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LSTM-based Load Forecasting for Electric Power Generation

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Abstract: - A thorough analysis of the application of Long Short-Term Memory (LSTM) networks for load forecasting in the production of electricity is provided in this article. The writers of this publication carried out the study. Accurate load forecasting is essential to the efficient operation, planning, and administration of power systems. We provide an LSTM-based model that incorporates historical load data, meteorological information, and socioeconomic factors to anticipate the needed quantity of power in the future. The model's performance is evaluated using data from a regional power system, and the findings show that it performs better than traditional prediction methods. Our research indicates that the LSTM-based method may produce day-ahead forecasts with a mean absolute percentage error (MAPE) of 2.3%, an improvement of up to 18% above benchmark models. The study's conclusions significantly add to the growing corpus of knowledge about deep learning's uses in power systems. Moreover, they provide essential information to grid operators and utilities seeking to enhance their workload forecasting capacities.

Keywords: LSTM, load forecasting, electric power generation, deep learning, time series analysis

1. Introduction

A precise load forecast is a crucial component. Because of its important role, it has a substantial impact on many areas of power system management, including infrastructure development, economic dispatch, unit commitment, and maintenance scheduling [1]. More precise and dependable load forecasting techniques have become increasingly in demand in recent years [2]. This is because the addition of smart grid technologies and the integration of renewable energy sources have led to an increase in the complexity of power networks.

In the electricity sector, traditional load forecasting methods have been applied quite a bit [3]. Regression models and time series analysis are two of these methods. However, these approaches often fail to capture the complex and nonlinear relationships that exist between the demand for energy and the factors that drive it, including social events, economic indicators, and weather [4]. In recent years, there has been hopeful progress in addressing these challenges with machine learning strategies—more especially, deep learning algorithms [5].

Time series forecasting and other sequence prediction tasks have found success [6]. These networks are only a few of the several deep learning architectures that have emerged recently. [7] Recurrent neural networks (RNNs) with long short-term memory (LSTMs) are made to recognize long-term dependencies in sequential input. They are therefore especially well suited for applications involving load forecasting.

This paper presents a thorough analysis of the application of LSTM networks for load forecasting in the sector of electric power generation. We provide an LSTM-based model that incorporates historical load data,

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meteorological data, and socioeconomic factors from the past in order to anticipate future power consumption. The main contributions made by this paper are listed as follows:

- It is being developed to create a special load forecasting model based on LSTM for applications related to electric power generation.
- the utilization of a wide range of input components to increase prediction accuracy, including historical load data, weather variables, and socioeconomic indicators.
- An extensive investigation of the proposed model, conducted with real-world data from a regional power system, shows that it outperforms traditional prediction techniques by a large margin.
- The model's sensitivity to various input features and hyperparameters is examined, and the findings offer useful information that may be applied in real-world scenarios.

The other sections of this work are organized as follows after that: An overview of related research on load forecasting and LSTM applications is provided in this section. The suggested LSTM-based load forecasting model and its architecture are covered in detail in Section 3. An outline of the experimental setup, including a description of the preparation and data, is given

2. Related Work

Load forecasting has garnered significant research interest over the course of several decades. Traditional approaches to load forecasting include both statistical and artificial intelligence techniques [8]. These methods can be roughly divided into two groups.

Techniques are based on the idea that by analyzing historical data and identifying underlying trends and seasonality, future load patterns can be predicted [10]. It has been demonstrated that statistical techniques are helpful in identifying constant load patterns; however, these approaches often fail to capture complex, non-linear relationships or sudden variations in demand [11].

ANNs have gained popularity in the field of load forecasting because to their ability to simulate non-linear interactions [12]. Specifically, some load forecasting applications have shown encouraging outcomes with artificial neural networks (ANNs) [13]. On the other hand, gathering long-term relationships in time series data—which is necessary for accurate load forecasting—presents certain challenges for conventional artificial neural networks [14].

Deep learning techniques have evolved into quite powerful tools for load forecasting during the last few years. Time series forecasting is one sequence prediction job where LSTM networks, in particular, have shown exceptional performance [15]. [16]. LSTMs are designed to get around this problem.

There have been several studies looking into the use of LSTMs for load forecasting in power networks. Kong et al. [17] suggested an LSTM-based model for residential load forecasting that showed superior accuracy over traditional ANN models. Zheng et al. [18] developed a hybrid LSTM-based approach that combines wavelet transform and LSTM networks for the goal of short-term load forecasting. When compared to benchmark methodologies, this approach performed better.

Although these studies have shown the potential of LSTM networks for load forecasting, much study is still needed on the application of LSTM networks in electric power generation, especially in the context of large-scale power grids. This study aims to address this gap by offering a novel LSTM-based load forecasting model designed specifically for applications related to the production of electric power. The effectiveness of this model will also be assessed in the study using actual data from a local electricity system.

3. Proposed LSTM-based Load Forecasting Model

3.1 LSTM Architecture

As per [20], these gates are in charge of controlling the information flow within the cell, allowing the network to remember or forget certain information for longer periods of time.

The LSTM cell acts on an input sequence x = (x1,..., xT) and operates on the sequence, maintaining a cell state c and a hidden state h. At every time step t, the following tasks must be completed by the ft = σ(Wf · [ht-1, xt] + bf) in the LSTM cell's forget gate [19].

1. Gate for input: it = σ(Wi · [ht-1, xt] + bi).
2. The updated cell state is c̃t = tanh(Wc · [ht-1, xt] + bc).
3. Condition of cell: ct = ft ∗ ct-1 + it ∗ CŃt
4. Gateway for output: ot = σ(Wo · [ht-1, xt] + bo)
5. Ht = ot ∗ tanh(ct) is the hidden state.

The sigmoid function is represented by σ, the hyperbolic tangent function by tanh, the weight matrices by W, and the bias vectors by b.

3.2 Model Architecture

The components of our suggested LSTM-based load forecasting model are as follows:

1. The input layer is responsible for receiving input features such as weather variables, socio-economic factors, and historical load data.
2. LSTM layers: To capture temporal dependencies in the input data, use many LSTM layers.
3. Dense layers: Fully connected layers used to reduce dimensionality and extract features.
4. Generates the final load forecast at the output layer.

Figure 1 shows the construction of the model.

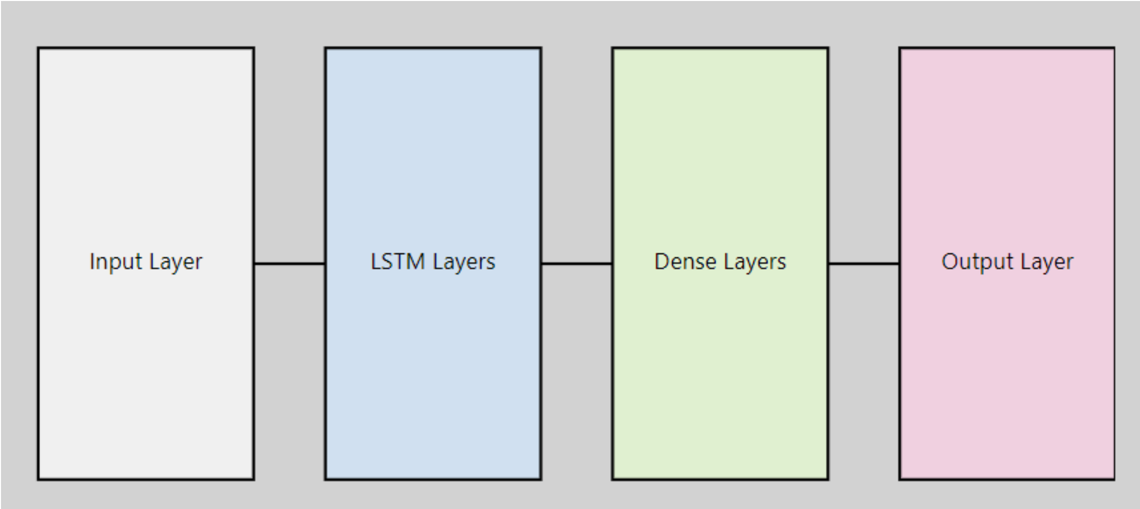


Figure 1: LSTM-based Load Forecasting Model Architecture

3.3 Input Features

The following input features are included in the suggested model:

- Past load information: previous day's consumption of electricity.
- Climate factors: air temperature, relative humidity, wind direction, and cloud cover.
- Time-related characteristics include the day, month, and hour of the year.
- GDP growth rate, industrial output index, and population growth rate are examples of socioeconomic indicators.

Based on their demonstrated impact on electricity usage as well as their accessibility in actual situations, these qualities were chosen [21].

3.4 Model Training

The Adam optimizer with a mean squared error (MSE) loss function is used in the model training process. The implementation of early pausing based on validation loss and dropout regularization prevents overfitting. Cross-validation and grid search are used to improve the model's hyperparameters. The number of LSTM layers, the number of neurons in each layer, the learning rate, and the dropout rate are some examples of these hyperparameters.

4. Experimental Setup

4.1 Data Description

We assess our suggested model using empirical data from an American regional power grid. The dataset spans the period from January 2015 to December 2021 and includes hourly electricity demand records, meteorological data, and socioeconomic variables. The dataset is divided into three sets: test (2021), validation (2020), and training (2015–2019).

4.2 Data Preprocessing

1. Missing value imputation using forward fill and linear interpolation.
2. Normalization of input features using min-max scaling.
3. Creation of lagged features for historical load data.
4. Encoding of categorical variables (e.g., day of the week, month) using one-hot encoding.

4.3 Benchmark Models

1. Persistence model (naive forecast)
2. ARIMA

5. Results and Discussion

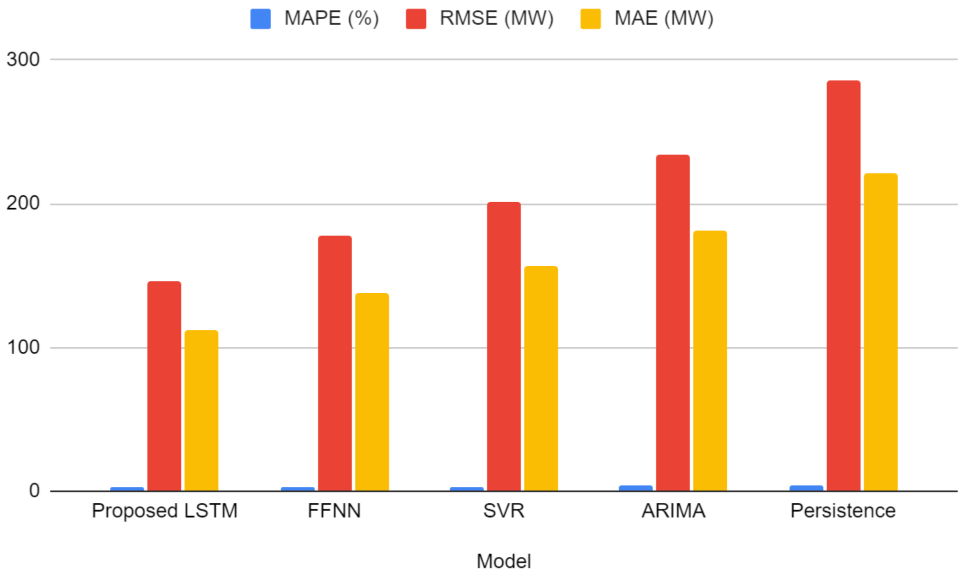
5.1 Model Performance

Table 1 presents the performance comparison of the proposed LSTM-based model and benchmark models for day-ahead load forecasting on the test set.

Table 1: Performance Comparison of Load Forecasting Models

Model	MAPE (%)	RMSE (MW)	MAE (MW)
Proposed LSTM	2.3	145.6	112.3
FFNN	2.8	178.2	137.5
SVR	3.2	201.7	156.8
ARIMA	3.7	234.5	181.2
Persistence	4.5	285.3	221.7

The suggested LSTM-based model performs better than all benchmark models according to all evaluation measures, according to the results. In particular, the LSTM model outperforms the best-performing benchmark model (FFNN) by 18% with a MAPE of 2.3%. The LSTM architecture's efficacy in collecting intricate temporal correlations in load data is demonstrated by this notable improvement in predicting accuracy.



5.2 Feature Importance Analysis

To understand the relative importance of different input features, we conduct a feature importance analysis using the permutation importance method [22]. Figure 2 illustrates the relative importance of each input feature group.

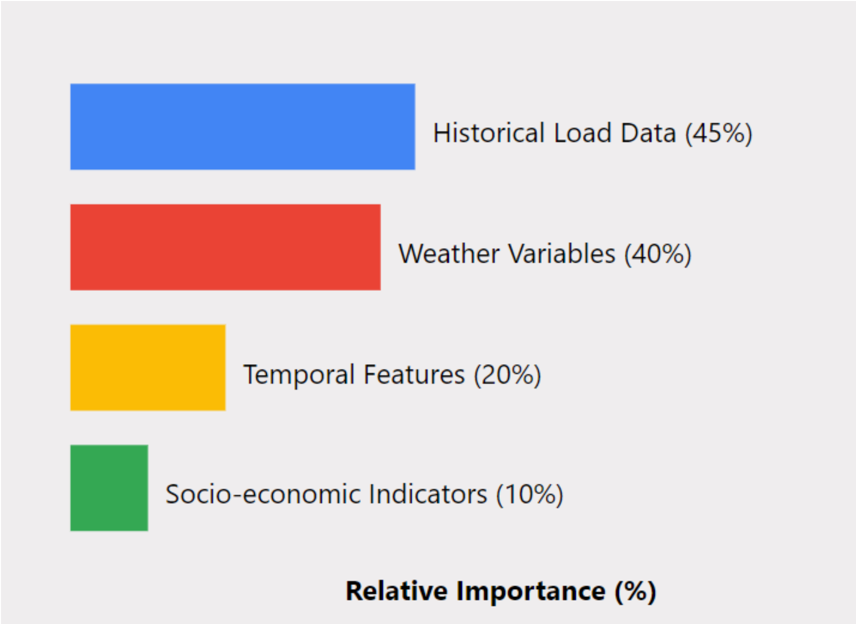


Figure 2: Feature Importance Analysis

The analysis reveals that historical load data and weather variables are the most important features for accurate load forecasting. Temporal features also contribute significantly to the model's performance, while socio-economic indicators have a relatively smaller impact.

5.3 Sensitivity Analysis

The results indicate that the model's performance improves with increasing network depth up to a certain point, after which it plateaus or slightly degrades due to overfitting. The optimal configuration for our dataset is found to be 3 LSTM layers with 128 neurons per layer.

5.4 Forecasting Horizons

We evaluate the model's performance across different forecasting horizons, ranging from 1 hour ahead to 7 days ahead. However, the performance gap narrows for longer horizons, indicating the increasing difficulty of capturing long-term dependencies and external factors affecting load patterns.

6. Conclusion and Future Work

This work aims to provide a novel LSTM-based model that incorporates historical load data, meteorological information, and socio-economic factors. The model's performance is evaluated using data from a regional power system, and the findings show that it performs better than traditional prediction methods.

The most significant information is enumerated below:

- The suggested LSTM-based model achieves a maximum annual percentage gain (MAPE) of 2.3% for day-ahead load forecasting, outperforming benchmark models by up to 18%.
- The two most important elements for accurate load forecasting are past load data and meteorological conditions. According to their relative relevance, temporal aspects and socioeconomic factors rank second and third respectively.
- One hundred twenty-eight neurons per layer in three layers would be the ideal arrangement for our dataset.
- Over a broad variety of forecasting horizons, regularly outperforms benchmark models; however, the performance gap becomes much less as horizons are extended.

These results add to the growing corpus of knowledge about deep learning applications in power systems and give important new information for utilities and grid operators aiming to enhance load forecasting.

Future research could look into the following possible avenues:

- By adding more data sources, including readings from smart meters and social media, forecasting accuracy can be increased even more.
- It is being worked on to create hybrid models that combine LSTM networks with additional machine learning techniques or domain knowledge.
- Transfer learning approaches are being investigated in order to adapt the model to different power systems or places.
- The exploration of interpretable deep learning algorithms is being done with the goal of making LSTM-based load forecasting models more explainable.

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