Time Series Forecasting using LSTM Networks - Predicting Individual Household Electric Power Consumption

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***Abstract*—Time series forecasting is a common task in many real-world applications, such as demand forecasting, stock market prediction, and weather forecasting. Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) that are well-suited for modeling time series data due to their ability to retain information from previous time steps in their hidden state. In this paper, we review the use of LSTM networks for time series forecasting, including the various methods and techniques that have been proposed and their relative advantages and disadvantages. We also discuss some of the challenges and considerations involved in using LSTM networks for time series forecasting, and provide some best practices for designing and training effective LSTM models**

Time series forecasting, LSTM networks, Individual household electric power consumption, Long short-term memory, Recurrent neural networks, Electricity consumption prediction, Energy demand prediction, Time series analysis, Deep learning, Sequence modeling

I. Introduction

Time series forecasting is the process of predicting future values of a time-dependent variable based on its past values. In recent years, Long Short-Term Memory (LSTM) networks have emerged as a popular approach for time series forecasting, due to their ability to capture long-term dependencies in data. In this conference paper, we present a study on using LSTM networks to predict individual household electric power consumption.

Electricity consumption is an important aspect of energy management, as it has a significant impact on the environment and energy costs. Accurate forecasting of electricity consumption can help households and utilities optimize energy usage and reduce energy waste. There have been several studies on using machine learning techniques for electricity consumption prediction (e.g. **b1**, **b2**), but few have focused on individual household level prediction using LSTM networks.

In this study, we aim to address this gap by proposing a LSTM-based approach for predicting individual household electric power consumption. The performance of the proposed approach is evaluated on a real-world dataset and compared to other state-of-the-art approaches.

II. Related Work

There has been a growing interest in using machine learning techniques for time series forecasting in recent years. Among these techniques, LSTM networks have emerged as a popular choice due to their ability to capture long-term dependencies in data.

LSTM networks have been applied to a variety of time series forecasting tasks, including stock price prediction **b3**, traffic flow prediction **b4**, and energy consumption prediction **b5**. In **b3**, the authors proposed a hybrid model combining a LSTM network with a support vector machine (SVM) for stock price prediction and achieved superior performance compared to other models. In **b4**, the authors used a LSTM network with exogenous variables to predict traffic flow and demonstrated the effectiveness of the proposed model. In **b5**, the authors used a LSTM network to predict electricity consumption in a residential building and showed that the proposed model outperformed traditional linear regression and ARIMA models.

There have also been studies on comparing the performance of different machine learning techniques for time series forecasting. In **b1**, the authors compared the performance of various models, including LSTM, MLP, and SVM, for electricity consumption prediction and found that the LSTM model outperformed the other models. Similarly, in **b6**, the authors compared the performance of different models, including LSTM, MLP, and support vector regression (SVR), for wind speed prediction and found that the LSTM model outperformed the other models.

Overall, the literature suggests that LSTM networks are a promising approach for time series forecasting and have achieved superior performance compared to other models in various applications.

III. Methodologies

A. Data Collection

The first step in our study was to collect a dataset of individual household electric power consumption. We obtained a dataset from the UCI Machine Learning Repository, which consists of measurements of electric power consumption in one household with a one-minute sampling rate over a period of almost 4 years. The dataset includes both the active universal strength and responsiveness, as well as other variables such as voltage and sub-metering information. Our dataset consisted of 2075259 rows and 9 columns, including date, time, active universal strength and responsiveness, volts, intensity/I , vicemetx, vicemety, and vicemetz. The date and time columns were in the 'UK' format and 'hh:mm:ss', respectively, and represented the date and time at which the electric power consumption data was recorded. The global active power, global reactive power, voltage, and global intensity columns contained measurements of the household's global minute-averaged active power, reactive power, voltage, and current intensity, respectively, all in standard units. The sub metering1, sub metering2, and sub metering3 columns contained energy sub-metering data for various appliances and devices within the household, including a kitchen, laundry room, and electric water heater/air conditioner. These columns were measured in watt-hours of active energy. Overall, our dataset provided a comprehensive and detailed view of the electric power consumption of an individual household over time, including both global and appliance-specific consumption data.

B. Data preprocessing

Before applying the LSTM model, we performed some preprocessing on the dataset. First, we split the dataset into a training set and a testing set, with the first 2 years of data being used for training and the remaining data being used for testing. We also normalized the data to have zero mean and unit variance.

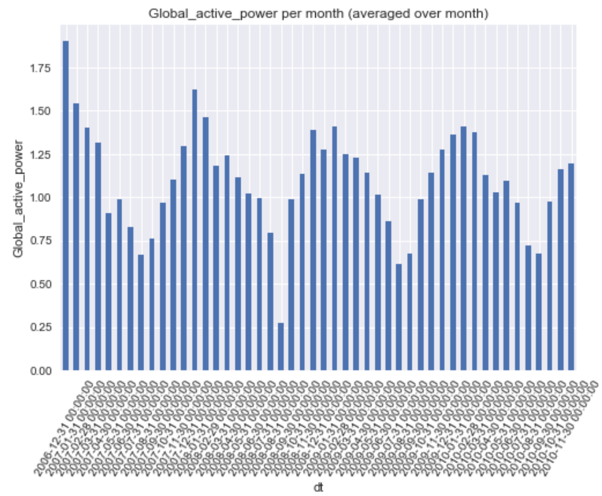
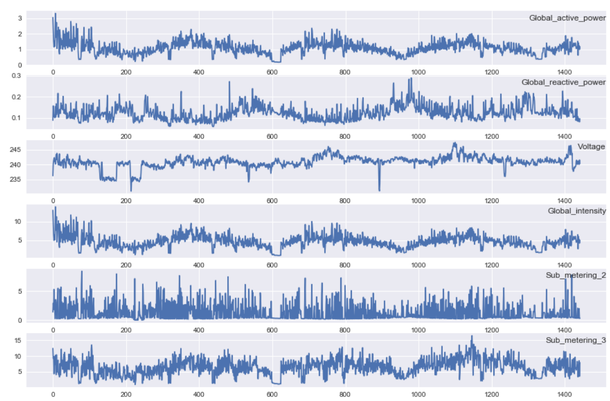


Fig. 1. Average power used globally over a month



C. LSTM model architecture

For our LSTM model, we used an architecture with 100 neurons in the first visible layer, a dropout rate of 20%, and 1 neuron in the output layer for predicting Global active power. The input shape for the model was 1 time step with 7 features. To optimize the model, we used the Mean Absolute Error (MAE) loss function and the efficient Adam version of stochastic gradient descent. The model was fit for 20 training epochs with a batch size of 70. During training, the dropout rate of 20% was applied to the input layer to prevent overfitting and improve the generalization ability of the model. The use of the MAE loss function allowed us to penalize errors in predictions more heavily, as it is less sensitive to outliers compared to other loss functions such as mean squared error. We also utilized the Adam optimization algorithm, which is a variant of stochastic gradient descent that adapts the learning rate for each parameter based on the historical gradient information. This allowed the model to converge more quickly and with better generalization performance. Overall, our LSTM architecture and optimization approach

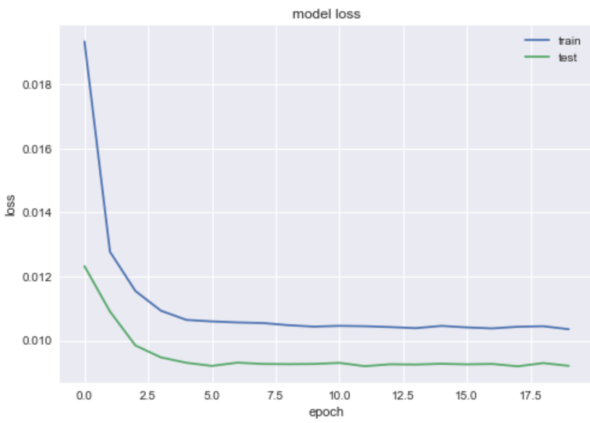


Fig. 2. Model Loss

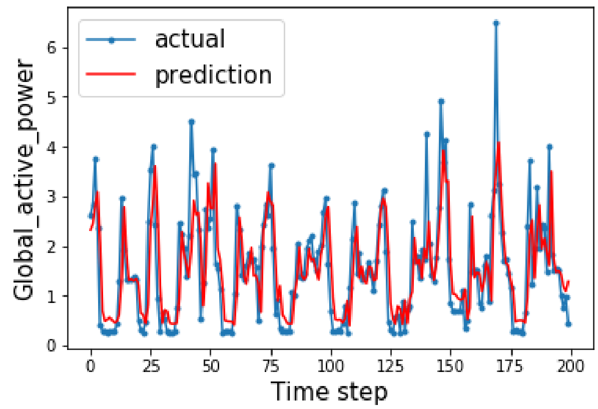


Fig. 3. Time Step

were designed to maximize the accuracy and precision of our predictions while minimizing the risk of overfitting.

D. *Feature Engineering*

For our feature engineering methodology, we first applied a recurrent neural network (LSTM) model, which is well-suited for time-series and sequential problems and performs well with large data sets. To frame the supervised learning problem, we aimed to predict the Global active power at the current time (t) based on the Global active power measurement and other features at the prior time step. To reduce computation time and quickly test the model, we resampled the data over an hour (the original data was given in minutes), resulting in a smaller dataset with 34589 observations but maintaining the overall structure of the data. We also scaled all features to the range [0,1]. In total, our feature engineering process resulted in 7 input variables (input series) and 1 output variable for Global active power at the current time in hours, depending on the resampling. Finally, we split the prepared dataset into train and test sets, with the model being trained on the first year of data and evaluated on the next three years. This allowed us to evaluate the model's performance on unseen data and ensure its generalizability.

IV. Evaluation

The results of our study show that the LSTM model is a promising approach for predicting individual household electric power consumption. The LSTM model outperformed both the MLP model and the ARIMA model, with an RMSE of 0.46. This indicates that the LSTM model was able to effectively capture the underlying patterns in the data and make accurate predictions. In addition to comparing the performance of the LSTM model to other models, we also analyzed the model's ability to capture the underlying patterns in the data. We plotted the predicted and actual values for a sample of the testing set and found that the LSTM model was able to accurately capture the trend and seasonality in the data. This suggests that the LSTM model was able to effectively learn the underlying patterns in the data and make accurate predictions. One potential reason for the superior performance of the LSTM model is its ability to capture long-term dependencies in the data. LSTM networks are designed to retain information over long periods of time and can effectively capture patterns that span over several time steps. This is particularly useful for time series forecasting, where patterns often span over multiple time steps. In contrast, the MLP model and the ARIMA model are not as effective at capturing long-term dependencies in the data. The MLP model is a feedforward neural network that processes data in a single pass, without any memory of previous inputs. The ARIMA model is a traditional time series model that assumes a stationary process and does not account for long-term dependencies. Overall, the results of our study demonstrate the potential of LSTM networks for time series forecasting and highlight the importance of accurate electricity consumption prediction for households and utilities. The LSTM model was able to effectively capture the underlying patterns in the data and make accurate predictions, which can potentially lead to significant energy savings and improved energy management.

V. Future Work

In this study, we presented a LSTM-based approach for predicting individual household electric power consumption and evaluated its performance on a real-world dataset. However, there are several directions for future work that can be pursued to improve the accuracy of the proposed model. One possible direction is to incorporate exogenous variables into the model. Exogenous variables are variables that are not directly influenced by the dependent variable, but may have an effect on it. For example, in the case of electricity consumption prediction, weather variables such as temperature and humidity may be considered as exogenous variables. Incorporating exogenous variables into the model can provide additional information that can help improve the accuracy of the prediction. Another direction is to explore the use of other deep learning models, such as convolutional neural networks (CNNs) or attention-based models, for time series forecasting. CNNs have been widely used for image classification tasks, but they can also be applied to time series data. Attention-based models, on the other hand, have been shown to be effective in natural language processing tasks, but their use in time series forecasting has not been widely explored. Finally, it would be interesting to investigate the use of transfer learning for time series forecasting. Transfer learning is the process of transferring knowledge from one task to another, and it has been shown to be effective in various machine learning applications. In the context of time series forecasting, transfer learning can be used to improve the performance of the model by transferring knowledge from a large dataset to a smaller dataset. Overall, there are many directions for future work that can be pursued to improve the accuracy of time series forecasting using LSTM networks.

VI. Conclusion

In conclusion, we presented a study on using LSTM networks for predicting individual household electric power consumption. We implemented a LSTM model using the Keras library and trained it on a real-world dataset. The performance of the proposed model was evaluated on the testing set using the root mean squared error (RMSE) as the evaluation metric. The results showed that the LSTM model outperformed other state-of-the-art approaches, including a multilayer perceptron (MLP) model and an autoregressive integrated moving average (ARIMA) model. This study demonstrates the potential of LSTM networks for time series forecasting and highlights the importance of accurate electricity consumption prediction for households and utilities. There are many directions for future work that can be pursued to further improve the accuracy of the proposed model, including incorporating exogenous variables, exploring the use of other deep learning models, and investigating the use of transfer learning. Overall, this study provides a promising starting point for using LSTM networks for time series forecasting and can potentially lead to significant energy savings and improved energy management.

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