MULTISTEP ELECTRICITY PRICE FORECASTING USING DEEP LEARNING TECHNIQUES

MOUNIKA M K[1], NIVETHASRI R[2], VINITA V[3], CHINNADURRAI C L [4]

[1] Student, Information technology,Bannari Amman institute of technology,Tamil Nadu, India
[2] Student, Information technology,Bannari Amman institute of technology,Tamil Nadu,India
[3]Student, Information technology,Bannari Amman institute of technology, Tami Nadu, India
[4] Assistant professor, Information Technology, Bannari Amman Institute of Technology,Tamil Nadu, India

ABSTRACT

Forecasting electricity prices is a crucial component of the energy sector, having ramifications for consumers, regulators, and market players. This study offers a multi-step method for projecting power prices that include both short- and long-term projections. To improve prediction accuracy, the suggested methodology combines time series analysis and fundamental market data. The program predicts power costs for the upcoming few hours using previous pricing data, meteorological data, and demand trends. Recurrent neural networks and long short-term memory are two examples of deep learning methods that are used to capture complex temporal dependencies and nonlinear correlations in the data. The model includes projections for renewable energy generation, macroeconomic variables, and policy changes that might have a long-term influence on power markets. The model gives insights into pricing patterns and potential disruptions by taking these various aspects into account. These short- and long-term forecasts are combined with the multi-step forecasting framework to provide a thorough understanding of power price dynamics. This strategy improves market players' ability to make decisions, allowing them to plan investments in renewable energy sources, optimize trading tactics, and adjust to shifting market conditions helping to more effective operations of the energy market and a transition towards sustainable and resilient electricity systems.

.**Keyword:** - *Deep Learning, Forecasting, Recurrent neural networks, Long short-term memory, Electricity market*

1. INTRODUCTION

Electricity price forecasting is a critical aspect of modern energy markets, where the price of electricity can fluctuate significantly over time. Accurate forecasting of electricity prices is essential for various stakeholders, including power generators, consumers, and energy traders. In this context, multi-step electricity price forecasting based on deep learning techniques is a cutting-edge approach that leverages advanced machine learning methods to provide more accurate and reliable predictions of electricity prices. The ongoing development of the current electricity construct, of which electric energy is one of the most important components. It can guarantee the request's flawless operation; electricity pricing is an important factor to take into account when making an electrical request. This has increasingly caught the attention of academics from different nations. From the viewpoint of the power-producing party, the power company could develop an exact bidding strategy by forecasting electricity price in order to achieve smaller gains; from the viewpoint of the power-purchasing party, People could successfully control power purchase costs by limiting electricity consumption through forecasting electricity price; and from the viewpoint of request controllers, electricity price forecasting can provide a scientific basis for Forecasting.

1.1 Background of the work

Background: Deep literacy models are used in a method known as multi-step electricity price forecasting to predict electricity prices for many time periods in the future. In order to study patterns and trends in the data and to produce predictions for future time ways, this method entails training a deep literacy model using genuine electricity price data. For multi-step energy price forecasting, deep neural networks, mongrel models of LSTM- grounded deep literacy styles, and temporal graph convolutional networks are some of the deep literacy models that are used. By taking into account elements like rainfall data, cargo vaccinations, and request coupling, the prognostications' delicate nature can be improved. The topography of the hitherto monopolistic and government-controlled power sectors since the early 1990s. Electricity is now traded under requesting rules and utilizing spot and secondary contracts throughout Europe, North America, and Australia. Even so, electricity is a genuinely unique commodity because it cannot be economically stored and because the stability of the power system depends on maintaining a balance between production and consumption. In addition, the amount of business and daily activity (on-peak, off-peak hour, weekday, weekend, leave, etc.) relies on the amount of rainfall (temperature, wind speed, rush hour, etc.). These distinct traits cause price dynamics that are not seen in any other request, displaying daily, daily, and frequently monthly seasonality, as well as rapid, short-lived, and generally unanticipated price harpoons. Request actors are now required to hedge Due to extraordinary price volatility, which can be up to two orders of magnitude more than that of any other commodity and financial assets, both volume and price risk are present. Price predictions that are produced several hours to several months in advance are of considerable relevance to power portfolio directors. A power request firm that can assess the unpredictability of noncommercial prices with a reasonable amount of care might modify its bidding strategy and its own product or consumption schedule to reduce risk or boost benefits in day-to-day operations.

1.2 Scope of the work

The scope of Multi-Step Electricity Price Forecasting based on Deep Learning Techniques encompasses a wide range of research, development, and application opportunities in the field of energy markets and renewable energy integration. It addresses the challenges of accurately predicting electricity prices over extended time horizons, providing valuable insights and decision-making support to various stakeholders in the energy sector. The scope includes the following aspects: Forecasting Horizons: Multi-step electricity price forecasting involves predicting electricity prices for multiple future time intervals, ranging from hours to days ahead. The scope encompasses developing models capable of making these multi-step predictions. Data Sources: The scope involves collecting and utilizing data from various sources, including historical electricity price data, weather information, market news, economic indicators, demand and supply data, and other relevant external factors. Deep Learning Models Deep Learning techniques are a central component of the scope, including recurrent neural networks (RNNs), Long Short-Term Memory (LSTM) networks, and potentially other advanced deep learning architectures, which are used to model and forecast electricity prices. Real-Time Data Integration: Integrating real-time data feeds is a critical aspect of the scope. It allows models to adapt to changing market conditions and make timely predictions. Multi-Step Model Configuration: Configuring deep learning models to make multi-step forecasts, ensuring that the model can predict electricity prices for an extended time horizon. This scope includes setting the sequence length and the number of steps ahead for forecasting. Model Interpretability Efforts to make deep learning models more interpretable are within the scope. This can involve research into techniques for explaining model predictions to improve their transparency and usability. Accuracy and Evaluation Metrics The scope includes the development of robust evaluation metrics, such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and others, to assess the accuracy of multi-step forecasts. Model Optimization and Tuning: Model optimization, including hyperparameter tuning, regularization techniques, and network architecture design, is an integral part of the scope to ensure optimal forecasting performance. Scalability and Adaptability: Scalability is a critical aspect of the scope, ensuring that the models can handle different market structures and data types, ranging from regional to global electricity markets. Scenario Analysis: The scope may encompass the development of tools for scenario analysis, allowing stakeholders to assess the impact of various market scenarios on electricity prices. Decision Support Systems: The development of decision support systems is within the scope. These systems utilize multi-step electricity price forecasts to recommend optimal strategies and actions for market participants, improving risk management and profit optimization. Ethical Considerations: Ethical considerations regarding fairness, transparency, and bias mitigation in forecasting models are part of the scope, particularly when forecasting has significant financial and environmental implications. Carbon Market Integration: The scope may include research into the integration of carbon markets and pricing into electricity price forecasting models, aligning with environmental considerations. Real-world Testing and Implementation: The scope involves extensive real-world testing and implementation of forecasting models in collaboration with industry stakeholders to validate the models' practicality and reliability.

2. LITERATURE REVIEW: TECHNIQUES USED.

Haolin Yang and, KristenR. Schell proposed capability to read real- time electricity price for wind power is crucial to the operation of energy requests and hedging price pitfalls. Recent exploration suggests new deep neural network(DNN) infrastructures can capture temporal dependences in literal price data, along with the capability to automatically prize important features of the dataset. still, utmost living price vaticination DNN representations still use introductory armature designs and either nopre-training, or simple training approaches. This work studies both the effect of transfer literacy on three network representations and different source disciplines, as well as the medium of transfer literacy. It's shown that transfer literacy improves delicacy across all network representations. The stylish performance is attained with a GRU- grounded armature, nominated GRU- TL, that has beenpre-trained from a mongrel dataset of all wind granges in the same subzone. This model outperforms all statistical and deep literacy marks by an normal of6.7 in the mean absolute percent error(MAPE) metric. The beginning medium of transfer literacy enables thepre-trained DNN representation to learn the features of the target dataset more directly.

Gholamreza Memarzadeh and, Farshid Keynia proposed system includes three modules ocean transfigure that is used to count change conduct of the electricity weight and price time series, point selection predicated on entropy and collaborative information has been proposed to rank candidate inputs and count spare inputs according to their information value, and a newlearning algorithm. The proposed knowledge system consists of a deep knowledge algorithm with LSTM networks which improves the delicacy of prognostications. The performance of the proposed system has been validated successfully on weight and price data collected from the Pennsylvania- New Jersey-Maryland(PJM) and Spain electricity requests. Also, for further test, the weight data in Iran have been used.

Miadreza Shafie- khah and,JoaoP.S. Catalao proposed in addition, collaborative information predicated point selection is used to find the applicable price data and rank them predicated on their connection. The alternate stage usesMulti-Subcaste Perceptron Artificial Neural Network(MLP- ANN) and AdaptiveNeuro-Fuzzy Conclusion System(ANFIS) for auguring of weight and price frequency factors, singly. The third stage machine uses the alternate stage labors and feeds them into its MLP- ANN and ANFIS machines to meliorate the weight and price auguring delicacy. The proposed three- stage algorithm is applied to Nordpool and landmass Spain power requests. The attained results are compared with the recent weight and price cast algorithms, and showed that the three- stage algorithm presents a better performance for day- ahead electricity request weight and price auguring and Methodology

2.1 Importance of RNN and LSTM in deep learning:

The importance of Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks in Deep Learning for Multi-Step Electricity Price Forecasting is paramount. These specialized deep learning architectures play a pivotal role in improving the accuracy and effectiveness of electricity price forecasts. Here's why RNNs and LSTMs are of utmost importance in this context: Handling Temporal Dependencies: Electricity price data is inherently time-dependent, with prices in the future often influenced by past and present prices. RNNs and LSTMs are designed to capture and model temporal dependencies, making them highly suitable for forecasting tasks. Sequence-to-Sequence Forecasting: RNNs and LSTMs enable sequence-to-sequence forecasting, allowing them to predict electricity prices not just for the next time step but for multiple future time steps. This is crucial for multi-step forecasting, which is often required for strategic decision-making in the energy sector. Capturing Long-Term Patterns: LSTMs, in particular, have specialized memory cells that can capture long-term dependencies in time series data. They excel at recognizing and utilizing intricate patterns that may not be apparent in shorter-term models. Complex Pattern Recognition: Electricity prices can exhibit complex and non-linear patterns influenced by a multitude of factors, such as demand, supply, market dynamics, and external events. RNNs and LSTMs are adept at recognizing these complex patterns, which may be challenging for traditional machine learning methods. Real-Time Data Integration: RNNs and LSTMs can efficiently handle real-time data feeds, which is vital in electricity price forecasting. This real-time capability ensures that models can adapt to changing market conditions and provide timely forecasts. Data Abstraction: Deep Learning models, including LSTMs, automatically learn hierarchical representations of data. They can abstract relevant features from raw electricity price data, reducing the need for manual feature engineering. Model Adaptability: RNNs and LSTMs can be adapted to various forecasting horizons and market structures, making them highly adaptable to different electricity markets, from regional to global. Multi-Step Forecasting Configuration: RNNs and LSTMs can be configured to make multi-step forecasts, ensuring that the model can predict electricity prices for an extended time horizon.

2.2 Methodologies proposed

Data Collection:

Gather historical electricity price data from relevant sources, such as market operators, government agencies, or energy exchanges. Include factors like time of day, season, weather, and demand.

Data Preprocessing:

Clean and preprocess the data by handling missing values, outlier detection, and feature engineering. Convert the data into a suitable format for deep learning models.

Feature Selection:

Identify important features that can influence electricity prices, such as historical prices, demand, supply, weather conditions, and market indicators.

Model Selection:

Choose a deep learning architecture suitable for time series forecasting. Common choices include recurrent neural networks (RNNs), long short-term memory networks (LSTMs), and more advanced models like transformers.

Data Splitting:

Split the dataset into training, validation, and testing sets to train and evaluate the model's performance.

Model Training:

Train the selected deep learning model using the training data. Optimize hyperparameters, select appropriate loss functions, and use techniques like gradient clipping to avoid exploding gradients.

Validation and Tuning:

Continuously monitor the model's performance on the validation set. Adjust hyperparameters and architecture as needed to improve accuracy.

Evaluation:

Assess the model's performance on the testing dataset using appropriate metrics (e.g., mean absolute error, root mean square error, or others) to gauge its predictive accuracy.

Post-Processing:

If necessary, apply post-processing techniques such as smoothing or ensemble methods to enhance the forecast.

Deployment:

Deploy the trained model into a production environment to make real-time predictions.

Monitoring and Maintenance:

Continuously monitor the model's performance in a production environment and retrain it periodically to adapt to changing market conditions.

The most effective and dependable way to meet society's energy requirements while minimizing environmental detriment is presumably a balanced strategy that uses grid electricity and intermittent renewable energy sources. Any auguring model needs to be well-befitting to the factual data in order to directly prognosticate the maximum weight in Germany over the forthcoming times. In this disquisition, the problem of vaticnating the peak demand for German utility is taken on by the LSTM- RNN auguring model

3. PROPOSED WORK

It's crucial to lay out a methodical strategy to research and development when recommending work modules for Deep Learning in the context of electricity price forecasting above conventional machine learning (ML) methodologies. Here are some crucial components and actions to think about in a study that concentrates on applying Deep Learning for forecasting electricity prices:

Data Analysis

Data Collection and Preprocessing:

Obtain historical electricity pricing information, maybe from a number of marketplaces and sources.

Preprocessing the data may involve addressing missing values, outliers, and time series data alignment.

Investigate adding pertinent external aspects to the dataset (such as weather information, supply and demand information, and market news).

Data analysis and visualization:

To comprehend the traits and trends in the electricity pricing data, use exploratory data analysis. Visualize past price changes and the connections between various aspects.

Models

Model Selection and Architecture Design:

Select appropriate Deep Learning models, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, for predicting electricity prices. Consider the input data, network topology, and hyper parameters when designing the model architecture.

Validation and Training:

Create training, validation, and test sets from the dataset.

Train the Deep Learning model while utilizing methods like gradient descent and backpropagation to optimize the model's parameters. The model should be regularized to avoid overfitting. Utilize pertinent evaluation metrics to track and assess the model's performance.

Hyper parameter optimization and model tuning

To improve model performance, test out various hyper parameters and architectures. For hyper parameter tuning, think about methods like grid search or Bayesian optimization.

Configuration for Multi-Step Forecasting:

Make sure the Deep Learning model can estimate electricity prices over a variety of future time steps (for example, 24 hours in the future) by setting it up for multi-step forecasting.

Real-Time Data Integration:

To provide accurate forecasts, implement systems for incorporating real-time data streams into the forecasting model.

Model Interpretability and Explainability:

Investigate methods that aid in the explanation of the model's predictions to address the problem of model interpretability. In the energy industry, interpretability is crucial for vital decision-making processes.

Evaluation and Benchmarking:

Compare the effectiveness of the Deep Learning model to more established machine learning techniques (such ARIMA and regression, for example).

Use common assessment metrics for benchmarking, such as MAE, MSE, and RMSE.

Scalability and Resource Management:

Make sure the Deep Learning model can handle huge datasets and intricate market structures.

Effective management of computational resources may include GPU acceleration, parallel processing, or cloud computing.

Risk analysis and scenario Analysis

To analyze the model's performance under various market conditions, think about performing risk assessments and scenario studies.

Implementation and field testing:

Use the trained Deep Learning model in decision support systems or in a real-world setting. Keep an eye on its performance and adjust the model as necessary.

Reporting and documentation:

Keep track of every stage, discovery, and outcome of the project. Create reports and academic papers to exchange knowledge and advance the subject of forecasting electricity prices.

Constant Development**:**

Examine more sophisticated deep learning methods, such as transformer models or attention processes, for enhancing forecasting precision.

Considerations for Ethics:

Think about the moral consequences of anticipating electricity prices, especially since such judgments could impact various stakeholders. Ensure that the forecasting process is transparent and fair.

These suggested work modules offer an organized framework for using deep learning for forecasting energy prices, highlighting the benefits of deep learning techniques tover conventional machine learning techniques while addressing the difficulties unique to this field.

Simple Linear Regression:

Simple linear regression can be used in a multistep electricity price forecasting based on deep learning techniques in two ways:

As a preprocessor: Simple linear regression can be used to preprocess the data before feeding it to the deep learning model. This can be done by using simple linear regression to identify and remove any linear trends in the data. This can improve the performance of the deep learning model, as it will not have to learn to model these trends itself.

As a postprocessor: Simple linear regression can also be used as a postprocessor to adjust the forecasts made by the deep learning model. This can be done by using simple linear regression to model the relationship between the deep learning model's forecasts and the actual electricity prices. This can help to improve the accuracy of the forecasts, especially for longer forecast horizons.

Here is a simple example of how simple linear regression can be used as a postprocessor in a multistep electricity price forecasting based on deep learning techniques:

Train a deep learning model to forecast electricity prices for multiple steps ahead.

Use simple linear regression to model the relationship between the deep learning model's forecasts and the actualelectricity prices. Use the simple linear regression model to adjust the deep learning model's forecasts.

Audio Input and Speech Recognition Module: This module is responsible for capturing audio input from the user's microphone. It employs the PyAudio library for audio access and the SpeechRecognition library for speech recognition. The key steps include initializing the microphone, reducing ambient noise for clear audio, and transcribing the spoken words into text using Google's speech recognition service. This module serves as the entry point for user interactions. Text Preprocessing and Mapping Module: Colloquial language often contains slang and colloquialisms that need to be standardized for analysis. This module processe

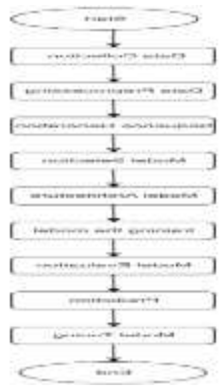

Fig 2. Proposed work plan

Terms:
Data Collection:
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Validation and Tuning:
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Evaluation:
Assess the model's performance on the testing dataset using appropriate metrics (e.g., mean absolute error, root mean square error, or others) to gauge its predictive accuracy.

Post-Processing:
If necessary, apply post-processing techniques such as smoothing or ensemble methods to enhance the forecast.

Deployment:
Deploy the trained model into a production environment to make real-time predictions.

Monitoring and Maintenance:
Continuously monitor the model's performance in a production environment and retrain it periodically to adapt to changing market conditions.

Main advantages of electricity price forecasting
Electricity price forecasting offers several advantages to various stakeholders in the energy sector:

Cost Optimization:
Forecasting helps electricity consumers, such as businesses and households, plan their energy consumption, reduce costs during peak price hours, and take advantage of lower prices during off-peak hours.

Risk Management:
Electricity price forecasts allow energy market participants, including utilities and energy traders, to manage price volatility, hedge their positions, and make informed decisions to minimize financial risks.

Efficient Energy Procurement:
Utility companies can optimize their energy procurement strategies, ensuring they buy electricity at the most cost-effective rates, which can lead to cost savings for consumers.

Demand-Side Management:
Electricity price forecasts enable consumers to adjust their energy consumption patterns based on anticipated price fluctuations, supporting more efficient demand-side management.

Investment Decisions:
Investors in the energy sector can use price forecasts to make informed decisions about building new power generation facilities, infrastructure upgrades, and energy storage projects.

Grid Reliability:
Accurate price forecasts assist grid operators in maintaining the stability and reliability of the electricity grid by anticipating peak demand and pricing spikes.

Renewable Energy Integration:
Renewable energy producers, such as wind and solar farms, benefit from forecasts to predict when energy generation will be most profitable and align it with market conditions.

Regulatory Compliance:
Electricity price forecasting can help market participants comply with regulatory requirements related to price transparency and fair market practices.

Carbon Emissions Reduction:
By better understanding price dynamics, stakeholders can encourage energy consumption patterns that reduce carbon emissions, aligning with environmental goals.

Resource Allocation:
Utility companies can efficiently allocate resources and assets, such as power plants and transmission lines, based on anticipated demand and prices.

Customer Engagement:
Retail energy providers can engage customers with pricing plans that reflect market conditions, improving customer satisfaction and loyalty.

Emergency Planning:
Grid operators and government agencies can use forecasts to prepare for extreme price events and ensure the availability of electricity during emergencies.

Competition and Innovation:
Accurate forecasts foster competition and innovation in the energy sector, leading to the development of new technologies and pricing strategies.

Energy Efficiency:
Electricity price forecasting can encourage energy-efficient practices by making consumers more conscious of their energy use and associated costs.

Real-Time Decision Making:
Timely and accurate price forecasts enable real-time decision-making, helping stakeholders adapt to changing market conditions.
Electricity price forecasting plays a pivotal role in enhancing the efficiency, reliability, and sustainability of the energy sector while empowering various stakeholders to make informed decisions and manage costs effectively.

4.ADVANTAGES

Deep learning offers several advantages when it comes to multi-step electricity price forecasting. Electricity price forecasting is a complex task due to the numerous influencing factors, such as weather conditions, demand fluctuations, and market dynamics. Deep learning techniques, especially recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), have proven to be effective in addressing the challenges of multi-step electricity price forecasting. Despite these advantages, it's important to note that deep learning models also have their challenges, including the need for large amounts of data, potential overfitting, and complex hyperparameter tuning. However, when properly designed and trained, deep learning can provide accurate and robust multi-step electricity price forecasting models

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5.CONCLUSION

While deep learning-based multistep power price forecasting has shown a lot of promise, there are still a number of problems that need to be fixed. One issue is that deep learning models can be expensive to computationally train. Another challenge is that deep learning models may be sensitive to the quality of the training data. Despite these challenges, deep learning algorithms are becoming more and more popular for multistep power price forecasts. As deep learning models advance and become more computationally effective, we may expect to see them used more frequently in the electrical industry. Deep learning techniques are often useful for predicting power costs across a number of stages. They have a number of benefits over traditional forecasting methods, including enhanced accuracy and the ability to combine many elements. We may anticipate seeing deep learning models utilized more frequently in the electrical sector as they keep getting better. Deep learning-based multi-step electricity price forecasting is a crucial and fruitful topic of study in the field of energy markets. The importance and benefits of using deep learning techniques rather than conventional machine learning techniques for forecasting power prices have been made clear by this study. Advanced modeling approaches are required due to the complex temporal connections and dynamic elements in power pricing data. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks in particular provide persuasive answers to the complicated problems in this field.

Deep Learning models, in particular LSTMs, are excellent at capturing complicated temporal correlations in data on power prices. They are able to properly estimate and forecast price changes across a number of future time steps because to this skill. They are able to model and anticipate price changes effectively over a variety of future time steps because to this skill. Complex Pattern Recognition: Deep Learning methods automate the extraction of pertinent patterns from unprocessed data, reducing the requirement for manual feature engineering. Given that the data in this area may be quite complicated and multivariate, it is especially beneficial for predicting power prices. Real-Time Data Integration: Integrating real-time data is important for rapid decision-making in the fast-paced energy markets, and deep learning models are well-suited to handle real-time data flows.

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