

Reliable Energy Consumption Analysis System

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Abstract:

Energy efficiency has emerged as a key component of sustainable development for people, companies, and governments alike in a time of growing urbanization and technological growth. This paper introduces the Advanced Energy Consumption Prediction System (AECPS), a sophisticated framework that harnesses machine learning to deliver precise, real-time forecasts of energy usage across residential, commercial, and industrial sectors. AECPS employs a dual-model approach—combining Linear Regression for baseline insights and Long Short-Term Memory networks (LSTM) for advanced time-series analysis—alongside robust data pre processing and interactive visualization tools. Preliminary results demonstrate LSTM superior accuracy (98.5%) over Linear Regression (65.2%), highlighting the system's potential to reduce waste, lower costs, and promote sustainable energy practices.

Keywords : Energy efficiency, Sustainable solutions , Energy consumption , Real-time data analysis , ML algorithms .

I. INTRODUCTION

In The world stands at a critical juncture where energy consumption patterns directly influence economic stability, environmental health, and societal well-being. in the past year alone, driven by industrial growth and increased reliance on digital

infrastructure. This surge, however, comes at a cost: fossil fuel dependency exacerbates climate change, while inefficient usage squanders finite resources. Traditional energy management systems, reliant on manual audits and static policies, struggle to keep pace with these dynamic challenges, often resulting in overuse, unexpected shortages, and missed opportunities for conservation

The Advanced Energy Consumption Prediction System (AECPS) emerges as a transformative solution to these issues, leveraging cutting-edge machine learning to analyze and predict energy usage with unprecedented accuracy. AECPS incorporates real-time data from smart meters, weather stations, and occupancy sensors to serve a variety of stakeholders, including households looking to maximize appliance use, businesses looking to streamline operations, and legislators creating greener urban plans.

Its objectives are threefold: to forecast energy needs with precision, to identify inefficiencies through actionable insights, and to foster sustainable practices that minimize environmental impact.

II .RESEARCH REVIEW

A smart energy consumption forecasting is important, especially for buildings as buildings' energy usage is increasing and almost reaches 40% of primary energy use in developed countries. A reliable energy consumption approach involves using energy efficiently and responsibly to meet

our needs while minimizing waste and environmental impact.

- **Accurately forecasting energy consumption :**

Particularly for solar energy, is a critical component in optimizing energy usage and ensuring efficient resource management. With the use of real-time weather forecasts, building-specific data, and previous data on solar energy consumption, sophisticated prediction models may produce accurate projections of future energy requirements.

- **Interpretability Challenges:**

Prominent interpretable machine learning expert Cynthia Rudin has dedicated a great deal of effort to tackling these issues. Her work is especially pertinent to energy systems, as interpretability can help develop practical plans for cutting consumption and increasing efficiency.

- **LSTM (Long Short-Term Memory Networks):**

Because it can identify long-term dependencies, this kind of deep learning model is especially well-suited for analyzing time series data. With an accuracy of 97.12%, the LSTM model was the best option for this prediction task, outperforming the Linear Regression model by a substantial margin.

Importance of Solar Energy:

One essential renewable resource that is essential to lowering dependency on fossil fuels and slowing down climate change is solar energy. Solar energy is a plentiful and clean energy source that reduces the environmental impact of conventional energy production, enhances air quality, and helps reduce greenhouse gas emissions.

Modules Used : The project is organized into several key modules, each responsible for a specific inspectorate energy consumption prediction system.

- **Data Ingestion Module:**

This module collects data for energy consumption prediction, including historical energy usage, weather forecasts (e.g., temperature), and building-specific details like the day of the week, working status, and number of employees. These inputs ensure accurate forecasting.

- **Feature Engineering and Data Preprocessing Module:**

In order to optimize data for improved model performance, this module applies transformations such log scaling, Standard Scaling (SS), and Min-Max Scaling (MMS) after extracting important features like weather and energy use from raw data for model training.

- **Modelling Module:**

The creation and validation of machine learning models for predicting energy usage are the main objectives of this module. It has an advanced LSTM Neural Network to capture intricate time series patterns and produce more precise forecasts, as well as a baseline Linear Regression model for simple predictions.

- **Prediction Engine Module:**

This module generates energy consumption predictions by running trained Linear Regression and LSTM models on new data. It compares the predictions from both models and selects the most accurate one for the final output, ensuring precise forecasting of future energy needs.

- **Deployment Module:**

This module deploys the best-performing model, typically an LSTM, to provide real-time energy consumption predictions. It continuously updates its forecasts based on incoming data and monitors model performance to ensure accuracy, implementing updates as new information becomes available

- **User Interface Module:**

This module offers an intuitive interface for users to interact with the system, view energy consumption predictions, and make informed decisions. It features visualizations such as graphs and charts for data trends and model performance, and provides comprehensive reports summarizing predictions, evaluations, and optimization recommendations.

III. PROPOSED APPROACH

iii.a. Python

Python is the best language to use while creating machine learning models for solar energy consumption due to its powerful libraries and tools. Libraries like scikit-learn simplify the use of linear regression for predictive modelling, while TensorFlow and Advanced methods for handling time-series data, such as Long Short-Term Memory (LSTM) networks, are made possible by Keras. Python is a flexible and effective option for creating and refining energy consumption models because of its ecosystem, which also includes Matplotlib for visualization and pandas for data manipulation.

iii.b. Machine Learning Algorithms Used

- **Linear Regression** was used as a baseline model to predict solar energy consumption, trained on historical data with features like temperature, day of the week, and building occupancy.
- **Accuracy** of the Linear Regression model was **63.74%**, highlighting its limitation in identifying intricate connections in the data.
- **LSTM Networks**, for better predictions, a kind of recurrent neural network intended for sequential data was employed.
- **Temporal Dependencies** the LSTM model successfully captured intricate patterns in time series data.
- **Accuracy** of the LSTM model was **97.12%**, significantly outperforming Linear Regression in prediction quality.
- **Conclusion:** Because of its exceptional performance, LSTM is the recommended option for precise estimates of solar energy use.

iii.c. Data Transformation Techniques

Log transformation was employed to stabilize variance and standardize the distribution of energy consumption data, which often spans multiple orders of magnitude. Applying the formula $(y' = \log(y))$, where (y) is the original value and (y') is the transformed value, helped reduce the variability and skewness in the data. This transformation made it easier for models,

particularly Linear Regression, to detect patterns and improve prediction accuracy.

It also addressed issues related to large fluctuations and outliers. However, it's important to note that log transformation cannot be applied to zero or negative values, necessitating the addition of a small constant to the data when these type of values are present.

iii.d. Data Preprocessing :

Data preprocessing is crucial in machine learning, involving the cleaning, transformation, and organization of raw data. The first step in this procedure is gathering historical building, weather, and energy data. To preserve continuity, interpolation or filling techniques are used to resolve missing values.

The datasets are then integrated based on timestamps to create a unified data set. Data transformation includes applying log transformation to reduce skewness and extreme values, and scaling features using Standard Scaling or Min-Max Scaling to ensure balanced contributions to the model training.

iii.e. Feature Extraction:

By generating valuable features from unprocessed data, feature extraction improves model performance. This entails determining important characteristics such as historical consumption trends, calendar information, meteorological conditions, and demographic data. While interaction features combine variables to reveal complicated interactions, time-based features, such as lag features, are employed to capture past values. Correlation analysis is used to control redundancy in feature selection, and tree-based models are used to analyze feature importance and rank the most significant characteristics for energy consumption prediction.

iii.f. Validation and Training the Model :

The Model Training and Validation module focuses on training machine learning models and evaluating their performance. Linear Regression was selected as a baseline model for its simplicity and trained using ordinary least squares (OLS) on historical consumption, weather, and calendar data. Back propagation through time (BPTT) was used to train the LSTM model, which is intended to handle time series data, in order to capture long-

term dependencies. Cross-validation was used to evaluate the models' performance and reduce overfitting, while grid search and other hyperparameter tuning methods were used to optimize the models' parameters and improve accuracy.

iii.g. Model Evaluation and Comparison:

The correctness of the trained models is evaluated by the Model Evaluation and Comparison module using performance metrics including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-Squared (R^2). A comparison between Linear Regression and LSTM models revealed that LSTM significantly outperformed Linear Regression, achieving 97.12% accuracy compared to 63.74%. Additionally, the strengths and weaknesses of each model were analyzed, considering factors like complexity, training time, and predictive accuracy, with LSTM emerging as the preferred model for deployment.

iii.h. Deployment and Prediction Process:

The LSTM model was deployed in a cloud-based environment for real-time solar energy consumption predictions. An API was integrated to allow external systems to send input data, such as weather forecasts and calendar details, for predictions. The system processes real-time data inputs and generates energy consumption forecasts for specific time intervals. Continuous monitoring ensures the model's accuracy, and retraining or tuning may be required if performance declines over time .

IV. Project Description

Important procedures like data preparation, combining historical energy, weather, and building data, and using log transformations and scaling for normalization were all part of the machine learning model for predicting energy usage.

- **Prediction Page:** Users input Global Reactive Power (kW), Voltage (V), and Global Intensity (A), then click "Predict" to trigger an LSTM model (97.12% accuracy) for real-time forecasting.



- **Analysis Page:** Displays outcomes with statistics (e.g., Mean Power: 1.09, Max Power: 11.12) and a table of sample data (date time, power metrics, sub-metering), supporting data visualization and optimization insights.



date	Global power (kW)	Global reactive power (kVAr)	Voltage (V)	Global intensity (A)	Sub-metering (1)
2025-05-01 12:00	1.09	0.5	230.0	4.74	1
2025-05-01 13:00	2.5	1.2	230.0	10.87	1
2025-05-01 14:00	1.2	0.6	230.0	5.22	1
2025-05-01 15:00	3.0	1.5	230.0	13.04	1
2025-05-01 16:00	1.8	0.9	230.0	7.83	1

- **Design:** Clean, dark-themed navigation ("Home," "Predict," "Compare Models") ensures usability, aligning with RECAS's goals of energy efficiency, sustainability, and real-time prediction.

V.CONCLUSION

- **Explores solar energy consumption** in buildings using time series data and machine learning models.
- **Integrates historical energy data**, weather data, and building-specific details for feature extraction.
- **Prepares data for forecasting** by applying transformations for improved accuracy.
- **Compares Linear Regression** with LSTM networks to capture complex long-term dependencies.
- **Deploys the best model** for real-time prediction with continuous monitoring and updates.
- **Optimizes energy consumption** by ensuring accurate and reliable forecasting.

- **Contributes to sustainability** by improving solar energy use and resource allocation.

FUTURE SCOPE

- **Expanded Data Sources:** Integrate additional factors like solar radiation, humidity, and electricity pricing to enhance prediction accuracy and adaptability.
- **IoT Integration for Real-Time Forecasting:** Leverage IoT sensors in buildings to collect real-time energy data, improving responsiveness and precision in predictions.
- **Advanced Machine Learning Techniques:** Utilize ensemble methods and hybrid models, such as combining LSTM with other algorithms, to enhance forecasting performance.
- **Scalability Across Larger Networks:** Extend the system's capabilities to predict energy consumption across multiple buildings, industrial zones, or even entire city grids.
- **Optimization and Smart Grid Integration:** Develop features for energy storage recommendations, usage optimization, and seamless integration with smart grids to improve efficiency.

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