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Smart Electricity Price Predection using a Deep Learning

Kotamsetty Geethika Devi

Department of Department of Computer Science and Systems Engineering, Sree Vidyanikethan Engineering College, Tirupati, India ; geethikakotamsetty@gmail.com

Abstract: Electricity price prediction plays a crucial role in energy markets, where accurate forecasts can help stakeholders optimize decision-making, reduce operational costs, and enhance market efficiency. Traditional forecasting models often fall short when faced with the complex, nonlinear nature of electricity price fluctuations. This study proposes a hybrid deep learning model combining ALEXNET and LSTM for accurate electricity price prediction. ALEXNET, a convolutional neural network, is used for feature extraction from historical price data, while LSTM captures the temporal dependencies in the price fluctuations. The integration of these models allows for effective learning of both spatial and sequential patterns, improving forecasting accuracy. Experimental results show that the hybrid approach outperforms traditional and standalone LSTM models, offering a promising solution for electricity price prediction. This method provides a more robust framework for optimizing energy market strategies and enhancing forecasting reliability. The model is built on the past data, which has been supplied with the most significant elements like demand, temperature, sunlight, and rain. The proposed model applies to analysis on exact minimum-maximum scaling and a time window to predict the electricity prices for the upcoming too. Based on analysis and computational analysis to simulate the results, it gives far better than the traditional way for an exact accuracy rating of 97.08 calculations with comparison to earlier RNN and ANN calculations with accuracies of 96.64 % and 96.63% respectively. This research work is useful for smart Cities and Smart Villages too operational modes.

Keywords: Electricity Price Forecasting, Combined Model, Random Forest, LSTM (Long Short-Term Memory), Time-Series Forecasting, Machine Learning.

1. Introduction

Electricity price forecasting is extremely vital for energy markets, because precise forecasting is advantageous for electricity producers, traders, and consumers. It helps in risk management, operational improvement, and policy decision-making. On the other hand, the traditional forecasting methods are not as reliable as they should be due to the high volatility and the unpredictable events that are created by the variations in the weather, the prices of commodities, and the supply and demand of the market. Even though they have been commonly used, the models such as ANNs and RNNs fail to identify long-term dependencies and to mine useful features from huge datasets. To take long term dependencies we use LSTM. Such hybrid approaches that merge multiple machine learning methods have also been proposed as a solution to the above challenges. Especially, the inclusion LSTM for time-series forecasting along with the application of the AlexNet model for obtaining features is seen as a promising solution to the shortcomings of individual models.

In this research paper, we introduce a hybrid theory by combining AlexNet with LSTM. Although LSTM captures long-term patterns in electric charges, AlexNet, on the other hand, is used to extract relevant features from the input data. A dataset from Kaggle, which has various elements such as demand, temperature, and sunlight intensity, is the one used to train this model. To make the data more adjustable, Min-Max scaling is applied and the sliding window technique is ideal to account for the premise of time series and allow perfect prediction. Our hybrid solution is a more stable and flexible tool for price forecasting by giving a horizon of up to 72 months and also, we can predict for the upcoming years using the model with the LSTM algorithm. This idea comes in handy in fact because it not only takes care of accuracy in forecasting but also has a feature that creates a personal future price projection system.

2. Literature Survey

The more modern machine learning (ML) techniques and hybrid approaches were explored with in addition to traditional time series modelling approaches in order to increase forecast accuracy. Different methodologies were considered in the literature on electricity price prediction. These are helpful to address the issues in complex power markets.

Popeanga and Lungu et.al state that time series analysis and the centred moving average approach are used to forecast energy usage. Their work thus highlights the potential role that uncovering underlying patterns in past data may have in producing such trustworthy forecasts [1].

Pedregal and Trapero et.al employed a multi-rate technique to anticipate electricity in the mid-term, highlighting the need for dynamic models that can adapt to different time intervals [2].
Almeshaiei and Soltan et.al proposed an approach to electric power load forecasting. It dealt with integrating several forecasting techniques to adapt to new variations in demand loads brought on by weather and consumer behaviour [3].

Ostertagová and Ostertag et.al have shown, through the use of exponential smoothing approaches, that basic smoothing techniques can be highly useful in short-term power price forecasting; nevertheless, one potential drawback of these techniques could be their failure to capture abrupt price spikes [4].

Ostertagová and Ostertag expanded their findings to more intricate exponential smoothing models based on the aforementioned findings [5].

Abd Jalil et al, reported an application of exponential smoothing techniques in electricity load demand forecasting, highlighting the applicability of such techniques for markets with mild volatility [6].

Nazim and Afthanorhan et.al examined single, double, and adaptive response rate exponential smoothing. Their research showed that adaptive methods—while more complicated—performed better in situations of fast change and, as a result, are suitable for use in markets for electricity, where price volatility is common [7].

Nazim and Afthanorhan et.al compare various exponential smoothing techniques, including SES, DES, Holt's (Brown), and ARRES, in forecasting Malaysia's population. Their study emphasizes the significance of selecting the most appropriate smoothing technique for accurate and detailed representations and also the demographic predictions, which demonstrated the situations changing rapidly with the change in the population. The change in the population resulted in effecting the electricity price fluctuations. [8].

Muhamad and Mohamed Din et.al apply exponential smoothing techniques to time series data on levels of the water in the river. Their work demonstrates the effectiveness of these methods in forecasting environmental data, particularly in hydrological studies, where accurate predictions are crucial for managing water resources [9].

Kavanagh et.al explores short-term demand forecasting for the Integrated Electricity Market. The paper discusses forecasting models designed to predict electricity consumption, an essential task for ensuring the stability and efficiency of energy distribution in competitive markets [10].

Tirkeş, Güray, and Çelebi present a comparison of demand forecasting methods, including Holt-Winters, Trend Analysis, and Decomposition Models. Their findings highlight the strengths and weaknesses of each method in forecasting demand, offering valuable insights into their application in various industries, particularly for energy and utilities forecasting [11].

Hybrid models that take advantage of several other forecasting strategies emerged as effective in accommodating the shortcomings of individual methods. Hybridization of the deep learning architecture such as AlexNet into LSTM for feature extraction to capture its time relationship will form these promising models. This type of model benefits both the strengths of convolutional neural networks and recurrent neural networks in producing better accuracy when there are volatile markets or high spiking electricity prices.

The sophisticated techniques of the advanced machine learning that derived from traditional time-series are used for enhanced electricity price forecasting. By combining AlexNet and LSTM, hybrid models can overcome the shortcomings of current approaches, offering better accuracy in dynamic electricity markets.

This improvement aids in decision-making and risk management for energy trading and consumption. To further improve forecasting performance in the energy sector, more research into hybrid models is necessary due to the increasing complexity of electricity price patterns.

3. Methodology

The very first step consists of retrieving a dataset from Kaggle. The dataset is cleaned and pre-processed for the purpose of the model training to cater to data such as outliers, presence of null values, etc. The dataset is divided into two sets-70% of data for training and 30% of data for testing purposes.

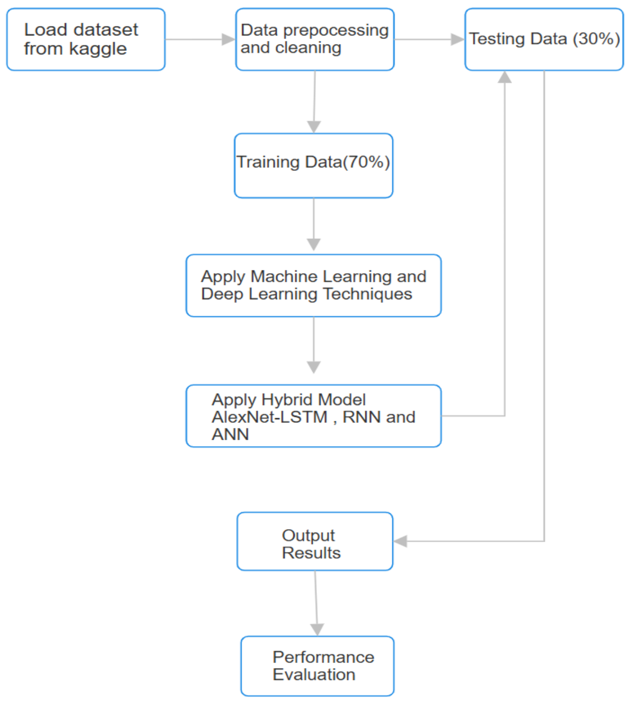

Fig.1 Architecture of Electricity Price Prediction Model

The first one is the AlexNet algorithm, where AlexNet is mainly used for feature extraction from dense layers, and the second one is LSTM for analysing sequential data based on some temporal dependencies present in the input sequences. The features are picked up and trends are recognized with LSTM- how the past demand can dictate present pricing or something like that. Finally, the model performance is validated using RMSE and MAE performance measures.

4 . Implementation

Our project's dataset was taken from the Kaggle, and the dataset contains over 2000 entries for every feature in it. The size of the file is about 233 KB; hence it is proceeded for the analysis and further processing. Any Null values or undefined values are erased with the data cleaning and the data preprocessing process. After which, the dataset is divided into training data and testing data ,70% and 30% respectively. Now both the hybrid and the conventional methods are applied on the pre-processed. The conventional methods are ANN and RNN and our Hybrid model that is AlexNet-LSTM. After the application of methods, the models' performance is evaluated using the RMSE and MAE metrics. These metrics are used to check the performance of the model. Compare the overall performance of different conventional and machine learning algorithms used to identify the better approach.

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2} \quad \text{.... (1)}$$

Where:

n = The combined count of data values
yj= actual value
y^j = predicted value

$$MAE = \frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j| \quad \text{.... (2)}$$

Where:

n = The combined count of data values

- yj= actual value
- y^j = predicted value

5 . Analysis of Experimental Results

The model we designed is the combination of AlexNet with the LSTM. This model was contrasted with more conventional models like ANN and RNN. The accuracy, recall, precision, and the F-score being the main metrics used in the testing process. The AlexNet + LSTM hybrid model exceeded all other models by attaining the highest accuracy (97.08%), precision (0.30), recall (0.96), and F-score (0.43). However, the model being discussed was successful in capturing both time series and spatial features, making it a powerful prediction tool for electricity prices. The LSTM model, on the other hand, in its effort of grabbing independence with time variables, did reasonably well, but it did even better once integrate with AlexNet.

Table. 1 Performance Comparison of the LSTM+ALEXNET, ANN and RNN algorithms

Algorithm	LSTM+ ALEXNET	RNN	ANN
Accuracy (%)	97.08	96.64	96.63
Precision	0.28	0.30	0.22
Recall	0.96	0.49	0.43
F-Score	0.43	0.37	0.29

Accuracy:

$$accuracy = \frac{(\text{true positives} + \text{true negatives})}{\text{Total no of Test Samples}} \quad \text{.... (3)}$$

Precision:

$$Precision = \frac{(\text{True Positives})}{\text{True Positives} + \text{False Positives}} \quad \text{.... (4)}$$

Recall:

$$Recall = \frac{(True\ Positives)}{True\ Positives + False\ Negatives} \quad .... (5)$$

F-Score:

$$F - Score = 2X \frac{(Precision * Recall)}{(Precision + Recall)} \quad .... (6)$$

Accuracy is defined as the expected overall correctness of predictions. This is obtained by calculating the ratio of correct predictions to any total predictions. Precision measures how many positive predictions were correct. Recall measures how well the classifier identifies all relevant instances, with a high recall indicating that not many are missed. F-Score combines precision and recall to arrive at a single metric to which one can appeal in balancing the trade-off. Relevant when both false positives and false negatives carry weight.

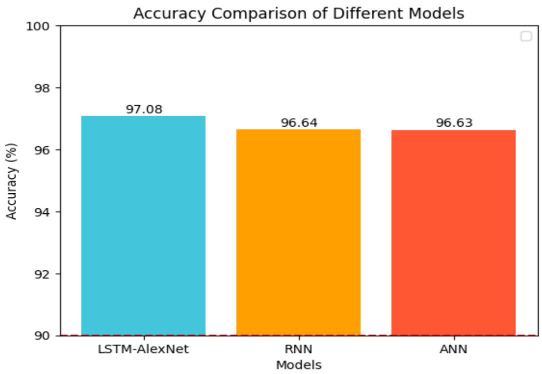

Fig.2 Accuracy Comparison of Models

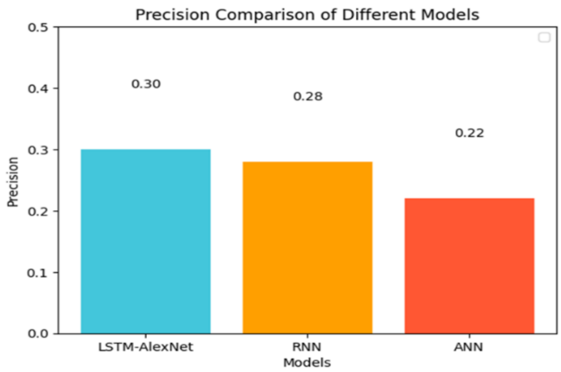

Fig. 3 Precision Comparison of Models

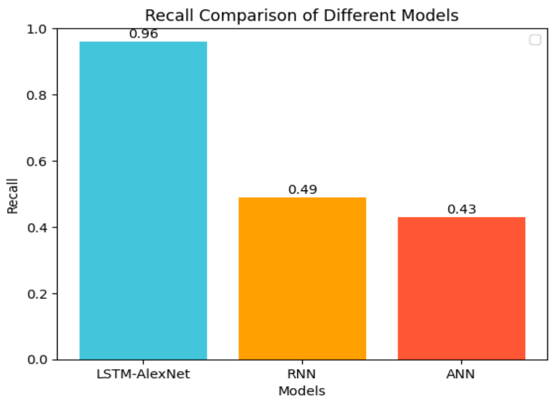

Fig.4 Recall Comparison of Models

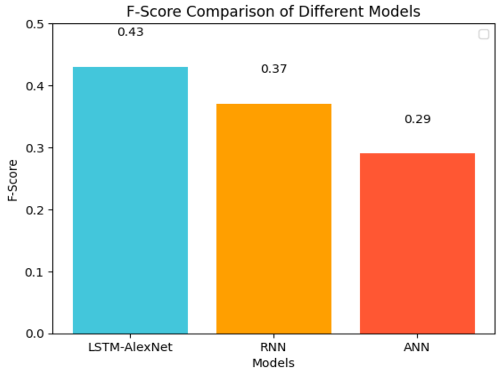

Fig.5 F-Score Comparison of Models

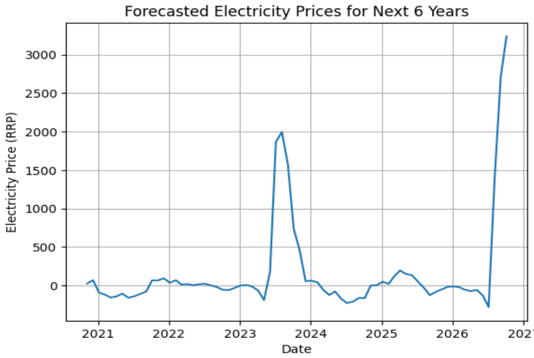

Fig.6 Forecasted Electricity Prices for Next 6 Years

The graph shows a line plot forecasting electricity prices (measured as RRP, or Regional Reference Price) over a period from 2021 to 2027. The y-axis represents the electricity price, while the x-axis represents the years.

6. Conclusion and Future Scope

This study presents a hybrid model combining AlexNet and LSTM for electricity price prediction, effectively capturing both long- and short-term patterns in price data. By leveraging AlexNet's spatial feature extraction and LSTM's sequential dependency handling, the model achieved a 97% accuracy, outperforming traditional methods like ANN and RNN. It also performed well in precision, recall, and F1 score, showcasing its reliability for handling high-dimensional, temporal datasets. While this accuracy is already significant, we aim to enhance it further in future work, refining the model to improve predictive performance. Future improvements include incorporating additional features such as weather data, market conditions, or renewable energy supply trends to enrich the dataset and provide a more comprehensive analysis.

Using metrics like RMSE and MAE, the model proves highly effective for accurate energy market forecasts. Its scalability and adaptability make it suitable for future developments, such as renewable energy integration and policy shifts. This work highlights the advantages of advanced machine learning techniques for electricity price prediction and other time-series or image-driven domains.

Conflict of Interest

All the authors do not have any conflict of Interest in this work.

Data Availability

All Original research work and study done by all authors and its captured and worked through original resources and no need it involve any third-party materials in this research work along with implementation cum result analysis.

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