Power Consumption Prediction Using Machine Learning

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***Abstract*—Energy is vital in the modern world, and resource management depends on our ability to estimate our energy consumption with enough accuracy. The goal of our initiative is to alter the way we utilize electricity. Its primary objectives are to ensure that invoices are correct, promote energy conservation, enhance billing transparency, and assist in forecasting future energy requirements. We want to tackle typical issues such as incorrect billing, insufficient real-time data, complex data patterns, and privacy concerns. Our work focuses on power consumption prediction through machine learning. Our model powered by LSTM algorithms tries to forecast how much energy we will use in the future by utilizing historical usage data and other variables. By doing so, we can more effectively use resources, distribute and manage energy, and advance sustainability.**

Keywords—Keywords Managing Resources, real-time data, complex data patterns, past usage data, LSTM algorithms.

I. Introduction

In modern times, electricity is the essential resource that drives everything. Consider how vital energy is to every facet of our existence. Being able to predict how much electricity and energy we'll require is crucial as our energy use increases [1]. Regretfully, there are certain problems with the way we now handle electrical bills. They make mistakes frequently, don't provide us with information in real time, and have trouble deciphering the intricate patterns in our energy use.

That's the purpose of our project. Our goal is to transform the way we handle power bills, not only to solve these problems. The intention is to use machine learning to significantly improve the forecast accuracy of electricity bills [2].

II. RELATED WORK

Reddy et al. [1] focused on utilizing machine learning algorithms like KNN, ANN, Random Forest, and XGBoost to properly anticipate power demand for efficient energy management. After preprocessing a full year's worth of hourly power usage data, the KNN model demonstrated an impressive

90.92% accuracy rate in power consumption prediction. Even while machine learning makes predicting more accurate, its successful use may need a large amount of processing power and knowledge. However, the excellent accuracy attained by the KNN model highlights the possible advantages of using machine learning to forecast power use.

The study "Estimating Electricity Consumption at City Level" by Gellert et al. [2] examines and contrasts many models, such as TBATS, fuzzy controllers, LSTM, and Markov models, for forecasting urban power usage. With a mean absolute error of 3.6 MWh, TBATS showed the highest accuracy and is the best option for accurate energy management since it successfully manages seasonality. Its enormous computing requirements and complexity, however, are significant drawbacks. Conversely, the fuzzy controller works well in situations when more rapid, yet less exact, predictions are needed. It is faster, simpler, and less accurate. The study emphasizes the necessity of striking a compromise between computing economy and accuracy when choosing the right model for city-level energy management, underscoring the financial significance of precise power forecasts.

In Ranjan et al. [3] study, the predictive power of many machine learning algorithms such as ANFIS, RF, SVR, LR, KNN, and ELM are evaluated. Precise forecasting is essential to maximise energy efficiency and minimize ecological damage. To increase accuracy, the paper proposes hybrid techniques that combine ML models with dimensionality reduction. These models may have issues with scalability and interpretability, even though they offer accurate predictions and effective training. Remarkably, at 85.7%, Support Vector Regression (SVR) and Linear Regression (LR) outperformed the Random Forest (RF) model in accuracy.

The ARIMA model is used in the S. et al. [4] study to anticipate home energy consumption, and the results show that the predictions are almost accurate when based on consumption patterns and historical data. The accuracy of current month consumption projections is increased when trend and seasonality are successfully removed from the data using the ARIMA model. The ARIMA model has the benefit of improving forecast accuracy by taking historical data into account. One drawback is that there may still be discrepancies between actual and anticipated values in the model, suggesting that it needs to be improved. All things considered, the ARIMA model shows promise as a method for predicting power usage in individual homes, and it may

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be improved in the future by utilizing methods such as neural networks.

Shahriar et al. [5] propose a unique method that makes use of machine learning techniques to anticipate the battery charge patterns of electric vehicles (EVs). The study attempts to estimate the length of an EV session and its energy use by utilizing past charging data in conjunction with weather, traffic, and event data. The ensemble learning model outperforms all prior approaches and has the best prediction performance. The study is conducted using the Adaptive Charging Network (ACN) dataset, which comprises charging records from a university campus. The efficacy of the models is verified by important metrics such symmetric mean absolute percentage error, coefficient of determination, mean absolute error, and root mean square error. The maximum accuracy is achieved by ensemble models, namely the Voting Regressor for session time and the Stacking Regressor for energy usage.

III. METHODOLOGY

A. Proposed Methodology

The proposed methodology for forecasting energy consumption in commercial and residential buildings.

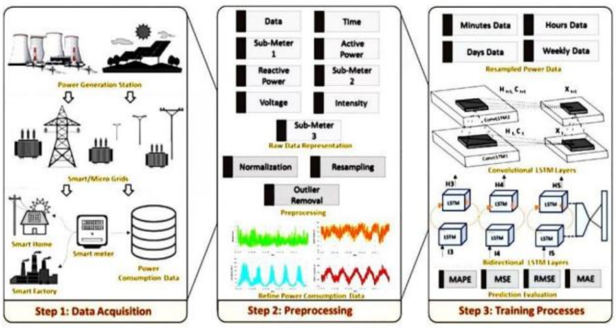

Fig. 1. Proposed Methodology

B. Data Collection

The household power consumption.txt dataset was collected via Kaggle. This dataset includes an extensive log of measurements of the amount of electricity used in a single household for over four years, from December 2006 to November 2010. With 2,075,259 observations in a rich time-series dataset, the data is taken at one-minute intervals. Data on voltage, current intensity, global reactive power, global active power, and three sub-metering areas—the kitchen, laundry room, and electric water heater/air conditioned are all included [18]. It helps with effective power management by analyzing and forecasting patterns of energy usage for tasks like clustering and regression.

C. Data Preprocessing

Resampling: Resampling of the household power consumption data involves changing the data frequency to various intervals, such as minutely, hourly, daily, and weekly. This process allows for different levels of data aggregation, making it easier to manage and analyze the data. Minutely resampling maintains the original detail for fine-grained analysis, useful for real-time monitoring and detecting short-term events. Hourly resampling reduces data volume by aggregating into 60-minute intervals, helping to observe daily patterns and peak usage times. Daily resampling aggregates data into daily values to highlight long-term trends and usage patterns, while weekly resampling smooths out daily fluctuations to identify broader weekly trends and seasonal patterns.

- Data Loading and Initial Parsing: The data is loaded from the 'household power consumption.txt' file. To facilitate the handling of time series, the date and time columns are parsed and merged into a single datetime index. To guarantee seamless processing, this phase additionally addresses any anomalies in the data format.
- Handling Missing Values: Missing values are identified and filled using statistical approaches, substituting the mean value of the corresponding columns, to maintain the integrity of the dataset. This is done to fill in the data gaps that can affect the model's performance and analysis.

$$X_{\text{missing}} = \frac{\sum X_{\text{observed}}}{N} \tag{1}$$

- Noise Removal: Several noise reduction methods are utilized to eliminate extraneous movements, guaranteeing that the data precisely portrays the fundamental patterns. [12] .It will improve the quality of the data by removing random fluctuations that might mask important trends.

$$\mathrm{MA}_t = \frac{1}{n}\sum_{i=0}^{n-1} X_{t-i} \tag{2}$$

Normalization: To guarantee consistency across various characteristics, the data values are scaled to a specified range, usually between 0 and 1. The range of data values is standardized in order to improve machine learning algorithms performance and convergence.

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{3}$$

Outlier Detection and Removal: To keep them from impacting the analysis, outliers are found using statistical metrics like standard deviations from the mean and then eliminated or modified to reduce high values that might mislead the results in order to increase the dataset's durability.

$$Z = \frac{X - \mu}{\sigma} \tag{4}$$

where μ is the mean of the dataset and σ is the standard deviation. Outliers can be defined as points where $|Z| >$ threshold. These outliers can be removed or replaced with a

suitable value, such as the mean or median of the non-outlier values.
Final Data Preparation: After completing the previous steps, the data undergoes a final check and any additional adjustments needed for the specific analysis or model requirements are made.To ensure the dataset is clean, consistent, and ready for analysis or machine learning tasks.
In order to efficiently use raw data for regression, clustering, and other analytical activities and ensure accurate and dependable findings, above preprocessing techniques are crucial.

D. Architecture

The machine learning algorithm that creates a model recognizes patterns in the training data and uses them to predict. Several algorithms like decision trees and neural networks, as well as more sophisticated models like ensemble techniques, can be applied. This design shows how a typical machine learning process might go from gathering raw data to generating predictions based on fresh data. It emphasizes the significance of every stage, from gathering data to choosing and refining the right model to using the model to get accurate predictions. Through effective learning from the data and good generalization to new, unseen data, this approach guarantees that the model can produce predictions that are accurate and dependable.

Fig. 2. Architecture

*Linear Regression Model:*In machine learning, linear regression is a fundamental and often utilized method. Assuming a linear relationship between the inputs and the output, it looks for the higher-dimensional hyperplane that minimizes the difference between the dependent variable's actual and expected values. This is a usual place to start when analyzing continuous data. In linear regression, the relationship between the dependent variable Y and the independent variables $X_1,X_2,...,X_n$ is modeled as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \epsilon \quad (5)$$

Here, β represents the coefficients, which are the parameters that the model learns during training to best fit the data. Each β coefficient indicates the strength and direction of the relationship between a particular independent variable and the dependent variable. The term ϵ represents the error term, which accounts for the variability in Y that cannot be explained by the linear relationship with the independent variables.

Neural Networks: A neural network is made up of layers of linked neurons, each of which applies an activation function after adding a bias term and a weighted sum of its inputs [15].Backpropagation is a technique used to train networks in which biases and weights are changed to reduce the discrepancy between the expected and actual outputs. For more complex patterns, a neural network might be used:

$$Y = f(WX + b) \quad (6)$$

In this equation:

- Y is the output of the neural network.
- f is an activation function, which introduces non-linearity into the model and allows the network to learn complex patterns. Common activation functions include the sigmoid, tanh, and ReLU (Rectified Linear Unit) functions.
- W represents the weights, which are the parameters that the model learns during training. These weights determine the strength and direction of the influence of the input features on the output.
- X represents the input features, which can be a vector or a matrix depending on the context.
- b is the bias term, which allows the model to shift the activation function to better fit the data.

Long Short Term Memory: The implementation of Long Short-Term Memory (LSTM) networks for predicting power consumption.The LSTM model is configured with hyperparameters such as the number of neurons, dropout rate, number of epochs, etc.The dataset is split into training (80%) and testing (20%) sets.The LSTM model is trained to learn temporal patterns and dependencies in the data.Performance metrics like Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) are used to evaluate the model.The trained LSTM model predicts future power consumption based on recent data. *LSTM Architecture:*The LSTM network consists of several components that manage the flow of information through the model, including forget, input, and output gates. *Input Sequence:* The model takes a sequence of past consumption values as input.
State Propagation: The forget, input, and output gates manage the flow of information through the LSTM cells, allowing the model to retain or discard information as needed.
Loss Function: Mean Squared Error (MSE) or Mean Absolute Error (MAE) is commonly used to measure the difference between the predicted and actual values.
Optimization: The model parameters are updated using an optimization algorithm like Adam or RMSprop to minimize the loss function.
Prediction: The trained model generates predictions based on the input data.

$$\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \quad (7)$$

This formula calculates the predicted electricity consumption using the learned coefficients.A graphical user interface

(GUI) is developed to allow users to input features and get predictions [16].

E. *Performance Evaluation*

The performance of the LSTM model is evaluated using the testing set.he performance evaluation includes several metrics such as RMSE (Root Mean Square Error), MAE (Mean
Absolute Error), and the loss function, which is based on Mean Squared Error (MSE).

Root Mean Squared Error (RMSE): Measures the square root of the average of squared differences between predicted and actual values.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (8)$$

Mean Absolute Error (MAE): Measures the average absolute difference between predicted and actual values.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (9)$$

IV. RESULTS AND ANALYSIS

The LSTM model was trained over 50 epochs with a batch size of 70. The document describes the use of the mean_squared_error loss function and the Adam optimizer.

Loss Curve: The loss curve typically tracks the MSE over the epochs to monitor the model's performance. A decreasing trend in the loss curve indicates that the model is learning and improving its predictions over time.

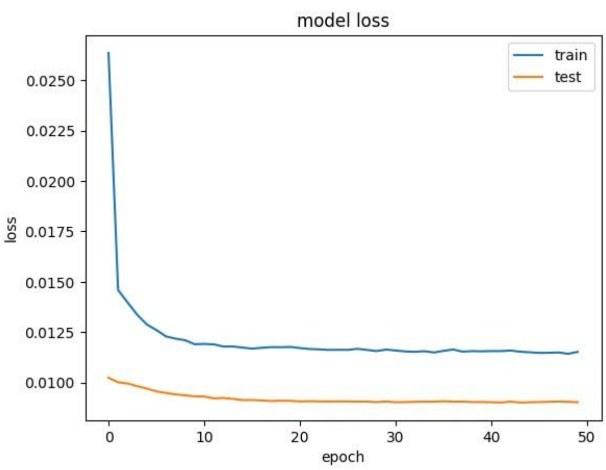

Fig. 3. Model Loss Curve

Data Resampling and visualization: Resampling the dataset was performed to reduce calculation time and improve predictability. The data was resampled on an hourly basis to balance the trade-off between computational efficiency and model accuracy. Data visualization techniques were used to understand the trends and patterns in power consumption over different time scales (monthly, daily, hourly). Figure 4,5,6,illustrates an example of a time series plot depicting the variation of a variable over time.

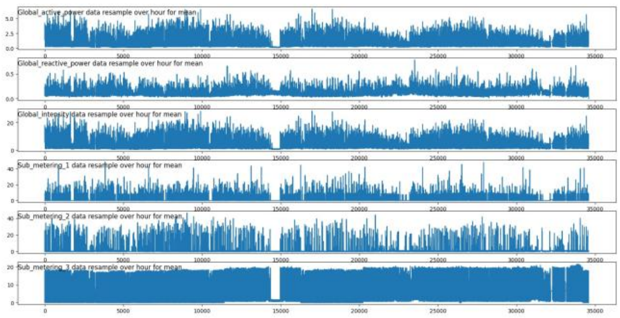

Fig. 4. Data Resampling for an hour

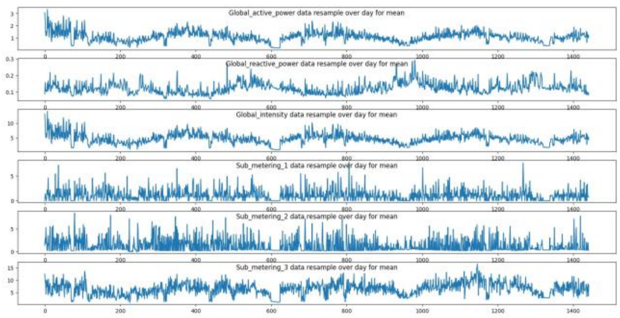

Fig. 5. Data Resampling for a Day

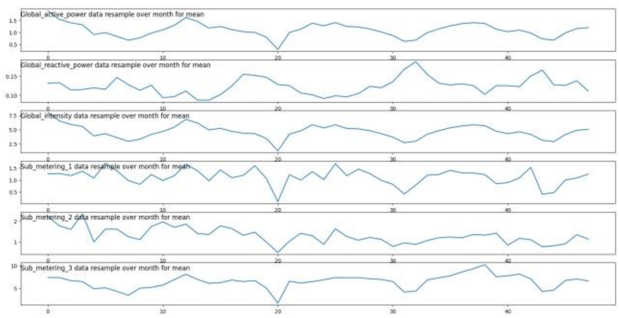

Fig. 6. Data Resampling for a Month

Therefore, processing all of the original data will result in an extremely expensive run time; however, processing data with big timeframe intervals (such as monthly) will have an impact on the model's predictability.

Using LSTM Model: For this project for power consumption prediction with Machine Learning, we used the LSTM model because it is very well suited for large time-series data. Given below, Figure 7 shows the Time step for 500 hours. Resampling time series data to a 500-hour frequency can help in analyzing long-term trends, detecting seasonal patterns, and reducing data size for more manageable analysis.

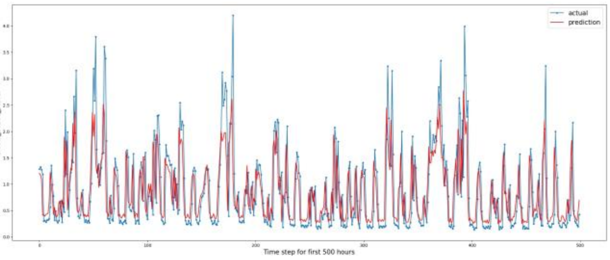

Fig. 7. Time Step for 500 hours

V. CONCLUSION AND FUTURE WORK

This study showed that machine learning algorithms can predict household electricity consumption using time series data. Preprocessing, including normalization, outlier removal, and 500-hour resampling, prepared the data for model training. Neural networks performed best due to their ability to capture complex relationships.

Future work will enhance models with external factors, explore advanced techniques, and develop real-time prediction systems integrated with smart grids for broader applications.

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