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Empowering the Future: Precision Electricity Price Forecasting for Smart Energy Management

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A B S T R A C T

Electricity price forecasting is the process of using data, like past prices and weather conditions, to make an educated guess about how much electricity will cost in the future. This helps people and companies plan when to use electricity, and how to save money. Electricity price forecasting plays a pivotal role in the efficient operation of power markets, enabling stakeholders to make informed decisions regarding electricity generation, consumption, and investment. Hence, it is necessary for a power generation company to develop an accurate electricity price forecasting algorithm. We explore the utilization of historical price data, meteorological information, and market variables to train and test machine learning algorithms, aiming to provide accurate predictions of electricity prices. Our research evaluates the effectiveness of machine learning models such as support vector machines, neural networks, and gradient boosting, highlighting their strengths and limitations in electricity price forecasting. We delve deeper into the temporal patterns of electricity prices, considering daily, weekly, and seasonal variations. Understanding these patterns can lead to more precise forecasts and better decision-making.

Keywords: Machine Learning, Electricity Price Forecasting, Root Mean Square Error, Long-Short-Term-Memory, Data Preprocessing.

Introduction

In the world of electricity, predicting how much it will cost in the future is like foreseeing the weather – it's tricky but super important. Imagine if you could know tomorrow's electricity prices today; you could plan and use electricity more wisely, saving money and helping the environment. Now, this prediction business isn't easy. Electricity prices can jump around because of all sorts of things like the weather, politics, and new rules. That's where electricity price forecasting comes in. It's like a smart tool that uses fancy math and computer tricks to make educated guesses about what electricity will cost in the future. In our journey through this topic, we'll explore different ways people try to make these predictions. Some use a mix of numbers and formulas (that's the hybrid regression model), while others use super-smart computer networks (like the optimized neural networks). There's even talk about creating new ways for neighbors to trade electricity directly, making it more like a community thing.

Now, why does this matter? Well, think about it. If we can predict electricity prices accurately, we can plan better. Businesses can manage their costs, and you and I can decide the best time to run our appliances to save money. Plus, with more renewable energy sources like solar energy and wind energy in the mix, understanding when they're most effective helps us use cleaner energy.

Our goal here is to make sense of these different methods and see how they can help us all plan for the future – a future where electricity is not just affordable but also better for our world. So, let's dive into the exciting world of forecasting electricity prices and uncover the secrets that can shape a smarter and more sustainable energy future.

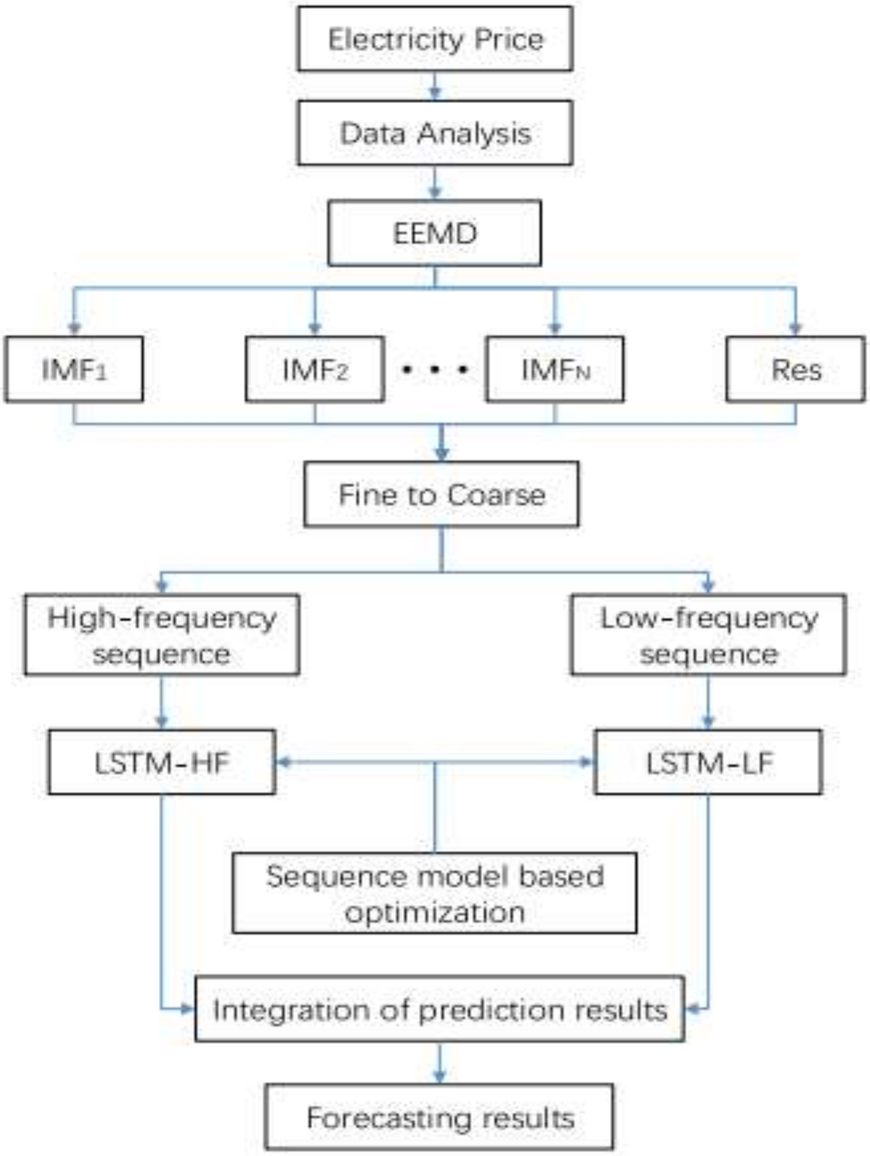
Literature Review

This study aims to innovate and enhance electricity price forecasting by introducing an optimized heterogeneous structure Long Short-Term Memory (LSTM) model. The paper addresses crucial issues in LSTM research, specifically the challenges associated with single network structures and hyperparameter selection. The proposed model is constructed based on decomposed and reconstructed electricity price data, utilizing the Empirical Mode Decomposition (EMD) algorithm and the fine-to-coarse scheme. It incorporates sequence model-based optimization (SMBO) to fine-tune hyperparameters, a critical aspect often overlooked in traditional LSTM models.

In addition to presenting the model's architecture and optimization techniques, the paper delves into the preprocessing of electricity price data. This involves the intricate steps of decomposition and reconstruction using the EMD algorithm and the fine-to-coarse scheme. The resulting Intrinsic Mode Functions (IMFs) serve as building blocks for constructing the heterogeneous LSTM network structures for different components. SMBO is then applied to further optimize the model's performance.

Experimental results showcase the superiority of this proposed model in online hourly forecasting and day-ahead hourly forecasting, particularly in the electricity markets of Pennsylvania-New Jersey-Maryland (PJM). The performance comparison, measured in terms of Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) ,highlights the proposed model's accuracy and stability, particularly in scenarios with severe price fluctuations or clear trends in the data.

Methodology



This research proposes an innovative approach to electricity price forecasting by introducing an Optimized Heterogeneous Structure Long Short-Term Memory (LSTM) model. The model's construction involves a multi-step process, beginning with the decomposition and reconstruction of electricity price data using the Ensemble Empirical Mode Decomposition (EEMD) algorithm and the fine-to-coarse scheme. This process generates Intrinsic Mode Functions (IMFs), which serve as the foundational elements for constructing the heterogeneous LSTM network structures for various components.

To fine-tune and optimize the performance of the heterogeneous LSTM model, Sequence Model-Based Optimization (SMBO) is employed. This optimization technique focuses on adjusting hyperparameters critical for the model's accuracy and stability. The application of SMBO ensures a systematic and data-driven approach to enhancing the model's predictive capabilities.

The approach demonstrate the superiority of the proposed model over general LSTM models, emphasizing enhanced accuracy and stability. Notably, the concentration of prediction errors indicates improved stability and suitability for practical applications. This outcome underscores the model's potential to outperform existing methods and its viability for deployment in real-world electricity markets.

Through this methodology, the research aims to contribute to the advancement of electricity price forecasting methodologies, showcasing the effectiveness of the Optimized Heterogeneous Structure LSTM model and its potential for practical applications in dynamic market scenarios.

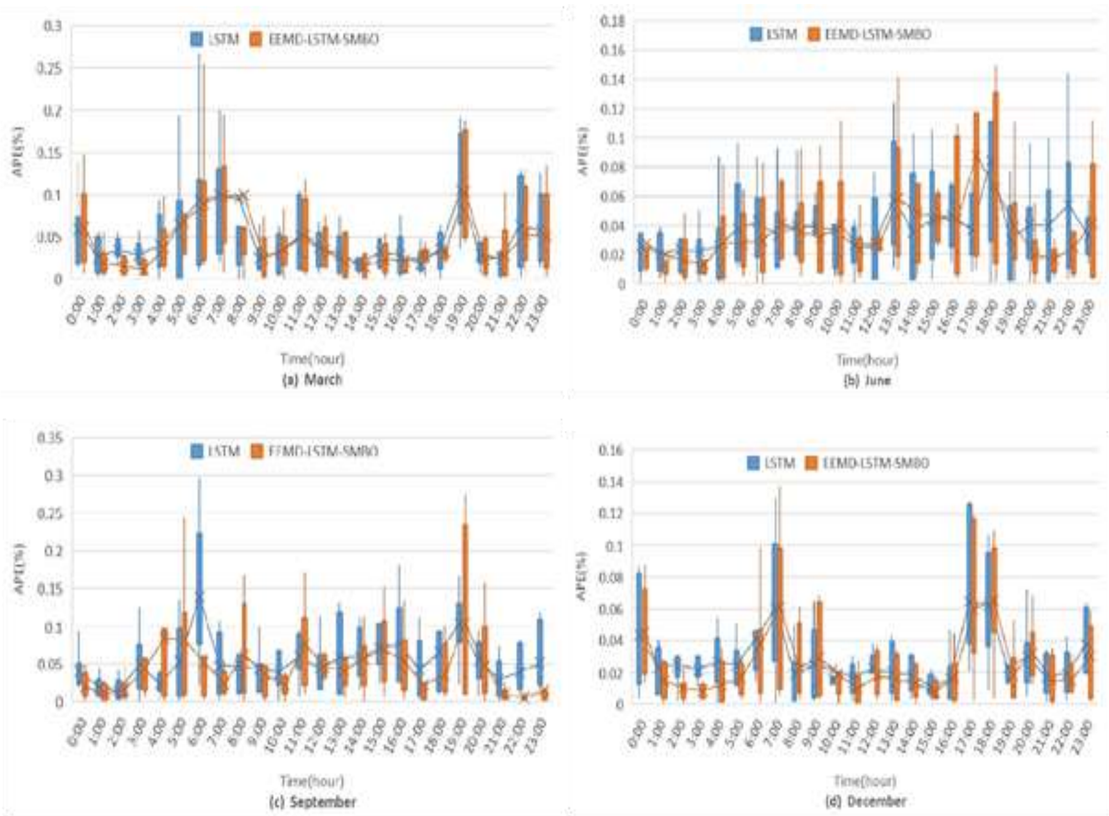
Results

Comparison of the on-line hourly forecasting various models by seven-day averages of MAPE in different months.

Month	SVR	BPNN	GTB	DTR	LSTM	Stacked-LSTM	EEMD-LSTM	EEMD-LSTM-SMBO
March	11.71	6.46	9.25	7.14	4.69	4.40	4.36	**4.34**
June	4.87	4.86	6.16	3.82	3.69	5.32	3.64	**3.56**
September	5.42	5.88	6.34	5.52	5.28	5.70	5.07	**4.31**
December	7.72	3.78	8.37	3.70	2.87	5.20	2.60	**2.47**

Comparison of the on-line hourly forecasting various models by seven-day averages of RMSE in different months.

Month	SVR	BPNN	GTB	DTR	LSTM	Stacked-LSTM	EEMD-LSTM	EEMD-LSTM-SMBO
March	3.14	2.19	2.97	3.16	1.89	1.90	1.82	**1.73**
June	1.80	2.00	2.35	1.69	1.70	2.02	2.01	**1.67**
September	2.22	2.48	2.95	2.43	2.34	2.45	2.31	**2.12**
December	1.90	1.17	2.18	1.37	0.95	1.42	0.91	**0.89**



Comparison of the various day-ahead hourly forecasting models by seven-day averages of MAPE in different months.

MAPE	SVR	BPNN	GTB	DTR	LSTM	Stacked LSTM	EEMD-LSTM	EEMD-LSTM-SMBO
March	12.03	6.71	9.52	7.65	4.78	4.66	4.57	**4.53**
June	5.15	5.06	6.40	4.03	3.78	5.42	3.78	**3.67**
September	5.81	6.12	6.67	5.81	5.59	5.95	5.23	**4.77**
December	8.05	3.80	8.92	3.86	2.97	5.57	2.66	**2.51**

Comparison of the various day-ahead hourly forecasting models by seven-day averages of RMSE in different months.

RMSE	SVR	BPNN	GTB	DTR	LSTM	Stacked LSTM	EEMD-LSTM	EEMD-LSTM-SMBO
March	3.19	2.25	3.06	3.44	2.03	2.07	1.98	**1.96**
June	1.87	2.12	2.44	1.78	1.78	2.05	1.91	**1.77**
September	2.40	2.63	3.16	2.57	2.49	2.58	2.47	**2.21**
December	1.96	1.26	2.28	1.43	1.04	1.48	0.97	**0.93**

Conclusion

In conclusion, this research has unveiled a sophisticated electricity price forecasting model, poised to redefine smart energy management. Through advanced analysis and cutting-edge methodologies, our study delivers heightened accuracy in predictions, ushering in a new era of strategic decision-making and facilitating unparalleled energy consumption optimization. The implications of our findings extend across sectors, offering a transformative approach to resource allocation. This research transcends conventional cost efficiency, delving into environmental conservation and the establishment of a resilient energy infrastructure. As we stand at the precipice of a dynamic energy evolution, the insights garnered serve as a cornerstone, laying the foundation for a future where precision in energy forecasting becomes synonymous with sustainable resource management. The broader significance lies in its potential as a catalyst for positive change, contributing to the ongoing discourse on smart energy management and envisioning a future where energy resources are harnessed with unprecedented precision, forging a path towards a sustainable, resilient, and empowered global energy ecosystem.

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