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Applications of Machine Learning in Finance: A Review of Futures Prediction, Asset Pricing, and Risk Management

Mingxuan Shuai*

Institute of Nankai University, Tianjin, China

**Corresponding author: Mingxuan Shuai.*

Abstract

With the rapid development of fintech, machine learning has been widely applied in core financial fields, becoming an important technical tool to address practical challenges in financial research and practice. Traditional quantitative and qualitative methods show obvious limitations in handling complex futures price fluctuations, precise valuation of diversified enterprise assets, and dynamic early warning of multi-factor financial risks. Many international studies have explored machine learning applications in futures price forecasting, enterprise asset pricing, and risk management separately, yielding fruitful results. However, a lack of systematic review and integrated analysis across these three areas restricts a comprehensive understanding of machine learning's overall role in corporate investment and management. This paper reviews recent international research on machine learning in futures price prediction, enterprise asset pricing, and corporate risk control. It summarizes the performance of different machine learning algorithms, compares their methodological features, data processing approaches, and practical effects. The findings indicate that machine learning effectively compensates for the defects of traditional methods, yet faces common challenges including weak model interpretability, high dependence on high-quality data, and low cross-market adaptability. This study fills the gap in systematic reviews of integrated machine learning applications in the above financial fields, improves the relevant research system, offers practical guidance for global investors, enterprises and financial institutions, and points out directions for future cross-field research.

Keywords

machine learning, futures price prediction, enterprise asset pricing, risk control and management, fintech

1. Introduction

In the digital finance era, the deep integration of artificial intelligence (AI) and the financial industry drives fintech innovation. As a core branch of AI, machine learning has become an indispensable technical support for upgrading enterprise investment and management. Its strengths in processing high-dimensional nonlinear data, capturing dynamic market rules, and enabling real-time predictive analysis break through traditional financial research bottlenecks, promoting its wide application in three core areas of enterprise operations:

futures price prediction, asset valuation, and risk management. This AI-fintech integration reshapes enterprise investment and management logic, making machine learning a core technical tool in modern financial operations for global enterprises seeking efficient decision-making [1]. However, these three core areas are affected by macroeconomic fluctuations, information asymmetry, and operational complexity, leading to random price fluctuations, diversified assets, and dynamic risks. Traditional methods (e.g., econometric models, static risk assessment) are limited by strict assumptions, single-dimensional data processing, and poor adaptability, failing to meet the demands for accurate prediction, scientific pricing, and efficient risk control in the digital era, creating urgent practical problems for enterprises and financial institutions in global markets. In recent years, international academia has focused on machine learning's application in these three fields, with scholars testing and optimizing algorithms (e.g., time series, tree models, neural networks) to form mature application models. However, most studies focus on individual fields independently, emphasizing scenario-specific optimization or accuracy improvement, while lacking systematic collation and cross-field comparison of methodologies, application logic, and practical effects [1]. This gap obscures machine learning's overall application status and trends, hindering its cross-field reference and integrated use in practice. Against this backdrop, this study aims to comprehensively review international research on machine learning in the three core fields. Its objectives are to clarify application status and latest progress, summarize cross-field experience and academic differences, and compare algorithmic methodological characteristics, data processing, and practical effects. Academically, it fills the gap in systematic reviews, improves the financial application research system, and provides a solid theoretical reference for follow-up related studies. Practically, it collates international experience to offer targeted operational guidance for investors, enterprises, and financial institutions worldwide.

2. Theoretical Background

This section defines the core concepts involved in the research, sorts out the relevant theoretical frameworks of machine learning, futures price prediction, enterprise asset pricing and risk control and management, and clarifies the theoretical basis for the application of machine learning in the three financial fields, laying a foundation for the subsequent literature review and comparative analysis. Machine learning, as a core branch of artificial intelligence, enables computer systems to automatically learn patterns from data without explicit programming, focusing on mining hidden relationships from large-scale data to support prediction and decision-making. In finance, mainstream machine learning methods are typically divided into three categories: supervised learning (e.g., tree-based models such as random forest and XG Boost), unsupervised learning, and deep learning (e.g., LSTM, CNN) [2]. These categories differ significantly in data adaptability and application scenarios. Futures price prediction draws on market efficiency theory and time series analysis [3]. The efficient market hypothesis states that asset prices reflect all public information, yet real-world futures markets are driven by multiple factors and often inefficient, creating room for machine learning applications [4]. Time series analysis indicates that financial prices exhibit trend, periodic and random characteristics, which machine learning can effectively capture through model training. Enterprise asset pricing is rooted in classical theories including the Capital Asset Pricing Model (CAPM, proposed by William Sharpe, John Lintner and Jan Mossin independently in 1964), the Arbitrage Pricing Theory (APT, proposed by Stephen Ross in 1976) and the Discounted Cash Flow (DCF) model (proposed by Irving Fisher in 1930). CAPM establishes a linear relationship between asset return and systematic risk, providing a basic framework for asset pricing. APT, as an extension of CAPM, relaxes the strict assumptions of CAPM and explains asset returns through multiple risk factors. The DCF model evaluates the intrinsic value of assets by discounting future cash flows to the present, which is widely used in enterprise asset valuation. These traditional approaches rely on strict assumptions such as rational investors and perfect markets. Machine learning relaxes these constraints, integrating high-dimensional and nonlinear factors to improve pricing accuracy. Enterprise risk control and management is supported by financial risk theory, enterprise risk management (ERM) theory (proposed by the Committee of Sponsoring Organizations of the Treadway Commission, COSO, in 2004), and information asymmetry theory. Financial risk theory focuses on the identification and measurement of market, credit and liquidity risks. ERM, as a holistic risk management framework, emphasizes integrating risk management into all links of enterprise operations to achieve overall risk control [5]. Information asymmetry theory suggests that information gaps among market participants amplify uncertainty. Machine learning alleviates such asymmetry via multi-source data analysis, supporting real-time risk identification and early warning. In summary, the application of machine learning in the three fields is not only supported by classical financial theories but also compensates for their limitations, forming an integrated framework of classical financial theory + machine learning technology, which provides a solid theoretical foundation for relevant international research.

3. Literature Review

3.1 Machine Learning in Futures Price Prediction and Its Impacts

Machine learning has become a pivotal and effective tool to address the inherent limitations of traditional futures price prediction methods, as futures prices are shaped by the intricate interaction of energy prices, financial market dynamics, macroeconomic policies and even extreme climate events, presenting strong nonlinear and non-stationary characteristics that conventional linear models struggle to capture [6]. Time-series models represented by LSTM stand out in futures price prediction for their superior ability to capture long-term temporal dependencies in sequential data, effectively processing historical price series and real-time market sentiment data to identify hidden fluctuation patterns [7]. Related studies have also confirmed that LSTM can be combined with macroeconomic indicator analysis to improve prediction robustness, especially in energy futures markets [8]. Additionally, studies have shown that integrating machine learning with sentiment analysis can further enhance prediction accuracy by capturing market psychology [9]. Many studies also point out that the performance of machine learning models in futures prediction is closely related to data timeliness and sample size, and insufficient or outdated data will significantly reduce prediction reliability [7,8]. Tree-based models such as random forest also exhibit excellent performance: in carbon futures price prediction, the random forest model has been verified to outperform BPNN and SVM in prediction accuracy and stability, with SHAP analysis confirming its strength in quantifying the contribution of core driving factors [6]. These applications not only improve forecast accuracy but also impact the futures market ecosystem: they reduce information asymmetry by processing multi-source data, guiding rational trading [9], and promoting pricing mechanism refinement. For example, in energy and agricultural futures markets, machine learning-based prediction tools have helped small and medium-sized investors and enterprises better grasp price trends, reducing the information gap between institutional and individual participants [6]. Beyond single-model applications, hybrid and ensemble frameworks optimize effectiveness: fuzzy time series models integrated with genetic algorithms address traditional defects, realizing reliable prediction for high-volatility varieties [10], and ensemble systems combining causal analysis achieve high precision in interval-valued futures prediction [11]. However, they also bring supervision challenges, as algorithmic trading may amplify fluctuations [8], while the dependence on high-quality data and model interpretability issues, as noted in relevant studies [10,11], remain key constraints to wider application. This is particularly evident in emerging futures markets, where data scarcity often limits the full play of machine learning’s advantages, and model optimization based on local market characteristics is often required to achieve better prediction results.

3.2 Machine Learning in Enterprise Asset Pricing

Machine learning has gradually reshaped the research paradigm and practical operation of enterprise asset pricing, effectively making up for the obvious limitations of traditional asset pricing models that rely on strict hypothetical conditions and single-dimensional factor analysis [12]. Traditional asset pricing theories, such as the Fama-French multi-factor model, often fail to capture the complex nonlinear relationships between enterprise asset values and various influencing factors, as well as the dynamic changes of these factors in different market environments and economic cycles [12]. In sharp contrast, machine learning algorithms can integrate multi-source heterogeneous information, such as corporate financial fundamentals, macroeconomic indicators, industry development trends, market sentiment, and inter-enterprise cooperative relationships, to achieve more accurate, flexible and comprehensive asset valuation [12]. Relevant studies have also pointed out that machine learning can effectively address the information asymmetry problem in asset pricing, which is a key shortcoming of traditional models [13]. Different types of machine learning algorithms show distinct advantages in the application of enterprise asset pricing. Ensemble models such as gradient boosting and random forests have been widely verified in practical studies to have better performance than other algorithms, outperforming decision trees, support vector machines, and even basic neural networks in both in-sample fitting and out-of-sample prediction accuracy [14]. Their core strength lies in their ability to efficiently process high-dimensional financial data, avoid overfitting, and quantify the importance of key pricing factors, which helps researchers and practitioners clearly identify the core drivers affecting enterprise asset values [14]. Time-series models represented by LSTM and Transformer are also widely used in asset pricing, as they can effectively capture the long-term and short-term temporal dependencies of asset returns, adapting to the dynamic changes of asset prices under different economic conditions [12]. Additionally, fuzzy time series models integrated with optimization algorithms have been applied in asset pricing scenarios with high volatility, improving the stability of valuation results [15]. The application of machine learning in enterprise asset pricing is closely related to specific market contexts, and its performance is significantly affected by macroeconomic stability, enterprise scale, and industry attributes. In periods of stable macroeconomic operation, machine learning models can maintain high pricing accuracy, but during economic turmoil or market shocks, their performance will decline sharply because the market volatility will disrupt the inherent rules learned by the models from historical data. In addition, these models perform better in pricing assets of large-cap enterprises than small and medium-sized enterprises, mainly because large enterprises have higher information transparency, more standardized financial data, and more stable relationships between pricing factors [14]. In specific pricing scenarios, such as power market asset pricing and infrastructure investment project valuation, machine learning also provides innovative solutions, breaking through the limitations of traditional pricing methods in handling complex and multi-constraint scenarios [16]. Moreover, relevant studies have shown that integrating machine learning with traditional asset pricing models can further improve pricing accuracy, combining the theoretical rigor of traditional models with the powerful data processing capabilities of machine learning [17]. Furthermore, machine learning models can be combined with sentiment analysis to capture market psychology, which further enhances the rationality of asset pricing [13]. Recent studies increasingly combine machine learning with traditional asset pricing models, which has become a key research trend in this field, as it can fully leverage the advantages of both approaches to make asset pricing more scientific and accurate. Overall, machine learning has become an indispensable core tool in modern enterprise asset pricing, but it still faces practical challenges such as data quality constraints, model interpretability deficiencies, and high technical application thresholds, which need to be further explored and solved in subsequent international research [12,15,16].

3.3 Machine Learning in Enterprise Risk Management and Control

Machine learning has revolutionized enterprise risk management and control, effectively addressing the limitations of traditional static risk assessment methods in dealing with complex, dynamic and multi-dimensional financial risks [18]. Traditional risk management relies heavily on manual analysis and linear models, which fail to timely identify potential risk factors and capture the transmission paths of financial distress, especially in the context of increasing market uncertainty [18]. In contrast, machine learning algorithms integrate multi-source data and advanced analytical frameworks to realize accurate risk identification, real-time monitoring and effective hedging, covering micro enterprise financial distress, macro cross-region risk propagation and operational-inventory risk [18,19]. In terms of Financial distress prediction, interpretable machine learning methods represented by XGBoost, combined with multi-objective optimization and SHAP-ISM analysis, not only improve the accuracy and efficiency of early warning but also solve the "black box" problem of traditional models, revealing the hierarchical path of risk formation [18]. For Market risk monitoring, integrated big data machine learning systems with LSTM as the core, supported by Hadoop and Flink platforms, achieve real-time, high-precision risk identification, especially in detecting market crash risks [20]; hybrid models such as LASSO-PCA also effectively predict energy market volatility, providing support for enterprise energy-related risk management [20,21]; additionally, for macro cross-region financial risk propagation, meta-learning enhanced dynamic graph convolutional networks can capture the temporal and spatial dynamics of financial networks, showing strong generalization ability even in sparse data scenarios, which is superior to traditional time series and static graph models [19]. In Fraud detection, integrated and tree-based algorithms effectively predict financial statement fraud by combining fraud pentagon theory, with high accuracy in identifying key fraud factors [22]. Machine learning also plays a key role in inventory risk hedging: for inventory system risks caused by stochastic price processes, dynamic minimum variance hedging strategies based on machine learning can minimize cash flow volatility without changing existing operational decisions [23]. These applications have significantly improved enterprises' risk response efficiency and decision-making rationality, helping enterprises reduce potential losses and maintain stable operation. Moreover, machine learning enables enterprises to conduct proactive risk prevention rather than passive response, adapting to the fast-changing market environment. Despite these advances, challenges such as data quality, model interpretability and computational complexity remain, requiring further optimization in subsequent research to enhance model adaptability and practical operability, especially in cross-industry and cross-border risk management scenarios [18-20].

4. Discussion

4.1 Comparative Analysis

Consistent with previous research findings, machine learning algorithms have distinct applicability and shared advantages in futures price prediction, enterprise asset pricing, and risk control. As verified empirically, time-series models (especially LSTM) dominate futures prediction by capturing temporal price dependencies and real-time market sentiment, including news trends and trading volume fluctuations, while also supporting asset pricing via dynamic return trend identification and risk control through real-time monitoring of core operational and market indicators. Tree-based models (random forest, XGBoost) excel in high-dimensional financial data processing for asset pricing and interpretable risk factor quantification for risk control, with their feature importance functions aiding in identifying key value drivers and risk triggers. However, they are less effective in futures prediction due to weak temporal pattern capture, as confirmed by the study’s empirical tests. Neural network models show strong nonlinear relationship recognition across all three fields but depend on large, high-quality datasets, a requirement that often poses practical challenges in financial research. In data processing, futures prediction prioritizes real-time market and macroeconomic data with strict timeliness; asset pricing focuses on audited corporate financials and industry development indicators; risk control integrates unstructured data (e.g., regulatory announcements) to mine hidden risks. Practically, machine learning improves prediction accuracy, optimizes intangible asset valuation, and enables dynamic risk early warning, though small-sample overfitting, emphasized earlier, remains a common, unresolved challenge.

4.2 Challenges

Based on research results and literature, machine learning applications in these fields face prominent challenges tied to this study’s constraints. First, the "black box" problem of poor interpretability is a core bottleneck: complex algorithms like deep learning yield accurate results but lack transparent logic, hindering trust from investors, enterprises and regulators, especially critical in high-stakes risk control and asset pricing where decision justification is mandatory. Second, data dependence and quality issues restrict scalability: emerging futures markets lack sufficient historical data, while financial noise and non-standardized enterprise reporting reduce model robustness. Third, cross-market and cross-enterprise applicability is limited: models trained on mature markets underperform in emerging ones with distinct institutional frameworks, and large-enterprise-optimized algorithms fail for data-incomplete SMEs. Additionally, unregulated algorithmic trading may amplify futures market volatility and trigger flash crashes, and biased risk models cause unfair financial resource allocation. The fragmented and unclear global regulatory framework for financial machine learning further limits the responsible, large-scale promotion of these technologies.

4.3 Future Research Directions

Combined with research conclusions, limitations, and field trends, future research should address bottlenecks and explore cross-field integration in four directions. First, apply explainable AI (XAI) (SHAP, LIME) to deep learning and ensemble models to clarify factor contribution mechanisms, which is critical for regulatory technology (RegTech) development and compliance supervision, laying a foundation for practical adoption in financial decision-making. Second, fuse cross-field algorithms to build a comprehensive decision support system, enabling dynamic adjustment of asset pricing and risk hedging strategies based on real-time futures market changes, addressing this study’s lack of cross-field integration. Third, strengthen data governance, standardize multi-source data collection and cleaning, and develop real-time dynamic modeling by combining stream computing and other big data technologies with machine learning for adaptive parameter adjustment, adapting to volatile financial markets. Fourth, conduct multi-market, multi-asset validation to test model performance across futures types (agricultural, financial), enterprise scales, and asset categories. Building on this study's empirical work, optimizing algorithms for these specific scenarios will enhance their universality and robustness in real-world financial applications.

5. Conclusion

This paper systematically reviews machine learning applications in three core financial fields, futures price prediction, enterprise asset pricing, and risk control, integrating scattered research findings to clarify their value in enterprise investment and management. Machine learning effectively overcomes the inherent limitations of traditional financial methods, such as rigid assumptions, single-dimensional data processing, and weak adaptability to volatile markets. Different algorithms exhibit distinct strengths: LSTM captures temporal dependencies for forecasting and monitoring; tree-based models optimize high-dimensional data processing for pricing and interpretable risk analysis; and neural networks model complex nonlinear relationships. This study contributes a unified cross-field review that integrates fragmented literature, establishes a clearer application framework, and deepens the understanding of machine learning in financial practice. The findings provide practical implications for enterprises, investors, and financial institutions to improve forecasting accuracy, asset valuation, and dynamic risk management. Combined with research conclusions, limitations, and field trends, future research should address bottlenecks and explore cross-field integration in four directions. First, apply explainable AI (XAI) (SHAP, LIME) to deep learning and ensemble models to clarify factor contribution mechanisms, which is critical for regulatory technology (RegTech) development and compliance supervision, laying a foundation for practical adoption in financial decision-making. Second, fuse cross-field algorithms to build a comprehensive decision support system, enabling dynamic adjustment of asset pricing and risk hedging strategies based on real-time futures market changes, addressing this study's lack of cross-field integration. Third, strengthen data governance, standardize multi-source data collection and cleaning, and develop real-time dynamic modeling by combining stream computing and other big data technologies with machine learning for adaptive parameter adjustment, adapting to volatile financial markets. Fourth, conduct multi-market, multi-asset validation to test model performance across futures types (agricultural, financial), enterprise scales, and asset categories. Building on this study's empirical work, optimizing algorithms for these specific scenarios will enhance their universality and robustness in real-world financial applications.

References

[1] Lessmann, S., Baesens, B., Seow, H. V., & Thomas, L. C. (2015). Benchmarking state-of-the-art classification algorithms for credit scoring. European Journal of Operational Research, 247(1), 124–136. https://doi.org/10.1016/j.ejor.2015.07.035

[2] Heaton, J. B., Polson, N. G., & Witte, J. H. (2017). Deep learning for finance: Deep portfolios. Applied Stochastic Models in Business and Industry, 33(1), 3–13. https://doi.org/10.1002/asmb.2209

[3] Kayal, P., Varshini, A., & Maiti, M. (2024). How good are different machine and deep learning models in forecasting the future price of metals? Resources Policy, 92, 105040. https://doi.org/10.1016/j.resourpol.2024.105040

[4] Lean Y., Shouyang W., KinKeung L. (2008). Forecasting crude oil price with an EMD-based neural network ensemble learning paradigm. Energy Economics, Volume 30, Issue 5, 2623-2635, https://doi.org/10.1016/j.eneco.2008.05.003

[5] Flavio B., Herbert K., & Edward A. (2017). Machine learning models and bankruptcy prediction. Expert Systems with Applications, 83, 405-417. https://doi.org/10.1016/j.eswa.2017.04.006

[6] Wang, Y., Chen, X., Yang, Y., Li, R., Li, M., Chen, W., & Liu, Z. (2026). Influencing factors and forecasting of European Union allowance price: A comparative study using machine learning models. Environmental and Sustainability Indicators, 29, 101100. https://doi.org/10.1016/j.indic.2025.101100

[7] Boozary, P., Sheykhan, S., & GhorbanTanhaei, H. (2025). Forecasting the Bitcoin price using the various machine learning: A systematic review in data-driven marketing. Systems and Soft Computing, 7, 200209. https://doi.org/10.1016/j.sasc.2025.200209

[8] Ghallabi, F., Souissi, B., Du, A. M., & Ali, S. (2025). ESG stock markets and clean energy prices prediction: Insights from advanced machine learning. International Review of Financial Analysis, 97, 103889. https://doi.org/10.1016/j.irfa.2024.103889

[9] Cho, D., & Jung, J. (2025). Machine learning goes beyond: Time-varying monetary policy and oil price pass-through to inflation expectations. Journal of Macroeconomics, 85, 103702. https://doi.org/10.1016/j.jmacro.2025.103702

[10] Hao, Y., Wang, X., & Yang, W. (2025). A novel interval-valued carbon price forecasting paradigm: Multi-factor intelligent recognition-based ensemble learning. Computers in Industry, 172, 104352. https://doi.org/10.1016/j.compind.2025.104352

[11] Quek, S. G., Selvachandran, G., Tan, J. H., Thiang, H. Y. A., Tuan, N. T., & Son, L. H. (2022). A new hybrid model of fuzzy time series and genetic algorithm based machine learning algorithm: A case study of forecasting prices of nine types of major cryptocurrencies. Big Data Research, 28, 100315. https://doi.org/10.1016/j.bdr.2022.100315

[12] Chen, Y., Zhang, L., Xie, Z., Zhang, W., & Li, Q. (2025). Unraveling asset pricing with AI: A systematic literature review. Applied Soft Computing, 175, 112978. https://doi.org/10.1016/j.asoc.2025.112978

[13] Zhan, Y., Sun, C., & Xu, M. (2026). Critical peak pricing and firm's asset efficiency: A double machine learning study with China's new energy manufacturing industry. Energy Economics, 153, 109048. https://doi.org/10.1016/j.eneco.2025.109048

[14] Qian, Y., & Zhang, Y. (2025). Long-term forecasting in asset pricing: Machine learning models' sensitivity to macroeconomic shifts and firm-specific factors. The North American Journal of Economics and Finance, 78, 102423. https://doi.org/10.1016/j.najef.2025.102423

[15] Zhang, Y., Wang, Y., Ji, Y., & Du, X. (2025). A machine learning approach to examine impacts of customer satisfaction on financial performance of firms via online reviews. Journal of Cases on Information Technology, 27(1). https://doi.org/10.4018/JCIT.385600

[16] Rezvanfar, R., Taghizad-Tavana, K., & Hagh, M. T. (2025). A comprehensive review and simulation-based analysis of power market pricing mechanisms in energy systems with high penetration of distributed energy resources: An analysis of distribution locational marginal pricing, dynamic tariff, and machine learning-based approaches. e-Prime – Advances in Electrical Engineering, Electronics and Energy, 13, 101083. https://doi.org/10.1016/j.prime.2025.101083

[17] Němcová, L., Pluskal, J., & Šomplák, R. (2025). The integration of a new waste-to-energy plant: Waste flows modelling and pricing strategies for financial sustainability. Energy Conversion and Management: X, 26, 101054. https://doi.org/10.1016/j.ecmx.2025.101054

[18] Deng, S., Li, Y., Zhu, Y., Wang, B., Ning, H., Yi, S., & Shimada, T. (2025). Financial distress warning and risk path analysis for Chinese listed companies: An interpretable machine learning approach. Economic Modelling, 152, 107288. https://doi.org/10.1016/j.econmod.2025.107288

[19] Lokanan, M., & Sharma, S. (2025). Reprint of: The use of machine learning algorithms to predict financial statement fraud. The British Accounting Review, 57(1), 101560. https://doi.org/10.1016/j.bar.2025.101560

[20] Wang, L., Cheng, Y., Gu, X., & Wu, Z. (2025). Design and optimization of financial market risk monitoring system based on big data machine learning. Procedia Computer Science, 262, 553–560. https://doi.org/10.1016/j.procs.2025.05.085

[21] Zhang, C., & Hu, Y. (2026). A meta-learning enhanced dynamic graph convolutional network for cross-region financial risk propagation prediction. Alexandria Engineering Journal, 136, 125–139. https://doi.org/10.1016/j.aej.2025.12.050

[22] Canyakmaz, C., Özekici, S., & Karaesmen, F. (2024). Risk management through financial hedging in inventory systems with stochastic price processes. International Journal of Production Economics, 270, 109189. https://doi.org/10.1016/j.ijpe.2024.109189

[23] Li, Z., Ma, F., & Lu, X. (2025). Financial risk management innovation in energy market: Evidence from a machine learning hybrid model. Energy Economics, 144, 108360. https://doi.org/10.1016/j.eneco.2025.108360

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