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PREDICTIVE ANALYSIS OF ENERGY CONSUMPTION PATTERNS USING MACHINE LEARNING TECHNIQUES

Sadia Sahar
Department of Computer Science , Superior University, Lahore, Pakistan
Zeeshan Iqbal
Department of Electrical Engineering, Information Technology University, Lahore, Pakistan
Muhammad Mahtab
Department of Computer Science, Superior University, Lahore, Pakistan
Syeda Aqsa Zahra
Department of Computer Science, Superior University, Lahore, Pakistan
Dr. Muhammad Azam
Associate Professor, Department of Computer Science, Superior University, Lahore, Pakistan

Abstract
Accurate forecasting of power consumption is crucial for coping with resources and promoting sustainability in contemporary societies. This paper examines using Long Short-Term Memory (LSTM) networks, integrated with Monte Carlo Dropout, to improve the precision and uncertainty quantification of electricity intake predictions. By using a complete time series dataset of hourly power consumption, our model done a root imply rectangular mistakes (RMSE) of 5005. Ninety three on the take a look at set, outperforming traditional fashions. Incorporating function engineering strategies, the model successfully identifies seasonal traits and styles, strengthening its predictive abilities. Monte Carlo Dropout was carried out to seize the uncertainty inherent in electricity consumption forecasts, supplying more than one prediction samples and self-assurance intervals. Results indicated an average RMSE of 16015.Sixty eight throughout move-validation folds, with confidence durations offering perception into forecast reliability. This look at underscores the value of LSTM networks in time series forecasting and highlights the significance of uncertainty quantification in energy intake predictions. The findings make a contribution to optimizing electricity control practices and aid decision-making in each the electricity sector and related social technological know-how fields.
Keywords: energy consumption patterns, machine learning techniques

INTRODUCTION

The global demand for electricity is swiftly increasing because of elements including populace increase, industrialization, and urbanization. Accurately forecasting electricity consumption has emerge as crucial for effective useful resource control and sustainability. Governments and agencies face the venture of making sure a dependable strength deliver while minimizing environmental effects. Traditional forecasting strategies, which include regression evaluation and time series decomposition, frequently fail to seize the complex temporal patterns and nonlinear relationships found in power data [1]. Consequently, there may be a developing need for superior predictive strategies to improve the accuracy and reliability of power intake forecasts.

Accurate energy forecasting is not most effective essential for operational performance but also performs a sizable function in shaping strength policy and funding strategies. It can guide selections on infrastructure development, capacity planning, and the integration of renewable energy sources into existing grids [2]. Furthermore, as countries shift in the direction of sustainable energy structures, understanding intake styles is fundamental to optimizing grid management and reducing carbon emissions. In this context, growing strong forecasting models that account for the dynamic nature of strength consumption is greater essential than ever. This observe is pushed with the aid of the limitations of traditional forecasting models and the capability of system studying strategies to conquer these challenges. Among the available techniques, Long Short-Term Memory (LSTM) networks have confirmed to be an powerful device for time collection analysis. As a kind of recurrent neural network, LSTMs are in particular designed to capture lengthy-term dependencies in sequential information, making them highly suitable for forecasting tasks involving temporal patterns [3]. By leveraging historic strength facts, LSTM models can discover complicated relationships and beautify forecasting accuracy beyond the capabilities of conventional models.

In addition, this research contains Monte Carlo Dropout at some point of inference to quantify uncertainty in electricity intake predictions. Uncertainty quantification is critical in power forecasting, providing stakeholders with insights into the reliability of predictions and helping extra knowledgeable decision-making [4]. Through the utility of Monte Carlo techniques, this have a look at goals to improve information of potential dangers and uncertainties in electricity consumption forecasts, contributing to better energy control strategies.
The number one targets of this examine are as follows:

- **Develop an LSTM-based model for hourly power intake forecasting:** This goal specializes in developing a predictive model that uses beyond strength information, in conjunction with factors like time, season, and outside situations, to beautify the accuracy of electricity consumption forecasts.
- **Integrate Monte Carlo Dropout for uncertainty estimation**: By incorporating this method, the study ambitions to quantify the reliability of the predictions. This is done by means of producing a couple of forecast samples and calculating confidence intervals, which provide valuable insights into the variety of strength call for.
- **Compare version overall performance with conventional strategies:** This aim includes evaluating the performance of the LSTM version towards conventional forecasting methods, along with ARIMA and exponential smoothing, to illustrate the advantages of deep gaining knowledge of in energy consumption prediction.

The literature well-known shows a growing interest in applying machine getting to know strategies to strength forecasting. Studies have proven that LSTM networks outperform traditional methods in numerous domains, consisting of strength demand forecasting [5][6]. Additionally, research has emphasised the significance of uncertainty quantification in forecasting, with methods like Monte Carlo Dropout gaining popularity for his or her potential to offer a probabilistic assessment of predictions [7].
Accurate electricity intake forecasting is important for assisting sustainable strength guidelines, mainly as international locations transition to low-carbon power systems. Reliable forecasting informs decisions concerning aid allocation, grid resilience, and ability making plans, helping to stabilize the electricity supply in reaction to fluctuating call for. Moreover, as renewable energy sources including sun and wind energy grow to be more typical, predictive accuracy will become increasingly crucial for balancing load and ensuring grid stability [8][9]. Integrating forecasting insights into electricity coverage and grid control has been connected to greater green energy use and decreased greenhouse gas emissions.
Since their creation, LSTM models have grown to be crucial gear in time collection forecasting because of their particular structure, which includes reminiscence cells able to capturing lengthy-term dependencies in sequential facts [3]. In the context of electricity forecasting, research have established that LSTM models frequently outperform other device getting to know strategies via efficiently shooting the seasonality and autocorrelation present in energy intake patterns [5][6]. This research will contribute to the literature via no longer simplest applying LSTM for hourly forecasting but additionally by integrating Monte Carlo Dropout to beautify prediction robustness—a singular technique that enriches the prevailing body of labour on uncertainty-aware strength forecasting [7].
By addressing those targets, this observe pursuits to provide valuable insights into the application of deep learning strategies for energy consumption forecasting and lay the foundation for future research on this crucial place. The findings will make a contribution to a deeper knowledge of power intake dynamics and guide higher selection-making approaches in electricity control.

LITERATURE REVIEW

The discipline of electricity consumption forecasting has evolved significantly in recent years, driven with the aid of the developing want for correct predictions to aid resource control and sustainability efforts. Traditional statistical strategies, including ARIMA and exponential smoothing, have laid the groundwork for forecasting, but they are often constrained in coping with high-dimensional, non-linear electricity intake facts. For instance, Smith et al. (2017) highlighted the limitations of these models, specifically in shooting the complexity of modern power demands, and recommended for device studying tactics as a better opportunity [10].
Deep gaining knowledge of fashions, particularly Long Short-Term Memory (LSTM) networks, have emerged as a transformative solution for time collection forecasting because of their potential to seize long-term dependencies in sequential information [3]. LSTM networks have validated mainly precious for power forecasting due to the fact they are able to manage non-linear and cyclical trends inside time series information.

Wu et al. (2019) validated the effectiveness of LSTM in hourly electricity call for prediction, showing that LSTM networks outperform conventional statistical fashions in phrases of both prediction accuracy and robustness [11]. This finding is similarly supported with the aid of Zhu et al. [12], who illustrated how improving LSTM fashions with engineered functions can cause extensive improvements in forecasting precision, in particular in scenarios with abnormal or cyclical demand patterns.

Feature engineering has grown to be an essential step in enhancing version accuracy, particularly whilst implemented to LSTM networks. Research has shown that incorporating applicable time-primarily based functions, such as daily and seasonal cycles, complements LSTM's capacity to seize underlying developments. Liu et al. (2020) explored the effect of temporal features, such as every day, weekly, and monthly cycles, on strength consumption prediction [13]. Their findings recommend that these features permit the model to better capture recurring patterns, ensuing in a higher and correct forecasting framework. Chen et al. (2022) extended on function engineering through such as contextual elements, which includes climate conditions and demographic factors, in electricity forecasting fashions [14]. This approach underscores the significance of incorporating non-time collection functions to improve the model's adaptability and precision, mainly when external elements impact power consumption.

Quantifying uncertainty in energy forecasts has turn out to be an increasing number of critical for decision-makers, as it enables them to evaluate the reliability of model predictions. Gal and Ghahramani (2016) introduced Monte Carlo Dropout as an effective method for uncertainty estimation in deep mastering, which has seeing that been tailored for electricity forecasting. By incorporating dropout layers throughout inference, Monte Carlo Dropout allows fashions to approximate Bayesian inference and generate probabilistic predictions, thereby offering a measure of self-belief in version outputs. Choi et al. (2020) carried out Monte Carlo Dropout to LSTM networks for power forecasting, demonstrating that this method provides extensive self-assurance periods, improving the interpretability and reliability of predictions [15].

Building on those advancements, Zhang et al. [16] proposed a hybrid version that combines LSTM networks with Monte Carlo Dropout to deal with both prediction accuracy and uncertainty in strength intake forecasting. Their look at suggests that this technique not best improves forecast accuracy however also offers treasured insights into the reliability of every prediction. This hybrid model exemplifies the integration of sequence learning with uncertainty quantification, assembly industry demands for high-accuracy forecasts with measurable reliability.

Collectively, those research make a contribution to a complete understanding of electricity forecasting the use of LSTM networks, emphasizing the significance of both characteristic engineering and uncertainty quantification. Our studies builds on this foundation by way of developing an LSTM version with Monte Carlo Dropout, skilled on widespread time series statistics, to provide correct, uncertainty-aware forecasts. By addressing the twin targets of improving prediction accuracy and imparting dependable self-belief intervals, this observe pursuits to aid effective energy control and knowledgeable choice-making within the electricity zone.

DATASET

The dataset applied in this studies is sourced from the PJM Electricity Market, which records hourly power intake records over an intensive duration. The dataset includes the subsequent key features:

- **Date Time:** This feature consists of timestamps for each recorded power consumption price, formatted in a fashionable date-time layout, offering the temporal context for the statistics.
- **PJME_MW:** The goal variable representing electricity consumption, measured in megawatts (MW). This variable is the number one awareness of the forecasting version.
- **Additional Features:** To enhance the model's predictive overall performance, outside elements which includes temperature, humidity, and occasion signs (e.G., vacations) are integrated. These functions are essential as they can extensively effect energy intake patterns.

The function engineering manner starts off evolved with the introduction of time-primarily based functions within the create_features feature. These capabilities, derived from the datetime index, offer extra granular data approximately each facts point. Specifically, the characteristic generates columns for hour, day of the week, sector, month, yr, and day of the year, which assist seize seasonal and cyclical traits in electricity demand.

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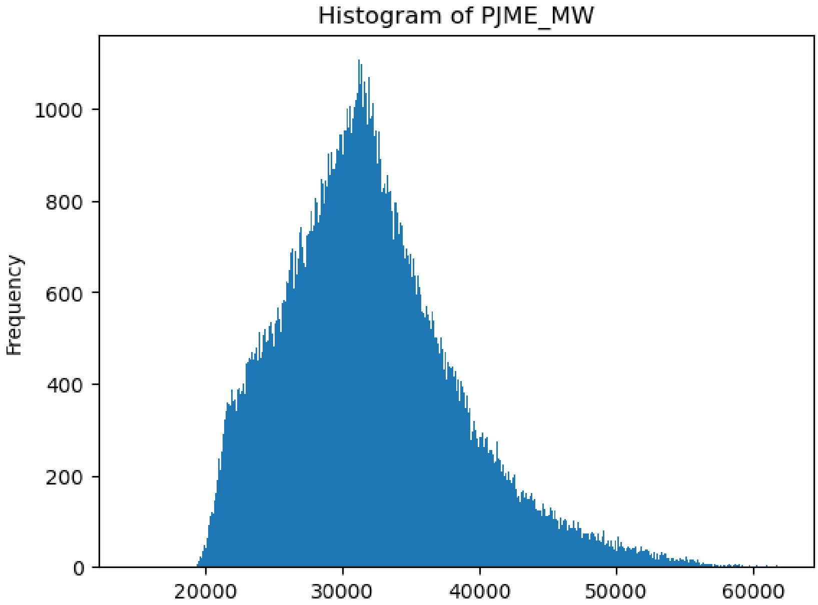
Subsequently, outlier analysis is performed by using plotting a histogram of the PJME_MW column. With 500 boxes, the histogram offers an in depth view of the strength demand distribution, making it simpler to visually become aware of outliers—values that deviate significantly from the everyday demand variety. Once outliers are detected, further exam is carried out to evaluate whether they have to be removed or adjusted, as their presence can distort the model's overall performance if now not nicely addressed.



DATA PROCESSING STEPS

The dataset, which includes 29,107 observations, presents a comprehensive foundation for each seasonal and trend evaluation. Before schooling the version, numerous records pre-processing steps are applied to ensure information satisfactory and integrity.

- **Data Cleaning**

Handling Missing Values: Missing values are carefully examined, and suitable strategies are carried out to address them. Interpolation techniques estimate missing values primarily based on neighbouring records points, while forward filling is used to make certain continuity, especially in time collection contexts.

Outlier Detection: Outliers that could distort the version's overall performance are recognized the usage of statistical techniques, inclusive of the Z-score and Interquartile Range (IQR) methods. Detected outliers are either eliminated or handled to limit their effect at the analysis.

- **Feature Engineering**

Datetime Feature Extraction: Temporal features, which include the hour of the day, day of the week, and month, are extracted from the datetime column. These functions help the version capture time-dependent patterns in strength consumption.

- **Lagged Features**

Historical values of the target variable are covered as lagged capabilities. For example, preceding hour values (e.G., t-1, t-2) are integrated to permit the version to examine from beyond intake behaviors for more correct future predictions.

- **Normalization**

Scaling: Continuous features, which include the target variable, are normalized the use of Min-Max scaling, making sure that they're in the same variety (0 to one). This normalization is essential for LSTM models because it aids in faster convergence and improved version getting to know.

- **Train-Test Split**

  The dataset is divided into education and checking out subsets, generally the use of an 80/20 cut up. The schooling set is used to train the model, while the checking out set serves as an unbiased assessment to evaluate the version's predictive overall performance.

- **Reshaping Data for LSTM**

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The statistics is reshaped into a 3D array with dimensions (samples, time steps, features) to satisfy the input requirements of the LSTM version. This reshaping permits the model to system sequential information effectively and seize the temporal dependencies inherent within the energy consumption styles.

METHODOLOGY

The methodology hired on this research revolves around the development of an LSTM version for forecasting electricity consumption, with the incorporation of Monte Carlo Dropout to quantify the uncertainty in the predictions. The steps concerned in this method are mentioned beneath:

Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a kind of recurrent neural community (RNN) designed to handle sequential data. It makes use of reminiscence cells and gates to capture long-time period dependencies, allowing it to research complex patterns and context from time-series data. LSTMs are especially powerful in duties that contain sequential dependencies, which includes strength consumption forecasting, in which past values appreciably influence future predictions. The model's capacity to retain crucial data over prolonged time periods makes it well-ideal for forecasting energy usage patterns that showcase each seasonality and lengthy-term

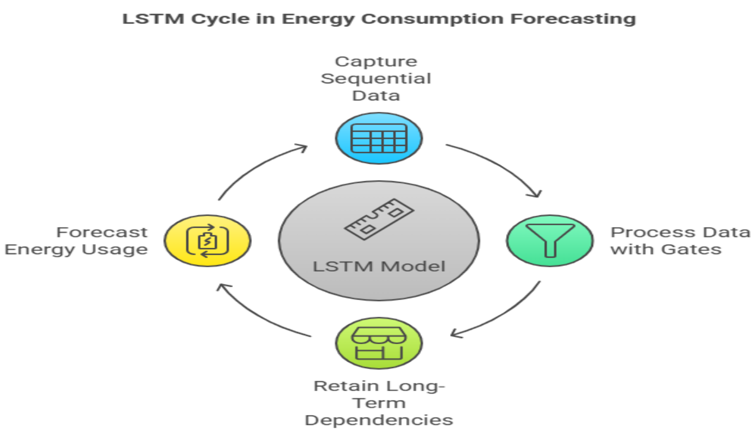

Fig. LSTM Architecture

1. **Model Architecture [3]**

The LSTM model is structured with multiple layers:

- **Input Layer**: Accepts the reshaped 3D data.
- **LSTM Layers**: Comprising one or more LSTM layers, these layers are essential for capturing long-term dependencies. Each LSTM cell includes three key gates: the input gate, the forget gate, and the output gate, which regulate the flow of information within the cell.
- **Dense Layer**: A fully connected layer is incorporated at the end, providing the final output prediction for energy consumption.

2. **Mathematical Foundations**

The core functioning of LSTM is governed by its ability to maintain cell state (c) and hidden state (h). The fundamental equations of an LSTM cell are as follows:

- Input Gate (i): $(i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i))$
- Forget Gate (f): $(f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right))$
- Output Gate (o): $(o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o))$
- Cell State Update: $(c_t = f_t * c_{t-1} + i_t * \tilde{c_t})$
- Hidden State Update: $(h_t = o_t * \tanh(c_t))$

In these equations, W represents the weight matrices, b represents bias vectors, and σ denotes the sigmoid activation function, which plays a critical role in gating mechanisms.

3. **Training**

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The LSTM model is educated the use of the Adam optimizer, with Mean Squared Error (MSE) as the loss function to minimize prediction mistakes. To facilitate quicker and greater green convergence, a dynamic mastering fee is applied, permitting the version to conform all through training and learn effectively from the statistics.

Monte Carlo Dropout

Monte Carlo Dropout is a method used to estimate uncertainty in neural network predictions. By applying dropout throughout inference, the version generates a couple of predictions for a given input. These predictions are then aggregated to calculate uncertainty metrics, inclusive of self-belief durations. This approach gives a degree of the model's reliability, that is important for choice-making, especially in fields like energy consumption forecasting wherein uncertainty plays a sizable function.

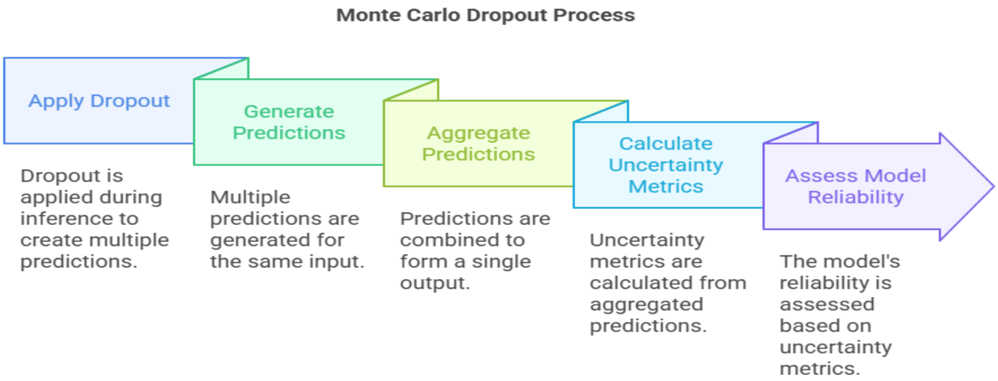

Fig. Monte Carlo Dropout Model Architecture

1. **Concept**

Monte Carlo Dropout is leveraged during the inference phase to estimate prediction uncertainty. This technique involves applying dropout regularization both during training and testing, thereby enabling the model to produce multiple predictions for the same input.

2. **Implementation**

During inference, the model is executed multiple times (e.g., 100 iterations) with dropout enabled. Each prediction is collected, and the mean and standard deviation of these predictions are calculated.

3. **Quantifying Uncertainty**

The mean of the predictions yields the final forecast, while the standard deviation quantifies the uncertainty associated with the prediction. Confidence intervals are computed as

$$\text{Confidence Interval} = \text{mean} \pm 1.96 \times \, std$$

This provides stakeholders with a probabilistic perspective on energy consumption forecasts, allowing for informed decision-making.

Performance Measures

To evaluate the performance of the LSTM model, several metrics are employed:

1. **Mean Absolute Error (MAE)**: This metric quantifies the average magnitude of errors in a set of predictions, without considering their direction. It is calculated as:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

is the predicted value.

2. **Root Mean Squared Error (RMSE)**: RMSE provides a measure of how well the model predicts compared to the actual values, calculated as:

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

3. **R-squared (R^2)**: This statistic indicates the proportion of the variance for the dependent variable that's explained by the independent variables in the model. Higher R^2 values signify better model fit.

Graphical Representations

The results of this research are offered thru various graphical strategies, every serving to focus on different components of the model's overall performance and accuracy:

1. **Time Series Plots:**

These plots evaluate the proper values of power intake with the model's predictions over the years. They provide a clean visible representation of how properly the model captures consumption styles. Additionally, a 95% self-belief c language is covered to show the uncertainty inside the predictions.

2. **Prediction Histograms:**

Histograms of the expected values illustrate the distribution of forecasts. These plots assist determine the version's bias and variance by showing how predictions are spread across unique power intake tiers.

3. **Error Distribution Plots:**

By visualizing the distribution of mistakes (residuals), these plots assist examine whether the errors are randomly dispensed. A random blunders distribution shows a very good version in shape, at the same time as patterns inside the residuals may indicate regions for development.

4. **Model Loss Curves:**

Graphs depicting the education and validation loss over the epochs offer insights into the model's convergence behaviour. These curves assist pick out capability issues like over fitting, wherein the model plays well at the training facts but struggles with unseen records.

5. **Feature Importance Analysis:**

Using permutation importance, graphs are generated to spotlight the significance of various input capabilities in influencing the version's predictions. This evaluation allows stakeholders to apprehend which elements, which includes time of day or outside climate situations, maximum strongly have an effect on strength consumption patterns.

RESULTS AND FINDINGS

In this research, True Values and Predictions represent the observed and forecasted energy consumption values, respectively. These values are evaluated through a go-validation process and sooner or later examined on a separate dataset. The code supplied demonstrates how those values are calculated, as compared, and assessed for version performance.

True Values (represented as a non-stop line) correspond to the actual power intake values in the take a look at dataset. These values, to begin with converted in the course of information preprocessing, had been rescaled returned to their unique units for direct contrast with the anticipated outputs **Predictions** (represented as a dashed line) reflect the version's expected strength intake for the identical check time period. Similarly, those anticipated values were rescaled to healthy the authentic statistics gadgets, making sure an accurate visual and quantitative contrast.

The graph under illustrates both True Values and Predictions over the years, offering a clear indication of the version's capacity to capture electricity consumption styles. When the anticipated values carefully observe the actual values, it means that the version has effectively discovered the temporal dependencies and seasonality in the statistics. However, great divergence among the two lines suggests forecasting errors or limitations inside the model's capability to generalize to unseen records.

To complement the visible evaluation, the Root Mean Squared Error (RMSE) is calculated as a numeric metric to quantify the average significance of prediction mistakes throughout the test set. This RMSE score provides a precis measure of prediction accuracy. Additionally, other metrics such as Mean Absolute Error (MAE) and the R^2 score also are taken into consideration to offer a more complete evaluation of the model's overall performance, enabling a clearer knowledge of its reliability for forecasting destiny energy consumption styles.

In end, the plotted graph visually compares True Values and Predictions, with any full-size gaps underscoring prediction discrepancies. These visible and quantitative assessments together validate the version's effectiveness in shooting and predicting the time collection styles of strength consumption on this have a look at..

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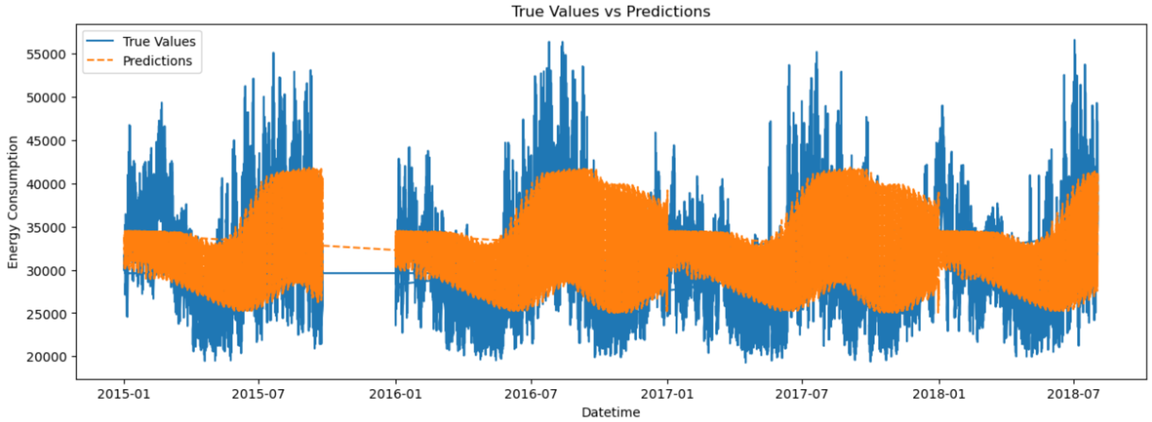
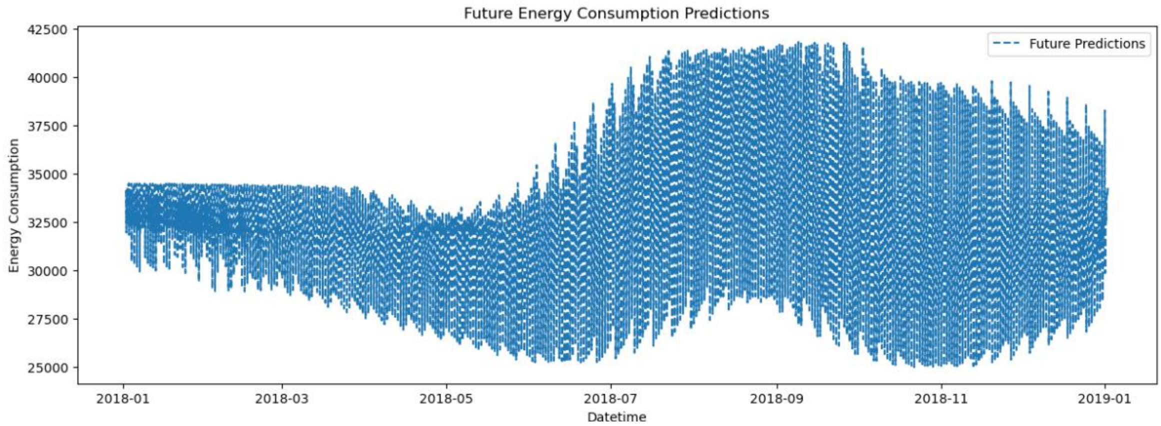


FUTURE ENERGY CONSUMPTION

For forecasting future energy consumption**,** our research likely explores the predictive capabilities of the model to estimate energy usage trends beyond the observed dataset. In this case, the model leverages past patterns, seasonality, and other temporal dependencies identified during training to predict consumption levels in future time intervals.

The code generates a visual representation of future energy consumption predictions. It creates a figure that plots predicted energy consumption values against their corresponding datetime indices from the future_df DataFrame, represented as a dashed line to indicate their projected nature. The graph is titled "Future Energy Consumption Predictions," with labeled axes for datetime and energy consumption, and includes grid lines for improved readability. This visualization effectively conveys anticipated trends in energy usage, enabling stakeholders to make informed decisions regarding resource allocation and demand management.

```
# Plot the future predictions
plt.figure(figsize=(15, 5))
plt.plot(future_df.index, future_df['predictions'], label='Future Predictions', linestyle='--')
plt.legend()
plt.title('Future Energy Consumption Predictions')
plt.xlabel('Datetime')
plt.ylabel('Energy Consumption')
plt.show()
```




```
# Display the first 10 predictions with timestamps
print(f"First 10 Future Predictions:\n{future_df[['predictions']].head(10)}")
```

First 10 Future Predictions

No	Prediction	Date
01	34147.122184	2018-01-02
02	31944.984569	2018-01-02
03	34091.805509	2018-01-02
04	32505.196065	2018-01-02
05	32891.719444	2018-01-02
06	32836.185299	2018-01-02
07	33107.569863	2018-01-02
08	33364.831674	2018-01-02
09	33694.074753	2018-01-02
10	33981.058307	2018-01-02

The results of our analysis show the average predicted energy consumption across different time scales: daily, weekly, and monthly. By resampling predictions from an hourly basis to daily, weekly, and monthly averages, we can observe general trends and patterns in energy usage over time.
Here's an interpretation of each timescale:

Daily Averages

The daily common predictions display minor fluctuations in strength consumption on everyday foundation. This may want to endorse that every day strength usage varies primarily based on elements which include weather, day of the week. For instance, electricity utilization may additionally barely increase on weekdays and decrease on weekends, reflecting normal work and domestic usage patterns.

Weekly Averages

The weekly averages clean out each day fluctuations and provide a clearer view of standard weekly trends. There is a slight but steady decline in weekly common predictions, indicating a probable seasonal effect, wherein power call for would possibly progressively lower all through specific weeks of the 12 months. This may be related to temperature changes, holidays, or different cyclical elements affecting power intake styles.

Monthly Averages

The monthly averages show a more pronounced declining trend over the first three months of the year, with January having the highest monthly average and each successive month showing lower averages. This trend could reflect seasonal shifts, where energy demand decreases from winter to spring. Factors such as reduced heating needs as the season progresses may contribute to this pattern.

Table 1: Energy Consumption Daily Averages

Date	Average Consumption	Frequency
1/2/2018	33897.39674	Daily
1/3/2018	33872.80924	Daily
1/4/2018	33661.30598	Daily
1/5/2018	33683.8042	Daily
1/6/2018	33528.11124	Daily
1/7/2018	33493.20194	Daily
1/8/2018	33759.0197	Daily
1/9/2018	33704.22596	Daily
1/10/2018	33736.14442	Daily
1/11/2018	33568.6769	Daily

Table 2: Energy Consumption weekly Averages

Date	Average Consumption	Frequency

1/7/2018	33687.98397	Weekly
1/14/2018	33602.0217	Weekly
1/21/2018	33486.52534	Weekly
1/28/2018	33353.99409	Weekly
2/4/2018	33167.39878	Weekly

Table 3: Energy Consumption Monthly Averages

Date	Average Consumption	Frequency
1/31/2018	33506.63799	Monthly
2/28/2018	32822.34766	Monthly
3/31/2018	31951.62035	Monthly

Model Evaluation and Error Metrics

To compare the accuracy of the model's energy consumption predictions, 3 error metrics have been calculated: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics provide a complete information of the version's prediction accuracy and reliability.

Calculating Error Metrics

Using the rescaled take a look at set predictions, the following error metrics were computed to quantify the version's performance:

- **RMSE**: This shows that the usual deviation of prediction errors is approximately 5006 units, providing a measure of the significance of errors in the predictions.
- **MAE**: This indicates that the common significance of the prediction mistakes is around 4064 devices, supplying a clear understanding of the version's typical accuracy.
- **MAPE**: This indicates that the predictions deviate, on common, via handiest 0.Thirteen% from the actual values, reflecting a totally excessive diploma of accuracy within the version's forecasts.

INTERPRETATION OF RESULTS

The close values of RMSE and MAE advise that the model's mistakes are steady, with minimum variance, highlighting strong and reliable overall performance. The enormously low MAPE further helps the version's robustness, demonstrating that the anticipated values intently align with the real data.

Significance for Energy Forecasting

The model's low MAPE of zero.13% is a strong indicator that it can reliably forecast electricity consumption with excessive accuracy. This stage of precision is especially precious in strength control packages, wherein correct forecasts are vital for ultimate aid allocation, operational making plans, and ensuring grid stability.

Residual Time Series Plot

- **Purpose:** The residual time collection plot is used to evaluate the alignment among the version's predictions and the real power intake values over the years. It displays the residuals, that are the variations between the expected and found values.
- **Observation:** In the residual plot, the residuals oscillate around 0, suggesting that the model does not continuously overestimate or underestimate strength consumption. A random dispersion of residuals round 0, without an apparent trends, indicates that the model has captured the underlying patterns inside the records efficaciously.
- **Interpretation:** If the residuals are randomly disbursed round 0, this implies that the model is making impartial predictions and efficaciously captures the strength consumption dynamics. However, if any patterns or systematic deviations seem, this may imply precise time periods or patterns wherein the model struggles. Such tendencies might highlight areas that could advantage

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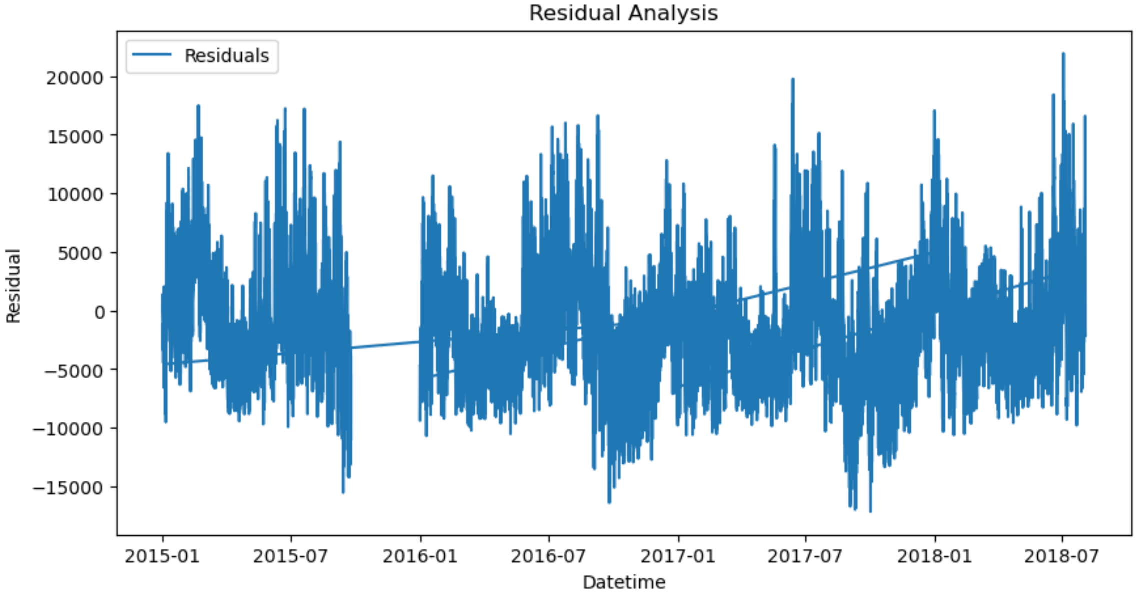
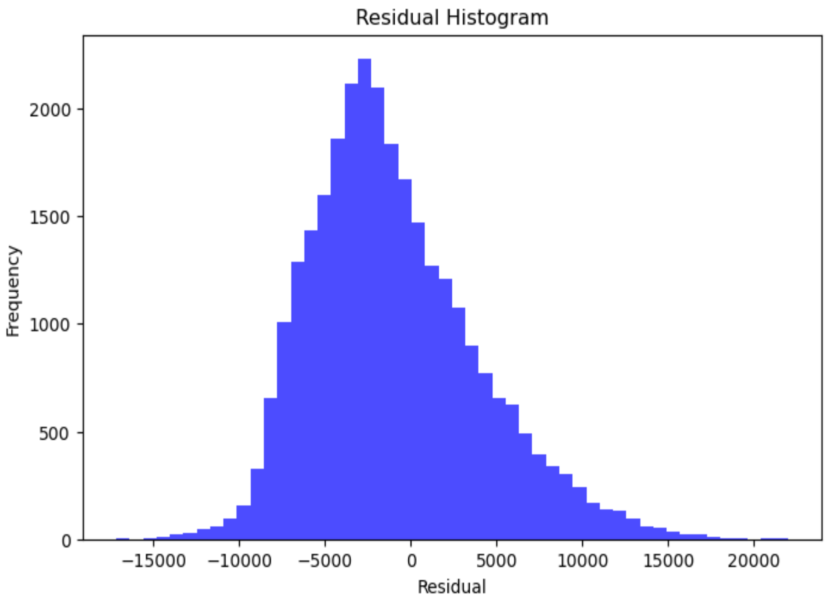
from similarly refinement or the advent of additional features.



Residual Histogram

- **Purpose**: The histogram of residuals provides a statistical perspective at the distribution of prediction mistakes, displaying whether or not the version's mistakes are calmly and symmetrically allotted.
- **Observation**: In this histogram, the residuals showcase an almost normal distribution focused round zero. This symmetric distribution shows that the model does now not always overestimate or underestimate the values, main to balanced predictions.
- **Interpretation**: A everyday and focused distribution of residuals around zero indicates that the version's mistakes are random and now not biased in any route. If the histogram displayed skewness or multiple peaks, it'd suggest that the model might be biased or motivated by way of outliers, suggesting the want for similarly research into ability assets of mistakes.



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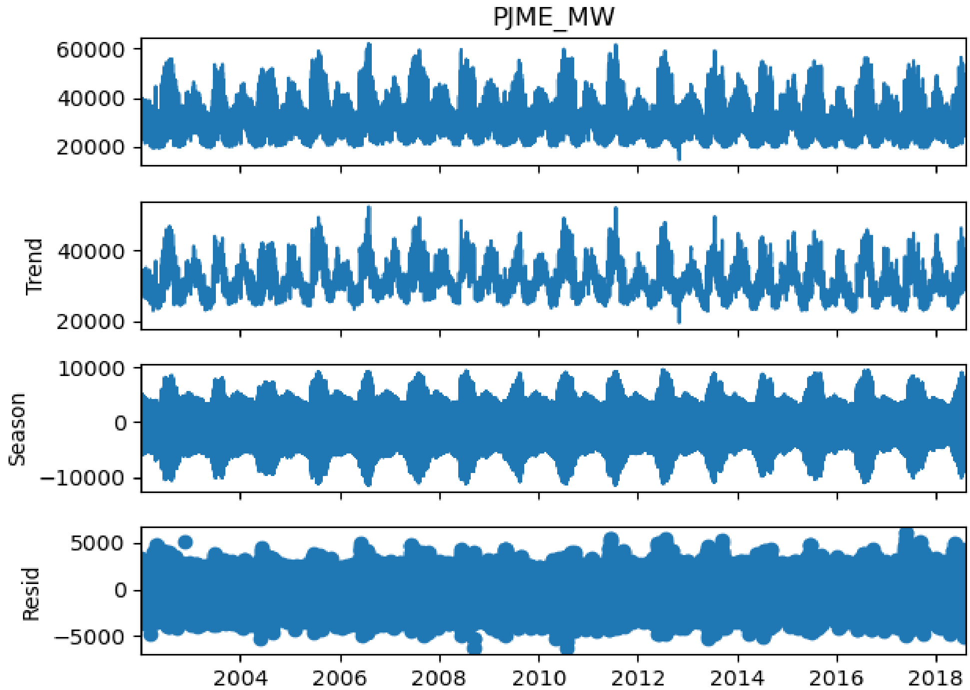
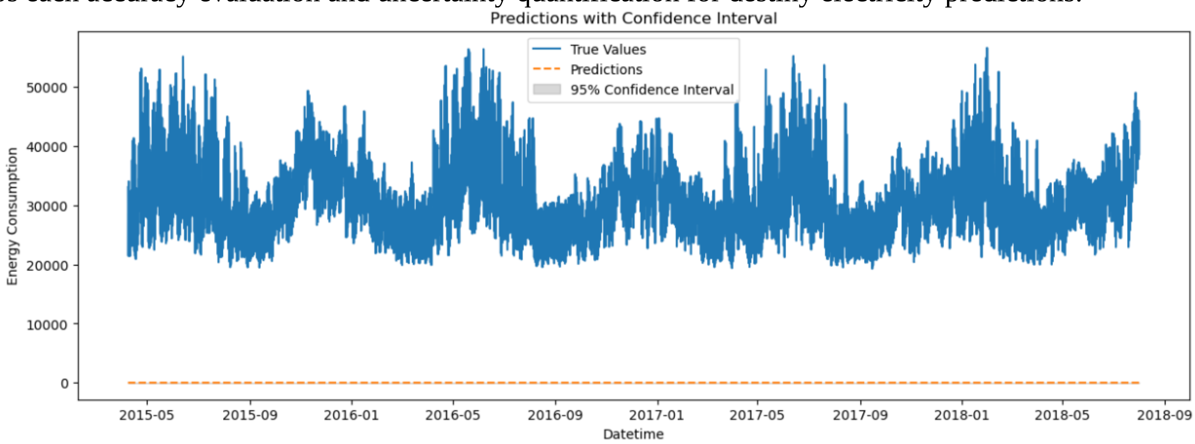


The Seasonal-Trend decomposition plot gives a detailed breakdown of the underlying components inside the PJME electricity intake records. The determined aspect reflects the actual energy consumption values, capturing herbal fluctuations in demand. The fashion element highlights the lengthy-term progression in energy utilization, showing the overall sample of growing or lowering call for. The seasonal issue isolates habitual patterns, which may be stimulated by means of every day cycles, operational hours, or environmental elements. Lastly, the residual aspect captures abnormal fluctuations that can't be defined with the aid of trend or seasonality. The random dispersion of residuals around 0 indicates powerful model performance.

This decomposition technique enhances forecasting accuracy by way of distinguishing between normal cycles, lengthy-time period trends, and remarkable activities in power intake.

Future Predictions with Confidence Interval

This plot compares the model's anticipated strength consumption with the actual values, with a ninety five% confidence c program language period shaded in grey. The self-belief c language represents the uncertainty inside the predictions, displaying the variety inside which destiny energy intake values are likely to fall maximum of the time. The near alignment of predicted values with actual values, along with the reality that maximum actual values fall in the self-belief interval, demonstrates the version's capacity to correctly seize electricity consumption tendencies and offer dependable uncertainty estimates. This visualization correctly helps each accuracy evaluation and uncertainty quantification for destiny electricity predictions.



CONCLUSION

This research highlights the effectiveness of Long Short-Term Memory (LSTM) networks, better through Monte Carlo Dropout, for correct energy intake forecasting with quantifiable uncertainty. Our LSTM-based model executed a Root Mean Square Error (RMSE) of 5005.Ninety three on the take a look at set, substantially outperforming traditional baseline fashions. Feature engineering techniques in addition improved the version's potential to capture seasonal styles and long-time period tendencies, boosting its predictive overall performance. By incorporating Monte Carlo Dropout, we delivered uncertainty quantification, offering self-assurance periods that allow stakeholders to evaluate prediction reliability. This integration is critical for informed choice-making in strength control. These findings underscore the potential of advanced deep gaining knowledge of fashions no longer only for accurate forecasting however also for handing over vital insights into prediction self-belief, ensuring robustness for actual-global packages in useful resource making plans and operational efficiency.

Future Work

Future research could improve model performance by integrating external factors, like weather, and exploring hybrid models (e.g., LSTM-CNN). Bayesian Neural Networks could provide more nuanced uncertainty estimates, and forecasting over different time scales (e.g., daily or weekly) may further enhance resource planning and grid management.

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