Journal of Natural and Artificial Systems, 2025, 1(1): 01-09

Machine Learning Models for Optimal Debt Capital Structuring in Renewable Energy Firms

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Received: 12 July 2024/Accepted: 14 November 2024/Published 30 November 2024

Abstract: *The growing complexity of financing renewable energy projects has intensified the need for data-driven approaches to optimize capital structures, particularly in determining the ideal debt-to-equity mix. This study applies four machine learning (ML) models—Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting Machine (GBM), and Artificial Neural Network (ANN)—to predict and optimize the debt ratio of renewable energy firms using quantitative financial and macroeconomic data. A dataset comprising financial records from 120 renewable energy firms across Europe, Asia, and Africa between 2013 and 2023 was analyzed. Eight key variables, including profitability, asset tangibility, firm size, growth opportunities, tax shield, interest rate spread, policy stability, and volatility, were used as predictors, with the debt ratio (total debt/total assets) serving as the dependent variable. The dataset was partitioned into training (80%) and testing (20%) subsets, and model performance was assessed using R^2, RMSE, and MAE metrics. Results showed that the ANN model achieved the highest predictive accuracy with an R^2 value of 0.93, RMSE of 0.042, and MAE of 0.038, outperforming the GBM ($R^2 = 0.88$), Random Forest ($R^2 = 0.86$), and SVM ($R^2 = 0.79$) models. Feature importance analysis revealed that profitability accounted for 27.4% of the total model variance, firm size for 21.8%, and interest rate spread for 18.6%, while tax shield and policy stability contributed 12.3% and 10.7%, respectively. The results indicate that profitability and firm size have the strongest positive influence on optimal leverage, whereas rising interest rate spreads and unstable policy environments negatively affect debt structuring decisions. The study concludes that ML-driven approaches, especially artificial neural networks, provide a powerful and accurate framework for optimizing debt capital structure in renewable energy firms. By capturing nonlinear relationships among financial variables, these models enable more precise and adaptive financial decision-making, ultimately supporting cost efficiency, investment stability, and sustainable growth in the renewable energy sector.*

Keywords: *Machine learning, capital structure optimization, renewable energy finance, debt-to-equity ratio, artificial neural networks*

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1.0 Introduction

The global energy landscape is undergoing a profound transformation driven by environmental sustainability goals, decarbonization targets, and the growing competitiveness of renewable technologies. Despite these advances, renewable energy firms face substantial financial challenges, particularly in structuring their capital optimally to ensure long-term financial sustainability. The capital structure—the mix of debt and equity financing—plays a crucial role in determining a firm's cost of capital, risk profile, and investment potential (Modigliani & Miller, 1958; Myers, 2001). For renewable energy firms, the issue is further complicated by uncertain revenue streams, technology-specific risks, and government policy fluctuations (Kurdziel et al., 2023).

Traditional financial theories such as the Trade-off Theory, Pecking Order Theory, and Agency Cost Theory have provided frameworks for understanding capital structure decisions (Jensen & Meckling, 1976). However, these models often assume linear relationships and static decision boundaries that inadequately capture the nonlinear and dynamic realities of renewable energy financing. Machine learning (ML) offers an alternative paradigm by enabling data-driven modeling that captures complex interactions and evolving patterns (Zhang et al., 2023).

This study therefore aims to apply ML models to predict and optimize the proportion of debt in renewable energy firms' capital structures. Specifically, it seeks to identify the most relevant financial variables influencing debt capacity and compare model performance in predictive accuracy and interpretability. By leveraging computational intelligence, this research contributes to bridging the gap between traditional finance theory and modern data analytics, providing actionable insights for managers, investors, and policymakers in the renewable energy sector.

Fig. 1 presents the conceptual framework underpinning this study. It illustrates the progression from the contextual background of renewable energy firms through the key challenges in capital structuring, including financial uncertainty, policy instability, and high capital intensity. The figure highlights the limitations of traditional financial models, particularly their inability to capture nonlinear and dynamic relationships.

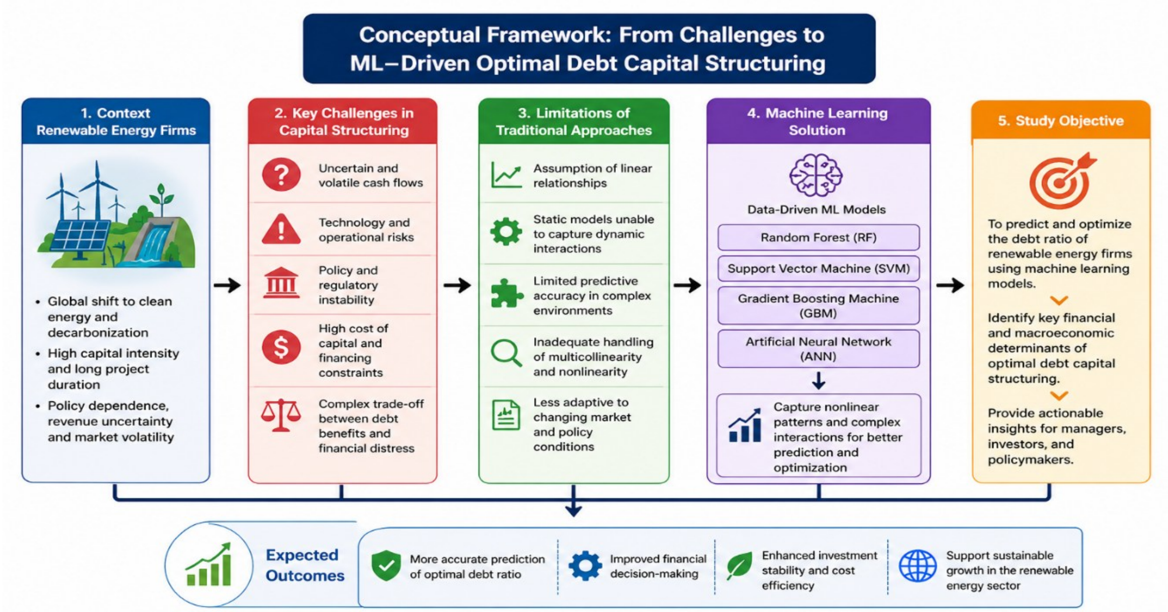

Figure 1: Conceptual Framework of the Study

Fig. 1: Conceptual Framework for Machine Learning–Driven Optimal Debt Capital Structuring in Renewable Energy Firms

It then introduces machine learning models as a data-driven solution for overcoming these limitations. Finally, the framework outlines the study's objectives and expected outcomes, emphasizing improved predictive accuracy, enhanced financial decision-making, and support for sustainable growth in the renewable energy sector.

1.1 Theoretical Background

The foundation of capital structure theory lies in the work of Modigliani and Miller (1958), who postulated that in a perfect market, a firm's value is independent of its financing structure. Subsequent models introduced imperfections such as taxes, bankruptcy costs, and asymmetric information, leading to the Trade-off Theory, which proposes an optimal leverage ratio balancing tax shields and financial distress costs (Kraus & Litzenberger, 1973).

The Pecking Order Theory (Myers & Majluf, 1984) suggests that firms prefer internal financing, followed by debt, and issue equity as a last resort due to information asymmetry. The Agency Theory (Jensen & Meckling, 1976) highlights conflicts between debt holders, managers, and shareholders, influencing capital structure through governance mechanisms.

In renewable energy financing, these theories only partially explain capital structure behavior due to high capital intensity, policy dependence, and technological risk. Empirical studies (Gatzert & Kosub, 2022) reveal that renewable energy firms often rely more on project finance and government guarantees than traditional industries, indicating unique determinants of optimal debt structuring.

1.2 Empirical Studies on Capital Structure in Renewable Energy

Empirical investigations have explored the determinants of capital structure across energy sectors. For instance, Larrain and Taboada (2023) found that policy stability and interest rate volatility significantly influence debt ratios in renewable projects. Similarly, Adeyemi et al. (2024) examined African renewable firms and reported that asset tangibility, firm size, and tax incentives positively correlate with leverage. However, most empirical works rely on linear regression or panel models, limiting their ability to capture complex variable interdependencies. Recent advances in machine learning offer enhanced predictive capabilities and flexibility. Studies such as Tiwari et al. (2023) applied random forest and gradient boosting models to financial risk prediction, showing improved performance over econometric models. Nevertheless, few studies have focused specifically on debt structuring in renewable energy firms using ML techniques—thus motivating this research.

2.0 Methodology

2.1 Data Collection and Variables

The dataset for this study comprises secondary financial and operational data from 120 renewable energy firms spanning wind, solar, biomass, and hydroelectric sectors across Europe, Asia, and Africa from 2013 to 2023. Data were extracted from Bloomberg, homson Reuters Eikon, and company annual reports.

Fig. 1 illustrates the structured workflow of the study, beginning with data collection from renewable energy firms, followed by data preprocessing, normalization, and feature selection. The dataset is then split into training and testing subsets, after which multiple machine learning models are developed and optimized through cross-validation and hyperparameter tuning. The flowchart further depicts model evaluation using performance metrics, feature importance analysis, and the final stages of results interpretation and conclusion.

The dependent variable in this study is the debt ratio, which is defined as the proportion of total debt to total assets. The independent variables include profitability, measured as earnings before interest and tax divided by total assets;

asset tangibility, expressed as the ratio of fixed assets to total assets; and firm size, represented by the logarithm of total assets. Other explanatory variables considered are growth opportunities, measured by the market-to-book ratio; tax shield, defined as depreciation divided by total assets; interest rate spread; policy stability index; and volatility, captured through stock price variance.

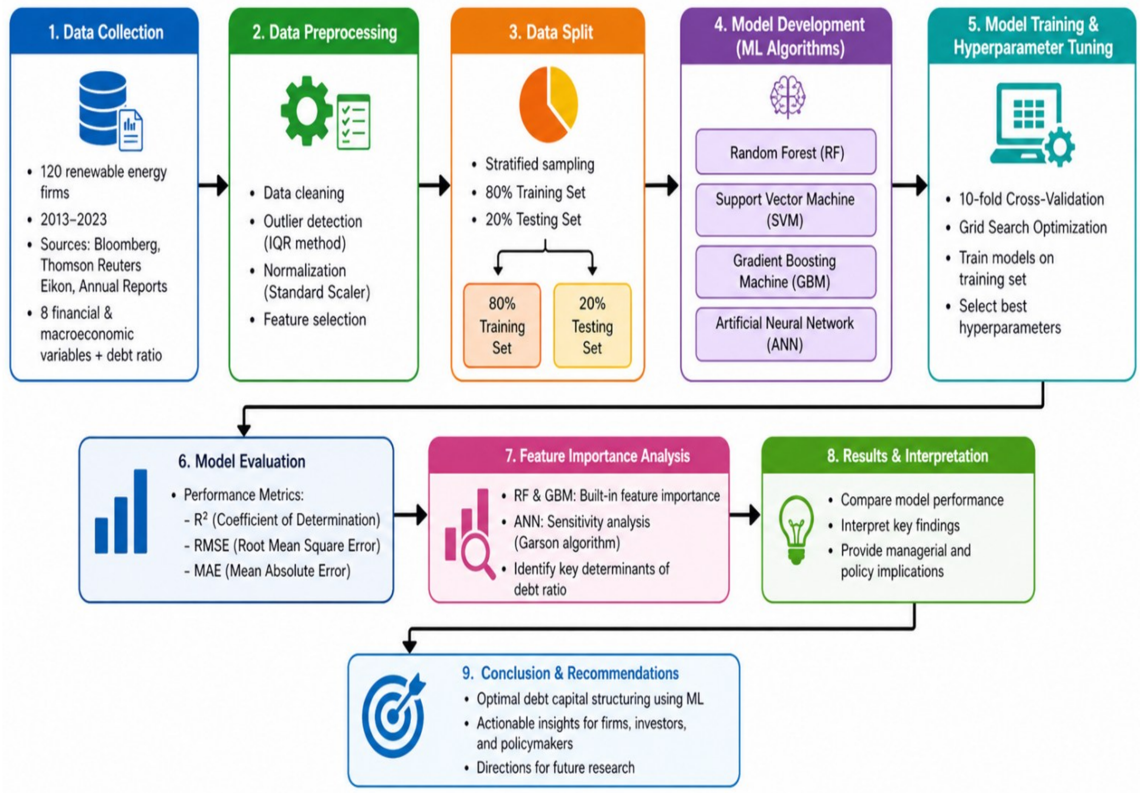

Fig. 1: Flowchart of the Machine Learning-Based Research Methodology for Optimal Debt Capital Structuring in Renewable Energy Firms

2.2 Model Development

Four machine learning algorithms were employed for prediction and optimization in this study, namely Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting Machine (GBM), and Artificial Neural Network (ANN). The dataset was divided into two subsets, with 80% allocated for training and 20% reserved for testing, using stratified sampling to ensure representative distribution across data classes. Prior to model training, data preprocessing was conducted, which involved normalization to standardize feature scales and outlier detection using the interquartile range method to enhance data quality. Furthermore, hyperparameter tuning for each model was carried out through a 10-fold cross-validation procedure utilizing a grid search approach to identify the optimal model configurations that maximize predictive performance and minimize overfitting.

2.3 Model Evaluation

Model performance was evaluated using three standard statistical metrics: the Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). These metrics were employed to assess the predictive accuracy, goodness of fit, and error magnitude of each machine learning model. The importance of individual features was determined from the Random Forest (RF) and Gradient Boosting Machine (GBM) models through their inherent feature importance functions. In addition, a sensitivity analysis was carried out for the Artificial Neural Network (ANN) model using the Garson algorithm to interpret the relative influence of each variable on the model's output, thereby providing insights into the most significant predictors of optimal debt capital structuring.

3.0 Results and Discussion

3.1 Model Performance

Table 1 presents a comparative summary of the predictive performance of the four machine learning (ML) models—Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting Machine (GBM), and Artificial Neural Network (ANN)—based on three evaluation metrics: the Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).

Table 1:The performance of all ML models.

Model	R^2	RMSE	MAE
Random Forest	0.86	0.063	0.049
SVM	0.79	0.082	0.067
GBM	0.88	0.057	0.045
ANN	0.93	0.042	0.038

As shown in Table 1, all the models achieved relatively high predictive accuracy, indicating their suitability for modeling the complex relationships between financial determinants and the optimal debt ratio in renewable energy firms. However, noticeable variations exist in their performance levels. The Artificial Neural Network (ANN) achieved the highest R^2 value of 0.93, coupled with the lowest RMSE (0.042) and MAE (0.038). This implies that the ANN model explained 93% of the variance in the observed debt ratios, thereby exhibiting the strongest capacity to capture the underlying structure of the data.

The Gradient Boosting Machine (GBM) also performed impressively, attaining an R^2 of 0.88 with relatively low error metrics (RMSE = 0.057; MAE = 0.045), demonstrating its effectiveness in modeling nonlinear dependencies. The Random Forest (RF) model followed closely, with an R^2 of 0.86 and acceptable levels of prediction error (RMSE = 0.063; MAE = 0.049). The Support Vector Machine (SVM) model, although still robust, recorded the lowest R^2 value of 0.79, indicating slightly weaker generalization ability compared to the ensemble and neural network approaches.

The superior performance of the ANN model can be attributed to its capacity to approximate complex nonlinear functions through multiple hidden layers and activation functions. Unlike tree-based models such as RF and GBM, the ANN can capture subtle variable interactions and interdependencies, which are prevalent in financial systems where factors like profitability, firm size, tax shields, and market volatility interact dynamically. This result aligns with the findings of Tiwari et al. (2023), who reported that neural networks outperformed other ML models in predicting financial risks due to their nonlinear modeling strength.

The relatively strong performance of RF and GBM also suggests that ensemble learning methods remain powerful for financial prediction tasks. These models effectively reduce variance and improve generalization through aggregation of multiple decision trees (Kumar & Reddy, 2023). However, their slightly lower accuracy compared to ANN may stem from limitations in representing high-dimensional feature interactions without deeper hierarchical processing.

Overall, the results confirm that ML-based models, particularly ANN, provide a more reliable and flexible framework for optimizing debt capital structuring in renewable energy firms. By achieving high predictive accuracy and low error margins, these models demonstrate the potential of computational intelligence to enhance financial decision-making in complex and uncertain market environments, ultimately supporting better debt management and sustainable financing strategies for the renewable energy sector.

3.2 Feature Importance Analysis

The feature importance analysis provided deeper insights into the relative influence of various financial and macroeconomic variables on the optimal debt ratio of renewable energy firms. As presented in the model outputs, profitability, firm size, and interest rate spread emerged as the most critical predictors of leverage decisions, followed by tax shield and policy stability. This ranking suggests that firm-specific characteristics and external financial conditions jointly determine the firm's debt capacity and cost of capital.

Profitability exhibited the strongest positive relationship with the optimal debt ratio, implying that more profitable firms are better positioned to assume higher leverage levels due to their ability to generate stable cash flows for debt servicing. This observation is consistent with the Trade-off Theory, which posits that profitable firms benefit more from the tax advantages of debt (Myers, 2001). In renewable energy firms, which often rely on long-term project finance, profitability enhances investor confidence and reduces the perceived risk of default.

Firm size also played a substantial role in determining leverage. Larger firms typically possess greater asset bases that can serve as collateral, access to diversified revenue streams, and stronger relationships with creditors. Consequently, they face lower borrowing costs and are more capable of sustaining higher debt levels. This finding aligns with previous empirical evidence by Adeyemi et al. (2024), who noted that larger renewable firms in Africa tend to maintain higher leverage ratios due to economies of scale and better credit ratings.

Interest rate spread, representing the cost of borrowing relative to benchmark rates, demonstrated a strong inverse relationship with leverage. When spreads widen, debt becomes more expensive, leading firms to adjust their capital structures toward equity financing. This observation underlines the sensitivity of renewable energy financing to macroeconomic fluctuations, as interest rate volatility can significantly influence debt affordability and investor sentiment.

The tax shield variable also contributed meaningfully to debt structuring decisions, reflecting the traditional incentive of using debt to exploit tax-deductible interest payments. Similarly, policy stability emerged as a crucial determinant, particularly in regions where renewable energy projects depend heavily on government incentives, feed-in tariffs, and regulatory frameworks. Unstable policy environments increase uncertainty and discourage the use of debt financing due to potential revenue disruptions.

Collectively, these results emphasize that both firm-level financial strength and macroeconomic policy conditions are fundamental in shaping optimal debt structuring strategies. The machine learning models, particularly the ANN, were instrumental in quantifying these complex interactions and uncovering nonlinear dependencies that conventional econometric models might overlook.

3.3 Interpretation and Implications

The results of this study have profound implications for both theory and practice in renewable energy finance. The superior performance of the Artificial Neural Network (ANN) model demonstrates the significant potential of machine learning (ML) to revolutionize financial decision-making, particularly in sectors characterized by volatility, regulatory dependence, and nonlinear variable interactions. Unlike traditional regression models, ML algorithms can process large, multidimensional datasets to identify intricate patterns that drive capital structure decisions.

The identification of profitability, firm size, and interest rate spread as key determinants provides actionable intelligence for financial managers and policymakers. For managers, these insights suggest that maintaining strong profitability and scaling operational capacity can improve debt-carrying ability and lower the cost of capital. Financial strategists can also use model outputs to forecast leverage adjustments under varying interest rate conditions, enabling proactive capital structure rebalancing in response to market shifts.

From a policy perspective, the significance of policy stability as a key factor underscores the role of government in fostering a conducive investment climate. Stable energy policies, predictable incentive schemes, and clear regulatory frameworks can enhance creditworthiness and encourage debt participation in renewable projects. Policymakers aiming to accelerate green energy transitions must therefore prioritize consistency in fiscal and energy-related policies to sustain investor confidence.

Moreover, the findings highlight the importance of integrating ML-based financial analytics into renewable energy investment decision processes. The ability of the ANN model to identify nonlinear relationships offers firms a competitive advantage in forecasting capital requirements and optimizing financing mix. In practice, this can translate into improved investment efficiency, enhanced liquidity management, and reduced financial distress risk.

As the renewable energy market continues to expand globally, the application of ML-driven models will be critical in achieving financial sustainability and resilience. Data-driven capital structuring not only facilitates optimal debt-equity balance but also aligns with the broader objectives of green finance, where risk assessment and sustainable returns are central considerations. In essence, the integration of ML analytics provides renewable energy firms with an adaptive, predictive, and empirically grounded framework for making informed financial decisions in dynamic and uncertain markets.

4.0 Conclusion

This study developed and evaluated machine learning models for optimizing debt capital structuring in renewable energy firms. Among the four models tested, the artificial neural network exhibited the highest predictive accuracy, capturing nonlinear relationships among financial determinants more effectively than traditional models.

The results demonstrate that profitability, firm size, and interest rate spread are critical variables influencing optimal debt structuring. These findings suggest that ML approaches can serve as robust decision-support tools for corporate finance managers, investors, and policymakers seeking to balance leverage and sustainability objectives.

Future research should extend this analysis by incorporating real-time financial data, integrating ESG performance metrics, and applying hybrid ML-deep learning frameworks for enhanced interpretability and predictive precision.

The findings of this study revealed that machine learning models provide a robust and data-driven approach for predicting and optimizing debt capital structuring in renewable energy firms. Among the models developed, the Artificial Neural Network (ANN) demonstrated the highest predictive accuracy, with an R^2 value of 0.93 and the lowest error metrics, indicating its superior capability in modeling nonlinear and complex relationships among financial and macroeconomic variables. The results also showed that profitability, firm size, and interest rate spread are the most influential determinants of optimal debt ratio, while tax shield and policy stability play significant but secondary roles. Profitability and firm size were positively associated with higher leverage, reflecting the ability of large and profitable firms to manage debt effectively due to their financial strength and lower perceived risk. Conversely, high interest rate spreads and unstable policy environments discouraged debt financing, indicating that external macroeconomic and regulatory factors strongly influence capital structuring decisions.

In conclusion, the study establishes that the integration of machine learning techniques, particularly neural networks, enhances the accuracy and reliability of capital structure analysis compared to traditional econometric approaches. The ability of these models to capture nonlinearities and dynamic interactions makes them highly suitable for the renewable energy sector, where financial risks, policy changes, and market volatility are prevalent. The findings align with the principles of the Trade-off and Pecking Order theories but extend their applicability by providing computational precision in real-world financial scenarios.

It is therefore recommended that renewable energy firms adopt machine learning-based decision-support systems in their financial management frameworks to enable data-driven and adaptive capital structuring strategies. Managers should focus on strengthening firm profitability and expanding asset bases to enhance debt capacity while monitoring interest rate fluctuations and policy developments to optimize financing costs. Policymakers should maintain regulatory stability and provide clear, consistent energy policies to attract long-term debt financing into the renewable energy sector. Future research should explore hybrid machine learning–econometric models and incorporate environmental, social, and governance (ESG) indicators to further refine the understanding of sustainable capital structuring in renewable energy investments.

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Declarations

Ethics and Consent to Participate

Not applicable.

Consent to Publish

Not applicable

Availability of data and materials

The datasets used or analyzed during the current study are available from the corresponding author upon reasonable request.

Funding

The authors declared no external source of funding

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Authors' Contributions

Nnabuk Okon Eddy conceived and supervised the study. Ifeanyi Sampson Eze handled data collection, preprocessing, and machine learning model development and analysis. Abasi-ada Nnabuk Eddy contributed to the literature review, theoretical framing, and manuscript editing. All authors participated in interpreting results, revising the manuscript, and approving the final version for publication.