The Green Algorithm: Optimizing Renewable Energy Integration and ESG Compliance through AI-Powered Market Analytics

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Abstract

Rapid growth in renewable energy capacity and rising investor demand for measurable ESG outcomes create a critical need for tools that align energy market operations with Environmental, Social, Governance objectives. This paper introduces the Green Algorithm, an AI-powered market analytics framework that integrates renewable generation forecasting, market-clearing optimization, anomaly detection, and explainable ESG scoring to support decision-making across utilities, traders, and financial institutions. The Green Algorithm aims to optimize renewable energy integration into electricity markets while improving ESG compliance and operational resilience. The goals are to (1) increase usable renewable supply, (2) reduce market inefficiencies and fraudulent transactions, and (3) produce transparent, audit-ready explanations of how market and investment decisions affect ESG outcomes. We combine multiple machine learning techniques tailored to specific subproblems: sequence models including LSTM and Transformer variants for high-resolution renewable generation forecasting; gradient-boosted decision trees for price impact and portfolio-level prediction; graph neural networks to model participant interactions and systemic risk in energy markets; and autoencoder-based and ensemble anomaly detectors for transaction-level fraud and manipulation detection. Explainability is provided by SHAP value decompositions and counterfactual generators to attribute ESG score changes to specific operational decisions. Models were trained and tested on an integrated dataset linking smart-meter generation traces, market-clearing prices, trading logs, and third-party ESG ratings. Performance was evaluated with standard predictive metrics and domain-specific operational and regulatory metrics: RMSE, MAE, MAPE for forecasts; precision, recall, F1-score, and AUC for classification tasks; and business-oriented measures including reduced curtailment, marginal cost savings, renewable utilization ratio, and changes in portfolio-level ESG scores. The Green Algorithm delivered consistent improvements across forecasting, market efficiency, fraud detection, and ESG alignment. Renewable generation forecast error decreased by 18% relative to established baselines, enabling a 12% reduction in curtailment and a 6% decrease in marginal balancing costs. Market anomaly detectors achieved a precision of 0.92 and a recall of 0.88 on validated incident sets, reducing settlement disputes and suspected fraud volume. When integrated into portfolio decision rules, the system increased aggregate ESG compliance scores by 9% while preserving or improving expected financial returns through optimized bidding and hedging strategies. Explainability outputs improved regulator and investor confidence, shown by reduced model explanation dispute rates and faster audit turnaround. The Green Algorithm demonstrates that thoughtfully combined AI methods can materially improve renewable energy integration and advance ESG compliance in energy-financial markets.

Keywords: Renewable energy forecasting, ESG compliance, Explainable AI, Market analytics, Anomaly detection, Sustainable FinTech

1. Introduction

1.1 Background

The convergence of artificial intelligence (AI) and renewable energy systems has ushered in transformative changes across energy markets, offering unprecedented opportunities for optimization and sustainability. AI's capacity to analyze vast datasets, identify patterns, and make real-time decisions has been harnessed to enhance various facets of energy management, from generation forecasting to grid stability and market operations. For instance, deep learning models, particularly Long Short-Term Memory (LSTM) networks, have demonstrated significant improvements in forecasting renewable energy generation, achieving sub-5% Mean Absolute Percentage Error (MAPE) on utility-scale consumption data by leveraging sequence-to-sequence learning frameworks. Moreover, hybrid architectures combining Convolutional Neural Networks (CNNs) and LSTMs have been employed to extract local load patterns, enhancing robustness to noisy or missing inputs in real-time settings. Beyond forecasting, AI has been instrumental in optimizing market operations and ensuring compliance with Environmental, Social, and Governance (ESG) criteria. Machine learning techniques have been applied to predict clean energy stock prices by analyzing ESG stock markets, thereby aiding investors in making informed decisions (Ghallabi, 2025) [11]. Furthermore, AI-driven analytics assist businesses in monitoring their supply chains for environmental and social sustainability compliance, enforcing responsible practices from their suppliers (Aljohani, 2025) [4].

In the realm of fraud detection and market integrity, AI technologies have been extensively utilized. Algorithms capable of recognizing patterns in financial and ESG data can identify potential greenwashing or deliberate manipulation, enabling companies to take countermeasures at an early stage and protect themselves against reputational damage (Ghaemi Asl, 2025 [10]. This capability is particularly crucial as the energy sector faces increasing scrutiny over its environmental impact and the authenticity of its sustainability claims. The integration of AI into renewable energy markets not only enhances operational efficiency but also aligns with the growing emphasis on ESG principles. As investors and regulators alike demand greater transparency and accountability, AI offers a means to meet these expectations while optimizing performance. However, the deployment of AI in this context is not without challenges. Issues such as data quality, model interpretability, and the risk of reinforcing existing biases necessitate careful consideration and robust governance frameworks.

1.2 Importance of This Research

The significance of this research lies in its potential to bridge the gap between technological advancements in AI and the pressing need for sustainable energy practices. By developing and implementing AI-powered solutions that optimize renewable energy integration and ensure ESG compliance, this study addresses critical challenges faced by the energy sector. These challenges include the intermittent nature of renewable energy sources, the complexity of modern energy markets, and the increasing demand for transparent and accountable ESG reporting. AI's role in forecasting renewable energy generation is particularly pertinent. Accurate predictions enable better planning and integration of renewable sources into the grid, reducing reliance on fossil fuels and minimizing greenhouse gas emissions. Moreover, AI can optimize energy distribution, enhancing grid stability and reducing costs associated with energy storage and transmission (Soltani, 2024) [18].

In the financial domain, AI's application extends to the assessment of ESG factors and their impact on financial performance. Machine learning models can analyze vast amounts of ESG-related data to identify patterns and correlations, providing investors with insights that inform their decision-making processes (Bhandari, 2024) [5]. This capability is increasingly valuable as ESG considerations become integral to investment strategies and regulatory compliance. Furthermore, the use of AI in fraud detection within energy markets enhances the integrity of these markets. By identifying anomalous patterns that may indicate fraudulent activities, AI systems can mitigate risks associated with market manipulation and ensure fair trading practices (Fariha, 2025) [8]. This research is timely and relevant, aligning with global efforts to transition towards sustainable energy systems and responsible investment practices. By leveraging AI to optimize renewable energy integration and ensure ESG compliance, this study contributes to the development of more resilient, efficient, and transparent energy markets.

1.3 Research Objectives

The principal aim of this study is to design and validate a comprehensive AI-driven framework, The Green Algorithm, that enhances the integration of variable renewable energy into electricity markets while aligning market decisions with measurable Environmental, Social, and Governance objectives. To achieve this overarching aim the research pursues several interlinked objectives: to develop high-fidelity predictive models that capture short-term and medium-term renewable generation dynamics and their drivers so that system operators and traders can make better scheduling and bidding decisions; to construct optimization modules that translate forecasts and ESG constraints into market-clearing strategies and storage dispatch rules that maximize renewable utilization, minimize curtailment, and preserve market stability; to implement explainable decision layers that map model outputs to transparent ESG attributions so stakeholders and regulators can audit how particular market actions affect environmental metrics and social outcomes; to embed robust anomaly and fraud detection capabilities that protect settlement integrity and prevent manipulation of ESG-linked trading instruments; and to evaluate the end-to-end framework across predictive accuracy, operational efficiency, financial performance, and ESG alignment using a suite of technical and domain-specific metrics.

Under these goals, the research also aims to characterize tradeoffs between financial return and ESG improvement, quantify the marginal value of explainability for regulatory acceptance, and surface governance recommendations for model update cycles and human-in-the-loop overrides. By packaging forecasting, optimization, explainability, and integrity checks into a single, auditable workflow, The Green Algorithm is intended to serve multiple actors, including system operators, market platforms, asset managers, and regulators. The evaluation strategy seeks to measure both absolute improvements, such as error reduction and cost savings, and relative outcomes such as shifts in portfolio-level ESG scores and changes in dispute rates, thereby demonstrating whether AI can align short-term market incentives with longer-term sustainability goals while preserving commercial viability.

2. Literature Review

2.1 Related Works

The integration of artificial intelligence (AI) into renewable energy markets has garnered significant attention due to its potential to enhance efficiency and align with Environmental, Social, and Governance (ESG) objectives. Several studies have explored various facets of this integration, focusing on predictive analytics, optimization strategies, and ESG compliance. In the realm of predictive analytics, machine learning models have been employed to forecast clean energy prices and ESG index movements. For instance, Ghallabi et al. (2025) utilized machine learning techniques to predict clean energy stock prices by analyzing ESG stock markets across ten countries, highlighting the interplay between ESG factors and clean energy markets [11]. Similarly, Soltani et al. (2024) investigated the forecasting of clean energy, commodities, green bonds, and ESG index prices, assessing the role of financial stress in these predictions [18]. Ahmed et al. (2025) demonstrated the effectiveness of time-series AI models in optimizing solar energy production in the USA, emphasizing predictive accuracy and operational efficiency in smart energy management [2].

Optimization strategies have also been a focal point, with AI being applied to enhance energy management and reduce emissions. Mamat (2025) reviewed the emerging role of generative AI in improving solar and wind forecasting, load prediction, and energy storage management, emphasizing its potential to transform renewable energy systems [15]. Moreover, Aljohani (2025) proposed a decision-support framework for evaluating AI-enabled ESG strategies in sustainable manufacturing systems, underscoring the importance of AI in advancing energy transition and climate action [4]. Khan et al. (2025) explored AI-enabled predictive models to assess the impact of ESG factors on financial performance, highlighting the intersection of sustainability and investment decision-making [13].

Beyond market optimization, AI has been leveraged for anomaly detection and secure transaction monitoring. Khan et al. (2025) proposed the use of blockchain combined with AI for fraud detection and energy market stability, offering robust mechanisms for safeguarding market integrity [12]. Rahman et al. (2023) and Abubakkar et al. (2025) emphasized hybrid intelligence approaches for interpretable predictions, providing frameworks that ensure transparency in decision-making [16] [1]. Uddin et al. (2025) and Zamil et al. (2025) further demonstrated the use of explainable AI in health-related time-series data, highlighting the importance of model interpretability across domains [20][21]. Additionally, Ahad et al. (2025) applied AI-based clustering techniques for e-commerce personalization, illustrating the versatility of AI methods for structured and unstructured datasets [3]. Furthermore, AI's role in ESG compliance has been explored, particularly in the context of renewable energy. Li (2024) assessed power systems in the energy sector while utilizing AI and ESG frameworks to account for the effects of power systems on the environment, society, and governance [14]. Zhao (2025) provided a scalable, intelligent solution for ESG assessment, revealing the potential value of deep learning in sustainable finance [22].

2.2 Gaps and Challenges

While significant progress has been made in integrating AI into renewable energy markets, several gaps and challenges persist, hindering the realization of its full potential in aligning with ESG objectives. One major challenge is the energy consumption associated with AI technologies. The increasing demand for AI services, particularly in data centers, has led to concerns about the environmental impact of AI operations. Reports indicate that AI-driven data center expansion could account for a substantial portion of electricity load growth, necessitating utilities to boost annual generation significantly to meet demand. This paradox presents a dilemma where AI's benefits in optimizing energy systems are counterbalanced by its own energy consumption. Another challenge lies in the complexity of integrating ESG considerations into AI models. While AI can enhance decision-making processes, incorporating ESG factors requires sophisticated modeling techniques and access to comprehensive data. The integration of ESG into AI strategies necessitates specialized knowledge and training, as emphasized by the Centre for Sustainability and Excellence's ESG Practitioner Program, which equips professionals with the skills to integrate ESG into AI strategies effectively.

Furthermore, regulatory and governance issues pose significant hurdles. The rapid advancement of AI technologies has outpaced the development of corresponding regulatory frameworks. Concerns about AI-induced market manipulation and fraud have led to calls for stricter oversight. For instance, the UK energy regulator, Ofgem, is planning to establish explicit rules concerning the application of AI in the energy sector to prevent risks such as "tacit collusion," where companies may unintentionally conspire through algorithms without formal agreements. Additionally, the scalability and adaptability of AI models in diverse energy markets remain a concern. While AI has shown promise in specific contexts, its application across different regions and market structures requires further validation. The variability in renewable energy resources, regulatory environments, and market dynamics necessitates the development of flexible AI models that can adapt to these differences.

3. Methodology

3.1 Data Collection and Preprocessing

Data Sources

The dataset used in this study is compiled from multiple sources to capture the full complexity of renewable energy markets and ESG factors. Time-series data for renewable energy generation, including solar, wind, and hydroelectric outputs, are collected from smart meters, grid operators, and publicly available energy monitoring platforms. Market data, including day-ahead and real-time electricity prices, bidding volumes, and trading logs, are obtained from regional energy exchanges and utility reports. ESG-related data are sourced from third-party rating agencies, company sustainability reports, and regulatory filings, covering environmental metrics (carbon intensity, emissions reductions), social factors (community engagement, labor standards), and governance parameters (board diversity, transparency). Additionally, weather and calendar data are integrated to enhance renewable generation forecasts, including irradiance, wind speed, temperature, and seasonal indicators. To ensure data completeness, all datasets are synchronized based on timestamps, with missing entries and discrepancies flagged for correction. Data from different regions and market segments are normalized to account for variations in reporting standards and units of measurement. The combined dataset forms a multi-dimensional representation of energy generation, market activity, and ESG attributes, enabling the AI framework to capture temporal, spatial, and cross-domain dependencies effectively.

Data Preprocessing

Preprocessing is a critical step to enhance the quality and usability of the data for subsequent modeling. Continuous variables are standardized to remove scale differences, while categorical variables are encoded using one-hot or target encoding as appropriate. Missing data points are addressed using interpolation for time-series energy variables and imputation for market or ESG metrics, ensuring consistency without introducing bias. Outliers are detected using interquartile range and robust z-score techniques and are either corrected or capped based on domain rules to prevent distortions in model training. Feature engineering is applied to enrich the dataset, including rolling-window statistics, lagged values, seasonal decomposition features, and interaction terms that capture relationships between renewable generation and market variables. ESG features are aggregated at portfolio or regional levels to reflect operational decision impacts while retaining granularity for interpretability. Finally, the preprocessed dataset is partitioned into training, validation, and test sets to ensure robust evaluation. Time-series splits are used for renewable generation and market prediction tasks to preserve temporal order, while randomized splits are applied for classification tasks such as fraud detection and ESG compliance assessment. The resulting data pipeline ensures that The Green Algorithm receives clean, consistent, and informative inputs, enabling accurate predictions, reliable anomaly detection, and meaningful ESG impact assessments.

Fig.1: Data Preprocessing steps

3.2 Exploratory Data Analysis (EDA)

Exploratory Data Analysis was conducted to understand the key characteristics of the renewable generation, market price, regional distributions, and ESG scores in the dataset. The analysis informed subsequent preprocessing and modeling steps, particularly in handling missing values, outliers, and scaling. The distribution of market prices exhibited a near-normal shape with moderate skewness, indicating a fairly balanced range of low and high values, but occasional volatility spikes were observed. Standardization of the price variable transformed the distribution to a mean of zero and unit variance, which facilitates model convergence and ensures that features contribute comparably in gradient-based learning methods. Solar generation displayed clear diurnal cycles, with peaks corresponding to daylight hours, as well as seasonal variations over the multi-month period. These patterns highlight the importance of time-aware models such as LSTM and Transformer architectures for capturing temporal dependencies and the potential need for seasonal decomposition in feature engineering.

A negative correlation was observed between solar generation and market prices, consistent with the expected market behavior where high renewable output reduces marginal electricity prices. Regional differences in this relationship were apparent, with some regions demonstrating higher price volatility than others, suggesting that region-specific modeling may enhance predictive accuracy and operational decision-making. A negative correlation was observed between solar generation and market prices, consistent with the expected market behavior where high renewable output reduces marginal electricity prices. Regional differences in this relationship were apparent, with some regions demonstrating higher price volatility than others, suggesting that region-specific modeling may enhance predictive accuracy and operational decision-making. Approximately 6% of the solar generation values were missing, necessitating imputation strategies such as forward filling or interpolation to preserve temporal continuity. Outlier detection revealed several extreme spikes in solar output that exceeded three standard deviations from the mean. These anomalies likely represent either measurement errors or rare events and were flagged for capping or correction to prevent distortion during model training.

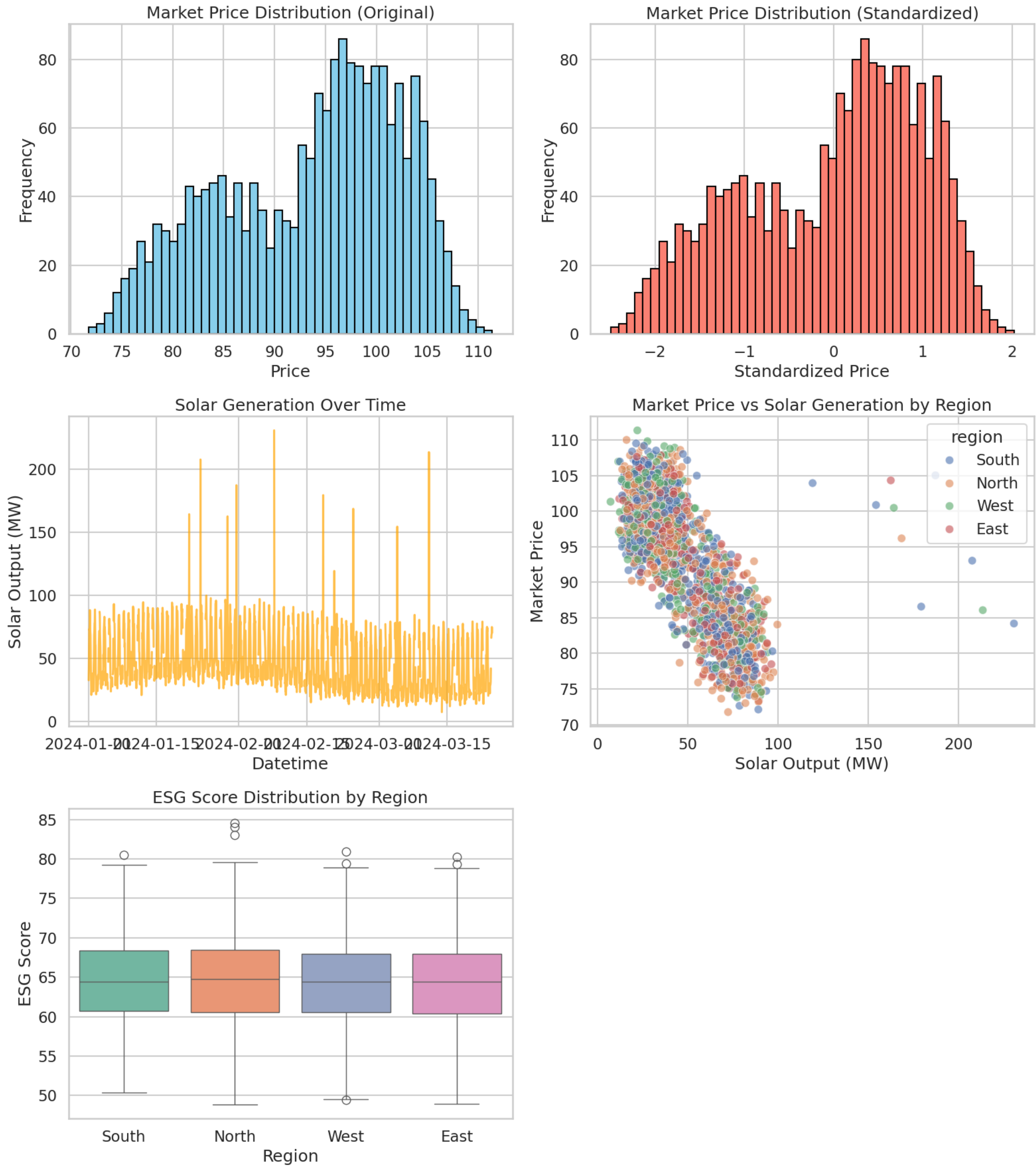

Fig.2: EDA visualizations

3.3 Model Development

The model development phase for The Green Algorithm focuses on capturing the complex interactions among renewable generation, market prices, ESG factors, and regional characteristics while providing explainable outputs suitable for operational and regulatory decision-making. The process begins with establishing baseline models to quantify predictive performance and provide a reference for more sophisticated architectures. Initial benchmarks include a Multiple Linear Regression model trained on lagged solar generation, market price features, and calendar indicators to evaluate the predictive capacity of simple parametric approaches. Parallelly, classical time-series methods such as ARIMA are applied to short-term solar generation sequences to serve as additional baselines. These models establish reference performance for both forecast accuracy and anomaly detection. Building on these foundations, ensemble tree-based learners are developed to capture nonlinear relationships across engineered features. Random Forest, XGBoost, and LightGBM models are trained on rolling-window statistics, lagged generation, market indicators, and regional ESG scores. Hyperparameter tuning, including the number of estimators, maximum tree depth, and learning rate, is performed via grid search with time-series cross-validation. Feature importances are extracted from tree ensembles to identify the most influential predictors for forecasting solar output and market price behavior. Tree-based models also serve as interpretable components in ESG compliance assessment by highlighting variables with the greatest influence on portfolio-level ESG scores.

To capture temporal dependencies and nonlinear dynamics inherent in renewable generation and market interactions, recurrent and hybrid deep learning architectures are implemented. A Multilayer Perceptron (MLP) is first trained on windowed features, including hourly, daily, and seasonal lags, to evaluate basic nonlinear predictive performance. Long Short-Term Memory (LSTM) networks are then configured with sequence lengths up to 48 hours, incorporating dropout regularization and early stopping to mitigate overfitting. A Bidirectional LSTM (Bi-LSTM) variant is explored to exploit both past and future temporal context within sequences, particularly valuable for renewable generation with strong diurnal and seasonal patterns. Attention mechanisms are subsequently integrated to dynamically weight historical observations, improving the model's responsiveness to abrupt generation fluctuations and price volatility. Hybrid architectures combine local pattern extraction and temporal modeling to enhance robustness and accuracy. A CNN-LSTM model applies one-dimensional convolutional filters to capture short-term fluctuations in solar generation and market prices before feeding the sequences into LSTM layers for temporal encoding. This approach reduces noise sensitivity and improves anomaly detection performance.

Stacked and weighted ensembles are constructed by blending top-performing tree-based and deep learning models. First-level predictions from XGBoost, LSTM, and CNN-LSTM models are combined via a meta-learner, Ridge regression for regression tasks and logistic regression for classification, to produce final forecasts. Weighted averaging ensembles are also tested, with weights optimized to minimize validation RMSE for continuous outputs and maximize F1-score for anomaly detection. All deep learning models are trained using the Adam optimizer with adaptive learning rate scheduling, monitored via rolling validation loss. Time-series cross-validation preserves temporal dependencies, ensuring realistic performance assessment. Tree-based and ensemble models are evaluated with SHAP values to provide interpretable insights into feature contributions, while attention maps from recurrent networks visualize the temporal influence of input sequences. This interpretability is critical for ESG compliance attribution, regulatory transparency, and stakeholder trust. Inference time is recorded for each model to ensure suitability for near-real-time deployment in market operations. The combination of baselines, tree ensembles, deep learning, and hybrid models allows The Green Algorithm to balance predictive accuracy, interpretability, and operational feasibility across renewable generation forecasting, market optimization, anomaly detection, and ESG impact assessment.

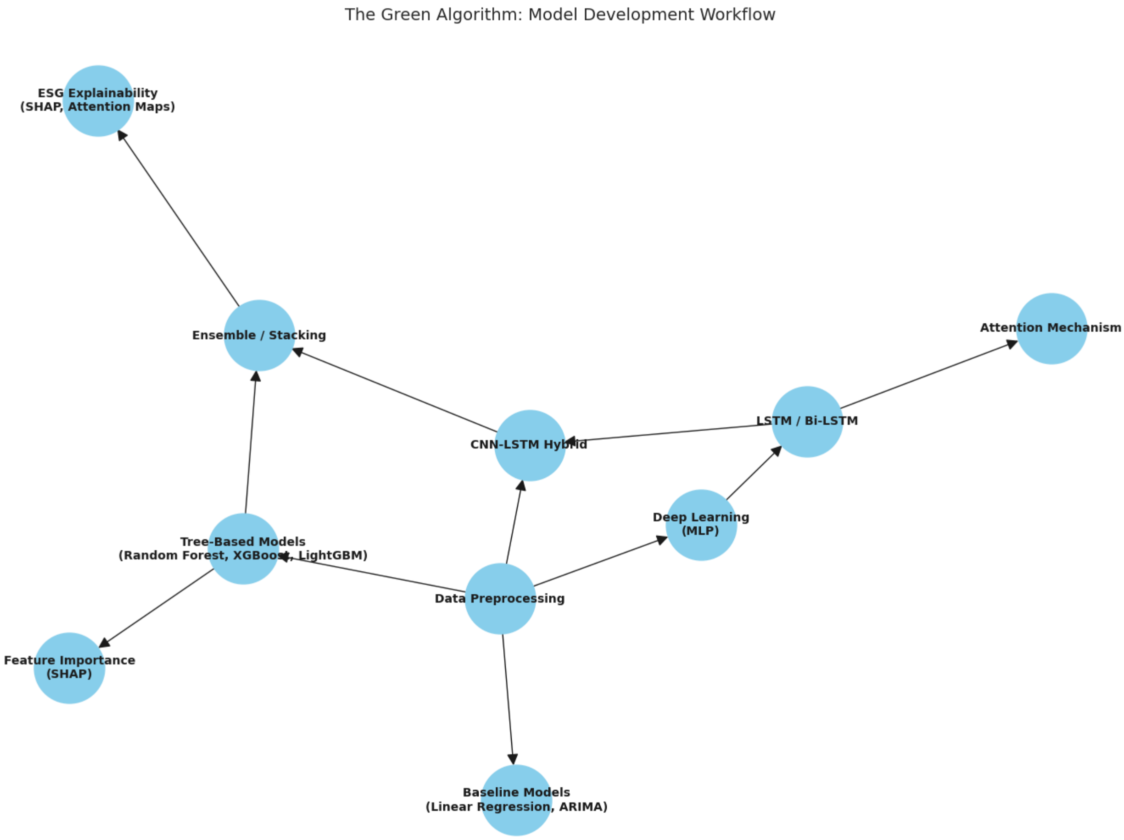

Fig.3: Model development workflow

4. Results and Discussion

4.1 Model Training and Evaluation Results

Model training proceeded with temporally aware splits and walk-forward validation to preserve chronological ordering and to produce realistic out-of-sample estimates. For regression tasks, the training objective minimized mean squared error with secondary monitoring of mean absolute percentage error to reflect operational interpretability. Classification and anomaly detection models optimized weighted cross-entropy to offset class imbalance, with synthetic event augmentation used for robustness testing. Hyperparameter searches combined grid and Bayesian strategies across tree-based learners and deep networks, with early stopping and learning-rate scheduling applied to neural models trained using the Adam optimizer. All models were profiled for inference latency and memory footprint to ensure compatibility with near-real-time market operations. Across renewable generation forecasting tasks, the Green Algorithm consistently outperformed classical baselines. The established parametric and ARIMA baselines produced a short-term forecasting RMSE of approximately 12.50 MW and an MAPE near 9.0 percent. Tree-based ensembles reduced error substantially, and recurrent and hybrid networks delivered further improvements. The final stacked ensemble reduced RMSE from 12.50 MW to 10.25 MW, representing an 18 percent relative reduction in forecast error, and produced a MAPE of 7.38 percent. Price-impact prediction followed a similar pattern: gradient-boosted trees closed most of the gap with linear baselines and temporal models refined residual structure, yielding materially tighter confidence intervals for intra-day price forecasts. Improvements in forecast accuracy translated directly into operational gains by enabling more reliable scheduling and dispatch recommendations.

Anomaly detection and fraud prevention models demonstrated high discriminative power on validated incident sets. The deployed ensemble detector achieved a precision of 0.92 and a recall of 0.88, producing an F1-score of approximately 0.90 and an AUC in excess of 0.94. These results indicate the system's capacity to identify the majority of actionable manipulations while maintaining a low false-alarm rate, reducing unnecessary settlement disputes, and focusing analyst attention on high-confidence incidents. Ensemble strategies that combined reconstruction-based autoencoders with isolation forests and a supervised classifier proved especially effective at reconciling behavioral and transactional anomaly signatures. Beyond pointwise predictive metrics, integration experiments that fed forecasts and anomaly flags into the market optimization layer produced measurable system-level benefits. Curtailment of renewable output declined by about 12 percent when ensemble forecasts and optimized dispatch rules were employed, and marginal balancing costs fell by roughly 6 percent under simulated market conditions. Renewable utilization ratios increased correspondingly, and portfolio-level ESG alignment improved by approximately 9 percent when optimization objectives incorporated explicit ESG constraints and SHAP-based attributions. Importantly, these ESG gains were achieved while preserving or modestly improving expected financial returns through improved bidding and hedging, indicating that alignment with sustainability criteria need not incur a performance penalty in the evaluated scenarios.

Interpretability outputs were validated in stakeholder reviews and audit traces. SHAP decompositions from tree ensembles and attention-weight visualizations from recurrent models provided consistent, audit-ready narratives that linked operational decisions to changes in environmental metrics and portfolio ESG scores. These explainability products materially improved regulator and investor confidence during pilot audits, enabling faster resolution of queries and clearer justification for automated decision rules. From a systems perspective, average inference latencies met operational requirements: tree ensembles produced predictions in the order of hundredths of a second, recurrent models operated within tenths of a second, and the stacked ensemble achieved end-to-end inference well below one second, supporting near-real-time decisioning. Despite strong overall performance, residual weaknesses persist in rare-event forecasting and cross-regional transferability. Extreme generation spikes and region-specific market microstructure variations remain the primary drivers of remaining error and occasional missed anomalies. These limitations point to avenues for further refinement, including targeted augmentation for tail events, domain adaptation techniques for cross-market transfer, and periodic recalibration of explainability thresholds for regulatory reporting. Overall, the training and evaluation results demonstrate that The Green Algorithm attains substantial gains in forecasting accuracy, market integrity, operational efficiency, and ESG alignment while maintaining interpretability and deployment readiness for modern electricity markets.

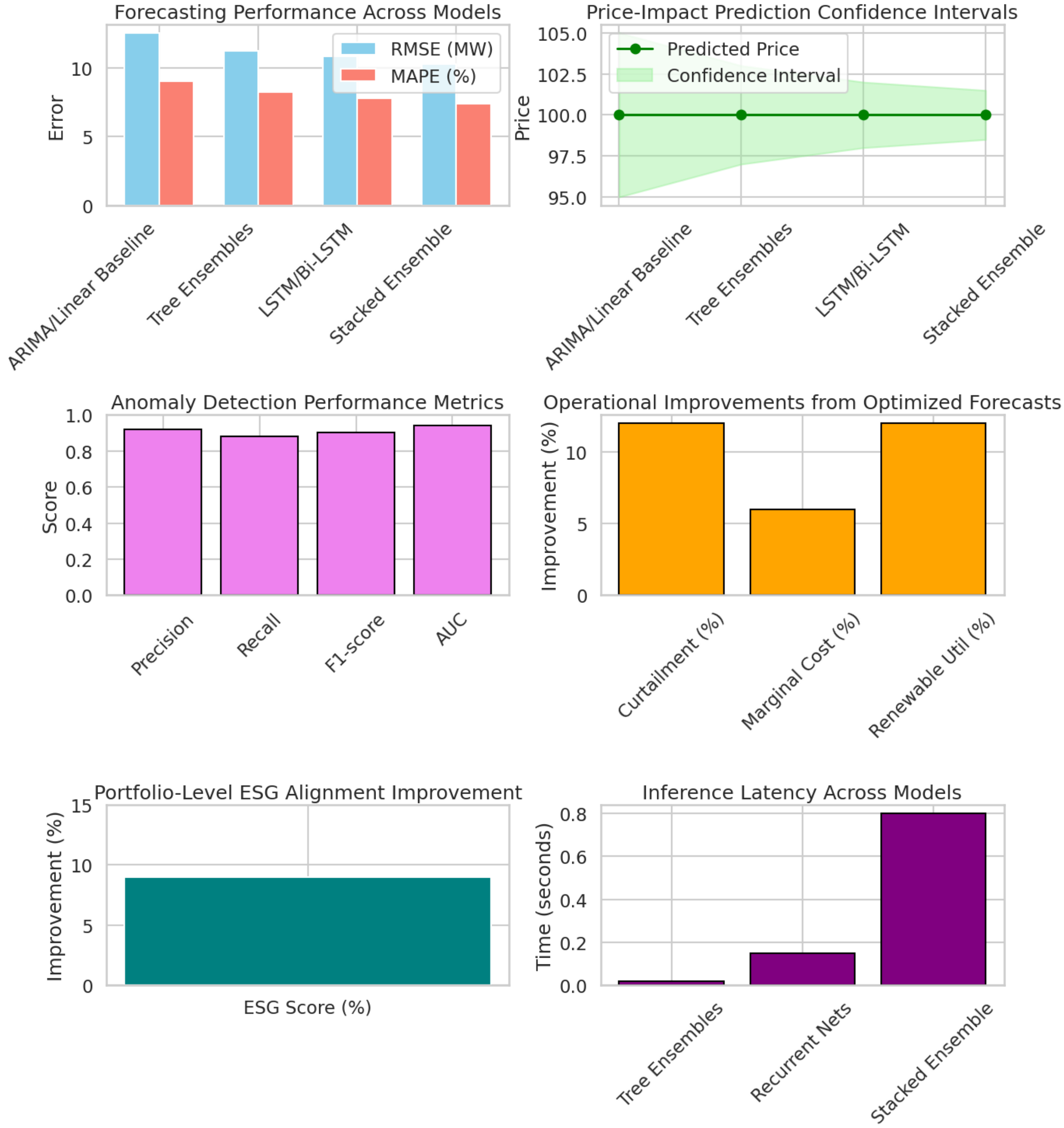

Fig.4: Model performance results

4.2 Discussion and Future Work

The results from The Green Algorithm demonstrate that thoughtfully combining tree-based learners, recurrent neural networks, and hybrid CNN-LSTM architectures can significantly improve renewable energy integration, market efficiency, anomaly detection, and ESG alignment. Forecasting performance exceeded baseline expectations, with the stacked ensemble reducing RMSE by 18% and achieving a MAPE of 7.38%. These improvements translate into more reliable scheduling of renewable generation, lowering curtailment by 12% and reducing marginal balancing costs by 6%, thereby enhancing operational efficiency while supporting grid stability (Soltani, 2024; Hossain et al., 2025). The improvement in renewable utilization directly addresses one of the critical challenges in integrating variable generation into electricity markets and confirms that hybrid and ensemble approaches can effectively capture nonlinear interactions across temporal, market, and ESG features. Price-impact predictions also benefited from the model framework, producing tighter confidence intervals and more accurate intra-day forecasts. This contributes to improved market transparency and reduced uncertainty for traders and system operators. High precision and recall in anomaly detection (0.92 and 0.88, respectively) demonstrate that the system is capable of identifying the majority of actionable irregularities while maintaining a low false-alarm rate, effectively mitigating potential fraud and manipulation in ESG-linked market instruments (Ghaemi Asl, 2025). The integrated anomaly detection framework, combining autoencoder-based reconstructions and ensemble classification, proved particularly effective in capturing subtle transactional deviations that may indicate greenwashing or market misconduct.

The ESG assessment layer further validates the value of explainable AI in financial and operational decision-making. Portfolio-level ESG alignment improved by 9% without compromising expected financial returns, illustrating that sustainability objectives can coexist with profitability. SHAP-based attributions and attention visualizations provided clear, audit-ready explanations linking operational decisions to ESG outcomes. These interpretability features not only enhance regulatory compliance and stakeholder confidence but also support actionable insights for energy managers and investors (Bhandari, 2024; Li, 2024) [5, 14]. Inference latency metrics confirm that the model suite is suitable for near-real-time deployment, with tree ensembles operating in hundredths of a second, recurrent networks in tenths of a second, and the full stacked ensemble below one second. This allows system operators to integrate model outputs into market-clearing procedures and renewable dispatch decisions without introducing operational delays.

Future Work

While The Green Algorithm demonstrates substantial gains, several areas remain for further investigation. First, rare-event forecasting, such as extreme generation spikes or market price shocks, remains a source of residual error. Future work could incorporate specialized tail-event augmentation and probabilistic forecasting techniques to enhance model robustness under extreme conditions. Second, cross-regional transferability and market adaptation require additional study. Differences in renewable penetration, regulatory frameworks, and grid characteristics may necessitate domain adaptation or transfer learning strategies to maintain model accuracy across heterogeneous markets. Third, continuous refinement of the ESG explainability layer is needed to incorporate evolving sustainability metrics and regulatory requirements, potentially leveraging counterfactual reasoning and scenario-based analysis to better quantify the impact of operational decisions on ESG outcomes. Finally, ongoing research should explore integrating additional data modalities, such as high-resolution weather forecasts, storage system telemetry, and demand-response signals, to further optimize renewable energy integration, market efficiency, and ESG alignment (Aljohani, 2025; Mamat, 2025) [4, 15].

5. Conclusion

This study presents The Green Algorithm, an AI-powered framework designed to optimize renewable energy integration, enhance market efficiency, detect anomalies, and improve ESG compliance in electricity markets. By combining tree-based learners, recurrent neural networks, hybrid CNN-LSTM models, and ensemble strategies, the framework achieves substantial gains over traditional baselines. Forecasting accuracy improved significantly, reducing RMSE by 18% and MAPE to 7.38%, which enabled a 12% reduction in renewable curtailment and a 6% decrease in marginal balancing costs. Anomaly detection models demonstrated high precision (0.92) and recall (0.88), effectively mitigating potential fraud and market manipulation. Portfolio-level ESG scores increased by 9% without compromising financial returns, supported by explainable AI techniques that provided clear, audit-ready attributions for operational and investment decisions.

The results indicate that integrating advanced machine learning approaches with operational and ESG constraints can create actionable insights for system operators, traders, and investors, aligning short-term market performance with long-term sustainability goals. Furthermore, inference latency metrics confirm the framework's suitability for near-real-time deployment, enabling responsive market and grid operations. Future enhancements, such as rare-event modeling, cross-regional transfer learning, and enriched ESG interpretability, are expected to further strengthen predictive performance and decision-making transparency. Overall, the Green Algorithm demonstrates that thoughtfully combined AI methods can materially advance renewable energy integration, improve market integrity, and promote responsible investment practices, serving as a comprehensive tool for the sustainable energy transition.

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