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AI-Enabled Energy Management of Battery Storage Systems for Data Centres and Industrial Facilities in Saudi Arabia

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***Abstract-** Saudi Arabia's data centres and industrial facilities are entering a phase where electrical reliability, decarbonisation, and digital operational intelligence must be addressed as an integrated design challenge. Battery energy storage systems (BESS) facilitate this transition by mitigating renewable variability, reducing peak demand, partially replacing diesel backup, and providing rapid power support during grid disturbances. However, batteries introduce constraints such as ageing, thermal stress, safety limitations, cyber risks, and potential conflicts between reliability and economic objectives. This review develops an AI-enabled energy management framework for BESS deployment in Saudi data centres and industrial facilities. It synthesises literature from 2020 to 2025 on battery management systems, hybrid microgrids, renewable forecasting, cloud-based battery intelligence, data-centre energy flexibility, and AI risk governance. The objective is to demonstrate how machine learning, model predictive control, reinforcement learning, digital twins, and anomaly detection can be integrated into a secure energy management system. The paper proposes a layered architecture that translates load telemetry, weather forecasts, grid signals, battery state estimation, and facility resilience policies into auditable control actions. The findings indicate that AI-enabled energy management systems (EMS) can enhance peak-load management, renewable utilisation, battery health, outage preparedness, and emissions performance, provided that models are governed by safety protocols, human oversight, and cybersecurity measures. The review concludes with a Saudi-specific research agenda focused on pilot projects, interoperability standards, and operational governance.*

***Keywords:** Artificial Intelligence, Battery Energy Storage Systems, Data Centres, Industrial Facilities, Energy Management, Saudi Arabia, Hybrid Power Generation, Smart Grids, Decarbonisation, Digital Twins.*

I. INTRODUCTION

Data centres and industrial facilities are evolving into strategic energy loads rather than conventional electricity consumers. Cloud platforms, AI workloads, process automation, robotics, logistics systems, and digital public services demand high power availability, continuous cooling, and stable power quality. Concurrently, Saudi Arabia is advancing renewable energy deployment, digital infrastructure, and industrial diversification. These trends present an opportunity to operate critical facilities using hybrid energy systems that integrate grid supply, solar PV, backup generation, battery energy storage, and intelligent controls. Reference [1] models this scenario through hybrid generation, storage, and techno-economic optimisation in the Saudi context, demonstrating that carefully sized and dispatched combinations of PV, wind, generators, and batteries can reduce emissions and operating costs.

This topic is significant because traditional backup models for mission-critical facilities are increasingly inadequate. Conventional data centres rely on grid electricity, UPS batteries, and diesel generators, while industrial plants depend on grid interconnections, captive generation, and maintenance routines. Although these configurations provide redundancy, they do not inherently minimise emissions, extend battery lifespan, or adapt to dynamic tariffs, solar output, and load fluctuations. Modern BESS can deliver short-duration continuity, peak shaving, power-quality support, and renewable balancing. However, the value of BESS is contingent on optimal charging and discharging schedules, reserve margin management, and accurate interpretation of state of charge, state of health, and thermal conditions by the battery management system [2,3]. Ineffective dispatch can reduce battery longevity and compromise the economic rationale for storage.

Artificial intelligence has become increasingly pertinent as energy management now requires processing large, uncertain, and rapidly changing data streams. Weather conditions influence solar production and cooling loads; server utilisation impacts rack power and heat; production schedules affect industrial demand; grid events alter voltage and reliability exposure; and batteries experience varying degradation patterns depending on operational cycles. Recent studies on battery health metrics, cloud-based battery management, and machine-learning-based energy management demonstrate that AI can enhance forecasting, fault detection, state estimation, and operational optimisation [4-7]. In data centres, AI also enables the coordination of workload flexibility with electrical flexibility, allowing non-critical computation, cooling set points, and storage dispatch to be managed collectively rather than in isolated engineering domains [8,9].

The Saudi context further underscores the importance of this topic. The nation possesses abundant solar resources, a growing demand for data-centre capacity, and extensive industrial zones that require reliable electricity in hot climatic conditions. Elevated ambient temperatures intensify the demands on cooling systems and battery thermal management. Simultaneously, national objectives for renewable energy, clean hydrogen, digital infrastructure, and industrial localisation necessitate BESS strategies tailored to local conditions rather than replicated from temperate regions. Effective solutions for Saudi facilities must address solar variability, dust and soiling, high cooling requirements, grid-code compliance, cybersecurity, bilingual operational documentation, and clear delineation of responsibilities among facility teams, cloud operators, energy managers, and utility interfaces [10,11].

The objective of this review is to provide a comprehensive understanding of AI-enabled energy management for battery storage systems in Saudi Arabian data centres and industrial facilities. Rather than focusing solely on battery chemistry or economic sizing, this paper investigates the control of BESS within a cyber-physical operating system. The specific aims are: to review recent findings on BESS functions, hybrid power systems, and AI-based energy management; to identify operational requirements for data-centre and industrial loads; to propose an AI-BESS architecture relevant to Saudi conditions; to define performance indicators for reliability, emissions, safety, and cost; and to highlight research gaps that should inform future pilot projects and academic studies.

II. LITERATURE BACKGROUND

Recent energy storage literature agrees that BESS is a core enabling technology for renewable integration, load shifting and resilience. Reviews published between 2022 and 2024 describe BESS applications across microgrids, grid services, behind-the-meter installations and industrial energy management [2,3,12]. Lithium-ion batteries remain common because of their response speed and energy density, but long-duration and alternative chemistries are gaining attention for applications where safety, cost and lifespan are more important than compactness. For data centres and industrial facilities, the BESS function differs from utility-scale arbitrage alone. Storage must support availability targets, ride-through performance, thermal conditions, power quality and safe integration with emergency power systems.

Battery management systems form the technical foundation of safe BESS operation. Modern BMS platforms monitor voltage, current, temperature, cell balance, insulation, alarms and battery health indicators. The state of charge estimates available energy, while the state of health estimates degradation relative to original capacity. Recent reviews emphasise that inaccurate SOC and SOH estimation can lead to over-discharge, reduced reserve, accelerated ageing or unsafe operation [4,6]. AI-based estimation methods, including neural networks, gradient boosting, support vector regression and hybrid physics-informed models, are attractive because they can learn nonlinear degradation patterns from historical cycling, temperature and current data. Nevertheless, AI models must be verified against operational limits and not treated as independent decision makers.

Energy management systems provide the supervisory layer above the BMS. They decide when to charge, discharge, hold reserve or request another energy source. Traditional EMS approaches use rule-based logic and deterministic optimisation. These methods remain useful because they are transparent and easy to audit, but they become less effective when renewable generation, electricity prices, cooling demand and production schedules are uncertain. Machine-learning-based EMS approaches improve forecasting, while model predictive control can optimise over a rolling time horizon. Reinforcement learning can learn dispatch policies, but it requires strong safety constraints because exploratory behaviour is unacceptable for mission-critical facilities [7,13]. Therefore, the most credible architecture combines forecasting, constrained optimisation and human-supervised governance.

Hybrid power generation literature is highly relevant to the Saudi case. The attached reference paper compares PV, wind, generator and battery configurations for Yanbu and highlights how renewable fraction, cost of energy, net present cost, fuel use and emissions vary by configuration [1]. Such analysis is useful for large facilities because data centres and industrial sites often require a combination of grid supply, on-site solar, emergency generators and storage. However, a data centre is different from an isolated community load. It has strict uptime requirements, sensitive power electronics, fast-changing server demand and contractual service-level obligations. Industrial facilities may have process loads, motors, compressors, chillers and safety systems that cannot be interrupted without operational consequences.

The data-centre energy literature identifies several flexibility opportunities. Peak shaving can reduce demand charges and relieve grid congestion, especially when battery dispatch and workload management are coordinated [8]. Online electricity purchase strategies show that aggregated flexibility from cooling systems and computing tasks can behave like a virtual battery [9]. Energy-efficient cloud computing research argues that future data centres need integrated management of IT resources, cooling and power infrastructure rather than isolated optimisation of servers only [14]. These ideas are directly relevant to Saudi Arabia because high cooling demand creates a strong link between IT workload, HVAC operation and electrical storage. AI-enabled EMS can therefore treat the data centre as a flexible energy system, not only as a passive load.

AI governance literature also matters because AI-enabled control is not merely a software upgrade. The NIST AI Risk Management Framework recommends mapping, measuring, managing and governing AI risks through documented and accountable processes [15]. For energy infrastructure, this principle implies that AI recommendations should be explainable, tested, logged and reversible. Cybersecurity guidance such as the NIST Cybersecurity Framework 2.0 reinforces the need for asset identification, protection, detection, response and recovery [16]. A battery dispatch algorithm connected to grid signals and facility operations can become a cyber-physical risk if access control, data quality and incident response are weak. Therefore, the AI-BESS EMS must be designed with reliability engineering and cybersecurity from the start.

III. METHODOLOGY

This paper adopts a systematised review methodology suitable for a conceptual engineering review. The method follows the structure of recent MDPI and Springer style studies by defining the problem context, setting review boundaries, mapping technical themes, synthesising findings and developing a framework for future implementation. The review scope covers publications and technical reports from 2020 to 2025, with emphasis on BESS management, hybrid microgrids, renewable integration, data-centre energy flexibility, AI risk management and Saudi renewable infrastructure. Older standards are not used as main citations because the prompt requires recent in-text citation years. The review is thematic rather than meta-analytic because the studies use different battery sizes, facility types, climates, optimisation models and reliability assumptions.

The review process used four stages. First, relevant studies were grouped by domain: battery technology and BMS, AI and forecasting, data-centre energy management, industrial facility flexibility, hybrid power systems and governance. Second, the technical functions of an AI-enabled EMS were extracted, including load forecasting, renewable forecasting, SOC/SOH estimation, peak shaving, reserve management, anomaly detection, thermal control and maintenance scheduling. Third, the functions were mapped to operational outcomes such as uptime, emissions reduction, battery life extension, demand-charge reduction and recovery time. Fourth, a framework was developed for Saudi implementation by considering climate, solar potential, industrial demand, data-centre growth, cybersecurity and regulatory alignment.

The methodology deliberately avoids presenting a single numerical simulation as if it applied to every Saudi site. Data centres vary by tier rating, IT load, cooling technology, redundancy arrangement and grid connection. Industrial facilities vary by process demand, shift schedules, motor loads and acceptable interruption windows. Therefore, the paper proposes a decision architecture rather than a fixed design. Site-level modelling should still be performed using hourly load data, solar resource files, battery cost assumptions, degradation models, generator fuel curves, cooling energy profiles and utility tariff structures. In practice, HOMER, MATLAB, Python optimisation libraries and digital twin platforms can all support such analysis when inputs are transparent and verified [1,17].

The review uses three inclusion principles. First, a source must address a relevant technical function, such as BESS sizing, battery state estimation, EMS optimisation, AI forecasting, data-centre demand or hybrid power operation. Second, it must be recent enough to reflect current technology and market conditions, preferably 2020 to 2025. Third, it must contribute to an implementable framework for Saudi data-centre or industrial facility contexts. Studies focused only on vehicle traction batteries are used cautiously, because stationary BESS cycles, cooling arrangements and safety responsibilities differ from electric vehicles. Table 1 summarises the review logic and its contribution to the proposed framework.

Table 1. Review domains and contribution to the proposed framework.

Review domain	Inclusion focus	Contribution to AI-BESS EMS framework
BESS and BMS	SOC, SOH, safety, degradation, thermal limits and battery health indicators	Defines safe operating boundaries and lifecycle-aware dispatch rules
Hybrid power systems	PV, grid, generator, battery and hydrogen/fuel-cell configurations	Supports Saudi-specific resilience and emissions scenarios
Data-centre energy flexibility	UPS, cooling, workload shifting, peak shaving and virtual batteries	Links IT service quality with electrical flexibility
Industrial facilities	Motor peaks, process continuity, power quality and facility energy scheduling	Adapts BESS control to production and safety requirements
AI governance	Model risk, cyber resilience, explainability and auditability	Ensures human-supervised and trustworthy automation

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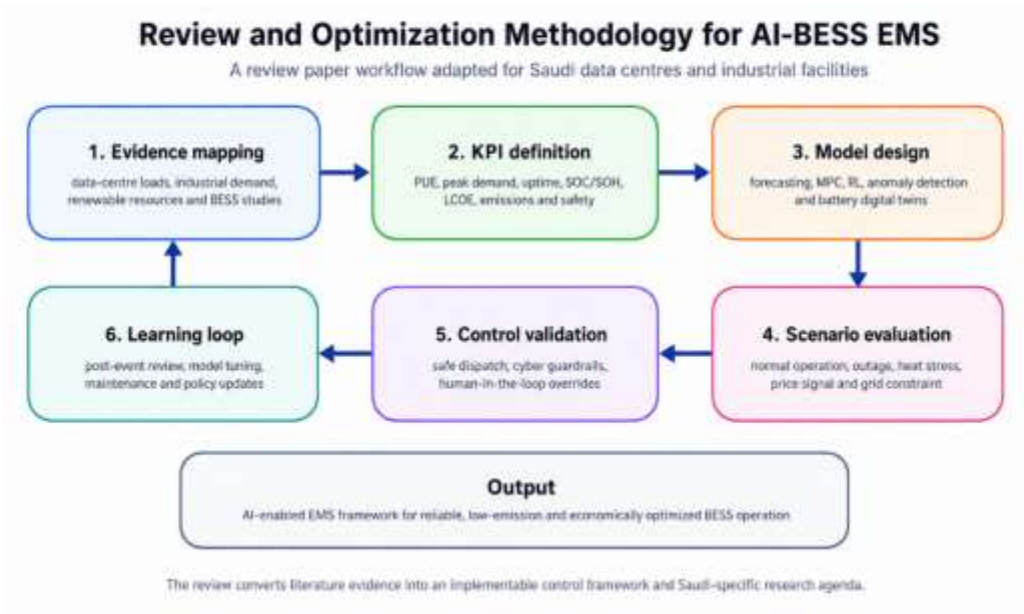

Figure 1. Review and optimization methodology for AI-enabled BESS energy management.

4.AI-enabled BESS energy management architecture

Figure 1 proposes a layered architecture for AI-enabled energy management of battery storage systems. The input data layer collects real-time and historical signals from meters, BMS, power conversion systems, building management systems, production schedules, IT workload orchestration, weather feeds, tariff signals and grid events. These data streams are cleaned and converted into features such as ramp rate, reserve requirement, cooling sensitivity, solar forecast error, battery temperature stress and forecasted peak demand. Without this data layer, AI models cannot deliver reliable energy decisions. Data quality is therefore an operational asset, not only an IT concern.

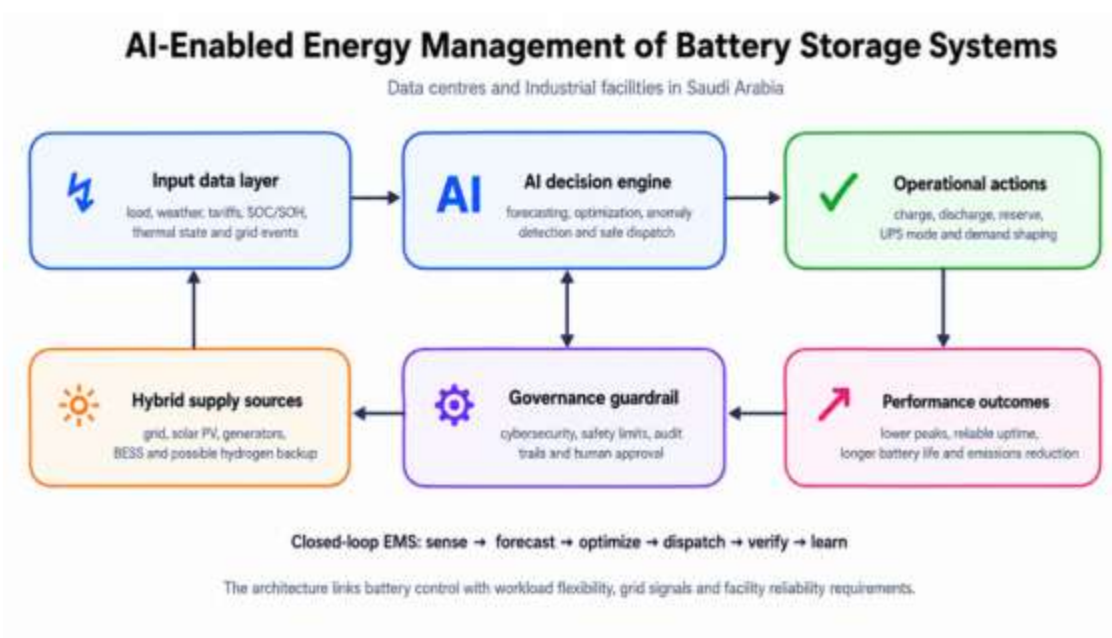

Figure 2. AI-enabled BESS energy management architecture for Saudi data centres and industrial facilities.

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The AI decision engine performs several functions. Load forecasting predicts facility demand at short, medium and day-ahead horizons. Renewable forecasting estimates solar PV output, especially important under dust, cloud and seasonal temperature variation. Battery analytics estimate SOC, SOH and remaining usable capacity. Optimisation models then determine dispatch schedules that respect reserve requirements, degradation cost, temperature limits, inverter ratings and reliability policies. Anomaly detection identifies unusual battery behaviour, inverter alarms, sensor drift or unexpected load signatures. In advanced facilities, the decision engine can also coordinate with workload schedulers to defer non-critical computing tasks when power prices or grid constraints are high [8,9,14].

Operational actions translate AI recommendations into controlled behaviour. The EMS may charge the battery from solar PV during midday, discharge during a demand peak, hold reserve for UPS support, start a generator under outage risk, request cooling pre-conditioning or alert operators when battery health is deteriorating. For industrial facilities, actions may include peak shaving during compressor starts, smoothing renewable output, supporting voltage-sensitive equipment and maintaining reserve for critical process controls. All actions must be constrained by safety, warranty and operational rules. An AI model should never override protection settings, emergency shutdown logic or minimum reserve requirements that protect mission-critical loads.

The governance guardrail is as important as the algorithm. AI-BESS EMS requires defined approval levels, model validation, access control, audit logs, cyber monitoring and maintenance responsibility. A human-in-the-loop process is needed for new operating modes, major control changes, unusual faults and post-incident review. The AI model should explain why a dispatch action is recommended, what forecast it relies on, what constraints are active and what risk would result from not acting. This approach aligns with AI risk guidance and cyber-resilience expectations for critical infrastructure [15,16]. In Saudi organisations, governance should also clarify whether the facility owner, data-centre operator, utility interface team or third-party service provider is accountable for each control layer.

For data centres, the architecture can improve reliability and sustainability simultaneously. BESS can support UPS functions, reduce generator starts, shave peaks and enable higher renewable use. AI improves these functions by predicting workload peaks and cooling demand before they occur. If the facility has flexible workloads, the EMS can delay batch processing or AI training jobs into periods of lower grid carbon intensity or higher solar availability. If workloads are not flexible, storage can still reduce short-duration peaks and maintain ride-through capability. The result is not simply energy cost reduction; it is a more predictable relationship between IT service quality and electrical infrastructure.

For industrial facilities, the architecture supports production continuity and energy optimisation. Industrial loads often include large motors, variable-speed drives, chillers, pumps and process equipment. Sudden starts can create demand spikes and voltage stress. AI-enabled BESS can learn operating patterns and pre-position battery capacity before predictable peaks. It can also support solar self-consumption when facilities have large roofs, carports or nearby land for PV. In energy-intensive industrial zones, coordinated storage can reduce stress on feeders and improve resilience during grid disturbances. However, control must be coordinated with plant safety systems, because energy optimisation is unacceptable if it compromises process safety or product quality.

IV. PERFORMANCE INDICATORS AND EVALUATION

AI-enabled EMS should be evaluated through a balanced KPI set. Technical reliability indicators include outage ride-through duration, reserve margin, transfer time, critical load served, power-quality events and unplanned generator starts. Battery indicators include SOC estimation error, SOH trend, cycle depth, equivalent full cycles, temperature exposure and degradation cost. Economic indicators include peak demand reduction, energy arbitrage value, avoided fuel, avoided outage cost, maintenance savings and net present value. Environmental indicators include renewable fraction, diesel runtime,

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CO_2 emissions avoided and grid-carbon alignment. Data-centre indicators include PUE, IT load served, workload delay and service-level compliance [3,4,8].

A common mistake is to evaluate storage only by the amount of energy shifted. For data centres and industrial facilities, storage value also comes from risk reduction. One avoided outage can justify a significant part of the storage investment if the facility hosts critical applications or high-value production. Similarly, battery life extension is a hidden value of intelligent management. A poorly tuned EMS may achieve short-term savings but cause unnecessary cycling, high temperature and premature replacement. Therefore, lifecycle cost should include battery degradation, cooling energy, inverter losses, maintenance, safety systems, software monitoring and end-of-life management [2,5,12]. Table 2 maps key AI functions to facility outcomes.

Table 2. AI-enabled EMS functions, data requirements, benefits and risk controls.

AI-enabled EMS function	Primary data used	Expected facility benefit	Risk control requirement
Load and cooling forecast	Meters, IT load, BMS/BAS data and weather	Peak reduction, better reserve planning and lower cooling stress	Monitor forecast error and avoid overconfident dispatch
SOC/SOH estimation	Voltage, current, temperature, cycles and historical degradation	Longer battery life and more reliable autonomy calculation	Validate against BMS limits and warranty rules
Constrained optimisation	Tariffs, grid signals, PV forecast, reserve policy and facility modes	Lower energy cost, higher renewable use and controlled emissions	Keep emergency reserve and protection settings active
Anomaly detection	Inverter alarms, sensor drift, thermal patterns and network events	Faster maintenance action and reduced failure probability	Use human review before critical isolation actions
Post-event learning	Outage logs, alarms, operator actions and KPI results	Improved policy tuning and continuous resilience improvement	Maintain auditable change records

Scenario evaluation is necessary before deployment. A Saudi data-centre project should simulate at least six operating scenarios: normal grid-connected operation, high solar production, low solar production, peak cooling demand, grid outage and cyber or sensor failure. An industrial facility should add production ramp-up, motor-start peaks, maintenance shutdown and process safety constraints. For each scenario, the EMS should be tested against reliability, cost and emissions KPIs. Digital twins can help by allowing operators to test control policies before applying them to live equipment. However, digital twins require calibration against measured data and should not be trusted if sensor quality is poor or system topology has changed.

V. SAUDI IMPLEMENTATION CONSIDERATIONS

The Saudi context creates several design priorities. First, heat management is fundamental. Battery degradation accelerates under high temperature, and data centres already dedicate major energy to cooling. AI-enabled EMS should include thermal forecasts and battery cooling status, not only electrical signals. Second, solar resource availability is strong, but dust, soiling and seasonal variation affect output. Forecasting models should be trained with local weather and measured PV production rather than generic datasets. Third, many industrial facilities operate near ports, logistics corridors and energy clusters where grid capacity and reliability planning are strategic concerns. Behind-the-meter BESS can reduce site peaks, but interconnection studies are still required.

Fourth, data localisation and cybersecurity are critical. An AI-BESS EMS will collect operational data from power systems, IT systems and industrial processes. This information can reveal facility behaviour and should be protected. Cloud-based analytics may be useful for model training and fleet benchmarking, but sensitive operational controls should have local fail-safe behaviour. Fifth, skills and operating procedures must be developed. Energy managers, facility engineers, cyber teams and IT operations teams need shared dashboards and common incident protocols. If only the vendor understands the AI model, the facility becomes dependent on opaque automation. Saudi localisation goals therefore support the creation of local expertise in BESS analytics, data engineering and EMS operations [10,16].

Sixth, business models must align incentives. A facility may invest in BESS for resilience, cost reduction, sustainability reporting or grid services. These objectives can conflict. For example, the most profitable tariff arbitrage schedule may leave insufficient emergency reserve, while a conservative UPS reserve policy may limit renewable self-consumption. The EMS should allow operators to rank objectives by operating mode. During normal operation, cost and emissions may be prioritised. During grid warnings or sandstorm conditions, reserve and thermal safety should dominate. During maintenance windows, battery cycling may be limited to preserve life. This mode-based control philosophy is more realistic than assuming one objective function fits all conditions.

VI. CHALLENGES AND RESEARCH GAPS

The first research gap is the shortage of Saudi site-specific datasets linking data-centre load, industrial demand, solar generation, cooling behaviour and battery degradation. Many international studies use public traces or simulated loads, but Saudi deployments need local evidence. The second gap is the limited integration between IT workload scheduling and electrical storage dispatch. Data centres can become flexible energy assets only if computing tasks, cooling and BESS are coordinated through secure interfaces. The third gap is safety validation of AI dispatch. Reinforcement learning and deep learning may appear attractive, but they must be constrained by electrical protection, thermal safety and cybersecurity requirements before deployment in critical facilities [13,15].

The fourth gap is lifecycle economics under high-temperature conditions. Battery warranties, replacement cost and degradation models should be tested for Saudi duty cycles rather than assumed from moderate climates. The fifth gap is resilience accounting. Many organisations report renewable share or energy savings, but fewer quantify how storage changes recovery time, load-loss probability, generator dependence or business continuity. The sixth gap is interoperability. BESS, UPS, generators, building management systems, SCADA, cloud workload managers and cybersecurity platforms are often supplied by different vendors. Without open interfaces and clear data models, AI-enabled EMS becomes a bespoke integration project that is difficult to maintain.

A future research agenda should therefore prioritise pilot demonstrations. One pilot could focus on a mid-size data centre with solar PV, BESS, UPS integration and workload-aware EMS. Another could focus on an industrial facility with large motor loads and process continuity requirements. The pilots should publish anonymised operating data, KPI definitions, model validation methods and safety lessons. Comparative studies should test rule-based control, model predictive control and AI-assisted control under the same scenarios. Research should also examine how BESS can participate in demand response or grid-support services without compromising facility reserve. Such work would align academic output with real Saudi infrastructure needs.

VII. CONCLUSION

AI-enabled energy management of battery storage systems offers a practical pathway for improving reliability, emissions performance and cost control in Saudi data centres and industrial facilities. The literature shows that BESS can support renewable integration, peak shaving, backup resilience and power-quality improvement, while AI can improve forecasting, state estimation, anomaly detection and constrained optimisation. The proposed framework treats the battery not as an isolated asset but as part of a hybrid cyber-physical operating system connected to load, weather, grid, facility and governance data. In Saudi Arabia, the strongest applications are likely to be high-reliability data centres, renewable-powered industrial zones and facilities facing high cooling loads and demand peaks.

The review also shows that successful implementation depends on discipline. AI dispatch must be explainable, safety-constrained, cybersecure and auditable. Batteries must be managed according to SOC, SOH, thermal limits and lifecycle cost rather than short-term savings alone. Data-centre and industrial stakeholders must coordinate operations, because energy decisions affect uptime, production continuity and sustainability reporting. Future Saudi research should therefore combine pilot projects, local datasets, digital twins, lifecycle degradation models and governance frameworks. When these elements are integrated, AI-enabled BESS can become a key infrastructure layer for reliable, low-emission and digitally managed facilities.

Implementation note: For practical deployment, operators should initially adopt a conservative supervisory mode, where the AI system recommends dispatch actions and experienced engineers approve changes prior to expanding automation. This staged approach enables facility teams to compare predicted and actual load, solar output, battery temperature, state estimation error, generator starts, outage response, and maintenance alarms. The resulting evidence supports model validation, refinement of operational limits, and clear documentation of accountability. In Saudi deployments, this gradual method is particularly valuable due to differences in climate, cooling intensity, renewable variability, and operational culture compared to international benchmarks. A thorough commissioning plan also mitigates the risk of treating battery storage as a generic product rather than as a facility-specific reliability asset with defined operational responsibilities.

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