International Journal of Technology and Applied Science (IJTAS)
E-ISSN: 2230-9004 ● Website: www.ijtas.com ● Email: editor@ijtas.com

ECOWATT AI: An Intelligent Platform for Smart Energy Consumption Monitoring and Carbon Emission Optimization

Dr. Pramod[1], Vinayprakash[2], Yashaswini G D[3], Yashaswini R[4], Sharanya[5]

[1]Professor and Head, Computer Science and Design Department, PES Institute of Technology and Management, Shivamogga, Karnataka, India.
[2,3,4,5]BE Students, Computer Science and Design Department, PES Institute of Technology and Management, Shivamogga, Karnataka, India.

Abstract:
Electricity use in homes, campuses and small facilities keeps rising, yet most people only ever see it as a single figure on a monthly bill. They cannot tell when they use the most, where the waste is, or what the consumption costs the environment. This paper presents **ECOWATT AI**, an AI-assisted energy management platform that brings monitoring, prediction, carbon estimation and advice into one application. Users enter or upload consumption data. The system cleans it, studies daily, weekly and monthly patterns, forecasts future demand with regression models such as Linear Regression and Random Forest, flags unusual usage with an anomaly detector, and converts consumption into estimated carbon emissions through an emission factor. A recommendation layer turns these findings into practical saving tips shown on an interactive dashboard. The application is built with a React front end, a Flask REST back end, an SQLite database and scikit-learn, and protects user data with JWT authentication, bcrypt password hashing and HTTPS/TLS. In a feedback-based evaluation on a five-point scale, the platform received an average rating of 4.5, with the highest score for overall usefulness. Accuracy testing on large real-world smart-meter datasets has not yet been done and is left for future work. The project supports UN Sustainable Development Goals 7 and 13.

Keywords: Smart Energy Management, Artificial Intelligence, Machine Learning, Energy Consumption, Carbon Emission, Energy Prediction, Anomaly Detection, Sustainability.

1. INTRODUCTION

Ask a household how much electricity it used last week and most will not know. The meter keeps a running total, the bill arrives once a month, and in between there is very little to connect a habit with a cost. That gap matters. Wasted electricity raises bills, strains the grid and adds to carbon emissions, and none of it is visible to the person who could change it.

Traditional monitoring tools, such as meters, manual readings and basic digital portals, tell users what has been used. They rarely say what will be used next, whether today looks unusual, or what to do about it. Machine learning can fill part of that gap, because it can learn usage patterns from past data and use

them for forecasting and for spotting readings that do not fit. The difficulty is that these abilities usually sit in separate tools, and the user is left to piece them together.

ECOWATT AI was designed to close that gap in one place. It lets a user record consumption, see how it changes over time, receive a forecast, see the estimated carbon emissions, and read concrete advice for cutting waste. The interface is meant for ordinary users, so results are shown as dashboards and short messages and not as raw tables. The system also stays modest about its role: it gives guidance and does not control any appliance or promise a particular saving.

The main objectives of the work are:

1. To let users monitor and understand their electricity consumption in a simple way.
2. To predict future consumption from historical usage patterns using machine learning.
3. To estimate the carbon emissions that result from the electricity used.
4. To identify unusual or excessive consumption and point out where energy may be wasted.
5. To generate personalized energy-saving recommendations.
6. To present energy, forecast and emission data through clear dashboards.
7. To support informed decisions and encourage responsible, sustainable energy use.

2. LITERATURE REVIEW

Early energy monitoring relied on electricity meters and manual readings, which give basic usage figures but little analysis. Digital platforms and smart-meter systems improved on this by offering charts and reports, so that daily and monthly changes became easier to see. Even so, many of these systems stop at monitoring and leave the interpretation to the user.

Machine learning has become a common route to better forecasting. Din and Marnerides applied deep neural networks to short-term power load forecasting [2], and Waheed and Xu used a data-driven deep-learning approach to short-term load forecasting for sustainable energy management [3]. Among general-purpose methods, Breiman's random forests [4] and the boosted-tree system XGBoost by Chen and Guestrin [5] are widely used for regression on tabular data of the kind that energy records produce. A broader review of machine-learning-driven smart electric power systems is given in [1].

A second line of work looks at the wider smart-grid setting. Fang et al. surveyed the smart grid as a whole [10]. Tiwari and Pindoriya reviewed automated demand response, covering metering infrastructure, communication technology and optimization models [6]. Mahmood et al. examined how digitalization affects smart grids, renewable energy and demand response [7], Toderean et al. reviewed demand-response optimization for buildings connected to smart grids [8], and Assad et al. reviewed computational methods for smart grids, demand response and optimization [9].

Taken together, these studies show that forecasting, optimization and grid-level coordination are well explored. What is less common is a single application aimed at the end user that joins monitoring, prediction, carbon estimation, anomaly detection and recommendations, and explains the result in plain terms. ECOWATT AI targets that space. Its contribution is the integration of these functions in one usable platform and not a new learning algorithm.

3. METHODOLOGY

The platform follows a modular layered design. A web interface shows data to the user, a back end handles application logic and communication, a database stores records, and a set of AI/ML modules

performs the analysis. Figure 1 gives an overview of how these parts connect.

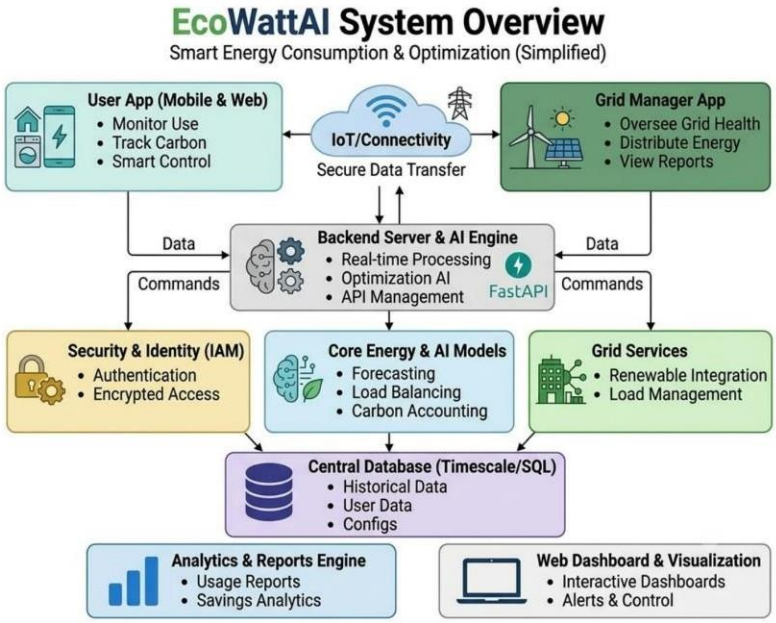

Figure 1: *System Architecture of the Proposed ECOWATT AI Platform*

Data moves through the system in a fixed order: energy data, preprocessing, analysis, prediction, carbon calculation, optimization, recommendations and finally the dashboard. The sub-sections below describe each part.

3.1 Requirements:

The functional requirements are that users can register and log in securely, enter and monitor consumption, view daily, weekly and monthly usage, see forecasts and estimated emissions, receive alerts or comparisons for unusual consumption, and read energy-saving recommendations. The non-functional requirements cover usability, security, privacy, reliability, reasonable response time, maintainability, scalability, accuracy and accessibility. One requirement is worth stressing: predictions and recommendations must be presented as supporting insight and must not replace the user's own decisions.

3.2 Data Preprocessing and Feature Engineering:

Raw consumption data is rarely clean. The system removes duplicate records, handles missing or inconsistent values, drops irrelevant fields and converts the rest into a format the models can use. Useful features are then derived, including previous usage, time of day and week, and recent usage patterns.

3.3 Consumption Prediction:

Future consumption is estimated by a regression model trained on the user's historical data. Linear Regression gives a simple, easily explained baseline, and Random Forest can capture non-linear behaviour such as peaks at particular hours. The model learns the relationship between the engineered features and observed usage, and returns expected consumption values that are shown as forecasts on the dashboard.

3.4 Anomaly Detection and Pattern Analysis:

Statistical analysis identifies trends, peak periods and variations in the usage pattern. On top of this, an anomaly detector such as Isolation Forest marks readings that differ strongly from the usual behaviour. These readings are highlighted so that the user can look into a faulty appliance, a forgotten load or an

unusually heavy day.

3.5 Carbon Emission Estimation:

Emissions are estimated from the electricity consumed and the emission factor, that is, the carbon dioxide equivalent produced per unit of electricity:

Carbon Emission = Energy Consumption × Emission Factor

Because the result depends on which emission factor is chosen, the figures should be read as estimates and not as exact measurements.

3.6 Optimization and Recommendations:

The optimization step looks for consumption that could be reduced without lowering the level of use the person actually needs. A recommendation module then combines simple rules with the model outputs to produce suggestions, for example shifting a heavy load away from peak hours or checking a device that consumes more than expected.

3.7 Security and Data Handling:

User data is protected at several levels. Data in transit is secured with HTTPS/TLS, and sensitive stored data can be encrypted with AES-256. Passwords are never stored in plain form and are hashed with bcrypt, while JSON Web Tokens (JWT) handle authentication and authorize access to protected API calls.

3.8 Software Stack:

The technologies used to build the platform are listed in Table 1.

Table 1: Software Stack

Component	Technology	Purpose
Front end	React.js, HTML, CSS, JavaScript	Responsive interface and interactive dashboard
Back end	Python, Flask (REST API)	Authentication, data processing, prediction requests and carbon calculations
Database	SQLite	Users, consumption records, predictions and emission data
Machine learning	Scikit-learn	Prediction, pattern analysis and anomaly detection
Security	JWT, bcrypt, HTTPS/TLS, AES-256	Authentication, password protection and encryption
Tools	Git, GitHub, Visual Studio Code	Version control and development

4. MODELING AND ANALYSIS

Figure 2 shows how a request travels through the platform. The user signs in and opens the web interface, which sends data to the Flask back end. The back end validates it and stores it, and the preprocessing stage cleans and prepares it. The AI/ML stage then produces the predicted consumption in kWh, usage-pattern analysis, high-consumption detection and the carbon estimate. Optimization and recommendations follow, and the results are saved in the database and displayed on the dashboard together with alerts and reports.

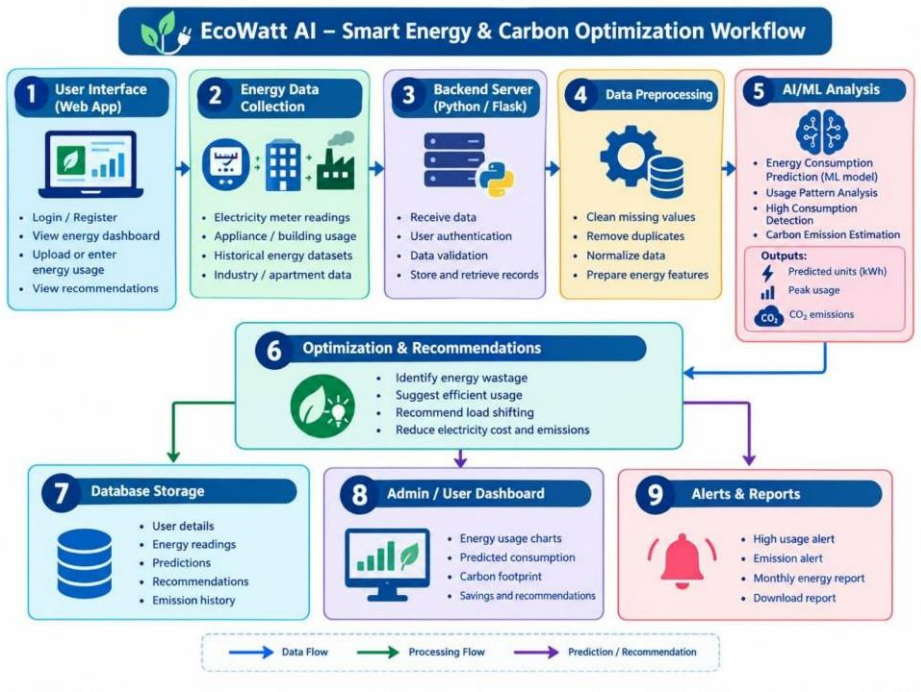

Figure 2: *Integrated Processing Workflow of ECOWATT AI*

4.1 Implementation Modules:

The implementation is divided into six modules. The **User Management** module covers registration, login and access control. **Energy Monitoring** lets users enter and track daily, weekly and monthly consumption. **Energy Analysis** studies patterns and highlights excessive use. The **AI-Assisted** module handles prediction, anomaly detection, carbon estimation and recommendations. The **Dashboard** module displays results through charts and summaries, and the **Database** module stores and retrieves every record the other modules need.

4.2 Testing Approach:

Testing is planned at three levels. Unit tests check individual functions such as input validation, login, consumption and carbon calculations and the prediction function. Integration tests check that the interface, back end, database and AI modules exchange information correctly. Usability testing checks whether a user can enter data, read the dashboard and understand the advice. Table 2 lists representative test cases and the behaviour expected from each. They form the test plan for the prototype, and a pass or fail result should be recorded against each case as testing is completed.

Table 2: Representative Test Cases

Test case	Expected result
Enter valid energy data	Data is accepted and stored successfully
Enter incomplete or invalid data	An appropriate error message is displayed
Log in with invalid details	Access is denied with an error message
Calculate carbon emissions from test inputs	The expected emission value is generated
Process data through the prediction module	Predicted consumption is generated and displayed

An unusual consumption pattern is entered	The system identifies and highlights it
Unauthorized user opens a protected function	Access is restricted

RESULTS AND DISCUSSION

4.3 Application Interface:

Figure 3 shows the sign-in page of the ECOWATT AI Smart Grid portal. Authorized users enter an e-mail address and password to reach the dashboard, and the page also offers a remember-me option, password recovery and account creation.

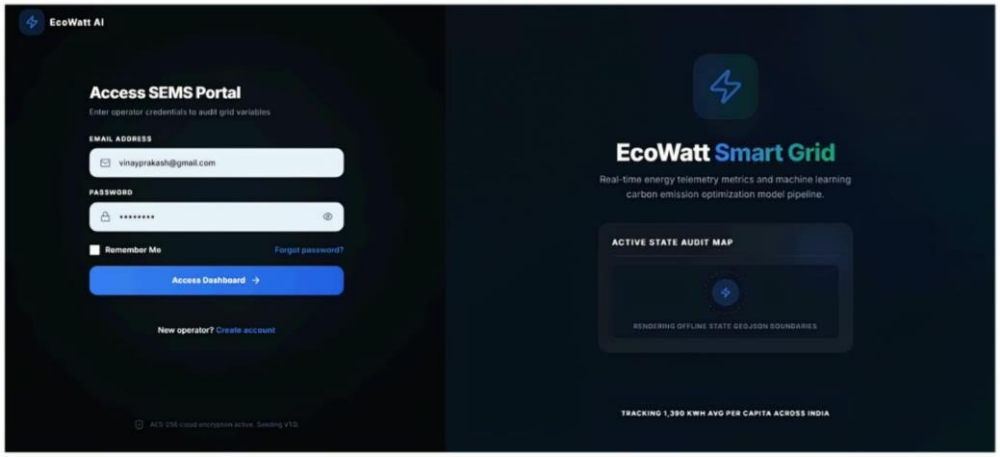

Figure 3: *ECOWATT AI Login Page*

Figure 4 shows the monitoring dashboard. A live map of India colours each state by its consumption status. Beside the map are a breakdown of electricity use by level (peak, high, medium, low and off-peak), a 30-day trend chart and a panel of AI-generated insights with a button to produce a report. Summary cards at the bottom give total consumption, carbon dioxide avoided and a seven-day forecast. The values visible in the figure come from the prototype and illustrate the layout and the kind of information provided.



Figure 4: *ECOWATT AI Monitoring Dashboard*

4.4 Comparison with Existing Systems:

Table 3 compares ECOWATT AI with conventional monitoring approaches. The main difference is that prediction, carbon estimation, anomaly detection and recommendations are available together and not in separate tools.

Table 3: Comparison of Existing Systems with ECOWATT AI

Feature	Existing / conventional systems	ECOWATT AI
Platform	Manual, basic digital or separate tools	One integrated AI-based platform
Monitoring	Manual meter reading or basic monitoring	Continuous energy consumption monitoring
Prediction	Limited or rule-based estimation	Machine-learning-based consumption prediction
Carbon emission	Manual calculation or basic estimation	Automatic calculation from consumption
Optimization	Manual analysis and fixed saving practices	AI-assisted, personalized recommendations
Data analysis	Basic or static reports	Interactive analytics and dashboards
Forecasting	Limited or unavailable	Daily consumption forecasts
Decision support	Mostly manual	AI/ML-assisted decision support

4.5 User Feedback Evaluation:

The platform was evaluated on five aspects: ease of use, consumption monitoring, prediction accuracy, effectiveness of the saving recommendations and overall usefulness. Scores were collected on a scale of 1 to 5, where 1 is poor and 5 is excellent. Table 4 gives the average scores.

Table 4: Average Evaluation Scores (out of 5)

Sl. No.	Evaluation parameter	Average score
1	Ease of use (user interface)	4.6
2	Energy consumption monitoring	4.5
3	Energy prediction accuracy	4.4
4	Effectiveness of energy-saving recommendations	4.3
5	Overall system usefulness	4.7

The average across the five parameters is 4.5 out of 5. Overall usefulness scored highest at 4.7, which suggests that users found the platform helpful for managing their energy. Recommendations scored lowest at 4.3, so that module has the most room to grow, mainly through more personalized suggestions drawn from each user's own pattern. These scores reflect user opinion. They are not a measure of forecasting error, which needs a separate study on larger and more representative datasets.

4.6 Limitations:

- The quality of predictions depends on how much and how good the historical data is.
- Carbon estimates change with the emission factor that is used.
- The prototype is not yet connected to real-time smart meters or IoT devices.
- The benefit of any recommendation depends on whether the user acts on it.

5. CONCLUSION

This paper presented ECOWATT AI, a platform that helps users monitor electricity consumption, forecast future demand, spot unusual usage, estimate carbon emissions and receive practical advice, all from one dashboard. By joining these functions and explaining results in plain terms, it aims to turn raw consumption data into decisions a person can act on. User feedback on a five-point scale averaged 4.5, and the work contributes to UN Sustainable Development Goal 7 (Affordable and Clean Energy) by promoting efficient use of electricity, and to Goal 13 (Climate Action) by helping users understand and reduce the emissions linked to their usage.

Future Scope: The next steps are integration with real-time smart meters and IoT devices for automatic data collection, training and testing the prediction models on larger datasets with measured error metrics, more personalized recommendations based on individual usage patterns, and richer analytics with more detailed trends, comparisons and emission insights.

ACKNOWLEDGEMENT

The authors thank Dr. Pramod, Professor and Head, Department of Computer Science and Design, for his guidance, support and encouragement throughout this work. They also thank the Department of Computer Science and Design, PES Institute of Technology and Management, Shivamogga, for providing the facilities needed to carry it out, and the teaching and non-teaching staff, family and friends who helped along the way.

REFERENCES:

1. “Machine learning driven smart electric power systems: Current trends and new perspectives,”

Applied Energy, vol. 272, p. 115237, 2020.
2. G. M. U. Din and A. K. Marnerides, "Short term power load forecasting using deep neural networks," in *2017 International Conference on Computing, Networking and Communications (ICNC)*, 2017.
3. W. Waheed and Q. Xu, "Data-driven short term load forecasting with deep neural networks: Unlocking insights for sustainable energy management," *Electric Power Systems Research*, vol. 232, p. 110376, 2024.
4. L. Breiman, "Random forests," *Machine Learning*, vol. 45, pp. 5–32, 2001.
5. T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2016, pp. 785–794.
6. Tiwari and N. M. Pindoriya, "Automated demand response in smart distribution grid: A review on metering infrastructure, communication technology and optimization models," *Electric Power Systems Research*, p. 107835, 2022.
7. M. Mahmood, P. Chowdhury, R. Yeassin, M. Hasan, T. Ahmad, and N.-U.-R. Chowdhury, "Impacts of digitalization on smart grids, renewable energy, and demand response: An updated review of current applications," *Energy Conversion and Management: X*, vol. 23, p. 100790, 2024.
8. L. Toderean, T. Cioara, I. Anghel, E. Sarmas, V. Michalakopoulos, and V. Marinakis, "Demand response optimization for smart grid integrated buildings: Review of technology enablers landscape and innovation challenges," *Energy and Buildings*, vol. 326, p. 115067, 2025.
9. U. Assad, M. A. S. Hassan, U. Farooq, A. Kabir, M. Z. Khan, S. S. H. Bukhari, Z. u. A. Jaffri, J. Oláh, and J. Popp, "Smart grid, demand response and optimization: A critical review of computational methods," *Energies*, vol. 15, no. 6, p. 2003, 2022.
10. X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid—the new and improved power grid: A survey," *IEEE Communications Surveys & Tutorials*, vol. 14, no. 4, pp. 944–980, 2012.