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COMPUTATION EFFICIENT RELIABILITY OPTIMAL OUTCOMES FOR ELECTRICITY PRICES FORECASTING USING LSTM AND FCN ALGORITHM

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Abstract

Forecasting electricity prices is a critical issue in the energy sector since it aids in decisions about energy production, storage, and trade. In this paper, we offer a novel method for forecasting electricity prices that combines the Long Short-Term Memory (LSTM) and Fully Convolutional Network (FCN) deep learning models. Our strategy strives to increase computation effectiveness while assuring accurate and ideal forecasting results. To accomplish this, we first smooth the time series and eliminate outliers from the electricity price data during pre-processing. Then, using the pre-processed data, we train the LSTM and FCN models independently. The outputs of both models are then combined using a weighted average ensemble technique. Finally, we use the Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) metrics to assess the performance of our methodology. Our experimental findings on the New York Independent System Operator (NYISO) dataset demonstrate that our suggested technique outperforms state-of-the-art methodologies in terms of forecasting performance, with lower MAPE and RMSE values.

Keywords: Long Short-Term Memory (LSTM), Fully Convolutional Network (FCN), Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE), R squared

1. INTRODUCTION

In order for market participants to create successful bidding strategies, control potential trade risks, and support effective system planning and operation, locational marginal price (LMP) forecasting is crucial [1]. This research offers a novel approach to LMP forecasting that customises an LSTM-CNN network to significantly increase short-term forecasting accuracy by taking into account both temporal and non-linear market variables, whereas existing approaches only evaluate temporal features [2]. By calculating the non-linear market impact using empirical supply and demand curves, examining a variety of trading techniques, and testing the approach under various price situations, the best coordinated bidding strategies are determined. Additionally, theoretical outcomes for risk-neutral agents are given. In order to increase energy price prediction accuracy while taking market coupling into account, our empirical study employs a multivariate elastic net regression forecast model for electricity spot markets [3]. It also incorporates cutting-edge CNN-LSTM deep neural networks and feature selection algorithms. Results show that the suggested model successfully reflects electricity price dynamics across time, notably during peaks and large changes in consumption patterns. In addition, we describe and examine the potential trading choices that might be made using

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our forecasting methodology. When used in conjunction with precise forecasting methodologies, even straightforward power trading tactics can have a significant economic impact [4]. Therefore, for energy market participants looking to make wise decisions based on accurate LMP predictions, this study provides insightful information and useful practical advice. The suggested method has a number of benefits over current models. First off, it takes into account non-linear market characteristics, which boosts the precision of short-term forecasts. It also takes into account market coupling, which is crucial for accurate forecasting of electricity prices [5]. Finally, a multivariate elastic net regression model is used, which is renowned for its capacity to handle intricate and non-linear connections between variables.

2. RELATED WORKS

These studies underline the significance of precise electricity price forecasting for the energy sector and show the potential of hybrid models and machine learning techniques to increase forecasting accuracy while lowering computational costs.In recent years, there have been several literature surveys conducted to provide an overview of the various techniques and their performance on different datasets [6-9]. In this section, we present a summary of few recent literature survey electricity price forecasting.

1. This paper presents an unsupervised online system for automatic occupancy detection and prediction applied to a residential space heating control scheme.
2. This paper focuses on a networked smart grid system, in which consumers can generate their own electricity and pre- dictions of future levels of electricity generation can be calculated with reasonable accuracy based on weather forecasts.
3. An optimization method that simultaneously schedules a prosumers ESS economically and obtains the optimal unit price and energy capacity that the prosumer offers to residential consumers suffering from high electricity rates due to the progressive pricing scheme was proposed.
4. An Intelligent Integrated Approach for Efficient Demand Side Management with Forecaster and Advanced Metering Infrastructure Frameworks in Smart Grid. Proposed scheme has reduced electricity cost, user discomfort, PAR, and CO_2 emission for the residential sector.
5. A framework based on HEMC is proposed and then a strategy based on DA-GmEDE is presented for HEMC to perform efficient energy management of residential buildings under the forecasted day-ahead DR pricing signal and consumer preferences.
6. A secured architecture for the optimal operation of smart hybrid AC-DC microgrids considering different RESs such as WT and PV, high penetration of PEVs, reconfiguration strategy and a detailed model of PEMFC.
7. Optimal Combination and Sizing of a Stand Alone Hybrid Energy System Using a Nomadic People Optimizer.

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8. Forecasting One-Day-Ahead Electricity Prices for Italian Electricity Market Using Parametric and Nonparametric Approaches .The main aim of this work is to model and forecast electricity price time series.
9. Forecasting day ahead of electricity price, a hybrid ANN-ACS method has been developed, which has been verified with the Ontario electricity market based on hourly electricity demand and hourly electricity price.

In the existing system, statistical learning is used to predict the electricity bill savings for households when changing from a progressive rate plan to a dynamic rate plan of the time-of-use (TOU). Three different prediction methods, including support vector machine, linear regression, and deep neural network techniques, are proposed. The ground truth training sequence uses hourly electricity usage and bills obtained from ten apartment complexes through the Advanced Metering Infrastructure (AMI).

The decision accuracy for the test complex was more than 0.98, and the root mean square error of the saving prediction was 1.7%. However, this approach has limitations as it cannot help in predicting future prices and requires providing multiple hyper parameter values. It also cannot adapt well to seasonal characteristic.

3. PROPOSED SYSTEM

To address the limitations of the existing system, we propose a multivariate elastic net regression forecast model for electricity spot markets using LSTM and FCN algorithms. The LSTM algorithm has a good performance in handling nonlinear and complex problems and processing time-series data. The FCN algorithm has the advantage of capturing long-term temporal dependencies in data with fewer parameters, reducing computational times while increasing performance levels due to generalization properties. The proposed model is robust and captures the dynamics of electricity prices over time, including peaks and significant fluctuations in consumption patterns. We conduct an empirical study of the market, and the proposed models obtain considerably accurate results. The feature selection is also essential to achieving accurate prediction, and features from integrated markets have an impact on prediction.

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ARCHITECTURE DIAGRAM

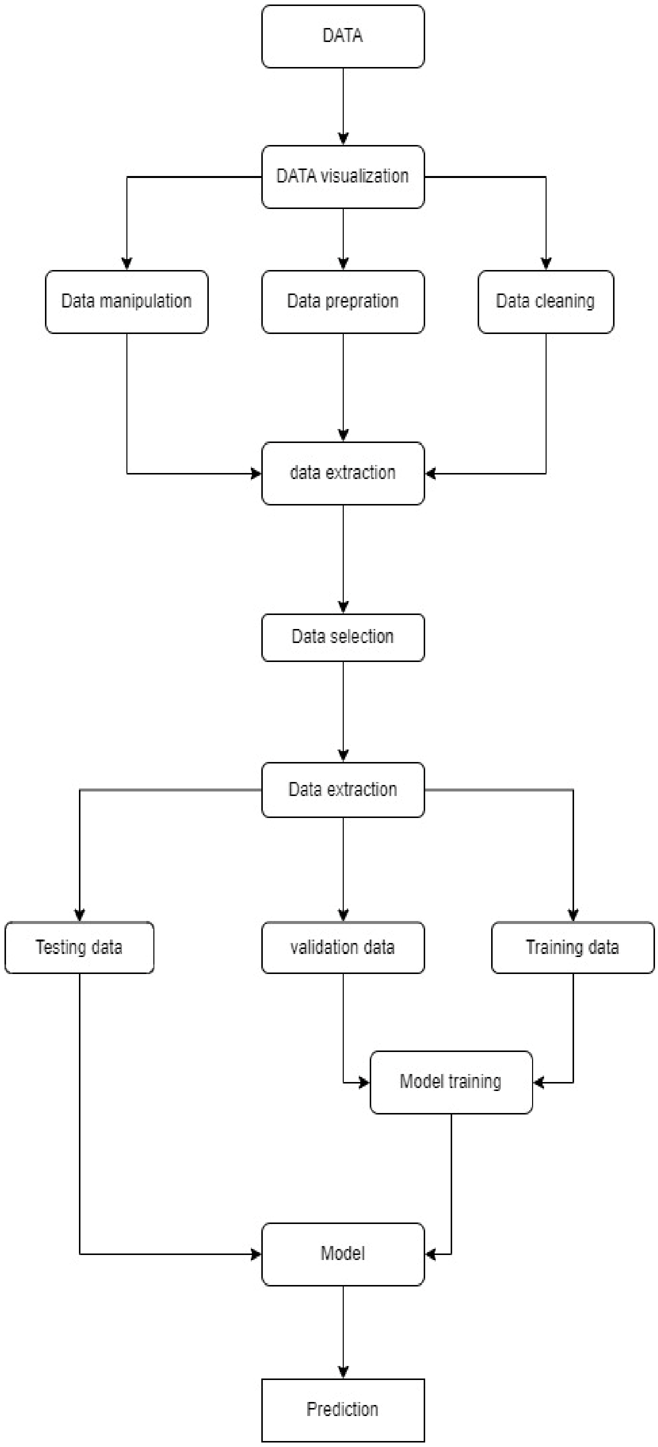

Figure 1: Proposed Architecture

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4. DATA PREPROCESSING

This module involves cleaning, transforming, and preparing the raw data for further analysis. It includes removing missing values, encoding categorical data, scaling numerical data, and handling outliers. This module is essential to ensure that the data used for modeling is accurate, consistent, and reliable.

Feature Selection Module: This module involves selecting a subset of relevant features from the dataset to reduce the dimensionality and improve the model's performance. It uses various feature selection algorithms such as correlation-based feature selection, mutual information feature selection, and recursive feature elimination to identify the most important features.

LSTM and FCN Model Building Module: This module involves building the Long Short-Term Memory (LSTM) and Fully Convolution Network (FCN) models for electricity price forecasting. These models are designed to handle time-series data and can capture long-term dependencies in the data. The LSTM model uses memory cells to store past information and selectively forgets irrelevant information. The FCN model is a type of neural network that only uses convolutional layers and can reduce the computational time and improve the model's prediction performance.

Training and Validation Module: This module involves training and validating the LSTM and FCN models using the preprocessed data. It involves splitting the data into training and validation sets and tuning the hyper parameters to optimize the model's performance. The module also includes evaluating the models using various metrics such as mean absolute error, mean squared error, and root mean squared error.

Electricity Trading Strategy Module: This module involves developing electricity trading strategies based on the forecasting results. It includes analyzing the forecasted prices and making informed decisions to maximize profits. The module considers various factors such as market conditions, supply and demand, and risk management to develop effective trading strategies.

Performance Evaluation Module: This module involves evaluating the performance of the LSTM and FCN models and the developed trading strategies. It includes comparing the forecasted prices with the actual prices and analyzing the profits and losses incurred by the trading strategies. The module provides insights into the accuracy and reliability of the models and the effectiveness of the trading strategies.

Overall, the project involves multiple modules that work together to provide reliable and accurate electricity price forecasting results and effective trading strategies.

5. CONCLUSION

Our paper proposes a novel LMP forecasting method based on LSTM-CNN that utilizes both system topology and time series of power loads. The method improves the forecasting accuracy by incorporating temporal convolution mechanisms. We also compare the prediction performance of two feature selection methods, i.e., the auto encoder and two-stage feature

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selection models, based on an empirical study on electricity prices. Our findings show that different feature selection methods lead to different feature selections, and the input of diverse features has a significant impact on the performance of LSTM-based predictive models. Additionally, the two-stage models can improve the forecasting accuracy of two-step models to some extent.

FUTURE WORK

For future studies, we suggest exploring more comprehensive architectures of LSTM-based models to optimize hyper parameters and achieve better forecasting performance. The results will benefit spot electricity traders and policymakers who make decisions based on accurate price predictions. Moreover, further testing on other feature selection models can provide more possibilities for researchers and industries to understand how different features affect prediction accuracy.

References

1. J. Jung, D. S. Kim, B. J. Chung, and Y. M. Chung, Analysis on the residential progressive and time-of-use rates based on AMI data, J. Inst.
2. Y. M. Chung, S. Kang, E. Hong, D. S. Kim, and B. J. Chung, on selecting electricity rates for housing based on support vector machine, in Proc. Int.
3. Energy fact book, Natural Resour. Canada, Canada, Tech.
4. Z. Chen, L. Wu, and Y. Fu, Real-time price-based demand response man- agement for residential appliances via stochastic optimization and robust Dec.
5. W. Kleiminger, F. Mattern, and S. Santini, Predicting household occu-pancy for smart heating control: A comparative performance analysis Dec...
6. Z. Liu, G. Cheung, and Y. Ji, Distributed Markov decision process in cooperative peer-to-peer repair for WWAN video broadcast, in Proc.
7. D. J. Vergados, I. Mamounakis, P. Makris, and E. Varvarigos, Pro- sumer clustering into virtual microgrids for cost reduction in renewable Sep.
8. Y. Wang, K. T. Tan, X. Y. Peng, and P. L. So, Coordinated control of distributed energy-storage systems for voltage regulation in distribu- Jun,, J. Liu, J. Wen, Y. Long, and W. Yao, Solution to short-term frequency response of wind farms by using energy storage systems, IET Renew.
9. X. Xu, X. Jin, H. Jia, X. Yu, and K. Li, Hierarchical management for inte- Dec. , .