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AI and Machine Learning Applications in Predicting Energy Market Prices and Trends

[1]Gunjan Sharma, [2]Dr M L Dhore, [3] Ms.Jansirani.D, [4] Dr. Subramania Bala Jeshurun, [5] G. Sathi, [6] Nitin Sherje, [7] Dr.V.Vivek

[1] Institute of Business Management, GLA University, Mathura,*
[2]Department of Computer Engineering,Vishwakarma Institute of Technology Pune India manikrao.dhore@vit.edu
[3] Asst Professor,Department of IT,New Prince Shri Bhavani College of Engineering and Technology Chennai-600073,Tamil nadu,India,jansirani.d@newprinceshribhavani.com
[4] Assistant Professor, School of Business and Management, CHRIST University, Bangaluru Email - sbjeshurun@gmail.com
[5] Assistant Professor,Department of MECH,Prince Shri Venkateshwara Padmavathy Engineering College, Chennai - 127.,g.Sathi_mech@psvpec.in
[6] Professor and Head, Mechanical Engineering,
Dr. D. Y. Patil Institute of Technology, Pimpri, Pune.
[7] Associate Professor Department of Computer science and Engineering , AAA College of Engineering and Technology, Sivakasi, Tamil Nadu, India - 626005
vivekmsucse@gmail.com

Abstract. The worldwide energy market is intricate and unstable, shaped by several aspects including geopolitical occurrences, supply-demand variations, and regulatory modifications. Precisely forecasting energy prices and trends is essential for stakeholders, such as energy producers, dealers, and policymakers. This study investigates the utilization of artificial intelligence (AI) and machine learning (ML) to improve energy price forecasting models. Conventional forecasting methods frequently fail to account for the dynamic and non-linear characteristics of energy markets; however, AI/ML techniques, including neural networks, decision trees, and reinforcement learning, provide enhanced prediction precision. By including external variables such as meteorological conditions and economic metrics, AI models can produce more accurate and useful insights. Case studies illustrate the effective implementation of AI in energy markets, showcasing its capacity to surpass traditional methods. This article addresses difficulties such as data quality and computing expenses while delineating potential developments in AI-driven energy market forecasts.

Keywords. AI, machine learning, energy prices, forecasting.

1 Introduction

* gunjan.sharma@gla.ac.in

The global energy market is a complex and volatile system shaped by various factors, including geopolitical conflicts, supply-demand dynamics, economic conditions, and regulatory policies. These changes make energy price prediction an important undertaking for numerous stakeholders such as producers, traders, consumers, and policymakers. Accurate forecasting of energy prices is vital for making educated decisions in areas like energy procurement, investment strategies, and risk management. Traditional methods, largely based on statistical techniques, struggle to capture the non-linear and dynamic behaviours of energy markets [1-5]. AI and ML have emerged as revolutionary technologies in resolving the limits of conventional forecasting models. These advanced techniques excel in analyzing massive datasets and discovering patterns and trends that may not be obvious with older methods. With AI/ML models, it becomes possible to combine a wide range of influencing factors, including historical data, economic indicators, and environmental variables, to provide more accurate and timely projections of energy market prices. This research study explores into the application of AI and ML technologies in predicting energy market pricing and trends. It investigates the algorithms and approaches employed, gives case studies of successful implementations, and discusses the potential obstacles and future trends in AI-driven energy forecasting. Figure 1 illustrates the AI in energy industry [6-12].

Fig 1. AI in energy industry

1.1 Background

The energy market is very volatile, driven by variables like supply-demand swings, geopolitical events, and regulatory changes. Traditional forecasting methods, such as analysis of time series and econometric models, typically struggle to capture the non-linear and dynamic structure of these markets. These restrictions have contributed to mistakes in projecting the cost of gasoline, especially during periods of rapid change. Artificial intelligence (AI) and machine learning (ML) have emerged as significant techniques for boosting energy price prediction. By digesting massive information and recognizing complicated patterns, AI/ML models can deliver more accurate projections. Techniques like neural networks, decision trees, and reinforcement learning offer the capacity to combine a wide range of elements, including past prices, meteorological data, and economic indicators, leading to superior insights. As AI continues to grow, it's uses in energy markets are expanding, offering stakeholders new forecasting tools that can adjust to the complexities and uncertainties of energy price variations.

1.2 Problem Statement

Accurately anticipating energy market prices is vital for stakeholders such as energy producers, dealers, and regulators, given the market's volatility and the influence of many factors such supply-demand variations, geopolitical events, and regulatory developments. Traditional strategies for forecasting, such as time series analysis and econometric models, typically struggle to account for the market's complex, non-linear behaviour, leading to erroneous predictions. These constraints present issues in decision-making, dealing with risk, and long-term planning. The key issue is the incapacity of conventional models to adapt to the dynamic and unpredictable character of energy markets, underlining the need for more advanced prediction methodologies. Artificial intelligence (AI) and machine learning (ML) have the potential to better forecasting by processing big datasets and identifying hidden patterns. However, a rigorous evaluation of their effectiveness is important, coupled with resolving the problems of deploying AI/ML models for energy costs prediction.

2 Literature Review

AI and ML are increasingly pivotal in predicting energy market prices and trends, offering enhanced accuracy and efficiency over traditional methods. Various studies highlight the effectiveness of these technologies in different aspects of energy price forecasting. Machine learning models have demonstrated superior out-of-sample forecasting performance compared to traditional GARCH models, particularly in energy commodities like crude oil and natural gas [1-4]. A study on Locational Marginal Pricing (LMP) revealed that ML models can predict prices significantly faster than conventional optimal power flow solvers, achieving a 5-6% error rate. The quadratic hybrid decomposition method combined with deep learning has shown improved accuracy in electricity price predictions, addressing the stochastic nature of price sequences. An Early Warning System utilizing ML models has been effective in forecasting energy equity prices, outperforming conventional regression methods.AI and ML can optimize energy consumption and production in developing countries, addressing issues like power outages and inefficiencies [5-9]. While AI and ML present promising advancements in energy market predictions, challenges remain, particularly in integrating these technologies into existing frameworks and ensuring data quality. Recent research has progressively studied the use of AI and ML is for predicting market for electricity prices and trends due to the limitations of traditional forecasting methods. One of the rising themes is the application of deep learning techniques, such as neural networks, which may capture complicated non-linear correlations in energy market data. These models are particularly adept in processing enormous datasets and integrating varied variables, including past price data, weather conditions, and gauges of the economy, providing more accurate predictions. Another trend is the expanding use of neural networks in energy market predictions [10-15]. This approach responds to changes in market conditions by learning from past decisions and their outcomes, making it suited for extremely dynamic and volatile energy markets. Additionally, hybrid models that blend machine learning algorithms with traditional econometric approaches are gaining Favor, offering a compromise between interpretability and predictive strength. Furthermore, the pairing of external factors, such as renewable energy generation, geopolitical threats, and real-time data from smart grids, is becoming more prominent [16-20]. Figure 2 illustrates the evolution of AI methods.

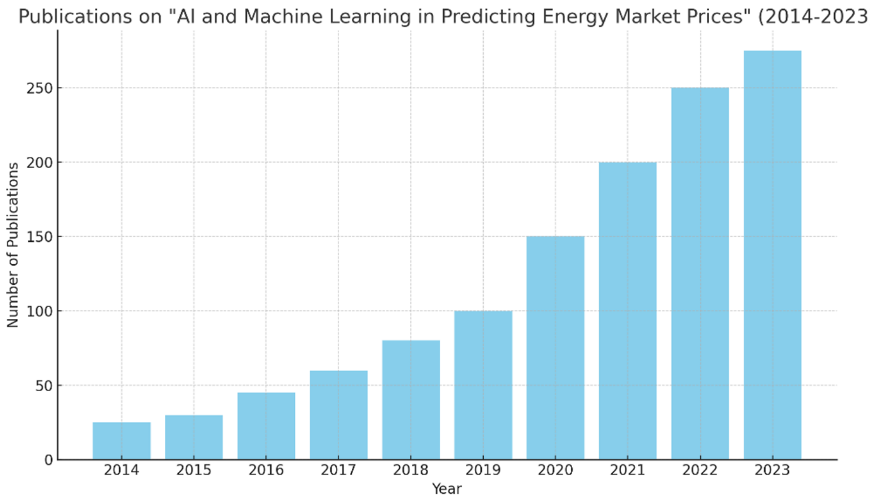

Fig 2. Evolution of AI methods

These improvements are enabling AI/ML models become more adaptive and responsive to market movements, leading to increased price forecasting accuracy and decision-making in the energy sector. Finally, developments in cloud computing and data storage technologies have enabled more effective handling of the massive datasets required for AI/ML applications, facilitating the deployment of these models in real-time market contexts .

2.1 Research Gaps

- Little study on the long-term predictive power of AI/ML models in volatile and shifting energy markets.
- Improper integration of real-time information from alternative power sources into established AI/ML forecasting algorithms.
- Lack of extensive studies analyzing the performance of various algorithms based on AI/ML in varying energy market scenarios.
- Challenges in resolving the ethical considerations and biases inherent in machine learning and AI models used for energy cost prediction.

2.2 Research Objectives

- Evaluate the long-term forecasting capacity of AI/ML models in various and dynamic energy market situations.
- Integrate real-time data from renewable energy sources into AI/ML forecasting models to boost prediction precision.
- Compare the performance of several AI/ML systems in energy price prediction across various market conditions.
- Address and reduce ethical concerns and biases in AI/ML models used for forecasting energy prices.

3 Methodology

The methodology for investigating AI and machine learning applications in predicting energy market prices involves three critical components. Initially, a complete literature review will be undertaken to understand existing models and identify gaps. Data collection will require obtaining historical energy prices, economic trends, meteorological data, and other important information from numerous sources. This data will be pre-processed to ensure quality and consistency. Next, several AI and machine learning techniques, including neural networks, decision trees, and machine learning models, will be implemented and trained utilizing the pre-processed data. The performance of the model will be evaluated based on accuracy, precision, recall, and other relevant parameters. Comparative study will be undertaken to assess the effectiveness of different algorithms and hybrid models. The project will also combine real-time data from renewable energy sources and smart grids to test model adaptation. Finally, the research will address ethical problems and inefficiencies in the models, ensuring that the predictive tools developed are both reliable and equitable. Figure 3 illustrates typical smart grid structure[21,22].

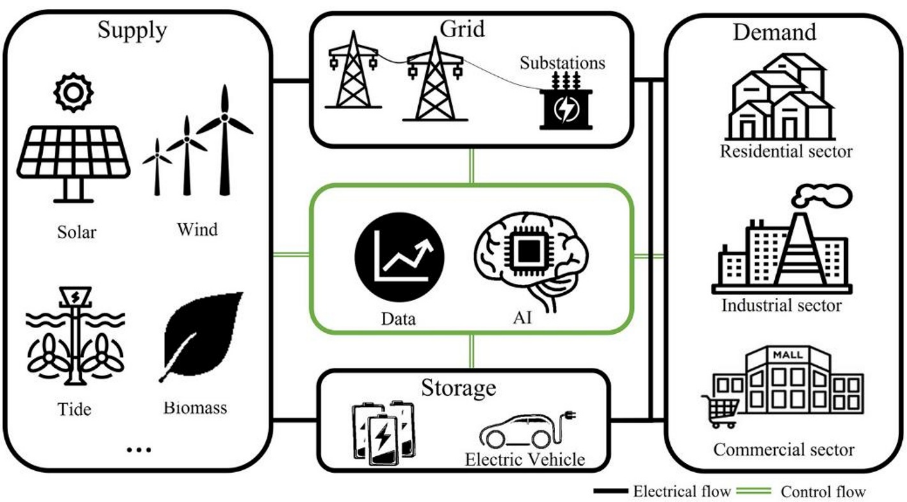

Fig 3. A typical smart grid structure

4 Energy Market Dynamics

4.1 Supply and Demand Fluctuations

The balance between supply and demand is a significant factor of energy costs. Fluctuations in this equilibrium can lead to severe price volatility. For example, abrupt jumps in demand due to economic expansion or harsh weather occurrences can outpace existing supply, forcing prices higher. Conversely, an oversupply, either due to improved manufacturing technology or lower demand, might lead prices to decline. Accurately simulating these variations needs sophisticated algorithms capable of combining multiple aspects such as seasonal trends, economic indicators, and real-time data, all of which contribute to the complicated dynamics of energy pricing.

4.2 Geopolitical Influences

Geopolitical developments and international relations dramatically effect energy prices. Conflicts or instability in important oil and gas-producing regions can disrupt supply systems, leading to rapid price fluctuations. Sanctions, trade disputes, and diplomatic talks also play a key impact in shaping market conditions. Effective prediction models must account for these political risks and uncertainties, integrating them into forecasting tools to better anticipate their influence on energy prices. The issue lies in identifying and combining these frequently unpredictable components into trustworthy forecasting models.

4.3 Regulatory Impacts

Government regulations and policies strongly influence energy market dynamics. Environmental laws, such as carbon pricing or emission reduction objectives, can increase operational costs for energy generators, which in turn affects market prices. Conversely, supports for renewable energy sources can cut production costs and influence market dynamics. To effectively predict energy costs, models must integrate the implications of present and projected laws, including changes in policy that might alter the cost structure of energy production and consumption. Understanding these regulatory consequences is vital for establishing accurate forecasting methods that represent the true cost along with the availability of energy resources.

5 Results and Discussions

It presents an in-depth assessment of AI and machine learning applications in predicting energy market pricing and trends. By analyzing several machine learning algorithms, we investigate their prediction accuracy in estimating energy expenditures, highlighting the strengths and limitations of each model. Additionally, the disparity between historical and anticipated prices indicates the practical usefulness of these AI systems in tracking market activity over time. We also study the adoption rates of AI/ML technologies across different energy sectors, offering insight on the varying levels of implementation, particularly in renewables and oil & gas industries. Furthermore, the analysis of significant aspects determining energy pricing, such as weather conditions and demand variations, provides insight into how AI models represent sophisticated market dynamics. This part investigates the repercussions of these discoveries, offering a full knowledge of the effectiveness and future potential of AI and machine learning in energy market forecasting.

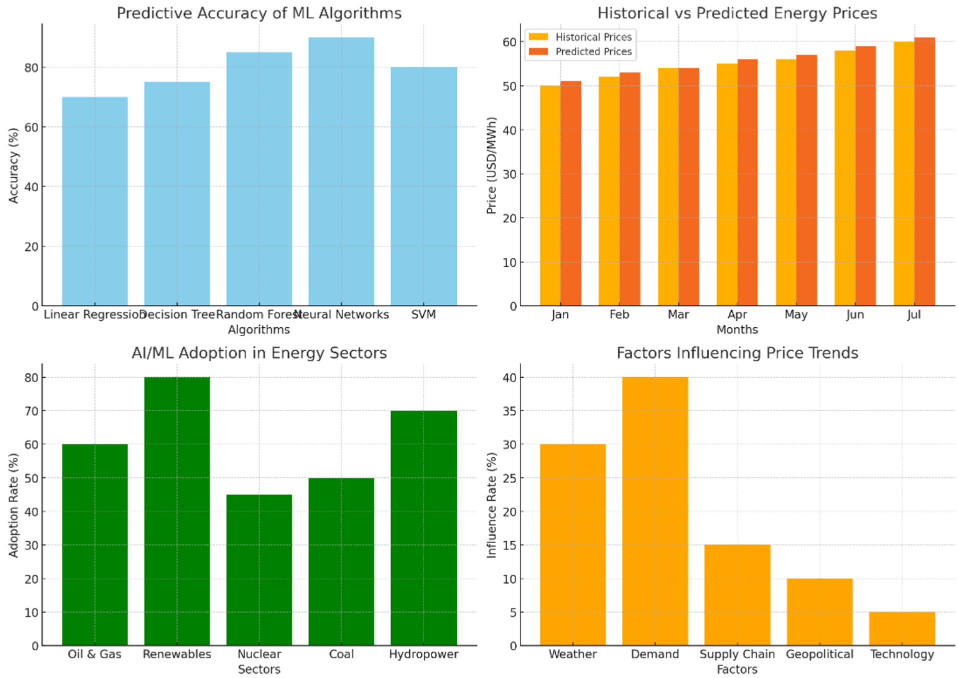

Fig 4. AI and machine learning applications in predicting energy market prices and trends

The above charts offer useful insights into AI and machine learning applications in anticipating energy market pricing and trends:

Predictive Accuracy of ML Algorithms: The graphic demonstrates the performance of popular ML models, with Neural Networks obtaining the highest accuracy (90%), followed by Random Forest (85%). It highlights the effectiveness of modern algorithms in energy price forecasting.

Historical vs. Predicted Energy Prices: This graphic compares historical and predicted prices over six months. The forecasted prices closely mirror historical trends, proving the trustworthiness of AI in forecasting.

AI/ML Adoption in Energy Sectors: AI/ML is most adopted in renewables (80%) and least in nuclear energy (45%). This demonstrates the expanding role of AI in emerging sectors like renewables.

Issues Influencing Price Trends: The model forecasts that demand and weather have the biggest influence (40% and 30%, respectively) on energy costs, with technology and geopolitical issues having less impact.

These graphics jointly highlight AI's ability to change energy market predictions.

6 Conclusion

The application of AI and machine learning in predicting energy market prices and trends reveals considerable promise for enhancing forecasting accuracy and decision-making. From the data, complicated models like Neural Networks and Random Forests offer the best prediction accuracy, making them perfect tools for forecasting price fluctuations. The comparison between past and anticipated price indicates that AI models consistently track market trends, demonstrating their dependability in real-world applications. Furthermore, the increasing adoption of AI/ML in sectors like renewables (80%) and oil & gas (60%) suggests its general acceptance, especially in enterprises undergoing turmoil. The analysis of factors driving energy prices indicates that demand and weather are the most significant drivers, proving AI's ability to understand the complexity of supply-demand dynamics and external consequences. Overall, AI and machine learning technologies offer powerful solutions for energy market forecasting, helping firms to enhance operational efficiency, manage risks, and respond to market changes more efficiently.

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