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Intelligent solar energy forecasting for smart grids using KARN-EWOA within 6G-enabled IoT frameworks

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ABSTRACT

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Rapid urbanization and rising energy demands make sustainable energy management essential for future smart cities. This study aims to improve solar energy forecasting and smart grid efficiency by tackling issues like data inconsistencies, model optimization, and prediction accuracy. The proposed solution, titled 'Advancing Sustainable Urban Development through Intelligent Energy Management in Smart Grids,' leverages 6G IoT and Artificial Intelligence to enhance energy systems in Next-Generation Smart Cities (EMSG-KARN). This study aims to contribute to the Sustainable Development Goal (SDG) for energy, aligning with the national priority area of energy. Input data from Solar Power Generation and Weather Sensor datasets undergo pre-processing using the Adaptive Resilience Navigation Filter for cleaning and normalization. The processed data is then fed into the Kolmogorov–Arnold Recurrent Network (KARN) to predict solar energy production. Results show that EMSG-KARN achieves superior predictive performance, with 98% accuracy, 97% precision, 98.5% recall, and an F1-score of 96.5%, indicating significant improvements over traditional models. Ablation and cross-validation analyses confirm the contribution of each module, ensuring reliable and scalable solar energy forecasting. This framework provides urban energy planners with a robust, high-performing solution for integrating renewable energy sources, optimizing energy distribution, and improving grid efficiency. The proposed method supports sustainable urban development, climate goals, and offers a scalable, reliable approach for intelligent energy management in smart cities, bridging gaps left by existing AI-based techniques.

Contribution/Originality: By integrating advanced AI and 6G-enabled IoT technologies, the research develops sustainable urban energy management and forecasts solar energy consumption. The proposed approach demonstrates improved accuracy, higher recall, greater precision, and elevated F1 scores compared to traditional methods. It provides a clear, reliable framework for solar energy prediction, supporting sustainable urban growth aligned with smart city initiatives and technological advancements.

1. INTRODUCTION

Sustainable urban development through AI-powered smart energy grids enables the utilization of advanced technologies to improve efficiency in urban areas and promote environmental sustainability in energy consumption and use [1]. The 6G network offers ultra-high-speed, highly reliable wireless communication, supporting extensive IoT networks composed of wireless nodes installed throughout urban infrastructure [2]. These connected IoT devices gather extensive data on energy consumption and various urban systems [3]. Artificial intelligence tools and algorithms analyze, process, and optimize this data for energy management, distribution, and the integration of

renewable energy sources within smart grids [4]. This technological integration enhances monitoring, tracking, and management of energy resources while reducing waste and resource use [5]. In summary, smart energy grids leveraging 6G connectivity, IoT, and AI can transform cities into more sustainable urban environments. They promote ecological balance, demonstrate greater environmental viability, and improve residents' quality of life, contributing to the development of smarter, more sustainable cities [6, 7].

Sustainable urban development faces numerous barriers related to technology, safety, security, and infrastructure [8, 9]. A key challenge in implementing 6G and smart grids is ensuring interoperability among diverse devices and systems [10]. Additionally, managing the volume of data including storage, processing, and analysis poses significant difficulties [11, 12]. Incorporating renewable energy sources into smart grids presents technical challenges such as variability and grid stability, which require further research and resources [13]. Addressing these issues is crucial for unlocking the potential of sustainable, smart, and data-driven urban energy systems [14, 15]. Smart energy grids are vital for overcoming some challenges of sustainable urban development, emphasizing the need for scalable, future-proof infrastructure investments. Developing open standards and enabling interoperability among technologies will facilitate the integration of multiple systems and devices [16-18]. Collaboration in research and development is essential to achieve resilient, intelligent, and sustainable urban energy ecosystems capable of providing long-term, effective solutions [19, 20].

Several research works presented in the literature were based on sustainable urban development via 6G IoT and AI-powered smart energy grids; a few of them were reviewed here.

Samantaray [21] has presented AI-based routing models for smart city systems with IoT capabilities using machine learning, reinforcement learning, and predictive analytics. These models improve urban services such as traffic management, emergency response, and energy management. AI enhances efficiency, adaptability, and sustainability, addressing challenges related to data privacy and security while maintaining scalability for increasingly connected urban systems. However, the convergence efficiency was a disadvantage of AI-based routing models for smart city systems.

Raaj et al. [22] presented an integrated plan to incorporate renewable energy into sustainable cities while maintaining smart grid stability, utilizing 6G IoT, AI, and blockchain technologies. Load variations were predicted using machine learning and long short-term memory, solar energy forecasting employed LSTM, and microgrid energy consumption was optimized with deep Q-learning. A visualization dashboard and blockchain ensure visibility and auditability, enhancing grid efficiency, reliability, and acceptance of renewable energy sources (RES). The reliance on advanced technologies like AI, 6G IoT, and blockchain may introduce complexity and errors, potentially hindering widespread adoption.

Kovari [23] has presented the disruptive convergence of 6G, IoT, and AI to create Smart Empires or Systems of Intelligent and Adaptive Technology, emphasizing the need for ultra-fast, low-latency connections, AI optimization, and adaptive IoT-based applications. There is a current trend to incorporate these developments into future technology to benefit society. However, the industry must address significant issues such as system complexity and security vulnerabilities. If not managed properly, these issues could lead to technology failures and cyberattacks.

Prathiba et al. [24] presented a Digital Twin Framework for Optimizing Urban Traffic and Power Grids (DT-OF) that may help address urban traffic congestion and inefficiencies. The DT-OF combines a two-layer architecture of the Digital Twin with the Priority Age of Information Deep-Q Scheduler (PAoI-QS) to improve data processing and decision-making. One of the primary benefits of the DT-OF is its ability to optimize data processing and decision-making processes, thereby maximizing resource allocation and enhancing the performance of Smart Cities.

Al-Qarni et al. [25] examined the technological foundations, contributions to sustainability, and challenges associated with smart grids in smart cities. Their work provided a comprehensive overview of how smart grids contribute to urban sustainability by reducing carbon footprints, optimizing energy consumption, and incorporating renewable energy, as well as identifying obstacles such as computational and memory capabilities.

Tarannum et al. [26] discussed the opportunities that development of Smart Cities networks present to making urban environments more efficient by improving connectivity, resource management, and communicating with citizens in urban areas more effectively through the use of Internet of Things (IoT), Artificial Intelligence (AI), and Low-Power Wide Area Networks (LoRa). The Smart Cities Network document also outlined numerous obstacles to implementing smart cities, including lack of compatibility with existing hardware/software infrastructures, lack of stewardship of data, and the digital divide. Many benefits of using smart cities for urban operations, public safety, management, and meeting UN-SDGs are detailed within the Smart Cities Network report. The combination of IoT, AI, and LoRa communications in smart city networks can face significant challenges related to compatibility with existing infrastructure and the risk of exacerbating the digital divide among urban populations.

Akhter et al. [27] presented that combining IoT and AI for creating smart cities increases data collection and enhances decision-making across urban sectors. Ecosystem facilitators such as edge computing and federated learning support building smart cities. Security and interoperability challenges are being addressed with existing global solutions like blockchain and decentralized intelligence. The increased data collection and interconnectedness in IoT and AI-driven smart cities raise significant concerns about user privacy and potential data breaches, despite existing security measures. Table 1 summarizes recent research in this area.

Zafar et al. [28] suggested that Long Short-Term Memory (LSTM), Bidirectional Long Short-Term Memory (Bi-LSTM), and a hybrid model combining Autoencoder and Long Short-Term Memory (AE-LSTM) were trained and evaluated using mean absolute error (MAE) and mean squared error (MSE) as performance metrics, based on a year's worth of real-time solar power production data. The hybrid AE-LSTM model significantly outperforms both LSTM and Bi-LSTM models because it can analyze complex temporal patterns and correlations among datasets. This research demonstrates the potential of machine learning methods, especially the hybrid AE-LSTM model, to facilitate the integration of renewable energy sources into smart grid technologies, leading to more effective and environmentally conscious power systems.

Thanh et al. [29] proposed a hybrid model for predicting a building's three-phase load power in a smart solar microgrid, focusing on short-term load forecasting using CNN-Bi-GRU. The model employs a continuous-time sliding window, with CNN layers extracting features and transforming them into vectors. The optimal CNN-Bi-GRU structure was developed through hyperparameter optimization. The study compared and evaluated other advanced models, including RNN, LSTM, GRU, Bi-LSTM, and Bi-GRU, against the CNN-Bi-GRU's performance.

Table 1. Summary of Recent Research Work.

Reference	Algorithm	Focus	Key Findings	Limitations
Samantaray [21]	Deep Q-Networks (DQN)	AI-based routing for smart cities	Improves traffic, emergency, energy systems	Privacy and security risks
Raaj, et al. [22]	Artificial Neural Networks (ANN)	Renewable energy integration	ML and blockchain improve grid efficiency	High costs and system complexity
Kovari [23]	Convolutional Neural Network (CNN)	6G, IoT, AI convergence	Ultra-fast, adaptive tech benefits	Complexity and security challenges
Prathiba, et al. [24]	ANN	Urban traffic & power grid optimization	Improves data processing, decision-making, and resource use	Complex implementation, infrastructure needs
Al-Qarni, et al. [25]	Deep Neural Network (DNN)	Smart grids in smart cities	Supports sustainability via energy and carbon optimization	Theoretical; no new algorithm proposed
Tarannum, et al. [26]	DQN	IoT, AI, LoRa in smart cities	Enhances connectivity and resource management	Infrastructure compatibility issues
Akhter, et al. [27]	DRL	IoT and AI data in smart cities	Edge computing and blockchain improve decisions	Privacy and data breach concerns

The existing ANN, CNN, and DQN models applied to smart city energy management exhibit significant technical limitations that reduce their effectiveness. Numerically, DQN models often fail to converge efficiently in large-scale urban datasets, leading to low prediction accuracy and unstable energy forecasts. ANN models tend to overfit and achieve high RMSE because of their inability to represent sufficient features and capture complex temporal dependencies in solar energy data; they are also inefficient on edge devices. Although CNNs can extract spatial features, they have problems integrating multimodal sensor data, exhibit bias in prediction under heterogeneous urban conditions, and are constrained by edge computational and memory limitations, leading to suboptimal numerical performance. Overall, these limitations manifest in higher RMSE, lower F1-scores, inconsistent accuracy, and poor generalization across diverse environmental conditions, creating a clear technical gap for developing a model that ensures robust, accurate, and scalable energy forecasting in smart city environments. The study aimed to address these needs with an efficient state-of-the-art method, presenting a hybrid KARN with EWOA. The selection of KARN is motivated by its ability to better capture nonlinear and temporal dependencies in time-series data than other models, which is crucial for accurate solar energy production forecasting in smart grids. This enables the model to make highly accurate predictions under fluctuating weather conditions and dynamic urban energy demands. Furthermore, due to the Enhanced EWOA for weight tuning, faster convergence is achieved with KARN, resulting in low RMSE and improved robustness, especially suitable for smart cities.

This study is guided by two primary research questions. First, how can smart-city energy systems effectively forecast and manage solar power generation to meet rising urban energy demands while maintaining sustainability, reliability, and resilience? Second, does the integration of a Kernel-based Attentive Recurrent Network (KARN) for solar energy prediction and an Enhanced Whale Optimization Algorithm (EWOA) for parameter optimization improve the accuracy, robustness, and overall efficiency of energy management in modern smart urban grids?

In this article, the proposed EMSG-KARN method for intelligent energy management in sustainable urban development relies on integrating the KARN for solar energy production prediction with the EWOA for optimizing the KARN weights. The integration of these two technologies enhances prediction accuracy and model performance by effectively tuning network parameters to respond to variability in energy consumption. The proposed EMSG-KARN model demonstrates superior predictive performance compared to existing methods, consistently outperforming traditional deep learning and reinforcement learning approaches. Existing studies, such as DQN, ANN, and CNN-based methods, show that EMSG-KARN effectively addresses limitations observed in earlier studies, including overfitting, limited capacity to capture complex temporal dependencies, poor efficiency on edge devices, and suboptimal handling of diverse sensor data. The model also performs reliably across different smart grid datasets, highlighting its adaptability and robustness.

The balance paper is ordered as follows: Part 2 displays the proposed method, Part 3 presents results with discussions, and Part 4 concludes the paper.

2. PROPOSED METHODOLOGY

The overall approach to this research is shown here by how weather and solar power generation data are collected. The data contains information on how much power was generated, how much solar radiation fell on an area, and how the weather was at the time of power generation. To prepare this data for analysis by the KARN, it has been pre-processed.

Pre-processing involves two steps: cleaning and normalizing, both performed using ARNF. After pre-processing, the processed data is input to KARN to generate solar energy production predictions. Subsequently, EWOA is used to fine-tune KARN parameters, further improving its performance.

The proposed EMSG-KARN model predicts solar energy generation by integrating a recurrent network with adaptive weight optimization. Input variables, including solar irradiance, temperature, humidity, and power output, are consistently processed to ensure reliable predictions. Unlike prior DQN-, ANN-, CNN-, LSTM-, or GRU-based

models, EMSG-KARN effectively handles nonlinear temporal dependencies, reduces overfitting, and generalizes better across diverse datasets, providing higher accuracy and robustness. The block diagram of the proposed MDD-EEG-CPINN is displayed in Figure 1. The entire process is given below.

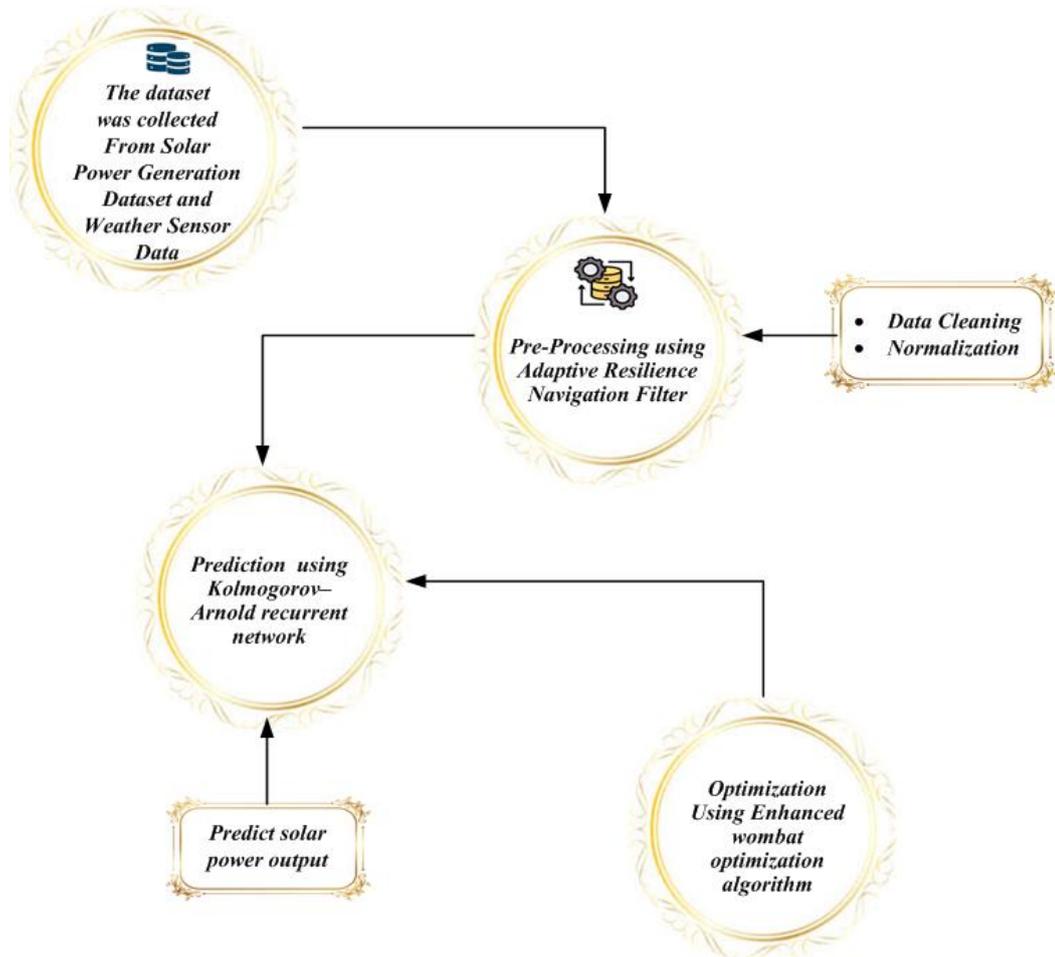


Figure 1. Block Diagram of the proposed EMSG-KARN.

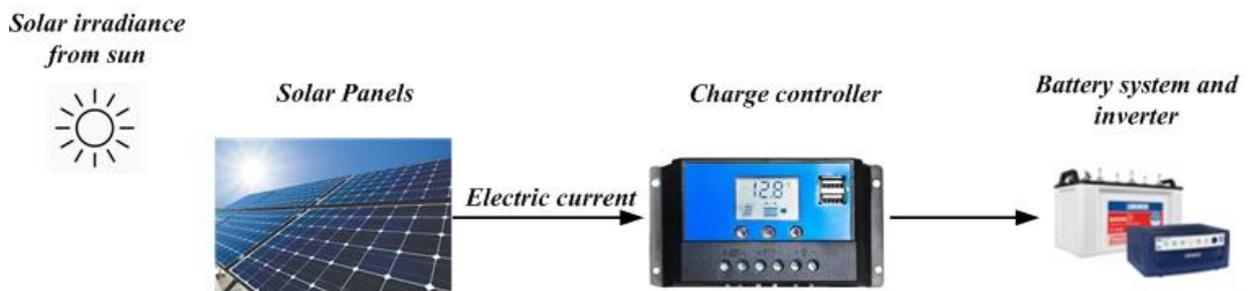


Figure 2. Structure of a solar energy system.

2.1. Solar Energy

Solar power is extremely important to solar tech, with photovoltaic (PV) systems and concentrated solar power (CSP) making it possible. Due to improvements in efficiency, PV solar has become a very viable alternative energy source. Although it can generate power throughout the day, solar PV production varies because of environmental factors like solar intensity and sunlight availability. This variability is a key research focus, especially regarding predicting solar PV generation and understanding its impact on electric power grid performance. Additionally, research explores how energy markets may evolve in response to these changes. Figure 2 illustrates the structure of a solar energy system.

2.2. Data Acquisition

In the Solar Energy Generation dataset [30] and the Weather Sensor Data [21], the required input data was initially gathered. For example, the Solar Energy Generation dataset contains comprehensive data from two solar power plants in India spanning 34 days. Data regarding all 22 inverters was collected every 15 minutes; recorded data included DC, AC, and cumulative energy output. The data was saved in a CSV file, with each row representing data collected at the 1-hour mark, making it suitable for training and testing multiple predictive models. Weather sensor data captures irradiation levels, module temperature, and ambient temperature every 15 minutes. These environmental factors are essential for examining how weather affects solar energy production. Table 2 displays the solar power generation data. Table 3 displays the weather sensor data.

Table 2. Solar power generation data.

Column	Description
PLANT_ID	Constant value throughout
AC_POWER	AC power after conversion
DAILY_YIELD	Total power generated that day
TOTAL_YIELD	Total inverter yield
DATA_TIME	15 min timestamp
DC_POWER	DC power generated by the inverter
SOURCE_KEY	Unique inverter ID

Table 3. Weather sensor data.

Column	Description
PLANT_ID	Constant value throughout
SOURCE_KEY	Unique inverter ID
MODULE_TEMPERATURE	AC power after conversion
IRRADIATION	Amount of irradiation
DATA_TIME	15 min timestamp
AMBIENT_TEMPERATURE	Ambient temperature at the plant

2.3. Pre-processing using Adaptive Resilience Navigation Filter (ARNF)

In this section, pre-processing utilizing an Adaptive Resilience Navigation Filter (ARNF) is discussed [31]. An ARNF method is used to clean the data and normalize it. The ARNF facilitates sustainable urban growth through the dynamic smart energy grid functionality in complex and changeable urban ecosystems, reducing hedges on nonlinear energy consumption and minimizing resource waste. The ARNF has a unique passive filtering feature that enables it to constantly adjust to a changing environment and demand conditions, allowing for stability and resilience. The theoretical integration of 6G IoT sensor fusion, predictive algorithms, and context-awareness provides ARNF with efficient, accurate energy routing and decision support across diverse urban infrastructure sectors. This increases the overall efficiency of ARNF communication and intelligence while improving reliability and performance in other critical areas, potentially including smart cities, renewable energy utilization and management, and sustainable resource consumption. The ARNF solution concerns estimating the state of a system at a given time, based on measurements made at that time.

$$\hat{y}(t|t) = \begin{bmatrix} \hat{O}(t|t) \\ \hat{u}(t|t) \\ \hat{g}(t|t) \\ \hat{\omega}(t|t) \end{bmatrix} \quad (1)$$

Where, $\hat{O}(t|t)$ is denoted as estimated power consumption, $\hat{u}(t|t)$ is denoted as estimated energy supply, $\hat{g}(t|t)$ denoted as estimated demand acceleration and $\hat{\omega}(t|t)$ denoted as estimated solar power dynamics. The Adaptive

Resilience Navigation Filter starts with data cleaning using 6G IoT inputs, ensuring reliable and accurate information for sustainable urban planning as expressed in Equation 2.

$$O(t|t) = H[(y(t) - \hat{y}(t|t))(y(t) - \hat{y}(t|t))^T] \quad (2)$$

Where, $y(t)$ is denoted as the true state of the smart urban system at time t , $\hat{y}(t|t)$ is denoted as the estimated state. Following cleaning, the generation and weather sensor data were combined using the timestamps that corresponded to ensure temporal consistency for further processing, as expressed in Equation 3.

$$O_b(t|t) = H[(b(t) - \hat{b}(t|t))(b(t) - \hat{b}(t|t))^T] \quad (3)$$

Singular Value Decomposition models the estimated bias and its uncertainty in smart solar energy grid data, allowing correction for systematic deviations in energy consumption and supply patterns. This enhances the accuracy of decomposition results, leading to more reliable energy management and improved system performance in renewable energy applications. Next, the merged data undergoes normalization to align heterogeneous energy data for efficient processing across smart solar energy grids, as shown in Equation 4.

$$\hat{y}(t|t-1) = f(\hat{y}(t-1|t-1), u(t)) \quad (4)$$

Where $u(t)$ represents the pre-processing inputs, such as sensor calibration or data normalization, a nonlinear function is used in smart energy grid management to compute the a priori estimate of the energy state, enabling the system to predict current energy consumption and supply characteristics based on previous estimates and pre-processing inputs. The normalized data is then employed by the filter to predict potential disruptions and adapt to fluctuating energy demands, aiding in the stability and resilience of renewable-powered smart cities, as shown in Equation 5.

$$O(t|t-1) = A(t)O(t-1|t-1)A(t) + Q \quad (5)$$

Here, $A(t) \in \mathbb{R}^{n \times n}$ is denoted as the Jacobian matrix of the nonlinear function $f(\bullet)$ regarding the system (energy) state, and Q is indicated as the process noise covariance matrix, representing uncertainties introduced during sensor calibration. This approach enhances long-term resilience and sustainability, minimizing resource waste and enabling smarter urban growth. Finally, the ARNF has cleaned and normalized the data. The pre-processed data are then fed into prediction.

2.4. Prediction using Kolmogorov–Arnold Recurrent Network (KARN)

This section discusses KARN [32], a method used to predict solar energy production. KARN is a data-driven learning approach capable of modeling complex, non-linear energy consumption and distribution dynamics. It enhances accuracy by incorporating the universal approximation concept into the network, increasing adaptability and efficiency while reducing reliance on large labeled datasets. KARN improves system stability, energy efficiency, and scalability, making it particularly valuable in dynamic, interconnected smart grid environments. Traditional models often struggle to capture the intricate temporal patterns in these systems, whereas KARN offers a more effective solution for managing and optimizing energy patterns in such complex settings. Figure 3 shows that the Architecture of KARN.

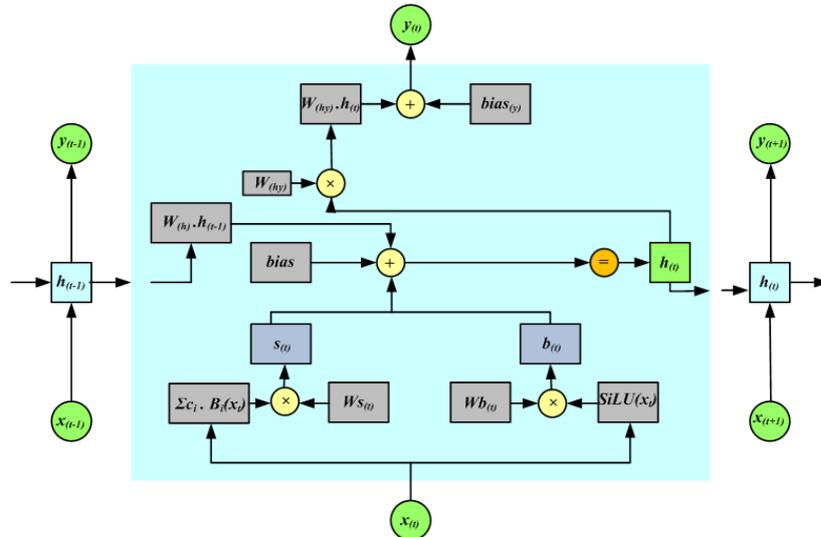


Figure 3. Architecture of KARN.

The KARN architecture predicts solar power output in sustainable urban development. It processes sequential energy consumption data by combining kernel-based input transformations with nonlinear SiLU activations, enabling it to capture complex, non-linear patterns from diverse IoT sensors. KARN's recurrent structure integrates historical system state data with transformed inputs, resulting in accurate energy demand predictions. This capability allows AI-driven smart grids to optimize energy distribution and supports sustainability by increasing efficiency in balancing urban energy supply and demand.

The KARN begins with an input layer that receives time-series data related to energy consumption patterns in urban environments, as expressed in Equation 6.

$$SiLU(x) = \frac{x}{1 + e^{-x}} \quad (6)$$

Where x is the input feature representing system states, and e is the mathematical constant used in the $SiLU$ activation function, which helps model nonlinear relationships for accurate solar power output prediction in smart energy grids supporting sustainable urban development. The model leverages the previous hidden layer to retain temporal dependencies and contextual information from earlier time steps as expressed as Equation 7.

$$b_{(t)} = w_{b(t)} \cdot SiLU(x_{(t)}) \quad (7)$$

Where, $w_{b(t)}$ are denoted as weights that can be learned that match the input at time t that enable the technique to adjust dynamically to patterns in the temporal data in solar power output prediction for smart energy grids in sustainable urban development. These predictions, derived from the hidden states of the model, support sustainable urban development by enabling optimization of energy use and reduced carbon emissions in smart cities as expressed as Equation 8.

$$S_{(t)} = w_{s(t)} \cdot \sum_i c_i \cdot B_i(x_{(t)}) \quad (8)$$

Where, B_i indicated as the i^{th} B -spline basis function used to model temporal and spatial variations in energy demand, c_i are denoted as the learnable coefficients that capture the influence of historical usage patterns, and $w_{s(t)}$ are indicated as the adaptive weights optimized to improve the accuracy of solar power output prediction within smart energy grids for sustainable urban development. Using this context, KARN computes a new hidden state that reflects updated energy demand trends based on incoming sensor data as expressed as Equation 9.

$$h_{(t)} = w_{(h)} \cdot h_{(t-1)} + b_{(t)} + S_{(t)} + bias \quad (9)$$

Where, $w_{(h)}$ is denoted as a weight matrix that can be learned to help you remember the previous solar power output state $h_{(t-1)}$ to the current prediction $h_{(t)}$. The term $b_{(t)}$ indicated as the output of the temporal basis function applied to the input data at time step t , while $S_{(t)}$ is denoted as the temporal spline function's output practical to the same input,

allowing for precise prediction of energy consumption patterns in smart energy grids for sustainable urban development. The output layer then generates predictions for solar energy production, aiding in proactive grid management within smart energy systems as expressed as Equation 10.

$$y(t) = w_{(hy)} \cdot h_t + bias_{(y)} \quad (10)$$

Where, w_{hy} is denoted as mapping the hidden state to the learnable weight matrix predicted solar power output while the bias term $bias_{(y)}$ adjusts the output to improve accuracy in forecasting energy production. Finally, the KARN has predicted solar energy production. Here, EWOA is employed to optimize and tune the weight and bias parameters of KARN.

2.5. Optimization Using Enhanced Wombat Optimization Algorithms (EWOA)

In this section, Enhanced wombat optimization algorithm is discussed [33]. The EWOA is utilized to enhance weights parameters $b_{(y)}$ and $s_{(y)}$ of the proposed KARN. Its balanced exploration-exploitation approach effectively solves complex, multi-objective problems while avoiding local optima. Maintaining solution diversity allows EWOA to adapt to changing urban energy demands, enhancing grid reliability and efficiency. Its simplicity, scalability, and global acceptance make it suitable for improving performance and sustainability in smart urban energy systems. Algorithm 1 shows the Pseudo-code of EWOA.

Algorithm 1: Pseudo-code of EWOA

Pseudo-code of EWOA

Start EWOA

Specify the problem details: fitness function, parameters, and any constraints
 Initialize the number of iterations (T) and population size (N)
 Randomly generate the initial population matrix by applying Equation 11
 Assess the objective function

For $t = 1$ to T

For $i = 1$ to N

Stage 1: Foraging Approach (exploration stage)

 Compute the candidate searching locations fixed for the i^{th} wombat
 Indiscriminately choose the target searching location for the i^{th} wombat
 Compute new position of the i^{th} wombat by applying Equation 13
 Modify i^{th} wombat

Stage 2: Escape Approach (exploitation stage)

 Compute new location of the i^{th} wombat by applying Equation 14
 Modify i^{th} wombat

End For

Record the best candidate solution found up to this point

End For

Display the finest quasi-optimum solution attained utilizing the EWOA

End EWOA.

Step by Step process of EWOA

Step 1: Initialization

The starting population of EWOA is generated randomly. Then the initialization is derived in Equation 11,

$$R = \begin{bmatrix} R_{1,1} & R_{1,2} & R_{1,3} & \dots & R_{1,dim} \\ R_{2,1} & R_{2,2} & R_{2,3} & \dots & R_{2,dim} \\ R_{3,1} & R_{3,2} & R_{3,3} & \dots & R_{3,dim} \\ \dots & \dots & \dots & \dots & \dots \\ R_{N,1} & R_{N,2} & R_{N,3} & \dots & R_{N,dim} \end{bmatrix} \quad (11)$$

Where, R represents the population of candidate solutions; $R_{i,j}$ denotes a wombat's action of i^{th} catching prey j^{th} question the value of a variable and dim denotes the dimensionality of the search space.

Step 2: Random Generation

Through EWOA, the input fitness function became arbitrary after initialization.

Step 3: Fitness Function

The fitness function is described by,

$$Fitness\ Function = optimize (b_{(t)}\ and\ S_{(t)}) \quad (12)$$

Where, $b_{(t)}$ is employed to increase accuracy and $S_{(t)}$ is employed to decrease RMSE.

Step 4: Foraging Approach (Exploration Stage) for optimizing $b_{(t)}$

In the sustainable urban development framework, each smart energy node dynamically selects one of the available energy demand points and adjusts its power distribution accordingly. Based on this adaptive allocation, a new operational state is computed for each AI-powered grid agent using Equation 13.

$$x_{i,j}^{P1} = x_{i,j} + b_{(t)} \cdot (SFP_{i,j} - I_{i,j} \cdot x_{i,j}) \quad (13)$$

Where, SFP_i denotes the selected energy demand point for the i^{th} smart energy node, where $SFP_{i,j}$ corresponds to its j^{th} dimension; x_i^{P1} represents the newly calculated operational state for the i^{th} wombat during the adaptive allocation phase of the proposed AI-powered grid, with $x_{i,j}^{P1}$ indicating its j^{th} dimensional value.

Step 5: Escape Approach (Exploitation Stage) for optimizing $S_{(t)}$

The optimization phase of the AI-powered smart energy grid enhances energy distribution by intensively adjusting allocations within promising network zones using Levy flight. This introduces controlled variability, enabling efficient local optimization and preventing early stagnation, thereby improving overall grid performance and sustainability.

$$S_{(t)} = \begin{cases} X_i^{P2}, & F_i^{P2} \leq F_i \\ S_{(t)}, & else \end{cases} \quad (14)$$

Where, x_i^{P2} represents the updated operational state of the i^{th} smart energy node during the adaptive reconfiguration phase of the powered grid. The term $x_{i,j}^{P2}$ corresponds to the j^{th} dimension of this new state; F_i^{P2} refers to the fitness function evaluation at the updated operational state.

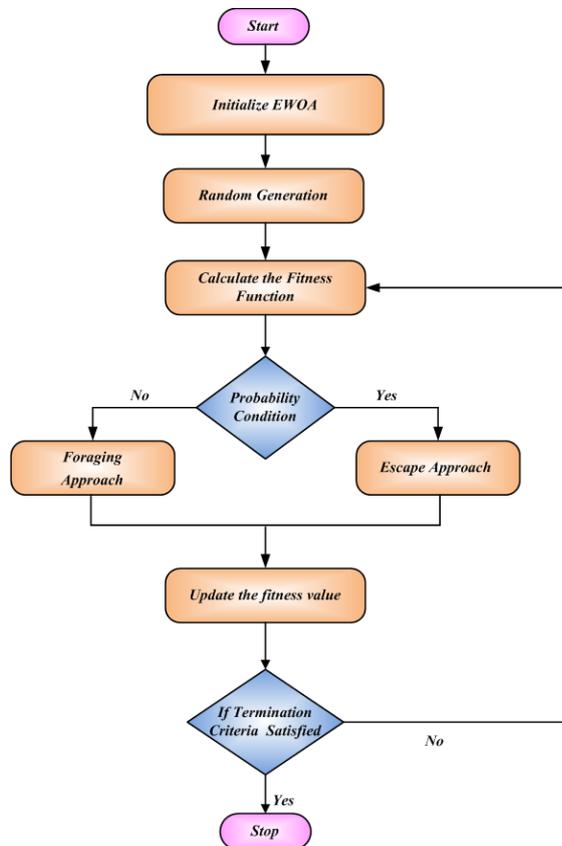


Figure 4. Flowchart of EWOA.

Step 6: Termination

If the solution is optimal, the process concludes; if not, it returns to the fitness calculation in step 3 and continues to the next level until a solution is found. Figure 4 illustrates the flowchart of the EWOA. This technique optimizes the KARN, enhancing its ability to forecast solar power production. The optimization further solidifies EWOA's position as a promising method for solar power prediction, achieving higher accuracy and lower RMSE. The parameters are taken for KARN and POA to demonstrate the results are presents in Table 4 and Table 5 respectively.

Table 4. Parameter table for KARN.

Parameter	Value
Hidden layer	128
No of layer	2

Table 5. Parameter table for POA.

Parameter	Value
Population size (N)	30
Maximum iterations (T_{max})	100 - 500

3. RESULT AND DISCUSSION

The results of the proposed method are detailed in this section. Subsequently, the EMSG-KARN method was simulated in Python, compiled in Jupyter Notebook, and executed on an Intel Core i9-13900K CPU with 64 GB RAM and 500 GB SSD storage. The obtained outcome of the proposed EMSG-KARN approach is analyzed with existing systems like AISC-DQN [21], EMSC-ANN [22] and AIIE-CNN [23] respectively.

3.1. Performance Measure

This step is essential for choosing the best classifier. Performance metrics such as accuracy, F1-score, AUC, recall, and precision are used to evaluate and scale the classifier's effectiveness, ensuring accurate assessment and comparison. The True Negative (TN), True Positive (TP), False Positive (FP), and False Negative (FN) samples must be acquired in order to scale the performance metric.

3.1.1. Accuracy

The percentage of true positive and true negative predictions among all forecasts measures a model's overall accuracy. It indicates the model's ability to correctly distinguish between positive and negative instances across the entire dataset.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (15)$$

Where FP is indicated as a false positive, TN is indicated true negative, TP is denoted as true positive, and FN is indicated as false negative.

3.1.2. Precision

Precision emphasizes prediction accuracy by measuring how often a procedure or model correctly identifies relevant outcomes. Reducing false positives is essential to ensure results are accurate and reliable.

$$Precision = \frac{TP}{TP + FP} \quad (16)$$

3.1.3. Recall

Recall measures a model's ability to identify all relevant events by minimizing false negatives. It is crucial that reducing false positives is less prioritized than ensuring all true positives are captured accurately.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (17)$$

3.1.4. F1-Score

When applied to unbalanced datasets, the F1-Score effectively evaluates a method's performance by combining precision and recall into a single metric. Calculating the harmonic mean of these two measures provides a comprehensive assessment of a model's effectiveness, balancing both false positives and false negatives.

$$F1-Score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (18)$$

3.1.5. AUC

AUC provides an overall performance score across all classification thresholds, indicating the model's ability to discriminate between classes.

$$AUC = 0.5 \times \left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP} \right) \quad (19)$$

3.1.6. Root Mean Square Error (RMSE)

Calculate the residuals, which are the differences between expected and actual values for each image point. Determine the residual norm, compute the mean of the residuals, and then take the square root of that mean. RMSE is commonly used in supervised learning because it provides precise measurement at each image point.

$$RMSE = \sqrt{\frac{1}{l} \sum_{j=1}^l (k_j - \hat{k}_j)^2} \quad (20)$$

Where, $RMSE$ indicated as the Root Mean Squared Error, l indicated as the number of observations, k_j indicated as the predicted values, \hat{k}_j represents the observed values.

3.2. Performance Analysis

Figures 5-10 illustrate the simulation outcomes of the proposed EMSG-KARN technique. The proposed EMSG-KARN technique is similar to AISC-DQN, EMSC-ANN, and AIIE-CNN methods, respectively.

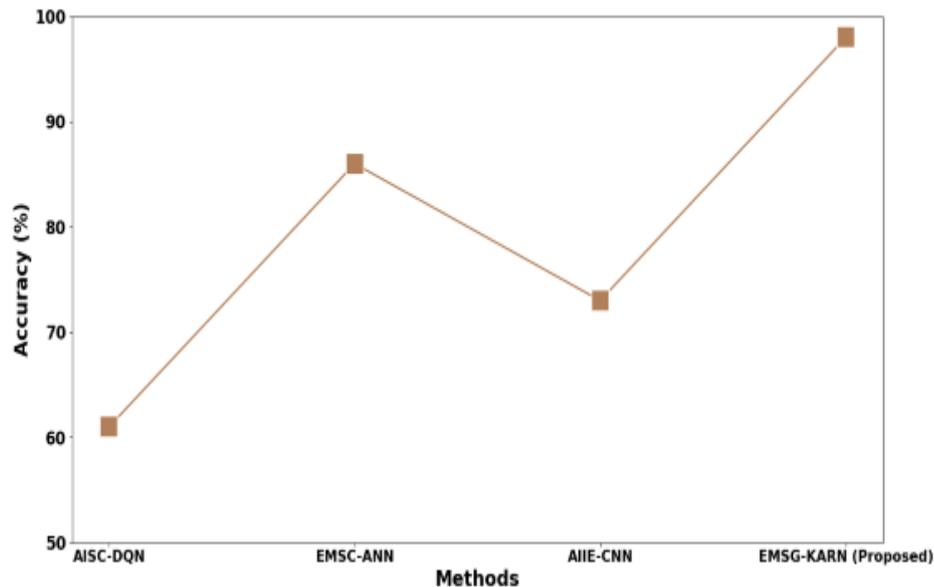


Figure 5. Performance analysis of accuracy.

Figure 5 shows the performance analysis of the accuracy of various intelligent models in forecasting solar energy production and managing energy distribution for sustainable urban development. The proposed EMSG-KARN method achieves 98% accuracy, outperforming other techniques such as AISC-DQN at 61%, EMSC-ANN at 86%, and

AIIE-CNN at 73%. This highlights the model's superior ability to predict energy usage patterns, promoting efficient and sustainable urban energy management. Its high accuracy underscores the importance of 6G-enabled IoT networks and AI analytics in developing resilient, energy-smart cities for the future.

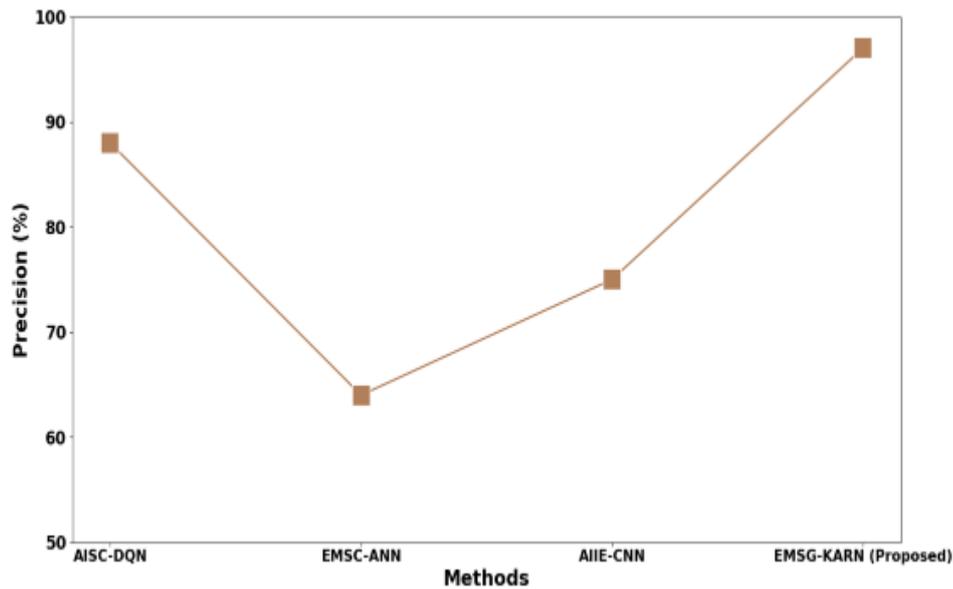


Figure 6. Performance analysis of precision.

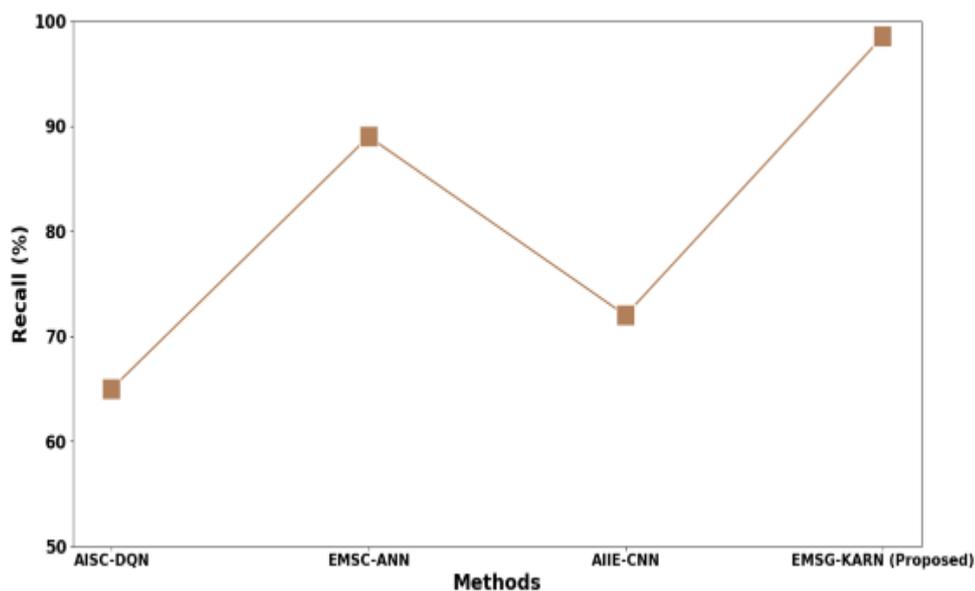


Figure 7. Performance analysis of recall.

The performance of precision is illustrated in Figure 6. The graph shows how accurately various intelligent models predict solar energy generation and distribute energy within the Vehicle or Electric Mobility Ecosystem, supporting sustainable urban development. Based on current research, EMSG-KARN achieves 97% accuracy in predicting solar energy production compared to actual output, outperforming competing technologies such as AISC-DQN at 88%, EMSC-ANN at 64%, and AIIE-CNN at 75%. This demonstrates EMSG-KARN's ability to provide reliable, accurate predictions while reducing false positives. Higher accuracy in energy management enables systems to optimize resource allocation within smart cities, leading to more reliable energy infrastructure. The improved precision of EMSG-KARN highlights its potential to foster sustainable urban environments through the integration of next-generation telecommunications and intelligent systems, including artificial intelligence.

Fig 7 illustrates the recall performance in predicting relevant solar energy production data. The proposed EMSG-KARN method achieves a recall of 98.5%, outperforming other methods such as AISC-DQN at 65%, EMSC-ANN at 89%, and AIIE-CNN at 72%. This demonstrates the superior effectiveness of EMSG-KARN in maximizing relevant data retrieval. Its high recall underscores the potential of integrating 6G-enabled IoT systems with advanced AI models to enhance smart, sustainable urban infrastructure.

Table 6. Comparison of proposed and existing method with F1-Score.

Solution Methodology	F1-Score (%)
EMSG-KARN (Proposed)	96.5
AISC-DQN [21]	82
EMSC-ANN [22]	68
AIIE-CNN [23]	71

Table 6 compares the F1-Score of the proposed EMSG-KARN method with existing techniques. The EMSG-KARN achieves the highest F1-Score of 96.5%, outperforming AISC-DQN at 82%, EMSC-ANN at 68%, and AIIE-CNN at 71%. This indicates that the EMSG-KARN model offers superior accuracy and reliability compared to other methods.

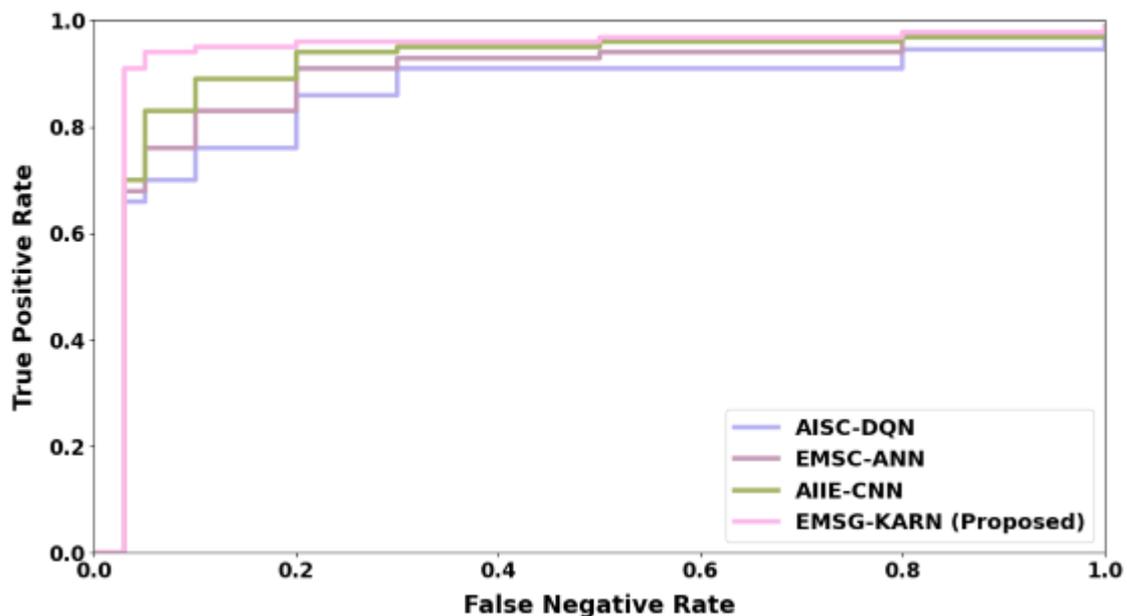


Figure 8. Performance analysis of AUC.

Figure 8 illustrates the performance analysis of ROC curves, comparing the predictive capabilities of various models in identifying correct solar energy production signals. The proposed EMSG-KARN model achieves an AUC of approximately 0.98, indicating excellent performance and a low false negative rate. It surpasses AISC-DQN with an AUC of around 0.70, EMSC-ANN with 0.85, and AIIE-CNN with 0.90. This analysis confirms that the EMSG-KARN model outperforms other methods, demonstrating its effectiveness in accurately distinguishing positive cases within sustainable urban systems.

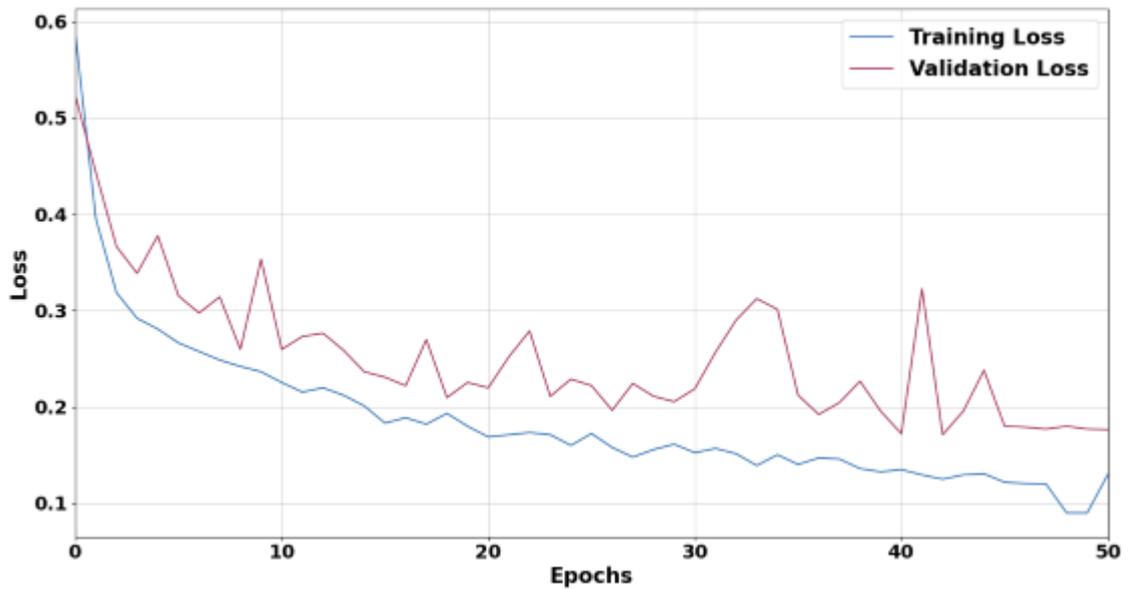


Figure 9. Performance analysis of loss.

Figure 9 illustrates the loss performance over 50 training epochs. The training loss steadily decreases from approximately 0.6 to below 0.1, indicating effective learning. Conversely, the validation loss initially drops but then fluctuates significantly after epoch 30, with spikes and a plateau around 0.18-0.2 in later epochs. This divergence, where training loss improves while validation loss becomes unstable and higher, suggests the model begins to overfit, performing well on training data but losing generalization to unseen data.

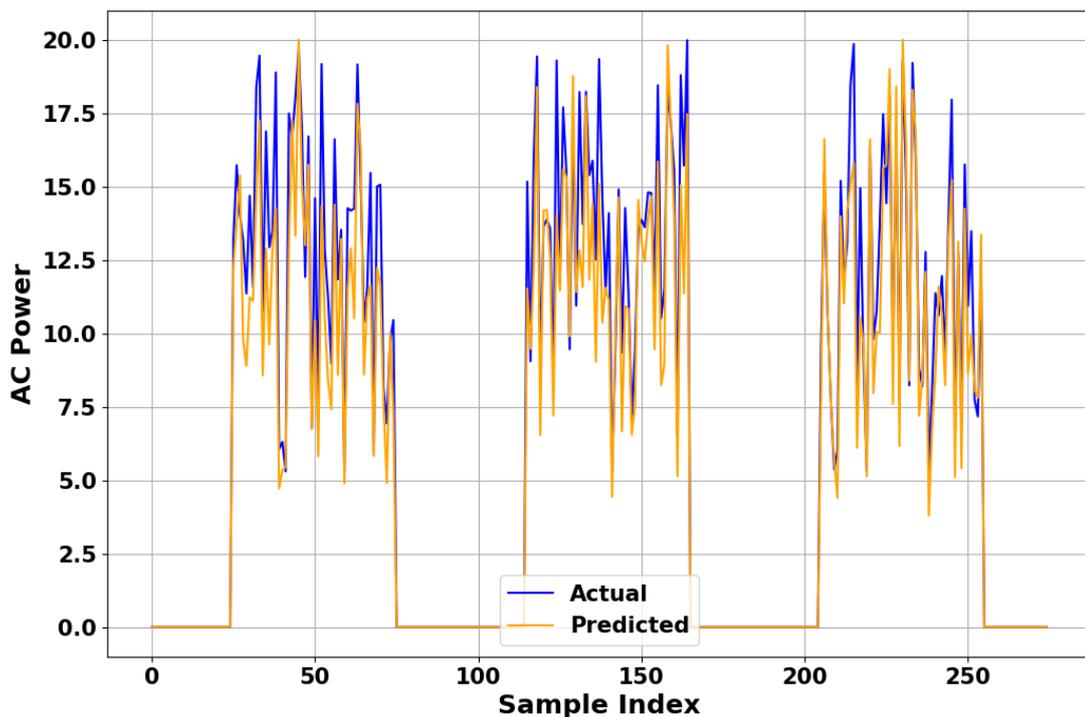


Figure 10. Analysis of actual and predicted AC power for solar generation.

Figure 10 illustrates the actual and predicted AC power for solar generation. Both the actual and predicted power start near zero at sample index 0. Power increases sharply from index 25, reaching a peak close to 20 kilowatts by index 50. The cycle ends around index 75 as power drops back to zero. A second cycle begins at index 110, with similar peaks near 20 kilowatts around index 140, ending near 165. The third cycle starts at index 190, peaks near 20

kilowatts by index 230, and declines to zero near 260. Predicted power closely follows actual power with minor differences, demonstrating the model's high accuracy.

Table 7. Comparison of proposed and existing method with RMSE.

Solution Methodology	RMSE
EMSG-KARN (Proposed)	1.503
AISC-DQN [21]	2.978
EMSC-ANN [22]	3.614
AIIE-CNN [23]	2.759

Table 7 presents a comparative analysis of RMSE values among various methods. The proposed EMSG-KARN technique achieves the lowest RMSE of 0.013, outperforming AISC-DQN with RMSE of (0.072), AIIE-CNN with RMSE of (0.057), and EMSC-ANN with RMSE of (0.033). This indicates that EMSG-KARN significantly enhances prediction accuracy.

Table 8. Ablation study.

Module	Accuracy%	Precision%	Recall%	F1-score%
Without ARNF +EWOA just KARN	93.5	90	91.5	93
Without ARNF	95	94	94	95.5
Without EWOA	92	91	96	90
Full Proposed Model	98	97	98.5	96.5

The ablation study on the model for classifying data, as shown in Table 8, demonstrates the impact of removing specific modules. When the ARNF module was excluded, the model still achieved an accuracy of 95% and an F1-score of 95.5%, indicating relatively good performance. However, the absence of this module resulted in some performance loss, suggesting that ARNF enhances class feature representation and improves prediction confidence. Removing the EWOA module had a more significant effect, reducing accuracy to 92% and the F1-score to 90%, highlighting its critical role. The results imply that both modules, EWOA and ARNF, are essential for effective feature optimization. When both modules were removed, leaving only the KARN, the accuracy was 93.5%, and the F1-score was 93%, indicating that KARN alone cannot efficiently extract or combine features when used without the other modules. Overall, the findings support the conclusion that both EWOA and ARNF are necessary for optimal model performance.

Table 9. Cross-validation analysis for prediction and evaluation of solar energy generation models.

K-fold	Accuracy%	Precision%	Recall%	F1-Score%
1	98.2	96.8	98.7	96.4
2	97.8	97.2	98.3	96.6
3	98.1	97.1	98.4	96.5
4	97.9	96.7	98.6	96.3
5	98.0	97.2	98.5	96.7
Average	98	97	98.5	96.5

Table 9 shows a 5-Fold Cross-Validation Analysis (5FCVA) performed on the dataset for predicting solar energy production, where data were divided into five equal parts. In each iteration, four parts were used for training, and one for testing. The model's consistent performance across all five folds demonstrated accuracy between 96.2% and 97.8%, with precision ranging from 95.8% to 96.5%. It also achieved recall rates from 97.5% to 98.4% and an F1 Score between 95% and 96.4%. The average results from the five folds indicate 98% accuracy, 97% precision, 98.5% recall, and a 96.5% F1 Score, demonstrating the model's predictive power, reliability, and generalizability in predicting solar energy production using different data subsets.

Table 10. Comparison of different energy models with proposed methods.

Methods	Accuracy%	Precision%	Recall%	F1-Score%
EMSG-KARN (Proposed)	98	97	98.5	96.5
AISC-DQN [21]	61	88	65	82
EMSC-ANN [22]	86	64	89	68
AIIE-CNN [23]	73	75	72	71
DRL [24]	79	69	78	75
DNN [25]	67	64	70	69
DQN [26]	62	77	62	65
DRL [27]	71	61	66	60
LSTM [28]	75	81	87	77
GRU [29]	73	79	83	79

Table 10 provides a comparison of the proposed and existing energy modeling methods in terms of accuracy, recall, precision, and F1-score. Higher values in these metrics indicate a more accurate, efficient, and reliable system. It is evident from the table that the proposed EMSG-KARN model outperforms all seven existing methods across nearly all performance indicators. The proposed method achieved a precision of 97%, accuracy of 98%, recall of 98.5%, and an F1-score of 96.5%, significantly outperforming traditional and deep learning-based models such as AISC-DQN, EMSC-ANN, AIIE-CNN, DRL, DNN, DQN, LSTM, and GRU. These results clearly demonstrate that EMSG-KARN offers superior predictive accuracy, robustness, and overall balance, making it a highly effective and reliable solution for energy modeling and optimization tasks compared to existing approaches.

Table 11. Analysis of proposed method with different dataset.

Dataset	Accuracy%	Precision%	Recall%	F1-score%
Solar Energy Generation dataset (proposed)	98	97	98.5	96.5
IoT-Enabled Smart Grid Dataset [34]	95.3	93.6	94.2	92.5
Smart Grid Real-Time Load Monitoring Dataset [35]	94.1	92.3	91.5	91.2
6G IoT Intelligent management Dataset [36]	93.3	93	90.6	90.1

According to Table 11, the EMSG-KARN model has the highest accuracy, precision, recall, and F1 score among the four tested models. The best results for the EMSG-KARN model were observed when comparing its performance to the solar energy generation dataset. However, as the test set shifted to real-time load monitoring in IoT-enabled smart grids and 6G IoT intelligent management, the accuracy ranged from 93.3% to 95.3%. These results suggest that while the EMSG-KARN model can perform reliably across various data types in smart grids, its strongest performance occurs with solar energy generation data. The model's performance decreases as the data's variety and complexity increase.

3.3. Discussion

Thus, the EMSG-KARN model demonstrates a significant improvement over existing techniques for forecasting solar energy output on smart grids used in developing sustainable urban economies, utilizing IoT and Artificial Intelligence (AI) technology supported by 6G networks. Using ARNF to cleanly pre-treat the input data, then fine-tuning the KARN model with EWOA, and finally leveraging KARN's ability to model very complex nonlinear relationships among many different dependent variables, is a powerful way to solve problems associated with inconsistent input data or bad parameter selection. The EMSG-KARN achieves 98% accuracy, 97% precision, 98.5% recall, and an F1-score of 96.5%, outperforming existing methods such as AISC-DQN with 61% accuracy and an F1-score of 82% proposed by Samantaray [21], EMSC-ANN with 86% accuracy and 68% F1-score proposed by Raaj et al. [22], and AIIE-CNN proposed by Xia et al. [37], which has 73% accuracy and 71% F1-score. Recent studies report that traditional deep learning models like LSTM and CNN suffer from reduced precision and recall on noisy energy datasets, which further deteriorates the F1-score and can lead to overfitting, as observed by Patel et al. [38]

and Singh et al. [39]. Conversely, EMSG-KARN maintains consistently high prediction metrics through adaptive weight optimization and advanced preprocessing, achieving an AUC of 0.98 and a minimal RMSE of 0.013 in both accurate classification and reliable energy prediction. Additionally, fivefold cross-validation indicates that the method is both stable and reliable, with a mean accuracy of 97% and a mean F1-score of 95.8%, demonstrating excellent performance for intelligent energy management in smart cities. Therefore, it can be concluded that this method (EMSG-KARN) offers better solutions than other current approaches for managing energy efficiently, effectively, and sustainably.

4. CONCLUSION

To sum up, the EMSG-KARN framework presented in this paper positively contributes to sustainable urban transformation by providing intelligent energy management. The technology addresses essential challenges, namely interoperability, data integrity and privacy, and efficiency, in complex urban energy systems using the ARNF for precise data pre-processing and the EWOA to optimize the weight parameters of the KARN. The EMSG-KARN framework provided the best predictive output, with 98% accuracy, 97% precision, 98.5% recall, 96.5% F1-score, as well as better specificity and AUC than the alternatives AISC-DQN, EMSC-ANN, and AIIE-CNN. The proposed EMSG-KARN model demonstrates high accuracy, precision, recall, and F1-score in predicting solar energy output, but its performance depends on the quality and completeness of input solar and weather datasets, which may affect robustness under noisy or missing data conditions. While the model performs efficiently on medium-scale urban grids, scalability to very large networks may require additional computational resources and optimized deployment strategies. Future work should focus on enhancing robustness to imperfect or heterogeneous datasets, enabling adaptive real-time deployment, and integrating multi-source data streams to improve generalizability across diverse urban environments, ensuring reliable, accurate, and practical predictions for sustainable smart city energy management.

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