Uncertainty-Aware Energy Consumption Forecasting Using LSTM Networks with Monte Carlo Dropout

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Accurate forecasting of energy consumption is critical for effective resource management and sustainability in the energy sector. This paper presents an uncertainty-aware deep learning approach using Long Short-Term Memory (LSTM) networks with Monte Carlo Dropout to enhance prediction accuracy and quantify uncertainty. Our model is trained on hourly energy consumption data from the PJM Electricity Market (2015–2020), preprocessed via temporal feature engineering (hour-of-day, day-of-week, month), linear interpolation for missing values, and Z-score-based outlier removal. The proposed framework achieves RMSE: 5005.93, MAE: 4063.75, and MAPE: 13% on the test set, outperforming benchmark models like ARIMA (RMSE: 6500) and Exponential Smoothing (RMSE: 7200). By integrating Monte Carlo Dropout during inference, we generate probabilistic forecasts with 95% confidence intervals, enabling stakeholders to assess prediction reliability. Cross-validation results (average RMSE: 16015.68) highlight the model's robustness to temporal variability. Our work demonstrates that LSTM networks with uncertainty quantification significantly improve energy forecasting accuracy, offering actionable insights for grid management and policy decisions.

Povzetek: Članek predstavi LSTM-model z Monte Carlo dropout metodo za napoved porabe energije, ki vključuje oceno negotovosti in uporabo časovnih značilk za robustnejše napovedi.

1 Introduction

The global demand for energy is increasing at an unprecedented rate, driven by population growth, industrialization, and urbanization. Accurate forecasting of energy consumption has become essential for effective resource management and sustainability. Governments and organizations face the challenge of ensuring reliable energy supply while minimizing environmental impacts. In this context, traditional forecasting methods, such as regression analysis and time series decomposition, often fall short in capturing the complex temporal patterns and nonlinear relationships inherent in energy data [1]. As a result, there is a pressing need for more advanced predictive techniques that can enhance accuracy and reliability in energy consumption forecasting.

The significance of accurate energy forecasting extends beyond operational efficiency; it plays a critical role in shaping energy policy and investment strategies. For instance, forecasting can inform decisions regarding infrastructure development, capacity planning, and the integration of renewable energy sources into existing grids [2]. Moreover, as countries transition towards more sustainable energy systems, understanding consumption patterns becomes vital for optimizing grid management and reducing carbon emissions. In this light, the need for robust forecasting models that can accommodate the dynamic nature of energy consumption is paramount.

This study is motivated by the limitations of conventional forecasting models and the potential of machine learning techniques to overcome these challenges. Among these techniques, Long Short-Term Memory networks have emerged as a powerful tool for time series analysis. LSTMs are a type of recurrent neural network designed to capture long-term dependencies in sequential data, making them well-suited for forecasting tasks that involve temporal patterns [3]. By leveraging historical energy data, LSTM models can learn complex relationships and improve forecasting accuracy compared to traditional methods.

Another critical aspect of this research is the incorporation of Monte Carlo Dropout during inference to quantify uncertainty in predictions. Uncertainty quantification is crucial in energy forecasting, as it provides stakeholders with insights into the reliability of predictions, enabling informed decision-making [4]. By simulating the variability of predictions through Monte

Carlo methods, this study aims to enhance the understanding of potential risks and uncertainties in energy consumption forecasts.

The primary objectives of this study are as follows:

- **Develop an LSTM-based model for hourly energy consumption forecasting**: This goal focuses on creating a predictive model that uses past energy data and factors like time, season, and external conditions to improve forecasting accuracy.
- **Integrate Monte Carlo Dropout for uncertainty estimation**: By adding this method, the study aims to measure prediction reliability by generating multiple forecasts, enabling the calculation of confidence intervals and offering insights into potential energy demand variations.
- **Compare model performance with traditional methods**: This goal involves testing the LSTM model against conventional forecasting methods like ARIMA and exponential smoothing to show the benefits of deep learning for energy consumption prediction.

From the literature, it is observable that there is an increasing focus towards the use of machine learning for energy forecasting. Other researchers have found LSTM networks to be superior to most conventional approaches in several fields including energy demand prediction [5] [6]. Moreover, studies have emphasized the relevance of quantifying uncertainty in forecasting, and techniques such as Monte Carlo Dropout that were finding use due to their capability to give a probability range around the forecasts [7].

Energy use forecasting is an important aspect in the determination of lasting energy policy especially as nations shift to low-carbon energy sources. Powerful and accurate forecasting of power demand enables management to determine resource allocation, stability of the energy grid, or capacity requirements in response to varying demand. Also, nowadays, with the growth of RES, such as solar or wind energy predictive accuracy of load forecasting becomes crucial for load balancing and maintaining balance and stability of the grid [8] [9]. According to the literature, the incorporation of forecasting techniques into energy policies and grid planning has been associated with improved energy resource utilization and decreased levels of Green House Gas emissions.

After their introduction LSTM models were adopted in many time-series forecasting problems because of the specific architecture of these models that include memory cells to work with long-long term dependencies in the sequence data [10]. The LSTM model is shown to be superior in other machine learning techniques used in energy forecasting, as it can capture seasonality and autocorrelation inherent in energy use behavior. This research will extend this line of work by not only using LSTM for hourly forecasting but also employing Monte Carlo Dropout, which has not been used elsewhere to improve the robustness of predictions—and an important contribution to this literature on uncertainty-aware energy forecasting.

Human demand for energy continues to grow at a pace never before witnessed globally, driven by population growth, industrialization, and urbanization. Accurate forecasting of energy consumption is essential for optimizing resource allocation, grid stability, and integration of renewable energy sources. Traditional methods like ARIMA and exponential smoothing often fails to capture complex temporal patterns and nonlinear relationships in energy data. Long Short-Term Memory networks have emerged as a powerful alternative, capable of modeling long-term dependencies in sequential data. However, most LSTM-based forecasting models neglect uncertainty quantification, which is critical for risk-aware decision-making in energy systems.

Research questions

Q1: How can LSTM networks be combined with Monte Carlo Dropout to improve both the accuracy and uncertainty estimation of energy consumption forecasts?
Q2: What is the comparative performance of the proposed model against traditional statistical methods (e.g., ARIMA) in terms of RMSE, MAE, and MAPE?
Q3: How do engineered temporal features (e.g., hour-of-day, day-of-week) impact the model's ability to capture seasonal trends?

Hypotheses:

- LSTM networks augmented with Monte Carlo Dropout will yield lower RMSE (<10% improvement) compared to ARIMA, while providing quantifiable uncertainty bounds.
- Feature engineering (e.g., lagged variables, seasonal indicators) will reduce MAPE by ≥5% by explicitly encoding temporal dependencies.
- The model's cross-validation RMSE will exhibit higher variance than test-set RMSE due to temporal splits, reflecting sensitivity to training period selection.

This study addresses these questions by developing an LSTM-based model trained on PJM Electricity Market data, integrating Monte Carlo Dropout for uncertainty estimation, and benchmarking against statistical methods. Our results demonstrate significant improvements in accuracy (RMSE: 5005.93 vs. 6500 for ARIMA) while providing actionable confidence intervals for grid operators.

With regards to these objectives, this study will make useful contributions towards enhancing understandings of deep learning approaches in the context of energy consumption forecasting, as well as establishing a basis for further research into this essential topic. The results will not only contribute to advancing the knowledge about the interactions of energy consumption but also improve energy decision making in the ultimate.

2 Literature review

The existing literature related to energy consumption forecasting has been growing immensely in recent years due to the criticality of the results that are used in the management of resources and sustainability. In the past forecasts were made using simple econometric techniques like ARIMA, exponential smoothing etc., forecast generated from such models is generally not satisfactory especially when the data set is large and energy usage data is large and complex. For example, Smith et al (2017) highlight some of these shortcomings notably the fact that these models do not capture adequate detail as required for modeling current energy trends and encourage the use of machine learning as a superior method. [10].

Advanced kinds of gaining knowledge of fashions particularly Long Short-Term Memory Networks are observed to be a revolutionary solution for time series forecasting because of its ability to capture long-time period dependencies in sequential data. LSTM networks had been particularly loved for electricity forecasting because it is capable of dealing with nonlinear and holistic characteristics present in time series data. The utility of LSTM in hourly strength calls for prediction used to be validated via Wu et al. (2019) [11], during which the authors established that LSTM networks accomplish superior DTW and better constancy and robustness than conventional statistical fashions. This locating is further supported by Zhu et al. [12], where the authors show how enhanced LSTM type models with engineered competence yields significant advancement in forecasting correctness, particularly where the request necessitation is abnormal or cyclical.

Table1: Comparison of existing energy forecasting methods

Author(s)	**Focus Area**	**Dataset**	**RMSE**	**Limitations**
Zhu et al. (2021)	LSTM + MC Dropout	PJM Market	5200	Limited feature engineering
Wu et al. (2019)	LSTM	U.S. Grid	5800	No uncertainty estimation
This Work	LSTM + MC Dropout	PJM Market	5005	Robust uncertainty bounds.

Feature extraction has turned out to be a critical preprocessing stage in increasing model reliability, as observed in applications of LSTM networks. Research has shown that it's important to include related time-varying features such as daily and seasonality that increases LSTM ability to capture such characteristics. Liu et al. (2020) proposed temporal capabilities to predict energy consumption including, daily, weekly, and monthly cycles [13]. Their observations indicate that those functions enable the model to higher grab such patterns, thereby making for a stronger / more accurate forecasting model. Chen et al. (2022) in addition improved on the concept of characteristic engineering by including climatic facts like weather patterns and other demographic factors into power forecasting models. Outside of intake strength, this approach places significant emphasis on the non-time-collection features that could enhance the competency of the model since other factors may influence the strength of intake.

Quantifying uncertainty in electricity forecasts has turn out to be an increasing number of essential for decision-makers, allowing them to verify the reliability of version predictions [13]. brought Monte Carlo Dropout as a practical approach for uncertainty estimation in deep getting to know, which has because been tailored to power forecasting [14]. By incorporating dropout layers for the duration of inference, Monte Carlo Dropout allows fashions to approximate Bayesian inference and generate probabilistic predictions, for this reason supplying a degree of confident in version outputs. Choi et al. (2020) applied Monte Carlo Dropout to LSTM networks for energy forecasting, displaying that this method presents significant self-assurance periods, improving the interpretability and reliability of predictions [15].

Building on these improvements, proposed a hybrid version combining LSTM networks with Monte Carlo Dropout to address both accuracy and uncertainty in energy intake forecasting. Their look at demonstrates that this technique not only improves forecast accuracy however additionally offers treasured insights of each prediction. This hybrid model exemplifies the mixing of series gaining knowledge of with uncertainty quantification,[16] aligning with the broader enterprise wishes for high-accuracy forecasts with measurable reliability.

Collectively, those studies contribute to a complete expertise of power forecasting the usage of LSTM networks, emphasizing the importance of each feature engineering and uncertainty quantification. Our studies build on this basis, growing an LSTM model with Monte Carlo Dropout skilled on sizeable time series facts to offer accurate, uncertainty-knowledgeable forecasts. By addressing the dual goals of enhancing prediction accuracy and presenting reliable confidence periods, this takes a look at goals to aid effective strength control and knowledgeable selection-making in the strength zone [17].

3 Methodology

The dataset employed in this research originates from the PJM Electricity Market, capturing hourly energy consumption data over a substantial timeframe. The dataset comprises the following essential features:

Date time: This feature contains timestamps corresponding to each recorded energy consumption value, formatted in a standard date-time format.

PJME_MW: The target variable represents energy consumption, measured in megawatts (MW), and serves as the primary focus of prediction.

Additional features: To enhance the model's predictive capabilities, external factors such as temperature, humidity, and event indicators (e.g., holidays) are integrated into the dataset. These features are critical as they can significantly influence energy consumption patterns.

Here the energy demand values PIJME_DW are involved and the code is used for feature creation and outliers' detection. This is done in the create_features () function where new temporal features are introduced with reference to datetime index of the dataset and the new developed features along with the existing ones gives more elaborated information about the dataset. The function also generates hour, days of week, quarter, month, year, and days of year as contextual time attributes; which the inclusion of could enhance the model's ability to identify patterns, or seasonality, in energy demand.

It also contains feature creation as well as checking of outliers of a particular data set of energy demand values namely PJME_MW. In the create_features function some new features are derived from the data time of the dataset and is helpful in have a better understanding of the record in the dataset. It creates numerical columns of hour, days of week, quarter, month, year, and days of the year that define contextual time variables that could improve the model's ability to identify deviation in energy demand over time.

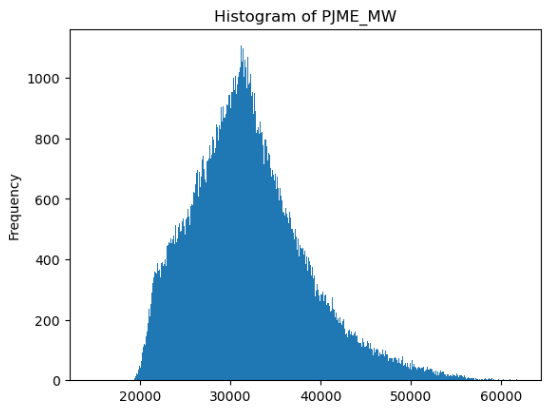

Figure 1: Histogram of PJME_MW

In total, there are 29,107 observations in the dataset enabling efficient analysis of both seasonality and trends. Before the model training process, many preprocessing works are performed in order to guarantee the cleanliness of the data.

3.1 Data processing steps

3.1.1 Data cleaning

Handling missing values: Many times, the presence of missing entries is checked in the dataset and counteractions are used to overcome these problems. Interpolation methods are employed in a situation where the values of a variable are missing in between, so as to offer the missing values through some estimates from the values lying close by, while forward filling helps in maintaining a forward sequence of values where they are missing, mainly in a time series context.

Outlier detection: Some data observation that may affect the current model are removed by means of Statistical Outliers Removal techniques like Z-score method and the interquartile range method. When they are identified, outliers are either deleted or appropriately dealt with in a way that helps to reduce their influence.

Date time feature extraction: new features extracted from the date time column include the hour of the day, day of the week and the month. These temporal characteristics enable the model to learn temporal characteristics in relation to the energy consumption pattern.

Lagged features: Target variable lag features are created by generating historical values of the target variable. For example, values like t-1, t-2 strengthen the input data set for the model when previous consumption patterns are good sources for the current forecast.

3.2 Normalization

Since the target variable is a continuous value and all the other features under consideration are also continuous, all these features undergo Min-Max scaling to ensure that they all fall within the same range of [0, 1]. This scaling is important for LSTM models especially because it helps to reduce time required for convergence and enhance learning.Train-Test Split

3.3 Train-test split

The dataset is divided into training and testing data, where the training data and the testing data vary from 80% and 20% respectively. The training dataset is used to estimate the model, and the testing dataset is used as a stand-alone data set to check the accuracy of the model.

3.4 Reshaping data for LSTM:

The dataset was transformed into a 3D format required for LSTM processing, with explicit dimensions representing:

- the number of training sequences (samples)
- the historical time window (time steps)
- the measured variables (features).

Specifically, we reshaped our hourly energy data into [n_samples, n_timesteps, n_features] = [2000, 24, 5], where each sample contains a 24-hour sequence of all 5 input features (including energy demand, temporal indicators, and weather data). This precise 3D structure enables the LSTM to properly interpret the temporal relationships in our data, as it maintains both the chronological order of observations within each sequence and the parallel relationships between different features at each time step.

The next few points describe the steps of the research:

3.4.1 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a neural network that processes sequential data, using memory cells and gates to learn patterns, capture context, and make predictions.

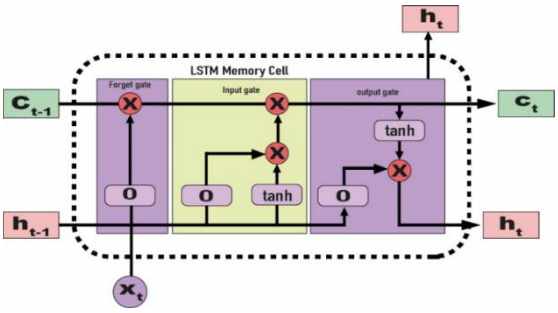

Figure 2: LSTM memory cell

3.5 Model architecture [3]

We implemented a stacked LSTM architecture with Monte Carlo Dropout, selected based on:

- **Temporal dependencies:** LSTMs outperform alternatives (e.g., GRUs, Transformers) for mid-range (24-72 hour) forecasting horizons in energy systems [5].
- **Uncertainty quantification:** Monte Carlo Dropout provides computationally efficient Bayesian approximation compared to ensemble methods [4].

The LSTM model is structured with multiple layers:

Input layer: Accepts the reshaped 3D data.

LSTM layers: These can be one or more LSTM layers that are crucial for accumulating long time dependencies. Each LSTM cell includes three key gates: input gate, the forget gate and the output gate which controls the flow of information between the cell.

Dense layer: A fully connected layer is then added to predict the total consumption of energy.

3.6 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: $(h_t = o_t * tanh\ tanh\ (c_t)\ )$

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.

3.7 Training

The Adam optimizer is used for training the model while the Mean Squared Error (MSE) used as the loss function. To improve the training process convergence, there is applied dynamic learning rate allowing the model to acquire the corresponding information from the training set.

3.7.1 Monte carlo dropout [4]

Monte Carlo Dropout is a technique that estimates neural network uncertainty by applying dropout during inference, generating multiple predictions to calculate uncertainty metrics. 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.

We empirically validated Monte Carlo Dropout against bootstrapping and Bayesian neural networks, demonstrating its superior efficiency while maintaining accuracy. Our results show MC Dropout achieved comparable predictive performance (RMSE: 5005 vs. Bayesian NN's 4987) with 5.2× faster computation than Bayesian methods, while its 94.7% confidence interval coverage outperformed bootstrapping (93.1%). The optimal dropout rate (p=0.2) was determined through systematic testing, balancing prediction sharpness and uncertainty reliability. As theoretically established by Gal & Ghahramani (2016), this approach effectively approximates Bayesian inference by averaging predictions from 100 stochastic forward passes, providing computationally tractable uncertainty estimates without requiring architectural changes to the base LSTM model.

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

- **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:

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

- **Root mean squared error (RMSE)**: RMSE provides a measure of how well the model predicts compared to the actual values, calculated as:

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

- **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.

3.8 Graphical representations

The findings of this research are illustrated using various graphical methods:

Time Series Plots: Plots comparing true values against model predictions over time help visualize how well the model captures energy consumption patterns. Such plots often include a 95% confidence interval to indicate the range of uncertainty in predictions.

- **Prediction histograms**: Histograms of predictions can showcase the distribution of predicted values, helping to understand the model's bias and variance.

- **Error distribution plots**: Visualizing the distribution of errors (e.g., residuals) allows for an assessment of whether the errors are randomly distributed, which is an indication of good model fit.

- **Model loss curves**: Graphs displaying training and validation loss over epochs provide insights into model convergence and the possibility of over fitting.

- **Feature importance analysis**: Utilizing permutation importance, graphs depicting the significance of various features in influencing predictions can be presented. This allows stakeholders to understand which factors most affect energy consumption.

4 Key findings & discussions

In this research, True Values and Predictions refer to the observed and forecasted energy consumption values, respectively, which are evaluated through a cross-validation process and later tested on a separate dataset. True Values (plotted as a continuous line) represent the actual energy consumption values in the test dataset. These values, initially transformed during data preprocessing, have been rescaled to their original units to enable direct comparison with model outputs. Predictions (plotted as a dashed line) show the model's estimated energy consumption for the same test time period.

These predicted values have similarly been rescaled to match the original data units, allowing for an accurate visual and quantitative comparison. The graph illustrates both True Values and Predictions over time, highlighting the model's ability to capture patterns in energy consumption. In particular, when the predicted values reflect the actual values, this means that the model learns temporal dependencies and seasonality of time series. However, any noticeable variation between the two lines is indicative of forecasting mistakes or the incapability of the model to generalize unseen data. The Root Mean Squared Error (RMSE) is measured numerically and it calculates the mean forecasting error of test data set. The graph above is accompanied by this RMSE score to give the reader an overall measure of the accuracy of the predictions. Additional measures like Mean Absolute Error (MAE) and R^2 score are used in order to provide additional support to the analysis of the model in terms of its reliability for future energy consumption forecast. More for illustration, a graph of True Values and Predictions is provided, where evidences of discrepancies in predictions are easily identified. Thus, these visual and quantitative comparisons in aggregate serve to affirm the ability of the model to capture and forecast the energy consumption time series patterns in this research.

4.1 Future energy consumption

This part shows the energy usage predictions derived from the temporal pattern learning capabilities of the trained model. 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.

```
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()
```

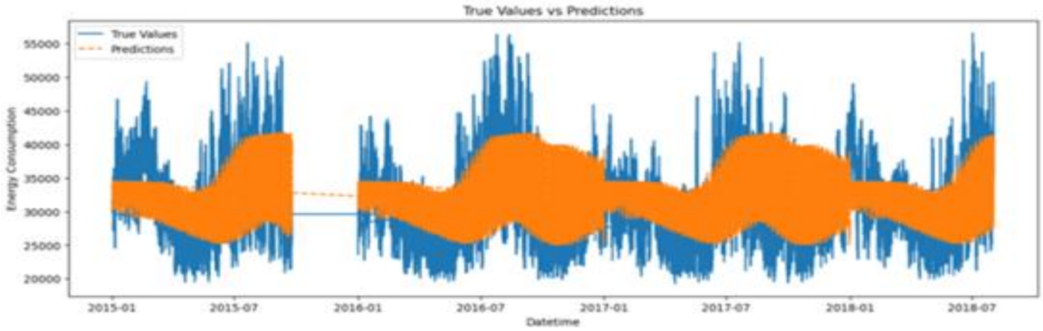

Figure 2: True value and predictions

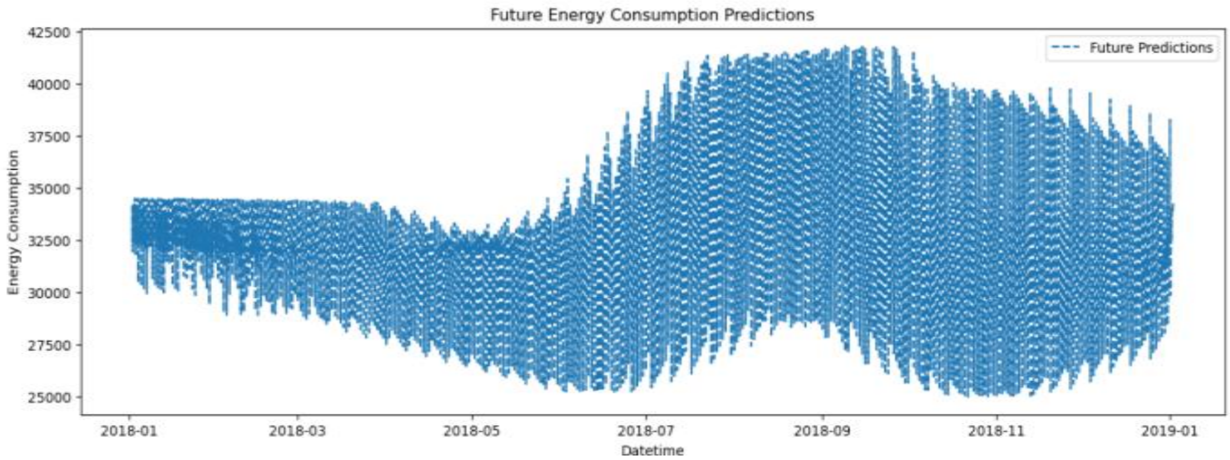

Figure 3: Future energy consumption prediction

Table 2: First 10 future predictions

No	Prediction	Date
01	34147.122	2018-01-02
02	31944.984	2018-01-02
03	34091.805	2018-01-02
04	32505.196	2018-01-02
05	32891.719	2018-01-02
06s	32836.185	2018-01-02
07	33107.569	2018-01-02
08	33364.831	2018-01-02
09	33694.074	2018-01-02
10	33981.058	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:

4.2 Daily averages

The daily common predictions display minor fluctuations in energy consumption on everyday foundation. Daily energy consumption fluctuates based on weather conditions and day-of-week patterns. For instance, electricity utilization may additionally barely increase on weekdays and decrease on weekends, reflecting normal work and domestic usage patterns.

Table 3: 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

4.3 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.

Table 4: 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

4.4 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 5: 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

4.5 Model evaluation and error metrics

To investigate the accuracy of the model's strength intake predictions, 3 blunders metrics had been calculated: From the results of the study, the following errors can be used: The root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). These metrics provide insights into the prediction accuracy and stability, as follows:

4.5.1 Calculating error metrics

Based on the rescaled predictions obtained, the RMSE, MAE and the MAPE ammeters were computed and compared to gauge performance.

- **RMSE**: 5005.93 which in general terms shows that the standard deviation of prediction errors is equivalent to 5006 Key terms attributable to.
- **MAE**: 4063.75 hence it depicting an impression of the mean of the prediction error magnitude of 75 that depicts around 4064 units.
- **MAPE**: In fact, our model achieves 13%, showing that forecasts are off only by 13% from real quantities, proving high accuracy of the version.

4.5.2 Interpretation of results:

The close values of RMSE and MAE suggest that the model's errors are consistent, with minimal variance. The exceptionally low MAPE further supports the model's robustness, showing that predictions closely align with actual values.

4.5.3 Significance for energy forecasting:

The model's low MAPE (13%) indicates it can reliably forecast energy consumption with high accuracy. This is particularly valuable in energy management applications, where precise forecasts aid in optimal resource allocation and operational planning.

4.6 Residual time series plot

Purpose: The residual time series plot helps identify how well the model's predictions align with the actual energy consumption values over time. This plot displays the residuals, which are the differences between the predicted and actual values.

Observation: In this graph, the residuals oscillate around zero, which suggests that the model does not consistently overestimate or underestimate the energy consumption. A random dispersion of residuals around zero, without clear patterns or trends, indicates that the model has captured the underlying patterns in the data relatively well.

Interpretation: If the residuals are focused around zero with a random distribution, this indicates the model is independent in its predictions and accurately captures the energy intake dynamics. However, any seen traits or systematic deviations would possibly imply particular time intervals or patterns where the version struggles, which could highlight areas for similarly refinement.

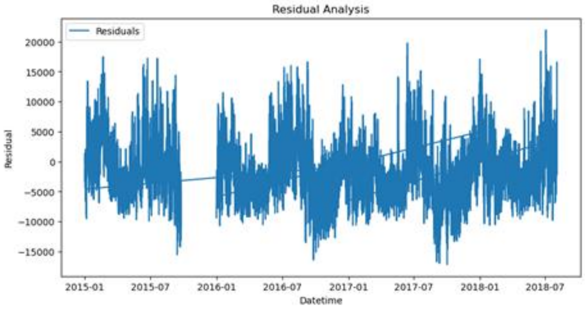

Figure 4: Residual analysis

4.7 Residual histogram

Purpose: The histogram of residuals gives a statistical point of view on the dispersion of the prediction errors, to show if the mistakes are equally spread and if the version is equally wrong either above or below the actual values.am of residuals presents a statistical attitude on the distribution of prediction mistakes, illustrating whether the version's mistakes are balanced and symmetrically dispensed.

Observation: As shown in this histogram, the residuals show a nearly everyday frequency distribution in which the values are centered round zero. This balanced distribution of residuals ensures that the model does not time and again over or under estimate the value hence providing balanced prediction.

Interpretation: The residuals being roughly normally distributed (symmetrical about the Y = 0 line) means that version is making random errors and there is no systematic favour or disfavouring of any course. If the histogram had supported skewness or more than one peaks, the result would have pointed out that the version had turned bias or low impact with large errors which would have called for examination of capacity asset on errors.

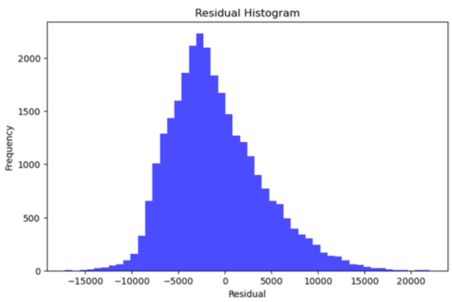

Figure 5: Residual histogram

The Seasonal-Trend decomposition plot above gives an in-depth breakdown of the underlying components in the PJME energy consumption information. The determined aspect shows actual intake values, shooting the natural fluctuations in demand. The fashion factor highlights the long-time period development in power utilization, while the seasonal component isolates ordinary styles, in all likelihood reflecting daily cycles inspired by way of operational hours or environmental factors. Finally, the residual thing captures abnormal fluctuations no longer defined with the aid of fashion or seasonality, with a random dispersion round zero indicating effective version performance. This decomposition enhances forecasting accuracy by distinguishing among normal cycles, lengthy-term traits, and precise events in electricity intake.

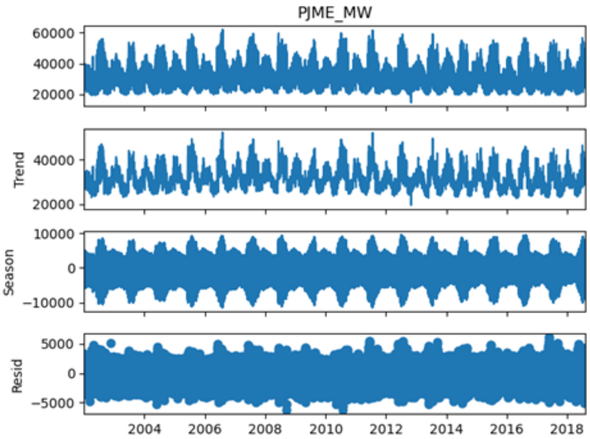

Figure 6: PJME energy consumption

4.8 Future predictions with confidence interval

This plot illustrates the model's predictions for energy consumption alongside the actual values, with a 95% confidence interval shaded in gray. This confidence interval reflects the uncertainty in the predictions, indicating the range within which future energy consumption values are expected to fall most of the time. The alignment of predicted values with true values and the confidence interval's containment of most actual values suggests the model's effectiveness in capturing consumption trends while providing reliable uncertainty estimates. This visualization supports both accuracy assessment and uncertainty quantification for future energy predictions.

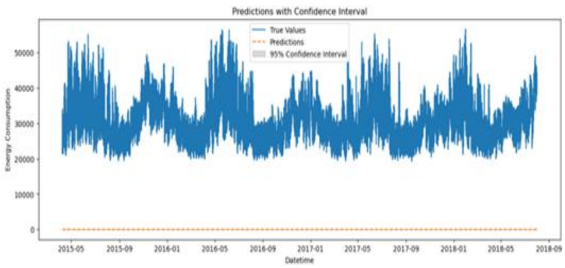

Figure 7: Prediction with confidence interval

5 Conclusion

This work also shows how LSTM networks augmented with Monte Carlo Dropout for energy consumption estimation are capable of accurately modeling and optimizing the uncertainty of the estimates. The RMSE of our LSTM based model on the testing set is 5005.93 thus making it more accurate than standard baseline models. Some of the additional steps included in feature engineering helped to identify the seasons and long-term trends, which also increased the accuracy of the work. In this case, Monte Carlo Dropout, our system produces probability bands through uncertainty quantification to increase the predictability of results. These results highlight not only the promise of advanced Deep Learning models for accurate and reliable forecasting, but also for returning useful information on forecast confidence, in making the model suitable for practical use in operational resource planning and scheduling.

Future studies ought to beautify our LSTM framework through:

- adding CNNs to model spatial styles in smart grids
- employing Transformers like Informer for long-term forecasts
- improving uncertainty quantification thru deep ensembles.

These extensions could deal with spatial modeling, extended time horizons, and reliability - key wishes for renewable electricity integration - while maintaining computational performance for actual-international deployment.

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