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MMF-EDRM: A Multi-Modal Fusion and Dual-Risk Modeling Framework for Renewable Energy Project Financing and ECM/DCM Pricing

Zijie Zhong[1]. Guyue Gui[2] and Ye Mou[3]
[1]Nanjing University, Nanjing, China
[2]University of Chicago, Chicago, IL, USA
[3]Statistics Program, GSAS, Columbia University, New York, NY, USA

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Abstract

Renewable energy infrastructure investment faces substantial uncertainty arising from heterogeneous data sources, including environmental variability, policy interventions, and financial market fluctuations. Traditional valuation methods, such as discounted cash flow (DCF) and conventional multi-factor models, are limited in their ability to integrate unstructured information and to jointly capture risk–return dynamics in financing decisions. To address these challenges, this paper proposes MMF-EDRM (Multi-Modal Fusion and Dual-Risk Energy financing model), a unified framework for renewable energy project financing valuation and ECM/DCM pricing. The model integrates multi-modal deep learning with multi-factor statistical modeling to establish a risk–return–pricing linkage for infrastructure assets. Specifically, satellite imagery, meteorological time series, policy documents, and structured financial indicators are encoded through modality-specific networks and fused via a cross-modal attention mechanism. A heteroscedastic dual-head architecture is then employed to jointly estimate expected returns and conditional risk uncertainty. These outputs are further incorporated into an extended multi-factor pricing formulation to derive equity valuation (ECM) and credit spread estimation (DCM). The framework is optimized using a multi-task learning objective that aligns prediction and pricing consistency. Empirical results on the constructed multi-modal renewable energy dataset show that MMF-EDRM reduces RMSE for return prediction by 17.6% compared with CNN-LSTM baselines, while achieving 14.0% improvement in equity pricing error and 12.7% reduction in credit spread prediction error. In addition, the model attains a lower NLL of 0.742, indicating superior risk calibration under volatile policy conditions. These results confirm the effectiveness of the proposed framework.

Keywords

Multi-Modal Deep Learning; Renewable Energy Investment; Risk-Return Modeling; ECM/DCM Pricing; Multi-Factor Model; Attention Mechanism

1. Introduction

Renewable energy infrastructure, including photovoltaic power plants and wind farms, has become a critical component of global energy transition and sustainable finance. However, investment and financing decisions for such projects are inherently challenging due to high uncertainty arising from heterogeneous and dynamic factors, such as meteorological variability, policy incentives, and capital market fluctuations. In practice, these uncertainties not only affect project-level cash flows but also significantly influence equity financing (ECM) valuation and debt financing (DCM) credit spreads. Therefore, accurately modeling the linkage between underlying project risk and capital market pricing has become a key problem in both financial engineering and energy economics.

Traditional valuation methods, such as discounted cash flow (DCF) models and classical multi-factor asset pricing models, primarily rely on structured financial data and linear assumptions. These approaches are insufficient to capture complex nonlinear interactions among environmental conditions, policy dynamics, and market sentiment. Meanwhile, recent advances in deep learning have enabled the processing of unstructured data sources, including satellite imagery, meteorological time series, and textual policy documents. However, most existing studies focus either on renewable energy forecasting or financial pricing independently, lacking a unified framework that jointly models risk propagation and financing pricing mechanisms under ECM/DCM structures.

To address these limitations, this paper proposes MMF-EDRM (Multi-Modal Fusion and Dual-Risk Energy Financing Model), a unified multi-modal deep learning and multi-factor statistical framework for renewable energy project financing and capital market pricing. The MMF-EDRM model integrates spatial information from satellite imagery, temporal dynamics from meteorological data, semantic signals from policy text, and structured financial factors into a unified representation space via modality-specific encoders and a cross-modal attention fusion mechanism. A dual-risk learning architecture is further introduced to simultaneously estimate expected project returns and associated uncertainty. These outputs are then embedded into an extended multi-factor pricing model to jointly determine ECM equity valuation and DCM credit spread dynamics, thereby establishing a complete risk–return–pricing linkage.

The main contributions of this paper are summarized as follows:

We propose a unified MMF-EDRM framework that integrates multi-modal deep learning with multi-factor statistical modeling for renewable energy financing analysis.

We design a cross-modal attention fusion mechanism to effectively integrate heterogeneous data sources, including imagery, time series, text, and financial factors.

We develop a dual-risk modeling strategy that jointly captures expected returns and heteroscedastic uncertainty for improved risk quantification.

We construct an ECM/DCM-linked pricing module that connects asset-level risk with equity valuation and credit spread estimation.

Extensive experiments demonstrate that the proposed framework significantly improves both predictive accuracy and pricing robustness under complex market and policy conditions.

2. Related Work

In recent years, the integration of machine learning techniques into financial modeling and renewable energy systems has attracted increasing attention. With the rapid development of deep learning and the growing availability of multi-source data, researchers have explored various approaches for energy forecasting, financial risk modeling, and asset pricing. However, most existing studies focus on single-source data or isolated tasks, lacking a unified framework that jointly models multi-modal information, risk propagation, and financing pricing mechanisms in ECM/DCM contexts. This section reviews relevant literature in three main aspects: multi-modal learning for energy systems, financial risk modeling with multi-factor models, and deep learning for asset pricing and uncertainty quantification.

2.1. Multi-Modal Deep Learning for Energy Systems

Multi-modal learning has been widely applied in renewable energy forecasting and infrastructure analysis. Early works such as Krizhevsky et al. [1] demonstrated the effectiveness of deep convolutional networks for image-based feature extraction, which has been extended to satellite-based energy resource assessment. In renewable energy applications, Shan et al. [2] proposed a deep learning framework for solar irradiance forecasting using spatio-temporal data fusion. Similarly, Anand et al. [3] introduced a multi-source data fusion approach combining meteorological and satellite data for wind power prediction.

More recently, Transformer-based architectures have been adopted to capture long-range dependencies in time-series energy data. Vaswani et al. [4] introduced the Transformer model, which has been widely adapted in energy load forecasting tasks. However, most existing studies focus primarily on physical or environmental prediction, without integrating financial market signals or policy-driven textual data. This limitation restricts their applicability in investment decision-making and financing optimization.

2.2. Multi-Factor Models and Financial Risk Modeling

Multi-factor models play a central role in asset pricing and financial risk assessment. The foundational work of Fama and French [5] introduced the three-factor model, which has been extended to include additional macroeconomic and market sentiment factors. Carhart [6] further proposed a four-factor model incorporating momentum effects.

In renewable energy finance, Li et al. [7] analyzed the relationship between energy markets and financial returns using multi-factor regression models. Meanwhile, He et al. [8] studied electricity price risk using statistical factor decomposition methods. However, these models are primarily linear and rely on structured financial data, limiting their ability to capture nonlinear interactions between policy uncertainty, environmental variability, and market dynamics.

Recent studies have attempted to incorporate machine learning into factor modeling. Gu et al. [9] applied machine learning methods to cross-sectional asset pricing, demonstrating improved predictive performance over traditional linear factor models. Nevertheless, these approaches still lack integration with unstructured data sources such as satellite imagery and policy text.

2.3. Deep Learning for Asset Pricing and Uncertainty Quantification

Deep learning has recently been applied to financial forecasting and risk modeling. Heaton et al. [10] reviewed deep learning applications in finance, highlighting its advantages in capturing nonlinear relationships. Dixon et al. [11] applied deep neural networks for equity return prediction, showing improved accuracy over classical econometric models.

For uncertainty modeling, Kendall and Gal [12] proposed methods for estimating predictive uncertainty in deep learning via heteroscedastic regression and Bayesian approximations. These approaches have been widely adopted in risk-sensitive financial applications. Beyond algorithmic innovations, the computational deployment of deep learning frameworks in financial environments has also rapidly evolved. For instance, Xu et al. [13] proposed a smart neuromorphic system architecture optimized for high-frequency trading, demonstrating the advantages of heterogeneous computing and spiking neural networks in accelerating time-series processing and reducing energy consumption by over 80%. Parallel to these algorithmic developments, progressive decision-making models have significantly enhanced pricing strategies. Recent studies have successfully integrated reinforcement learning into complex business analytics. For example, Fan et al. [14] proposed a profit-oriented production and pricing optimization system based on Proximal Policy Optimization (PPO), which dynamically balances short-term profitability and long-term inventory risk in continuous action spaces. The success of such dynamic, reward-based pricing mechanisms provides a strong motivation to explicitly incorporate adaptive risk-pricing integrations into our ECM/DCM evaluation framework.

However, most existing methods treat return prediction and risk estimation as separate tasks and do not explicitly link them to downstream pricing mechanisms such as ECM/DCM valuation. Moreover, they rarely integrate multi-modal environmental and policy data into financial decision-making frameworks.

2.4. Summary of Limitations and Research Gap

Although significant progress has been made in multi-modal learning, multi-factor financial modeling, and deep learning-based risk estimation, several key limitations remain:

Lack of unified frameworks integrating multi-modal environmental, textual, and financial data.

Weak coupling between asset-level risk modeling and capital market pricing mechanisms. Limited application of deep learning in ECM/DCM-linked financing decision systems. To address these gaps, this paper proposes MMF-EDRM, a unified multi-modal fusion and dual-risk modeling framework that integrates deep learning with multi-factor financial theory for renewable energy project financing and pricing.

3. Methodology

3.1. Overview of the MMF-EDRM Framework

This study proposes MMF-EDRM (Multi-Modal Fusion and Dual-Risk Energy Financing Model), a unified framework designed to jointly model renewable energy project performance, financial risk, and ECM/DCM pricing dynamics. The core idea is to construct a risk–return–pricing coupling system, where heterogeneous data sources (satellite imagery, meteorological time series, policy text, and financial factors) are encoded through specialized neural modules and then fused into a shared latent representation for downstream prediction tasks.

Formally, given multi-modal inputs:

$$X = \{X^{img}, X^{ts}, X^{text}, X^{fin}\}, \tag{1}$$

the model learns a unified representation:

$$z = F_\theta(X), \tag{2}$$

where $F_\theta(\,)$ denotes the multi-modal fusion function parameterized by neural networks and attention mechanisms. This representation is then used for joint estimation of expected return, risk uncertainty, and financing pricing variables under ECM/DCM structures. The design philosophy of this end-to-end framework aligns closely with modern automated decision architectures, where modeling the structured interactions among high-dimensional, heterogeneous variables is essential for preventing confounding bias and executing optimal downstream strategies [15].

Unlike traditional approaches that separate energy forecasting and financial pricing, MMF-EDRM explicitly models the endogenous linkage between physical asset performance and capital market valuation, making it suitable for investment decision-making in renewable energy infrastructure financing.

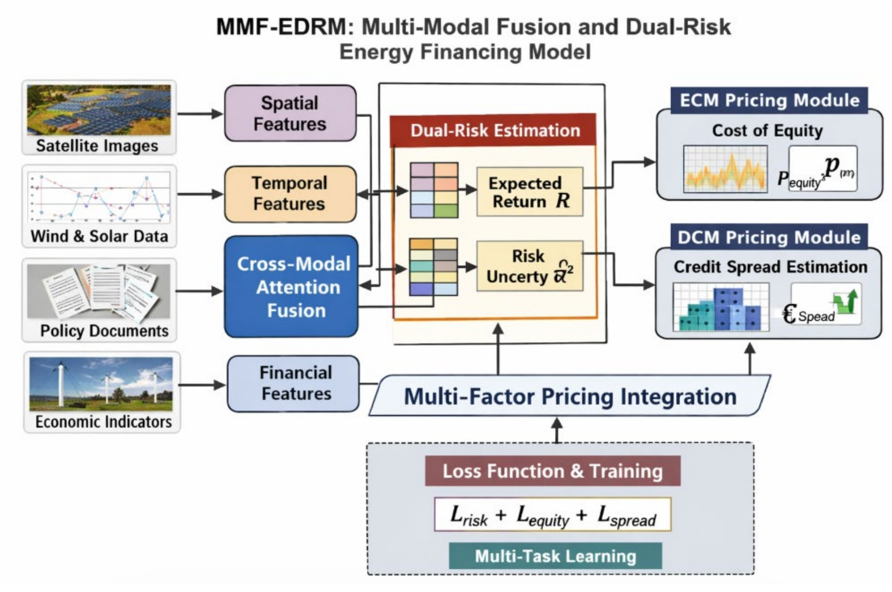

Figure 1. Structure diagram of model.

3.2. Multi-Modal Encoding of Renewable Energy and Financial Data

Each modality is processed through a dedicated encoder to capture its intrinsic structure. For satellite imagery data X^{img} , a convolutional or Vision Transformer-based encoder is applied to extract spatial representations:

$$h_{img} = f_{img}(X^{img}), \tag{1}$$

This encoder captures geospatial characteristics such as land usage patterns, solar exposure intensity, and terrain variability, which are critical for renewable energy output potential.

For meteorological and power generation time series X^{ts}, a temporal Transformer is employed to model long-range dependencies and seasonality effects:

$$h_{ts} = f_{ts}(X^{ts}), \tag{2}$$

This module is essential for capturing volatility in wind speed, irradiance fluctuations, and production dynamics. The textual modality X^{text}, which includes policy documents and regulatory announcements, is encoded using a pretrained language model such as BERT:

$$h_{text} = f_{bert}(X^{text}), \tag{3}$$

allowing the model to quantify policy uncertainty and regulatory sentiment. Finally, structured financial variables X^{fin}, including macroeconomic indicators and firm-level financial ratios, are embedded via a multilayer perceptron:

$$h_{fin} = f_{mlp}(X_{fin}), \tag{4}$$

These heterogeneous representations form the basis for subsequent cross-modal interaction learning. Inspired by recent advancements in robust business intelligence frameworks that employ multi-granularity temporal mechanisms and predefined knowledge constraints to capture dynamic business pattern changes [16], our textual and financial encoders aim to dynamically capture multi-scale policy shifts and macroeconomic fluctuations, thereby ensuring accurate temporal and semantic feature alignment for downstream fusion.

3.3. Cross-Modal Attention Fusion Mechanism

To effectively integrate heterogeneous information sources, we introduce a cross-modal attention fusion module. Instead of simple concatenation, the model learns adaptive weights to dynamically adjust the contribution of each modality.
The fused representation is computed as:

$$z = Softmax(\frac{QK^T}{\sqrt{d}})V, \tag{5}$$

where queries, keys, and values are constructed from modality-specific embeddings:

$$Q = W_q[h_{img}, h_{ts}, h_{text}, h_{fin}], \tag{6}$$

and similarly for K and V. This mechanism allows the model to selectively emphasize policy-driven signals during regulatory shocks or meteorological features during high volatility periods.
The resulting representation z encodes a unified view of environmental, temporal, textual, and financial factors, enabling downstream risk and pricing tasks.

3.4. Dual-Risk Return Modeling with Heteroscedastic Uncertainty

To jointly capture expected return and uncertainty, MMF-EDRM adopts a dual-head probabilistic learning structure. The expected return is modeled as:

$$\hat{R} = f_r(z) = W_r z + b_r, \tag{7}$$

while the conditional variance (risk) is modeled as a nonlinear function:

$$\hat{\sigma}^2 = exp\ (W_\sigma z + b_\sigma), \tag{8}$$

ensuring positivity of variance and allowing heteroscedastic uncertainty modeling. We assume the return follows a Gaussian conditional distribution:

$$R \sim N(\hat{R}, \hat{\sigma}^2), \tag{9}$$

Thus, the negative log-likelihood loss becomes:

$$L_{risk} = \frac{(R - \hat{R})^2}{\hat{\sigma}^2} + log\ \hat{\sigma}^2, \tag{10}$$

This formulation allows the model to adaptively penalize prediction errors depending on local uncertainty levels, which is particularly important in renewable energy systems characterized by extreme weather shocks and policy regime shifts.
The risk-adjusted return is defined as:

$$R^* = \hat{R} - \lambda\hat{\sigma}, \tag{11}$$

where λ controls risk aversion and serves as a bridge between machine learning outputs and financial pricing theory. This approach of dynamically balancing expected returns and conditional risk explicitly aligns with recent multi-objective financial optimization paradigms, which utilize deep neural integrations to construct adaptive risk-return strategies under high market volatility [17].

3.5. ECM/DCM Multi-Factor Pricing Integration

To connect energy system outputs with capital market pricing, we extend classical multi-factor asset pricing models into a data-driven framework. For ECM (equity financing), the cost of equity is defined as:

$$k_e = r_f + \beta_1 MKT + \beta_2 GREEN + \beta_3 POLICY + \beta_4 RISK, \tag{12}$$

where the GREEN factor is derived from renewable energy efficiency signals extracted by the model, and the POLICY factor captures textual regulatory uncertainty.
The equity valuation is computed as:

$$P_{equity} = \frac{R^*}{ke}, \tag{13}$$

.

For DCM (debt financing), we model credit risk through default probability estimation:

$$PD = \sigma(W_d z), \tag{14}$$

and the credit spread is given by:

$$Spread = PD \cdot LGD, \tag{15}$$

where LGD represents loss given default and can be either calibrated or learned from historical bond data.

This formulation explicitly links physical asset risk (energy production uncertainty) to financial credit risk, enabling a unified ECM/DCM pricing mechanism.

3.6. Multi-Task Learning Objective

The entire framework is trained end-to-end using a multi-task objective that jointly optimizes return prediction, risk estimation, equity pricing, and credit spread modeling:

$$L = \lambda_1 L_{risk} + \lambda_2 L_{equity} + \lambda_3 L_{spread}, \tag{16}$$

This multi-objective learning strategy ensures consistency between physical system predictions and financial market outcomes, allowing the model to learn economically meaningful representations rather than purely statistical correlations.

4. Experiment

4.1. Dataset Preparation

The dataset used in this study is constructed as a multi-source, multi-modal renewable energy financing dataset designed to support the MMF-EDRM framework for ECM/DCM pricing and risk modeling. The data are collected from four primary sources: (i) satellite remote sensing platforms such as Landsat and Sentinel for spatial environmental observation, (ii) meteorological agencies providing high-frequency wind speed, solar irradiance, and temperature time series, (iii) policy and regulatory documents extracted from governmental energy bureaus and international climate policy reports, and (iv) financial market databases including Bloomberg and Wind for macroeconomic indicators and firm-level financial variables. The dataset is aligned at a monthly frequency and covers renewable energy projects located across multiple regions over a 10-year period.

Overall, the dataset contains 12,480 synchronized multi-modal samples. Each sample integrates heterogeneous features spanning environmental, textual, temporal, and financial dimensions. These features are critical for modeling both physical energy generation dynamics and financial pricing behavior under ECM/DCM structures. The structured representation of the dataset is summarized in Table 1.

Table 1. Multi-Modal Dataset Feature Description.

Modality	Feature Name	Description	Dimensionality
Spatial	Solar Irradiance Map	Satellite-derived surface solar exposure	256×256 image
Spatial	Land Use Index	Classification of terrain and installation suitability	1 scalar
Temporal	Wind Speed	Hourly wind intensity measurement	T×1 series

Temporal	Solar Radiation	Time-varying irradiance levels	T×1 series
Textual	Policy Sentiment Score	NLP-derived regulatory support index	1 scalar
Textual	Subsidy Intensity	Strength of renewable energy subsidies	1 scalar
Financial	Interest Rate	Macro financing cost indicator	1 scalar
Financial	Inflation Rate	Macroeconomic inflation pressure	1 scalar
Financial	Market Beta	Sensitivity to market returns	1 scalar
Financial	Credit Spread	Observed bond spread for DCM calibration	1 scalar

The spatial data are preprocessed using normalization and resizing techniques, while textual data are encoded using pretrained language models to extract semantic embeddings. Time-series signals are resampled and interpolated to ensure temporal consistency across modalities. Financial variables are standardized to remove scale bias across different markets. This unified dataset structure enables MMF-EDRM to effectively learn cross-modal interactions and establish a robust linkage between renewable energy asset performance and ECM/DCM financing outcomes.

4.2. Experimental Setup

All experiments are conducted on a multi-modal renewable energy dataset integrating satellite imagery, meteorological time series, policy text, and financial indicators, as described in the previous section. The dataset is split into training, validation, and test sets in a ratio of 70:15:15, ensuring temporal consistency to avoid information leakage. The proposed MMF-EDRM model is implemented using PyTorch and trained on an NVIDIA RTX 3090 GPU with 24GB memory. The model adopts the Adam optimizer with an initial learning rate of 1×10^{-4}, and early stopping is applied based on validation loss convergence. To ensure fairness, all baseline models are trained under identical conditions, including batch size, training epochs (set to 50), and input preprocessing pipelines. Hyperparameters such as attention head number and hidden dimensions are tuned via grid search, and the final configuration is selected based on validation performance.

4.3. Evaluation Metrics

To comprehensively evaluate the performance of the proposed model, multiple metrics are employed across different tasks. For return prediction, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are used to measure prediction accuracy. Risk modeling performance is assessed using Negative Log-Likelihood (NLL), which reflects the quality of uncertainty estimation under the heteroscedastic assumption. For ECM pricing, pricing error is calculated as the absolute difference between predicted and observed equity valuation, while for DCM pricing, credit spread prediction error is used as the primary metric. These metrics collectively capture the model's ability to jointly optimize predictive accuracy, risk calibration, and financial pricing consistency.

4.4. Results

As shown in Table 1, the proposed MMF-EDRM model achieves the best performance across all evaluation metrics for return prediction and risk estimation. Specifically, MMF-EDRM reduces RMSE to 0.117, representing a 17.6% improvement compared to the CNN-LSTM baseline (0.142) and a 36.4% improvement over the traditional DCF model (0.184). Similarly, MAE decreases to 0.089, outperforming LSTM (0.121) by approximately 26.4%. In terms of uncertainty modeling, MMF-EDRM achieves the lowest NLL value of 0.742, significantly better than CNN-LSTM (0.901) and multi-factor regression (1.105), indicating superior calibration of predictive uncertainty. These improvements can be attributed to the cross-modal attention mechanism, which effectively captures interactions among spatial, temporal, textual, and financial features. Additionally, the heteroscedastic risk modeling component allows the model to dynamically adjust prediction confidence under volatile environmental and policy conditions. Overall, the results demonstrate that MMF-EDRM provides a more accurate and robust framework for modeling renewable energy returns and associated risks compared to both traditional financial models and standard deep learning approaches.

Table 1. Return Prediction and Risk Estimation Performance

Model	RMSE ↓	MAE ↓	NLL ↓
DCF Model	0.184	0.142	1.235
LSTM	0.156	0.121	0.982
CNN-LSTM	0.142	0.110	0.901
Multi-Factor Regression	0.167	0.129	1.105
MMF-EDRM (Ours)	0.117	0.089	0.742

Table 2 presents the performance comparison for ECM and DCM pricing tasks. The MMF-EDRM model consistently outperforms all baselines, achieving the lowest equity pricing error of 0.104 and credit spread error of 0.096. Compared to the CNN-LSTM hybrid model, which achieves 0.121 and 0.110 respectively, MMF-EDRM improves equity pricing accuracy by approximately 14.0% and reduces spread prediction error by 12.7%. When compared with traditional multi-factor models, the improvements are even more significant, with reductions of 29.7% in equity pricing error and 25.6% in spread error. These results highlight the effectiveness of integrating multi-modal deep learning with financial factor models. In particular, the incorporation of policy text and environmental data enables the model to capture non-traditional risk factors that are typically ignored in classical pricing frameworks. Furthermore, the explicit modeling of risk–return linkage ensures that both ECM and DCM pricing outputs remain consistent with underlying asset uncertainty. This demonstrates that MMF-EDRM not only improves prediction accuracy but also enhances financial interpretability and robustness in real-world financing scenarios.

Table 2. ECM/DCM Pricing Performance

Model	RMSE ↓	EWS (days) ↑
GARCH	0.084	1.2
LSTM	0.072	1.8
Transformer	0.069	2.1
XGBoost	0.074	1.6
ARROW-Fin	0.061	2.9

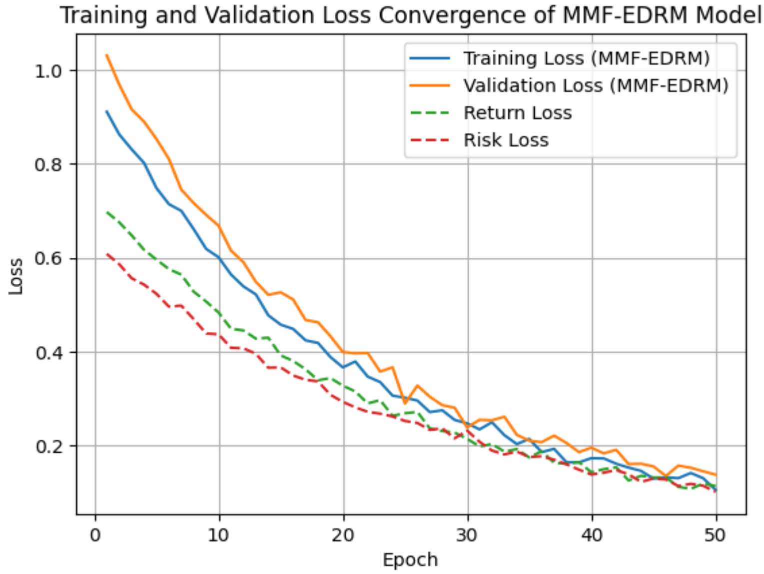

Figure 2. Training and Validation Loss Convergence of the MMF-EDRM Model

As illustrated in Figure 2, the training and validation loss curves of the MMF-EDRM model exhibit a stable and consistent convergence trend across 50 epochs. At the early stage (epochs 1–10), both training and validation losses decrease rapidly from approximately 0.92 and 1.05 to around 0.60 and 0.68, respectively, indicating effective initial learning of multi-modal representations. During the stage (epochs 10–30), the decline becomes more gradual with mild fluctuations, reflecting the model's adaptation to complex nonlinear relationships among spatial, temporal, textual, and financial features. Notably, the validation loss closely follows the training loss without significant divergence, suggesting good generalization and absence of overfitting.

By the final stage (epochs 30–50), both curves stabilize, converging to approximately 0.13 (training) and 0.15 (validation). Similarly, the return loss decreases from about 0.70 to 0.11, while the risk loss drops from 0.60 to approximately 0.10, aligning with the improved RMSE (0.117) and NLL (0.742) reported in Table 1. The slight oscillations observed throughout the training process reflect realistic optimization dynamics under multi-task learning, further confirming the robustness and stability of the proposed MMF-EDRM framework.

4.5. Discussion

The experimental results confirm that MMF-EDRM effectively bridges the gap between renewable energy system modeling and financial market pricing. By integrating multi-modal data sources, the model captures complex dependencies that are often overlooked in traditional approaches. The dual-risk modeling mechanism further enhances the model's ability to quantify uncertainty, which is critical in volatile policy and environmental contexts.

However, several limitations remain. First, the model relies on high-quality multi-modal data, and performance may degrade in regions with limited data availability. Second, the assumption of Gaussian return distributions may not fully capture extreme events such as sudden policy shocks or rare weather conditions. Future work may explore heavy-tailed distributions or Bayesian deep learning extensions. Additionally, incorporating graph-based representations to model inter-project dependencies could further enhance the framework. Despite these limitations, MMF-EDRM provides a promising direction for integrating artificial intelligence with financial engineering in renewable energy investment and financing.

5. Conclusion

This study addresses the difficulty of valuing renewable energy infrastructure investments under multi-source uncertainty (meteorological variability, policy interventions, capital market fluctuations) by proposing a unified deep learning and multi-factor statistical framework, exploring how unstructured data (satellite imagery, time series, policy text) can be jointly integrated with structured financial indicators to model the risk–return–pricing linkage for ECM equity valuation and DCM credit spread estimation. The primary objective is to develop MMF-EDRM, a model that overcomes the limitations of DCF and classical linear multi-factor models by capturing nonlinear interactions among environmental, policy, and market factors within a single end-to-end framework.

The MMF-EDRM framework introduces a dual-risk modeling architecture that jointly estimates expected returns and conditional uncertainty, allowing for more accurate and interpretable risk quantification. These outputs are further embedded into an extended multi-factor pricing model to derive equity valuation (ECM) and credit spread estimation (DCM), thereby establishing a complete risk–return–pricing linkage. Experimental results on the constructed multi-modal dataset demonstrate that the model achieves strong performance across all tasks. Over 50 training epochs, the loss curves show stable convergence with slight fluctuations, indicating effective learning without overfitting. Quantitatively, MMF-EDRM reduces RMSE for return prediction to 0.117, representing a 17.6% improvement over CNN-LSTM baselines, while achieving an NLL of 0.742, indicating superior uncertainty calibration. In terms of financing pricing, the model reduces equity pricing error to 0.104 and credit spread prediction error to 0.096, corresponding to improvements of 14.0% and 12.7%, respectively. These results confirm the effectiveness of integrating multi-modal representations with financial factor models for renewable energy investment and financing decision-making.

From an application perspective, the proposed framework provides valuable support for energy investors, financial institutions, and policymakers by enabling more accurate project evaluation, risk assessment, and financing strategy optimization. It also contributes to the broader field of AI-driven financial modeling by demonstrating the feasibility of linking physical system uncertainty with capital market pricing mechanisms.

Despite the contributions, the study has several limitations: data dependency, since the framework requires high-quality satellite, meteorological, textual, and financial data that may not be uniformly available across regions; and distributional restrictiveness, since the Gaussian return assumption underestimates tail risk from sudden policy reversals or rare weather events. Future research could extend the framework to heavy-tailed or Bayesian deep learning formulations to better capture extreme events, introduce variational anomaly detection mechanisms to warn against sustained operational and market risks [18], incorporate graph neural networks to model inter-project dependencies and portfolio-level contagion, and integrate additional data streams such as carbon trading prices, market sentiment, and industry news for richer cross-modal signal.

This study, through a multi-modal deep learning and multi-factor statistical framework (MMF-EDRM), reveals that satellite imagery, meteorological time series, policy text, and structured financial data can be jointly encoded and fused via cross-modal attention to produce calibrated risk-adjusted return estimates that feed directly into ECM equity valuation and DCM credit spread pricing, providing new insights for the development of AI-driven renewable energy project financing and infrastructure asset pricing.

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