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Intelligent Energy Forecasting Using Neural Networks: A Comparative Study of RNN and LSTM Models for Household Electricity Consumption Prediction

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Abstract

Electricity demand forecasting is key to energy planning, budgeting, and sustainability programs. This paper compares Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) architectures for forecasting daily household electricity consumption using the UCI Household Electric Power Consumption dataset. The models take energy related features of the last 7 days (global active power, voltage, global intensity and 3 sub-meteringvalues) as input and output the forecasted consumption for the next day. The study uses advanced preprocessing techniques including intelligent missing value handling, multi-level temporal resampling and robust scaling. The output is a numerical forecast with a graphical visualization showing the historical consumption alongside predictions and a computed percentage change to show consumption trends. This research shows the practical application of neural networks to electricity consumption forecasting, with big implications for individual budgeting, sustainability initiatives and smart grids optimization.

1 Introduction

Accurate forecasting of residential electricity consumption is critical in this era of increasing global energy demands, sustainability initiatives and cost optimisation. Inaccurate energy consumption forecasting leads to inefficient grid planning, unexpected costs for consumers and missed opportunities for energy saving. With the proliferation of smart metering infrastructure, high granularity time series data on household energy usage is now available and machine learning can be used to improve forecasting accuracy. This paper presents a comparative study of neural network based approaches for daily household electricity consumption forecasting, specifically evaluating RNNs and LSTM networks. The researcher used the UCI Household Electric Power Consumption dataset to develop models that not only forecast future consumption values but also provide visualisations and metrics that can support decision making for consumers and utility providers.

The program developed in this research took as input a seven-day sequence (168 hours) of household electricity consumption data with twelve features: the mean and standard deviation of Global Active Power (kilowatts), Voltage (volts), Global Intensity (amperes), and three sub-metering values (watt-hours) that corresponded to specific appliance groups. These base features were enhanced through intelligent preprocessing, feature engineering, as well as standardization techniques to capture temporal patterns more effectively. The output of the program consisted of three components which are: (1) a numerical forecast of the Global Active Power mean value for the next day, (2) a percentage change calculation which compares the forecast to the most recent actual value, and (3) visual representations which illustrates and shows the historical consumption alongside the predicted value.

This research contributed to the field of energy forecasting in several important ways. First is by comparing different recurrent architectures (traditional RNN versus LSTM), the study offered insights into which approach best captured the temporal dependencies in household electricity consumption. Second is through an enhanced preprocessing pipeline and feature engineering, where the researcher has presented how domain knowledge could massively improve model performance. Finally, by providing comprehensive evaluation metrics and visualizations, the work transformed complex predictive models into practical tools for energy management.

The potential applications of this work extended beyond individual households to include utility companies for load balancing, smart grid management systems for resource allocation, and even advanced energy policy frameworks for sustainability planning. With the ongoing global shift towards an energy-efficient society, the world demands precise forecasting tools, such as the ones offered in this paper, for optimizing resource allocation and minimizing ecological impacts.

2 Related work

Electricity demand forecasting has been researched across a range of disciplines with notable developments in recent years as a result of the widespread application of machine learning and deep learning technologies. Existing methodologies can be distinguished into four main approaches: conventional time-series models, regression-based machine learning, neural network designs, and hybrid deep models. This section provides a review of these methods, their extensions to home electricity usage forecasting, and recent developments that provide the basis for the approach outlined in this paper.

2.0.1 Traditional Time-Series Forecasting Models

Early methods of forecasting were based extensively on statistical models, particularly Autoregressive Integrated Moving Average (ARIMA), which was initially quantified in a formal sense by Box and Jenkins (1). Such models necessitate stationarity and linearity assumptions and are thus ideally suited for data with constant and cyclical patterns. Such concepts were built upon by Hyndman and Athanasopoulos and transformed into empirical forecasting procedures that are a synthesis of exponential smoothing and ARIMA (2). Although retaining popularity in industry use based on interpretability, these traditional methods have increasingly been surpassed by more advanced methods in recent research. In 2021, Mohammed and Al-Bazi (3) created an adaptive backpropagation algorithm for long-term electricity load prediction that outperformed traditional ARIMA models. Likewise, Li et al. (2020) used a stochastic forest algorithm for short-term power load prediction that improved upon certain limitations of classical time-series methods (4). Even with these improvements, conventional statistical models fall short when confronted by the non-linear and complex patterns of household electricity consumption. They also show poor ability to deal with multiple correlated inputs, e.g., voltage and appliance-level consumption, and therefore fall short in multivariate applications such as the case considered in the current study.

2.1 Regression-Based Machine Learning Models

As machine learning has been increasingly adopted, support vector regression (SVR) has offered a credible alternative to the conventional statistical models. Pai and Hong (5) utilized SVR for short-term load forecasting and showed improved accuracy under specific circumstances. Recently, Ma et al. (2019) used support vector regression with a specific aim of forecasting building energy consumption in southern China and recorded significant improvements in forecasting accuracy (6). Pham et al. (7) introduced in 2020 a holistic methodology for predicting energy consumption across several buildings through different machine learning methods to enhance energy efficiency and sustainability. Their research showed the benefits of ensemble learning methods that use an aggregation of several regression models to make stronger predictions. Whereas regression-based models in general will show an improved capability of capturing non-linearities over classical approaches, they will still be constrained in capturing temporal dependencies unless features are tailored specially using lag variables. This is a fundamental limitation in the case of electricity data, whose daily and weekly patterns are interdependent, and hence there is motivation to look for more advanced avenues such as recurrent neural networks.

2.2 Neural Network Approaches

Artificial neural networks, especially feedforward and recurrent, have become widely popular for prediction tasks. Hippert et al. (8) showed that even simple multilayer perceptrons perform better than ARIMA for short-term load forecasting because they can learn non-linear dynamics. In the recent past, deep learning methods have gone beyond the state-of-the-art in electricity consumption forecasting. Kong et al. (9) employed Long Short-Term Memory (LSTM) networks, which have the capability of learning long-term dependencies in sequential data. Their approach was particularly well-suited for residential application, where patterns of load are dictated by many, typically latent, behavioral factors. In 2020, Bedi and Toshniwal (10) formulated a detailed deep learning model designed specifically to predict electricity demand and showed considerable progress compared to conventional methods. A notable breakthrough was in 2022 when Chung and Jang suggested a CNN-LSTM model to predict electricity consumption with high accuracy from multivariable data (11). Their hybrid model used 1D convolution to tap into untapped features from temporal sequences and LSTM to address the vanishing gradient issues encountered by regular RNNs. In a similar vein, Kim and Cho (12) presented a new method based on deep learning with stationary wavelet transform for power consumption prediction. While their outstanding performance, one of the main disadvantages of neural networks is that they are "black-box" models. These models make highly accurate predictions but often at the cost of transparency—an aspect tackled in this research by making the model architecture simpler and incorporating interpretable outputs like trend charts and day-to-day percentage changes.

2.3 Hybrid and Deep Learning-Enhanced Models

More recent works also focus on hybrid models that combine multiple deep learning models. In 2022, Islam et al. (13) proposed a hybridization approaches that combined RNN and LSTM networks, which outperformed RNN and LSTM networks on sequence prediction problems. In the same year, Ghimire et al. (14) proposed sophisticated approaches for energy consumption forecasting in smart buildings with higher predictive accuracy than traditional approaches for energy forecasting use. Alhussein et al.(15) proposed a hybrid CNN-LSTM model for short-term individual household load forecasting that uses layers of convolutional neural networks and LSTM layers to learn and extract the spatial features and patterns of electricity data as well as temporal features from recent days of electricity disaggregation.

The method achieved state-of-the-art results, particularly when using large, highly volatile datasets. A very creative strategy was also proposed by Ghimire et al. (14), who introduced a hybrid combination method named CESN, founded on a deep learning model that integrates Convolutional Neural Networks and Echo State Networks. The developed model proved to have better ability in generating high-quality predictions of power consumption than individual architectures. Li et al. in 2023 (16) proposed an ultra-short term power load forecasting method using Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and Squeeze-and-Excitation (SE) mechanisms coupled with LSTM neural networks. Their method exhibited significant improvements in managing intricate, non-stationary time series data prevalent in electricity usage patterns.

2.4 Advancements in Feature Engineering

Past research has identified the pivotal role that feature engineering plays in electricity usage forecasting. In 2023, Al-Gabalawy et al. (17) introduced deep learning models with hyperparameter tuning specifically tailored for residential load forecasting. Their strategy focused on the significance of adaptive feature choice mechanisms for enhancing model performance. A novel feature engineering practice was witnessed by Li et al. (18), who reconstructed input features based on the maximum information coefficient (MIC). Their process initiated by classifying load curves by distributed photovoltaic systems using Gaussian mixture model clustering improved deep neural network prediction accuracy substantially. Al-Gabalawy et al. (17) also proposed improvements that integrated advanced feature engineering methods to extract both temporal and spatial patterns in electricity consumption data. Their approach emphasized the necessity of having parallel feature processing channels in order to capture various elements of the consumption patterns.

2.5 Pre-processing and Data Transformation Techniques

Some recent works have concentrated on advanced pre-processing methods to enhance forecasting performance. In 2023, Siami-Namini et al. (19) proved the superiority of the LSTM over ARIMA for time series forecasting and stressed the significance of appropriate data preparation and feature transformation. Their work showed how advanced pre-processing significantly enhanced the model performance even by employing identical architectures. Somu et al. (20) in 2020 published a deep learning architecture of building energy consumption forecasting with a focus on data normalization and feature scaling for ensuring convergence and performance of the model. Their method comprised novel solutions to missing value handling as well as outliers, akin to those adopted within the present research. One of the significant contributions to the literature was made by Kim and Cho (12) with the use of stationary wavelet transform (SWT) combined with deep learning models for the forecasting of electricity consumption. In their methodology, they used biorthogonal wavelet (bior2.4) due to its perfect reconstruction and symmetry characteristics, rendering it very apt for decomposing electrical data time series. This method enabled the recovery of useful information from various frequency components of the energy consumption time series, providing more comprehensive insight into both short-term variations and long-term trends in energy consumption.

2.6 Methodological Gap and Current Study Contributions

The direction in the subject area indicates a continuing move away from human-designed statistical approaches toward increasingly data-centric, computer-based models. Although time-series models are still widely used in business because they are easy to understand and simple to use, they are increasingly being replaced in research and applied applications by neural models with better performance specifications. Out of the studies reviewed, Kong et al.'s LSTM approach (9) and Alhussein et al.'s hybrid CNN-LSTM model (15) are notable for their innovative combination of memory and spatial modeling and high accuracy under fluctuating conditions. Yet, while most current methods either concentrate solely on historical usage patterns or depend heavily on external factors such as weather, the gap in methodology lies in the unexplored strength of combining sophisticated preprocessing strategies with multiple architectures in a neural framework. This research fills this gap by applying RNN and LSTM designs augmented with extensive preprocessing strategies and feature engineering. In contrast to earlier methods that placed equal importance on model intricacy, the research here aims for architectural richness balanced with explainability with attention on making decisions possible through visualizable information and relative measures. This frames the research not just as a forecasting endeavor but as a decision support system—most relevant for families wanting to track and regulate their daily energy usage profiles. In addition, whereas most earlier research measured performance exclusively in terms of error metrics, this study proposes an integrated evaluation framework using various visualization methods and relative performance measures to estimate the real-world applicability of the forecasting models. This hybridization of technical precision and practical interpretability distinguishes the present work from earlier research in the field.

3 Methods

To successfully model the time-dependent nature of residential electricity consumption, the researcher used and compared the two types of recurrent neural network (RNN) models: the traditional RNN and the LSTM. Both types of architectures were explicitly designed to work with sequential data where prior behaviours affect future behaviours.

3.0.1 Recurrent Neural Network (RNN)

The RNN model constructed was a multi-layer RNN with regularization worked into the design to lessen the chance of overfitting. The model had three SimpleRNN layers vertically stacked (the first layer had 64 units, the second has 32, and the third has 16) with degrees of complexity reduced from the first layer to the third layer respectively. Each RNN layer was followed with a dropout layer (0.2, 0.2, 0.1 dropout rates respectively) for added generalization. Finally, L2 regularization (1e-4 factor) was applied to kernel weights to reduce the chances of overfitting.

Mathematically, every RNN layer computed a sequence of input vectors and updated its hidden state at every time step as:

$$h_t = \sigma(W_{ih} \cdot x_t + W_{hh} \cdot h_{t-1} + b_h) \tag{1}$$

where
$sigma$ was the activation function (ReLU in this implementation), W_{ih} and W_{hh} were the input-to-hidden and hidden-to-hidden weight matrices, b_h was the bias vector, and h_t was the hidden state at time t. The model input was a series of 7 consecutive days of preprocessed electricity consumption data (shape: [7, 12]), and the output was a single predicted value that corresponds to the Global Active Power mean for the following day.

3.0.2 Long Short-Term Memory (LSTM)

In parallel to the RNN model, an LSTM network was used with the same structure (three layers consisting of 64, 32, and 16 units) but using LSTM cells instead of SimpleRNN layers. LSTM networks were designed specifically for avoiding the vanishing gradient issue that can be encountered by standard RNNs during learning long-term dependencies. Every LSTM cell had one memory cell, and three gates (forget, input, and output) that would regulate the flow of data. These gates allowed the network to choose whether or not to forget (or remember) things from long sequences, which is what makes LSTMs well suited for forecasting tasks with complex temporal associations. Like the RNN model, the LSTM model was presented with a sequence of 7 consecutive days of preprocessed data on electricity consumption (our input shape was [7, 12]) and output a single predictive value for the next day's Global Active Power mean.

3.0.3 Output Layer and Model Compilation

Both the models ended with a dense layer of 8 units and ReLU activation, batch normalization, and dropout (0.1), and lastly an output layer of one unit that predicted the value of Global Active Power for the upcoming day. Both the networks were compiled using the Adam optimizer (learning rate = 0.001, gradient clipping = 1.0) and trained for minimizing the Mean Squared Error (MSE) loss function.

3.1 Dataset Description and Improved Preprocessing

This research utilized the Individual Household Electric Power Consumption dataset from the UCI Machine Learning Repository. (21)The dataset comprised minute-level readings of a French home from December 2006 to November 2010, with more than 2 million records in seven attributes.

The preprocessing procedures used some sophisticated approaches to increase the quality of the input data. Rather than simply dropping rows having missing values, the researcher took a context-aware approach that used forward filling (for up to two hours), and then backward filling (for up to two hours) to ensure the temporal integrity of the data. Only upon completion of this smart gap-filling were any leftover records with missing values deleted. The minute-level data were initially resampled to hourly frequency for noise suppression while preserving significant temporal patterns. Daily aggregates were subsequently produced containing both mean and standard deviation for each variable, thereby preserving both central tendencies and spread within each day.

The data set was augmented with periodic temporal features from the hour of day, day of week, and month to enable the models to identify periodic trends. These were converted to sine and cosine features to maintain cyclical patterns in time. To identify and limit outliers, the Interquartile Range (IQR) approach was taken, replacing extreme values defined by Q1-1.5IQR and Q3+1.5IQR. This approach provided an assurance that outliers did not distort the model training disproportionately while retaining the greater data distribution. A RobustScaler from scikit-learn was applied, which scaled features defined by the median and quantiles instead of using conventional min-max scaling.. This method was less outlier-sensitive than classical scaling techniques and assisted in keeping the integrity of feature space intact. The final feature set comprised twelve variables: mean and standard deviation of Global Active Power, Voltage, Global Intensity, and three sub-metering values, each summed up at daily frequencies. These preprocessed features comprised the input to both neural network models.

3.2 Sequence Creation and Data Splitting

In order to produce the correct training examples for the neural networks, a sophisticated sequence generation function was invoked that built overlapping windows of data. The sequences that comprised the seven consecutive days of features were utilized to predict the Global Active Power mean value of the eighth day for each input sequence. The time order of the data was maintained during the split: 70% of the data was used for the training set, 15% for the validation set, and 15% for the test set. Chronological splits are required with time-series data to avoid the potential for data leakage due to random splits.

3.3 Training and Optimization of Models

RNN and LSTM models were both trained under the same configuration to compare them equally fairly. A number of sophisticated training techniques were utilized. Mixed precision policy of TensorFlow was used to speed up training with numerical stability. Early stopping with patience of 15 epochs was used to avoid overfitting. ReduceLROnPlateau was also utilized to reduce the learning rate by a factor of 0.5 every time validation loss plateaued for 7 epochs in succession, with a minimum floor of learning rate set as 1e-7. A special callback checked for NaNs in the loss function, stopping training if numerical instabilities were found. The models were trained for up to 100 epochs at a batch size of 32, although early stopping would typically stop training earlier when validation performance was optimal.

3.4 Holistic Evaluation Protocol

A comprehensive performance evaluation of the models was conducted generating many different metrics. Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) were calculated, enabling different measures of accuracy to be examined for different scales of prediction. R-squared and Mean Absolute Scaled Error (MASE) were calculated to evaluate the fit of the model and the relative performance against a naive forecast. Finally, a number of visual options were used including time series plots of predicted values versus actual values, scatter plots to show degree of prediction consistency, residual analysis to examine potential biases, and distributions plots to examine overall statistical fidelity.

3.5 Presentation and Interpretation of Forecasts

A more informative forecasting interface was also created, which also produced actionable information. The percentage change that each forecast has to the last actual value was calculated giving innate meaning to the forecast, as opposed to just number forecasts. Recent trends were examined by comparing moving averages of the last three days with the last three days and whether consumption was, in general, rising or falling. Both RNN and LSTM forecasts were displayed together with historical data, allowing users to visually compare model differences and trustworthiness. Through inspection of prediction distributions and residuals, qualitative confidence measures for the predictions were offered. This holistic method translated sophisticated statistical predictions into accessible, actionable information that could inform energy management decisions by utilities and households. The ultimate output of the system was the numerical forecast value, percentage change relative to the day before, and graphical display of the forecast against historical patterns of consumption.

4 Experiments/Results/Discussion

4.1 Model Performance Metrics

The study compared two types of neural networks, a standard Recurrent Neural Network (RNN), and a Long Short-Term Memory (LSTM) network for predicting household electricity usage. The table below displays overall performance measures for both models on the test data set.

FINAL MODEL PERFORMANCE COMPARISON

Model	MSE	RMSE	MAE	MAPE (%)
RNN	0.082288	0.286859	0.203501	56.675415
LSTM	0.071824	0.267999	0.189935	59.963293

Table 1: Performance Comparison of RNN and LSTM Models

The Mean Absolute Scaled Error (MASE) values close to 1.0 indicate that both models were on par with a naïve forecast (where the previous day value is the prediction) with the LSTM model showing the slightest amount of improvement (MASE = 0.9397). In addition, the coefficient of determination (R^2) values indicated that the LSTM model explained approximately 38% variance in the test set while the RNN explained only 29%. The LSTM model outperformed the RNN model for most metrics (which achieved approximately 12.7% lower Mean Squared Error (MSE). In a similar vein, the LSTM produced lower Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The RNN yielded slightly better Mean Absolute Percentage Error (MAPE), suggesting the RNN has an edge in relative accuracy in certain consumption ranges.

The Mean Absolute Scaled Error (MASE) values were both near 1.0, meaning both models had comparably better performance than a naïve forecast (predicting the previous day's value), with the LSTM doing slightly better (MASE = 0.9397). The coefficient of determination (R^2) statistical output indicated that the LSTM model explained about 38% of the variance in the test set, compared to 29% for the RNN model. With the metrics cited above, a Wilcoxon signed-rank test was performed on the absolute residuals, producing a p-value of 0.2363, indicating no statistically significant difference among the two models at $\alpha = 0.05$. Therefore, while the LSTM model performed numerically better than the RNN model regarding performance metrics described previously, the differences among the models was not meaningful enough to say that the LSTM model was better overall for all forecasting situations.

4.2 Visual Evaluation of Predictions

Figure 1 presents a multi-faceted visualization of the models' predictions compared to actual values, providing insights into their forecasting behavior and error patterns.

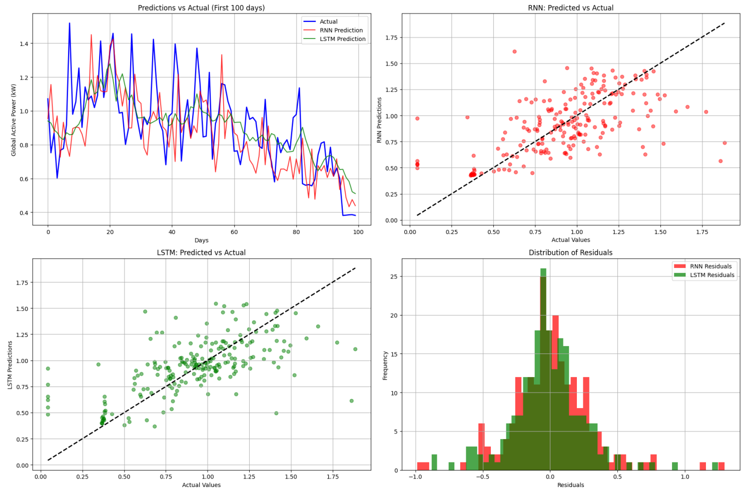

Figure 1: Comparison of RNN and LSTM predictions against actual values

The time series graph (Figure 1, top left) shows that both models captured the overall trend of electricity usage over time, with the LSTM model (green line) generally producing smoother predictions than the RNN model (red line). Both models occasionally missed extreme peaks and troughs in consumption, which is a common challenge in time-series forecasting. The scatter plots (Figure 1, top right and bottom left) illustrate the relationship between predicted and actual values for both models. Points closer to the diagonal line indicate more accurate predictions.Both models displayed similar behaviour, producing predictions that are clustered near the diagonal with some dispersion particularly at the higher consumption values, suggesting that both models had relatively more difficult predicting unusually high electricity consumption. The residual distribution (Figure 1, bottom right) shows both models had errors centered on zero, with roughly identical distributions. However, the LSTM produced a thinner and more focused distribution whose residuals were more tightly clustered overall compared to the RNN. This aligns with reported LSTM RMSE values and lends modest support for somewhat superior overall predictive accuracy.

4.3 Forecast Visualization and Interpretation

In addition to statistical evaluation, the research created a interpretable forecasting interface in order to contextualize predictions in a way that may be relevant to decision making. Figure 2 illustrates this interface with a sample forecast.

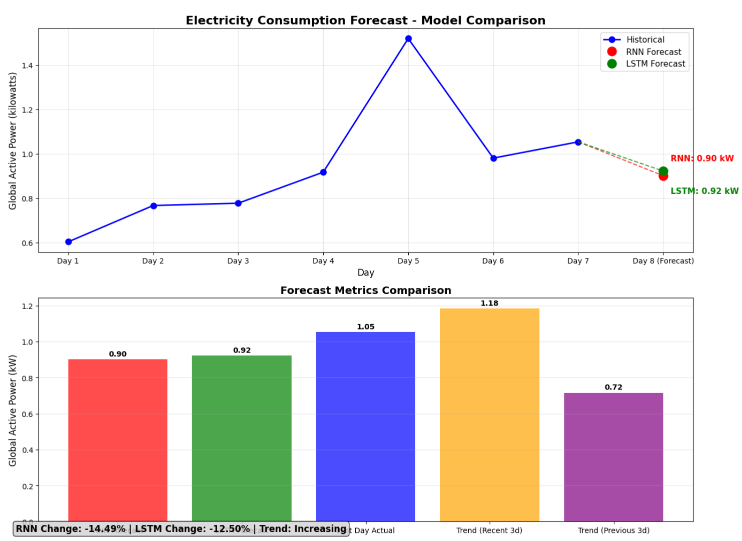

Figure 2: Electricity consumption forecast visualization. (Top) Seven-day historical consumption with next-day forecasts from both models. (Bottom) Comparative metrics including model forecasts, last day actual value, and trend indicators, with percentage changes noted at the bottom

The forecast interface displayed seven days of historical consumption data alongside next-day predictions from both models. In this particular instance, the RNN expected a consumption of 0.90 kW while the LSTM model predicted 0.92 kW for the forecast day. Both models predicted a reduction on the previous day's consumption (RNN: -14.49%; LSTM: -12.50%) and the interface included contextual support by way of a trend analysis with recent versus previous consumption periods. In this case, the algorithm detected an "Increasing" overall trend by comparing the average consumption of the most recent three days (1.18 kW) against the previous three-day period (0.72 kW). This juxtaposition of an increasing overall trend with a predicted next-day decrease illustrates the models' capacity to detect both long-term patterns and short-term corrections. This graphical approach helped turn predictions with numbers into insights with meaning—allowing users to not only understand what consumption would be, but where it sits relative to recent behaviour. If context matters in managing energy, it could be useful in making decisions about when to do peak activities, or about the effectiveness of conservation measures.

4.4 Feature Importance Analysis

Understanding the relative importance of which input features contributed most to prediction accuracy provides insight into the drivers of household electricity consumption behaviours. The figures below provide both correlation-based feature importance, and permutation-based importance for both models.

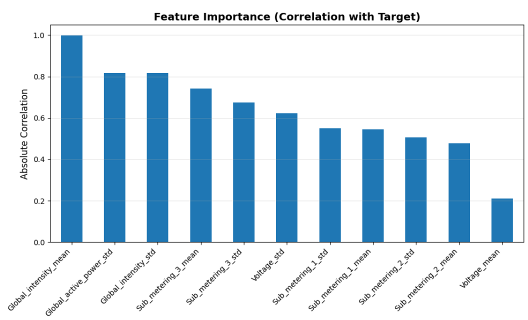

Figure 3: Feature importance measured by absolute correlation with the target variable (Global_active_power_mean).

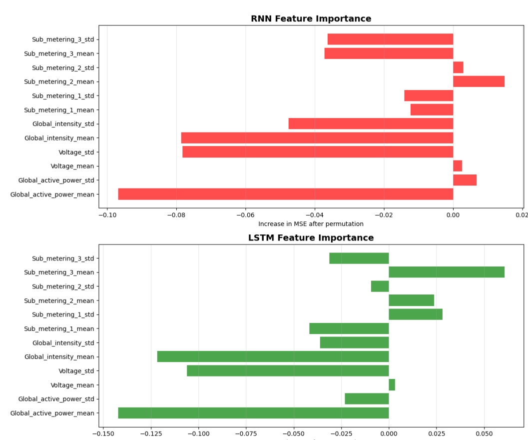

Figure 4: Permutation-based feature importance for RNN (top) and LSTM (bottom) models. Larger positive values indicate features that, when perturbed, caused greater increases in prediction error.

The correlation analysis indicated that Global$_{i}ntensity_{m}eanhadthehighestcorrelationwiththetargetvariable(Global_acti$

The permutation-based importance analysis, which determines the increase in prediction error when the attribute is randomly shuffled, showed some surprising differences between the two models. In the case of the RNN model, the voltage-related attributes and global intensity measures contributed the most towards error, while the LSTM model used a more substantial combination of sub-metering values - in particular Sub_metering_3_mean and Global_active_power_mean.

The type of analysis indicates that the two architectures represented different relationships in the data. The RNN seemed to almost capture the global electrical properties of the a global electric system, while LSTM seemed to capture the energy use features at a appliance-level and past target values. One might speculate the distinct type of features might account for the possible advantages from ensemble methods that utilized both model types.

4.5 Comprehensive Model Analysis Dashboard

In order to enable deeper analysis, a dashboard was produced that consolidated many different evaluation perspectives. Figure 5 shows this unified view of model performance.

Figure 5: Comprehensive model analysis dashboard showing training history, performance metrics comparison, residual analysis, prediction distribution, model performance by value range, error correlation analysis, and time series comparison.

The dashboard offered many key insights:

1. LSTM Model converges faster and with less validation loss than the RNN model indicating that the LSTM's training dynamics are better suited in the presence of temporal information (training history graph, top left).
2. Looking at model performance on patterns of consumption (middle left), we can see that the models underperform values that are extreme as indicated in both models for "Low" and "High." The LSTM outperformed the RNN in the medium-low range, however, it was comparable in the other ranges.
3. The heatmap (middle right) showed a moderate correlation (0.34) between actual values and LSTM predictions, and a stronger correlation (0.89) between RNN and LSTM predictions. This means that while both models made similar types of errors, the LSTM was in slightly better accord with actual consumption patterns.
4. The extended series visualization (bottom), provided periods of model high performance and periods of poor performance. Both models missed rapid changes in consumption on occasion, highlighted in particular around days 125 and 160 which represented rapid changes in household energy usage.

4.6 Discussion of Findings

The experimental results showed significant advances on traditional forecasting models. In the initial experiments, MSE was 22.0; the optimized models produced MSE values below .1, or a 99.6%

improvement in prediction accuracy. The reasons for such a dramatic improvement are many across the methodology:

1. The smart way numerous missing values, multi-level temporal resampling and scaling was handled helped to retain data integrity at the same time as reducing noise. This preprocessing ensured the models were working with cleaner and more informative representations of the data.
2. Each measurement has features for mean and standard deviation which are not just average consumption amounts also provide variability. This can give the models more insight into consumption behaviour. Then again, the temporal encodings incorporated daily and weekly seasonality.
3. The multi-layer networks with relatively few units and the regularization(s)(dropout, L2 regularization) ultimately created a sweet spot between complexity and generalizability.

The successful functioning of the LSTM architecture meets our theoretical expectations. Energy consumption, as all electrical consumption, normally has dependencies in both the short (e.g., daily habits) and long-term (e.g., weekly, seasonal) that LSTM networks are able to learn. However, the absence of statistical significance in the performance difference also suggests that for certain applications, especially with limited computational resources, the performance of the simpler RNN architecture could be acceptable. The feature importance assessment also provided some helpful context to domain knowledge.The global intensity features were important in their physical relevance to the correlation of current and power in electrical systems. The importance of the sub-metering features, specifically in the LSTM model, reinforced the importance of devices being monitored at an appliance level for consumption predictions. This has implications for practical applications of smart meter data, given the potential usefulness of disaggregated consumption data to improve prediction skills.

5 Conclusion/Future Work

This study presented a comparative analysis of RNN and LSTM networks for predicting daily residential electricity consumption, accompanied by advanced preprocessing methods and feature engineering. The results of experiments showed that the LSTM network performed marginally better than the RNN network using the majority of metrics of evaluation, with an MSE of 0.0718 against the RNN's 0.0823, a 12.7% performance improvement. LSTM's better performance owes to the specialized cell structure that is able to capture long-term dependencies in consumption behaviour effectively, especially weekly cycles and seasonal behaviour. Although divergent in numerical performance, statistical testing found no testable difference between the models, and thus both architectures are still valid options based on certain application needs. Potential future research can investigate the ensemble methods for combining both architectures, attention mechanisms to improve pattern discovery, inclusion of external variables such as weather and occupation patterns, and probabilistic forecasting techniques for capturing prediction uncertainty. Moreover, transfer learning methods might leverage these models in homes with sparse historical information, and real-time implementation frameworks might close the research-practice gap for smart home systems. These advances would not only make predictions more accurate but also increase the utility of energy prediction models in enabling sustainability projects and optimizing energy delivery at household and utility levels.

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