© APR 2025 | IRE Journals | Volume 8 Issue 10 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV8I10-1719987

A Multi-Criteria Decision Model for Optimal Construction and Deployment of Battery Energy Storage Systems for Grid Support

IBUKUN OLAOLUWA ADENIJI[1], HABEEB SHITTU[2], OGHENEMAERO OTERI[3], MUJEEB A SHITTU[4]

[1]*Electric Power Research Institute*
[2]*Moffatt Nichol, Savannah, GA, US*
[3]*Bell Canada*
[4]*North Carolina Agricultural and Technical State University, Greensboro, USA*

Abstract- The increasing penetration of renewable energy sources and the growing need for grid stability have positioned Battery Energy Storage Systems (BESS) as critical infrastructure for modern power systems. However, the construction and deployment of BESS require complex decision-making processes that integrate technical, economic, grid, and environmental considerations. This paper presents a comprehensive review and proposes a multi-criteria decision model for the optimal construction and deployment of BESS for grid support. The study synthesizes existing literature on energy storage planning, grid optimization, and decision analytics to identify key factors influencing BESS deployment. The proposed model adopts a Multi-Criteria Decision Analysis (MCDA) framework, integrating weighted scoring and optimization techniques to evaluate alternative deployment strategies. Core technical parameters include capacity sizing and response time, which determine system performance and grid responsiveness. Economic factors such as capital expenditure (CAPEX), operational costs, and lifecycle cost analysis are incorporated to ensure financial viability. Grid-level considerations, including congestion relief and peak shaving, are evaluated to enhance system reliability and efficiency. Environmental dimensions, such as land use optimization and emissions offset potential, are also embedded to support sustainable energy transitions. The model establishes a structured decision pathway that enables utilities and policymakers to assess trade-offs across competing criteria and identify optimal deployment configurations. Unlike existing approaches that focus on isolated aspects of BESS planning, this framework provides an integrated construction-to-grid perspective, bridging engineering design, economic evaluation, and policy considerations. The findings highlight the importance of balancing performance, cost, and sustainability objectives in BESS deployment. This study contributes to the field by offering a scalable and adaptable decision-support model that can be applied across diverse energy systems, thereby facilitating informed decision-making and accelerating the adoption of energy storage technologies for resilient and sustainable grid operations.

Keywords: Battery Energy Storage Systems (BESS), Multi-Criteria Decision Analysis (MCDA), Grid Optimization, Energy Storage Planning, Peak Shaving and Congestion Relief, Sustainable Energy Systems

I. INTRODUCTION

1.1 Background and Role of BESS in Modern Power Systems

Battery Energy Storage Systems (BESS) have emerged as a cornerstone technology in modern power systems, particularly in the context of increasing renewable energy penetration and the transition toward low-carbon energy infrastructures. The intermittent nature of renewable energy sources such as wind and solar introduces variability and uncertainty into power systems, necessitating advanced solutions for maintaining grid stability and reliability. BESS provides critical functionalities such as frequency regulation, voltage support, and energy arbitrage, enabling grid operators to balance supply and demand in real time (Ahmed et al., 2022). These systems act as fast-response assets capable of injecting or absorbing power within milliseconds, thereby mitigating fluctuations and enhancing system resilience.

BESS plays a pivotal role in supporting grid operations across multiple levels, including transmission, distribution, and microgrid systems. The integration of grid-scale storage technologies allows for improved load leveling, peak shaving, and congestion management, which are essential for optimizing grid performance and reducing operational costs (Al-Saadi et al., 2023). For example, in solar-dominated grids, BESS can store excess energy during periods of high generation and discharge it during peak demand, effectively addressing the "duck curve" challenge. Additionally, advanced control strategies and AI-driven optimization models enable BESS to operate autonomously, adapting to dynamic grid conditions and enhancing decision intelligence. These capabilities position BESS as a critical enabler of sustainable and resilient power systems, supporting the integration of renewable energy while ensuring reliable and efficient grid operations.

1.2 Challenges in BESS Construction and Deployment Decisions

Despite the growing importance of BESS in modern power systems, the construction and deployment of these systems present significant technical, economic, and operational challenges. One of the primary challenges lies in determining optimal system sizing and placement, which requires balancing competing objectives such as cost efficiency, grid performance, and environmental impact. Large-scale BESS installations involve substantial capital investment, and inaccuracies in sizing or siting decisions can lead to underutilization or inefficiencies in system operation (Bhardwaj et al., 2025). Furthermore, the complexity of integrating BESS into existing grid infrastructures introduces challenges related to interoperability, system stability, and regulatory compliance.

The construction of BESS facilities involves considerations such as thermal management, safety protocols, and lifecycle degradation of battery components. High-density energy storage systems are susceptible to thermal runaway and require sophisticated monitoring and control mechanisms to ensure safe operation (Zhang et al., 2024). Additionally, the deployment process must account for grid-specific constraints, including network topology, load distribution, and renewable energy integration levels. Decision-making is further complicated by uncertainties in future energy demand, market conditions, and technological advancements. These challenges highlight the need for a structured decision model that integrates technical, economic, grid, and environmental factors to support optimal BESS construction and deployment strategies.

1.3 Objectives and Scope of the Study

This study aims to develop a comprehensive multi-criteria decision model for the optimal construction and deployment of Battery Energy Storage Systems (BESS) for grid support. The primary objective is to establish a structured framework that integrates technical, economic, grid, and environmental factors into a unified decision-making process. The model is designed to evaluate key parameters such as capacity sizing, response time, capital expenditure, lifecycle cost, congestion relief, peak shaving potential, land use, and emissions offset. By incorporating these diverse criteria, the study seeks to provide a holistic approach to BESS planning that aligns with both operational and sustainability objectives.

The scope of the study focuses on grid-scale BESS applications within modern power systems, particularly in environments characterized by high renewable energy penetration. It emphasizes the use of Multi-Criteria Decision Analysis (MCDA) techniques, including weighted scoring and optimization models, to assess trade-offs and identify optimal deployment strategies. The study does not involve empirical testing but provides a conceptual foundation for future implementation and validation. It aims to support utilities, planners, and policymakers in making informed decisions that enhance grid reliability, economic efficiency, and environmental sustainability.

\1.4 Structure of the Paper

The paper is structured into six main sections to ensure a logical and systematic presentation of the proposed decision model. The first section introduces the background, challenges, and objectives of the study, establishing the context for the research. The second section reviews existing literature on energy storage technologies, grid integration, and decision-making

© APR 2025 | IRE Journals | Volume 8 Issue 10 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV8I10-1719987

models, identifying key gaps that inform the development of the proposed framework.The third section presents the theoretical foundations of the decision model, outlining the key technical, economic, grid, and environmental criteria used in the analysis. The fourth section introduces the proposed multi-criteria decision model, detailing its architecture, methodology, and integration of decision variables. The fifth section focuses on model application, including scenario analysis, sensitivity assessment, and decision support for stakeholders. The final section discusses the contributions, practical implications, and future research directions, providing insights into how the model can be extended and applied in real-world energy systems.

II. LITERATURE REVIEW

2.1 Energy Storage Technologies and Grid Applications

Energy storage technologies, particularly Battery Energy Storage Systems (BESS), have become essential components of modern power systems, supporting grid stability, renewable energy integration, and operational flexibility. Lithium-ion batteries dominate grid-scale applications due to their high energy density, efficiency, and declining costs, although alternative technologies such as sodium-sulfur and flow batteries are gaining traction for long-duration storage (Akinyele & Rayudu, 2021; Ahmed et al., 2022; Al-Saadi et al., 2023; Babatunde et al., 2022). These systems perform critical functions including frequency regulation, voltage support, and energy arbitrage, enabling power systems to maintain balance between supply and demand in real time (Chen et al., 2024; Sun et al., 2023; Lindner et al., 2023; Adeniji et al., 2025). The integration of BESS into grid infrastructure is further enhanced by advanced control strategies and predictive maintenance frameworks that improve system reliability and performance (Ekechi, 2023; Yeboah et al., 2024; Ogunwole et al., 2021; Okonkwo et al., 2024).

BESS plays a pivotal role in mitigating the intermittency of renewable energy sources such as wind and solar. By storing excess energy during periods of low demand and discharging it during peak demand, BESS enables peak shaving and congestion relief, thereby enhancing grid efficiency (Sun et al., 2023; Lindner et al., 2023; Chen et al., 2024; Ahmed et al., 2022). Additionally, BESS supports microgrid operations, black-start capabilities, and resilience against grid disturbances. Emerging applications include hybrid systems that combine BESS with renewable generation and advanced AI-driven control models to optimize energy dispatch and system stability (Babatunde et al., 2022; Al-Saadi et al., 2023; Akinyele & Rayudu, 2021). These developments highlight the central role of energy storage technologies in enabling sustainable and reliable power systems.

2.2 Existing Decision Models for BESS Deployment

Existing decision models for BESS deployment primarily focus on optimization-based approaches that aim to determine optimal sizing, siting, and operational strategies. These models often employ techniques such as multi-objective optimization, genetic algorithms, and linear programming to balance competing objectives including cost, performance, and reliability (Gu et al., 2022; Gurung et al., 2023; Oikonomou et al., 2022; Zhou et al., 2024). Economic considerations, particularly capital expenditure and lifecycle cost analysis, are central to these models, ensuring that BESS investments remain financially viable (Kebede et al., 2022; Junior et al., 2021; Paliwal et al., 2024). Additionally, decision models incorporate grid-level factors such as load demand patterns, renewable energy penetration, and network constraints to optimize deployment strategies.

Despite their effectiveness, many existing models are limited in scope, focusing on specific aspects of BESS deployment rather than providing a holistic framework. For instance, techno-economic models often neglect environmental and social factors, while optimization models may overlook governance and operational considerations (Ekechi, 2024; Yeboah et al., 2025; Ogunwole et al., 2023; Okonkwo et al., 2023). Recent advancements include the integration of AI-driven decision models that leverage machine learning algorithms to improve predictive accuracy and adaptability (Adeniji et al., 2025; Zhou et al., 2024; Gurung et al., 2023; Kebede et al., 2022). However, the lack of unified frameworks that integrate technical, economic, grid, and environmental criteria remains a significant limitation. This underscores the need for multi-criteria decision models that provide comprehensive and balanced decision-making approaches for BESS deployment.

2.3 Gaps in Integrated Technical-Economic-Environmental Models

Despite significant advancements in BESS planning and optimization, there remains a critical gap in the development of integrated models that simultaneously consider technical, economic, grid, and environmental factors. Most existing models focus on isolated dimensions, such as economic optimization or grid performance, without addressing the interdependencies between these factors (Grimaldi et al., 2024; Silva et al., 2023; Moreno et al., 2021; Sarker et al., 2021). For example, while peak shaving models effectively reduce demand variability, they often neglect lifecycle cost implications and environmental impacts such as land use and emissions offset. Similarly, reliability-focused models prioritize system stability but may overlook economic feasibility and policy considerations (Khezri et al., 2023; Wu et al., 2024; Zhang et al., 2024).

From a systems perspective, the absence of integrated decision frameworks limits the ability of stakeholders to evaluate trade-offs and make informed decisions. Governance and operational considerations, including maintenance strategies, supply chain resilience, and regulatory compliance, are often underrepresented in existing models (Ekechi& Fasasi, 2022; Yeboah et al., 2024; Ogunwole et al., 2023; Okonkwo et al., 2024). Furthermore, environmental factors such as emissions reduction and land use optimization are rarely incorporated into decision-making processes, despite their importance in sustainable energy planning as seen in Table 2. These gaps highlight the need for comprehensive multi-criteria decision models that integrate technical performance, economic viability, grid impact, and environmental sustainability into a unified framework, enabling more effective and balanced BESS deployment strategies.

Table 1: Gaps in Integrated Technical–Economic–Environmental BESS Decision Models

Gap Area	Description	Key Limitations in Existing Models	Implications for BESS Deployment
Fragmented Modeling Approaches	Models address technical, economic, or grid aspects separately rather than holistically	Lack of integration across performance, cost, and sustainability dimensions	Leads to suboptimal decisions and incomplete evaluation of deployment options
Inadequate Trade-Off Analysis	Limited ability to assess interactions between competing criteria	Peak shaving or reliability models ignore lifecycle cost and environmental impacts	Reduces decision accuracy and limits strategic planning effectiveness
Missing Governance and Operational Factors	Insufficient inclusion of maintenance, supply chain resilience, and regulatory compliance	Operational risks and long-term system reliability not fully captured	Increases uncertainty and reduces sustainability of BESS projects
Limited Environmental Integration	Environmental factors such as emissions reduction and land use often excluded	Sustainability metrics not embedded in decision frameworks	Hinders alignment with energy transition goals and policy requirements

III. THEORETICAL FRAMEWORK AND DECISION CRITERIA

3.1 Technical Factors: Capacity Sizing and Response Time

Capacity sizing and response time are fundamental technical parameters in the design and deployment of Battery Energy Storage Systems (BESS) for grid support. Capacity sizing determines the energy storage capability required to meet specific grid demands, such as peak load support, frequency regulation, and renewable energy integration. Optimal sizing involves balancing energy capacity and power rating to ensure system efficiency while minimizing overinvestment. Advanced optimization models, including stochastic and multi-objective approaches, are increasingly used to determine optimal BESS configurations under varying load and generation conditions (Gurung et al., 2023; Ishraque et al., 2022; Farakhor et al., 2024). These models account for uncertainties in renewable generation and demand fluctuations, ensuring that storage systems are neither underutilized nor overstressed. Additionally, AI-driven control strategies enhance sizing decisions by incorporating predictive analytics and adaptive learning mechanisms (Adeniji et al., 2025; Ahmed et al., 2022).

Response time is equally critical, particularly for applications such as frequency regulation and grid stabilization, where rapid system response is required to maintain power quality and reliability. BESS technologies offer significantly faster response times compared to conventional generation systems, enabling near-instantaneous adjustments to grid conditions. Studies demonstrate that reducing response latency improves system stability and reduces the risk of cascading failures in interconnected grids (Gupta et al., 2025; Ahmed et al., 2022). Furthermore, integrating predictive maintenance and lifecycle management frameworks enhances system responsiveness by ensuring optimal operational readiness (Yeboah et al., 2025; Okonkwo et al., 2023). Technical optimization must also consider degradation effects and thermal management to sustain long-term performance (Ekechi, 2024; Ogunwole et al., 2021). These combined factors underscore the importance of aligning capacity sizing and response time within a unified technical decision framework for efficient BESS deployment.

3.2 Economic Factors: CAPEX, OPEX, and Lifecycle Cost Analysis

Economic evaluation is a central component of BESS deployment, encompassing capital expenditure (CAPEX), operational expenditure (OPEX), and lifecycle cost analysis. CAPEX includes costs associated with battery procurement, installation, land acquisition, and infrastructure integration, while OPEX covers maintenance, energy losses, and operational management. Lifecycle cost analysis extends this evaluation by incorporating degradation, replacement costs, and residual value over the system's lifespan (Zakeri & Syri, 2021; Kebede et al., 2022). Advanced economic models integrate these variables to determine the total cost of ownership and assess the financial viability of BESS projects. For example, energy arbitrage strategies utilize price differentials in electricity markets to generate revenue, thereby offsetting investment costs (Grimaldi et al., 2024; Junior et al., 2021).

Economic optimization requires aligning cost considerations with technical performance and grid requirements. AI-driven financial models enhance decision-making by forecasting market trends, optimizing dispatch strategies, and minimizing operational costs (Silva et al., 2023). Additionally, lifecycle management frameworks ensure cost efficiency by optimizing maintenance schedules and extending battery lifespan (Ekechi, 2023; Yeboah et al., 2024). Supply chain considerations, including procurement and logistics, also influence cost structures and must be integrated into decision models (Okonkwo et al., 2024; Ogunwole et al., 2021). The integration of CAPEX, OPEX, and lifecycle analysis within a multi-criteria decision framework enables stakeholders to evaluate trade-offs between cost, performance, and sustainability, ensuring economically viable and efficient BESS deployment strategies.

© APR 2025 | IRE Journals | Volume 8 Issue 10 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV8I10-1719987

3.3 Grid and Environmental Factors: Congestion Relief, Peak Shaving, Land Use, and Emissions

Grid and environmental factors play a critical role in determining the optimal deployment of BESS, particularly in addressing congestion, peak demand, land use, and emissions reduction. Congestion relief is achieved by strategically placing BESS in transmission and distribution networks to manage power flows and reduce bottlenecks. This enhances grid reliability and prevents overload conditions in critical infrastructure (Lindner et al., 2023). Similarly, peak shaving applications enable BESS to store energy during low-demand periods and discharge during peak demand, reducing stress on generation systems and lowering operational costs (Sarker et al., 2021; Sun et al., 2023). These functionalities are particularly important in grids with high renewable penetration, where variability in generation requires flexible and responsive energy storage solutions (Smith & Johnson, 2024; Adeniji et al., 2025).

Environmental considerations include land use optimization and emissions reduction, which are essential for sustainable energy planning. BESS deployment must balance spatial requirements with environmental impact, ensuring minimal disruption to ecosystems while maximizing energy storage capacity. Additionally, energy storage systems contribute to emissions reduction by enabling higher integration of renewable energy sources and reducing reliance on fossil fuel-based generation (IRENA, 2025). Operational frameworks that incorporate reliability and maintenance considerations further enhance environmental performance by extending system lifespan and reducing waste (Ekechi& Fasasi, 2022; Yeboah et al., 2025). Furthermore, integrating BESS within resilient infrastructure and supply chain systems ensures sustainable deployment and long-term grid stability (Okonkwo et al., 2024; Ogunwole et al., 2021) as seen in Table 2. These combined grid and environmental factors highlight the importance of incorporating sustainability and system efficiency into multi-criteria decision models for BESS deployment.

Table 2: Grid and Environmental Factors in BESS Deployment Optimization

Factor Category	Description	Key Mechanisms/Applications	Impact on Grid and Sustainability
Congestion Relief	Strategic placement of BESS to manage power flow and reduce network bottlenecks	Load balancing, transmission support, distributed storage siting	Improves grid reliability, prevents overload, enhances power flow efficiency
Peak Shaving	Use of BESS to store energy during low demand and discharge during peak periods	Demand shifting, energy arbitrage, load leveling	Reduces peak load stress, lowers operational costs, improves grid stability
Land Use Optimization	Efficient allocation of physical space for BESS infrastructure with minimal environmental disruption	Site selection models, compact system design, co-location with renewables	Minimizes ecological impact, optimizes infrastructure footprint, supports sustainable planning
Emissions Reduction	Reduction of carbon emissions through enhanced integration of renewable energy and reduced fossil fuel dependence	Renewable energy storage, grid decarbonization strategies, lifecycle optimization	Supports sustainability goals, lowers carbon footprint, promotes clean energy transition

IV. PROPOSED MULTI-CRITERIA DECISION MODEL

4.1 Model Architecture and Decision Workflow

The architecture of the proposed multi-criteria decision model for Battery Energy Storage Systems (BESS) construction and deployment is designed as a layered and modular system that integrates data acquisition, analytical processing, and decision intelligence. At the foundational level, the model incorporates data inputs from grid conditions, load demand profiles, renewable generation variability, and economic cost parameters. These inputs are processed through a decision workflow that includes preprocessing, normalization, and parameter weighting stages to ensure consistency and comparability across criteria. Advanced analytical modules, including optimization algorithms and AI-driven control systems, are embedded within the architecture to evaluate alternative deployment scenarios (Ahmed et al., 2022; Al-Saadi et al., 2023; Babatunde et al., 2022; Adeniji et al., 2025). The workflow further integrates multi-objective optimization techniques, such as NSGA-II, to simultaneously address competing objectives including cost minimization, reliability enhancement, and grid stability (Gu et al., 2022; Gurung et al., 2023; Farakhor et al., 2024).

From a systems perspective, the decision workflow operates as a closed-loop process where outputs from the decision model are continuously validated against operational performance metrics. Feedback mechanisms are incorporated to refine model parameters and improve decision accuracy over time. For instance, real-time grid performance data can be used to recalibrate capacity sizing and response time parameters, ensuring that the deployed BESS remains aligned with evolving grid requirements. The architecture also supports scalability through distributed processing and modular integration, allowing the model to adapt to different grid sizes and configurations. This structured workflow ensures that decision-making is both systematic and adaptive, enabling utilities and policymakers to evaluate BESS deployment strategies with a high degree of precision and reliability.

4.2 MCDA Methodology: Weighted Scoring and Optimization Techniques

The Multi-Criteria Decision Analysis (MCDA) methodology forms the core analytical engine of the proposed model, enabling the systematic evaluation of BESS deployment alternatives across multiple dimensions. The methodology employs a weighted scoring approach in which each decision criterion—technical, economic, grid-related, and environmental—is assigned a relative weight based on its importance to overall system objectives. These weights are derived through expert judgment, sensitivity analysis, or analytic hierarchy processes, ensuring that the model reflects real-world priorities. Each alternative deployment scenario is then scored against these criteria, and aggregate scores are computed to rank the alternatives (Kebede et al., 2022; Ishraque et al., 2022; Junior et al., 2021; Adeniji et al., 2025). This approach provides a transparent and interpretable framework for decision-making, allowing stakeholders to understand the trade-offs between competing objectives.

In addition to weighted scoring, the model incorporates optimization techniques to identify optimal solutions under complex constraints. Multi-objective optimization algorithms are used to balance conflicting goals such as minimizing cost while maximizing grid reliability and environmental benefits. For example, peak shaving optimization models evaluate the ability of BESS to reduce load peaks while considering operational costs and battery degradation (Sun et al., 2023; Grimaldi et al., 2024; Zhou et al., 2024; Kebede et al., 2022). These optimization processes are further enhanced by AI-driven predictive models that estimate future grid conditions and demand patterns, enabling proactive decision-making. The integration of weighted scoring and optimization techniques ensures that the MCDA framework is both robust and flexible, capable of addressing the complex and dynamic nature of BESS deployment decisions.

4.3 Integration of Technical, Economic, Grid, and Environmental Criteria

The integration of technical, economic, grid, and environmental criteria is a defining feature of the proposed multi-criteria decision model, enabling a holistic evaluation of BESS deployment strategies. Technical factors such as capacity sizing and response time are critical for determining system performance and grid responsiveness. Capacity sizing ensures that the BESS can meet energy demand requirements, while response time influences its ability to provide ancillary services such as frequency regulation and voltage support (Akinyele & Rayudu, 2021; Li et al., 2023; Sarker et al., 2021). These technical parameters are closely linked to grid-level considerations, including congestion relief and peak shaving, which enhance the reliability and efficiency of power systems (Lindner et al., 2023; Li et al., 2023; Adeniji et al., 2025).

Economic and environmental factors are equally important in ensuring the sustainability and feasibility of BESS projects. Economic evaluation includes capital expenditure (CAPEX), operational costs, and lifecycle cost analysis, which determine the financial viability of deployment options (Zakeri & Syri, 2021; Ekechi, 2024; Akinyele & Rayudu, 2021). Environmental considerations, such as land use optimization and emissions offset potential, are integrated to support sustainable energy transitions and minimize ecological impact. The model aligns these diverse criteria through a unified evaluation framework that captures interdependencies and trade-offs. For instance, increasing capacity may improve grid reliability but also raise costs and land requirements, necessitating careful optimization. By integrating these criteria, the model provides a comprehensive decision-making tool that balances performance, cost, and sustainability objectives in BESS construction and deployment.

V. MODEL APPLICATION AND DECISION ANALYSIS

5.1 Scenario-Based Evaluation of BESS Deployment Options

Scenario-based evaluation provides a structured approach for analyzing alternative BESS deployment strategies under varying technical, economic, and grid conditions. In this study, scenarios are constructed based on different combinations of capacity sizing, response time, grid demand profiles, and renewable energy penetration levels. For instance, high-capacity BESS scenarios are evaluated for their ability to provide congestion relief and peak shaving during periods of high demand, while smaller, distributed systems are assessed for localized grid stability and voltage regulation (Gu et al., 2022; Gurung et al., 2023; Li et al., 2023; Sun et al., 2023). Additionally, scenarios incorporating high renewable penetration examine the effectiveness of BESS in mitigating intermittency and enhancing frequency stability, particularly in wind- and solar-dominated systems (Ahmed et al., 2022; Babatunde et al., 2022; Al-Saadi et al., 2023; Lindner et al., 2023).

From a modeling perspective, the scenario-based approach integrates Multi-Criteria Decision Analysis (MCDA) with optimization techniques to evaluate trade-offs across competing objectives. Each scenario is assessed using weighted scoring based on technical performance, economic cost, grid impact, and environmental benefits. For example, a scenario prioritizing rapid response time may achieve superior frequency control but incur higher CAPEX due to advanced battery technologies (Zhou et al., 2024; Adeniji et al., 2025). Conversely, scenarios focusing on lifecycle cost optimization may favor moderate-capacity systems with longer operational lifespans. The integration of AI-driven control models further enhances scenario evaluation by enabling dynamic adaptation to changing grid conditions. This structured evaluation framework allows stakeholders to identify optimal deployment strategies that balance performance, cost, and sustainability objectives in diverse operational contexts.

5.2 Sensitivity Analysis and Trade-Off Assessment

Sensitivity analysis is employed to quantify the influence of key decision variables on the performance and feasibility of BESS deployment strategies. Parameters such as battery capacity, response time, capital cost, degradation rate, and electricity price variability are systematically varied to assess their impact on system performance and economic viability. For example, increasing battery capacity enhances peak shaving capability but also raises capital expenditure and operational complexity (Kebede et al., 2022; Rahman et al., 2021; Wu et al., 2024; Paliwal et al., 2024). Similarly, variations in electricity price differentials significantly affect the profitability of energy arbitrage strategies, highlighting the importance of market conditions in deployment decisions (Grimaldi et al., 2024; NREL, 2025; Junior et al., 2021).

Trade-off assessment within the MCDA framework enables the identification of optimal balance points between competing criteria. For instance, prioritizing grid reliability may require higher investment in advanced battery technologies, while cost minimization strategies may limit system performance under extreme conditions. Environmental considerations, such as land use and emissions offset, further complicate decision-making by introducing additional constraints and objectives. AI-driven optimization techniques enhance sensitivity analysis by enabling adaptive evaluation of parameter interactions and system dynamics (Zakeri & Syri, 2021). This approach allows decision-makers to explore multiple scenarios and identify robust solutions that remain effective under varying conditions. Ultimately, sensitivity analysis provides critical insights into the resilience and flexibility of BESS deployment strategies, supporting informed and data-driven decision-making processes.

5.3 Decision Support for Utilities and Policymakers

The proposed multi-criteria decision model serves as a robust decision-support tool for utilities and policymakers by providing a structured framework for evaluating BESS deployment strategies. Utilities can utilize the model to optimize grid operations by selecting configurations that enhance reliability, reduce congestion, and support renewable energy integration. For example, grid-forming BESS systems can provide virtual inertia and frequency control, improving system stability in low-inertia grids (Velasquez et al., 2023; Shahidehpour et al., 2022; Moreno et al., 2021; Wang et al., 2024). Additionally, the model enables utilities to address challenges such as the “duck curve” by deploying BESS for peak shaving and load balancing, thereby enhancing grid flexibility (Smith & Johnson, 2024; Jaradat & Khatib, 2025; IRENA, 2025; Zhang et al., 2024).

For policymakers, the model provides a decision pathway for evaluating the economic, environmental, and social impacts of BESS deployment. By incorporating lifecycle cost analysis, emissions reduction potential, and land use considerations, the framework supports the development of policies that promote sustainable energy systems. Furthermore, AI-driven decision intelligence enhances policy formulation by enabling scenario analysis and predictive modeling of future grid conditions (Adeniji et al., 2025). The integration of regulatory and technical criteria ensures that policy decisions are aligned with both market dynamics and infrastructure requirements. This holistic approach bridges the gap between engineering design, economic planning, and policy development, enabling stakeholders to make informed decisions that support long-term grid resilience and sustainability.

VI. CONTRIBUTIONS, IMPLICATIONS, AND FUTURE DIRECTIONS

6.1 Key Contributions of the Integrated Decision Model

The integrated multi-criteria decision model developed in this study advances the state of Battery Energy Storage System (BESS) planning by unifying technical, economic, grid, and environmental dimensions into a single analytical framework. A primary contribution lies in its construction-to-grid perspective, where decisions are not limited to siting or sizing but extend across the full lifecycle of deployment, from infrastructure design to operational grid support. The model systematically incorporates technical parameters such as capacity sizing and response time, enabling precise evaluation of system performance under dynamic grid conditions. Simultaneously, it embeds economic variables including capital expenditure, operational costs, and lifecycle cost optimization, allowing stakeholders to assess long-term financial viability alongside technical efficiency.

© APR 2025 | IRE Journals | Volume 8 Issue 10 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV8I10-1719987

Another key contribution is the integration of grid-level objectives such as congestion relief and peak shaving with environmental considerations including land use efficiency and emissions offset potential. This holistic approach ensures that BESS deployment strategies are aligned with both operational reliability and sustainability goals. The application of Multi-Criteria Decision Analysis (MCDA), supported by weighted scoring and optimization techniques, provides a transparent and structured decision pathway that can be adapted to different grid configurations and policy contexts. Furthermore, the model introduces feedback-driven decision intelligence mechanisms that enable continuous refinement based on real-time system performance. This capability enhances adaptability and resilience, particularly in grids with high renewable penetration. By bridging engineering design, economic planning, and policy evaluation, the model establishes a comprehensive decision-support tool that addresses the complexity of modern energy systems and provides a scalable foundation for future energy infrastructure development.

6.2 Practical Implications for Energy Planning and Policy

The proposed decision model offers significant practical value for energy planners, utilities, and policymakers by providing a structured framework for evaluating BESS deployment strategies in complex grid environments. For utilities, the model enables data-driven planning of storage infrastructure by quantifying the trade-offs between system performance, cost efficiency, and grid reliability. For instance, planners can use the model to determine the optimal capacity and placement of BESS units to alleviate transmission congestion while maintaining cost constraints. The integration of response time metrics further supports the design of systems capable of delivering fast frequency regulation and voltage stabilization, which are critical for maintaining grid stability in renewable-dominated networks.

From a policy perspective, the model facilitates evidence-based decision-making by incorporating environmental and economic criteria into the evaluation process. Policymakers can use the framework to assess the impact of different regulatory scenarios, such as incentives for emissions reduction or land-use constraints, on BESS deployment outcomes. The inclusion of lifecycle cost analysis and emissions offset metrics supports the development of policies that balance economic feasibility with sustainability objectives. Additionally, the model provides a transparent decision pathway that enhances stakeholder engagement and accountability, as each decision criterion and weighting can be explicitly defined and adjusted. This is particularly important in large-scale infrastructure projects where multiple stakeholders, including regulators, investors, and communities, are involved. By aligning technical feasibility with policy goals, the model supports the development of integrated energy strategies that promote grid resilience, economic efficiency, and environmental sustainability.

6.3 Future Research Directions and Model Extensions

Future research should focus on enhancing the robustness and applicability of the proposed decision model through empirical validation and methodological extensions. One important direction involves the integration of real-time data streams and adaptive learning algorithms into the model, enabling dynamic decision-making based on evolving grid conditions. This could involve the incorporation of machine learning techniques for predictive modeling of demand patterns, renewable generation variability, and battery degradation, thereby improving the accuracy and responsiveness of deployment decisions. Additionally, extending the model to include stochastic optimization methods would allow for the explicit consideration of uncertainty in key parameters such as energy prices, load demand, and renewable output.

Another promising area for extension is the incorporation of advanced battery technologies and hybrid energy storage systems into the decision framework. As new storage technologies with varying performance characteristics and cost structures emerge, the model can be adapted to evaluate their comparative advantages and integration potential. Furthermore, future research should explore the inclusion of socio-economic factors, such as community acceptance and job creation, to provide a more comprehensive assessment of BESS deployment impacts. The development of sector-specific adaptations of the model, tailored to urban, rural, and industrial energy systems, would also enhance its practical relevance. Finally, integrating the model with digital twin platforms and simulation environments could enable scenario testing and real-time optimization, providing a powerful tool for both planning and operational decision-making in next-generation energy systems.

REFERENCES

[1] Aazami, R., Heydari, O., Tavoosi, J., Shirkhani, M., &Mosavi, A. (2022). Optimal control of an energy storage system in a microgrid for reducing wind power fluctuations. Sustainability, 14(10), 6183.

[2] Abayateye, J., Corigliano, S., Merlo, M., & Zimmerle, D. (2022). BESS primary frequency control strategies for power systems. Energies, 15(3), 990.

[3] Adeniji, I. O., Shittu, H., Liadi, K. O., Shittu, M. A., Elumilade, R. A., & Oteri, O. (2025). Mitigating harmonic distortion in urban distribution networks using hybrid AI-based control models. International Journal of Advanced Multidisciplinary Research and Studies, 5(6), 2055–2068.

[4] Ahmed, H. M., et al. (2022). Enhancement of power system stability using battery energy storage systems: A comprehensive survey. *IEEE Access*, *10*, 43105–43128.

[5] Akinyele, D., & Rayudu, R. (2021). Review of energy storage technologies for sustainable power systems. Sustainable Energy Technologies and Assessments, 42, 100838.

[6] Al-Saadi, M., Al-Greer, M., & Phan, V. T. (2023). A review of grid-scale battery energy storage systems: Technologies, control strategies, and grid integration. *Journal of Energy Storage*, *68*, 107721. https://doi.org/10.1016/j.est.2023.107721

[7] Aneke, M., & Wang, M. (2022). Energy storage technologies and real-life applications. Applied Energy, 179, 350–377.

[8] Arani, M. F., et al. (2021). Analysis of grid-scale BESS in supporting inertia and frequency control. *IEEE Transactions on Power Systems*, *36*(3), 2548–2559.

[9] Babatunde, O. M., et al. (2022). Recent advances in the integration of battery energy storage systems into the smart grid: A review.*Energy Reports*, *8*, 10023–10045.

[10] Bhardwaj, A., et al. (2025). Standardizing BESS construction protocols for global grid integration. *Renewable Energy Focus*, *52*, 101234.

[11] Chen, H., Cong, T. N., Yang, W., Tan, C., Li, Y., & Ding, Y. (2021). Progress in electrical energy storage system: A critical review. Progress in Natural Science, 21(4), 291–312.

[12] Chen, M., et al. (2024). Adaptive virtual inertia control for BESS in systems with low rotational inertia. *IEEE Transactions on Power Systems*, *39*(1), 455–467.

[13] Choudhury, S. (2022). A review of energy management systems in microgrids with BESS. *Journal of Energy Storage*, *48*, 103857.

[14] Das, C. K., et al. (2021). Impact of grid-scale BESS on power system reliability: A probabilistic approach. *Electric Power Systems Research*, *194*, 107084.

[15] Datta, U., Kalam, A., & Shi, J. (2021). A review of key functionalities of battery energy storage system in renewable energy integrated power systems. Energy Storage, 3(5), e224.

[16] Deliu, A.-D., & Cazacu, E. (2025). Utility-scale battery energy storage: Technologies, control strategies, and planning methods. Technium Journal of Applied Sciences, 30, 252–261.

[17] Dunn, B., Kamath, H., & Tarascon, J. M. (2021). Electrical energy storage for the grid: A battery of choices. Science, 334(6058), 928–935.

[18] Ekechi, A. T. (2023). Framework for lifecycle management and recycling of spent lithium-ion battery components. International Journal of Multidisciplinary Research and Growth Evaluation, 4(6), 1271–1290. https://doi.org/10.54660/.IJMRGE.2023.4.6.1271-1290

[19] Ekechi, A. T. (2024). Framework for energy efficiency enhancement through process

parameter optimization in power systems. International Journal of Advanced Multidisciplinary Research and Studies, 4(6), 2709–2730. https://doi.org/10.62225/2583049X.2024.4.6.5357

[20] Ekechi, A. T., & Fasasi, T. S. (2022). Conceptual framework for process safety and operational reliability in FPSO-based energy systems. International Journal of Artificial Intelligence Engineering and Transformation, 3(1), 19–37. https://doi.org/10.54660/IJAIET.2022.3.1.19-37

[21] Emon, I., Jowel, A. R., Jawad, A., & Nahid-Al-Masood. (2023). Frequency control participation of BESS in wind-dominated systems. Energy Reports, 10, 1268–1286.

[22] Farakhor, A., Wu, D., Wang, Y., & Fang, H. (2024). Scalable optimal power management for large-scale BESS. IEEE Transactions on Transportation Electrification, 10, 5002–5016.

[23] Fernandez, C., et al. (2021). A review of control strategies for BESS in islanded microgrids. *Renewable and Sustainable Energy Reviews*, *143*, 110931.

[24] Gao, Y., et al. (2023). Dynamic performance of BESS in microgrids with high PV penetration. *Applied Energy*, *330*, 120352.

[25] Grimaldi, A., Minuto, F. D., Brouwer, J., &Lanzini, A. (2024). Profitability of energy arbitrage using BESS considering degradation. Journal of Energy Storage, 95, 112380.

[26] Gu, T., Wang, P., Liang, F., Xie, G., & Zhang, X. (2022). Optimal placement of BESS using NSGA-II. Journal of Energy Storage, 52, 104716.

[27] Gupta, R., et al. (2025). Impact of BESS response time on primary frequency control in isolated grids. *Journal of Renewable Energy and Environment*, *12*(1), 45–58.

[28] Gurung, S., et al. (2023). Optimal placement and sizing of BESS for grid reliability and power quality enhancement. *Energy Reports*, *9*, 512–523.

[29] Hannan, M. A., et al. (2021). Battery energy storage system: A review of technologies, optimization, and control. *Renewable and Sustainable Energy Reviews*, *150*, 111496.

[30] Ibrahim, H., Ilinca, A., & Perron, J. (2021). Energy storage systems—Characteristics and comparisons. Renewable and Sustainable Energy Reviews, 111, 3577–3613.

[31] IRENA. (2025). *Battery energy storage systems: Key to renewable power supply-demand gaps*. International Renewable Energy Agency. https://www.irena.org/publications/2025/Aug/BESS-Renewable-Power

[32] Ishraque, M. F., et al. (2022). Optimal sizing and scheduling of BESS for grid-connected hybrid systems. *Energy Reports*, *8*, 215–226.

[33] Jaradat, T., & Khatib, T. (2025). BESS integration for renewable energy penetration. Frontiers in Energy Research, 100106.

[34] Junior, P. R., Rocha, L. C. S., Morioka, S. N., & Bolis, I. (2021). Economic analysis of BESS investments. Energies, 14(2503).

[35] Kebede, A. A., et al. (2022). A techno-economic analysis of grid-scale lithium-ion and sodium-sulfur battery storage. *Applied Energy*, *306*, 118046.

[36] Ketjoy, N., Muna, Y. B., &Kaewpanha, M. (2026). AI-driven optimization of grid-scale BESS. Batteries, 12(1), 31.

[37] Khan, A. A., et al. (2022). Reliability evaluation of power grids with multiple BESS using Markov models. *International Journal of Power and Energy Systems*, *42*(2).

[38] Khezri, R., et al. (2023). Reliability and stability analysis of power systems with high penetration of renewables and BESS. *IEEE Transactions on Sustainable Energy*, *14*(2), 945–957.

[39] Kim, J., et al. (2021). Reliability modeling of BESS considering degradation for grid-connected applications. *IEEE Access*, *9*, 12345–12356.

[40] Kumar, P., et al. (2024). Role of AI in predictive maintenance of grid-scale BESS for long-term reliability. *IEEE Industrial Electronics Magazine*, *18*(1), 34–45.

[41] Lee, H., et al. (2024). Next-generation LFP batteries for grid-scale storage: A stability

analysis. *Journal of Power Sources*, *592*, 233912.

[42] Lee, Y. R., Kang, H. J., & Kim, M. K. (2022). Combined PV and BESS optimal operation in microgrids. IEEE Access, 10, 27453–27466.

[43] Li, J., et al. (2022). Frequency stability enhancement of modern power systems using BESS-based virtual inertia control. *IEEE Transactions on Smart Grid*, *13*(3), 2056–2067.

[44] Li, S., Xu, Q., & Huang, J. (2023). Integrated application of BESS for peak and frequency regulation. Journal of Energy Storage, 59, 106459.

[45] Lindner, M., Peper, J., Offermann, N., &Häger, U. (2023). Operation strategies for congestion management using BESS. IET Generation, Transmission & Distribution, 17, 589–603.

[46] Liu, H., et al. (2023). Coordinated voltage control of BESS and traditional regulators in active distribution networks. *International Journal of Electrical Power & Energy Systems*, *148*, 108933.

[47] Luo, X., et al. (2021). Overview of multi-energy storage technologies for power system stability. *Journal of Modern Power Systems and Clean Energy*, *9*(3), 473–488.

[48] Luo, X., Wang, J., Dooner, M., & Clarke, J. (2021). Development of energy storage technologies. Applied Energy, 137, 511–536.

[49] Ma, Z., Jia, M., Koltermann, L., & Sauer, D. U. (2023). Grid-tied modular BESS configurations and control. Journal of Energy Storage, 74, 109272.

[50] Martinez, E., et al. (2025). Impact of second-life EV batteries on grid reliability: A systematic review. *Resources, Conservation and Recycling*, *212*, 107987.

[51] Moreno, R., et al. (2021). Providing ancillary services with BESS: Economic and reliability benefits. *Nature Energy*, *6*(4), 382–392.

[52] Mousavi, S. A., et al. (2022). Design and control of grid-scale BESS for voltage regulation in distribution networks. *Sustainable Energy, Grids and Networks*, *29*, 100585.

[53] Mudakir, M. (2024). BESS for mitigating renewable intermittency. Energy and Power Engineering Journal.

[54] Nguyen, T. A., et al. (2023). Grid-scale energy storage systems: A review of technology, application, and safety. *Journal of Power Sources*, *561*, 232744.

[55] NREL. (2025).*Cost projections for utility-scale battery storage: 2025 update*. National Renewable Energy Laboratory (NREL). https://docs.nrel.gov/docs/fy25osti/93281.pdf

[56] Ogunwole, O., Okonkwo, C. S., Agbabiaka, J., Mayo, W., & Okeke, O. T. (2021). Supply chain resilience framework for critical infrastructure and gas processing plants. Shodhshauryam International Scientific Refereed Research Journal, 4(4), 444–461. DOI: 10.32628/SHISRRJ214462

[57] Oikonomou, K., et al. (2021). Enhancing the reliability of power systems with large-scale battery storage integration. *Reliability Engineering & System Safety*, *210*, 107519.

[58] Oikonomou, K., et al. (2022). Optimal siting and sizing of battery energy storage systems for grid reliability enhancement. *Electric Power Systems Research*, *205*, 107743.

[59] Okonkwo, C. S., Agbabiaka, J., Mayo, W., & Okeke, O. T. (2024). Conceptual framework for digital supply chain governance in energy and infrastructure sectors. Gyanshauryam International Scientific Refereed Research Journal, 7(4), 335–356. DOI: 10.32628/GISRRJ247423

[60] Okonkwo, C. S., Agbabiaka, J., Mayo, W., & Okeke, O. T. (2024). Framework for secure and scalable supply chain systems supporting national energy reliability. International Journal of Advanced Multidisciplinary Research and Studies, 4(6), 2816–2826.

[61] Okonkwo, C. S., Mayo, W., & Okeke, O. T. (2023). Conceptual model for asset lifecycle management and inventory visibility. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10(1), 809–824.

[62] Paliwal, P., et al. (2024). BESS construction and siting for optimal grid reliability: A comparative

study. *Energy Conversion and Management*, *302*, 118123.

[63] Patel, S., et al. (2022). Machine learning based frequency regulation using BESS. *Electric Power Systems Research*, *209*, 107936.

[64] Rahman, F. S., et al. (2021). Reliability-based sizing of BESS in a grid-connected hybrid renewable system. *Energies*, *14*(14), 4211.

[65] Rehman, S., et al. (2023). Battery storage integration in power grids. Energy Reports, 9, 321–335.

[66] Salkuti, S. R. (2021). A review on battery energy storage system for the resilience of smart grid. *International Journal of Power Electronics and Drive Systems*, *12*(4), 2264–2272.

[67] Santos, S. F., Gough, M., Fitiwi, D. Z., &Catalão, J. P. (2022). Influence of BESS on transmission grids. IEEE Systems Journal, 16, 1508–1519.

[68] Sarker, M. R., et al. (2021). Peak shaving using BESS. Applied Energy, 302, 117–135.

[69] Shahidehpour, M., et al. (2022). Large-scale BESS for enhancing the resilience and reliability of urban power grids. *IEEE Power and Energy Magazine*, *20*(4), 48–59.

[70] Siddique, A., et al. (2023). Cyber-physical security of grid-scale BESS: Challenges and mitigation. *IEEE Access*, *11*, 15642–15660.

[71] Silva, R., et al. (2023). Economic assessment of hybrid BESS and pumped hydro for grid stability. *Energy Conversion and Management*, *291*, 117289.

[72] Smith, J., & Johnson, L. (2024). BESS role in mitigating duck curve issues in high-solar grids. *Energy Policy*, *184*, 113882.

[73] Sun, C., et al. (2023). Optimization of BESS for peak shaving and reliability enhancement in distribution grids. *Journal of Energy Storage*, *60*, 106678.

[74] Sun, Y., et al. (2023). Optimal dispatch of BESS in smart grids. IEEE Transactions on Smart Grid, 14, 456–468.

[75] Tan, X., et al. (2025). Advanced thermal management systems for safe BESS construction. *Advanced Energy Materials*, *15*(2), 2400123.

[76] Tasneem, O., Tasneem, H., & Xian, X. (2025). Lithium-ion battery technologies for grid-scale storage. Next Research, 2, 100297.

[77] Thompson, R., et al. (2024). Grid-scale sodium-ion battery construction: Initial findings on grid stability. *Energy Storage Materials*, *65*, 103124.

[78] Vasconcelos, A., Monteiro, A., Costa, T., & Maciel, A. (2023). Microgrid sizing with BESS. Energies, 16(8095).

[79] Velasquez, M. A., et al. (2023). Grid-forming BESS for black start and islanded operation: A field study. *IEEE Transactions on Energy Conversion*, *38*(2), 889–901.

[80] Wang, Y., et al. (2023). Small-signal stability analysis of power systems with grid-forming BESS. *International Journal of Electrical Power & Energy Systems*, *145*, 108621.

[81] Wang, Y., et al. (2024). Large-scale BESS control using reinforcement learning. IEEE Transactions on Power Systems, 39, 1123–1135.

[82] Wu, Z., et al. (2024). Quantifying the contribution of BESS to long-term power system reliability. *IEEE Transactions on Reliability*, *73*(1), 112–125.

[83] Yang, J., et al. (2022). Coordinating BESS and HVDC for power system stability enhancement. *Electric Power Systems Research*, *212*, 108456.

[84] Yang, Z., Zhang, J., Kintner-Meyer, M., Lu, X., & Liu, J. (2022). Electrochemical energy storage for green grids. Chemical Reviews, 111(5), 3577–3613.

[85] Yeboah, B. K., Enow, O. F., Ike, P. N., &Nnabueze, S. B. (2024). Program design for advanced preventive maintenance in renewable energy systems. Shodhshauryam, 7(2), 138–156.

[86] Yeboah, B. K., Enow, O. F., Ike, P. N., &Nnabueze, S. B. (2025). Conceptual framework for condition-based maintenance as a utility reliability program. Global Journal of Engineering and Technology Research, 1(2), 55–63.

[87] Zakeri, B., & Syri, S. (2021). Life cycle cost analysis of storage systems. Renewable and Sustainable Energy Reviews, 42, 569–596.

[88] Zaman, M. S., et al. (2022). Impact of BESS on the reliability of wind-integrated power systems.

IET Generation, Transmission & Distribution, *16*(5), 903–915.

[89] Zhang, Y., et al. (2024). Construction and operational challenges of ultra-large scale battery storage: A systematic analysis. *Applied Energy*, *355*, 122289.

[90] Zhao, H., et al. (2023). Grid stability enhancement using hybrid storage. Applied Energy, 325, 119–134.

[91] Zhao, T., et al. (2021). Impacts of BESS on the transient stability of power systems with high renewable penetration. *IET Renewable Power Generation*, *15*(12), 2689–2701.

[92] Zhou, G., et al. (2024). Multi-objective optimization of BESS construction for urban reliability. *Sustainable Cities and Society*, *102*, 105123.