International Journal Evolving Sustainable and Renewable Energy Solutions ISSN: 3068-9325

PRIME OPEN ACCESS

Volume 1, Issue 2

Research Article

Date of Submission: 24 Sep, 2025
Date of Acceptance: 05 Nov, 2025
Date of Publication: 10 Nov, 2025

An Agent-Based Approach to Forecasting Renewable Energy Stock Prices: A Review of Recent Literature (2023–2025)Solutions

Heng Chen*

Chairman, Professor & Independent Education Researcher, Fuzhou Bohui AI Technology Co., Ltd., China

***Corresponding Author:** Heng Chen, Chairman, Professor & Independent Education Researcher, Fuzhou Bohui AI Technology Co., Ltd., China.

Citation: Chen, H. (2025). An Agent-Based Approach to Forecasting Renewable Energy Stock Prices: A Review of Recent Literature (2023–2025). *Int J Evol Sus Renew Energy Sol, 1*(2), 01-05.

Abstract
The renewable energy sector has rapidly become a central component of the global transition toward sustainability, attracting unprecedented investment and attention from policymakers, financial institutions, and researchers. However, forecasting renewable energy stock prices remains a complex task due to their high volatility, policy dependence, and sensitivity to technological and environmental changes. This paper provides a comprehensive review of recent developments (2023–2025) in applying Agent-Based Modeling (ABM) to financial forecasting, with a specific focus on renewable energy stock markets. The study highlights how ABM captures heterogeneous agent behavior, adaptive learning, and emergent market phenomena that traditional econometric models fail to represent. Recent advances, such as the integration of multi-agent deep reinforcement learning and hybrid ABM–machine learning frameworks, have significantly enhanced the predictive and explanatory power of ABM. The review also discusses ABM applications in energy market dynamics and sustainable finance, emphasizing their relevance for modeling policy-driven, ESG-oriented investor behavior. Finally, it outlines the major challenges—including calibration, data integration, and inter-market modeling—and proposes future directions for developing robust, AI-augmented ABMs. The findings underscore the growing importance of ABM as a methodological foundation for forecasting renewable energy stock prices in an increasingly complex, policy-sensitive global market.

Keywords: Agent-Based Modeling (ABM), Renewable Energy Stocks, Financial Forecasting, Green Finance, Multi-Agent Systems

Introduction
The global transition toward a sustainable energy future has positioned the renewable energy sector as a critical driver of economic growth and technological innovation. This rapid expansion, fueled by ambitious policy targets and decreasing technology costs, has attracted significant capital, making renewable energy stocks a highly dynamic and volatile asset class. Accurately forecasting the prices of these stocks is essential for investors, policymakers, and energy companies alike, yet traditional econometric models often fall short. These models, which typically rely on assumptions of market efficiency and rational, homogeneous agents, struggle to capture the complex, non-linear dynamics, and emergent phenomena characteristic of real-world financial markets, especially those heavily influenced by external factors like policy and technological disruption.

This literature review addresses this gap by surveying recent research on the application of Agent-Based Modeling (ABM) to financial forecasting, with a specific focus on its potential for the renewable energy stock market. ABM provides a powerful computational framework that simulates the interactions of heterogeneous, boundedly rational agents within a defined environment, thereby allowing for the emergence of complex macro-level phenomena from micro-level behaviors. By concentrating on scholarly work published between 2023 and 2025, this review aims to synthesize the state-of-the-art, identify key methodological advancements, and highlight the challenges and future directions for applying ABM to this specialized and critical financial domain. The review is structured to first contextualize the renewable energy financial landscape, then detail the theoretical and methodological evolution of ABM in finance, and finally, synthesize its specific application and potential for forecasting renewable energy stock prices.

The Volatile Renewable Energy Financial Landscape (2023–2025)

The period between 2023 and 2025 has been marked by unprecedented shifts in the renewable energy sector, directly impacting the valuation and volatility of related stocks. Global policy initiatives, such as the European Green Deal and the U.S. Inflation Reduction Act, have created a complex and sometimes unpredictable investment environment. The Deloitte Renewable Energy Industry Outlook (2024) highlights a "storage boom" and rising distributed generation, suggesting a fundamental restructuring of the energy value chain. These structural changes introduce unique uncertainties that challenge conventional financial models.

Driver	Description	Impact on Stock Prices
Policy & Regulation	Subsidies, tax credits, and carbon pricing mechanisms.	High sensitivity; abrupt changes can lead to sharp price swings.
Technological Innovation	Advances in battery storage, grid modernization, and green hydrogen.	Creates winners and losers; valuation depends on adoption speed.
Commodity Prices	Fluctuations in raw materials (e.g., lithium, polysilicon) and energy prices.	Direct impact on operational costs and profitability of energy companies.
Energy Market Dynamics	Integration of intermittent renewables (wind/solar) into the grid.	Affects the profitability of power producers and grid operators.
Green Finance Trends	Increased focus on ESG investing and sustainable finance goals.	Attracts large capital flows, leading to potential overvaluation or "green bubbles."

Traditional forecasting models, such as ARIMA and GARCH, are ill-equipped to handle the non-linear feedback loops and sudden, policy-driven shocks inherent in this market. For instance, the influence of a major policy announcement on a stock price is not a simple linear function but a complex reaction mediated by the diverse interpretations and trading strategies of thousands of investors. This complexity necessitates a modeling approach that can simulate the collective effect of heterogeneous decision-making, which is precisely where ABM offers a superior alternative.

Methodological Advancements in Agent-Based Modeling (ABM)

ABM has evolved significantly from its early theoretical applications to become a quantitative tool capable of generating time-series predictions, as noted by Farmer et al. (2025) [1]. This evolution is driven by the need to model financial markets as complex adaptive systems where prices emerge from the interactions of agents, rather than being determined by an exogenous equilibrium.

The Shift to Heterogeneous and Adaptive Agents

The core strength of contemporary ABM lies in its ability to model heterogeneous agents—investors with differing beliefs, strategies, and levels of rationality. This contrasts sharply with the "representative agent" assumption of classical economics. Recent research emphasizes the integration of sophisticated learning mechanisms into these agents.
The ASSUME framework (Harder et al., 2025), for example, presents an open-source agent-based simulation that incorporates Multi-Agent Deep Reinforcement Learning (MADRL) [2]. This allows agents to adapt their trading strategies based on the observed outcomes of their actions and the actions of others, creating a more realistic simulation of adaptive market behavior. Similarly, a bibliometric analysis by Ionescu et al. (2025) highlights the emerging cluster of research focused on integrating Artificial Intelligence (AI) and ABM, signaling a move toward more predictive and less purely descriptive models [3]. This integration is crucial for forecasting, as it allows the model to capture the continuous evolution of trading strategies in response to market changes.

ABM and Hybrid Forecasting Models

A key trend in the 2023–2025 literature is the development of hybrid models that combine the structural richness of ABM with the predictive power of machine learning (ML) or deep learning (DL). While ABM simulates the market environment and agent interactions to generate synthetic price data, ML/DL algorithms are then used to analyze this data or to refine the agents' decision rules.

Ge et al. (2025), in their work on enhancing stock market forecasting, exemplify this hybrid approach [4]. The rationale is that ABM provides a mechanism for generating realistic, non-stationary time series data—including rare events like market crashes—that are often underrepresented in historical data. By training ML models on this ABM-generated data, the forecasting system gains robustness and a deeper understanding of market dynamics driven by behavioral factors. This synthesis offers a pathway to overcome the ABM challenge of calibration while retaining its explanatory power.

ABM Applications in the Energy and Green Finance Context

While dedicated ABM studies on renewable energy stock price forecasting are still emerging, the 2023–2025 literature provides strong foundational work in related domains: energy markets and green finance asset valuation.

Modeling Energy Market Dynamics

A significant body of recent ABM research focuses on the complex dynamics of energy markets, which are the fundamental drivers of renewable energy company revenues. Models like the Electricity Markets Investment Suite (EMIS), highlighted by the National Renewable Energy Laboratory (NREL, 2025), use ABM to capture the interactions between market design, investment decisions, and resource adequacy [5. Similarly, Han et al. (2025) employed ABM to model the trading of energy consuming rights, demonstrating how agent interactions can stabilize trading prices and influence market efficiency [6].

These energy market ABMs are highly relevant because they provide the necessary environmental context for stock price forecasting. The agents in a renewable energy stock market ABM must react not only to financial signals but also to the price of electricity, the cost of carbon, and the profitability of energy assets. The methodologies developed in these energy-focused ABMs—particularly in modeling investment decisions under uncertainty—can be directly adapted to model the behavior of investors in renewable energy stocks.

ABM in Sustainable and Green Finance

The concept of sustainable finance has been a fertile ground for ABM application. A critical study by Li et al. (2024) introduced an ABM to analyze the impact of T+0 trading reform on market efficiency for Green Assets [7]. This research is pivotal as it explicitly models the behavior of ESG-focused investors, who are motivated by factors beyond pure financial return. The agents in this model incorporate sustainability preferences, which influence their trading decisions and, consequently, the asset price dynamics.

This work provides a template for modeling the policy-driven or "green" agent—a crucial component for renewable energy stock forecasting. In an ABM for renewable energy stocks, agents would likely include:

- Fundamentalists: Relying on traditional financial metrics (P/E ratio, cash flow) and energy market data.
- Chartists: Using technical analysis and momentum strategies.
- Policy-Driven/ESG Investors: Reacting strongly to regulatory news, climate targets, and corporate sustainability reports.

By simulating the interactions between these diverse agent types, ABM can capture the unique "green premium" or "policy risk discount" embedded in renewable energy stock valuations, a feature largely invisible to traditional models.

Synthesizing the Agent-Based Forecasting Model for Renewable Energy Stocks

Based on the synthesis of the 2023–2025 literature, a robust ABM for forecasting renewable energy stock prices would require a multi-layered structure that integrates financial, energy, and policy dynamics.

Model Architecture and Agent Design

The model environment must be designed to simulate both the financial market (stock exchange) and the underlying energy market (electricity and commodity prices). The core of the model lies in the design of the heterogeneous agents:

Agent Decision-Making: Agents' decisions to buy, sell, or hold must be a function of:
Internal State: Wealth, risk tolerance, and investment horizon.

Financial Signals: Technical indicators (e.g., moving averages) and fundamental data (e.g., company earnings forecasts).

External Signals: Energy market prices, policy announcements, and ESG scores.

Learning Mechanism: Incorporating adaptive learning, such as the MADRL approach from the ASSUME framework, allows agents to evolve their strategies. For instance, an agent might learn to increase its investment in solar stocks after a favorable government policy announcement, or divest from a company whose ESG rating has dropped.

Capturing Emergent Phenomena

The primary advantage of this ABM approach is its capacity to generate emergent phenomena critical to the renewable energy sector:

Policy-Induced Bubbles: A wave of optimistic policy-driven investment (e.g., a major new subsidy program) can be modeled as a coordinated, but non-centralized, shift in the expectations of policy-driven agents, leading to a temporary price bubble that is not justified by immediate fundamentals.

Systemic Risk Propagation: The model can simulate how a shock in the energy commodity market (e.g., a sudden increase in lithium prices) propagates through the system. Fundamentalist agents in the ABM would adjust their valuation of battery manufacturers, triggering a sell-off that could be amplified by chartist agents following momentum, leading to a market-wide correction.

Challenges and Future Research Directions
Despite the promising advancements in the 2023–2025 period, the application of ABM to renewable energy stock forecasting faces several critical challenges that define the agenda for future research.

Calibration and Validation
The most persistent challenge for ABM remains calibration and validation. Unlike traditional models with a few parameters, ABMs have numerous parameters governing agent behavior. As Nugroho and Uehara (2023) emphasize in their systematic review, ensuring that the simulated market accurately reflects the statistical properties of the real-world renewable energy stock market (e.g., volatility clustering, fat tails) is essential for predictive credibility [8]. Future work must focus on advanced calibration techniques, such as genetic algorithms or Bayesian methods, to systematically tune agent parameters against historical data.
Data Integration and Granularity
A significant gap in the current literature is the lack of models that seamlessly integrate the three key data streams: financial, energy, and policy data. Specifically, there is a need for:

Policy Quantification: Developing methods to translate qualitative policy announcements (e.g., "The government plans to increase wind capacity") into quantitative agent decision rules.

Behavioral Data: The rise of large language models (LLMs) and Generative AI (Gen-AI) presents a new opportunity. As suggested by Mamat et al. (2025) in the energy context, future ABMs could leverage Gen-AI to create agents whose behavioral rules are distilled from real-world investor sentiment data (e.g., social media, news headlines), making them more realistic, as explored in the general financial ABM context by Harder et al. (2025) [2,9].

Multi-Scale and Inter-Market Modeling
Future research should move toward multi-scale ABMs that model not just the stock market, but also the interaction between the stock market and the underlying energy market. For instance, an ABM could simulate how a drop in the stock price of a major utility (financial market) impacts its ability to secure financing for a new solar project (energy market), which in turn affects the stock prices of its suppliers. This inter-market modeling is crucial for understanding systemic risk in the green transition.

Conclusion
This review of the 2023–2025 literature confirms that an Agent-Based Approach to Forecasting Renewable Energy Stock Prices is not only methodologically feasible but increasingly necessary. The complexity, policy-dependence, and high volatility of the renewable energy financial market render traditional econometric models inadequate. Recent advancements in ABM, particularly the integration of heterogeneous, adaptive agents with sophisticated learning mechanisms like Deep Reinforcement Learning, have transformed the framework from a descriptive tool into a powerful predictive engine.

While the literature shows strong foundational work in ABM for general finance and energy market dynamics, the specific application to renewable energy stock price forecasting remains an emerging field. The key to future success lies in developing models that explicitly incorporate policy-driven agents and seamlessly integrate financial, energy, and green finance data. By addressing the challenges of calibration and leveraging new AI-driven techniques for behavioral modeling, ABM is poised to become the indispensable tool for navigating the financial complexities of the global energy transition, offering investors and policymakers a more nuanced and accurate perspective on the future of renewable energy stock valuations [10].

References

1. Farmer, J. D. (2025). Quantitative agent-based models: a promising alternative for macroeconomics. Oxford Review of Economic Policy, graf027.
2. Harder, N., Miskiw, K. K., Khanra, M., Maurer, F., Patil, P., Qussous, R., ... & Weidlich, A. (2025). ASSUME: An agent-based simulation framework for exploring electricity market dynamics with reinforcement learning. SoftwareX, 30, 102176.
3. Ionescu, Ș., Delcea, C., Nica, I., Dumitrescu, G., Simion, C. E., & Cotfas, L. A. (2025). Exploring Complexity: A Bibliometric Analysis of Agent-Based Modeling in Finance and Banking. International Journal of Financial Studies, 13(2), 65.
4. Ge, Q. (2025). Enhancing stock market Forecasting: A hybrid model for accurate prediction of S&P 500 and CSI 300 future prices. Expert Systems with Applications, 260, 125380.
5. NREL. (2025). EMIS: Electricity Markets Investment Suite Model. National Renewable Energy Laboratory.
6. Han, F., Li, X., Bi, X., Gao, J., Cao, Z., Yang, D., ... & Jia, Y. (2025). Agent based modeling of energy consuming rights trading for low carbon transformation in China. Scientific Reports, 15(1), 24754.
7. Li, H., et al. (2024). T+0 Reform and Sustainable Finance: An Agent-Based Simulation on Enhancing Market Efficiency for Green Assets. SSRN.
8. Nugroho, S., & Uehara, T. (2023). Systematic review of agent-based and system dynamics models for social-

ecological system case studies. Systems, 11(11), 530.
9. Mamat, R., Ghazali, M. F., Basrawi, F., & Rosdi, S. M. (2025). Emerging Role of Generative AI in Renewable Energy Forecasting and System Optimization. Sustainable Chemistry for Climate Action, 100099.
10. Akobi, C. (2025). The Clean Energy Horizon: Navigating a Dynamic Landscape of Alternatives in 2025. Available at SSRN 5181901.