Al-Farouk journal of sciences
Volume (2), Issue (3) (JUNE, 2026)
ISSN: 3135-2359

مجلة الفاروق للعلوم
المجلد (2) ملحق العدد 3 يونيو 2026
ردمد: 3135-2359

AI-Driven Solar Energy Optimization for Sustainable Development in Libya

Taher Abdallah Galouz, Mustafa Ahmed Ben Hkoma[2]
[1]Division of Electronic Engonnering, Faculty of Engineering,,
Unversity of Sabrata, Sabrata, Libya
[2]Sustainable Development Research Center
taher.galouz@sabu.edu.ly
https://doi.org/10.1002/sd.70915
m_hkoma2017@yahoo.com
https://orcid.org/0009-0006-6814-8468
Received: 29/6/2026 Revised: 20/7/2026 Accepted: 28/7/2026 Publication: 15/8/2026

Abstract
This study examines the potential of Artificial Intelligence (AI) to optimize solar-energy utilization and support sustainable development in Libya, considering the country's substantial solar resources alongside the operational and infrastructural constraints of its electricity system. The study adopted a descriptive, analytical, and comparative approach, critically synthesizing Libyan and international literature on solar photovoltaic (PV) potential, AI-based PV and load forecasting, Battery Energy Storage System (BESS) optimization, grid-aware energy management, reliability, resilience, and sustainability. The findings indicate that Libya's primary challenge is not the scarcity of solar resources, but the limited capacity to convert this potential into reliably forecasted, efficiently stored, and grid-compatible electricity. AI techniques can improve PV and load forecasting and provide predictive intelligence for BESS scheduling and energy management; however, forecasting accuracy alone does not ensure operational value unless it is integrated with storage and grid-management decisions. The analysis further demonstrates that BESS should be considered an AI-coordinated flexibility resource, with optimization accounting for state of charge, degradation, uncertainty, cost, reliability, and reserve requirements. Moreover, AI cannot substitute for physical grid-support infrastructure but can enhance the forecasting, scheduling, and coordination of available resources. Based on these findings, the study proposes an integrated pathway: Solar and Weather Data → AI Forecasting → PV/Load Prediction → BESS Optimization → Grid-Aware Energy Management → Reliability and Energy-Efficiency Improvement → Sustainable Development. The study concludes that AI-driven solar optimization could contribute to reducing fossil-fuel dependence, improving renewable-energy utilization, strengthening electricity-system reliability and resilience, and supporting Libya's environmental, economic, technological, and social sustainability. Nevertheless, successful implementation requires reliable energy data, digital and grid modernization, cybersecurity, skilled human resources, supportive regulation, and empirical validation using Libyan operational datasets.

Keywords: Artificial Intelligence; Solar Energy; Photovoltaic Systems; Battery Energy Storage Systems; Energy Optimization; Grid-Aware Energy Management; Sustainable Development; Libya.

1 | Introduction

The global transition toward low-carbon energy systems has accelerated the deployment of renewable-energy technologies, particularly solar photovoltaic generation, as countries seek to reduce dependence on fossil fuels, enhance energy security, and support sustainable development. This transition is especially relevant to hydrocarbon-dependent economies, where renewable energy can simultaneously contribute to economic diversification, environmental protection, and long-term energy resilience. In the Libyan context, renewable energy has been identified as an important alternative capable of reducing dependence on conventional fuels while supporting the economic, environmental, and social dimensions of sustainable development (Ben Hkoma et al., 2023a).

Libya possesses particularly favorable conditions for solar-energy development due to its geographical location, extensive desert areas, high solar irradiation, and large available land resources. Previous studies consistently identify solar PV as one of the most promising renewable options for diversifying the national electricity mix and reducing fossil-fuel-based generation (Almaktar & Shaaban, 2021). Nevertheless, the presence of abundant solar resources alone does not guarantee an efficient energy transition, because large-scale photovoltaic penetration must also account for electricity-network limitations, operational variability, protection requirements, and system reliability.

The technical challenge is therefore no longer limited to increasing installed solar capacity, but extends to improving how solar generation is forecast, managed, stored, and integrated into the power system. Evidence from the Libyan electricity network demonstrates that grid-connected PV can influence voltage profiles, losses, harmonics, short-circuit behavior, and protection-system performance, confirming that renewable expansion requires detailed assessment of grid strength and operational conditions (Alasali et al., 2023).

Within this context, artificial intelligence has emerged as a promising enabling technology for improving the operational efficiency of renewable-rich power systems. Machine learning, deep learning, reinforcement learning, and hybrid intelligent methods are increasingly used for renewable-generation forecasting, load prediction, battery scheduling, voltage and frequency control, fault diagnosis, predictive maintenance, demand response, and real-time energy management. AI is particularly valuable because it can process nonlinear, high-dimensional, and time-dependent energy data and convert them into predictive and optimization-based decisions (Zhou, 2022).

For solar-energy systems, one of the most important AI applications is photovoltaic power forecasting. Solar generation is strongly affected by irradiance, temperature, cloud conditions, and historical operating patterns, and inaccurate forecasts increase uncertainty in generation scheduling and balancing. AI-based forecasting can reduce this uncertainty by integrating meteorological and operational data, thereby supporting more effective reserve allocation, storage scheduling, and renewable-energy dispatch. In this sense, artificial intelligence enables the transition from reactive management of solar variability toward anticipatory and data-driven operation.

Energy storage represents the second essential component of intelligent solar optimization. Battery energy storage systems can smooth renewable variability, shift energy across time, support frequency regulation, provide reserve capacity, and improve the operational flexibility required for higher PV penetration. However, their contribution depends strongly on appropriate sizing, state-of-charge management, degradation control, and coordination with renewable generation. Intelligent scheduling can therefore improve the technical and economic performance of storage by determining when batteries should charge, discharge, or preserve reserve capacity according to forecasted solar generation and system demand (Galouz & Ben Hkoma, 2026).

The integration of AI, solar PV, and storage is especially significant for Libya because the country's renewable-energy transition is constrained not only by technological issues but also by weaknesses in network infrastructure, monitoring systems, data availability, institutional coordination, investment conditions, and regulatory frameworks. Previous Libyan research has highlighted financing, technical, institutional, legislative, political, and security barriers that continue to limit the effective exploitation of renewable resources despite their considerable potential (Ben Hkoma et al., 2023b). Thus, intelligent solar-energy optimization should be developed in parallel with improvements in measurement systems, communication infrastructure, data governance, and grid modernization.

Accordingly, this study addresses AI-Driven Solar Energy Optimization for Sustainable Development in Libya by examining how artificial intelligence can support solar-generation forecasting, operational optimization, energy-storage coordination, and more efficient grid integration. The study adopts the premise that Libya's energy transition should move beyond the simple expansion of renewable capacity toward an integrated model in which solar resources, digital intelligence, storage flexibility, and grid-support technologies operate collectively. Such an approach can contribute to improving energy efficiency, reducing fossil-fuel dependence, strengthening electricity-system resilience, and advancing sustainable development in Libya (Galouz & Ben Hkoma, 2026).

2 | Research Problem

Despite Libya's substantial solar-energy potential, the effective utilization of photovoltaic resources remains constrained by generation variability, limitations in grid infrastructure, weak monitoring and data systems, insufficient storage coordination, and broader technical and institutional barriers. At the same time, artificial intelligence offers advanced capabilities for solar forecasting, operational optimization, battery scheduling, predictive maintenance, and intelligent grid coordination. However, the Libyan context still lacks an integrated framework that systematically connects these AI capabilities with solar-energy optimization and sustainable-development objectives. The research problem therefore lies in determining how AI can be effectively employed to improve the efficiency, reliability, flexibility, and sustainability of solar-energy systems in Libya, while accounting for the operational constraints of the national electricity system.

2.1 | Research Questions

1. What is the current potential and operational context of solar-energy utilization in Libya in relation to sustainable development?
2. To what extent can artificial intelligence improve the forecasting accuracy and operational efficiency of solar photovoltaic generation in Libya?
3. How can AI-based optimization improve the scheduling and management of battery energy storage systems integrated with solar PV?

4. How can AI-supported coordination contribute to improving grid integration, reliability, and resilience under increasing solar-energy penetration?
5. What integrated AI-driven framework can be proposed to optimize solar-energy utilization and support sustainable development in Libya?

3 | Study Objectives

Consistent with the five research questions, this study aims to:

1. Assess the potential and operational context of solar-energy utilization in Libya and its relevance to sustainable development.
2. Examine the role of artificial intelligence in improving solar PV forecasting accuracy and operational efficiency.
3. Evaluate the potential of AI-based optimization for improving battery energy-storage scheduling and coordination with solar generation.
4. Analyze the contribution of AI-supported coordination to enhancing solar-grid integration, reliability, and electricity-system resilience.
5. Develop an integrated AI-driven solar-energy optimization framework capable of supporting efficient renewable-energy utilization and sustainable development in Libya.

4 | Literature Review

4.1 | Solar Energy Potential and Operational Context in Libya

Libya possesses a combination of geographical, climatic, and spatial characteristics that makes solar photovoltaic energy one of the most strategically relevant renewable resources for its future electricity system. The country lies within the global Sun Belt, contains extensive sparsely populated desert areas, and experiences high levels of direct and global solar irradiation over much of its territory. These characteristics create favorable conditions for both utility-scale PV installations and decentralized systems supplying remote communities, public facilities, agriculture, water systems, and isolated loads. Maka et al. (2021) showed that Libya has substantial opportunities for PV development and argued that solar electricity could contribute significantly to addressing electricity shortages and diversifying a generation mix that remains overwhelmingly dependent on hydrocarbons. Their assessment is particularly important because it moves the discussion beyond theoretical solar-resource availability and identifies the possibility of employing PV in several operational configurations, including residential, remote, and grid-connected applications.

The importance of this resource must, however, be considered within the structural characteristics of Libya's electricity sector. High solar irradiation does not automatically result in a high share of solar electricity, because the conversion of physical resource potential into reliable electrical energy depends on generation infrastructure, transmission capacity, network flexibility, institutional readiness, financing, technical expertise, and regulatory support. Maka et al. (2021) identify a considerable discrepancy between the country's PV potential and its actual utilization, demonstrating that the principal challenge is increasingly one of resource conversion and system integration rather than resource scarcity. This distinction is fundamental to the present research because an energy strategy based solely on increasing installed PV capacity may reproduce existing weaknesses if the resulting generation cannot be efficiently predicted, stored, dispatched, and absorbed by the network.

Solar PV is nevertheless particularly compatible with Libya's electricity-demand characteristics. High temperatures increase cooling and air-conditioning requirements during daylight hours, producing a degree of temporal correspondence between solar generation and electricity consumption. Maka et al. (2021) note the importance of residential electricity demand in the Libyan load structure, while Maka and Alabid (2022) emphasize the broader contribution that solar-energy technologies can make to sustainable development through cleaner electricity, reduced environmental impacts, and expanded renewable-energy applications. Solar PV should consequently be viewed not merely as an additional generation technology but as an instrument through which electricity supply, environmental objectives, technological modernization, and socioeconomic development can be progressively connected.

The operational value of solar PV nevertheless depends strongly on environmental conditions. High ambient temperature can reduce module conversion efficiency, while dust accumulation, atmospheric aerosols, seasonal variations, wind conditions, and extreme climatic events can alter output and increase maintenance requirements. These factors are particularly relevant in desert environments and imply that nominal PV capacity cannot be treated as equivalent to continuously available power. Consequently, solar-resource assessment needs to progress from static annual irradiation maps toward temporally resolved datasets incorporating irradiance, ambient and module temperature, wind speed, cloud cover, dust conditions, historical PV production, and equipment operating variables. Such datasets form the information layer required for intelligent forecasting and optimization.

The spatial dimension is equally important. Large centralized PV installations can exploit economies of scale but may require transmission reinforcement and expose the electricity system to concentrated renewable variability. Distributed PV, by contrast, can generate electricity close to consumption points, reduce some transmission requirements, and support remote areas, although widespread distributed generation introduces additional challenges related to voltage regulation, bidirectional power flows, protection, monitoring, and coordination. Accordingly, the optimal solar strategy for Libya is unlikely to be based exclusively on either centralized or distributed PV. A diversified architecture combining utility-scale solar parks, distributed PV, storage-equipped microgrids, and selected stand-alone systems would provide greater operational flexibility.

The transition toward such an architecture requires that planning criteria extend beyond the conventional levelized cost of electricity. Reliability, grid strength, storage requirements, curtailment risk, transmission availability, environmental impact, maintenance accessibility, data connectivity, and local demand profiles should also influence investment decisions. This is consistent with recent Libyan research on PV–BESS configurations. Altayf et al. (2024), for example, applied multi-criteria decision-making to alternative PV and hybrid storage configurations for a clinic in southern Libya and explicitly combined reliability and cost indicators such as net present cost, loss-of-power-supply probability, and levelized cost of energy. Their results illustrate the value of multi-dimensional rather than single-criterion renewable planning.

A further challenge is the mismatch between deterministic planning assumptions and the stochastic character of renewable generation. Solar availability, demand, storage condition, equipment availability, and network operating states are uncertain variables. Sakki et al. (2022) argue that renewable-energy design should explicitly recognize and quantify uncertainty rather than optimize systems around single deterministic trajectories. Their stochastic simulation–optimization perspective is particularly relevant to Libya because climatic variability and limitations in historical operational datasets increase the uncertainty surrounding long-term PV performance and short-term dispatch decisions.

Consequently, the central issue for Libya is not simply how much solar power can be installed, but how much solar electricity can be reliably utilized by the electricity system under changing environmental and operating conditions. This reframing establishes the rationale for AI-driven optimization. The country's high solar potential provides the physical resource, but data-driven forecasting, storage flexibility, intelligent scheduling, and grid-aware control are required to transform this resource into reliable electricity. The present study therefore considers Libya's solar potential as the first layer of a broader intelligent energy architecture rather than as an independent measure of renewable-energy readiness.

4 | Artificial Intelligence for Solar PV and Load Forecasting

The stochastic nature of photovoltaic generation makes forecasting one of the most important functions in renewable-rich electricity systems. Solar output depends on a complex interaction among irradiance, temperature, cloud movement, humidity, wind, atmospheric conditions, module characteristics, and historical operating states. Electricity demand is similarly influenced by temperature, hour of the day, season, working patterns, economic activities, and consumer behavior. Traditional statistical approaches can capture relatively simple relationships but often face limitations when applied to nonlinear, high-dimensional, and rapidly changing systems. Artificial intelligence provides an alternative because machine-learning and deep-learning algorithms can learn complex patterns directly from historical and real-time datasets and continuously transform those patterns into forecasts relevant to operational decision-making.

The development of AI-based solar forecasting has progressively moved from conventional artificial neural networks toward more sophisticated temporal and hybrid architectures. Modern models include random forests, support-vector machines, gradient boosting, recurrent neural networks, long short-term memory networks, gated recurrent units, convolutional neural networks, attention mechanisms, and Transformer-based architectures. These approaches differ in their computational requirements, interpretability, sensitivity to data quality, and ability to represent temporal dependencies. The current paper therefore does not assume that one AI algorithm is universally optimal. Instead, model selection should depend on forecasting horizon, available data, local climatic conditions, computational capacity, and the operational purpose for which the prediction will subsequently be used.

This distinction between forecast accuracy and forecast utility is particularly important. A model can produce a statistically accurate PV forecast but still offer limited system value if its output is not delivered at the appropriate horizon or cannot be incorporated into storage and dispatch decisions. Very-short-term forecasting may support ramp-rate management and real-time control; intraday forecasting can assist storage scheduling; and day-ahead forecasts can support generation commitment, reserve allocation, energy purchases, and operational planning. Therefore, forecast horizon should be explicitly aligned with the control decision that the prediction is intended to support.

Input-variable selection represents another critical issue. A robust solar-forecasting model should incorporate historical PV output alongside relevant meteorological variables such as irradiance, ambient temperature, cloud cover, wind speed, humidity, and potentially satellite or numerical weather-prediction information. For Libya, dust concentration and module temperature may also provide valuable explanatory information because desert conditions can substantially affect PV performance. The integration of meteorological and operational information is supported by recent work combining machine learning with numerical weather models, where the purpose is not merely to reproduce historical patterns but to improve anticipation of future PV variability and therefore the information available to energy-management systems (Buonanno et al., 2024).

Deep learning offers particular advantages for temporal prediction because renewable-generation data are sequential. LSTM and GRU architectures can preserve information across time and capture dependencies that may be difficult for static regression algorithms to identify. More recent hybrid approaches combine CNN-based feature extraction with recurrent or Transformer structures, allowing models to represent both local temporal features and longer-term dependencies. However, increasing architectural sophistication also increases computational burden and may reduce explainability. In a developing-grid context, the most complex model is therefore not automatically the most appropriate.

This issue has particular relevance for Libya because data availability may initially represent a more serious constraint than algorithm availability. AI performance depends on representative, consistent, correctly synchronized, and sufficiently granular datasets. Missing meteorological measurements, unreliable sensors, discontinuous historical PV production records, or inconsistent load information can significantly degrade forecasting performance. The deployment of AI-driven solar management must consequently be accompanied by improvements in smart metering, meteorological stations, supervisory control and data acquisition, data storage, communication systems, and data-quality procedures.

Physics-informed and hybrid approaches may partially mitigate these limitations. Instead of allowing an algorithm to learn exclusively from data, physical knowledge of PV conversion, temperature effects, irradiance relationships, inverter limits, and system constraints can be embedded within the learning architecture. This can improve plausibility and potentially reduce the quantity of training data required. Such an approach is particularly attractive for Libya because it provides a middle ground between purely physical models, which may be computationally demanding or require unavailable parameters, and purely data-driven models, which may fail when conditions differ substantially from their training data.

AI-based load forecasting should operate alongside PV forecasting rather than as a separate task. From the perspective of energy management, the critical variable is often not gross PV production but the net load, defined conceptually as electricity demand minus renewable production. Forecasting generation without simultaneously estimating demand can therefore provide an incomplete representation of the flexibility required from batteries and the grid. The proposed framework accordingly combines PV and load prediction before the BESS-optimization stage, consistent with the conceptual structure already developed in the paper. The figure in the current manuscript explicitly moves from solar/weather data to AI forecasting and then to PV/load prediction before storage optimization.

The value of forecasting in the present study is therefore operational rather than merely statistical. AI prediction constitutes the information bridge between uncertain solar resources and controllable system resources. Forecasts are intended to inform charging and discharging decisions, reserve allocation, PV curtailment, grid exchange, and dispatch. The relevant evaluation question consequently changes from “Which model has the lowest RMSE?” to “Which forecasting architecture produces sufficiently accurate, robust, and timely information to improve downstream energy-management decisions?” This system-level interpretation is central to the proposed AI-driven solar-energy optimization framework.

4.1 | AI-Based BESS Optimization and Solar Energy Management

Battery energy storage systems constitute the principal flexibility layer between variable photovoltaic generation and time-varying electricity demand. Solar PV generates electricity when irradiance is available, whereas consumers require energy according to independent demand profiles. Without flexibility, periods of excess PV generation may result in curtailment or reverse power flows, while periods of insufficient solar production require conventional generation or grid imports. BESS can shift electricity across time, absorbing renewable surplus and releasing stored energy when it provides greater technical or economic value. However, storage itself does not guarantee efficient operation; its performance depends on sizing, state-of-charge management, depth of discharge, charging efficiency, degradation, reserve requirements, and interaction with the electricity network. Optimization is therefore fundamental to the economic viability of PV–BESS systems. Oversized batteries increase investment costs and may remain underutilized, whereas undersized batteries may be unable to absorb renewable surpluses or supply required flexibility. Altayf et al. (2024) demonstrate this trade-off in a Libyan context through an autonomous hybrid storage application in southern Libya. Their analysis compares alternative PV–BESS combinations using several criteria and multiple MCDM methods, explicitly balancing reliability and economic performance. Such results are particularly relevant to the present research because they demonstrate that storage selection cannot be reduced to capacity alone; cost, reliability, loss-of-supply probability, and lifecycle considerations should be evaluated together.

Operational optimization introduces a second level of complexity after sizing. Once battery capacity is installed, an energy-management system must continuously decide whether to charge, discharge, remain idle, or preserve energy for anticipated future requirements. These decisions depend on predicted PV output, expected load, electricity price where applicable, battery SOC, network constraints, reserve needs, and expected future uncertainty. A battery that discharges aggressively during a moderate demand period may have insufficient energy available during a later system peak or grid contingency. Consequently, myopic optimization based solely on current conditions can produce globally inefficient outcomes.

AI-based optimization can address this temporal dependency. Reinforcement learning, deep reinforcement learning, evolutionary optimization, particle-swarm optimization, and hybrid predictive-control approaches can evaluate sequential operating decisions and adapt policies to changing system states. Unlike simple threshold-based controllers, intelligent algorithms can incorporate multiple variables simultaneously and optimize actions over a future horizon. Their potential is particularly significant when PV and demand forecasts are available, because storage decisions can then become anticipatory rather than reactive.

Nevertheless, battery degradation must be explicitly incorporated into the optimization problem. Frequent cycling, high depth of discharge, extreme SOC values, high temperatures, and aggressive charging can accelerate battery ageing. An optimization algorithm that minimizes short-term electricity cost while ignoring degradation may therefore create an apparently optimal dispatch that increases lifecycle costs. The objective function should consequently include a battery-health or degradation component alongside renewable utilization, operating cost, and reliability.

Uncertainty also needs to be considered. A battery schedule based on a single deterministic solar forecast may fail when actual PV production differs substantially from predicted output. Probabilistic forecasts, scenario-based optimization, stochastic programming, and robust optimization provide possible solutions. Sakki et al. (2022) emphasize that renewable-system design and assessment should explicitly incorporate multiple sources of uncertainty, supporting the argument that future PV–BESS optimization for Libya should not rely exclusively on perfect-forecast assumptions.

The BESS objective should also vary according to system location and purpose. In an urban grid-connected installation, economic dispatch and peak reduction may be important. In a remote microgrid, continuity of supply and preservation of critical loads may dominate. In a weak-grid location, voltage and frequency support may carry greater value. In a hospital or other critical facility, reliability can outweigh pure economic optimization. Thus, a single universal storage-control policy is unlikely to be appropriate across all Libyan applications.

A multi-objective formulation is therefore more suitable. The optimization function can conceptually minimize operating cost, renewable curtailment, power losses, battery degradation, and unserved energy while maximizing renewable self-consumption, reliability, and reserve availability. The weighting of these objectives can then be adapted according to application. This is consistent with the broader scientific contribution identified in the current manuscript, which argues that existing studies frequently optimize one or two outcomes while failing to integrate solar utilization, storage condition, grid reliability, cost, fossil-fuel displacement, and sustainability.

The present research therefore conceptualizes BESS not simply as an electricity-storage device but as an AI-coordinated flexibility resource. Solar and load forecasts provide expectations about future conditions; the optimization layer translates those expectations into charging and discharging decisions; and the grid-aware layer subsequently ensures that these decisions remain compatible with electricity-network constraints. This functional separation—prediction → optimization → coordination—provides a clearer engineering architecture than approaches in which AI forecasting and storage control are investigated independently.

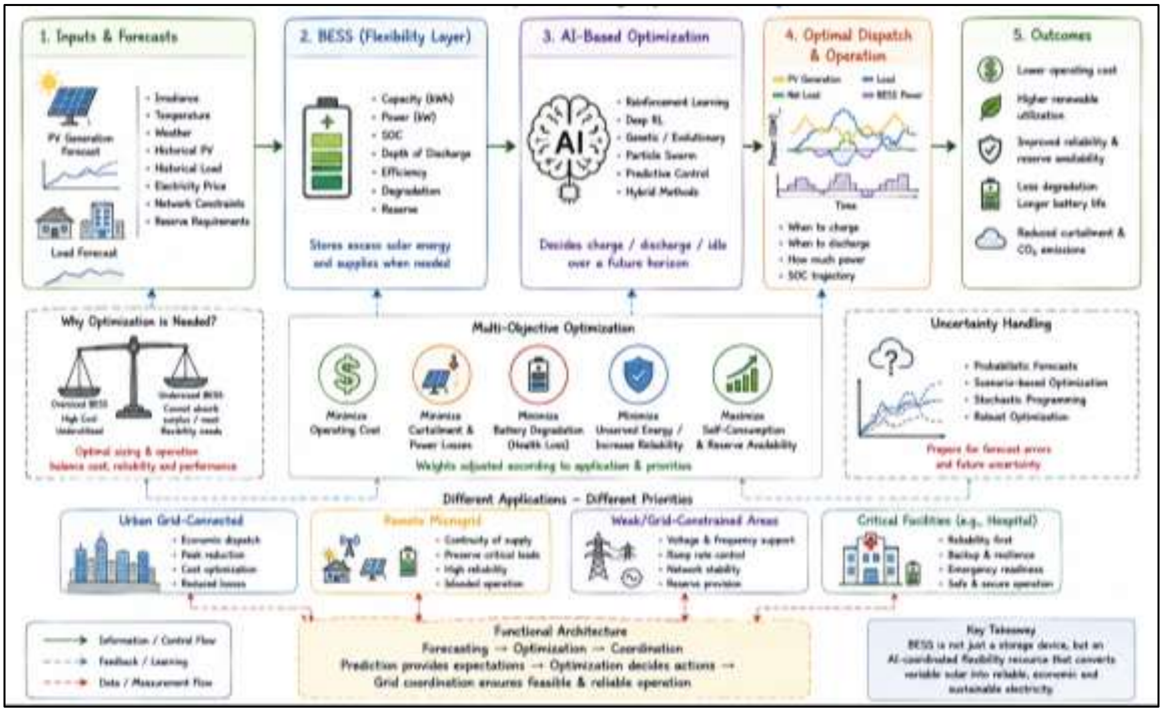

Figure 2. AI-Based BESS Optimization and Solar Energy Management
From forecast to optimal storage operation and system value

4.2 | Grid-Aware Energy Management, Reliability, and Resilience

High penetration of inverter-based photovoltaic generation changes the operational characteristics of electricity networks. Conventional power systems were designed primarily around synchronous generators whose mechanical inertia, voltage-control capabilities, and fault-current behavior contributed naturally to network stability. PV generation is interfaced through power-electronic converters and therefore interacts with the network differently. As PV penetration increases, voltage regulation, frequency response, congestion, harmonics, protection coordination, ramping, reserve requirements, and system strength become increasingly important. For Libya, these considerations are particularly significant because renewable integration must occur within an electricity system that already experiences infrastructure and reliability challenges.

A grid-aware energy-management strategy differs from conventional PV optimization because it does not maximize renewable generation independently of network conditions. Instead, the dispatch of PV, BESS, and other flexible resources is constrained by technical operating limits. Voltage must remain within permissible boundaries, transmission and distribution equipment must not exceed thermal ratings, battery SOC must remain within safe limits, and sufficient flexibility must be maintained to respond to forecast errors or contingencies. Grid awareness therefore converts solar optimization from a generation problem into a coordinated power-system problem.

Artificial intelligence can contribute to this process through state estimation, congestion prediction, voltage forecasting, fault detection, anomaly identification, predictive maintenance, and adaptive dispatch. Machine-learning models can identify complex relationships among network measurements that may not be adequately represented through simple deterministic thresholds. However, AI should not be interpreted as a replacement for physical grid-support assets. It cannot itself provide stored energy, voltage strength, or transmission capacity; rather, it improves the scheduling and coordination of the physical resources that provide these services.

This distinction has important implications for the proposed framework. AI forecasting estimates future renewable generation and demand, BESS provides dispatchable flexibility, and grid-aware energy management determines how that flexibility should interact with network requirements. Under high solar output and low demand, for example, the controller may prioritize battery charging or limited curtailment to avoid voltage violations. During declining solar generation and increasing evening demand, it may discharge stored energy to reduce ramping requirements. During a network disturbance, reserve capacity may be preserved for reliability rather than normal economic operation.

Reliability and resilience should also be distinguished. Reliability generally concerns the ability of the electricity system to provide adequate and continuous service under expected operating conditions, whereas resilience emphasizes the capacity to anticipate, absorb, respond to, and recover from significant disturbances. Intelligent solar-plus-storage systems can contribute to both. Accurate forecasting improves preparedness, optimized BESS operation provides operational flexibility, predictive maintenance reduces avoidable equipment failures, and coordinated dispatch can support restoration and critical loads during disturbances.

Microgrids offer a particularly relevant application. Solar PV combined with storage and intelligent energy management can support remote communities and critical facilities while reducing dependence on long transmission corridors. During normal conditions, a microgrid can exchange energy with the wider system; during disturbances, suitably designed systems may operate in an islanded mode and prioritize critical demand. Such applications could be valuable for geographically dispersed Libyan communities, healthcare facilities, water systems, telecommunications, and strategic infrastructure.

The growing digitalization required for AI-based grid management nevertheless introduces cybersecurity and governance challenges. Smart meters, sensors, communications, remote-control devices, cloud platforms, and AI models expand the cyber-physical attack surface. Data corruption can also produce incorrect forecasts or dispatch decisions even without a malicious attack. Accordingly, intelligent renewable-energy systems should incorporate data validation, secure communication, access controls, redundancy, model monitoring, and fallback operating modes. Safety-critical control should not depend exclusively on an opaque algorithm without deterministic engineering safeguards.

Another challenge is explainability. Grid operators need to understand why an intelligent controller recommends a particular action, especially when that action influences battery reserves, renewable curtailment, or network constraints. Explainable AI is therefore more important for operational decision support than for purely academic prediction. Model accuracy, computational speed, robustness, interpretability, and safe behavior should be evaluated together.

For Libya, the practical implementation pathway should therefore be progressive. AI can initially support advisory functions such as PV/load forecasting, anomaly detection, and predictive maintenance. Subsequent stages can introduce optimized BESS scheduling and dispatch recommendations. More advanced deployment may eventually involve closed-loop grid-aware control after sufficient data, validation, communication, cybersecurity, and operator confidence have been established. Such sequencing reduces implementation risk while allowing digital capabilities to mature alongside physical grid modernization.

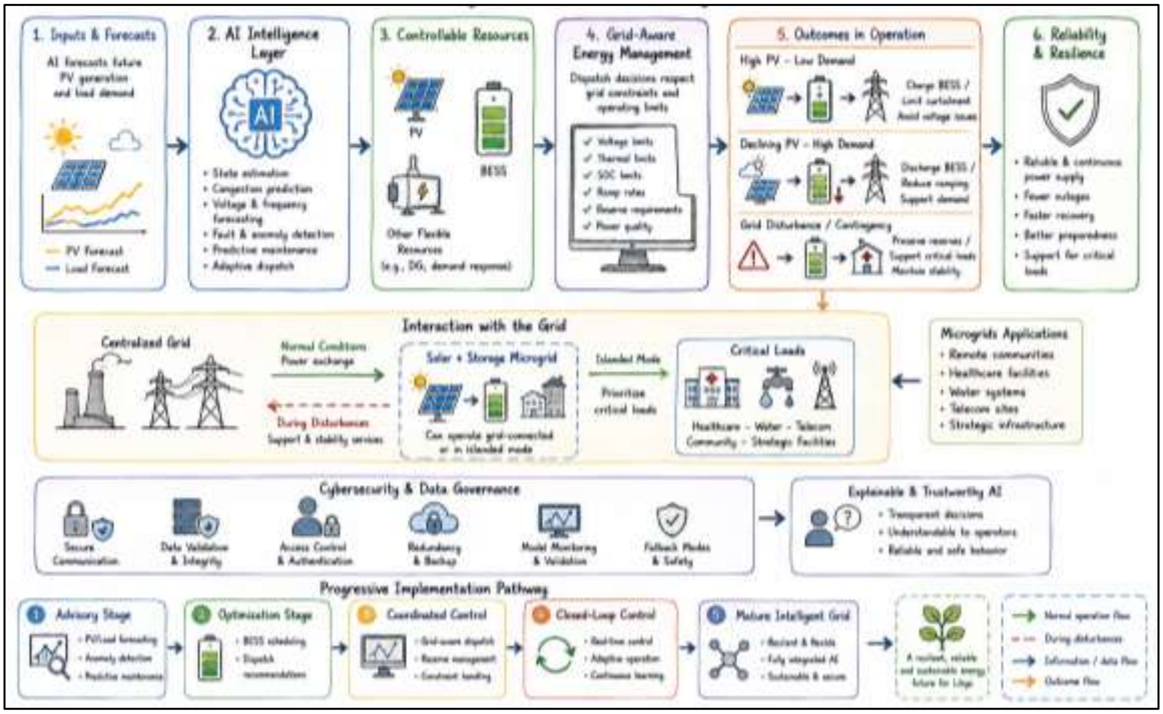

Figure 3. Grid-Aware Energy Management, Reliability, and Resilience AI – Driven Intelligent Coordination of PV Storage and the Grid

4.3 | AI-Driven Solar Optimization for Sustainable Development in Libya

The ultimate justification for AI-driven solar-energy optimization extends beyond technical improvements in forecasting or battery dispatch. Its strategic significance lies in the capacity to connect renewable-energy resources with broader sustainable-development objectives. Solar electricity can reduce fossil-fuel consumption and associated greenhouse-gas emissions, diversify the energy mix, improve energy access, support productive economic activity, and strengthen energy security. Maka and Alabid (2022) argue that solar-energy technologies have an important role in achieving sustainable development because they provide a clean and increasingly competitive source of energy with applications extending across multiple economic and social sectors.

The environmental dimension is the most direct. Replacing part of fossil-based electricity generation with PV reduces operational carbon emissions and local air pollutants. Yet the sustainability contribution of AI does not arise from AI itself; rather, it arises from increasing the proportion of available renewable energy that can be effectively utilized. Better forecasts can reduce avoidable curtailment, optimized BESS can shift excess solar electricity to periods of higher demand, and grid-aware management can enable higher renewable penetration without compromising operating limits. Thus, the environmental pathway can be represented as better intelligence → higher renewable utilization → lower fossil generation → lower environmental impact.

The economic dimension is equally important for a hydrocarbon-producing country. Fossil fuels used for domestic electricity production have an opportunity cost, while inefficient electricity infrastructure can impose direct and indirect economic losses. Solar PV can diversify electricity production, but the economic value of solar assets depends on their utilization and lifecycle performance. AI-driven maintenance can reduce unplanned outages, optimized storage can limit unnecessary cycling, and predictive dispatch can reduce operating inefficiencies. Intelligent optimization therefore has the potential to improve the return generated from renewable and storage investments rather than merely increasing installed capacity.

Energy security provides a third dimension. Dependence on a narrow generation portfolio increases exposure to fuel-supply constraints, infrastructure failures, and other disruptions. A diversified electricity system incorporating distributed solar, storage, and intelligent microgrids can create multiple pathways for supplying critical loads. This does not imply replacing the national grid with decentralized systems; rather, decentralized intelligent resources can complement centralized generation and improve flexibility.

The social dimension emerges through the relationship between reliable electricity and essential services. Healthcare, education, telecommunications, water pumping, public administration, and productive enterprises all depend on dependable energy. In remote areas, solar-plus-storage systems can potentially improve access where grid expansion is costly. The Libyan PV–BESS application examined by Altayf et al. (2024) is instructive because it applies renewable generation and hybrid storage to a clinic in southern Libya and evaluates configurations according to reliability as well as cost. This demonstrates how technical renewable optimization can be directly connected to the continuity of socially critical services.

Sustainable development also requires attention to technological and institutional capacity. AI-based solar systems need trained engineers, data scientists, grid operators, maintenance personnel, cybersecurity specialists, and policy expertise. Investment in intelligent renewable energy can therefore stimulate human-capital development and encourage collaboration among universities, research institutions, utilities, technology companies, and public authorities. The energy transition can thus serve as a platform for technological modernization rather than only a change in electricity-generation source.

At the policy level, intelligent solar-energy deployment requires coordinated standards for grid connection, BESS safety, data interoperability, cybersecurity, renewable forecasting, inverter functionality, and environmental assessment. Policy should also encourage systematic collection and responsible sharing of meteorological, load, PV-generation, and grid-performance data because these datasets form the foundation of effective AI models. Without adequate data governance, AI-driven energy management may remain confined to isolated pilot projects.

The sustainability framework proposed in this study therefore rejects a narrow technology-centered interpretation. AI is treated as an enabling intelligence layer, PV as the renewable-generation layer, BESS as the flexibility layer, and the electricity network as the physical delivery layer. Sustainable development represents the final performance layer through which the combined system is evaluated. This interpretation is consistent with the research gap already established in the manuscript: international research frequently evaluates AI through technical or economic indicators, whereas Libyan renewable-energy research often discusses sustainability at a macro level without explicitly linking AI forecasting and operational optimization to sustainable outcomes.

This pathway transforms AI from a stand-alone prediction technology into a decision-support architecture for Libya's energy transition. The scientific value of the framework lies not in claiming that AI alone can solve Libya's electricity challenges, but in demonstrating how data-driven intelligence can coordinate solar generation, storage, demand, and grid constraints more effectively. The resulting model therefore provides a logical foundation for future empirical research, simulation studies, pilot PV–BESS projects, and policy development directed toward an increasingly intelligent, resilient, and sustainable Libyan electricity system.

Figure 4. Contribution **to** the four Dimensions for Sustainable Development

5 | Literature Review

The literature relevant to AI-driven solar-energy optimization can be classified into three closely connected streams: studies examining Libya's renewable and solar-energy potential, studies developing artificial-intelligence models for photovoltaic forecasting, and studies integrating forecasting with storage and intelligent energy management. Rather than treating these streams separately, the following review critically examines twenty studies according to their objectives, methodological focus, principal findings, and relevance to the Libyan context.

Almaktar and Shaaban (2021) aimed to evaluate the prospects of renewable energy as an alternative pathway for addressing Libya's growing energy demand and reducing its dependence on hydrocarbons. The study focused on the country's renewable-resource base, including solar PV, wind, biomass, geothermal, and other renewable options, while also considering energy efficiency and storage technologies. The results revealed that solar PV and onshore wind represent the most promising renewable resources for Libya and estimated considerable photovoltaic productivity across the country. However, the study remained primarily at the level of resource and technology assessment and did not develop an intelligent operational framework capable of predicting PV generation or optimizing storage and grid interaction.

Ben Hkoma et al. (2023a) sought to analyze the future of renewable energy in Libya and its contribution to sustainable development. The study focused on renewable-resource availability, economic and environmental benefits, investment prospects, and the institutional and legislative constraints affecting renewable-energy deployment. It revealed that Libya possesses substantial solar and wind resources and that renewable energy can contribute to environmental protection, energy independence, and economic diversification. Nevertheless, its descriptive-analytical approach did not address the engineering question of how variable solar generation could be forecast, optimized, stored, and integrated intelligently into the national electricity system.

Ben Hkoma et al. (2023b) examined renewable energy as an economically viable and sustainable alternative for electricity production in Libya. The study concentrated on the feasibility of increasing renewable-energy utilization and identified financial, technical, institutional, legislative, political, and security constraints. It showed that solar energy has considerable potential, particularly in remote and desert areas, but that practical implementation remains substantially below the country's resource potential. Critically, the analysis highlighted implementation constraints but did not consider AI-based forecasting, optimal BESS scheduling, or adaptive energy-management strategies, leaving the digital-intelligence dimension largely unexplored.

Alasali et al. (2023) aimed to determine how a 10-MW grid-connected photovoltaic plant would affect the Libyan electricity network. Unlike predominantly resource-oriented Libyan studies, this research focused explicitly on engineering indicators associated with PV-grid integration, including voltage behavior, power losses, harmonics, short-circuit conditions, protection performance, and power-system stability. The findings demonstrated that adding PV capacity to the Libyan grid changes operating and protection conditions and therefore requires careful technical assessment. The study substantially advances understanding of grid-side constraints, but it evaluates a predetermined PV installation rather than an intelligent system that anticipates generation variability and dynamically optimizes PV, storage, and network operation.

Alkhayat and Mehmood (2021) aimed to systematically classify deep-learning approaches used for wind and solar-energy forecasting. Their review focused on forecasting horizons, datasets, preprocessing, recurrent neural networks, convolutional architectures, hybrid models, and probabilistic forecasting. The study revealed that hybrid approaches and recurrent architectures such as LSTM and GRU dominate the forecasting literature and that probabilistic and multi-step forecasts are becoming increasingly important. A critical limitation relevant to the present study is that most datasets examined originated from technologically advanced contexts, particularly China, the United States, and Australia, illustrating the geographical underrepresentation of North African weak-grid systems such as Libya (Alkhayat & Mehmood, 2021).

Feng et al. (2021) sought to provide a taxonomical assessment of artificial-intelligence applications for integrating photovoltaic systems into electricity grids. The study focused on four major AI functions: solar forecasting, PV-array and fault detection, system-design optimization, and optimal control. It demonstrated that AI can contribute well beyond simple generation prediction by supporting detection, optimization, and operational control. Nevertheless, the authors concluded that AI applications to PV-grid integration were still less mature than mainstream AI applications, indicating that forecasting and optimization techniques should be evaluated within realistic electricity-system constraints rather than as isolated computational exercises (Feng et al., 2021).

Jebli et al. (2021) aimed to improve solar-energy forecasting using machine-learning models guided by Pearson correlation analysis. The study focused on identifying the most influential meteorological variables and comparing linear regression, support vector regression, random forest, and artificial neural networks using data from the semi-arid Moroccan city of Errachidia. The results showed that ANN and random forest achieved superior prediction accuracy and that ANN performed particularly well for short-term forecasting. Its semi-desert case is geographically relevant to Libya; nevertheless, the study optimized prediction accuracy without linking the forecast outputs to battery scheduling, grid constraints, or sustainable-energy management decisions (Jebli et al., 2021).

Luo et al. (2021) developed a deep-learning framework for photovoltaic power forecasting that incorporated physical domain knowledge into an LSTM architecture. The research focused on overcoming one of the weaknesses of purely data-driven models by developing a physics-constrained LSTM and selecting relevant input variables through a two-stage procedure. The findings indicated that the proposed PC-LSTM was more robust than conventional LSTM and retained advantages when training data were sparse. This is particularly significant for data-limited environments such as Libya, although the model remained principally a forecasting architecture rather than an integrated operational optimization framework (Luo et al., 2021).

Mellit et al. (2021) aimed to compare alternative deep neural-network architectures for short-term photovoltaic-power forecasting. Their study examined LSTM, BiLSTM, GRU, BiGRU, CNN and hybrid CNN-LSTM/CNN-GRU architectures over different forecasting horizons. The analysis showed that advanced deep-learning models can achieve satisfactory prediction performance even under cloudy conditions, while multi-step forecasting remained comparatively challenging. The study therefore illustrates the predictive capabilities of deep learning but simultaneously shows that high model accuracy alone does not resolve the broader operational problem of transforming forecasts into optimal storage and grid decisions (Mellit et al., 2021).

Qu et al. (2021) aimed to enhance day-ahead hourly PV-power forecasting by developing an attention-based CNN-LSTM model incorporating multiple relevant and target variables. The study focused on capturing both short- and long-term temporal dependencies in multivariate PV data. Its results demonstrated improved forecasting performance compared with alternative structures and highlighted the importance of selecting suitable memory lengths for different prediction horizons. Despite this methodological advancement, the model was evaluated primarily through forecast errors and did not explicitly translate improved forecasts into measurable improvements in BESS operation, grid reliability, or renewable-energy utilization (Qu et al., 2021).

Abdel-Basset et al. (2021) introduced the PV-Net deep-learning framework to improve short-term photovoltaic-energy forecasting. The research focused on combining spatiotemporal learning, convolutional operations, modified GRU structures, and residual connections to reduce dependence on intensive manual feature engineering. The study demonstrated that the proposed architecture could effectively capture the temporal behavior of real PV-production data. However, as with much of the forecasting literature, the primary optimization criterion remained predictive performance rather than system-level outcomes such as renewable curtailment, battery degradation, operating costs, or resilience (Abdel-Basset et al., 2021).

Luo and Zhang (2022) aimed to overcome the static nature of conventional offline PV forecasting by proposing an adaptive deep-learning framework capable of continuously learning from newly arriving observations. The study focused on a two-phase adaptive LSTM strategy for day-ahead photovoltaic generation forecasting and demonstrated the benefits of updating the forecasting model as operating conditions evolve. This adaptive characteristic is highly relevant to Libya, where seasonal temperature, dust, irradiation, and network conditions may change considerably; however, the adaptive learning process was not extended to real-time energy-storage or grid-dispatch optimization.

Garip and Ozdemir (2022) shifted the literature from forecasting toward optimization by developing a framework for determining optimal PV and battery-energy-storage capacities in a grid-connected microgrid. The study focused on minimizing total energy costs through an energy-management algorithm integrated with particle swarm optimization. The findings demonstrated that coordinated optimization of PV and BESS sizing can provide greater economic value than treating the two resources separately. Nevertheless, the framework relied on optimization rather than AI-based predictive intelligence and therefore did not fully integrate uncertainty-aware solar forecasting with real-time BESS decision-making (Garip & Ozdemir, 2022).

Miraftabzadeh et al. (2023) aimed to improve day-ahead photovoltaic-power forecasting through transfer learning and deep neural networks. The study focused particularly on overcoming limited data availability by transferring knowledge between datasets and operating contexts. It showed that transfer-learning strategies can support accurate PV prediction while reducing the dependence on large site-specific datasets. This approach has potential relevance for Libya, where extensive high-quality historical PV datasets may initially be unavailable, but the study did not extend transfer learning into storage, dispatch, or network-resilience decisions (Miraftabzadeh et al., 2023).

Cantillo-Luna et al. (2023) compared machine- and deep-learning techniques for photovoltaic generation forecasting, including XGBoost, random forest, support-vector regression, multilayer perceptron, LSTM and a proposed ConvLSTM1D model. The study focused on the practical problem of forecasting distributed PV when data quality and availability are heterogeneous. It revealed that the relative performance of forecasting techniques depends strongly on data structure and model configuration rather than on the universal superiority of a single algorithm. This finding cautions against transferring an internationally successful model directly to Libya without local calibration and comparative validation (Cantillo-Luna et al., 2023).

Al-Ali et al. (2023) proposed a hybrid CNN-LSTM-Transformer architecture for solar-energy production forecasting. The study focused on exploiting complementary strengths of convolutional networks for feature extraction, LSTM for temporal dependencies, and Transformer mechanisms for longer-range relationships. The findings supported the value of hybrid architectures for improving short-term solar forecasts. However, increasingly complex models impose higher computational and data requirements, creating an important trade-off for developing electricity systems where digital infrastructure, computation, explainability, and data continuity may be constrained (Al-Ali et al., 2023).

Durán et al. (2024) moved beyond stand-alone forecasting by developing a forecast-based energy-management system for a microgrid with high photovoltaic penetration. The study focused on combining an LSTM forecasting model with an optimal EMS that manages BESS state of charge and allocates power among system components. It demonstrated the practical value of linking prediction to operational dispatch rather than evaluating forecasting accuracy as an end in itself. This integration is particularly relevant to the present study, although its microgrid application was developed outside Libya and did not

incorporate the technical weaknesses, regulatory conditions, or sustainability priorities of the Libyan power system (Durán et al., 2024).
Radhi et al. (2024) investigated multiple machine-learning approaches for short-term photovoltaic-power forecasting. The study focused on comparing alternative prediction models under a common dataset and evaluation framework, thereby emphasizing the importance of algorithm selection for short forecasting horizons. The results reinforced the usefulness of ML for reducing PV uncertainty but also indicated that model performance is highly sensitive to input data and implementation choices. Accordingly, the findings support a context-sensitive modelling strategy rather than assuming that the most complex architecture is necessarily the most suitable for Libya (Radhi et al., 2024).
Buonanno et al. (2024) aimed to improve photovoltaic-production forecasts by combining machine-learning techniques with numerical weather models. The research focused on the relationship between weather information, PV variability, and energy-system decision making, particularly in grids and microgrids containing generation, loads, and storage. It showed that integrating weather prediction with ML can improve the information available for managing grid imbalances. Nevertheless, the study primarily addressed the forecasting layer and did not construct a multi-objective sustainable optimization model balancing energy yield, storage health, cost, reliability, and environmental objectives simultaneously (Buonanno et al., 2024).
Galouz and Ben Hkoma (2026) provided the closest conceptual bridge to the present research by critically evaluating grid-forming inverters, energy-storage systems, and AI-based control for renewable-energy integration and grid resilience in Libya. The study revealed that these technologies perform complementary rather than substitutable functions: GFM provides dynamic voltage and frequency support, ESS supplies controllable energy and flexibility, while AI provides forecasting, optimization, fault detection, predictive maintenance, and intelligent coordination. It proposed a layered GFM–ESS–AI resilience architecture for Libya and argued that AI should function as a supervisory intelligence layer rather than as a replacement for physical grid-support resources. Nevertheless, the study remained a critical comparative review and did not develop or test a solar-specific AI optimization model linking PV forecasting, BESS scheduling, grid constraints, and sustainable-development indicators.

5.1 | Critical Synthesis of Previous Studies

A critical reading of the reviewed literature reveals substantial progress but also considerable fragmentation. The Libyan stream has convincingly established that solar energy is technically promising and strategically important for reducing fossil-fuel dependence and strengthening sustainable development (Almaktar & Shaaban, 2021; Ben Hkoma et al., 2023a, 2023b). More technically oriented work, particularly Alasali et al. (2023), further demonstrates that higher PV penetration cannot be evaluated solely through annual energy production because voltage, protection, losses, harmonics, and short-circuit behavior are also affected. Yet most Libyan studies remain concentrated on resource potential, feasibility, barriers, or grid impact after renewable installation, rather than intelligent prediction and proactive operational optimization.
The international AI-forecasting stream provides a much richer methodological base. ANN, random forest, LSTM, GRU, CNN, attention mechanisms, Transformers, transfer learning, physics-constrained learning, and hybrid architectures have all demonstrated the

capacity to improve solar/PV forecasts (Jebli et al., 2021; Luo et al., 2021; Mellit et al., 2021; Qu et al., 2021; Miraftabzadeh et al., 2023; Al-Ali et al., 2023). Reviews of the field nevertheless show that forecasting research is geographically concentrated in data-rich countries and that hybrid and deep models dominate current development. This creates an important transferability problem: high accuracy obtained under one climate, network, data-acquisition architecture, or PV technology cannot automatically be assumed under Libyan conditions.

A second weakness is the excessive emphasis in much of the literature on forecast accuracy as the final outcome. Improvements in RMSE, MAE, or (R^2) are technically useful, but they do not by themselves demonstrate that a forecasting model reduces curtailment, improves battery utilization, strengthens grid reliability, decreases operating cost, or advances sustainability. Studies such as Garip and Ozdemir (2022) and Durán et al. (2024) move closer to a system-level perspective by connecting PV production with BESS and energy management, demonstrating that coordinated forecasting and storage decisions can create greater operational value.

A further issue concerns model complexity versus operational applicability. Hybrid deep architectures may improve predictive accuracy, yet their advantages can be offset by high data requirements, computational burden, lower interpretability, and difficulties in adaptation to unseen operating conditions. This is particularly relevant to Libya, where intelligent renewable deployment must develop alongside measurement infrastructure, communications, data governance, digital grid models, and cybersecurity. Consequently, the most technically complex AI algorithm is not necessarily the most suitable one; suitability should instead be evaluated according to accuracy, robustness, data availability, computational cost, explainability, grid function, and implementation readiness.

5.2 | Research Gap

Despite the breadth of the literature, a clear multi-dimensional research gap remains. First, a geographical gap exists because relatively few AI-based solar-optimization studies have been developed and validated specifically for Libya or comparable North African weak-grid conditions. Existing Libyan literature primarily establishes renewable potential and deployment barriers, whereas most advanced AI models are developed using international datasets.

Second, a technological-integration gap remains because forecasting, BESS optimization, grid support, fault detection, and energy management are frequently investigated as separate problems. Even sophisticated PV-forecasting models generally terminate at the prediction stage, while storage studies frequently assume that renewable forecasts are already available and sufficiently accurate.

Third, there is an optimization gap. Existing research typically optimizes one or two objectives—forecasting error, operating cost, self-consumption, or battery size—rather than simultaneously considering solar utilization, BESS state of charge and degradation, grid reliability, energy cost, fossil-fuel displacement, and sustainability outcomes.

Fourth, there is a grid-context gap. Libya's network characteristics—weak-grid locations, long transmission corridors, system-reliability challenges, limited monitoring, and protection constraints—are rarely embedded directly within AI solar-energy optimization

models. The findings of Alasali et al. (2023) indicate that these constraints cannot be ignored when PV penetration increases.
Finally, there is a sustainability-integration gap. The international literature predominantly evaluates AI through technical or economic metrics, while Libyan renewable-energy studies discuss sustainable development mainly at the macro level. Few studies explicitly create a causal operational pathway linking AI → improved forecasting → optimized PV/BESS operation → improved grid performance → reduced fossil-fuel dependence → sustainable-development outcomes.

5.3 | Scientific Contribution of the Present Study

The present study addresses these limitations by proposing a context-specific AI-Driven Solar Energy Optimization Framework for Libya that moves beyond isolated forecasting toward integrated intelligent energy management. Its primary contribution lies in connecting five normally fragmented dimensions within a single analytical architecture: solar-resource and operational assessment, AI-based PV forecasting, intelligent BESS scheduling, grid-aware coordination, and sustainable-development performance.
Unlike studies that evaluate AI solely through prediction error, the proposed framework treats forecasting as an input to decision making. Predicted PV generation and electricity demand are intended to inform BESS charging and discharging, operational scheduling, reserve allocation, and grid interaction. The conceptual pathway can therefore be expressed as:

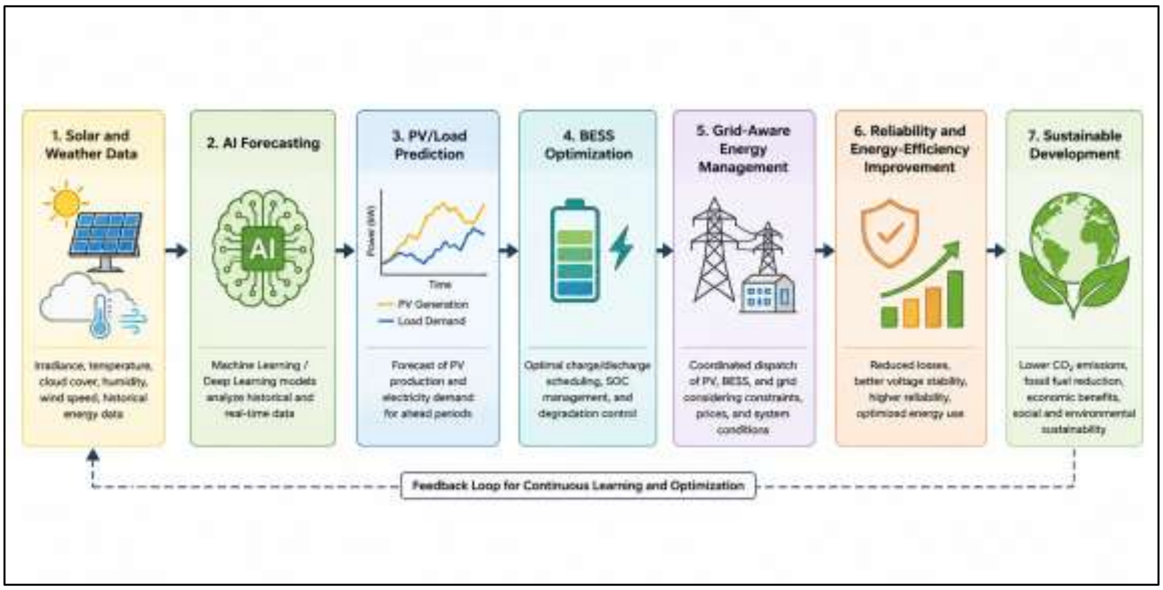

Figure 1. Proposed AI-Driven Solar Energy Optimization Framework for Sustainable Development in Libya

The scientific novelty is consequently not the isolated application of AI to solar forecasting—which is already well established—but its contextual integration with storage, grid constraints, and sustainability objectives within the Libyan power-system environment. This transforms the research problem from "How accurately can solar generation be predicted?" into the more strategically important question: "How can AI convert Libya's abundant solar resource into optimally managed, reliable, resilient, and sustainable electricity?”

6 | Methodology

This study adopts a descriptive, analytical, and comparative approach to examine the role of artificial intelligence in optimizing solar-energy utilization and its potential contribution to sustainable development in Libya. The descriptive dimension is used to characterize Libya's solar-energy potential and operational context and to identify the major technological components associated with intelligent solar-energy systems, including AI-based PV and load forecasting, battery energy storage systems (BESS), and grid-aware energy management. This approach is consistent with the study's objectives, which progress from assessing the Libyan solar-energy context to examining forecasting, storage optimization, grid integration, and ultimately developing an integrated AI-driven framework. The analytical dimension critically examines the findings of previous studies by interpreting the relationships among solar variability, forecasting accuracy, storage flexibility, grid constraints, reliability, energy efficiency, and sustainable-development outcomes. Rather than merely reporting previous findings, the analysis evaluates their methodological strengths, limitations, assumptions, and practical relevance to the Libyan electricity system. The comparative dimension is employed to compare Libyan and international studies in terms of research context, AI techniques, forecasting approaches, BESS applications, grid-integration requirements, and reported technical and sustainability outcomes. Particular attention is given to areas of agreement and disagreement between studies and to the extent to which results obtained in data-rich and technologically advanced electricity systems can be transferred to Libya, given differences in climatic conditions, data availability, grid infrastructure, and institutional readiness. This comparison is especially important because the reviewed literature shows that international studies have largely concentrated on advanced AI forecasting and optimization techniques, whereas Libyan studies have focused predominantly on renewable-energy potential, implementation barriers, and conventional grid impacts. Through the integration of description, analysis, critical interpretation, and comparison, the study synthesizes the available evidence to develop a context-specific conceptual framework linking solar and weather data, AI forecasting, PV/load prediction, BESS optimization, grid-aware energy management, reliability and energy-efficiency improvement, and sustainable development. The proposed framework is therefore treated as an evidence-based conceptual model, rather than an experimentally validated AI model, and provides a foundation for subsequent empirical testing and simulation using Libyan solar, meteorological, load, storage, and grid data.

7 | Results and Discussion

The findings of the present study, derived from the descriptive, analytical, and comparative synthesis of the reviewed literature, indicate that the central challenge facing solar-energy development in Libya is not the scarcity of the solar resource, but the limited capacity to convert this abundant resource into reliably forecasted, optimally stored, grid-compatible, and sustainably utilized electricity. This interpretation directly addresses the first research question concerning Libya's solar-energy potential and operational context. The reviewed evidence consistently confirms that Libya possesses favorable solar irradiation, extensive land availability, and substantial opportunities for both centralized and distributed PV applications. This finding agrees with Almaktar and Shaaban (2021), who identified solar PV as one of Libya's most promising renewable-energy alternatives, and with Ben Hkoma et al. (2023a), who linked renewable-resource development to economic diversification, environmental protection, and sustainable development. It is also consistent with Ben Hkoma et al. (2023b), who demonstrated that solar energy can constitute an economically and environmentally viable alternative for electricity production, particularly in remote and desert regions. Nevertheless, the current study extends these findings by arguing that resource abundance should not be interpreted as equivalent to renewable-energy readiness. High solar irradiation has limited strategic value if generation cannot be accurately anticipated, excess production cannot be stored, and electricity cannot be integrated without creating voltage, protection, congestion, or reliability problems. This interpretation is supported by the theoretical framework of the study, which explicitly distinguishes physical solar potential from effective system utilization.

Regarding the second research question, the analysis indicates that AI can substantially improve the predictive intelligence required for managing variable solar generation, but forecasting accuracy alone should not be treated as the ultimate measure of success. The reviewed international literature provides strong evidence that ANN, random forest, LSTM, GRU, CNN, attention mechanisms, Transformers, transfer learning, and physics-informed architectures can outperform simpler forecasting approaches under appropriate conditions. Jebli et al. (2021), for example, demonstrated the effectiveness of ANN and random forest for solar prediction in a semi-arid environment, while Mellit et al. (2021) showed that deep neural architectures can achieve satisfactory short-term PV forecasting performance under changing weather conditions. Similarly, Qu et al. (2021) demonstrated improved day-ahead prediction using an attention-based CNN-LSTM architecture, whereas Al-Ali et al. (2023) showed the potential of combining CNN, LSTM, and Transformer mechanisms. These findings collectively support the second objective of the present study concerning the role of AI in improving PV forecasting. However, they also reveal an important limitation: much of the literature assesses success primarily through statistical indicators such as RMSE, MAE, and R2. The present analysis therefore differs conceptually from studies that treat lower prediction error as an end in itself; it interprets forecasting as an input to operational decision-making, where its actual value depends on whether improved predictions lead to better storage scheduling, reserve allocation, curtailment management, and grid operation. This distinction between *forecast accuracy* and *forecast utility* is explicitly developed in the theoretical framework.

A further critical result is that no single AI architecture can be considered universally optimal for the Libyan context. Although increasingly sophisticated deep-learning and hybrid models frequently report superior predictive performance, this superiority is conditional on the quantity, quality, temporal resolution, and representativeness of the underlying data. Cantillo-Luna et al. (2023) similarly found that relative forecasting performance depends strongly on dataset characteristics and model configuration, while Luo et al. (2021) demonstrated that incorporating physical domain knowledge can improve model robustness when training data are limited. Miraftabzadeh et al. (2023), through transfer learning, likewise provided an alternative for circumstances where extensive site-specific datasets are unavailable. These results are especially relevant to Libya because the national challenge may initially be data readiness rather than algorithmic sophistication.

Consequently, adopting computationally intensive architectures merely because they outperform simpler models in international datasets could be methodologically misleading. A model producing marginally lower forecasting error but requiring unavailable high-resolution datasets, substantial computational resources, or opaque decision processes may have less practical value than a simpler, robust, and interpretable model. This supports the study's critical position that algorithm selection for Libya should balance accuracy with robustness, explainability, data requirements, computational cost, and operational applicability.

The third research question concerns the role of AI-based optimization in BESS scheduling and management. The comparative evidence indicates that BESS represents the operational bridge between uncertain solar production and controllable electricity supply, but the benefits of storage depend fundamentally on how it is sized and managed. Garip and Ozdemir (2022) demonstrated that coordinated optimization of PV and BESS capacity can produce greater economic benefits than treating the two resources independently. More importantly for Libya, Altayf et al. (2024) showed through a southern Libyan application that storage-system selection requires simultaneous consideration of economic and reliability criteria rather than capacity alone. The current study agrees with these findings but extends them by interpreting BESS not simply as a storage asset, but as an AI-coordinated flexibility resource whose charging, discharging, reserve preservation, and idle states should respond dynamically to predicted PV production, expected demand, SOC, network constraints, and uncertainty. This directly responds to the third study objective and shifts the analytical emphasis from *how much battery capacity should be installed* toward *how intelligently installed capacity should be operated*.

Nevertheless, the analysis also identifies a weakness in storage optimization studies that emphasize short-term economic performance without sufficiently accounting for battery degradation and uncertainty. Aggressive cycling can improve short-term renewable utilization or reduce grid imports while simultaneously accelerating battery ageing and increasing lifecycle costs. Similarly, deterministic scheduling based on a single PV forecast may produce technically attractive solutions that deteriorate when actual solar output deviates from the forecast. Sakki et al. (2022) emphasized the need to incorporate uncertainty explicitly into renewable-system design and optimization. The present study supports this position and argues that a Libya-oriented BESS strategy should therefore be multi-objective and uncertainty-aware, balancing operating cost, renewable curtailment, unserved energy, battery degradation, reserve availability, and reliability. This finding also implies that different Libyan applications should not necessarily employ identical optimization weights: economic objectives may dominate urban grid-connected installations, whereas reliability may reasonably receive greater weight in hospitals, remote settlements, water systems, telecommunications, and other critical infrastructure. Such contextual differentiation represents an important departure from one-size-fits-all storage optimization.

The fourth research question addresses grid integration, reliability, and resilience. Here, the findings demonstrate that maximizing PV production independently of network conditions is neither technically sufficient nor necessarily desirable. Alasali et al. (2023) showed specifically for the Libyan grid that a 10-MW grid-connected PV plant can influence voltage, losses, harmonics, short-circuit conditions, protection performance, and system stability. Their findings reinforce the current study's conclusion that increasing renewable penetration changes the problem from one of energy production to one of coordinated power-system operation. AI can support this transition through voltage and load forecasting, state estimation, congestion prediction, anomaly detection, predictive maintenance, and adaptive dispatch. However, the present study critically rejects an overly technology-centric interpretation in which AI itself is assumed to provide grid stability. AI cannot physically supply stored energy, transmission capacity, inertia-like response, or voltage strength; rather, it improves the coordination and scheduling of the physical assets that provide these capabilities. This interpretation is consistent with Galouz and Ben Hkoma (2026), who concluded that AI, energy storage, and grid-support technologies perform complementary rather than substitutable functions.

This finding also clarifies the distinction between reliability and resilience, concepts that are sometimes treated interchangeably in renewable-energy research. Reliability concerns maintaining adequate electricity service under expected conditions, whereas resilience concerns the system's ability to anticipate, absorb, respond to, and recover from major disturbances. The analysis suggests that AI–PV–BESS integration can contribute to both, but through different mechanisms. Improved forecasting and storage scheduling can support normal operational reliability, while reserve preservation, intelligent microgrid operation, anomaly detection, predictive maintenance, and prioritized supply of critical loads can enhance resilience. Durán et al. (2024) provide important supporting evidence because their forecast-based microgrid energy-management system links LSTM prediction with BESS SOC management and optimal dispatch. Unlike forecasting studies that terminate at prediction accuracy, their approach demonstrates the operational benefits of connecting prediction with action. Yet the current study extends this logic to Libya by incorporating weak-grid conditions, infrastructure limitations, reliability requirements, and sustainable-development objectives that were outside the scope of their case study.

From a comparative perspective, a significant difference emerges between the Libyan and international research streams. Libyan studies have successfully established renewable-resource potential, economic and environmental opportunities, implementation barriers, and some grid-integration consequences (Almaktar & Shaaban, 2021; Ben Hkoma et al., 2023a, 2023b; Alasali et al., 2023). In contrast, international research has advanced much further in AI forecasting, hybrid deep learning, adaptive models, transfer learning, and intelligent energy management (Luo & Zhang, 2022; Miraftabzadeh et al., 2023; Al-Ali et al., 2023; Durán et al., 2024; Buonanno et al., 2024). The comparison therefore reveals not an absence of Libyan renewable-energy research, but an integration deficit: national studies tend to stop at potential, feasibility, barriers, or grid impact, while advanced international studies frequently optimize isolated technological components without accounting for Libya's specific electricity-system constraints. This explains the geographical and technological-integration gaps identified in the literature review.

The fifth research question brings these strands together by asking what integrated AI-driven framework is appropriate for Libya. The synthesis indicates that the greatest potential contribution of AI arises not from any individual algorithm but from functional integration across the complete energy-management chain. Accordingly, the study proposes the sequence Solar and Weather Data → AI Forecasting → PV/Load Prediction → BESS Optimization → Grid-Aware Energy Management → Reliability and Energy-Efficiency Improvement → Sustainable Development. This differs from much of the reviewed literature because forecasting is not treated as the final technological output.

Instead, forecast information feeds storage decisions; storage provides controllable flexibility; grid-aware management constrains those decisions according to physical network requirements; and the combined technical improvements are ultimately assessed according to reliability, efficiency, fossil-fuel displacement, environmental impact, and sustainable-development value. This integrated architecture constitutes the main analytical result of the study and directly responds to the fragmentation identified in the previous literature.

The sustainable-development implications of this framework require equally careful interpretation. The study finds that AI does not produce sustainability directly. Rather, sustainability emerges through the operational improvements that AI enables. Better forecasts can reduce unnecessary renewable curtailment; improved BESS scheduling can increase the usable share of solar generation; grid-aware coordination can facilitate greater PV penetration without compromising technical limits; and higher renewable utilization can reduce fossil-fuel consumption and associated emissions. Economically, intelligent operation can improve utilization of capital-intensive PV and storage assets and reduce avoidable system inefficiencies. Socially, more reliable solar-plus-storage systems could strengthen electricity provision to healthcare, education, water pumping, telecommunications, remote settlements, and productive activities. These conclusions are consistent with the broader sustainability arguments of Ben Hkoma et al. (2023a) and with the solar-development perspective discussed in the theoretical framework, but the current study advances the argument by explicitly identifying the causal-operational pathway through which AI may contribute to sustainability.

At the same time, the findings should not be interpreted as evidence that deploying AI alone will resolve Libya's electricity-sector challenges. This is an important critical qualification. AI performance is dependent on measurement infrastructure, reliable communications, high-quality meteorological and operational datasets, smart meters, SCADA systems, cybersecurity, technical expertise, institutional coordination, and appropriate regulatory standards. Ben Hkoma et al. (2023b) identified financial, technical, institutional, legislative, political, and security barriers to renewable deployment in Libya, while the present analysis indicates that digitalization introduces additional requirements related to data governance, interoperability, cybersecurity, and explainability. Therefore, technological modernization and institutional modernization must progress together. Otherwise, sophisticated AI systems risk remaining isolated pilot applications rather than becoming operational components of the national energy transition.

Overall, the comparative discussion supports all five analytical objectives of the study but also qualifies them. Libya has substantial solar potential, yet solar potential without operational intelligence is insufficient; AI can enhance forecasting, yet forecast accuracy without decision integration has limited system value; BESS can provide flexibility, yet storage without degradation- and uncertainty-aware optimization can be economically inefficient; intelligent coordination can enhance grid performance, yet AI cannot substitute for necessary physical grid reinforcement and support technologies; and renewable-energy optimization can advance sustainable development, yet technical innovation without institutional, data, human-capital, and regulatory readiness is unlikely to achieve system-wide transformation. These findings collectively reinforce the scientific contribution of the present study: rather than proposing AI as an isolated forecasting technology, it conceptualizes AI as a supervisory intelligence layer connecting solar-resource information, PV/load prediction, storage flexibility, grid constraints, reliability, efficiency, and sustainable-development outcomes within the specific operational context of Libya.

8 | Conclusions

This study concludes that the transition toward sustainable solar-energy utilization in Libya should not be approached primarily as a question of expanding photovoltaic capacity, but as a system-level transformation in which solar resources, artificial intelligence, battery energy storage, grid-aware operation, and institutional readiness are integrated within a unified energy-management architecture. The descriptive, analytical, and comparative assessment confirms that Libya possesses substantial solar potential; however, the principal constraint is the country's limited ability to convert this physical resource into electricity that can be accurately forecasted, efficiently stored, intelligently dispatched, and reliably integrated into the national grid. Accordingly, solar-resource abundance alone cannot be regarded as evidence of renewable-energy readiness. Effective utilization requires the simultaneous development of forecasting capabilities, storage flexibility, grid-support mechanisms, monitoring infrastructure, and operational intelligence. This conclusion directly responds to the study's first objective and reframes Libya's renewable-energy challenge from one of resource availability to one of resource optimization and system integration.

The study further concludes that artificial intelligence can play a strategically important role in reducing the operational uncertainty associated with variable solar generation. Machine-learning, deep-learning, hybrid, transfer-learning, and physics-informed approaches provide considerable potential for improving PV and load forecasting; nevertheless, the evidence demonstrates that forecast accuracy should not constitute the final objective of AI deployment. The practical value of forecasting lies in its capacity to improve subsequent operational decisions, including battery charging and discharging, reserve allocation, renewable curtailment, demand–generation balancing, and grid interaction. Consequently, the most appropriate AI model for Libya is not necessarily the model producing the lowest statistical forecasting error, but the one that provides an effective balance among accuracy, robustness, interpretability, computational requirements, data availability, and operational usefulness. This conclusion is particularly significant under Libyan conditions, where the availability, continuity, and quality of meteorological, PV-generation, load, and grid data may initially represent a greater limitation than access to advanced algorithms.

With respect to energy storage, the study concludes that BESS should be understood not merely as an additional technological component but as the principal controllable flexibility layer connecting uncertain solar generation with electricity demand and network requirements. Its contribution depends not only on installed capacity but, more importantly, on intelligent operation. AI-supported optimization can transform BESS management from reactive charging and discharging into anticipatory decision-making based on forecasted PV production, expected load, state of charge, reserve requirements, network constraints, and uncertainty. However, economically and technically sustainable storage operation requires multi-objective optimization that explicitly considers battery degradation, lifecycle cost, renewable curtailment, unserved energy, reliability, and reserve availability. The study therefore rejects a universal BESS control strategy and concludes that optimization priorities should vary according to application, particularly between urban grid-connected systems, remote communities, hospitals, water facilities, telecommunications infrastructure, and other critical loads.

Regarding grid integration, the findings lead to the conclusion that higher PV penetration cannot be sustainably achieved by maximizing solar generation independently of network conditions. Increasing inverter-based generation introduces challenges associated with voltage regulation, system strength, protection coordination, harmonics, congestion, frequency response, and operational flexibility. AI can strengthen grid operation through forecasting, state estimation, predictive maintenance, anomaly detection, congestion prediction, and adaptive dispatch, but it cannot substitute for the physical assets required to maintain grid stability. AI should therefore be treated as a supervisory intelligence layer coordinating PV, BESS, grid-support technologies, and network resources rather than as an independent source of stability. This distinction is particularly relevant to Libya, where intelligent renewable-energy deployment must advance alongside reinforcement and modernization of the electricity infrastructure.

The comparative analysis also reveals a structural imbalance in the existing knowledge base. Libyan research has established the country's renewable-resource potential, economic and environmental benefits, implementation barriers, and some technical implications of grid-connected PV, whereas international research has progressed substantially toward sophisticated AI forecasting, adaptive learning, hybrid deep-learning architectures, storage optimization, and intelligent microgrid management. The principal research deficiency is therefore not simply a shortage of Libyan renewable-energy studies but an integration gap between resource assessment, predictive intelligence, storage optimization, grid constraints, and sustainability performance. Furthermore, the direct transfer of AI models developed in data-rich and technologically advanced electricity systems to Libya cannot be assumed to produce equivalent performance without local calibration and validation under Libyan climatic, infrastructural, operational, and data conditions.

Accordingly, the central scientific conclusion of the study is represented by the proposed integrated pathway: Solar and Weather Data → AI Forecasting → PV/Load Prediction → BESS Optimization → Grid-Aware Energy Management → Reliability and Energy-Efficiency Improvement → Sustainable Development. The significance of this framework lies in moving beyond fragmented applications of AI. Forecasting becomes an input to optimization rather than an end in itself; BESS converts predictive information into controllable flexibility; grid-aware management ensures that optimization respects physical network constraints; and technical improvements are ultimately evaluated according to reliability, efficiency, renewable utilization, fossil-fuel displacement, and sustainable-development outcomes. Thus, the contribution of AI arises primarily from its capacity to connect prediction with operational action and system-level performance.

From a sustainable-development perspective, the study concludes that AI contributes indirectly rather than autonomously to sustainability. Its environmental value derives from enabling greater utilization of available solar electricity, reducing avoidable curtailment and potentially decreasing fossil-fuel generation and associated emissions. Its economic value lies in improving utilization of PV and storage investments, reducing operational inefficiencies, and supporting more efficient energy management. Its social value emerges through the potential improvement of reliable electricity supply to healthcare, education, water systems, telecommunications, remote communities, and productive activities. Its technological and institutional value lies in encouraging digital infrastructure, technical skills, research capacity, data governance, and collaboration among utilities, universities, research institutions, policymakers, and technology providers. Sustainability should therefore be interpreted as the final performance outcome of an integrated socio-technical system, rather than as an automatic consequence of adopting AI or solar PV.

Finally, the study concludes that successful implementation of the proposed framework requires parallel technological and institutional transformation. High-quality meteorological and operational datasets, smart metering, SCADA and communication infrastructure, secure data platforms, interoperability standards, cybersecurity safeguards, skilled human resources, appropriate grid codes, BESS standards, financing mechanisms, and coordinated regulatory policies are essential prerequisites. Without these enabling conditions, advanced AI applications may remain isolated demonstrations with limited national impact. The proposed framework should therefore be regarded as an evidence-based conceptual architecture rather than an experimentally validated AI model, consistent with the methodology adopted in this research. Its next scientific stage should involve empirical validation using Libyan solar, meteorological, load, battery, and grid datasets, followed by simulation and pilot-scale testing under representative weak-grid, urban, remote, and critical-infrastructure conditions. In this sense, the study establishes a foundation for shifting Libya's solar-energy strategy from the question of how much renewable capacity can be installed toward the more consequential question of how intelligently, reliably, resiliently, and sustainably that renewable capacity can be utilized.

9 | Recommendations

Based on the conclusions of the study, the following recommendations are proposed:

1. Develop a national AI-driven solar-energy strategy that integrates PV generation, AI forecasting, BESS, and grid-aware energy management rather than treating these technologies as separate initiatives.
2. Establish a national renewable-energy data infrastructure for collecting high-resolution solar irradiation, weather, PV generation, electricity demand, battery, and grid-operational data required for developing and validating AI models.
3. Prioritize locally validated AI forecasting models by testing machine-learning, deep-learning, hybrid, and physics-informed approaches under Libyan climatic conditions, particularly high temperatures, dust, and variable irradiation.
4. Integrate AI forecasting directly with BESS operation, enabling predictive charging, discharging, reserve management, and peak-load support based on anticipated PV production and electricity demand.
5. Adopt multi-objective BESS optimization that balances operating cost, battery degradation, renewable-energy utilization, curtailment, reliability, reserve availability, and lifecycle performance rather than focusing exclusively on short-term economic benefits.
6. Implement grid-aware renewable-energy management, ensuring that increasing PV penetration is coordinated with voltage limits, frequency requirements, protection systems, transmission constraints, and overall grid stability. This follows directly from the study's finding that PV expansion cannot be optimized independently of network conditions.

7. Launch pilot AI–PV–BESS projects in representative Libyan environments, including urban grids, weak-grid regions, remote communities, hospitals, water facilities, and other critical infrastructure, before progressing toward large-scale national deployment.
8. Modernize digital and physical grid infrastructure simultaneously through smart meters, SCADA systems, intelligent sensors, secure communication networks, grid-support technologies, and cybersecurity mechanisms necessary for reliable AI-based operation.
9. Strengthen national technical and institutional capacity by developing specialized training and research programs in AI, renewable-energy forecasting, BESS management, smart grids, cybersecurity, and energy-data analytics, supported by collaboration among universities, research centers, utilities, government institutions, and industry.
10. Establish an enabling regulatory and investment framework covering grid codes, BESS safety, data governance and interoperability, cybersecurity, renewable forecasting, intelligent inverter requirements, and incentives for AI-enabled renewable projects, while evaluating future investments against measurable technical, economic, environmental, and social sustainability indicators rather than installed renewable capacity alone.

References

- Abdel-Basset, M., Hawash, H., Chakrabortty, R. K., & Ryan, M. (2021). PV-Net: An innovative deep learning approach for efficient forecasting of short-term photovoltaic energy production. *Journal of Cleaner Production, 303*, 127037. DOI
- Al-Ali, E. M., Hajji, Y., Said, Y., Hleili, M., Alanzi, A. M., Laatar, A. H., & Atri, M. (2023). Solar energy production forecasting based on a hybrid CNN-LSTM-Transformer model. *Mathematics, 11*(3), 676. DOI
- Alasali, F., et al. (2023). Assessment of the impact of a 10-MW grid-tied solar system on the Libyan grid in terms of the power-protection system stability. *Clean Energy, 7*(2), 389–407. DOI
- Alkhayat, G., & Mehmood, R. (2021). A review and taxonomy of wind and solar energy forecasting methods based on deep learning. *Energy and AI, 4*, 100060. DOI
- Almaktar, M., & Shaaban, M. (2021). Prospects of renewable energy as a non-rivalry energy alternative in Libya. *Renewable and Sustainable Energy Reviews, 143*, 110852. DOI
- Almaktar, M., & Shaaban, M. (2021). Prospects of renewable energy as a non-wires alternative for grid capacity expansion in Libya. *Solar Energy, 224*, 1185–1197.
- Ben Hkoma, M. A., Omar, A. W., Milad, O. A. A., & Abdlsalam, A. S. (2023a). The future of renewable energies in Libya and their impact on achieving sustainable development: An analytical prospective study. *African Journal of Advanced Pure and Applied Sciences, 2*(4), 172–186. DOI
- Ben Hkoma, M. A., Omar, A. W., & Mohamed, T. M. (2023b). Renewable energies are an economical and sustainable alternative for producing electrical energy in Libya. *African Journal of Advanced Pure and Applied Sciences, 2*(3), 556–567.
- Buonanno, A., Caputo, G., Balog, I., Fabozzi, S., Adinolfi, G., Pascarella, F., Leanza, G., Graditi, G., & Valenti, M. (2024). Machine learning and weather model combination for PV production forecasting. *Energies, 17*(9), 2203. DOI

- Cantillo-Luna, S., Moreno-Chuquen, R., Celeita, D., & Anders, G. (2023). Deep and machine learning models to forecast photovoltaic power generation. *Energies, 16*(10), 4097. DOI
- Durán, F., Pavón, W., & Minchala, L. I. (2024). Forecast-based energy management for optimal energy dispatch in a microgrid. *Energies, 17*(2), 486. DOI
- Feng, C., Liu, Y., & Zhang, J. (2021). A taxonomical review on recent artificial intelligence applications to PV integration into power grids. *International Journal of Electrical Power & Energy Systems*, 107176. DOI
- Galouz, T. A., & Ben Hkoma, M. A. (2026). From renewable energy integration to grid resilience in Libya: A critical comparative review of grid-forming inverters, energy storage, and AI-based control. *Journal of Sustainable Research in Applied Sciences, 3*(2), 156–186. DOI
- Garip, S., & Ozdemir, S. (2022). Optimization of PV and battery energy storage size in grid-connected microgrid. *Applied Sciences, 12*(16), 8247. DOI
- Jebli, I., Belouadha, F.-Z., Kabbaj, M. I., & Tilioua, A. (2021). Prediction of solar energy guided by Pearson correlation using machine learning. *Energy, 224*, 120109. DOI
- Koresh, M. A., & Abzabez, A. A. (2026). The Future of the Libyan-European Geoeconomic Partnership in the Era of Global Energy Transition: A Conceptual Framework of Complex Interdependence. *Shihab Journal of Humanities*, *2*(2), 16-21.
- Luo, X., Zhang, D., & Zhu, X. (2021). Deep learning based forecasting of photovoltaic power generation by incorporating domain knowledge. *Energy, 225*, 120240. DOI
- Luo, X., & Zhang, D. (2022). An adaptive deep learning framework for day-ahead forecasting of photovoltaic power generation. *Sustainable Energy Technologies and Assessments, 52*, 102326. DOI
- Mellit, A., Massi Pavan, A., & Lughi, V. (2021). Deep learning neural networks for short-term photovoltaic power forecasting. *Renewable Energy, 172*, 276–288. DOI
- Miraftabzadeh, S. M., Colombo, C. G., Longo, M., & Foiadelli, F. (2023). A day-ahead photovoltaic power prediction via transfer learning and deep neural networks. *Forecasting, 5*(1), 213–228. DOI
- Qu, J., Qian, Z., & Pei, Y. (2021). Day-ahead hourly photovoltaic power forecasting using attention-based CNN-LSTM neural network embedded with multiple relevant and target variables prediction pattern. *Energy, 232*, 120996. DOI
- Radhi, S. M., Al-Majidi, S. D., Abbod, M. F., & Al-Raweshidy, H. S. (2024). Machine learning approaches for short-term photovoltaic power forecasting. *Energies, 17*(17), 4301. DOI
- Zhou, Y. (2022). Artificial intelligence in renewable systems for transformation towards intelligent buildings. *Energy and AI, 10*, 100182. DOI