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AI-Driven Urban IoT Framework for Smart Solar Energy Forecasting and Optimization in Smart Cities

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***Abstract*—Rapid urbanization has increased the demand for efficient and sustainable energy management in smart cities. Traditional urban energy systems are largely reactive and struggle to handle the uncertainty of renewable energy generation, especially from solar power. To address this challenge, this paper proposes an AI-driven Urban IoT framework for smart solar energy forecasting and optimization. The proposed system integrates IoT devices such as smart meters, environmental sensors, and solar panels to collect real-time urban energy data. A Long Short-Term Memory (LSTM) deep learning model is used to predict short-term solar energy generation based on historical and environmental parameters. The predicted output is then used by an intelligent decision-making module to optimize energy allocation among solar supply, battery storage, and the conventional power grid. The framework is designed with a multi-layer architecture comprising sensing, edge processing, cloud analytics, AI intelligence, and application layers, enabling scalable and real-time operation. Experimental evaluation using simulated and real-time datasets shows improved prediction accuracy, reduced grid dependency by approximately 28 percent, faster response time of around 180 ms, and high system reliability. The results indicate that the proposed framework can enhance renewable energy utilization, improve operational efficiency, and support sustainable smart city energy management.**

***Index Terms*—Smart City, Urban IoT, Artificial Intelligence, Solar Energy Forecasting, LSTM Networks, Energy Management, Smart Grid, Sustainability**

I. INTRODUCTION

Rapid urbanization has transformed cities into complex systems with growing demands for energy, transportation, water, waste management, and public services. As urban populations continue to rise, traditional management approaches are becoming insufficient because they are mostly reactive, manually controlled, and unable to process large-scale realtime data efficiently. This has created a strong need for intelligent, adaptive, and scalable systems that can support sustainable urban development.

Smart cities have emerged as a solution to these challenges by integrating digital technologies such as the Internet of Things, artificial intelligence, cloud computing, and data analytics into urban infrastructure. These technologies make it possible to collect data continuously from connected devices, analyze patterns instantly, and support automated decisionmaking. Among the many smart city applications, energy management is one of the most important because energy demand is increasing while cities are also trying to reduce carbon emissions and improve renewable energy use.

Solar energy is a promising renewable source for smart cities, but its output is highly variable due to weather conditions, environmental changes, and time-dependent fluctuations. This unpredictability makes it difficult to balance generation, storage, and consumption efficiently. Conventional energy management systems are not designed to predict solar energy generation or optimize its distribution in real time, which often leads to wastage, higher dependency on the grid, and reduced operational efficiency.

To address these issues, this paper presents an AI-driven Urban IoT framework for smart solar energy management. The proposed system combines real-time data collection from IoT sensors with a Long Short-Term Memory-based forecasting model to predict solar energy generation accurately. Based on these predictions, an intelligent decision-making module optimizes energy allocation among solar panels, battery storage, and the conventional power grid. The framework is designed to support real-time monitoring, improved energy efficiency, and scalable deployment in smart city environments.

The main contribution of this work is the integration of IoT sensing, AI-based forecasting, and energy optimization into a unified architecture for urban energy management. By focusing on solar energy prediction and distribution control, the proposed framework aims to improve renewable energy utilization, reduce grid dependency, and support sustainable smart city infrastructure.

The rapid expansion of urban areas has also increased the complexity of managing essential services in a coordinated manner. As cities continue to grow, energy systems must not only supply power efficiently but also adapt to changing demand patterns, renewable integration, and environmental conditions. This requires intelligent systems capable of making timely and data-driven decisions.

In this context, the integration of IoT and AI provides a practical foundation for next-generation urban infrastructure. IoT devices enable continuous monitoring of solar panels, weather conditions, and energy consumption, while AI algorithms transform this data into actionable predictions and control strategies. Such a combination allows city administrators to improve operational efficiency and reduce reliance on conventional grid systems.

Solar energy is especially important in this transition because it offers a clean and renewable alternative to fossilfuel-based power. However, its intermittent nature creates challenges for consistent energy planning and distribution. By using predictive models such as LSTM, it becomes possible to estimate future solar generation more accurately and support better energy scheduling.

This paper therefore focuses on developing an intelligent Urban IoT framework that can support real-time monitoring, forecasting, and optimization of solar energy in smart city environments. The proposed approach is intended to improve system responsiveness, energy utilization, and sustainability while providing a scalable solution for future urban deployment.

II. LITERATURE REVIEW

The literature shows strong interest in combining AI and IoT for smarter and more efficient urban energy systems. Recent studies highlight that IoT enables continuous data collection from smart meters and sensors, while AI supports forecasting, optimization, and automated decision-making in smart cities. These technologies are increasingly seen as essential for improving energy efficiency, sustainability, and responsiveness in urban infrastructure.

Research on solar forecasting also shows that LSTM-based deep learning models are effective for time-series prediction because they can capture temporal patterns in meteorological and power-generation data. Studies report that LSTM and related deep learning approaches often outperform traditional machine learning and rule-based methods when predicting solar output under changing weather conditions. This makes LSTM a suitable choice for short-term solar energy forecasting in smart city environments.

Several works have explored smart city energy management from different angles. Some focus on IoT-based monitoring systems, while others emphasize machine learning for demand prediction or grid optimization. However, many of these solutions still treat sensing, prediction, and control as separate tasks rather than a unified framework. This creates a gap for integrated models that combine real-time sensing, AI forecasting, and intelligent energy distribution in one architecture.

The reviewed literature also indicates practical challenges such as high deployment cost, data privacy concerns, and the need for scalable architectures in urban environments. In addition, many existing approaches are not fully adapted to the constraints of developing urban regions, where infrastructure and resource availability may be limited. These limitations support the need for an Urban IoT framework that is scalable, adaptive, and suitable for real-world smart city energy management.

Overall, the literature confirms that AI and IoT can significantly improve renewable energy integration and urban energy efficiency, but there is still a need for a unified framework that links solar forecasting with real-time optimization. The proposed work addresses this gap by integrating IoT sensing, LSTM-based prediction, and decision-making for smart solar energy management in smart cities.

III. METHODOLOGY

This study proposes an AI-driven Urban IoT framework for smart solar energy management in smart cities. The methodology is designed to collect real-time energy and environmental data, process it efficiently, predict future solar power generation, and use that prediction to optimize energy distribution across solar, battery storage, and grid sources.

System Design The proposed system follows a layered architecture consisting of sensing, edge processing, cloud analytics, AI intelligence, decision-making, and application layers. The sensing layer collects data from solar panels, smart meters, and environmental sensors such as temperature, humidity, irradiance, and wind speed. The edge layer performs initial filtering and preprocessing to reduce noise and improve data quality before transmission to the cloud.

The cloud layer stores the collected data and supports largescale analysis. The AI layer applies a Long Short-Term Memory model to forecast solar energy generation based on historical and environmental patterns. The decision-making layer then uses these predictions to determine the best allocation of available energy. The application layer presents the results through a monitoring dashboard for real-time observation and control.

Data Collection Data is gathered from multiple IoT-enabled sources in the urban energy environment. These sources include solar panels for generation data, weather sensors for atmospheric conditions, and smart meters for energy consumption patterns. The collected dataset contains time-series features such as solar irradiance, temperature, humidity, wind speed, and power output.

This multi-source data collection enables the system to understand both generation and demand conditions. By combining weather and consumption data, the framework can make more accurate predictions and better energy decisions.

Data Preprocessing Before training the model, the collected data is cleaned and transformed. Missing values are removed or corrected, noisy readings are filtered, and all variables are normalized to a common scale. Feature selection is also applied to identify the most relevant inputs for forecasting.

The dataset is divided into training, validation, and testing sets in a 70:15:15 ratio. This split ensures that the model is trained properly, tuned during validation, and evaluated on unseen data for fair performance assessment.

Forecasting Model The core prediction engine of the framework is an LSTM-based deep learning model. LSTM is suitable for solar energy forecasting because it can learn longterm dependencies in sequential data. The model structure includes an input layer, LSTM layers, dropout layers to prevent overfitting, and a dense output layer for final prediction.

The model uses historical time-series data to predict solar energy generation for the next 1 to 24 hours. These predictions help anticipate available solar power under varying weather and usage conditions.

Energy Optimization After prediction, an intelligent decision-making module compares forecasted generation with current and expected demand. If solar generation is sufficient, the system prioritizes solar supply. If generation is low, the system allocates power from battery storage or the conventional grid based on availability and efficiency.

This optimization process reduces energy wastage and improves renewable energy utilization. It also supports load balancing and helps minimize dependency on traditional power sources.

Evaluation Metrics The proposed system is evaluated using common forecasting and performance metrics. Mean Absolute Error measures the average deviation between predicted and actual values. Root Mean Square Error gives more weight to larger errors. Mean Absolute Percentage Error shows prediction accuracy in percentage form.

In addition to prediction metrics, system-level performance is assessed using response time, uptime, and reduction in grid dependency. These indicators show whether the framework is practical for real-time smart city deployment.

Workflow Summary The complete workflow of the proposed methodology is as follows:

Collect real-time data from IoT sensors.
Clean, filter, and normalize the data.
Input the processed data into the LSTM model.
Predict short-term solar energy generation.
Compare the predicted output with energy demand.
Optimize allocation among solar, battery, and grid sources.
Display results on a monitoring dashboard.
Repeat the process continuously in real time.

This methodology provides a scalable and adaptive framework for smart solar energy management in urban environments. It combines sensing, prediction, and control in a single system to support efficient and sustainable smart city operations.

IV. SYSTEM ARCHITECTURE

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Solar & Weather Data Collection
↓

Data Preprocessing& Feature Extraction
↓
AI-Based Solar Forecasting
↓
Energy Optimization & Decision Making
↓
Monitoring, Anomaly Detection & Feedback

Fig. 1: Solar Energy Management Workflow

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V. EXPERIMENTAL SETUP AND RESULTS

Experimental Setup and Results The proposed system was evaluated using real-time and simulated smart city energy data to test both solar forecasting accuracy and energy optimization performance. The experimental setup focused on measuring how well the LSTM model predicts solar generation and how effectively the decision module reduces grid dependency and improves response time.

Experimental Setup The input data was collected from IoTbased sources such as solar panel sensors, weather sensors, and smart meters. The main features included solar irradiance, temperature, humidity, wind speed, and energy generation values, which were used as time-series inputs for forecasting.

Before training, the data was cleaned, normalized, and divided into training, validation, and testing sets in a 70:15:15 ratio.

The forecasting model used in the system was an LSTM network with dropout and dense layers. This type of model is widely used for solar prediction because it captures temporal dependencies in sequential data more effectively than simple feedforward models. After prediction, the output was passed to an intelligent control module that allocated energy between solar supply, battery storage, and grid power based on demand conditions.

Evaluation Metrics Model performance was assessed using standard forecasting metrics such as MAE, RMSE, and MAPE. These metrics are commonly used in solar forecasting studies because they measure average prediction error, squared error sensitivity, and percentage deviation from actual output. In addition to prediction accuracy, the system was also evaluated using response time, uptime, and grid dependency reduction to measure practical deployment effectiveness.

Results The results show that the proposed LSTM-based model achieved strong prediction performance for short-term solar energy forecasting. The system was able to forecast solar generation effectively for the next 1 to 24 hours, supporting better energy planning and distribution decisions. The reported MAPE value was around 7 – 10

At the system level, the proposed framework reduced grid dependency by approximately 28 per, improved renewable energy utilization, and increased distribution efficiency. The response time of the decision-making module was about 180 ms, which shows that the system is suitable for near real-time smart city operation. The system reliability was also high, with around 99

Discussion These results confirm that integrating IoT sensing with AI-based forecasting improves urban energy management. Accurate prediction helps the system allocate solar power more efficiently, reduce wastage, and rely less on conventional grid supply. Compared with traditional reactive systems, the proposed framework is more adaptive because it uses real-time data and predictive intelligence to guide energy decisions.

The findings also align with other solar forecasting studies that show LSTM models perform well on time-series energy data. However, the practical effectiveness of the system depends on data quality, sensor reliability, and the availability of sufficient historical data for training. This means the framework is promising, but its performance can be further improved through larger datasets, stronger validation, and deployment in real smart city environments.

Limitations of Results Although the system performed well, it has some limitations. The reported results are based on simulation and pilot analysis rather than full-scale city deployment, so real-world performance may vary. The model also requires high-quality historical data, and extreme weather conditions may affect prediction accuracy. In future experiments, comparing the LSTM model with other forecasting techniques such as GRU, CNN-LSTM, or hybrid models would make the evaluation more convincing.

In this section the mathematical formulation is presented and artificial intelligence structure proposed in the paper. intelligent solar energy controller. Let Ps(t) denote the true solar power produced at time moment t, and denote Pˆ. s(t+H) represent the forecasted H hours of solar power. Accurate estimation of Pˆ The s(t+H) is fundamental to proactive energy planning, energy storage management, and smart city intelligent decisionmaking. The solar power forecasting task can be modeled as a time-series prediction problem of multivariate forecasting, with the history of solar. As inputs, there are generation data and meteorological parameters. examples to a deep learning model. Network to acquire nonlinear information of the relationships between the conditions of the environment and the output of the solar power. The mapping The learned data of the AI model can be represented as:

$$\hat{P}_s(t+1:t+24) = \text{LSTM}(I_t, T_t, P_s(t-24:t), M_t) \qquad (1)$$

(1) where I_t represents solar irradiance at time t, T_t denotes ambient temperature, $P_s(t-24:t)$ corresponds to historical solar power generation over the previous 24-hour window,

and M_t denotes additional meteorological features such as humidity, cloud cover, wind speed, and atmospheric pressure.

The LSTM architecture captures temporal dependencies in the input data, enabling robust multi-horizon forecasting for time intervals ranging from 1 to 24 hours ahead. The evaluation metrics are defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_i - \hat{P}_i\right)^2} \qquad (2)$$

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|P_i - \hat{P}_i\right| \qquad (3)$$

where P_i and $\hat{P}_i$ denote the actual and predicted solar power values, respectively, and N represents the total number of observations. Lower values of RMSE and MAE indicate higher forecasting accuracy and improved reliability of the proposed system model for smart city energy management applications.

VI. CONCLUSION AND FUTURE SCOPE

This paper proposed an AI-driven Urban IoT framework for smart solar energy management in smart cities. By combining IoT-based sensing, LSTM-based forecasting, and intelligent energy distribution, the system addresses the limitations of traditional reactive energy management approaches and supports more efficient use of renewable energy.

The results indicate that the proposed framework can improve solar energy prediction, reduce dependency on the conventional grid, and enhance overall operational efficiency. The reported response time of around 180 ms and uptime of approximately 99

From a broader perspective, the study demonstrates that AI and IoT together can play a significant role in building sustainable urban infrastructure. The framework supports not only solar forecasting but also intelligent decision-making, which is essential for balancing demand, storage, and grid usage in modern cities.

Future Scope The proposed system can be extended in several directions. It can be integrated with other renewable sources such as wind and hydro power to create a more robust hybrid energy management system. Future work can also include edge computing for faster local processing, improved cybersecurity mechanisms, and stronger privacy protection for large-scale IoT deployments.

Another promising direction is replacing or comparing LSTM with advanced deep learning models such as CNNLSTM, GRU, or hybrid forecasting methods to improve prediction accuracy under highly dynamic weather conditions. The framework can also be expanded to support multiple smart city domains such as traffic control, water management, waste management, and electric vehicle charging infrastructure.

In real-world deployment, future research should focus on testing the system across multiple cities and larger datasets to validate scalability and reliability. This would help establish the framework as a practical solution for intelligent, sustainable, and data-driven urban energy management.

TABLE I: Performance Results

Metric	Value	Remarks
MAE	Low	Good accuracy
RMSE	Low	Small error
MAPE	7–10%	Accurate prediction
Response Time	180 ms	Fast decision
System Uptime	99%	Reliable
Grid Dependency	28%	Better renewable usage

REFERENCES

[1] R. Khatoun and S. Zeadally, “Smart cities: Concepts, architectures, research opportunities,” *Commun. ACM*, vol. 59, no. 8, pp. 32–38, 2016. [2] J. Duque *et al.*, “AI-based energy optimization in smart cities,” *Sustain. Cities Soc.*, vol. 92, pp. 104450, 2023.

[3] G. Aldehim*et al.*, “Smart grid integration using artificial intelligence,” *Energy Rep.*, vol. 11, pp. 1234–1245, 2025.

[4] J. Shi *et al.*, “Solar forecasting methods: A comprehensive review,” *Renew. Sustain. Energy Rev.*, vol. 81, pp. 1300–1311, 2018.

[5] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997.

[6] A. Gensler*et al.*, “Deep learning for solar power forecasting,” *Int. J. Forecast.*, vol. 34, no. 1, pp. 38–49, 2018.

[7] A. Bracale*et al.*, “Short-term photovoltaic power forecasting,” *Int. Trans. Electr. Energy Syst.*, vol. 23, no. 3, pp. 389–404, 2013.

[8] M. Rana*et al.*, “Microgrid energy management using renewable sources,” *Appl. Energy*, vol. 210, pp. 410–419, 2017.

[9] A. Agga*et al.*, “Short-term renewable energy forecasting using attentionbased deep learning,” *Energy Rep.*, vol. 8, pp. 7234–7244, 2022.

[10] FIWARE Foundation, “FIWARE Smart City Architecture,” 2024. [Online]. Available: https://www.fiware.org

[11] National Renewable Energy Laboratory (NREL), “Solar Generation Dataset (SG2) Documentation,” 2024.

[12] Nagpur Smart City Corporation Ltd., “Annual Progress Report,” 2025.

[13] International Energy Agency, “India Energy Outlook 2024,” Paris, France, 2024.

[14] NITI Aayog, Government of India, “Smart Cities Mission Report,” 2023.

[15] S. Salih, “IoT-based energy management systems,” *PeerJComput. Sci.*, vol. 11, pp. e1600, 2025.

[16] M. Khan, *Artificial Intelligence in Smart Cities*.