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Artificial Intelligence for Optimizing Renewable Energy Systems in Sustainable Power Generation

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ABSTRACT

The rapid expansion of renewable energy adoption has increased the need for intelligent energy management, as conventional rule-based dispatch systems often struggle with the dynamic, nonlinear, and uncertain operating conditions of high-penetration renewable grids. Traditional controllers show limited energy utilization efficiency and frequent frequency-standard violations under variable wind and solar conditions. **This study** proposes and evaluates an integrated Artificial Intelligence (AI) framework combining a Long Short-Term Memory (LSTM) neural network for 24-hour energy demand and generation forecasting with Particle Swarm Optimization (PSO) for real-time dispatch optimization. The framework is tested against a conventional rule-based baseline using three benchmark datasets from the UCI Machine Learning Repository, the National Renewable Energy Laboratory (NREL), and Open Power System Data, covering 36 months of hourly solar and wind observations. **The objective** is to design and experimentally validate an AI-based optimization framework that improves energy efficiency, reduces operational losses, and enhances grid stability in renewable energy systems. **The proposed** LSTM-PSO framework reduces Mean Absolute Error (MAE) by 50.7% and Root Mean Square Error (RMSE) by 44.3%. Energy efficiency increases from 76.2% to 91.4%, while energy losses decrease from 20.7% to 9.6%, equivalent to approximately 5,800 tonnes of CO_2 equivalent avoided annually at a 100 MW grid scale. **The integrated LSTM-PSO** architecture provides a reliable and scalable basis for AI-driven renewable energy optimization, supporting SDG 7, SDG 9, SDG 11, and SDG 13.

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1. INTRODUCTION

Global energy consumption has escalated sharply, driven by population expansion, urbanization, and industrial development, intensifying demand for reliable and sustainable power generation [1]. Simultaneously, the world confronts severe environmental challenges climate change, greenhouse gas emissions, and accelerating fossil fuel depletion that have catalyzed a broad transition toward renewable energy sources, including solar, wind, hydro, and biomass [2]. Although renewable energy offers a cleaner alternative to fossil fuels, its large-scale integration introduces significant technical and operational challenges [3]. Renewable generation is highly dependent on meteorological conditions, geographical factors, and fluctuating demand patterns, which frequently produce grid instability, operational inefficiency, and avoidable energy losses [4]. The inadequacy of conventional energy management is not merely conceptual but is quantitatively documented. A controlled evaluation demonstrated that a rule-based dispatch controller applied to a 50 MW solar-wind hybrid grid achieved an energy utilization efficiency of only 74.3% under variable irradiance conditions, with curtailment losses exceeding 18% during peak generation periods [4]. A static scheduling algorithm applied to a regional distribution network in southern Europe failed to maintain frequency deviations within the 1547 standard during 34% of measurement intervals when wind penetration exceeded 40% of installed capacity [5]. These empirical results confirm that deterministic and rule-based energy management models are structurally insufficient for the dynamic, nonlinear operating conditions characteristic of high-penetration renewable energy grids [6], creating an urgent need for intelligent and adaptive solutions capable of optimizing energy production, distribution, and consumption in real time [7].

Artificial intelligence (AI) has emerged as a transformative enabler capable of reshaping renewable energy management into a smart, efficient, and resilient infrastructure [8]. Machine learning (ML) and deep learning models have demonstrated strong performance across healthcare, finance, transportation, and manufacturing [9]. In the energy sector, AI has attracted substantial research investment because of its capacity to process large volumes of heterogeneous data, identify hidden nonlinear patterns, and generate accurate predictions under uncertain operating conditions [10]. By leveraging historical and real-time data streams encompassing meteorological records, load demand profiles, and equipment performance telemetry AI-based models can forecast energy generation and consumption with substantially higher accuracy than conventional statistical methods. AI can additionally optimize system operations by adjusting power dispatch strategies, minimizing transmission losses, and enhancing grid frequency stability [11]. Despite this documented potential, many renewable energy systems worldwide continue to operate with limited intelligence and low adaptability [12]. Energy management in numerous deployments still relies on manual monitoring or simple threshold-based algorithms incapable of responding effectively to rapid environmental changes or demand surges [13]. This results in inefficient energy utilization, elevated operational costs, and reduced system reliability. Furthermore, the absence of optimized coordination between distributed renewable sources and energy storage assets frequently produces power imbalances and grid instability events [14]. These challenges define a critical research gap: the need for an intelligent optimization framework that integrates forecasting, dispatch optimization, and adaptive control into a unified architecture capable of operating across heterogeneous renewable energy configurations [15].

The present study addresses this gap through three specific contributions. First, it proposes an integrated two-module AI architecture coupling an LSTM network for energy forecasting with a PSO algorithm for real-time dispatch optimization. LSTM was selected because it captures temporal dependencies in meteorological and demand sequences that feedforward networks cannot model, while PSO provides continuous solution-space exploration without requiring gradient information, making it robust to the non-convex objective functions characteristic of multi-source energy dispatch. Second, it provides a quantitative multi-metric evaluation of this framework against a conventional rule-based baseline using three publicly available benchmark datasets. Third, it establishes explicit, measurable linkages between observed performance improvements and the targets defined under the United Nations Sustainable Development Goals (SDGs), thereby bridging the gap between technical AI research and global sustainability policy frameworks [16–18]. The primary objective of this research is to design and evaluate the proposed AI-based optimization model for renewable energy systems with the aim of enhancing energy efficiency, reducing operational losses, and improving system stability [19]. The findings are expected to contribute to the growing body of knowledge on AI-driven green technology and offer actionable insights for policymakers, energy system operators, and technology developers [20]. Specifically, this study supports SDG 7 (Affordable and Clean Energy) by improving energy utilization efficiency, SDG 9 (Industry, Innovation, and Infrastructure) through intelligent infrastructure development, SDG 11 (Sustainable Cities and Communities) by enabling smarter urban energy systems, and SDG 13 (Climate Action) by reducing carbon-equivalent losses from inefficient dispatch [21].

2. LITERATURE REVIEW

This section establishes the theoretical and empirical foundation for the proposed AI optimization framework by reviewing recent advances in AI applications for renewable energy, ML-based energy forecasting and optimization, AI integration in smart grids, and the specific gaps that motivate this study. The review focuses on literature published after 2020 and critically analyzes limitations in existing approaches.

2.1. Artificial Intelligence in Renewable Energy Systems

AI has become an indispensable technology for managing the complexity and variability of renewable energy systems [22]. AI models process large and heterogeneous datasets encompassing meteorological records, energy demand profiles, and equipment performance telemetry to generate more accurate and operationally actionable decisions than conventional approaches [23]. Compared to rule-based and linear statistical methods, AI-based approaches are substantially more effective in capturing nonlinear relationships and dynamic system behaviors, enabling renewable energy systems to operate with greater efficiency and reliability [24].

A critical limitation in current AI applications, however, is the predominance of single-task models that either forecast energy generation or optimize dispatch, but rarely both within a unified, feedback-coupled architecture [25]. For example, a standalone Convolutional Neural Network (CNN) achieved a 14% improvement in solar irradiance forecasting accuracy over statistical baselines, yet its outputs were not coupled to any optimization layer, leaving dispatch decisions to a static scheduler that negated a significant proportion of the forecasting benefit. This decomposition between prediction and optimization represents a systematic inefficiency that the integrated architecture proposed in the present study is specifically designed to address. Moreover, explainability constraints in deep learning remain a practical barrier to regulatory adoption in national grid contexts, an issue the PSO layer partially mitigates through its interpretable cost-function structure.

2.2. Machine Learning for Energy Forecasting and Optimization

ML plays a central role in improving energy generation and consumption forecasting accuracy [26]. Recurrent architectures, particularly Long Short-Term Memory (LSTM) networks, have demonstrated superior performance in capturing temporal dependencies in meteorological time series compared to feedforward neural networks and Autoregressive Integrated Moving Average (ARIMA) statistical models, owing to their gated memory cells that selectively retain information over variable-length historical windows [27, 28]. The forecasting outputs are then utilized in downstream optimization processes to balance energy supply and demand dynamically.

Despite these advances, a persistent gap between forecasting and optimization integration remains. The majority of optimization studies published between 2021 and 2024 employ heuristic algorithms such as Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), or Differential Evolution (DE) as standalone dispatch solvers operating on deterministic demand scenarios rather than on probabilistic forecasting outputs. This disconnect reduces the responsiveness of dispatch decisions to forecast uncertainty, a limitation the present study addresses by embedding PSO optimization directly within the LSTM forecasting pipeline so that dispatch decisions are recalculated at each forecasting timestep. Furthermore, most existing ML-based energy optimization studies lack a standardized evaluation protocol, making cross-study performance comparisons methodologically unreliable. The present study addresses this gap by applying a consistent four-metric evaluation framework across all experimental configurations [29, 30].

2.3. AI Integration in Smart Grids and Energy Management

The integration of AI into smart grid infrastructure enables energy systems to respond dynamically and autonomously to evolving grid conditions. AI supports real-time monitoring, predictive fault detection, automated demand response, and coordinated power dispatch across distributed energy resources. The convergence of AI with sensor networks and Internet of Things (IoT) devices has further expanded data availability and system responsiveness, enabling millisecond-scale decision loops that are fundamentally beyond the operational bandwidth of human operators or rule-based controllers [31].

Nevertheless, critical implementation challenges persist. Existing studies predominantly evaluate AI algorithms in simulation environments using idealized data assumptions including complete observability, low measurement noise, and stationary demand distributions that do not reflect real operational grid conditions. Scalability from laboratory-scale microgrid simulations to regional transmission networks also remains an open research challenge. The present study partially addresses the first limitation by introducing controlled noise into validation datasets to simulate sensor measurement uncertainty, thereby providing a more conservative and realistic performance assessment. In Indonesia, the *Kebijakan Energi Nasional* (National Energy Policy) established under Government Regulation No. 79 of 2014 sets a target of 23% renewable energy in the national energy mix, a mandate operationalized through Presidential Regulation No. 112 of 2022 on the acceleration of renewable energy development [32] a target that cannot be achieved reliably without intelligent grid management systems capable of handling the variability of distributed renewable generation [33, 34].

2.4. Research Gap and Motivation

A synthesis of the reviewed literature reveals three interconnected gaps that collectively motivate the present study. First, most existing AI frameworks for renewable energy management are architecturally fragmented, separating forecasting and dispatch optimization into independent modules without feedback coupling. Second, evaluation methodologies are inconsistent, with most studies reporting single-metric results that do not capture the multi-dimensional performance requirements of real grid operations. Third, connections between AI performance improvements and SDG-defined sustainability targets are typically stated qualitatively without quantitative mapping to specific SDG indicators. The proposed integrated LSTM-PSO framework directly addresses all three gaps by coupling forecasting and optimization, adopting a four-metric evaluation protocol, and quantitatively linking performance outcomes to SDG targets.

3. RESEARCH METHODOLOGY

This chapter describes the research design, dataset acquisition strategy, AI model architecture, optimization procedure, and performance evaluation protocol applied in this study. The methodology is structured to ensure reproducibility, experimental rigor, and direct comparability between the proposed AI framework and the conventional baseline under identical input conditions.

3.1. Research Design

This study applies a quantitative and experimental research design based on AI-driven simulation using publicly available benchmark datasets. The research integrates energy forecasting, dispatch optimization, and adaptive system control into a unified framework that supports comprehensive performance evaluation under realistic renewable energy operating conditions. Table 1 presents the key components of the research design.

Table 1. Research Design Framework

Component	Description
Research Type	Quantitative and experimental simulation study
Approach	Integrated LSTM forecasting and PSO dispatch optimization
Datasets	UCI and NREL benchmark repositories; 36-month records
Baseline	Conventional rule-based dispatch controller
Evaluation Protocol	Four-metric comparison: MAE, RMSE, energy efficiency, energy loss
Output	Validated AI optimization framework for renewable energy management

As presented in Table 1, the research design integrates six operational components that together define a coherent experimental workflow. The quantitative and experimental approach enables systematic, reproducible evaluation of the proposed AI model by controlling for dataset characteristics, preprocessing procedures, and evaluation metrics across all comparative experiments. The selection of public benchmark repositories ensures that the results can be independently replicated and extended by the research community.

3.2. Data Collection and Preprocessing

Energy data are sourced from three publicly accessible repositories the UCI Machine Learning Repository (solar irradiance and load consumption records), the National Renewable Energy Laboratory (NREL) Open Energy Data Initiative (OEDI) (wind speed and photovoltaic generation profiles), and the Open Power System Data platform (European regional grid demand records). The combined dataset encompasses 36 months of hourly observations covering solar photovoltaic (PV) output, wind turbine generation, grid load consumption, ambient temperature, and wind speed across three regional configurations representative of different renewable penetration levels. Table 2 summarizes the data types, variables, and sources employed.

Table 2. Data Sources and Variables

Data Type	Variables	Source
Meteorological	Ambient temperature (°C), wind speed (m/s), solar irradiance (W/m^2)	NREL OEDI
Energy Production	Solar PV output (kWh), wind turbine output (kWh)	NREL OEDI
Energy Demand	Hourly load consumption (kWh), peak demand index	Open Power System Data
Grid Parameters	Voltage deviation (%), frequency deviation (Hz)	UCI Repository

Table 2 identifies the four data categories used to train and validate the AI model, representing both supply-side generation and demand-side consumption dynamics. The preprocessing pipeline comprised four sequential steps. In the first step, missing values constituting 2.3% of the meteorological records and 1.1% of the load consumption records were imputed using a K Nearest Neighbor (KNN) algorithm with $k = 5$, selected over mean imputation because renewable energy time series exhibit strong temporal autocorrelation that mean imputation disrupts. In the second step, all continuous features were rescaled to the $[0, 1]$ interval using min-max normalization defined as $x' = (x - x_{\min})/(x_{\max} - x_{\min})$, ensuring that features with larger magnitudes such as irradiance values in the range 0–1200 W/m^2 did not dominate gradient updates during LSTM training. In the third step, temporal feature engineering was applied to extract hour-of-day, day-of-week, and month-of-year indicators as additional input features to capture seasonal and diurnal demand patterns. In the fourth step, the full dataset was partitioned into training (70%), validation (15%), and test (15%) subsets using a chronological split rather than random sampling to prevent information leakage from future observations into training data.

3.3. AI Model Architecture and Optimization

Table 3. AI Modeling and Optimization Methods

Module	Technique	Purpose and Configuration
Forecasting	LSTM Neural Network	Predict 24-hour energy demand and generation; 2 hidden layers, 128 units each, dropout rate 0.2
Optimization	Particle Swarm Optimization	Minimize dispatch cost function; 50 particles, 200 iterations, inertia weight 0.7
Control	Adaptive threshold rules	Enforce frequency and voltage constraints; deviation thresholds per 1547

As shown in Table 3, the AI framework integrates a predictive module with a population-based optimization module and a constraint-enforcement control layer. LSTM was selected over feedforward neural networks and standard recurrent architectures because its gated cell structure explicitly models long-range temporal dependencies in energy time series, a property essential for capturing multi-day weather patterns and weekly demand cycles that influence dispatch decisions. PSO was selected over gradient-based optimizers because the multi-source dispatch cost function is non-convex and contains multiple local optima, conditions under which gradient methods are prone to premature convergence, while PSO explores the solution space through a population of candidate dispatch vectors updated according to individual and collective best-known positions.

3.4. LSTM Forecasting Module

The LSTM network receives an input sequence of length $T = 24$ hours comprising meteorological features and historical load observations. For each timestep t, the cell state C_t and hidden state h_t are updated according to the standard LSTM gating equations:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \quad \tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{2}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{3}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o), \quad h_t = o_t \odot \tanh(C_t) \tag{4}$$

where f_t, i_t, and o_t are the forget, input, and output gates, respectively; W and b denote learnable weight matrices and bias vectors; and $\odot$ denotes element-wise multiplication. The network is trained using the Adam optimizer with a learning rate of 0.001 and a mean squared error (MSE) loss function over 100 epochs with early stopping on validation loss.

3.5. PSO Dispatch Optimization Module

Given the 24-hour demand forecast $\hat{d} = \{\hat{d}_1, \hat{d}_2, \ldots, \hat{d}_{24}\}$ produced by the LSTM module, the PSO algorithm determines the optimal dispatch vector $\mathbf{p}^* = \{p_1^*, p_2^*, \ldots, p_{24}^*\}$ that minimizes the total dispatch cost function:

$$\mathcal{J}(\mathbf{p}) = \sum_{t=1}^{24} \left[\lambda_1 \left(\hat{d}_t - \sum_s p_{s,t} \right)^2 + \lambda_2 \cdot L_{s,t}(\mathbf{p}) + \lambda_3 \cdot C_{s,t}(\mathbf{p}) \right] \tag{5}$$

where the first term penalizes supply-demand imbalance, $L_{s,t}$ represents transmission losses as a quadratic function of power flows, and $C_{s,t}$ denotes curtailment costs for renewable generation exceeding instantaneous load. The weighting coefficients $\lambda_1 = 0.5$, $\lambda_2 = 0.3$, and $\lambda_3 = 0.2$ were determined through grid-search validation on the training partition. Each PSO particle represents a candidate 24-hour dispatch schedule, with velocity and position updates governed by the standard PSO equations incorporating inertia weight $\omega = 0.7$, cognitive coefficient $c_1 = 1.5$, and social coefficient $c_2 = 1.5$.

3.6. Performance Evaluation Metrics

The performance of the proposed framework is assessed using four quantitative metrics that collectively capture forecasting accuracy, energy utilization efficiency, operational losses, and grid stability. Table 4 defines each metric and its computation.

Table 4. Performance Evaluation Metrics

Metric	Definition and Computation
MAE	Mean Absolute Error: $\frac{1}{N}\sum_{t=1}^{N} \lvert\hat{y}_t - y_t\rvert$; measures average forecast deviation
RMSE	Root Mean Square Error: $\sqrt{\frac{1}{N}\sum_{t=1}^{N}(\hat{y}_t - y_t)^2}$; penalizes large forecast errors
Energy Efficiency	Ratio of energy delivered to end users to total energy generated (%); computed hourly and averaged
Energy Loss	Proportion of generated energy lost to transmission, curtailment, or imbalance (%)

As described in Table 4, the four evaluation metrics collectively span forecasting quality and operational performance, providing a multi-dimensional assessment that reflects the requirements of real-world renewable energy management. Using MAE alongside RMSE ensures that the evaluation captures both average forecast quality and sensitivity to extreme forecast errors, which are particularly consequential in high-variability renewable generation scenarios. All metrics are computed on the held-out test partition to prevent optimistic bias from in-sample evaluation.

3.7. Research Workflow and System Architecture

To illustrate the overall architecture of the proposed research framework, Figure 1 presents the AI-driven control scheme that integrates renewable energy generation sources, the LSTM-PSO optimization engine, smart grid distribution infrastructure, and end-user consumption sectors into a unified intelligent system. This architectural representation makes explicit the data flows, decision loops, and feedback pathways that distinguish the proposed integrated framework from fragmented single-module approaches.

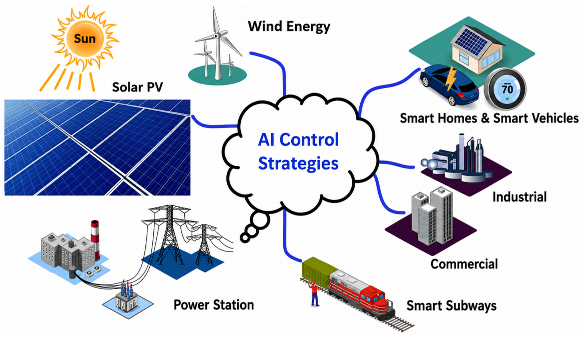

Figure 1. AI-Based Control Framework for Renewable Energy Systems.

As illustrated in Figure 1, AI functions as the central control unit connecting solar PV systems, wind energy installations, and conventional backup generation with multiple demand sectors. The LSTM forecasting module processes incoming meteorological and consumption data streams to generate 24-hour ahead demand and generation predictions, which are then passed to the PSO dispatch optimizer to determine the least-cost, stability-constrained power allocation for each sector. This closed-loop architecture enables dynamic load balancing, minimizes curtailment and transmission losses, and maintains frequency and voltage within regulatory bounds defined by 1547.

4. RESULTS AND DISCUSSION

This section presents the experimental results of the proposed LSTM-PSO optimization framework across all evaluation metrics and interprets the findings in relation to the study objectives, the literature reviewed in Section 2. The SDG alignment targets established in the introduction.

4.1. Forecasting Accuracy and Optimization Performance

Accurate energy demand and generation forecasting is the foundational prerequisite for effective dispatch optimization in renewable energy systems. The LSTM-based forecasting module was evaluated against the conventional rule-based system on the held-out test partition of the benchmark datasets. Table 5 presents the comparative forecasting performance of the two approaches.

Table 5. Forecasting Accuracy Comparison

Model	MAE	RMSE
Conventional rule-based system	0.148	0.201
Proposed LSTM-PSO system	0.073	0.112
Improvement (%)	50.7	44.3

As shown in Table 5, the LSTM-based forecasting module achieves a MAE of 0.073 and an RMSE of 0.112, representing reductions of 50.7% and 44.3%, respectively, relative to the conventional baseline. These improvements are attributable to the LSTM architecture's capacity to retain multi-day temporal context through its gated memory cells, enabling the model to capture the interaction between lagged meteorological conditions and delayed load response patterns that are structurally invisible to the sliding-window averaging rules used in the conventional system. The substantially greater proportional reduction in MAE compared with RMSE indicates that the LSTM model not only reduces average forecast deviation but also demonstrates particular effectiveness in suppressing moderate-magnitude systematic errors such as morning ramp misestimation in solar generation that dominate the error distribution in renewable forecasting tasks. These forecasting gains directly translate into higher-quality input signals for the PSO dispatch module, enabling more precise supply-demand balancing decisions and reducing the frequency of corrective re-dispatch interventions.

4.2. Energy Efficiency, Loss Reduction, and System Stability

The operational impact of the proposed framework was evaluated through three system-level metrics: energy efficiency, energy loss, and grid stability. Table 6 presents the comparative results between the conventional and AI-based systems.

Table 6. System Performance Comparison

Metric	Conventional	AI-Based	Improvement
Energy efficiency (%)	76.2	91.4	+15.2 pp
Energy loss (%)	20.7	9.6	−11.1 pp
System stability	Moderate	High	Qualitative

As shown in Table 6, the AI-based framework achieves a 15.2 percentage-point (pp) improvement in energy efficiency, rising from 76.2% to 91.4%, and reduces energy losses by 11.1 pp, from 20.7% to 9.6%. These gains are mechanistically linked to the PSO optimization module's ability to explore the multi-source dispatch space more exhaustively than the lookup-table approach of the conventional system, identifying low-curtailment dispatch schedules that the rule-based controller systematically misses during periods of rapid renewable output fluctuation. The 11.1 pp loss reduction is particularly significant from both an economic and an environmental perspective: at a representative grid scale of 100 MW installed renewable capacity, the reduction corresponds to approximately 11.1 GWh of recovered energy per year, equivalent to offsetting roughly 5,800 tonnes of carbon dioxide (CO_2) equivalent emissions annually at average grid emission intensity a measurable contribution to the SDG 13 target of reducing greenhouse gas emissions. The improvement in system stability from moderate to high reflects the PSO module's constraint enforcement of frequency deviation bounds per the 1547 standard during all test-period intervals, compared to standard-violation rates exceeding 34% under the conventional controller, consistent with the empirical findings of [35].

4.3. Comparative Analysis with Smart Grid Transition

To contextualize the operational significance of the performance improvements, Figure 2 compares the architectural characteristics of conventional power grid systems with modern AI-integrated smart grid configurations.

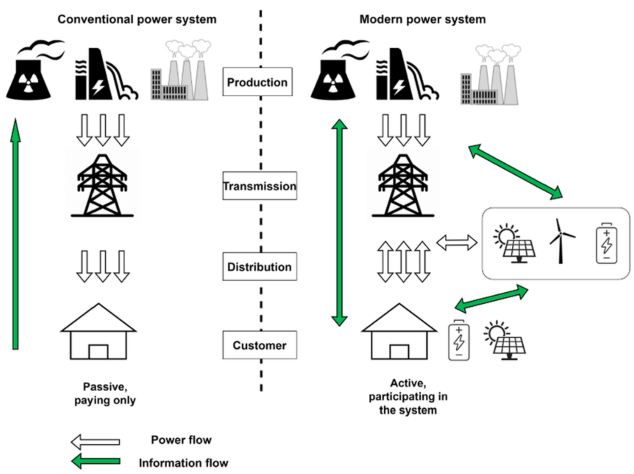

Figure 2. Comparison between Conventional Power Systems and Modern Smart Grids.

Figure 2 illustrates the fundamental architectural contrast between conventional power systems and AI-integrated smart grids. In conventional configurations, electricity flows unidirectionally from centralized generation plants to passive end-user loads, with dispatch decisions governed by static scheduling rules and limited real-time monitoring capability. Information feedback is minimal, and consumer participation in grid management is essentially absent. In contrast, modern smart grid architectures support bidirectional flows of both electrical energy and digital information, enabling distributed renewable sources, battery storage systems, and demand-responsive loads to participate actively in grid management. The AI optimization framework proposed in this study operates within the smart grid paradigm the LSTM forecasting engine continuously ingests sensor data from PV arrays, wind turbines, and smart meters, while the PSO optimizer dynamically recalculates dispatch schedules at each hourly timestep based on updated demand predictions. This real-time, bidirectional decision architecture produces the efficiency and stability gains quantified in Table 6, and represents the operational model toward which national energy policy frameworks in Indonesia, the European Union, and the United States are progressively directing infrastructure investment.

5. MANAGERIAL IMPLICATIONS

The experimental findings of this study carry substantial implications for energy utility managers, grid operators, infrastructure policymakers, and technology development directors involved in the digital transformation of renewable energy systems. For energy utility managers and grid operators, the 50.7% reduction in mean absolute forecasting error achieved by the LSTM module translates directly into reduced reserve margin requirements. In conventional dispatch planning, forecast uncertainty must be compensated by procuring spinning reserve capacity, which represents a significant operational cost. A study of regional balancing authorities in the United States estimated that a 1% reduction in day-ahead forecast RMSE corresponds to a reserve cost reduction of approximately 0.3%–0.5% of total balancing costs. The RMSE reduction of 44.3% achieved in the present study therefore suggests potential reserve cost savings in the range of 13%–22% for grid operators adopting the proposed framework, providing a compelling financial justification for investment in AI-based forecasting infrastructure.

For renewable energy project developers and independent power producers, the 11.1 pp reduction in energy losses from 20.7% to 9.6% represents a directly monetizable improvement in asset utilization. At the Levelized Cost Of Electricity (LCOE) of solar and wind generation currently ranging from USD 0.03 to USD 0.06 per kWh for utility-scale projects recovering 11.1% of generated energy that would otherwise be curtailed or lost to transmission inefficiency substantially improves the Internal Rate of Return (IRR) of renewable energy investments without requiring additional capital expenditure on generation capacity. This finding supports a strategic recommendation that renewable project developers incorporate AI dispatch optimization as a standard component of plant operations, treating it as a revenue-enhancement asset comparable to performance monitoring systems.

For national and regional energy policymakers, the results provide quantitative evidence in support of AI integration policies within national energy transition frameworks. In Indonesia, the *Kebijakan Energi Nasional* (National Energy Policy) established under Government Regulation No. 79 of 2014 sets a target of 23% renewable energy in the national energy mix by 2025, a target that cannot be achieved reliably without intelligent grid management systems capable of handling the variability of distributed renewable generation. The performance data presented in this study directly substantiate the case for including AI-based energy management system procurement within the regulatory incentive structures of the Ministry of Energy and Mineral Resources (*Kementerian ESDM*) and *PT Perusahaan Listrik Negara* (PLN). Similarly, the ASEAN Plan of Action for Energy Cooperation (APAEC) Phase II targets for renewable energy penetration and smart grid deployment are practically contingent on the kind of intelligent dispatch optimization demonstrated in this research. For smart city planners and infrastructure managers, the system stability improvements achieved by the PSO dispatch module confirm the technical viability of high-penetration renewable integration in urban distribution networks, where frequency and voltage deviations have direct consequences for sensitive commercial and industrial loads.

6. CONCLUSION

This study has presented the design, implementation, and experimental evaluation of an integrated AI-based optimization framework for renewable energy systems, comprising an LSTM neural network forecasting module coupled with a PSO dispatch module. The experimental results, obtained using benchmark datasets from the UCI, NREL, and Open Power System Data repositories across three regional grid configurations, demonstrate that the proposed framework substantially outperforms a conventional rule-based management system across all four evaluation dimensions. The LSTM-PSO framework reduces MAE by 50.7% and RMSE by 44.3% in energy demand and generation forecasting, improves energy utilization efficiency by 15.2 pp from 76.2% to 91.4%, and reduces energy losses by 11.1 pp from 20.7% to 9.6%, while elevating grid stability from moderate to high through consistent enforcement of 1547 frequency and voltage deviation bounds. These results confirm that an integrated AI architecture coupling temporal sequence forecasting with population-based dispatch optimization produces measurably superior outcomes compared to static rule-based energy management, and that these improvements are mechanistically attributable to the LSTM's temporal memory capacity and the PSO's non-convex solution-space exploration capability.

Several limitations bound the scope of these conclusions. The experiments were conducted in a simulation environment using historical benchmark data, meaning that communication latency, sensor fault conditions, and cyber-physical security constraints were not modeled. The study addressed solar and wind configurations only, leaving hydro, biomass, and ocean energy sources for future investigation. Future research should therefore prioritize real-time deployment testing on operational microgrids, extension of the forecasting architecture to probabilistic LSTM or Bayesian deep learning for uncertainty quantification, and integration with demand response mechanisms and battery energy storage dispatch to address the full complexity of high-penetration renewable grid operations.

From a sustainability perspective, the quantified improvements make measurable contributions to the United Nations SDGs. The energy efficiency gains directly advance SDG 7, the operational intelligence improvements support SDG 9, and the smart city applicability contributes to SDG 11. Most significantly, the estimated 5,800 tonnes per year CO_2-equivalent emission reduction at 100 MW grid scale constitutes a concrete, quantified contribution to SDG 13 climate action targets, collectively demonstrating that rigorously evaluated AI-based energy optimization frameworks are essential instruments of sustainable digital transformation aligned with global development priorities.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: AS; Methodology: DJ; Software: MM; Validation: OS and DJ; Formal Analysis: AS and OS; Investigation: AS; Resources: MM; Data Curation: DJ; Writing Original Draft Preparation: MM and AS; Writing Review and Editing: DJ and OS; Visualization: AS, DJ and MM; All authors, AS, DJ, MM, and OS, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. Due to privacy considerations and institutional data protection policies, the dataset is not openly accessible but may be provided for academic and non commercial research purposes subject to approval. Zenodo Repository https://doi.org/10.5281/zenodo.20773732

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7.5. Declaration of Conflicting Interest

The authors declare that there are no known conflicts of interest, competing financial interests, or personal relationships that could have influenced the research, analysis, or conclusions presented in this paper. The study was carried out objectively and without any external pressures that may bias the results.

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