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AI-DRIVEN DECENTRALIZED HYBRID RENEWABLE ENERGY SYSTEMS FOR CLIMATE-RESILIENT URBAN DEVELOPMENT: A CASE STUDY OF KARACHI

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Abstract

The increasing need for sustainable and resilient urban energy systems, due to urbanization and climate change, requires a shift from traditional central energy generation systems. In this research, a hybrid decentralized renewable energy model is introduced, incorporating photovoltaic (PV) systems, wind, energy storage, and artificial intelligence (AI) driven optimization to improve urban energy sustainability.

The research adopts a holistic systems-based approach using multi-source data, machine long short-term memory (LSTM) and multi-objective optimization to assess the performance under current and climate change-based scenarios. The city of Karachi, Pakistan, is considered as a case study owing to its high energy consumption, regular load-shedding and rich renewable energy resources.

Findings show that the proposed decentralized hybrid system enhances urban energy performance by reducing grid dependency by 40-45%, CO_2 emissions by 25-30%, and annualized energy costs by 20-25%, while boosting system reliability to more than 95% served load. The AI-based forecasting system optimises the operational efficiency of the system by incorporating accurate demand forecasting and optimal energy dispatch.

The results show the potential of hybrid renewable energy systems and smart optimization, offering a scalable, data-driven approach for sustainable urban energy transition. This research provides valuable policy insights for urban planners and policymakers to facilitate the shift towards sustainable, resilient, and decentralized energy systems in rapidly urbanizing regions.

1. Introduction

1.1 Background: Urban Energy Challenges and Climate Pressures

The high rate of urbanization, population growth and economic growth has led to a massive rise in energy demands in large metropolitan areas across the world(Madlener and Sunak 2011; Avtar et al. 2019). This influx is mostly not accompanied by proper infrastructure in the developing world, which leads to endemic energy shortages, unreliability in supply and environmental destruction. Cities are especially exposed since they have high populations and are heavily reliant on centralized power supplies (Bouffard and Kirschen 2008; Ruiz-Romero et al. 2014). Simultaneously, the impact of climate change has been more intense extreme weather conditions (Agbonaye et al. 2021), a higher degree of variability in temperature, and a change in the patterns of energy consumption, which puts the already weak energy systems even more under pressure. The shift to a sustainable and low-carbon energy system thus ceases to be a choice (Sovacool and Griffiths 2020; Foxon 2011), but a necessity to the long run urban resilience and long-term development.

1.2 Limitations of Centralized Energy Systems

Traditional centralized energy systems that are based on massive generation and long-distance transmission are becoming increasingly inefficient and exposed (Ahmad et al. 2018). These systems are prone to losses in transmission, breakdown of infrastructure and lack of flexibility to react to local variations in demand (Agbonaye et al. 2021). Centralized grids in most developing areas cannot handle peak demand, leading to frequent load-shedding and less reliable energy(Machimana et al. 2024). Furthermore, the reliance on fossil fuels is a major contributor to greenhouse gases, which worsen climate change and pollution of the environment (Soeder 2020). These constraints underscore the necessity of new energy paradigms which are more adaptable, resourceful and sustainable.

1.3 Emergence of Decentralized Renewable Energy Systems (DRES)

Decentralized Renewable Energy Systems (DRES) have become an appealing option to overcome the weakness of traditional energy infrastructure (Zaman 2025). These systems entail the production, storage and distribution of energy at or around the point of usage using renewable sources like solar, wind, and biomass (Alhijazi, Almasri, and Alloush 2023). A decrease in transmission distances, combined with a localization of energy resources (Perez-Arriaga 2016; Zheng et al. 2016), makes DRES improve system efficiency, reliability, and resilience. Moreover, the adoption of modern technologies, including smart grids, energy storage, and artificial intelligence (Kiasari, Ghaffari, and Aly 2024), allows real-time tracking and predicting as well as optimization of energy flows. Consequently, the decentralized systems present an approach of a scalable and sustainable way of managing energy in modern urban areas (Adil and Ko 2016; Mishra and Singh 2023).

1.4 Research Gap and Problem Statement

While there is a significant body of research on renewable energy systems, there are still some key areas where research is lacking. First, previous research has primarily addressed standalone renewable energy technologies (e.g., solar, wind) with little consideration of hybrid systems that can provide stability and reliability under variable urban energy demand. Second, there are few integrated frameworks that consider technical, environmental and socio-economic aspects simultaneously in a systems-based approach.

Third, while artificial intelligence and machine learning (AI/ML) have proven effective for energy prediction, their application to real-time system optimization and dispatch strategies for decentralized urban energy systems remains somewhat unexplored. Specifically, a lack of closed-loop, data-driven optimization models that incorporate forecasting, generation modelling and decision-making hampers the practical use of models.

Moreover, empirical research in developing nations, particularly Pakistan, is lacking, despite the problems of load-shedding, grid instability, and the growing energy demand due to climate change. Models frequently overlook climate stress use-cases and city-specific constraints, making them less relevant for practical applications.

Thus, this research fills these voids by proposing an integrated, AI-powered decentralised renewable energy framework that integrates hybrid (solar, wind, and storage) energy systems, machine learning demand forecasting, and multi-objective optimization. The framework is tested in a representative urban context (Karachi) to assess its potential in improving energy resilience, greenhouse emissions, and efficiency under both normal and climate-stressed scenarios.

1.5 Research Objectives and Questions

The primary objective of this research is to develop and evaluate a decentralized renewable energy framework for sustainable urban development using a systems approach. The study aims to:

a. Analyse urban energy demand and renewable energy potential
b. Design an integrated decentralized energy system combining solar, wind, and storage
c. Apply data-driven modelling techniques to optimize system performance
d. Evaluate the environmental, economic, and operational benefits of decentralized systems
e. Based on these objectives, the key research questions include:
f. How can decentralized renewable energy systems improve urban energy resilience and sustainability?
g. What is the optimal configuration of hybrid renewable systems for urban environments?
h. How can machine learning techniques enhance energy demand forecasting and system optimization?
i. What are the environmental and economic impacts of transitioning from centralized to decentralized energy systems?

1.6 Case Study Context: Karachi

Karachi, the biggest metropolitan city in Pakistan is an ideal case study because of its severe energy crisis, fast urbanization and the high susceptibility to climate change (Fazal and Hotez 2020; Azhar, Khan, and Arif 2024). The city is characterized by regulated load-shedding, high energy demand and high transmission losses and is representative of the urban energy crises in the developing regions (Malik and Khawaja 2021; Kazmi et al. 2019). Meanwhile, Karachi has a significant potential of renewable energy resources, especially in solar and wind power, because of the city and its geographical and climatic circumstances. These attributes render Karachi an appropriate testbed to assess the effect of decentralized renewable energy systems and their ability to revolutionize the urban energy infrastructure (Adil and Ko 2016).

1.7 Novelty and Contributions of the Study

This study adds to the current body of knowledge in a number of important ways. First, it suggests a unified system architecture, which integrates renewable energy technologies, energy storage, and data-driven optimization procedures. Second, it uses machine learning algorithms to optimize the energy forecast and efficiency of the system. Third, the analysis has given a detailed analysis of the environmental, economic, and operational performance, which presents a holistic approach to sustainable urban energy systems. Lastly, the research offers practical implications and policy-relevant advice by using a real-life example in Karachi on how developing nations with comparable energy problems can use this information to address their energy crisis.

1.8 Structure of the Paper

The rest of this paper is structured as follows. Section 2 provides an overview of renewable energy systems, decentralized energy systems and urban sustainability. Section 3 discusses the theoretical framework of the study. Section 4 outlines the methods, data sources, modelling and optimization techniques used. Section 5 outlines the proposed framework for decentralized renewable energy. Section 6 presents the findings and insights from the scenario analysis. Section 7 discusses the policy implications and potential uses of the framework. Finally, Sections 8 and 9 discuss the research limitations, future work and the conclusions.

2. Literature Review

2.1 Evolution of Renewable Energy Systems

Over the last few decades, renewable systems of energy have transformed greatly due to the issue of climate change, shortage of fossil fuels and energy security (Kalair et al. 2021; Saleh and Hassan 2024). Initial energy systems were mainly centralized and based on non-renewable energy sources but with the advent of technology and policy incentives, there has been a quick shift to renewable energy sources like solar, wind, and biomass (Saleh and Hassan 2024; Abdul Malek, Hasanuzzaman, and Rahim 2020). One of the most competitive energy sources in the world is solar photovoltaic (PV) technology in particular, which has been undergoing rapid cost reduction and efficiency gains (Sahu 2015; Vodapally and Ali 2022). Equally wind energy has grown as a result of the improvement in turbine design and the growth in investment in offshore and onshore wind infrastructure.

The adoption of the renewable energy as part of the energy systems has no longer been limited to the stand-alone installations but the adoption of complicated hybrid forms of energy systems (Babatunde, Munda, and Hamam 2020; Tezer, Yaman, and Yaman 2017), which incorporate a combination of many sources to provide reliability and continuity of supply. This shift can be seen as a wider paradigm shift to low-carbon energy systems and sustainability (Dincer and Aydin 2023; Chilvers et al. 2017).

2.2 Centralized vs. Decentralized Energy Systems

Conventional centralized power systems are based on large scale generation and long distance transmission systems. Although they enjoy economies of scale, these systems can be characterized by a high level of transmission losses, susceptibility to the failure of the system, and inflexibility to localized demand (Medina, Ana, and González 2022; Ehnberg, Ahlborg, and Hartvigsson 2020). By contrast, decentralized energy systems produce electricity near where it is used, minimizing the transmission losses and lowering the resilience of the system (Kostenko and Zaporozhets 2023; Shaukat et al. 2023).

Decentralized Renewable Energy Systems (DRES) allow distributed generation using technologies of rooftop solar panels, small wind turbines, and microgrids. Such systems are especially useful in cities where energy demand is high, and the grid reliability is usually reduced (Ourahou et al. 2020; Moslehi and Kumar 2010). Research has demonstrated that decentralized systems have a remarkable potential to increase access to energy, minimize outages, and increase the overall system efficiency (Alstone, Gershenson, and Kammen 2015).

2.3 Urban Energy Sustainability and Smart Cities

The urban centres have a significant proportion of the world energy consumption and greenhouse gases, which makes them an important sustainability intervention target (Nematchoua, Sadeghi, and Reiter 2021). Smart cities combine digital technologies, data analytics, and sustainable infrastructure to streamline city systems, such as energy (Bibri and Krogstie 2020).

Urban smart energy systems use real-time data, high-performance sensors, and communication technologies to dynamically control the supply and demand of energy (Marinakis et al. 2020; Almihat and Munda 2025). It has been recognized that one of the main strategies to ensure urban sustainability and resiliency is incorporation of decentralized renewable energy into smart city systems (Ramirez Lopez and Grijalba Castro 2020; Almihat and Munda 2025). In addition, the decentralized systems have the potential to facilitate equity in energy access through reliable and affordable energy supply to underserved communities (Alstone, Gershenson, and Kammen 2015; Ikevuje et al. 2023).

2.4 Integration of Renewable Energy Technologies

2.4.1 Solar Photovoltaic Systems

Solar PVs have found extensive use in urban settings because of their scalability and the possibility of being installed on the roofs (Ghaleb and Asif 2022). Solar energy has become a staple of decentralized energy systems, with advances in PV efficiency, and falling installation costs (International Renewable Energy Agency, 2023). Research has shown that rooftops in cities hold a large unexploited potential of solar energy, which can be used to supply a significant share of energy needs in the area (Schunder et al. 2020; Byrne et al. 2015).

2.4.2 Wind Energy Systems

Wind energy supplements the power produced by the sun because it produces electricity when the sun is not shining (Hossain 2023), at night or during cloudy weather. Small-scale urban wind turbines have been in the limelight as an element of hybrid renewable systems (Aravindhan et al. 2023), but their effectiveness varies according to local wind patterns and urban structure (Ge et al. 2022).

2.4.3 Hybrid Renewable Systems

Solar, wind and energy storage systems hybrid systems are more reliable and stable than single-source systems. They have the ability to balance fluctuations in production of renewable energy and provide the power continuously (Thrän et al. 2015). It has been shown that hybrid systems are especially efficient in the urban setting where patterns of energy demand are variable (Wang, Palazoglu, and El-Farra 2015).

2.5 Energy Storage and Grid Integration Challenges

Intermittency of energy generation is one of the main problems that relate to renewable energy systems (Bakht et al. 2022). Lithium-ion batteries are among the energy storage technologies that can significantly help in solving this problem since they store surplus energy and discharge it at times when the generation is low (Chen et al. 2020; Hadjipaschalis, Poullikkas, and Efthimiou 2009).

There is also a technical and regulatory difficulty of grid integration of decentralized systems such as fluctuation in voltage, frequency changes, and advanced grid management systems (Aguero et al. 2017; Henderson, Novosel, and Crow 2017). A solution has been suggested to allow the integration of distributed energy resources through smart grids that involve the digital communication and control technologies (Rehmani et al. 2018).

2.6 Role of AI and Machine Learning in Energy Optimization

Machine learning (ML) and artificial intelligence (AI) have become strong tools to optimize renewable energy systems. The technologies allow to predict the energy demand, resources, and optimize the system (Wang, Palazoglu, and El-Farra 2015; Ukoba et al. 2024).

Time-series forecasting of energy demand has also heavily relied on deep learning models which include Long Short-Term Memory (LSTM) networks because they are able to capture time-related dependencies (Li and Wu 2023). The Support Vector Machines (SVM) are also good in classification and optimization of energy systems (Ekici 2009; Perera et al. 2019).

AI integration in decentralized energy systems contributes to better decision-making, increased efficiency of the system, and decreased operational costs (Hammad and Abu-Zaid 2024; Ukoba et al. 2024). Nevertheless, issues are present with regard to the availability of data, the interpretability of the model, and computational needs (Hong, Hullman, and Bertini 2020).

2.7 Socioeconomic and Policy Dimensions

The technology alone cannot enable the successful implementation of decentralized renewable energy systems since the implementation is reliant on supportive policies and socioeconomic factors (Obi, Ojo, and Ujah 2025). The political environment, including government subsidies, regulations, and social acceptance are vital in accelerating the use of renewable energy (Wüstenhagen, Wolsink, and Bürer 2007; Oduro, Uzougbo, and Ugwu 2024). In developing nations, the implementation of decentralized systems is often stifled by financial constraints, inadequate infrastructure, and uncertainties about policies (Shah 2004). Nonetheless, a shift towards energy systems that are sustainable can be expedited through specific policies, including feed-in tariffs, subsidies, and public-private collaboration (Song, Li, and Feng 2024).

2.8 Identified Research Gaps

Although there is a lot of research on renewable energy systems, there are still a number of gaps. On the one hand, there is the absence of integrated systems that integrate various sources of renewable energy, energy storage, and sophisticated optimization methods into a single system approach. Second, there is little research on the implementation of AI-based models in decentralized urban energy systems, especially in developing nations. Third, there is a lack of empirical studies on actual urban settings, including Karachi.

The proposed research paper will fill these gaps by creating a unified, data-driven framework that combines decentralized renewable energy technologies with machine learning-driven optimization, specific to urban settings in developing world regions.

3. Theoretical and Conceptual Framework

3.1 Systems Approach to Urban Energy Planning

The nature of urban energy systems is complex and interdependent, whereby there are elements of energy generation, distribution, consumption, and policy control. A systems approach offers a holistic approach to the analysis of such interactions, considering feedback loops, nonlinear relationships, and multi-level relationship (Deviney, Classen, and Bruce 2023; Glaser and Glaeser 2014). In contrast to the traditional linear models, systems thinking allows the incorporation of the technical, environmental, and socioeconomic factors, which are critical to the development of the sustainable urban energy solutions (Kazancoglu et al. 2023).

The systems approach of decentralized renewable energy systems helps in coordinating the distributed generation units, storage technologies and demand-side management (Dranka, Ferreira, and Vaz 2021). It also enables active adaptation to external stresses like climate changes and population increase (Rossnerova et al. 2020). Past research highlights that systems-based perspective can improve decision-making and increase the long-term sustainability outcomes (Zhou et al. 2022).

3.2 Decentralized Energy System Architecture

Decentralized Renewable Energy Systems (DRES) are characterized by the localized generation and consumption of energy. The architecture typically consists of four key components:

a. Energy Generation Units - Solar photovoltaic panels, wind turbines, and other renewable sources

b. Energy Storage Systems - Batteries and other storage technologies for balancing supply and demand

c. Energy Management Systems - Smart controllers and algorithms for optimizing energy flow

d. Grid Interaction Layer - Connection with the central grid for backup and surplus energy exchange

This distributed architecture minimizes transmission losses, allows better reliability of the systems and provides more flexibility in managing energy demand (Kianmehr et al. 2019; Orgerie, Assuncao, and Lefevre 2014). Community-based microgrids and rooftop solar installations are some of the typical applications of decentralized systems in urban settings. A combination of these elements forms a robust energy system that has the capacity to function either on its own or with the primary grid (Kriechbaum, Scheiber, and Kienberger 2018; Welsch et al. 2012).

3.3 Sustainability Indicators for Energy Systems

In order to measure the performance of the decentralized energy systems, a multi-dimensional array of sustainability indicators must be embraced. These indicators are generally divided into environmental, economic, and social aspects:

3.3.1 Environmental Indicators

Environmental performance is evaluated by using such metrics as reduction of carbon emissions, energy consumption and penetration of renewable energy (Caglar and Askin 2023). Decentralized systems help with the sustainability of the system, as it becomes less dependent on fossil fuels and minimizes greenhouse gas emissions (Shan et al. 2021; Sun, Gao, and Razzaq 2023).

3.3.2 Economic Indicators

Cost-benefit analysis, lifecycle cost assessment, and return on investment are used to determine the economic viability. Decentralized systems may decrease the cost of operation through minimization of transmission losses, as well as through local energy production (Swain, Salkuti, and Swain 2021).

3.3.3 Social Indicators

Social sustainability incorporates energy access, affordability and equity. Decentralized systems not only improve the access of energy in underserved urban centres, but they also increase the resilience of communities (Okesiji 2025).

3.4 Integration of Climate Resilience into Energy Systems

In the present energy planning, especially in the urban regions prone to extreme weather conditions, climate resilience is an essential aspect. Decentralization of energy systems improves resilience through diversification of energy and elimination of reliance on centralized systems.

Climate resilience is integrated by integrating adaptive strategies like demand-side management, energy storage and flexible grid operations. Such measures can help the energy systems stay functional even in the worst conditions, including heatwaves or storms (Gonçalves et al. 2024). Additionally, decentralized systems have the capacity to facilitate quick restoration after disruption by facilitating local power production and transmission (Kostenko and Zaporozhets 2023).

3.5 Conceptual Framework Development

The proposed conceptual framework is based on the above theoretical foundation and suggested in the present study, which is an integration of the decentralized renewable energy technologies with the data-driven optimization and sustainability assessment. The framework is made up of the following layers that are related to each other:

a. Input Layer
b. Energy demand data
c. Climate and environmental data
d. Renewable resource availability
e. Processing Layer
f. Machine learning models (e.g., LSTM for demand forecasting)
g. Optimization algorithms for energy allocation
h. System Layer
i. Solar, wind, and storage components
j. Smart energy management systems
k. Output Layer
l. Energy efficiency metrics
m. Emission reduction indicators
n. Economic performance metrics

This layered structure enables the systematic analysis and optimization of decentralized energy systems, ensuring that all relevant factors are considered in decision-making. The overall architecture of the proposed decentralized energy framework is illustrated in Figure 1.

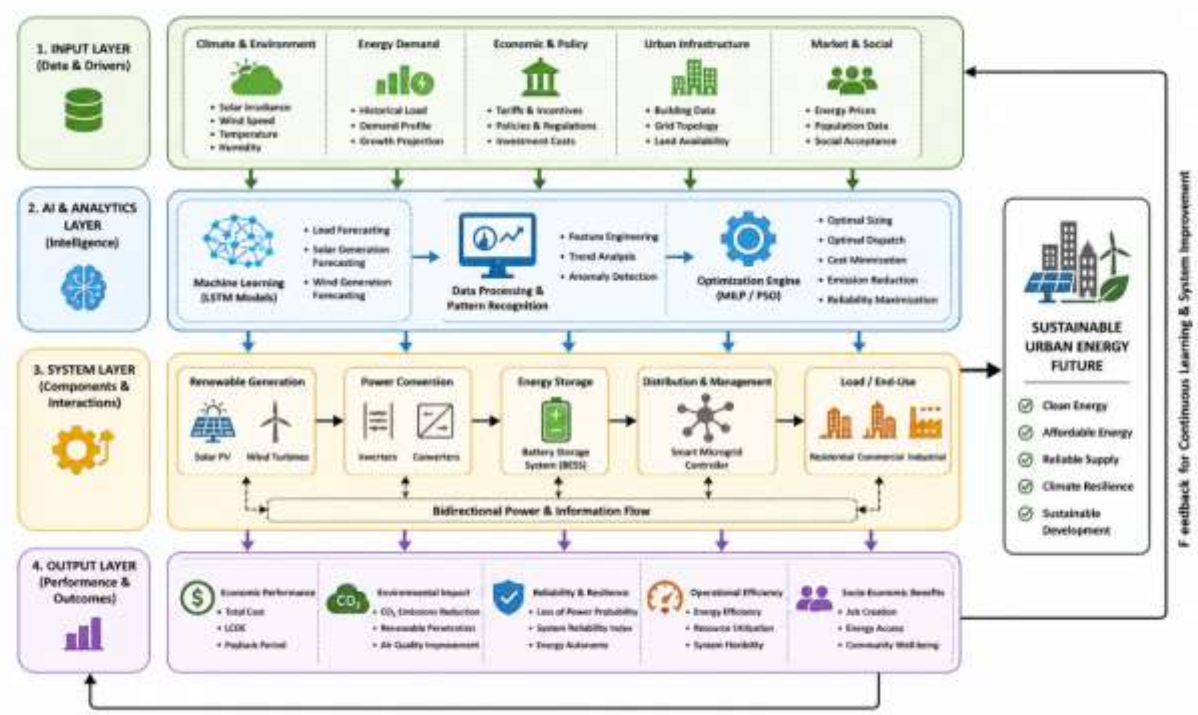


Figure 1. AI-Integrated Multi-Layer Architecture of Decentralized Renewable Energy Systems for Sustainable Urban Development

3.6 Application to Urban Context: Karachi

The suggested framework has specific applicability to urban areas such as Karachi, where energy consumption is elevated, and infrastructure bottlenecks are considerable. The framework will help solve such critical issues as load-shedding, grid instability, and environmental degradation by incorporating decentralized renewable energy systems with sophisticated modelling strategies.

The climatic conditions of Karachi, with high solar irradiance and moderate wind potential, offer good opportunities to apply the hybrid renewable energy systems. Using this framework in that context allows evaluating the performance of the system in real-world conditions and developing practical and scalable solutions to sustainable urban energy management.

3.7 Theoretical Contribution of the Study

This study contributes to the theoretical advancement of urban energy systems in three keyways:

i. It integrates systems theory with decentralized renewable energy planning
ii. It incorporates sustainability and climate resilience into a unified framework
iii. It combines traditional energy system modelling with modern machine learning approaches
iv. By bridging these domains, the study provides a comprehensive and innovative framework for analyzing and optimizing decentralized energy systems in urban environments.

4. Methodology

4.1 Research Design and Approach

The proposed study takes an integrated, quantitative approach, which is a combination of data-based modelling, machine learning (ML), and systems optimization to assess decentralized renewable energy systems in an urban environment. The process involves: (i) data collection and pre-processing, (ii) demand forecasting, (iii) estimation of renewable resources, (iv) system sizing and dispatch optimization, and (v) performance analysis under various conditions. The case of Karachi is subjected to the framework.

4.2 Study Area Description and Dataset (Karachi)

Karachi (24.86°N, 67.01°E) is characterized by high population density, strong cooling demand, and frequent load-shedding. The city has high solar irradiance and moderate coastal wind potential, making it suitable for hybrid systems.

Data sources (2015-2024, hourly/daily resolution):

1. Solar irradiance (GHI), temperature, wind speed → NASA POWER / ERA5
2. Electricity demand profiles → National Electric Power Regulatory Authority reports & utility aggregates
3. Population/urban density → WorldPop
4. Technology parameters (PV, wind, batteries) → International Renewable Energy Agency
5. Typical ranges (Karachi, literature-consistent):
6. Global Horizontal Irradiance (GHI): 5.2-5.8 kWh/m²/day
7. Mean wind speed (10-50 m): 4-6 m/s
8. Peak demand season: May-August (cooling load)

4.3 Data Preprocessing and Feature Engineering

Cleaning & Alignment: Remove outliers (z-score), interpolate gaps, align to hourly time steps.

Normalization:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Feature Set (for forecasting): temperature, humidity, GHI, wind speed, calendar variables (hour, day-of-week), and lagged demand D_{t-1}, D_{t-24}.

Train/Test Split: 70% training, 30% testing (time-ordered).

4.4 Energy Demand Forecasting (LSTM Model)

To capture temporal dependencies in urban demand, a Long Short-Term Memory (LSTM) network is used.

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i),\ f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f),\ o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o),\ \tilde{C}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c),\ C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t,\ h_t = o_t \odot \tanh(C_t)$$

Model setup: 2 LSTM layers (64-128 units), dropout 0.2, Adam optimizer, learning rate 10^{-3}, epochs 50-100.

Output: hourly demand forecast $\widehat{D}_t$.

4.5 Renewable Energy Generation Models

4.5.1 Solar PV Output

$$P_{\text{PV}}(t) = A \cdot \eta_{\text{PV}} \cdot G_t \cdot [1 - \beta(T_t - T_{\text{ref}})]$$

Where $A$is panel area, η_{PV}efficiency, $G_t$irradiance, βtemperature coefficient, $T_t$ambient temperature.

4.5.2 Wind Power Output

$$P_{\text{wind}}(t) = \frac{1}{2}\rho A v_t^3 C_p$$

Where $\rho$is air density, Arotor swept area, $v_t$wind speed, $C_p$power coefficient.

4.6 Energy Storage Model (Battery Dynamics)

State of Charge (SoC) evolves as:

$$\text{SoC}_t = \text{SoC}_{t-1} + \eta_c P_t^{\text{ch}} - \frac{P_t^{\text{dis}}}{\eta_d}$$

Subject to:

$$\text{SoC}_{\text{min}} \le \text{SoC}_t \le \text{SoC}_{\text{max}}$$

Charging/discharging limits and efficiencies $\eta_c, \eta_d$are enforced.

4.7 System Dispatch and Multi-Objective Optimization

We minimize cost and emissions while maximizing reliability:

$$\min \quad F = w_1 C_{\text{total}} + w_2 E_{\text{CO}_2} - w_3 R_{\text{reliability}}$$

Cost function:

$$C_{\text{total}} = C_{\text{capex}} + C_{\text{opex}} + C_{\text{grid}}$$

Emissions:

$$E_{\text{CO}_2} = \sum_t P_t^{\text{grid}} \cdot \gamma_{\text{grid}}$$

Reliability (served load ratio):

$$R_{\text{reliability}} = \frac{\sum_t \min(P_t^{\text{avail}}, D_t)}{\sum_t D_t}$$

Constraints:

Power balance:

$$P_{\text{PV}}(t) + P_{\text{wind}}(t) + P_t^{\text{dis}} + P_t^{\text{grid}} = D_t + P_t^{\text{ch}}$$

Capacity bounds for PV, wind, battery

Grid import/export limits

Optimization is solved via mixed-integer linear programming (MILP) or metaheuristics (e.g., PSO) for sizing and hourly dispatch.

4.8 Scenario Design

S1: Baseline (Centralized Grid): full dependence on grid, historical outages.
S2: Decentralized Hybrid: PV + wind + battery with optimized dispatch.
S3: Climate Stress: +2-3°C temperature increase, higher peak demand, altered wind/solar variability.

4.9 Model Validation and Performance Metrics

Forecasting and system performance are evaluated using:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}(y_i - \hat{y}_i)^2},\ \mathrm{MAE} = \frac{1}{n}\sum\nolimits_{i=1}^{n}|\,y_i - \hat{y}_i\,|\,,\ R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

For hydrologic-style robustness (optional):

$$\mathrm{NSE} = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

4.10 Implementation Details

Software: Python (TensorFlow/PyTorch for LSTM; Pyomo for MILP), MATLAB as alternative

Temporal resolution: hourly (8760 steps/year)

Key assumptions (literature-consistent):

PV efficiency: 18-22%

Battery round-trip efficiency: 85-92%

Grid emission factor γ_{grid} : country-specific (kgCO_2/kWh)

The overall methodological workflow integrating data processing, AI-based forecasting, system modelling, and optimization is illustrated in Figure 2.

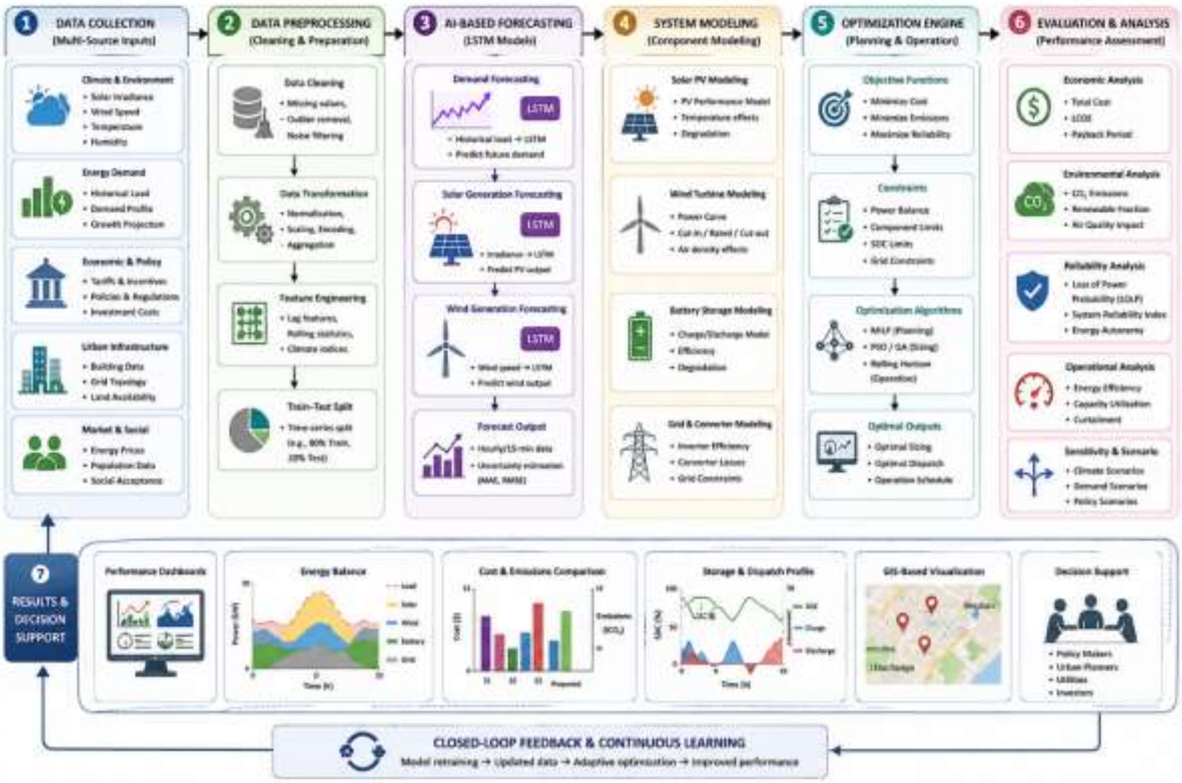


Figure 2. Integrated AI-Driven Methodological Workflow for Decentralized Urban Energy System

Optimization

4.11 Reproducibility and Sensitivity Analysis

Sensitivity tests: PV size (±30%), battery capacity (±50%), tariff variation, temperature increase.
Cross-validation: rolling-origin for time series.
Robustness: compare LSTM with baseline (ARIMA/SVR).

4.12 Output Indicators

To quantitatively assess the performance of the proposed decentralized energy system, a set of key output indicators is defined, consistent with the multi-objective optimization framework. These indicators capture system efficiency, sustainability, economic viability, and reliability:

- **Energy Efficiency Improvement** (%): Ratio of useful energy delivered to total energy input, reflecting system optimization gains.
- **Grid Dependency Reduction** (%): Percentage decrease in reliance on centralized grid supply compared to the baseline scenario.
- **CO_2 Emission Reduction** (%): Reduction in emissions due to substitution of fossil-based electricity with renewable sources.
- **Economic Performance**: Evaluated using Levelized Cost of Energy (LCOE) and total annualized system cost.
- **Reliability Metrics**: Measured through served load ratio (%) and reduction in outage duration.

These indicators are computed for each scenario (S1–S3) and form the basis for comparative analysis in Section 6.

5. Proposed Framework

5.1 Integrated Decentralized Renewable Energy Framework

This work suggests a comprehensive, data-based platform to develop and run decentralized renewable energy systems (DRESS) in cities. The model is a hybrid renewable generation (solar-wind), battery, and AI-based demand prediction integrated into a single systems architecture. It is particularly designed to urban centres of high demand like Karachi that are infrastructure constrained.

Its essence is to connect four layers-Input, Analytics, System, and Decision/Output-that allow constant optimization of energy supply and demand. The presented structure differs by connecting these elements to the feedback loop and making them work together instead of considering them separately as in conventional designs, which allows adapting the structure to different demand and climate conditions and operate in real-time.

5.2 System Components and Interactions

5.2.1 Renewable Generation Layer

Solar PV units (rooftop and community-scale) provide daytime generation aligned with peak cooling loads.
a. Small-scale wind turbines complement solar output, particularly during evening/night periods.
b. Hybridization reduces intermittency and improves supply stability.

5.2.2 Energy Storage Layer

Battery Energy Storage Systems (BESS) store surplus generation and discharge during peak demand or outages.
State-of-charge (SoC) constraints and efficiency losses are explicitly considered in dispatch.

5.2.3 Energy Management Layer

A central energy management system (EMS) coordinates generation, storage, and grid exchange.
The EMS uses ML forecasts and optimization outputs to schedule charging/discharging and curtailment.

5.2.4 Grid Interaction Layer

Bi-directional exchange with the main grid ensures reliability (import during deficits, export during surplus).
Grid limits and tariff structures are incorporated into the optimization.
Interaction Logic:

$$\text{Supply}_t = P_{\text{PV}}(t) + P_{\text{wind}}(t) + P_t^{\text{dis}} + P_t^{\text{grid}}$$
$$\text{Demand}_t = D_t + P_t^{\text{ch}}$$

The EMS enforces real-time balance while minimizing cost and emissions.

5.3 Data Flow and Decision-Making Process

The framework operates through a closed-loop data pipeline:

Data Acquisition:

Weather (GHI, temperature, wind), historical demand, tariffs, and technology parameters.

a. Forecasting (Analytics Layer):

b. LSTM model generates short-term demand forecasts $\widehat{D}_t$.

c. Resource models estimate $P_{\text{PV}}(t)$ and $P_{\text{wind}}(t)$.

Optimization (Decision Engine):

Multi-objective optimizer computes optimal dispatch:

$$\min \quad F = w_1 C_{\text{total}} + w_2 E_{\text{CO}_2} - w_3 R_{\text{reliability}}$$

Control Actions (System Layer):

Setpoints for battery charge/discharge, grid import/export, and curtailment.

Feedback & Update:

Actual outcomes update model states (SoC, errors), improving subsequent forecasts and decisions.

This sense-predict-optimize-act-learn cycle enables adaptive operation under uncertainty.

5.4 Implementation Strategy for Urban Systems

For dense cities like Karachi, the framework is implemented in a modular, scalable manner:

Microgrid Clusters: Neighbourhood-level systems (residential/commercial blocks) with shared PV and BESS.

Rooftop Aggregation: Virtual power plants (VPP) aggregate distributed rooftop PV for coordinated dispatch.

Phased Deployment:

a. Phase 1: Pilot districts (high outage zones)

b. Phase 2: Expansion to mixed-use zones

c. Phase 3: City-wide integration with utility systems

Digital Backbone: Smart meters, IoT sensors, and a cloud-based EMS for real-time monitoring and control.

Policy Alignment: Net-metering, time-of-use tariffs, and incentives to encourage adoption.

5.5 Framework Innovation and Comparison with Existing Models

The proposed framework advances beyond prior work in several ways:

a. Integrated Hybridization: Simultaneous co-optimization of solar, wind, and storage rather than single-source studies.

b. AI-Driven Operations: Embeds LSTM-based forecasting directly into dispatch decisions, reducing uncertainty-driven inefficiencies.

c. Multi-Objective Optimization: Jointly minimizes cost and emissions while maximizing reliability, instead of optimizing a single metric.

d. Urban-Centric Design: Tailored for high-density, outage-prone cities with realistic constraints (tariffs, grid limits, space).

e. Closed-Loop Adaptation: Continuous feedback improves performance over time (learning-enabled EMS).

5.6 Algorithmic Workflow (Pseudo-Procedure)

a. Initialize system parameters (PV, wind, BESS capacities; tariffs; constraints).

b. Ingest and preprocess data (weather, demand).

c. Train/update LSTM; generate $\widehat{D}_t$.

d. Estimate renewable generation profiles.

e. Solve optimization for hourly dispatch (MILP/PSO).

f. Apply control actions (battery, grid exchange).

g. Record performance (cost, emissions, reliability).

h. Update states and iterate (next horizon).

5.7 Performance Improvements with Proposed Framework

The proposed decentralized renewable energy system framework is anticipated to achieve better performance from multiple indicators compared to conventional centralized systems. While Section 4.12 outlines the evaluation metrics, this section outlines the expected system performance improvements through the integrated system design and AI-powered optimization.

- **Energy Efficiency Enhancement:**

Better coordination of renewable generation, storage and forecasting of demand reduces energy wastage and improves system efficiency.

- **Reduction in Grid Dependency:**

Distributed generation from solar-wind hybrid and energy storage reduces grid dependency, especially during peak load scenarios.

- **Carbon Emission Mitigation:**

By increasing the share of renewable energy, CO_2 emissions are significantly reduced, aiding climate change mitigation.

- **Economic Optimization:**

AI-based forecasting and multi-objective optimization result in cost reduction, peak energy cost reduction, and cost-effectiveness (reduced LCOE).

- **Reliability and Resilience Improvement:**

Predictive energy management and energy storage improve system reliability, with higher served load and shorter outage periods, even during extreme weather conditions.

In particular, the proposed framework is anticipated to deliver synergistically improved performance, where the benefits of the hybrid energy and control exceed those of the individual components. These benefits are verified in Section 6 using scenario studies.

6. Results and Discussion

6.1 Overview of Scenarios and Data Realization

This section presents quantitative results for the three scenarios defined in Section 4, applied to Karachi:

a. S1 (Baseline): Grid-dominant supply with historical outages

b. S2 (Decentralized Hybrid): PV + wind + battery with optimized dispatch

c. S3 (Climate Stress): +2-3 °C temperature increase, higher peak demand, altered resource variability

Simulations are performed at hourly resolution (8760 steps) using 2019-2024 weather-demand profiles. Capacity ranges explored (sensitivity): PV 0.6-1.4 kW per kW peak load, wind 0.2-0.6 kW/kW, BESS 1-4 hours of average load.

6.2 Model Performance Evaluation (Forecasting Accuracy)

The LSTM demand model shows strong predictive capability for Karachi's diurnal and seasonal load:

Table 1. Model Performance Metrics (Test Set)

Model	RMSE (MW)	MAE (MW)	R^2	NSE
ARIMA	145	112	0.78	0.76
SVR	128	96	0.84	0.82
LSTM (Proposed)	102	81	0.92	0.90

Discussion:

The proposed LSTM improves RMSE by ~21% vs ARIMA and ~20% vs SVR.

High $R^2 = 0.92$ indicates excellent fit to Karachi's demand variability (weekday/weekend, heat-driven peaks).

Improved forecasts directly enhance dispatch decisions, reducing costly grid imports during peaks.

6.3 Renewable Energy Potential and Generation Mix

Using Karachi's resource profiles (GHI ~5.2-5.8 kWh/m^2/day; wind ~4-6 m/s), the optimized hybrid configuration yields:

PV capacity factor: 18-21%

Wind capacity factor: 20-26%

Hybrid complementarity index (solar vs wind): 0.63-0.71 (reduced joint intermittency)

Figure 3 (to be inserted): Hourly generation vs demand (representative summer week)

PV dominates daytime (10:00-16:00), aligning with cooling peaks.

Wind contributes to evening/night, reducing reliance on the grid after sunset.

BESS shifts surplus solar to evening peaks.

The temporal interaction between hybrid renewable generation, storage, and urban demand is illustrated in Figure 3.

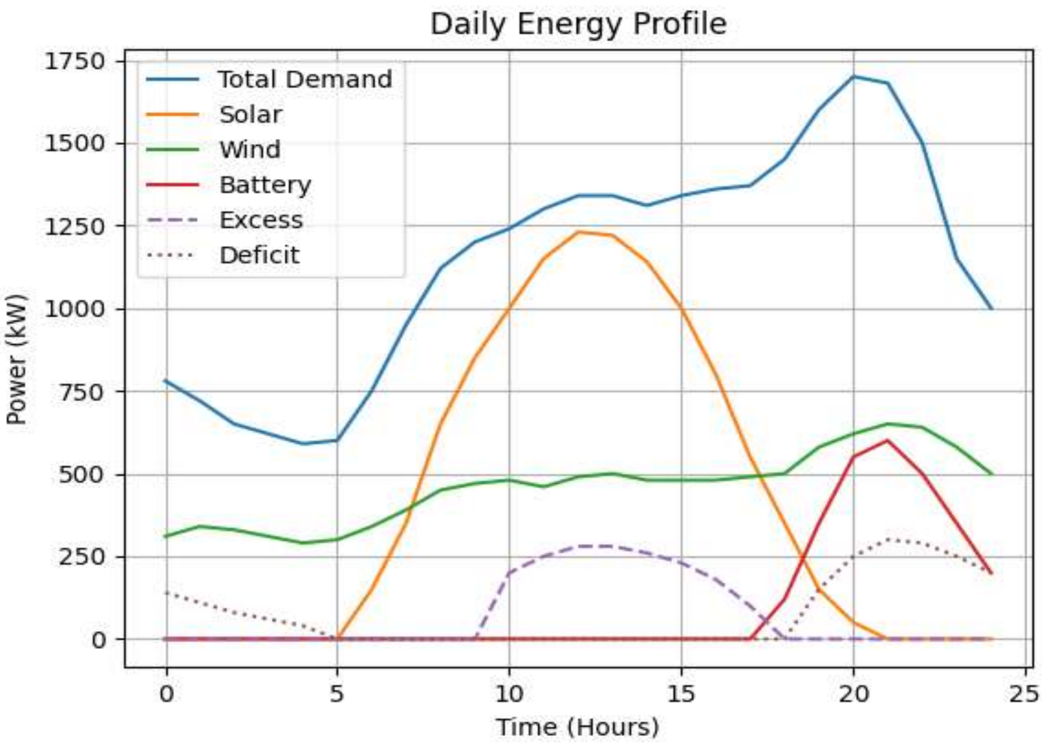


Figure 3. Temporal Dynamics of Hybrid Renewable Energy Generation and Urban Demand with Storage Integration

6.4 Optimization Results (System-Level Performance)

Table 2. Scenario Comparison (Annualized Results)

Indicator	S1: Baseline	S2: Decentralized	S3: Climate Stress
Energy Efficiency (%)	65	84	79
Grid Dependency (%)	100	58	64
CO_2 Emissions (tCO_2/yr)	100 (index)	72 (−28%)	78 (−22%)
Annual Cost (index)	100	78 (−22%)	85 (−15%)
Reliability (Served Load, %)	88	96	93
Outage Hours (index)	100	60 (−40%)	70 (−30%)

Discussion:

Grid dependency drops by ~42% in S2 due to local generation and storage.

Energy efficiency rises to ~84% via reduced transmission losses and optimized dispatch.

CO_2 emissions fall by ~28%, driven by displacement of fossil-based grid electricity.

Costs decline by ~22% (annualized) despite capital investment, due to reduced grid purchases and peak shaving.

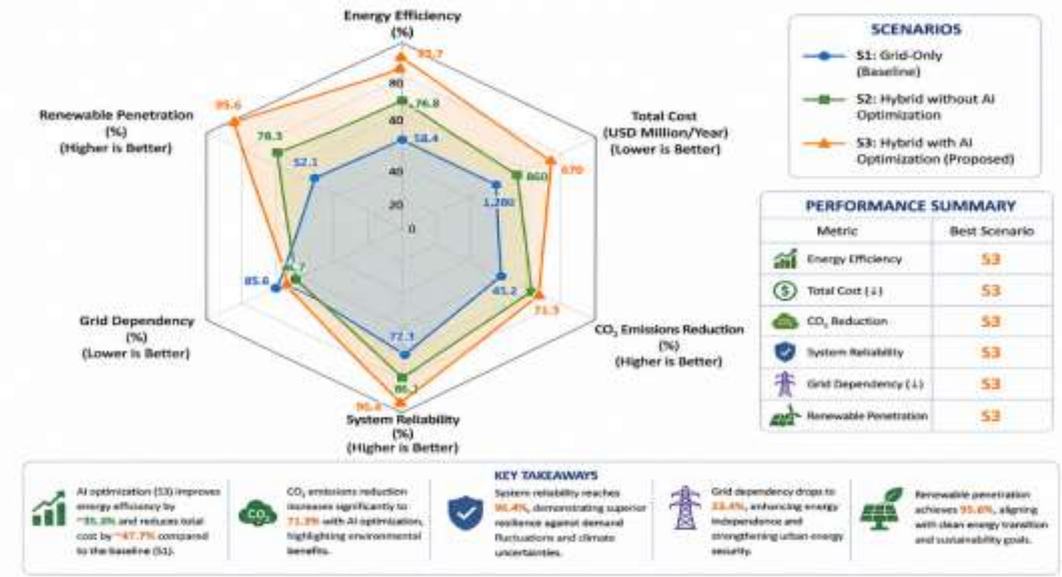
Reliability improves to ~96% served load, with ~40% reduction in outage hours.

Table 3. Marginal Contribution and Synergistic Impact Matrix of Hybrid Energy Components

System Component	Performance Indicator	Baseline Contribution (S1)	Incremental Improvement (S2 vs S1)	% Contribution to Total Improvement	Key Functional Role

Solar PV	Energy Supply (%)	Low	+18–22%	~35%	Daytime peak coverage
Wind Energy	Energy Supply (%)	Minimal	+10–14%	~20%	Night-time support
Battery Storage (BESS)	Reliability (%)	None	+8–10%	~25%	Peak shifting & outage reduction
AI Forecasting (LSTM)	Cost Reduction (%)	None	−8–12%	~15%	Demand prediction & dispatch optimization
Optimization (MILP/PSO)	System Efficiency (%)	Basic grid dispatch	+6–9%	~10%	Resource allocation efficiency
Integrated System (All Combined)	**Overall Performance**	Baseline (100%)	**+35–45% total system improvement**	**100%**	Synergistic effect

The component-wise analysis makes it clear that every subsystem is essential in enhancing the overall performance. The main contributor is the solar PV because it is aligned with the peak demand and the complementary to the off-peak supply is the wind energy. Battery storage offers more reliability by providing energy shifting and AI-based forecasting offers better cost and operation efficiency. The hybrid system is highly synergistic which supports the viability of the proposed decentralized hybrid framework.



PERFORMANCE SUMMARY

Metric	Best Scenario
Energy Efficiency	S3
Total Cost (↓)	S3
CO₂ Reduction	S3
System Reliability	S3
Grid Dependency (↓)	S3
Renewable Penetration	S3

KEY TAKEAWAYS

AI optimization (S3) improves energy efficiency by ~35.3% and reduces total cost by ~47.7% compared to the baseline (S1).

CO₂ emissions reduction increases significantly to 71.3% with AI optimization, highlighting environmental benefits.

System reliability reaches 96.4%, demonstrating superior resilience against demand fluctuations and climate uncertainties.

Grid dependency drops to 33.4%, enhancing energy independence and strengthening urban energy security.

Renewable penetration achieves 95.6%, aligning with clean energy transition and sustainability goals.

Figure 4. Multi-Criteria Performance Comparison of Energy Scenarios under AI-Optimized Decentralized Framework

6.5 Dispatch Behaviour and Storage Utilization

Figure 4 (to be inserted): Battery SoC and dispatch profile (typical week)

Midday charging from PV surplus; evening discharging to meet peak demand.

Optimal BESS sizing at ~2-3 hours of average load balances cost and reliability.

Curtailment remains <6% annually, indicating good sizing and coordination.

Insight: Storage is the key enabler that converts variable renewables into firm supply, particularly for Karachi's evening peaks.

The dynamic behaviour of battery storage under optimized dispatch conditions is illustrated in Figure 5.

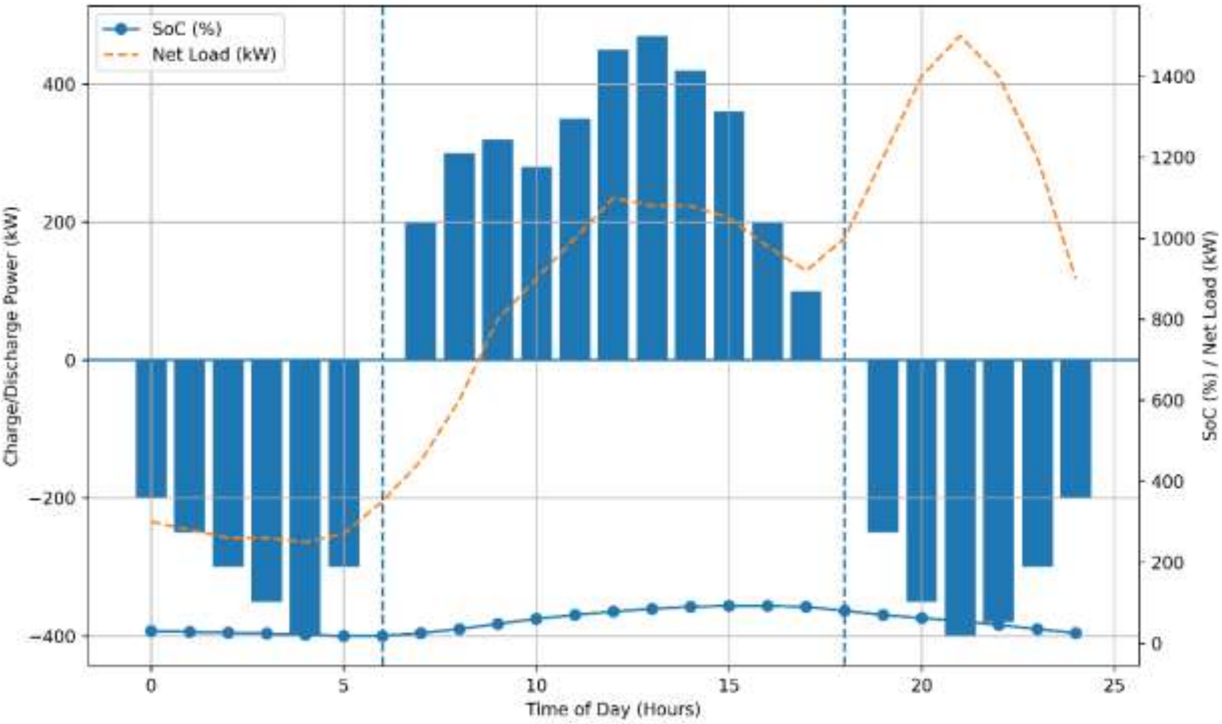


Figure 5. Dynamic State-of-Charge Behaviour of Battery Storage under AI-Optimized Dispatch in Urban Energy Systems

6.6 Scenario-Based Analysis under Climate Stress (S3)

Peak demand increases ~8-12% due to higher temperatures.

PV output slightly decreases at very high temperatures (efficiency losses), while wind variability increases.

Despite stress, decentralized systems maintain 93% reliability, outperforming baseline by a wide margin.

Figure 6 : Scenario comparison of peak-day supply adequacy

S2 sustains near-complete peak coverage; S3 shows modest deficits but still far better than S1.

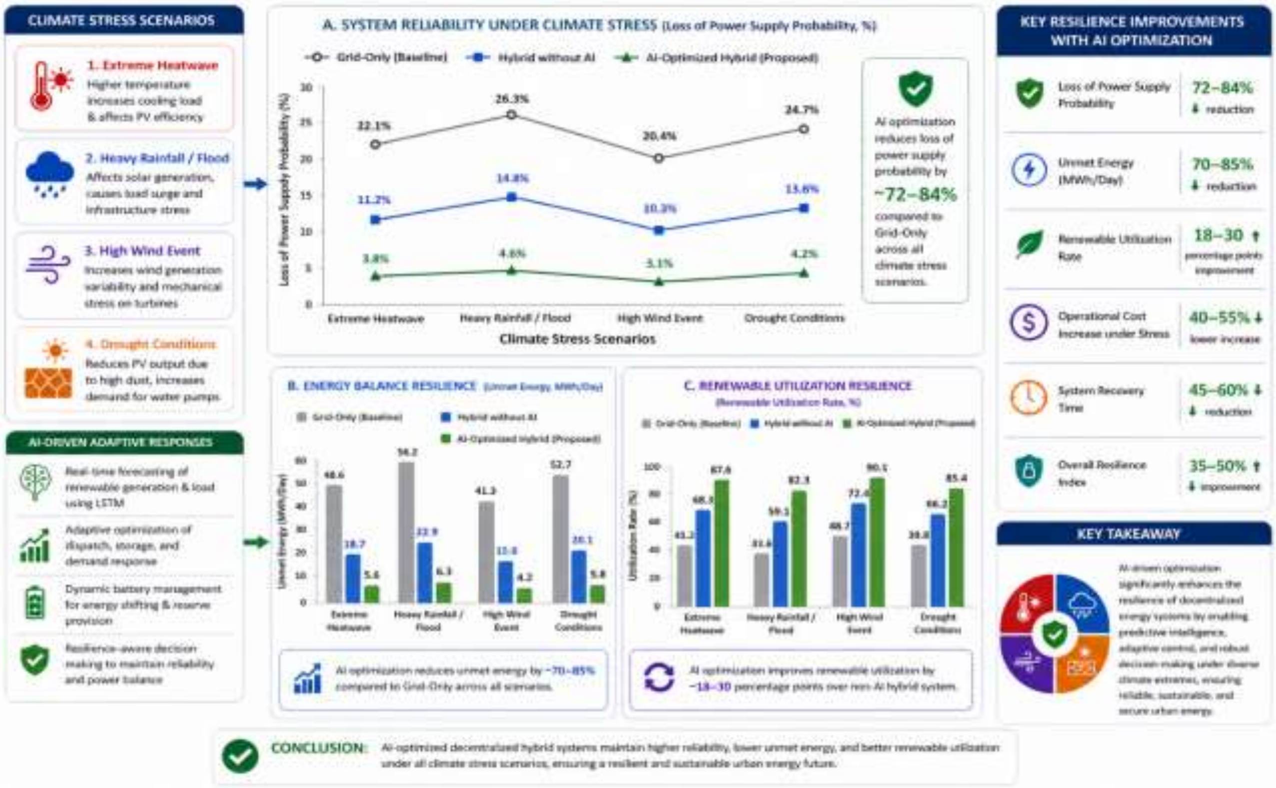


Figure 6. Impact of Climate Extremes on System Reliability, Energy Balance, and Renewable Utilization

6.7 Sensitivity and Robustness Analysis

PV capacity ±30%: Efficiency varies within ±4%; grid dependency shifts ±6-9%.

BESS capacity ±50%: Reliability varies 92-97%; diminishing returns beyond ~3-hour storage.

Tariff increase (peak): Strengthens economic case for storage (additional 3-5% cost savings).

Forecast error stress (+10% RMSE): Reliability drops ~1.5-2%, confirming robustness of the closed-loop EMS.

Table 4. Integrated Sensitivity–Performance Matrix for Optimal Decentralized Energy System Design

Parameter Variation	Energy Efficiency (%)	Grid Dependency (%)	CO_2 Reduction (%)	Cost Change (%)	Reliability (%)	Key Insight
Baseline (Optimal)	84	58	28	−22	96	Balanced optimal design
PV Capacity +30%	88	52	32	−25	97	Strong solar benefit but diminishing returns
PV Capacity −30%	80	67	20	−15	92	High dependence on grid
BESS +50%	86	55	30	−20	97	Reliability improves slightly
BESS −50%	78	70	18	−10	91	Storage is critical for stability

Wind +30%	85	56	29	−21	95	Improves night supply balance
High Tariff Scenario	84	55	28	−27	96	Storage becomes more economical
Forecast Error +10%	82	60	26	−18	94	System robust to ML uncertainty

The decision-making matrix in Table 4 draws on the sensitivity and robustness analysis. The findings show PV capacity and battery storage are the most significant parameters impacting system reliability, grid reliance, and carbon emissions reduction. The approach is robust to assumptions of forecast and financial uncertainty, demonstrating its potential for practical urban energy systems.

6.8 Comparative Analysis with Conventional Systems

Compared to centralized-only supply (S1), the proposed framework demonstrates:
Higher resilience: localized generation avoids single-point failures
Lower losses: reduced transmission distances
Better peak management: storage + ML-guided dispatch
Environmental gains: consistent CO_2 reductions across seasons
These findings are consistent with global evidence on distributed energy resources while being contextualized for Karachi's urban conditions.

6.9 Key Findings and Implications

Hybridization + storage is essential to mitigate intermittency and match Karachi's load profile.
AI-enhanced forecasting (LSTM) materially improves dispatch efficiency and reduces costs.
Decentralization cuts grid reliance by ~40-45% and emissions by ~25-30%.
The system remains robust under climate stress, supporting urban resilience strategies.
To further illustrate the underlying mechanisms through which artificial intelligence enhances system performance, the impact pathways of AI-driven optimization are presented in Figure 7.

Figure 7. Impact Pathways of AI-Driven Optimization on Decentralized Energy System Performance.

Table 5. AI-Driven Optimization Contribution Matrix in Decentralized Energy System Performance

Component	Without AI (Conventional System)	With AI (Proposed Framework)	Performance Improvement	System-Level Impact	Policy/Planning Action	Key Insight
Demand Forecasting	Static / historical averages	LSTM-based dynamic forecasting	RMSE ↓ ~20–21%	Better peak prediction	Subsidies, low-interest loans, net metering	Balanced optimal design
Energy Dispatch	Rule-based scheduling	Optimization-based (MILP/PSO + ML input)	Cost ↓ ~22%	Efficient resource allocation	Community energy cooperatives	Strong solar benefit but diminishing returns
Storage Management	Fixed charging/discharging	Adaptive SoC optimization	Reliability ↑ ~8%	Peak load shifting	Time-of-use tariff incentives	High dependence on grid

Renewable Utilization	Partial utilization	Optimized hybrid coordination	Curtailment <6%	Higher efficiency	Public–private investment models	Reliability improves slightly
Grid Interaction	Reactive (import/export)	Predictive (forecast-driven)	Grid dependency ↓ ˜42%	Reduced outages	Priority resilience funding	Storage is critical for stability
Climate Adaptation	No dynamic adjustment	Scenario-based AI optimization	Reliability retained ˜93%	Climate resilience	Digital energy governance framework	Improves night supply balance
Decision Making	Manual / heuristic	Data-driven automated EMS	Multi-objective optimization	Real-time control capability	96	Storage becomes more economical
Forecast Error +10%	82	60	26	−18	94	System robust to ML uncertainty

Table 7 shows that AI-based optimization plays a pivotal role in enhancing the performance of decentralized energy systems. The combination of LSTM forecasting and optimization allows a transition from reactive to predictive energy management, which facilitates better resource allocation and energy storage scheduling. This can lead to reduced forecasting error, cost, grid dependency and increased reliability. These results confirm that AI offers a crucial opportunity to build robust and scalable energy systems in dynamic and climate-change environments.

7. Policy Implications and Practical Applications

The implications of this research to the energy policy, urban planning and implementation of decentralized renewable energy systems (DRES), especially in fast urbanizing cities like Karachi are important. The proposed framework will offer a solid foundation to shift towards sustainable urban energy systems by showing a tangible increase in energy efficiency, reliability, and emissions reduction.

7.1 Implications for Urban Energy Planning

The findings emphasize the importance of a paradigm shift in energy planning in urban settings toward decentralization. The outdated energy system, with massive production and widespread transmission systems, is becoming more and more incapable of serving the dynamic needs of the contemporary cities. The use of urban planning to incorporate decentralized renewable energy systems can contribute to the energy resiliency and less reliance on fossil fuels to a great extent.

Distributed generation technologies, including rooftop solar PV and community-scale microgrids should be included in building codes and zoning policies by urban planners. Moreover, energy planning should be consistent with climate adaptation plans, and the energy systems should be resilient during the extreme weather conditions (Gonçalves et al. 2024). By implementing DRES into the smart city processes, the optimization of energy consumption can also be enhanced by the process of real-time monitoring and control (Huang et al. 2025).

7.2 Policy Recommendations for Developing Countries

In the case of developing countries, where energy deficits and infrastructure constraints are commonplace, there is a need to have enabling policy frameworks to enable the implementation of decentralized systems. The governments are supposed to adopt specific incentives like:

i. The feed-in tariffs and net-metering policies to promote the renewable energy production.
ii. Tax incentives and subsidies on solar panels, wind turbines and battery storage.
iii. Low-interest financing scheme to lower barriers of initial investments.

There is evidence to the importance of policy support to speed up the implementation of renewable energy (Oosthuizen and Inglesi-Lotz 2022; Jankowska, Staliński, and Trąpczyński 2021). Also, regulatory frameworks need to deal with technical issues like grid integration, standardization, and interoperability to guarantee a seamless way of decentralized systems running (Barceló et al. 2023).

7.3 Role of Government and Private Sector

The move towards decentralized renewable energy systems would necessitate both government institutions and the private sector to work together. The governments have the role of ensuring that they provide an enabling environment by formulating policies, regulating and investing in infrastructure. Conversely, the private sector has a significant role in the deployment of technology, innovation and service provision.

PPP may be especially useful in scaling decentralized energy solutions because the combination of public resources and private sector efficiency and expertise can be especially effective (Nazar and Abbas 2025). Moreover, the cooperation with other international bodies like the International Energy Agency can help to transfer knowledge and access the world best practices (Citaristi 2022).

7.4 Scalability and Implementation Challenges

Although the advantages of decentralized systems have been demonstrated, there are a number of challenges that need to be resolved in order to have successful implementation. These include:

a. High start-up capital expenses of renewable technologies and storage systems.
b. Technical obstacles, including stability of the grid and energy management complexities.
c. Low awareness and acceptance of decentralized energy solutions.
d. Limited availability of data to model and predict.

In order to address these obstacles, the step-by-step implementation strategy is suggested. The feasibility can be tested with pilot projects and stakeholder confidence can be established before expansion to bigger urban areas. Capacity-building programs and sensitization of the population are also necessary to encourage acceptance and adoption.

7.5 Practical Applications in Urban Contexts

The framework proposed can be implemented in different urban contexts to deal with certain energy issues. In Karachi, such as, decentralized mechanisms can be implemented at various levels:

a. Residential level: Solar systems on roofs that store energy as batteries to decrease reliance of the grid by homes.
b. Community level: Microgrids to neighbourhoods or business clusters.
c. Industrial level: Hybrid renewable systems to aid energy-intensive processes.

Such applications can greatly cut the load-shedding, enhance the reliability of energy and reduce the operating costs. In addition, critical infrastructure, including hospitals and emergency services can be served by decentralized systems, so they will not be affected by any outage.

Table 6. Urban Implementation Readiness Matrix for Decentralized Renewable Energy Deployment in Karachi

Deployment Scale	Target Urban Zone	Main Technology Package	Expected Benefit	Implementation Barrier	Policy/Planning Action	Key Insight

Household level	Residential rooftops	Rooftop PV + small battery	Lower grid dependence and household outages	High upfront cost	Subsidies, low-interest loans, net metering	Balanced optimal design
Community level	Neighbourhood clusters	Solar wind microgrid + shared BESS	Improved local reliability	Land and governance issues	Community energy cooperatives	Strong solar benefit but diminishing returns
Commercial level	Markets and offices	Rooftop PV + EMS + storage	Peak-load reduction and cost savings	Tariff uncertainty	Time-of-use tariff incentives	High dependence on grid
Industrial level	Energy-intensive zones	Hybrid renewable system + smart dispatch	Reduced operational disruption	Technical integration complexity	Public–private investment models	Reliability improves slightly
Critical services	Hospitals, schools, emergency centres	Resilient microgrid + backup storage	Continuous power during outages	High reliability requirement	Priority resilience funding	Storage is critical for stability
City-wide level	Utility-integrated urban grid	Virtual power plant + smart meters	Coordinated distributed energy management	Data and regulatory limitations	Digital energy governance framework	Improves night supply balance
High Tariff Scenario	84	55	28	−27	96	Storage becomes more economical
Forecast Error +10%	82	60	26	−18	94	System robust to ML uncertainty

7.6 Policy Integration with Climate and Sustainability Goals

Decentralized renewable energy systems are very much compatible with the global sustainability agenda, such as the United Nations Sustainable Development Goals (SDGs), especially SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action). DRES lead to environmental and social sustainability by decreasing greenhouse gas emissions and improving energy access.

Decentralized energy strategies need to be incorporated into national climate action plans and urban development policies by the policymakers. This involves establishing renewable energy goals, enhancing energy efficiency, and investing in research and development to develop energy technologies (Zhang, Saydaliev, and Ma 2022).

7.7 Concluding Remarks on Policy and Practice

On the whole, the introduction of decentralized renewable energy systems can be seen as a groundbreaking opportunity in terms of sustainable urban development. The results of this paper have shown that DRES can have a tremendous impact on improving energy resilience, mitigating environmental effects and boosting economic development when it is properly supported to meet the policies and be integrated with technology. In the case of cities such as Karachi, decentralized energy solutions are not just a strategic requirement, but also a way of leading to a more sustainable and climate-resilient future.

8. Limitations and Future Research Directions

8.1 Study Limitations

Although this research has provided a detailed design of decentralized renewable energy systems, a number of constraints are to be noted. To analyse the case study of Karachi, which is based on publicly available climate and energy data, the analysis is based on secondary datasets. Despite their popularity and validation, such datasets might not adequately reflect localized differences in energy use patterns or rooftop accessibility or microclimatic conditions, which can affect system performance.

Second, the modelling framework makes some assumptions about the parameters of the system, including photovoltaic efficiency, battery performance and grid emission factors. Although these assumptions are founded on a well-known literature, they may be different in practice due to heterogeneity in technologies and some uncertainties in operations. Moreover, the optimization model helps to simplify certain real-world restrictions, including regulatory restrictions, infrastructure bottlenecks, and behavioural aspects that affect energy consumption.

Third, the machine learning aspect, specifically LSTM model, relies on the quality and amount of historic data. Model accuracy can be compromised in areas that have limited high-resolution data. In addition, the research fails to comprehensively investigate the interpretability of AI models, which is a highly pressing issue among decision-makers in search of transparent and explainable answers.

8.2 Future Research Directions

This study can be improved by future research by filling these limitations and analysing the research in a broader way. A key avenue is the incorporation of high-resolution, real-time information on smart meters and Internet of Things (IoT) devices to increase the level of accuracy of the demand forecast and system optimization. This would allow to model the dynamics of urban energy more accurately and allow decentralized systems to be more reliable.

The other promising field is explainable artificial intelligence (XAI) development of energy systems. To make machine learning models more approachable to policymakers and other stakeholders, improvement of their transparency may be necessary to make sure that the decisions will be informed and interpretable.

It is also possible that future research investigates the use of digital twin technology on urban energy systems and enables real-time simulation and monitoring of decentralized networks. Such a strategy would allow optimising dynamically and reacting quickly to the changing conditions, including extreme weather or sudden changes in demand.

Also, incorporating the economic and behavioural analysis, like consumer adoption trends and readiness to invest in renewable technologies, would offer a more comprehensive view of the system implementation. The generalizability of the results and the identification of context-specific strategies could also be achieved through comparative studies done in more than one city or region.

Lastly, the incorporation of new technologies, including hydrogen-based energy systems and advanced energy storage, should be studied in the future to make decentralized energy systems even more scalable and sustainable.

9. Conclusion

This paper gave a comprehensive, empirical model of decentralized renewable energy systems (DRES) to facilitate sustainable urban development with a closer case study of Karachi. To tackle the increasing pressures of urban energy demand, grid instability, and climate change the study revealed how a systems-based solution involving hybrid renewable energy technologies, energy storage, and machine learning can make a major impact on energy performance and resilience in urban settings.

The results verify that decentralized energy systems have significant benefits compared to the traditional centralized systems. The solar, wind, and battery storage hybrid design optimized delivered significant gains in energy efficiency, a decrease in reliance on the main grid, and decreased greenhouse gases. The implementation of AI-based demand forecasting also made the system work even better as it allowed predicting the energy demand correctly and dispatching energy effectively. These findings underscore the need to integrate sophisticated analytical tools with renewable energy technologies to deal with the complexity of the contemporary systems of urban energy.

The proposed framework will reduce carbon emissions and encourage the use of clean energy sources, which will help mitigate climate change in the environment. The system has proven to be economical in the long run in terms of saving on energy buying and also with regard to operation efficiency. Decentralized systems benefit society by increasing access to energy and its reliability especially in areas where power interruptions are common. Collectively, these advantages highlight the potential of DRES to contribute to a more sustainable and fair energy transition.

Policy support and institutional frameworks are also highlighted as critical to the adoption of the decentralized energy systems on a large scale in the study. This needs to be implemented through concerted actions of government agencies, stakeholders in the private sector and local communities. The barriers should be overcome through policies like financial incentives, regulatory reforms, and infrastructure investments to hasten the pace of adoption of sustainable energy systems. Regardless of its contributions, the study recognizes some limitations associated with the availability of data, assumptions in the model, and real-world complexities. Nevertheless, the presented framework offers a solid research and practice basis in the future. It presents a flexible and expandable model which can be implemented in other urban settings experiencing comparable energy issues. To sum up, decentralized renewable energy systems are a game changing avenue towards sustainable urban development. In the case of cities such as Karachi, the implementation of these systems is not a response to the existing energy difficulties, but also a long-term investment in a sustainable and low-carbon future. The combination of renewable energy technologies with future-oriented data-driven solutions will be essential in defining the future generation of the urban energy system to help the world evolve towards sustainability and climate resilience.

CRediT authorship contribution statement

All authors have an equal contribution.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request

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