, t = 6.21, IBESS, beta = .24, t = 5.43, and MLPEM, beta = .22, t = 4.98. H1, H2, H3, and H4 have therefore all been supported. VIF values have ranged from 1.54 to 2.12, indicating that multicollinearity has not threatened coefficient interpretation, while the Durbin-Watson statistic of 1.91 has indicated acceptable independence of residuals. These results have fulfilled the objectives concerned with identifying relationships and determining the individual and collective predictive effects of the study variables. The findings have also supported Dynamic Capabilities Theory by showing that sensing through MLPEM, seizing through MOO and IBESS, and operational reconfiguration through MLOPF have each contributed significantly to the adaptive performance represented by GRRI. Among these capabilities, reconfiguration through ML-assisted OPF has emerged as the strongest statistical predictor, while the substantial R^2 has demonstrated that the integrated capability structure has accounted for a large proportion of observed differences in grid resilience and renewable energy integration performance.

Table 8: Correlation, Multiple Regression, and Hypothesis Testing Results

Hypothesis/ Model	Predictor or Relationship	Pearson r	Standardized Beta	t	VIF	p-value	Decision
H1	MLPEM -> GRRI	.68	.22	4.98	1.54	< .001	Supported
H2	MOO -> GRRI	.72	.28	6.21	1.88	< .001	Supported

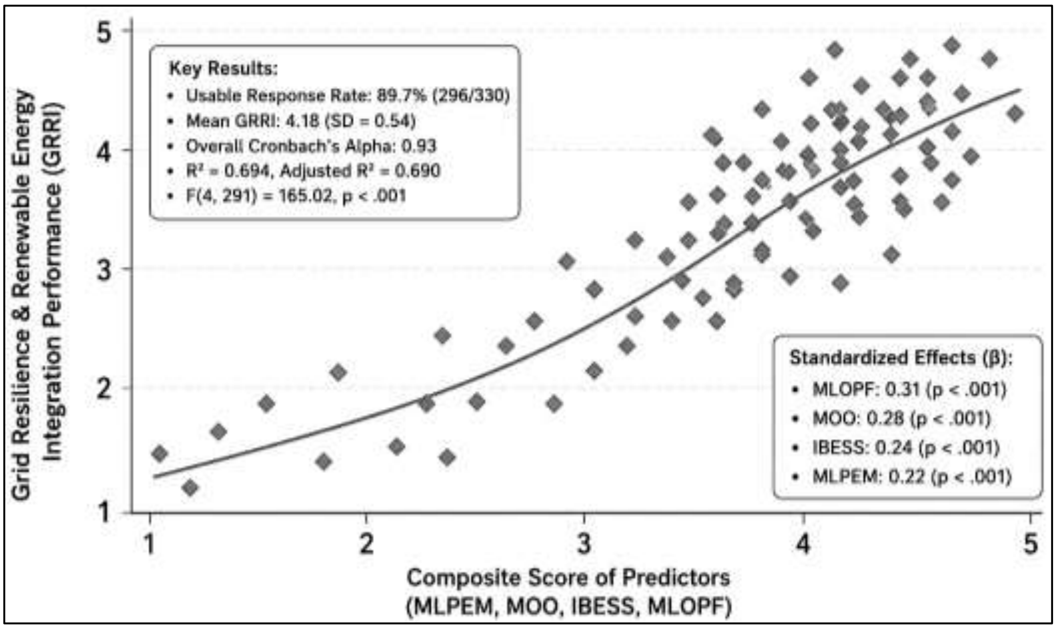
Hypothesis/ Model	Predictor or Relationship	Pearson r	Standardized Beta	t	VIF	p-value	Decision
H3	IBESS -> GRRI	.70	.24	5.43	1.76	< .001	Supported
H4	MLOPF -> GRRI	.75	.31	7.08	2.12	< .001	Supported
H5	Combined MLPEM + MOO + IBESS + MLOPF -> GRRI	R = .833	R^2 = .694	F (4,291) = 165.02	DW = 1.91	< .001	Supported

Model statistics: Adjusted R^2 = .690; N = 296.

FINDINGS

The findings of this study have demonstrated an overall positive and statistically significant pattern regarding the contribution of machine learning-driven energy management and optimal power flow to grid resilience and renewable energy integration in grid-connected photovoltaic-battery energy storage systems. A total of 330 questionnaires have been distributed, 305 responses have been returned, and 296 questionnaires have been retained as usable, producing a usable response rate of 89.7%. The five-point Likert-scale results have indicated comparatively strong implementation of all investigated constructs. Multi-Objective Energy Optimization has recorded the highest mean among the independent variables, M = 4.16, SD = 0.55, followed by Machine Learning-Assisted Optimal Power Flow, M = 4.13, SD = 0.57, Machine Learning-Based Predictive Energy Management, M = 4.11, SD = 0.58, and Intelligent Battery Energy Storage Management, M = 4.08, SD = 0.61. Grid Resilience and Renewable Energy Integration Performance has obtained an overall mean of M = 4.18, SD = 0.54, indicating a high perceived level of resilient and renewable-integrated system performance. Reliability analysis has shown satisfactory internal consistency, with Cronbach's alpha coefficients ranging from alpha = .84 to alpha = .91 across the five constructs and an overall reliability coefficient of alpha = .93. Pearson correlation analysis has revealed significant positive relationships between GRRI and MLPEM, r = .68, MOO, r = .72, IBESS, r = .70, and MLOPF, r = .75, with all relationships significant at p < .001. These results have supported the objectives concerned with identifying the direction and strength of associations among the study variables. Multiple regression analysis has further shown that the four independent variables have collectively explained 69.4% of the variance in Grid Resilience and Renewable Energy Integration Performance, R^2 = .694, Adjusted R^2 = .690, F(4, 291) = 165.02, p < .001. Among the predictors, Machine Learning-Assisted Optimal Power Flow has produced the strongest standardized effect, beta = .31, p < .001, followed by Multi-Objective Energy Optimization, beta = .28, p < .001, Intelligent Battery Energy Storage Management, beta = .24, p < .001, and Machine Learning-Based Predictive Energy Management, beta = .22, p < .001. Multicollinearity has not presented a concern, with VIF values ranging from 1.54 to 2.12, while the Durbin-Watson statistic of 1.91 has indicated acceptable independence of residuals.

Figure 9: Findings of The Study



Accordingly, H1, H2, H3, H4, and H5 have all been supported, demonstrating that the four machine learning-driven and optimization-based capabilities have individually and collectively contributed significantly to enhanced grid resilience and renewable energy integration performance.

DISCUSSION

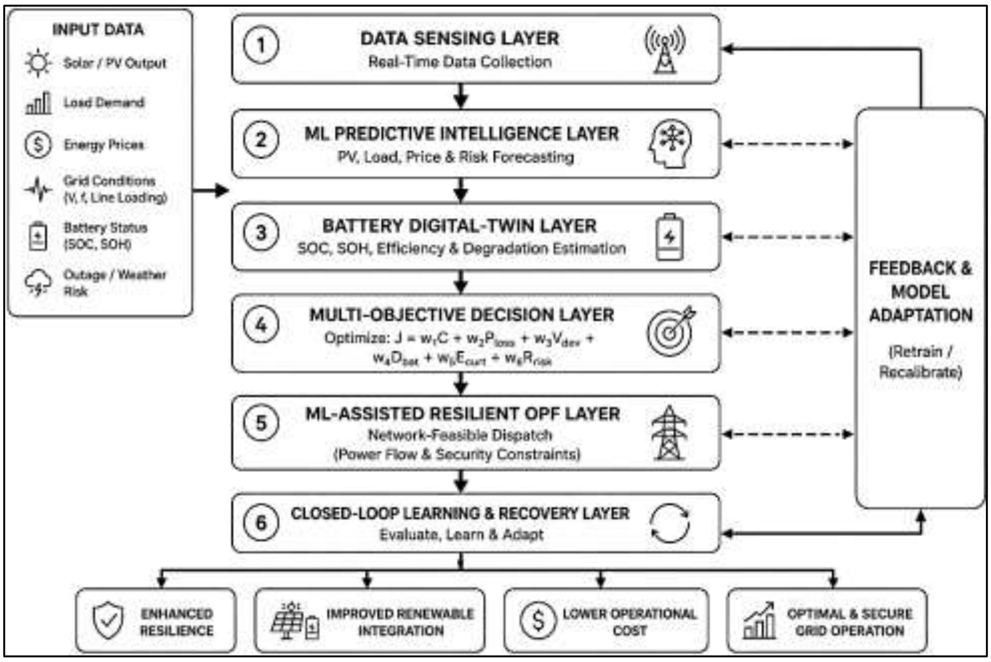
The findings have demonstrated that machine learning-driven predictive intelligence, multi-objective optimization, intelligent battery management, and machine learning-assisted optimal power flow have all been significantly associated with Grid Resilience and Renewable Energy Integration Performance within the examined grid-connected photovoltaic-battery energy storage environments. The descriptive findings have shown high evaluations for all explanatory constructs, with Multi-Objective Energy Optimization recording the highest independent-variable mean, M = 4.16, SD = 0.55, followed by Machine Learning-Assisted Optimal Power Flow, M = 4.13, SD = 0.57, Machine Learning-Based Predictive Energy Management, M = 4.11, SD = 0.58, and Intelligent Battery Energy Storage Management, M = 4.08, SD = 0.61. The dependent construct has achieved an overall mean of M = 4.18, SD = 0.54, suggesting that respondents have perceived relatively strong renewable integration, flexibility, disturbance response, and network-support capability. More importantly, the inferential results have demonstrated that all four explanatory variables have been significantly and positively related to GRRI. MLOPF has produced the strongest correlation, r = .75, followed by MOO, r = .72, IBESS, r = .70, and MLPEM, r = .68, with all relationships significant at $p < .001$. The regression model has further explained 69.4% of the variance in GRRI, R^2 = .694, Adjusted R^2 = .690, and has been statistically significant, F(4, 291) = 165.02, $p < .001$. These findings have been consistent with previous research showing that intelligent energy management can coordinate PV production, storage operation, electricity prices, and grid transactions more effectively than static scheduling approaches. Reinforcement-learning-based PV-battery management has previously shown that adaptive control can improve storage utilization and reduce operating costs under uncertain renewable generation and load conditions (Pervaz, 2025; Muriithi & Chowdhury, 2021). The present finding that MLOPF has emerged as the strongest predictor, beta = .31, $p < .001$, has also been consistent with earlier work demonstrating that deep-learning-based OPF methods can approximate complex mappings between system states and economically feasible dispatch solutions while reducing the computational burden of repeated optimization (Chowdhury, 2025; Pan et al., 2021). Similarly, the significant IBESS effect, beta = .24, has reinforced evidence that inaccurate representation of battery degradation can materially alter storage schedules and operational costs, confirming that intelligent battery management must account for more than state of charge alone (Badrul, 2025; Wang et al., 2020). Overall, H1 through H5 have been supported, indicating that prediction, optimization, battery flexibility, and network reconfiguration have operated as complementary rather than competing determinants of resilient renewable-energy integration.

From a practical perspective, the findings have indicated that utilities, renewable-energy developers, microgrid operators, energy managers, and power-system engineers should treat ML-enabled PV-BESS operation as an integrated control problem rather than implementing individual algorithms independently. The significant MLPEM coefficient, beta = .22, has suggested that predictive capability has provided an important first layer of operational intelligence because forecasts of photovoltaic generation, load demand, tariff conditions, and network states have enabled subsequent decisions to be made before imbalances occur. However, its smaller standardized effect relative to MOO and MLOPF has suggested that forecasting alone has not been sufficient to generate the highest level of resilience and renewable integration. Forecast information has needed to be transformed into concrete operating decisions. The stronger MOO coefficient, beta = .28, has therefore indicated that operators should configure energy-management systems to evaluate several objectives simultaneously, including grid purchases, renewable-energy utilization, power losses, peak demand, voltage conditions, battery degradation, and reserve requirements. Previous reinforcement-learning research has similarly demonstrated that grid-tied PV-battery scheduling can incorporate utility-energy costs and battery wear within the same decision process, producing lower operating costs when battery and grid transactions have been coordinated adaptively (Muriithi & Chowdhury, 2021; Nishat, 2025). The IBESS results have also carried direct operational importance. Battery management should include state-of-charge limits, state-of-health estimates, depth-of-discharge restrictions, charging and discharging efficiency, cycle ageing, and reserve-energy requirements. This interpretation has been supported by evidence that simplified battery-degradation models can create substantial deviations in calculated operating schedules and can produce additional real operating costs when the resulting schedules are applied (Sadia, 2025; Wang et al., 2020). Most importantly, the finding that MLOPF has produced the strongest standardized effect has indicated that the final quality of a PV-BESS energy-management decision has depended heavily on whether it can be implemented while satisfying electrical-network requirements. Utilities should therefore integrate predictive ML and storage scheduling with voltage limits, line constraints, active- and reactive-power requirements, congestion conditions, and system-security rules. This interpretation has also corresponded with resilience-oriented network planning in which renewable resources and BESS have been optimized jointly with network and resilience objectives rather than being treated as independent assets (Sadia, 2025; Shafiei et al., 2024). Practically, the statistical pattern has supported a layered architecture in which forecasting has informed optimization, optimization has directed battery utilization, and ML-assisted OPF has converted those decisions into network-compatible operating actions.

The findings have also provided substantive theoretical support for the Dynamic Capabilities Theory framework adopted in this study. Dynamic Capabilities Theory has conceptualized adaptive performance through sensing, seizing, and reconfiguring processes, and the present variables have allowed these theoretical dimensions to be operationalized within a technically complex energy-system environment. MLPEM has represented sensing because it has enabled the system to identify and anticipate changes in photovoltaic generation, demand, prices, battery conditions, and grid variables. Its significant relationship with GRRI, r = .68, and regression effect, beta = .22, have indicated that anticipatory information has been associated with higher resilience and renewable-integration performance. MOO has represented the seizing dimension because optimization has transformed available information into decisions among competing technical and economic alternatives. Its stronger relationship with GRRI, r = .72, beta = .28, has suggested that the value of sensing has increased when predicted information has been converted into coordinated resource-allocation decisions. IBESS has represented resource mobilization within the seizing and reconfiguration process because stored energy has been charged, retained, or discharged depending on changing operational conditions. Finally, MLOPF has represented the strongest reconfiguring capability because it has adjusted the physical operating state of the network through active-power allocation, reactive-power management, voltage regulation, congestion mitigation, and feasible grid exchange. Its leading standardized coefficient of beta = .31 has therefore been theoretically meaningful because reconfiguration has represented the stage at which prediction and optimization have ultimately been converted into physical system action. This interpretation has been consistent with research applying dynamic capabilities to electrical-energy digitalization, where sensing, seizing, and transformation have been identified as important capabilities for responding to changing digital and energy-system conditions (Idries et al., 2022; Tonay, 2025). The results have therefore extended the theoretical framework from a predominantly organizational interpretation toward an operational cyber-physical context in which information, algorithms, battery assets, and electrical-network constraints have interacted dynamically. The substantial R^2 of .694 has further indicated that the combined capability structure has accounted for a considerable proportion of variation in GRRI, which has been consistent with the theoretical proposition that adaptive performance emerges from coordinated capabilities rather than from a single resource. At the same time, the results have not implied that Dynamic Capabilities Theory alone has completely explained grid resilience, since approximately 30.6% of the observed variance has remained attributable to factors outside the model, potentially including inverter characteristics, network topology, communications reliability, cybersecurity, protection systems, weather severity, storage capacity, and regulatory conditions.

The limitations of the study have required careful consideration when interpreting these statistically strong findings. First, the cross-sectional design has measured the explanatory constructs and GRRI at a single period, meaning that the regression coefficients have represented statistical associations rather than definitive longitudinal causal effects. Although MLPEM, MOO, IBESS, and MLOPF have all produced significant positive coefficients, the design has not demonstrated that increasing one capability by a particular amount would automatically cause a corresponding increase in resilience performance over time. Second, the case-study-based and purposive sampling approach has concentrated on respondents with technical knowledge of PV-BESS, renewable-energy systems, grid operation, storage, and machine learning. This has improved the relevance of the responses but has limited the extent to which the numerical findings can be generalized to every electricity network, geographical region, regulatory regime, or PV-BESS architecture. Third, the study has relied on five-point Likert-scale evaluations rather than direct high-frequency measurements of voltage, frequency, battery SOC, renewable curtailment, outage duration, energy-not-served, line loading, or restoration time. The high mean values, ranging from 4.08 to 4.18, may also indicate some positive-response clustering or ceiling effects. This measurement structure differs from much of the earlier engineering literature, which has evaluated energy-management performance through simulation, optimization, or operational datasets. For example, battery-management research has demonstrated that alternative degradation models can generate markedly different dispatch schedules and cost outcomes under otherwise identical operating conditions, illustrating the value of direct technical validation alongside perception-based evaluation (Mohammad, 2026; Wang et al., 2020). Resilience-oriented BESS studies have similarly used benchmark networks and simulation-based resilience metrics to quantify system performance under specified operating conditions and disturbances (Jannatul, 2026; Shafiei et al., 2024). Fourth, the integrated GRRI construct has combined resilience and renewable-energy integration into one dependent variable. This approach has supported a parsimonious model but may have concealed differences between normal-operation renewable integration and disturbance-oriented resilience. Fifth, although VIF values between 1.54 and 2.12 have indicated acceptable multicollinearity and the Durbin-Watson statistic of 1.91 has supported residual independence, common-method variance may still have existed because predictor and outcome measures have been collected through the same questionnaire. These limitations have not invalidated the findings, but they have established boundaries around how the coefficients and hypothesis decisions should be interpreted and have identified specific methodological areas that subsequent research can strengthen.

Figure 10: Machine Learning-Driven Adaptive Multi-Objective PV-BESS Resilience Optimization Model (ML-AMPRO)



Future research should therefore move from the present cross-sectional perceptual model toward an integrated operational architecture that combines survey evidence with real-time power-system measurements, machine-learning prediction, battery digital-twin modelling, multi-objective optimization, and resilience-oriented OPF. A suitable extension is the proposed Machine Learning-Driven Adaptive Multi-Objective PV-BESS Resilience Optimization Model (ML-AMPRO). The model should contain six interacting layers. The first, a Data Sensing Layer, should collect solar irradiance, temperature, PV output, load demand, electricity prices, bus voltage, frequency, line loading, battery SOC, battery SOH, outage signals, and weather-risk information. The second, an ML Predictive Intelligence Layer, should employ ensemble learning, LSTM models, transformers, or probabilistic forecasting to generate short-term PV, demand, price, and disturbance-risk estimates. The third, a Battery Digital-Twin Layer, should continuously estimate SOC, SOH, temperature, efficiency, cycle ageing, and remaining usable capacity so that battery actions reflect physical degradation rather than idealized storage assumptions. This component has been supported by earlier evidence showing that degradation representation can materially change energy-management outcomes (Ahmed, 2026; Wang et al., 2020). The fourth, a Multi-Objective Decision Layer, should optimize a weighted or Pareto-based objective function such as J = w1C + w2Ploss + w3Vdev + w4Dbat + w5Ecurt + w6Rrisk, where C represents cost, Ploss power losses, Vdev voltage deviation, Dbat battery degradation, Ecurt renewable curtailment, and Rrisk resilience risk. The fifth, an ML-Assisted Resilient OPF Layer, should translate the selected schedule into network-feasible active- and reactive-power decisions while enforcing voltage, line-flow, inverter, and security constraints. The sixth, a Closed-Loop Learning and Recovery Layer, should compare predicted and observed outcomes and retrain or recalibrate the model after forecast errors, disturbances, or battery degradation. Resilience-oriented renewable and BESS planning has already demonstrated the importance of integrating storage capacity, network operation, cost, and resilience metrics within a multi-objective structure (Rahman, 2026; Shafiei et al., 2024). Future researchers could validate ML-AMPRO through longitudinal field data and IEEE 33-bus, 69-bus, and 118-bus test systems, compare reinforcement learning with supervised and physics-informed ML, separate renewable integration and resilience as distinct dependent outcomes, test mediating effects of battery flexibility, and examine whether MLOPF moderates the relationship between predictive energy management and resilience. Such an extension would directly address the current study's measurement and causal limitations while preserving the supported sensing, seizing, and reconfiguring structure of Dynamic Capabilities Theory.

$$J = w_1C + w_2P\_loss + w_3V\_dev + w_4D\_bat + w_5E\_curt + w_6R\_risk$$

CONCLUSION

This study has quantitatively examined the contribution of machine learning-driven multi-objective energy management and optimal power flow to Grid Resilience and Renewable Energy Integration Performance in grid-connected photovoltaic-battery energy storage systems. The research has adopted a quantitative, cross-sectional, case-study-based design and has analyzed 296 usable responses obtained from technically relevant professionals working across power systems, renewable energy, battery storage, grid operations, energy management, and machine learning. The findings have demonstrated that all four explanatory constructs have achieved high levels of perceived implementation, with Multi-Objective Energy Optimization recording M = 4.16, SD = 0.55, Machine Learning-Assisted Optimal Power Flow recording M = 4.13, SD = 0.57, Machine Learning-Based Predictive Energy Management recording M = 4.11, SD = 0.58, and Intelligent Battery Energy Storage Management recording M = 4.08, SD = 0.61. Grid Resilience and Renewable Energy Integration Performance has achieved M = 4.18, SD = 0.54. The inferential results have further confirmed strong and statistically significant positive relationships between GRRI and MLPEM, r = .68, MOO, r = .72, IBESS, r = .70, and MLOPF, r = .75, with all relationships significant at $p < .001$. The multiple regression model has explained 69.4% of the variance in GRRI, R^2 = .694, Adjusted R^2 = .690, F(4, 291) = 165.02, $p < .001$. MLOPF has emerged as the strongest predictor, beta = .31, followed by MOO, beta = .28, IBESS, beta = .24, and MLPEM, beta = .22. Accordingly, H1, H2, H3, H4, and H5 have all been supported. The findings have also remained consistent with Dynamic Capabilities Theory by demonstrating that sensing through predictive intelligence, seizing through optimization and battery resource mobilization, and reconfiguring through ML-assisted OPF have jointly explained resilient and renewable-integrated system performance. Overall, the study has established that effective PV-BESS performance has depended on the coordinated integration of prediction, optimization, storage intelligence, and network-aware power-flow control rather than on any single technological capability.

RECOMMENDATIONS

Based on the empirical findings, this study recommends that utilities, renewable-energy developers, grid operators, energy managers, and PV-BESS system designers adopt a more integrated machine learning-driven operating architecture in which forecasting, optimization, battery control, and optimal power flow are treated as connected components of one decision framework. Since Machine Learning-Assisted Optimal Power Flow has produced the strongest standardized effect on GRRI, beta = .31, organizations should prioritize the integration of ML-based OPF tools capable of supporting faster voltage regulation, active- and reactive-power allocation, congestion management, and network-feasible dispatch. Multi-Objective Energy Optimization, which has recorded beta = .28, should also be strengthened so that operating decisions simultaneously consider electricity cost, renewable-energy utilization, peak-demand reduction, power losses, battery degradation, reserve requirements, and grid-support objectives. Intelligent Battery Energy Storage Management should incorporate continuous SOC and SOH monitoring, degradation-aware charging and discharging limits, reserve-energy policies, temperature monitoring, and lifecycle considerations to prevent short-term economic optimization from reducing long-term battery performance. Machine Learning-Based Predictive Energy Management should combine PV generation forecasting, load-demand forecasting, electricity-price prediction, and grid-condition assessment so that decisions can be made before operating imbalances occur. Utilities should further improve the quality, frequency, and interoperability of operational data because ML performance depends heavily on reliable measurements from PV arrays, batteries, smart meters, weather stations, and network sensors. Cybersecurity and communication resilience should also be incorporated into intelligent PV-BESS design because highly connected energy-management architectures can become vulnerable to data manipulation or communication failure. Finally, organizations should implement continuous model validation and retraining procedures so that prediction and optimization algorithms remain aligned with changing load patterns, battery conditions, and network behavior. A staged implementation strategy beginning with predictive analytics, followed by multi-objective scheduling, battery digitalization, and ML-assisted OPF integration, would provide a practical pathway for strengthening grid resilience and renewable energy integration while maintaining technical feasibility and operational control.

LIMITATIONS

This study has several limitations that should be recognized when interpreting the statistical findings. First, the research has used a cross-sectional design, meaning that data have been collected at a single period rather than across multiple operational stages. Consequently, the significant regression relationships have demonstrated statistical association and predictive contribution but have not established strict long-term causality between MLPEM, MOO, IBESS, MLOPF, and GRRI. Second, the study has relied on a case-study-based purposive sample of technically experienced professionals, which has improved subject-matter relevance but has limited the generalizability of the findings to all utilities, geographic regions, regulatory systems, network configurations, and PV-BESS technologies. Third, the principal variables have been measured through a five-point Likert scale, meaning that the results have reflected professional perceptions rather than direct operational measurements such as voltage deviations, frequency excursions, renewable curtailment, energy-not-served, battery cycle counts, outage duration, restoration time, or real-time network losses. Fourth, the dependent variable has combined grid resilience and renewable energy integration into one integrated construct. Although this structure has supported a concise statistical model, it may have concealed differences between normal-operation renewable integration and disturbance-oriented resilience performance. Fifth, common-method bias may have been present because the independent and dependent variables have been measured using the same questionnaire. Sixth, technological heterogeneity among the investigated cases may have influenced respondent evaluations because differences in PV capacity, battery chemistry, inverter technology, ML algorithms, communication infrastructure, and grid topology have not been modeled separately. Finally, approximately 30.6% of the variance in GRRI has remained unexplained by the regression model, indicating that other factors such as cybersecurity, protection systems, communication reliability, inverter capability, weather severity, storage capacity, regulatory conditions, and network architecture may also affect resilient renewable-energy integration. These limitations define the boundaries of the present findings and identify areas that require stronger operational, longitudinal, and experimental validation.

REFERENCES

[1]. Abdel-Nasser, M., & Mahmoud, K. (2019). Accurate photovoltaic power forecasting models using deep LSTM-RNN. *Neural Computing and Applications*, *31*, 2727-2740. https://doi.org/10.1007/s00521-017-3225-z

[2]. Abdullah Mohammad, S. (2023). $CUGAO_2$ and $CUINS_2$ Quantum Dot Sensitization for Enhanced Photovoltaic Efficiency in Wearable Fiber-Shaped Solar Cells. *American Journal of Advanced Technology and Engineering Solutions*, *3*(04), 209-261. https://doi.org/10.63125/wysdvy71

[3]. Abdullah Mohammad, S. (2026). An AL/ML Integrated Framework for Process Optimization and Advanced Materials Integration in U.S. Oil and Gas Chemical Manufacturing: From Nanostructured Research to Industrial Application. *International Journal of Scientific Interdisciplinary Research*, *7*(1), 727-773. https://doi.org/10.63125/495txr49

[4]. Aghajani, G., & Ghadimi, N. (2018). Multi-objective energy management in a micro-grid. *Energy Reports*, *4*, 218-225. https://doi.org/10.1016/j.egyr.2017.10.002

[5]. Ahmed, D., Ebeed, M., Ali, A., Alghamdi, A. S., & Kamel, S. (2021). Multi-objective energy management of a micro-grid considering stochastic nature of load and renewable energy resources. *Electronics*, *10*(4), 403. https://doi.org/10.3390/electronics10040403

[6]. Almeida, M. P., Perpinan, O., & Narvarte, L. (2015). PV power forecast using a nonparametric PV model. *Solar Energy*, *115*, 354-368. https://doi.org/10.1016/j.solener.2015.03.006

[7]. Antonanzas, J., Osorio, N., Escobar, R., Urraca, R., Martinez-de-Pison, F. J., & Antonanzas-Torres, F. (2016). Review of photovoltaic power forecasting. *Solar Energy*, *136*, 78-111. https://doi.org/10.1016/j.solener.2016.06.069

[8]. Ashrafuzzaman, M. (2024). The impact of cloud-based management information systems on hrm efficiency: an analysis of small and medium-sized enterprises (SMES). *Academic Journal on Artificial Intelligence, Machine Learning, Data Science and Management Information Systems*, *1*(01), 40-56. https://doi.org/10.69593/ajaimldsmis.v1i01.124

[9]. Berecibar, M., Gandiaga, I., Villarreal, I., Omar, N., Van Mierlo, J., & Van den Bossche, P. (2016). Critical review of state of health estimation methods of Li-ion batteries for real applications. *Renewable and Sustainable Energy Reviews*, *56*, 572-587. https://doi.org/10.1016/j.rser.2015.11.042

[10]. Chen, Q., Kuang, Z., Liu, X., & Zhang, T. (2024). Application-oriented assessment of grid-connected PV-battery system with deep reinforcement learning in buildings considering electricity price dynamics. *Applied Energy*, *364*, 123163. https://doi.org/10.1016/j.apenergy.2024.123163

[11]. de la Torre, S., Gonzalez-Gonzalez, J. M., Aguado, J. A., & Martin, S. (2019). Optimal battery sizing considering degradation for renewable energy integration. *IET Renewable Power Generation*, *13*(4), 572-577. https://doi.org/10.1049/iet-rpg.2018.5489

[12]. Debasish, A. (2021). Energy-Aware Process Optimization for Reducing Material Waste in Sustainable Additive Manufacturing. *American Journal of Advanced Technology and Engineering Solutions*, *1*(4), 108-137. https://doi.org/10.63125/j0wk7j48

[13]. Debasish, A. (2022). Simulation-Based Thermal Management Framework for Reducing Energy Consumption in Advanced Manufacturing Systems. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 335–381. https://doi.org/10.63125/6fcj7c89

[14]. Debasish, A. (2023). Thermal Behavior Modeling for Predicting Process Instability in Additive Manufacturing Systems. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 485-528. https://doi.org/10.63125/b2nemb48

[15]. Debasish, A. (2024). AI-Based Quality Control Framework for Reducing Rework and Scrap in Additive Manufacturing Production. *Review of Applied Science and Technology*, *3*(04), 402–447. https://doi.org/10.63125/z29tv526

[16]. Debasish, A. (2025a). Design-for-Manufacturing Optimization for Improving Resilience in U.S. Additive Manufacturing Supply Chains. *American Journal of Interdisciplinary Studies*, *6*(02), 185-204. https://doi.org/10.63125/hxm3tb71

[17]. Debasish, A. (2025b). Physics-Informed Machine Learning for Predicting Thermal Distortion in Metal Additive Manufacturing. *American Journal of Scholarly Research and Innovation*, *4*(01), 943–989. https://doi.org/10.63125/ny974y17

[18]. Deihim, A., Apostolopoulou, D., & Alonso, E. (2024). Initial estimate of AC optimal power flow with graph neural networks. *Electric Power Systems Research*, *234*, 110782. https://doi.org/10.1016/j.epsr.2024.110782

[19]. Dominguez-Barbero, D., Garcia-Gonzalez, J., Sanz-Bobi, M. A., & Garcia-Cerrada, A. (2024). Energy management of a microgrid considering nonlinear losses in batteries through deep reinforcement learning. *Applied Energy*, *368*, 123435. https://doi.org/10.1016/j.apenergy.2024.123435

[20]. Duan, F., Eslami, M., Khajehzadeh, M., Basem, A., Jasim, D. J., & Palani, S. (2024). Optimization of a photovoltaic/wind/battery energy-based microgrid in distribution network using machine learning and fuzzy multi-objective improved Kepler optimizer algorithms. *Scientific Reports*, *14*, 13354. https://doi.org/10.1038/s41598-024-64234-x

[21]. Galvan, E., Mandal, P., & Sang, Y. (2020). Networked microgrids with roof-top solar PV and battery energy storage to improve distribution grids resilience to natural disasters. *International Journal of Electrical Power & Energy Systems*, *123*, 106239. https://doi.org/10.1016/j.ijepes.2020.106239

[22]. Guerrero, J. M., Vasquez, J. C., Matas, J., Garcia de Vicuna, L., & Castilla, M. (2011). Hierarchical control of droop-controlled AC and DC microgrids: A general approach toward standardization. *IEEE Transactions on Industrial Electronics*, *58*(1), 158-172. https://doi.org/10.1109/tie.2010.2066534

[23]. Gupta, S., Misra, S., Deka, D., & Kekatos, V. (2022). DNN-based policies for stochastic AC OPF. *Electric Power Systems Research*, *213*, 108563. https://doi.org/10.1016/j.epsr.2022.108563

[24]. Hanna, R., Kleissl, J., Nottrott, A., & Ferry, M. (2014). Energy dispatch schedule optimization for demand charge reduction using a photovoltaic-battery storage system with solar forecasting. *Solar Energy*, *103*, 269-287. https://doi.org/10.1016/j.solener.2014.02.020

[25]. Hannan, M. A., Lipu, M. S. H., Hussain, A., & Mohamed, A. (2017). A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations. *Renewable and Sustainable Energy Reviews*, *78*, 834-854. https://doi.org/10.1016/j.rser.2017.05.001

[26]. Hatziargyriou, N., Asano, H., Iravani, R., & Marnay, C. (2007). Microgrids. *IEEE Power and Energy Magazine*, *5*(4), 78-94. https://doi.org/10.1109/mpae.2007.376583

[27]. Hermundsdottir, F., Bjorgum, O., & Eide, A. E. (2024). Transition from fossil fuels to renewable energy: Identifying the necessary dynamic capabilities for a transition among Norwegian oil and gas companies. *Business Strategy and the Environment*, *33*(7), 6315-6334. https://doi.org/10.1002/bse.3826

[28]. Hoppmann, J., Volland, J., Schmidt, T. S., & Hoffmann, V. H. (2014). The economic viability of battery storage for residential solar photovoltaic systems: A review and a simulation model. *Renewable and Sustainable Energy Reviews*, *39*, 1101-1118. https://doi.org/10.1016/j.rser.2014.07.068

[29]. Hussein, H. M. (2024). A review of battery state of charge estimation and management systems: Models and future prospective. *WIREs Energy and Environment*, *13*(1), e507. https://doi.org/10.1002/wene.507

[30]. Idries, A., Krogstie, J., & Rajasekharan, J. (2022). Dynamic capabilities in electrical energy digitalization: A case from the Norwegian ecosystem. *Energies*, *15*(22), 8342. https://doi.org/10.3390/en15228342

[31]. Jannatul, F. (2025). Spinal Cord Injury and Neurorehabilitation Deep Learning–Based Prediction of Functional Recovery Trajectories After Traumatic Spinal Cord Injury. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 2865–2922. https://doi.org/10.63125/m738bh82

[32]. Jannatul, F. (2026). Predicting Falls and Mobility Decline Among Older Adults Using Longitudinal Functional Data and Ensemble Machine Learning. *International Journal of Scientific Interdisciplinary Research*, *7*(1), 581–631. https://doi.org/10.63125/56hans40

[33]. Jiang, B., Wang, Q., Wu, S., Wang, Y., & Lu, G. (2024). Advancements and future directions in the application of machine learning to AC optimal power flow: A critical review. *Energies*, *17*(6), 1381. https://doi.org/10.3390/en17061381

[34]. Jin, L., Kazemi, M., Comodi, G., & Papadimitriou, C. (2024). Assessing battery degradation as a key performance indicator for multi-objective optimization of multi-carrier energy systems. *Applied Energy*, *361*, 122925. https://doi.org/10.1016/j.apenergy.2024.122925

[35]. Khalilpour, R., & Vassallo, A. (2016). Planning and operation scheduling of PV-battery systems: A novel methodology. *Renewable and Sustainable Energy Reviews*, *53*, 194-208. https://doi.org/10.1016/j.rser.2015.08.015

[36]. Khezri, R., Mahmoudi, A., & Aki, H. (2022). Optimal planning of solar photovoltaic and battery storage systems for grid-connected residential sector: Review, challenges and new perspectives. *Renewable and Sustainable Energy Reviews*, *153*, 111763. https://doi.org/10.1016/j.rser.2021.111763

[37]. Kolodziejczyk, W., Zoltowska, I., & Cichosz, P. (2021). Real-time energy purchase optimization for a storage-integrated photovoltaic system by deep reinforcement learning. *Control Engineering Practice*, *106*, 104598. https://doi.org/10.1016/j.conengprac.2020.104598

[38]. Kroposki, B., Johnson, B., Zhang, Y., Gevorgian, V., Denholm, P., Hodge, B. M., & Hannegan, B. (2017). Achieving a 100% renewable grid: Operating electric power systems with extremely high levels of variable renewable energy. *IEEE Power and Energy Magazine*, *15*(2), 61-73. https://doi.org/10.1109/mpe.2016.2637122

[39]. Liang, X., Ge, W., Zhang, Z., Zheng, F., Jin, X., & Du, Z. (2024). Two-stage optimal scheduling for flexibility and resilience tradeoff of PV-battery building via smart grid communication. *Sustainable Cities and Society*, *116*, 105919. https://doi.org/10.1016/j.scs.2024.105919

[40]. Lotfi, A., & Pirnia, M. (2022). Constraint-guided deep neural network for solving optimal power flow. *Electric Power Systems Research*, *211*, 108353. https://doi.org/10.1016/j.epsr.2022.108353

[41]. Luo, X., Wang, J., Dooner, M., & Clarke, J. (2015). Overview of current development in electrical energy storage technologies and the application potential in power system operation. *Applied Energy*, *137*, 511-536. https://doi.org/10.1016/j.apenergy.2014.09.081

[42]. Luthander, R., Widen, J., Nilsson, D., & Palm, J. (2015). Photovoltaic self-consumption in buildings: A review. *Applied Energy*, *142*, 80-94. https://doi.org/10.1016/j.apenergy.2014.12.028

[43]. Mahfuj Ahmed, R. (2026). AI-Assisted Credit Evaluation Models for Improving Risk Assessment Accuracy in U.S. Banking Systems. *American Journal of Interdisciplinary Studies*, *7*(01), 387-425. https://doi.org/10.63125/aa031j21

[44]. Md Anisur Rahman, M. (2024). State Income Tax Differentials and High-Skilled Labor Mobility in The United States: A Time Series Analysis. *American Journal of Interdisciplinary Studies*, *5*(04), 222-267. https://doi.org/10.63125/295bsn47

[45]. Md Anisur Rahman, M. (2025). The Role of AI-Enabled Business Intelligence in Financial Risk Assessment and Liquidity Monitoring. *Review of Applied Science and Technology*, *4*(04), 195–246. https://doi.org/10.63125/p4eezd93

[46]. Md Anisur Rahman, M. (2026). AI-Driven Business Intelligence for Real-Time Fraud Risk Monitoring in Digital Payment Platforms: A Framework-Based Review. *International Journal of Scientific Interdisciplinary Research*, *7*(1), 527–580. https://doi.org/10.63125/0ef34271

[47]. Md Arif Uz, Z., Sharmin, S., & Md Abdur, R. (2025). Factors Influencing Behavioural Intention to Use he Innovative Open And Distance Learning Systems With The Role Of Continuance Intention. *American Journal of Scholarly Research and Innovation*, *4*(01), 202-220. https://doi.org/10.63125/pbjxp014

[48]. Md Ashfaq, S., & Abdullah Mohammad, S. (2022). CNT/PANI Composite Electrodes for Flexible Fiber-Shaped Dye-Sensitized Solar Cells: Synthesis, Characterization, and Photovoltaic Performance. *American Journal of Interdisciplinary Studies*, *3*(02), 221-274. https://doi.org/10.63125/m334mf41

[49]. Md Asif Ali Sheak, A., & Risha, A. (2022). The Role of IOT-Driven Energy Analytics in Improving Operational Efficiency and Sustainability in Modern Industrial Facilities. *American Journal of Interdisciplinary Studies*, *3*(04), 807-841. https://doi.org/10.63125/gm63q956

[50]. Md Kaium, H. (2023). A GIS-Based Multi-Criteria Decision-Support and Land-Suitability Optimization Framework for Climate-Resilient Urban and Regional Planning. *American Journal of Data Science and Analytics*, *4*(06), 43–103. https://doi.org/10.63125/wvq0sx87

[51]. Md Kaium, H. (2024). Machine Learning Enhanced GIS And AHP Modeling for High-Resolution Flood-Susceptibility Prediction, Vulnerability Assessment, and Risk Classification. *Review of Applied Science and Technology*, *3*(02), 92–140. https://doi.org/10.63125/fz8hv245

[52]. Md Kaium, H. (2025). Integrating Artificial Intelligence, Semantic Indoor Geospatial Modeling, And Network-Based Routing for High-Precision NG911 Emergency Location Intelligence. *International Journal of Scientific Interdisciplinary Research*, *6*(1), 616–670. https://doi.org/10.63125/5hc1xx56

[53]. Md Kaium, H. (2026). An Artificial Intelligence Integrated Geospatial Decision-Support Framework for Scenario-Based Climate-Adaptive Land-Use Optimization and Environmental Risk Reduction. *American Journal of Data Science and Analytics*, *7*(06), 425-483. https://doi.org/10.63125/nyc7sh45

[54]. Md Mahamud Pervaz, P. (2023). Integration of MES, SAP, And PI Historian Platforms for Real-Time Industrial Asset Performance Management. *Review of Applied Science and Technology*, *2*(04), 393–445. https://doi.org/10.63125/9ebtas97

[55]. Md Mahamud Pervaz, P. (2025). Development of a CMMS-Integrated Predictive Maintenance Framework for Industrial PLC and Drive Systems. *American Journal of Scholarly Research and Innovation*, *4*(01), 894–942. https://doi.org/10.63125/j33gtf31

[56]. Md Mahamud Pervaz, P. (2026). Implementation of an OSHA-Compliant Lockout/Tagout and Arc-Flash Hazard Mitigation Framework for U.S. Industrial Maintenance Operations. *American Journal of Interdisciplinary Studies*, *7*(02), 73-119. https://doi.org/10.63125/8ky04n07

[57]. Md. Abdur, R., & Iftekhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, *1*(4), 70-102. https://doi.org/10.63125/dyrpc387

[58]. Md. Rashedul, I., & Md Kaium, H. (2022). Development Of a Three-Dimensional Indoor Geospatial Network and Address Geocoding Framework for Next-Generation Emergency Dispatch and Response-Time Optimization. *Journal of Sustainable Development and Policy*, *1*(02), 245-292. https://doi.org/10.63125/tcw3mp48

[59]. Md. Shakhawat, H., & Md, F. (2024). Impact of Phishing Simulation Campaigns and Security Awareness Training on Human Risk Mitigation in Financial Institutions: A Quantitative Study. *American Journal of Data Science and Analytics*, *5*(10), 48-85. https://doi.org/10.63125/4j8h1484

[60]. Merei, G., Moshovel, J., Magnor, D., & Sauer, D. U. (2016). Optimization of self-consumption and techno-economic analysis of PV-battery systems in commercial applications. *Applied Energy*, *168*, 171-178. https://doi.org/10.1016/j.apenergy.2016.01.083

[61]. Mishra, S., Anderson, K., Miller, B., Warren, A., & Boyer, K. (2020). Microgrid resilience: A holistic approach for assessing threats, identifying vulnerabilities, and designing corresponding mitigation strategies. *Applied Energy*, *264*, 114726. https://doi.org/10.1016/j.apenergy.2020.114726

[62]. Mohammad Abir Chowdhury, S. (2023). Role of AI-Assisted Risk Assessment in Enhancing Audit Planning Efficiency and Risk Prioritization in Public-Safety Organizations. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 529–576. https://doi.org/10.63125/qd6nn437

[63]. Mohammad Abir Chowdhury, S. (2025). Application of Machine Learning and Anomaly-Detection Algorithms for Fraud Detection in U.S. Government Financial Operations. *American Journal of Interdisciplinary Studies*, *6*(02), 139-184. https://doi.org/10.63125/fkf19309

[64]. Mohammad Abir Chowdhury, S. (2026). Development Of a Machine-Learning Approach for Internal-Control Weakness Prediction and Audit-Risk Scoring In U.S. State Government Agencies. *American Journal of Data Science and Analytics*, *7*(06), 380-424. https://doi.org/10.63125/3v722074

[65]. Mohammad Abir Chowdhury, S., & Tonay, P. (2022). An Empirical Analysis of the Impact of Robotic Process Automation and Continuous Auditing on the Timeliness And Accuracy Of Financial Reporting Assurance. *International Journal of Business and Economics Insights*, *2*(4), 73-126. https://doi.org/10.63125/7p8dcr47

[66]. Mohammad Badrul, A. (2025). SCADA And IOT-Enabled Smart Water Metering: A Systematic Review of Resilient Supply Monitoring. *International Journal of Scientific Interdisciplinary Research*, *6*(1), 576–615. https://doi.org/10.63125/at8pnx81

[67]. Mohammad Badrul, A. (2026). A Machine-Learning Framework for Real-Time Non-Revenue Water Prediction in Aging Urban Distribution Networks. *American Journal of Interdisciplinary Studies*, *7*(02), 01-52. https://doi.org/10.63125/93km2h66

[68]. Mohammad Badrul, A., & Md. Mominul, H. (2023). Machine Learning–Based Assessment of Environmental and Public Health Risks in Sewerage Sludge Management Systems. *American Journal of Advanced Technology and Engineering Solutions*, *3*(02), 33-77. https://doi.org/10.63125/y3yfxa92

[69]. Mohammad Shoriful Hossan, S. (2022). A Performance-Based Framework for Arc-Flash Hazard Reduction and Electrical Reliability Improvement in Brownfield Industrial Distribution Systems. *Review of Applied Science and Technology*, *1*(04), 447-463. https://doi.org/10.63125/a70vj720

[70]. Moradi, M., Hoseini Abardeh, M., Vahedi, M., Salehi, N., & Azarfar, A. (2023). Multi-objective energy management of island microgrids with D-FACTS devices considering clean energy, storage systems and electric vehicles. *Clean Energy*, *7*(5), 1046-1057. https://doi.org/10.1093/ce/zkad045

[71]. Mst Kaniz, F. (2022). Language Access and Health Equity: Role of Multilingual Administrative Staff in Reducing Healthcare Disparities Among South Asian Immigrant Communities in The U.S. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 274–315. https://doi.org/10.63125/xqhss825

[72]. Mst Shamima, A. (2026). Enhancing Financial Accountability and Cost Control in North American Outpatient Clinics Through Data Science: A Mixed-Methods Healthcare Administration Study. *American Journal of Data Science and Analytics*, *7*(05), 01-41. https://doi.org/10.63125/wksgy749

[73]. Murad, M. D. H. R. (2026). Artificial Intelligence–Driven Enterprise Decision Support Systems: A Framework for Intelligent Business Process Automation in Digital Economies. *American Journal of Advanced Technology and Engineering Solutions*, *6*(01), 332-373. https://doi.org/10.63125/nnv83884

[74]. Muriithi, G., & Chowdhury, S. (2021). Optimal energy management of a grid-tied solar PV-battery microgrid: A reinforcement learning approach. *Energies*, *14*(9), 2700. https://doi.org/10.3390/en14092700

[75]. Nakabi, T. A., & Toivanen, P. (2021). Deep reinforcement learning for energy management in a microgrid with flexible demand. *Sustainable Energy, Grids and Networks*, *25*, 100413. https://doi.org/10.1016/j.segan.2020.100413

[76]. Nellikkath, R., & Chatzivasileiadis, S. (2022). Physics-informed neural networks for AC optimal power flow. *Electric Power Systems Research*, *212*, 108412. https://doi.org/10.1016/j.epsr.2022.108412

[77]. Nishat, J. (2023). Communicable Disease Prevention in a Post-Pandemic Era: A Global Review of Public Health Education, Surveillance, and Community-Level Interventions. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 630–678. https://doi.org/10.63125/mnqefj36

[78]. Nishat, J. (2025). Leveraging Machine Learning to Identify and Address Maternal Health Disparities in Underserved U.S. Communities. *American Journal of Data Science and Analytics*, *6*(12), 125-169. https://doi.org/10.63125/c2t7r719

[79]. Nishat, J. (2026). Predictive Analytics for Program Effectiveness: A Machine Learning Approach to Health Education Programs in the United States. *American Journal of Health and Medical Sciences*, *7*(03), 30–56. https://doi.org/10.63125/2vw42878

[80]. Nishat, J., & Jahanara, A. (2024). Machine Learning Approaches for Early Prediction of High-Risk Pregnancy in Underserved U.S. Populations. *American Journal of Interdisciplinary Studies*, *5*(04), 268-309. https://doi.org/10.63125/5gh5df13

[81]. Nishat, J., & Mst Kaniz, F. (2022). A Review of the Impact of Covid-19 On Maternal and Child Health Service Utilization in Bangladesh. *American Journal of Scholarly Research and Innovation*, *1*(02), 223–269. https://doi.org/10.63125/vgv5s742

[82]. Nuzhat Sadia, P. (2025). Integrating Business Intelligence Dashboards for Real-Time Supply Chain Visibility and Operational Decision Support. *American Journal of Data Science and Analytics*, *6*(12), 170-216. https://doi.org/10.63125/1es4f763

[83]. Nuzhat Sadia, P. (2026). An Integrated IT Management Framework for Scenario-Based Enterprise Analytics and Strategic Decision Optimization. *American Journal of Interdisciplinary Studies*, *7*(02), 120-168. https://doi.org/10.63125/3wtc3z49

[84]. Olivares, D. E., Mehrizi-Sani, A., Etemadi, A. H., Canizares, C. A., Iravani, R., Kazerani, M., Hajimiragha, A. H., Gomis-Bellmunt, O., Saeedifard, M., Palma-Behnke, R., Jimenez-Estevez, G. A., & Hatziargyriou, N. D. (2014). Trends in microgrid control. *IEEE Transactions on Smart Grid*, *5*(4), 1905-1919. https://doi.org/10.1109/tsg.2013.2295514

[85]. Pan, X., Zhao, T., Chen, M., & Zhang, S. (2021). DeepOPF: A deep neural network approach for security-constrained DC optimal power flow. *IEEE Transactions on Power Systems*, *36*(3), 1725-1735. https://doi.org/10.1109/tpwrs.2020.3026379

[86]. Panteli, M., Pickering, C., Wilkinson, S., Dawson, R., & Mancarella, P. (2017). Power system resilience to extreme weather: Fragility modeling, probabilistic impact assessment, and adaptation measures. *IEEE Transactions on Power Systems*, *32*(5), 3747-3757. https://doi.org/10.1109/tpwrs.2016.2641463

[87]. Parashar, S., Swarnkar, A., Niazi, K. R., & Gupta, N. (2019). Multiobjective optimal sizing of battery energy storage in grid-connected microgrid. *The Journal of Engineering*, *2019*(18), 5280-5283. https://doi.org/10.1049/joe.2018.9237

[88]. Park, S., Chen, W., Mak, T. W. K., & Van Hentenryck, P. (2024). Compact optimization learning for AC optimal power flow. *IEEE Transactions on Power Systems*, *39*(2), 4350-4359. https://doi.org/10.1109/tpwrs.2023.3313438

[89]. Peteraf, M., Di Stefano, G., & Verona, G. (2013). The elephant in the room of dynamic capabilities: Bringing two diverging conversations together. *Strategic Management Journal*, *34*(12), 1389-1410. https://doi.org/10.1002/smj.2078

[90]. Quoilin, S., Kavvadias, K., Mercier, A., Pappone, I., & Zucker, A. (2016). Quantifying self-consumption linked to solar home battery systems: Statistical analysis and economic assessment. *Applied Energy*, *182*, 58-67. https://doi.org/10.1016/j.apenergy.2016.08.077

[91]. Ranaweera, I., & Midtgard, O. M. (2016). Optimization of operational cost for a grid-supporting PV system with battery storage. *Renewable Energy*, *88*, 262-272. https://doi.org/10.1016/j.renene.2015.11.044

[92]. Real, A. C., Luz, G. P., Sousa, J. M. C., Brito, M. C., & Vieira, S. M. (2024). Optimization of a photovoltaic-battery system using deep reinforcement learning and load forecasting. *Energy and AI*, *16*, 100347. https://doi.org/10.1016/j.egyai.2024.100347

[93]. Riffonneau, Y., Bacha, S., Barruel, F., & Ploix, S. (2011). Optimal power flow management for grid connected PV systems with batteries. *IEEE Transactions on Sustainable Energy*, *2*(3), 309-320. https://doi.org/10.1109/tste.2011.2114901

[94]. Rony, S., & Md, A. (2026). Multi-Agency Coordination in Sustained Healthcare Supply Shortages: Lessons from Covid-19, Drug Shortages, and Critical Medical Supply Disruptions. *American Journal of Data Science and Analytics*, *7*(01), 181-221. https://doi.org/10.63125/5v6t8515

[95]. Rukaiya Khatun, M. (2026). Machine Learning–Based Transaction Risk Scoring Models for Financial Compliance Monitoring in Foreign Exchange Operations. *International Journal of Scientific Interdisciplinary Research*, *7*(1), 172–203. https://doi.org/10.63125/0nbg6w69

[96]. Sadia, Z. (2025). Predictive Analytics for Financial Performance Forecasting and Reporting Quality: Evidence from Data-Driven Financial Management Systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 2795–2812. https://doi.org/10.63125/zstqn346

[97]. Shabbir, N., Kutt, L., Astapov, V., Daniel, K., Jawad, M., Husev, O., Rosin, A., & Martins, J. (2024). Enhancing PV hosting capacity and mitigating congestion in distribution networks with deep learning based PV forecasting and battery management. *Applied Energy*, *372*, 123770. https://doi.org/10.1016/j.apenergy.2024.123770

[98]. Shafiei, K., Ghassem Zadeh, S., & Tarafdar Hagh, M. (2024). Planning for a network system with renewable resources and battery energy storage, focused on enhancing resilience. *Journal of Energy Storage*, *87*, 111339. https://doi.org/10.1016/j.est.2024.111339

[99]. Shaiful, M., Anisur, R., & Md, A. (2022). A Systematic Literature Review on the Role of Digital Health Twins in Preventive Healthcare For Personal and Corporate Wellbeing. *American Journal of Interdisciplinary Studies*, *3*(04), 1-31. https://doi.org/10.63125/negjw373

[100]. Shamsul, A. (2026). Electrical Engineering Approaches for AI-Enabled Autonomous Robotics in U.S. Industrial and Defense Applications. *International Journal of Scientific Interdisciplinary Research*, *7*(1), 72-110. https://doi.org/10.63125/h255cq52

[101]. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of sustainable enterprise performance. *Strategic Management Journal*, *28*(13), 1319-1350. https://doi.org/10.1002/smj.640

[102]. Tikkiwal, V. A., Singh, S. V., & Gupta, H. O. (2021). Multi-objective optimisation of a grid-connected hybrid PV-battery system considering battery degradation. *International Journal of Sustainable Engineering*, *14*(6), 1769-1779. https://doi.org/10.1080/19397038.2021.1982064

[103]. Tonay, P. (2025). Machine Learning for Fraud Detection in Enterprise Financial Systems. *American Journal of Advanced Technology and Engineering Solutions*, *1*(02), 304-318. https://doi.org/10.63125/d0fhp873

[104]. Tonay, P. (2026). The Role of AI-Based Decision Support in Financial Risk Management and Anomaly Detection. *American Journal of Data Science and Analytics*, *7*(06), 327-359. https://doi.org/10.63125/wnb54w77

[105]. Tonay, P., Md Maruf, I., & Al, A. (2024). Artificial Intelligence-Based Decision Support Systems and Managerial Performance. *American Journal of Advanced Technology and Engineering Solutions*, *4*(04), 154-184. https://doi.org/10.63125/wmz8dc67

[106]. Uddin, H. M. M., & Risha, A. (2024). Hybrid Cloud Security and Compliance in U.S. Enterprises: Addressing Data Privacy Risks and Governance Challenges. *American Journal of Scholarly Research and Innovation*, *3*(01), 153–197. https://doi.org/10.63125/qcy0cj46

[107]. Voyant, C., Notton, G., Kalogirou, S., Nivet, M. L., Paoli, C., Motte, F., & Fouilloy, A. (2017). Machine learning methods for solar radiation forecasting: A review. *Renewable Energy*, *105*, 569-582. https://doi.org/10.1016/j.renene.2016.12.095

[108]. Wang, F., Zhen, Z., Mi, Z., Sun, H., Su, S., & Yang, G. (2015). Solar irradiance feature extraction and support vector machines based weather status pattern recognition model for short-term photovoltaic power forecasting. *Energy and Buildings*, *86*, 427-438. https://doi.org/10.1016/j.enbuild.2014.10.002

[109]. Wang, S., Guo, D., Han, X., Lu, L., Sun, K., Li, W., Sauer, D. U., & Ouyang, M. (2020). Impact of battery degradation models on energy management of a grid-connected DC microgrid. *Energy*, *207*, 118228. https://doi.org/10.1016/j.energy.2020.118228

[110]. Weniger, J., Tjaden, T., & Quaschning, V. (2014). Sizing of residential PV battery systems. *Energy Procedia*, *46*, 78-87. https://doi.org/10.1016/j.egypro.2014.01.160

[111]. Wilden, R., Gudergan, S. P., Nielsen, B. B., & Lings, I. (2013). Dynamic capabilities and performance: Strategy, structure and environment. *Long Range Planning*, *46*(1-2), 72-96. https://doi.org/10.1016/j.lrp.2012.12.001

[112]. Wu, Z., Tazvinga, H., & Xia, X. (2015). Demand side management of photovoltaic-battery hybrid system. *Applied Energy*, *148*, 294-304. https://doi.org/10.1016/j.apenergy.2015.03.109

[113]. Yang, D., Kleissl, J., Gueymard, C. A., Pedro, H. T. C., & Coimbra, C. F. M. (2018). History and trends in solar irradiance and PV power forecasting: A preliminary assessment and review using text mining. *Solar Energy*, *168*, 60-101. https://doi.org/10.1016/j.solener.2017.11.023

[114]. Zakeri, B., & Syri, S. (2015). Electrical energy storage systems: A comparative life cycle cost analysis. *Renewable and Sustainable Energy Reviews*, *42*, 569-596. https://doi.org/10.1016/j.rser.2014.10.011