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An Economic Benefit Prediction Method for Investment Projects Based on An Improved Fuzzy Real Options Approach

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Abstract: To optimize current economic benefit forecasting methods and address their uncertainty and ambiguity in uncertain market environments, this study constructs a comprehensive economic benefit forecasting model for investment projects using an Improved Fuzzy Real Options (IFRO) method, a Bidirectional Long Short-Term Memory Network (BiLSTM), and a fuzzy clustering algorithm, thereby improving its forecasting accuracy. The study first analyzes the improved fuzzy Real Options (ROs) method, showing a Root Mean Square Error (RMSE) of 4.3 and a mean percentage error of only 1.1% when forecasting uncertainty risk in investment projects. Furthermore, the accuracy of investment decision-making reaches 92.1% after using this method to predict project uncertainty risk, demonstrating that the (IFRO) method can accurately assess the uncertainty risk of investment projects. The constructed economic benefit forecasting model is then evaluated, showing a trend prediction accuracy of 92.1%. After optimization based on the economic benefit forecasting results, the cost-benefit ratio of the decision-making project reaches 3.2, indicating that the constructed economic benefit forecasting model can accurately predict the economic benefits of investment projects. This model quantifies the uncertainty risks and enhances the accuracy of trend predictions, thereby providing enterprise managers with a multi-dimensional decision-making basis. It helps them dynamically adjust investment strategies and optimize resource allocation in complex market environments, ultimately achieving maximum returns under control.

Keywords: Real options method, economic benefit prediction, bidirectional long short-term memory network, fuzzy clustering algorithm, uncertainty, improved fuzzy real options method.

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1. Introduction

With the increasing complexity of the global economic environment and the intensification of market competition, predicting the Economic Benefits (EBs) of investment projects has become increasingly important in corporate strategic decision-making (Zhang et al., 2024; Liu et al., 2024). Although traditional investment decision-making methods are widely used in practice, they cannot fully capture the flexibility value of project investment in a highly uncertain market environment and are also difficult to effectively address market uncertainty and ambiguity (Suryanarayanan et al., 2024). At present, many scholars use various intelligent algorithms to predict the EBs of different project types to improve prediction accuracy. For example, Cheng et al. (2024) and Li et al. (2023) employed reinforcement learning algorithms and nonlinear models, respectively, to enhance the efficiency of EB forecasting. Additionally, Barja-Martinez et al. (2025) and Rubasinghe et al. (2024) utilized federated learning and convolutional neural networks to optimize EB prediction models, thereby improving their forecasting accuracy. However, current prediction models suffer from low predictive efficiency due to high uncertainty surrounding project information (Zhou et al., 2024).

The Real Options (ROs) approach can assess the uncertainty risks associated with investment projects (Najafi and M. Masih-Tehrani, 2025). However, this method still has limitations when dealing with ambiguous information and uncertain parameters in real-world investment problems (Zhu et al., 2023). Gradient fuzzy numbers can solve the problem description under an uncertain environment and improve the accuracy of the ROs method in capturing investment project risks (Xiao et al., 2024). Many people have studied the above two methods. For example, Xiao et al. (2024) optimized information capture capability using fuzzy numbers, achieving a 12.4% improvement. You et al. (2024) used the fuzzy ROs method to evaluate the solution's uncertainty risk when selecting a supplier's solution. Findings indicated that its evaluation accuracy could reach 92.6%. However, after gradient fuzzy number optimization, the fuzzy option method, because its membership function is often designed based on static assumptions, is difficult to adapt to dynamic changes in the market environment, leading to its failure in uncertain environments. While the Bidirectional Long Short-Term Memory Network (BiLSTM) can simultaneously capture the dependencies in the past and future of the time series by introducing a bidirectional gating mechanism, and is capable of adapting to the dynamic changes of the market environment, the Fuzzy Clustering (FC) algorithm can classify data based on data (Yang et al., 2024; Luo et al., 2023). This method is also often used in various data analyses. For example, Zhang et al. (2024) and Quadri et al. (2024) have respectively employed the FC algorithm and BiLSTM algorithm to enhance the predictive accuracy of their models.

In summary, while artificial intelligence has provided new tools for financial forecasting in recent years, it has generally overlooked uncertainty risks, leading to distorted benefit predictions. This study develops a hybrid forecasting model using AI algorithms to improve the accuracy and adaptability of investment benefit predictions. The novelty of this research manifests in several aspects: First, it improves the fuzzy ROs method by introducing adaptive membership functions. Second, it constructs an EB prediction algorithm that combines BiLSTM and FC layers to enhance prediction accuracy and stability. Finally, it establishes a comprehensive prediction model integrating the Improved Fuzzy Real Options (IFRO) method with the Bidirectional LSTM-Fuzzy Clustering (BLFC) algorithm, offering a new technical pathway for predicting the EBs of investment projects.

2. Methods and Materials

2.1. An IFRO Method Based on Trapezoidal Fuzzy Numbers

ROs serve as a strategic decision-making tool where physical assets function as the underlying assets for options (Elsisi et al., 2025; Yang et al., 2025). They integrate financial market principles into corporate investment evaluations, thereby enhancing the efficiency of project planning and oversight (Alateeq and Pedrycz, 2024; Guo et al., 2024). However, traditional RO methods mostly use triangular fuzzy functions to quantify uncertainty parameters, which have low accuracy in capturing the risks of investment projects and poor predictive performance for uncertainty (Zhan et al., 2023). Gradient fuzzy numbers can solve the problem description under an uncertain environment and can describe the degree of belonging of elements to fuzzy sets (FSs) through piecewise linear membership functions. This method can be used to describe the uncertainty risk in investment projects, thereby enhancing the accuracy of ROs in capturing the risks of investment projects and improving their EB prediction effect. The basic structure of the IFRO based on trapezoidal fuzzy numbers is presented in Fig. 1.

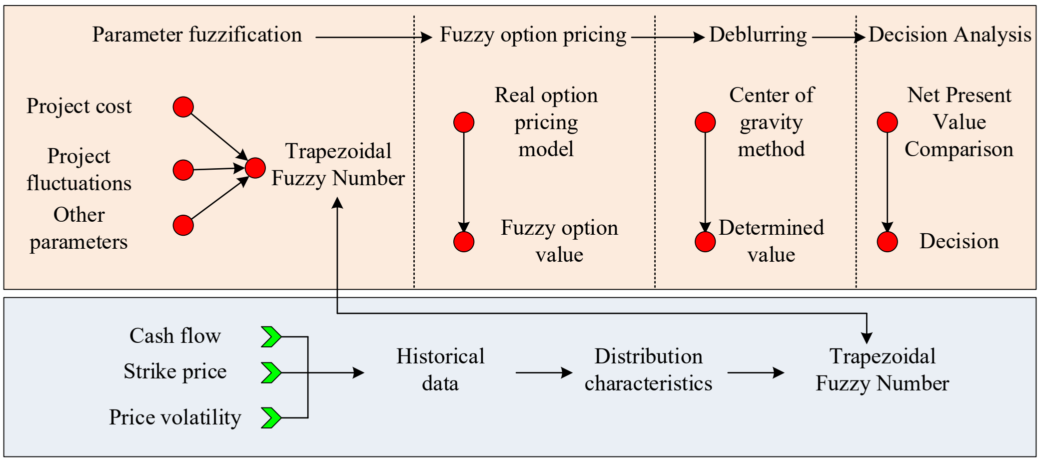


Fig. 1. Structure of IFRO

In Fig. 1, this method comprises four steps: parameter fuzzification, fuzzy option pricing, defuzzification, and decision analysis. During the parameter fuzzification stage, key variables such as cash flow, strike price, and volatility are first obtained. Subsequently, based on historical data, the four key points of the trapezoidal fuzzy number are determined, thereby converting uncertain parameters such as cost and volatility into fuzzy numbers. Its formula is presented in Eq. (1) (Chen et al., 2024).

$$\tilde{A}=(a,b,c,d), a \leqslant b \leqslant c \leqslant d \tag{1}$$

Eq. (1) represents the four key points of the trapezoidal fuzzy number. In Eq. (1), $\tilde{A}$ represents the trapezoidal fuzzy number, a represents the smallest possible value in the FS, b represents the left endpoint of the set with a membership degree (MD) of 1, c represents the right endpoint of the set with an MD of 1, and d represents the largest possible value in the FS. In fuzzy option pricing, the obtained trapezoidal fuzzy number is substituted into the traditional RO pricing model. The traditional RO pricing model is grounded in the Black-Scholes (BS) model, and the basic pricing process of the BS model is presented in Fig. 2.

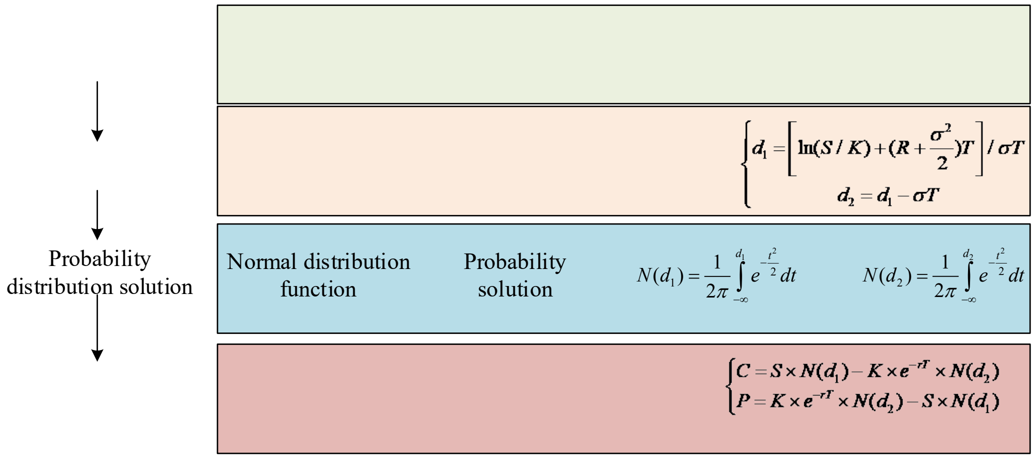


Fig. 2. Pricing process of BS model options

As shown in Fig. 2, the Black-Scholes (BS) model employs a four-step process for pricing Ros that includes parameter estimation, intermediate variable calculation, determination of the probability distribution, and option value computation. During parameter estimation, the project's asset value is used to estimate the project execution cost, the option's validity period, the risk-free interest rate, and volatility. Based on these estimated parameters, the two core variables of the BS model are calculated using Eq. (2) (Sawangtong and Najafi, 2025).

$$\begin{cases} d_1 = \left[\ln(S/K) + (R + \frac{\sigma^2}{2})T\right] / \sigma T \\ d_2 = d_1 - \sigma T \end{cases} \tag{2}$$

Eq. (2) represents the calculation method for the two variables in the BS model. In Eq. (2), d_1 and d_2 are two intermediate variables in the BS model, respectively, σ is volatility, S is the actual price of the underlying asset, T is the option's expiration time, and r is the risk-free interest rate. Then, the cumulative probability of the two variables is computed using the normal distribution function, as given in Eq. (3).

$$\begin{cases} N(d_1) = \frac{1}{2\pi}\int_{-\infty}^{d_1} e^{-\frac{t^2}{2}} dt \\ N(d_2) = \frac{1}{2\pi}\int_{-\infty}^{d_2} e^{-\frac{t^2}{2}} dt \end{cases} \tag{3}$$

Eq. (3) is the calculation formula for solving the key variables in the BS model. Finally, the value of the European call or put option is calculated using the BS model, as shown in Eq. (4) (Xiang, 2025).

$$\begin{cases} C = S \times N(d_1) - K \times e^{-rT} \times N(d_2) \\ P = K \times e^{-rT} \times N(d_2) - S \times N(d_1) \end{cases} \tag{4}$$

Eq. (4) is the calculation method for determining the value of European call options or put options. In Eq. (4), C is the call option and P is the put option price. When using trapezoidal fuzzy numbers for optimization, the parameters in Eq. (4) are replaced with trapezoidal fuzzy numbers. Then, fuzzy operation rules are used to calculate the final RO pricing formula. Defuzzification is the process of transforming the calculated fuzzy option value into a comparable definite value to support decision-making. The centroid method is used to calculate its final value, as shown in Eq. (5).

$$DV = \frac{\int x \cdot \mu\lambda(x) dx}{\int \mu\lambda(x) dx} \tag{5}$$

Eq. (5) is the calculation method for the final option value. In Eq. (5), x represents the elements in the dataset, and $\mu\lambda(x)$ represents the membership function in the dataset, with a value range between 0 and 1. Finally, a decision analysis is conducted, comparing the option value calculated by Eq. (5) with the traditional net present value. Based on the comparison results, it is determined whether to invest in this project.

2.2. EB Prediction Algorithm Combining BiLSTM and FC

After using the improved ROs method to predict the uncertainty in the economic returns of projects, it is also necessary to predict the EBs of projects based on this uncertainty, so as to show the specific future EBs of investment projects and thus determine the decision of the company's management on investment projects (Zhan et al. 2025). BiLSTM can capture bidirectional dependencies in time series via forward and backward LSTM layers, thereby predicting EBs for investment projects based on historical data. The basic structure of BiLSTM and the structure of bidirectional LSTM are presented in Fig. 3.

As shown in Fig. 3(a), BiLSTM simultaneously extracts forward and backward contextual features through bidirectional LSTMs. It concatenates hidden states at each time step to form a complete temporal representation, which is then mapped by a fully connected layer to obtain the final prediction. As shown in Fig. 3(b), LSTM consists of an Input Gate (IG), a Forget Gate (FG), an Output Gate (OG), Cell States (CSs), and a nonlinear Activation Function (AF). LSTM uses CSs to store information for a long time. During CS propagation, the CSs are updated based on the results of the FG and the IG, and the update formula is presented in Eq. (6) (Ben et al., 2025).

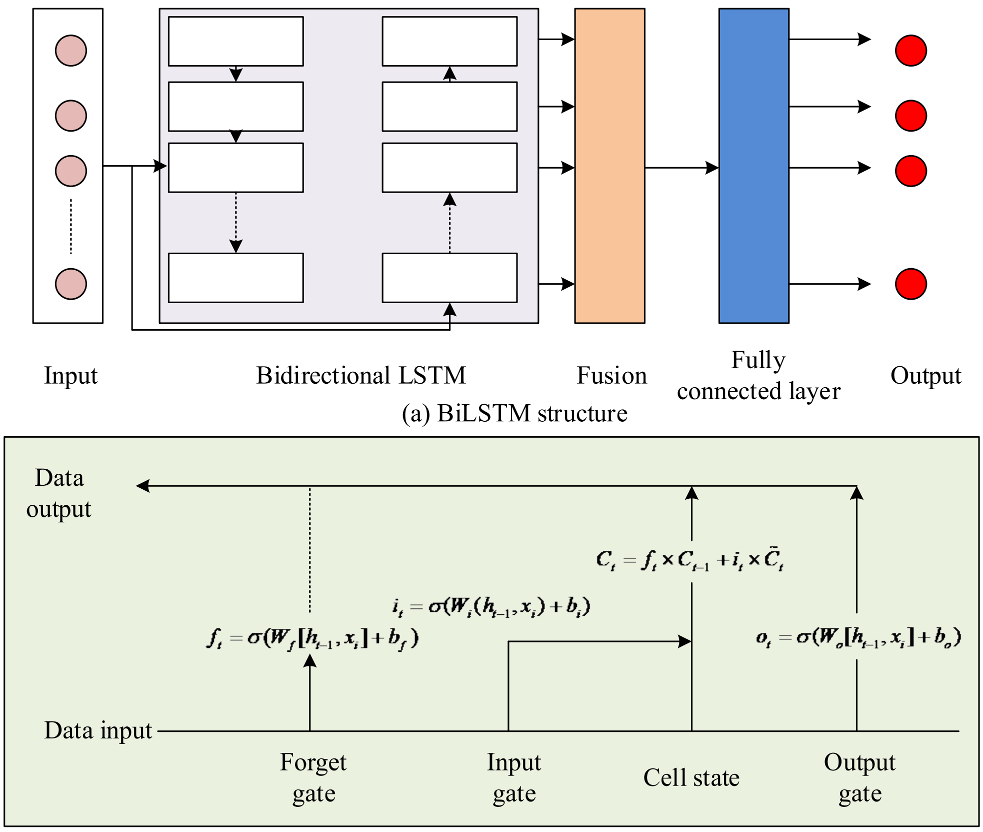


Fig. 3. BiLSTM and LSTM structures

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t. \tag{6}$$

Eq. (6) is the calculation formula for updating the cell state in LSTM. In Eq. (6), C_t is the CS at the current TS, C_{t-1} is the CS at the previous TS, f_t is the FG result, i_t is the IG result, and $\tilde{C}_t$ is the candidate CS at the current TS. The nonlinear AF refers to the use of tanh and sigmoid functions to introduce nonlinearity and enhance the model's expressive power. When used to predict the EBs of investment projects, the option-pricing sequence output by the improved RO method serves as input to the BiLSTM for prediction. Its flowchart is presented in Fig. 4.

As shown in Fig. 4, to predict the EBs of an investment project, IFRO is first used to calculate the option pricing sequence, and then the BiLSTM model is used to extract time-series features from the sequence data in both forward and reverse directions. In the fully connected layer, the high-dimensional features are mapped through the activation function to other EB prediction results, such as the amount of EBs, the level of EBs, and other EBs of the investment project, and then the results are output. After predicting EBs using BiLSTM, the investment project's risk level needs to be classified based on the economic prediction results to clearly display the project's risk, thereby helping managers make investment decisions. The FC algorithm can classify samples using a membership matrix, achieving data classification (Ji et al. 2025). This study uses the FC algorithm to classify BiLSTM predictions, thereby providing support for decision-making. The risk level classification process of investment projects based on FC is presented in Fig. 5.

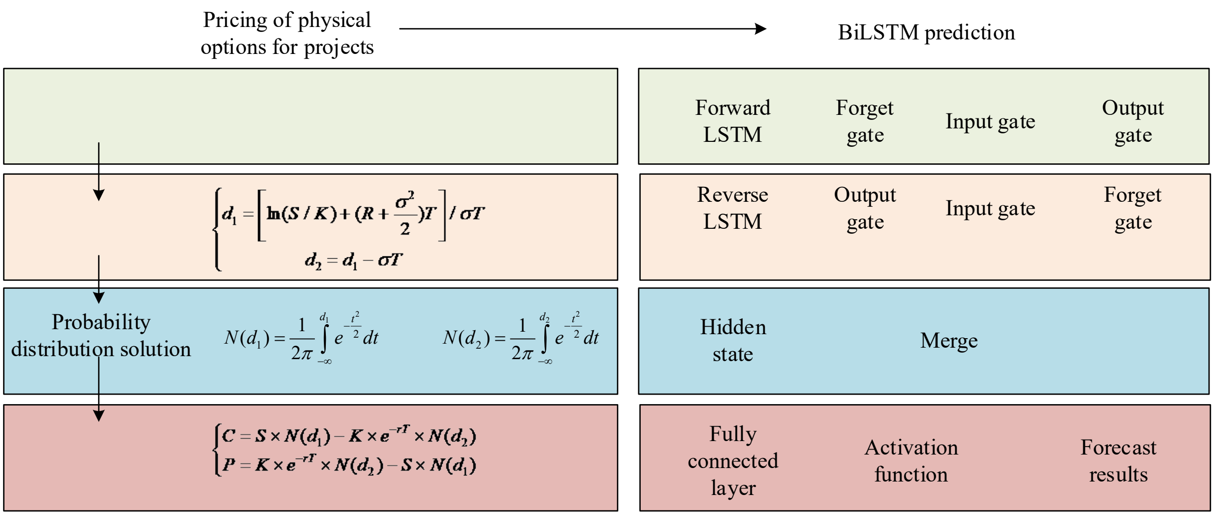


Fig. 4. IRFO BiLSTM prediction process

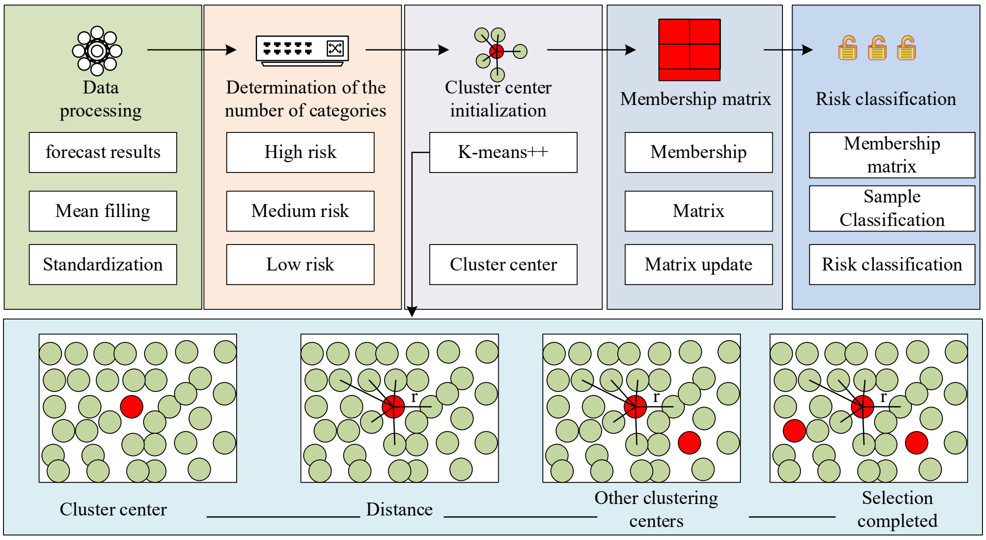


Fig. 5. Risk level classification process

As shown in Fig. 5, the economic forecast results for investment project outputs generated by BiLSTM are first processed when classifying the economic risk level of investment projects. Then, the data are standardized using a Z-score. After data processing, the number of clusters needs to be determined; an initial value of 3 is set, corresponding to high, medium, and low categories. Then, 3 cluster centers (CCs) are initialized using K-means++. When initializing with K-means++, a sample point is randomly selected as the first CC. Then, the minimum distance between other data and the selected CC is calculated. Other CCs are selected according to the probability distribution of the distance. The above process is repeated until 3 CCs are selected. After the CCs are selected, the membership matrix is calculated to describe the degree to which each sample point belongs to different CCs. The calculation formula is presented in Eq. (7).

$$u_{ij}=1/\sum_{k=1}\left(\frac{\| x_i-v_j \|^2}{\| x_i-v_k \|^2}\right)^{m-1} \tag{7}$$

Eq. (7) is the calculation method for the sample MD. In Eq. (7), u_{ij} represents the degree of membership, x_i represents a sample point, j represents the j-th cluster, C represents the number of clusters, m represents the fuzzy factor, v_j represents the center of cluster j, and v_k represents the center of cluster k. The MD between each sample point and the CC is calculated using Eq. (7), resulting in the MD matrix. The MD matrix is then updated using the formula shown in Eq. (8).

$$v_j=\left(\sum_{i=1}^{n}(u_j)^2 x_i\right)/\sum_{i=1}^{n}(u_j)^2 \tag{8}$$

Eq. (8) represents the method for updating the membership matrix. In equations (8), n represents the total sample size. The membership matrix and CCs are continuously updated until the change in CCs between two iterations is less than a preset value, or the max iteration count is reached. Finally, each sample point is assigned to the cluster with the highest MD according to the membership matrix, thus completing the classification of the investment project's risk level.

2.3. A Comprehensive Prediction Model Combining IFRO Method and BLFC

The uncertainty of investment projects is estimated using the IFRO method, and their EBs are predicted and classified using the BLFC model. Company management then conducts decision analysis on investment projects based on the EB predictions and classification results. The basic structure of the IFRO-BLFC model for comprehensive prediction of investment project EBs is presented in Fig. 6.

As shown in Fig. 6, the IFRO-BLFC integrated prediction model comprises a data input layer, a parameter fuzzification layer, a fuzzy option pricing layer, a BiLSTM EB prediction layer, an FC risk classification layer, and a decision support layer. In the data input layer, historical project household counts and industry indices are fed in. The parameter fuzzification layer then converts these inputs into trapezoidal fuzzy numbers. The pricing layer employs IFRO to calculate the project's option value. Subsequently, the prediction layer employs BiLSTM to output the project's EB forecast. The risk classification layer categorizes these forecast values into "high, medium, and low" risk tiers using the FC algorithm. Finally, the decision layer feeds this outcome back to relevant company management personnel. Based on these results, management decides whether to invest in the project or make other managerial decisions.

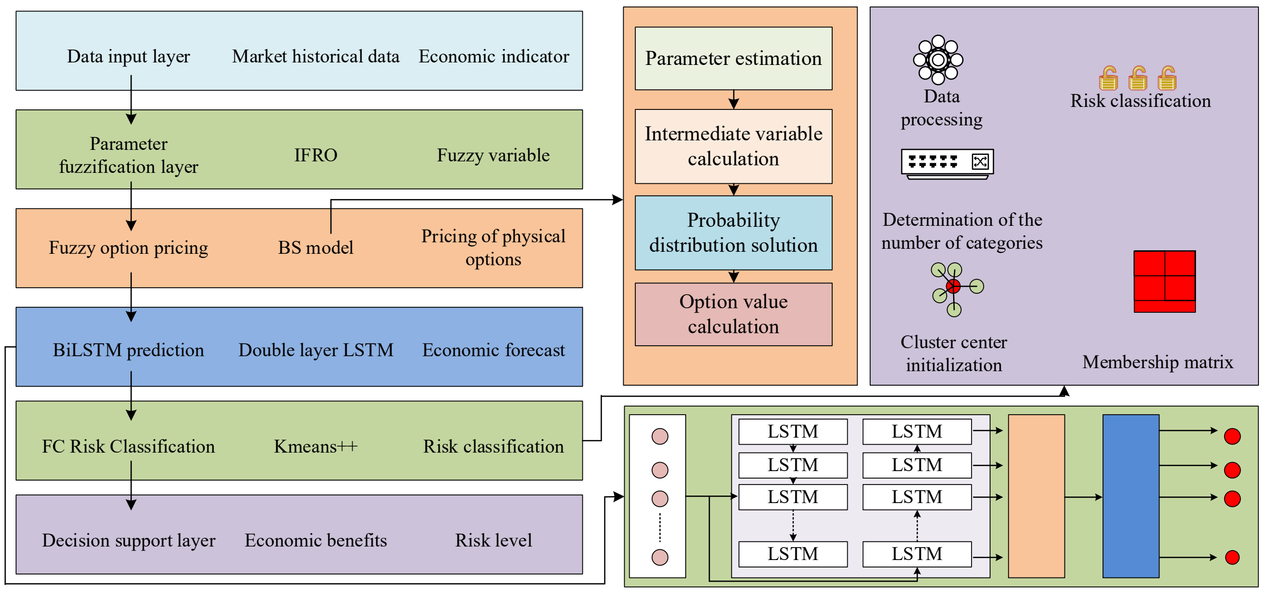


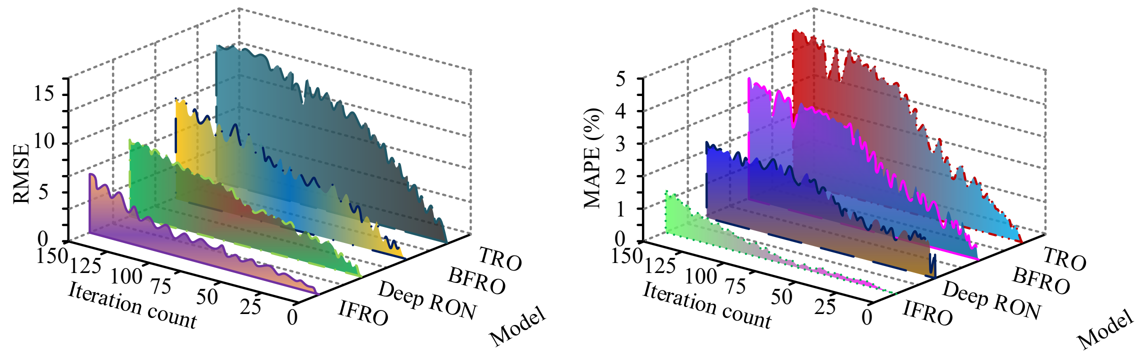
Fig. 6. IFRO-BLFC EB comprehensive prediction model

3. Results and Analysis

3.1. Validation of IFRO Method

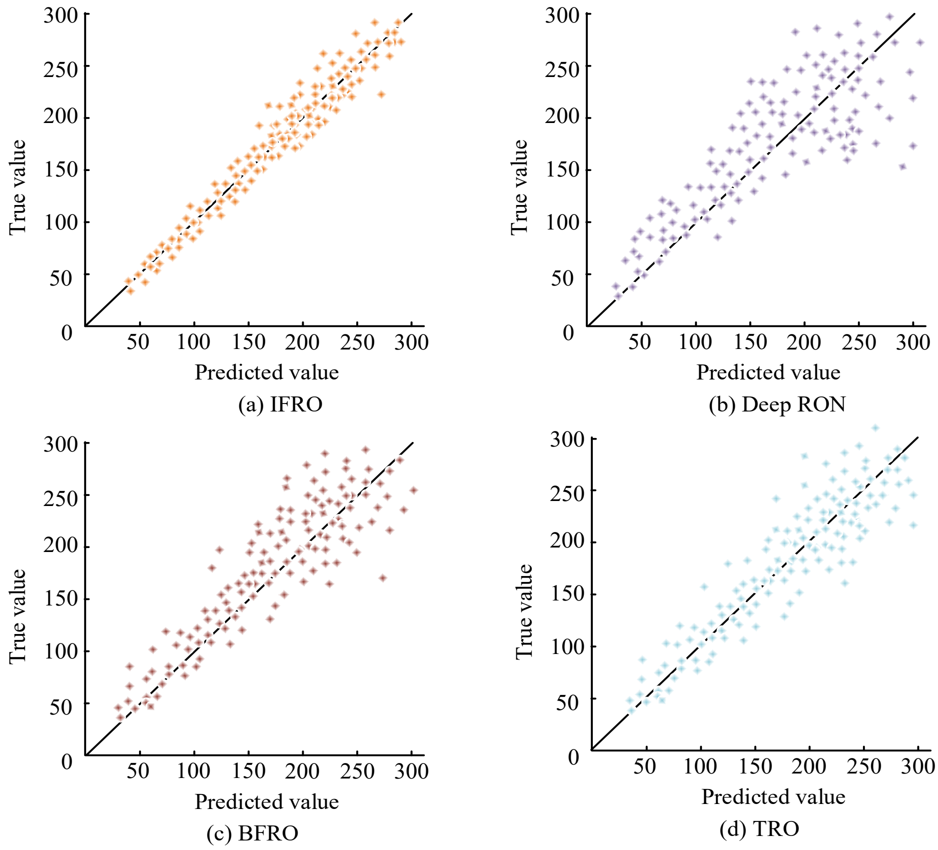
To confirm the efficacy of the introduced IFRO based on trapezoidal fuzzy numbers, this study compared its performance with that of Traditional Real Options (TRO), Bayesian Fuzzy Real Option (BFRO), and Deep Real Options Network (Deep RON). The experimental hardware configuration consisted of an Intel Xeon E5-2680 v4 @ 2.40GHz CPU, an NVIDIA Tesla V100 GPU, and 128GB of RAM; the software environment included the Ubuntu 20.04 LTS operating system, Python 3.8 programming language, and NumPy 1.21.5 as a dependency library. The dataset used was a real-world project dataset from a large energy investment company, covering 150 investment projects from 2014 to 2024. Each project includes all required parameters. The dataset was provided by the investment review department of a large domestic energy group. The time span covered from January 2014 to June 2024 and included 150 completed or stable-operating projects. The project types covered five categories: photovoltaic, wind power, energy storage, comprehensive energy services, and incremental distribution networks. The single project investment scale ranged from 0.8 to 12.4 billion yuan, with an average construction period of 2.3 years and an average operation observation period of 5.1 years. Each sample included key parameters, including the monthly risk-free interest rate, industry-implied volatility, cash flow sequence, initial investment cost, execution price, remaining option period, technical route dummy variable, and project risk level. After performing 3 spline interpolation to fill in the missing quarters of the cash flow sequence, a total of 150 complete samples and 7,800 quarterly observation points were obtained. In the literature on ROs and valuation, when the sample size was less than 200, a common practice was to use 70% for training and 30% for testing to balance the volume of training data and test robustness (Ali and Rafique, 2024). Therefore, this study randomly divided it into a training set and a test set in a 7:3 ratio. In this study, the dataset only contained 150 completed projects. If forced 5-fold or 10-fold cross-validation was conducted, each fold only had 21-30 projects, and all quarterly slices of the same project must be placed in the same fold to avoid information leakage, resulting in a training fold size that is too small, preventing the model from fully learning the long-term cash flow dependency relationship and instead increasing variance. Therefore, cross-validation experiments were not recommended. The study first compares the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) of the four approaches in predicting uncertainty risk in investment projects. The comparison outcomes are presented in Fig. 7.

Comparing Fig. 7(a) and Fig. 7(b), it is evident that IFRO achieved an RMSE of only 4.3 and a MAPE of just 1.1%, both lower than Deep RON, BFRO, and Traditional Real Options (TRO), demonstrating the highest accuracy in uncertainty risk prediction. The error between the Predicted Value (PV) and the Actual Value (AV) for the four methods in predicting EBs of investment projects was then compared, and the results are presented in Fig. 8



(a) RMSE (b) MAPE

Fig. 7. Comparison of RMSE and MAPE



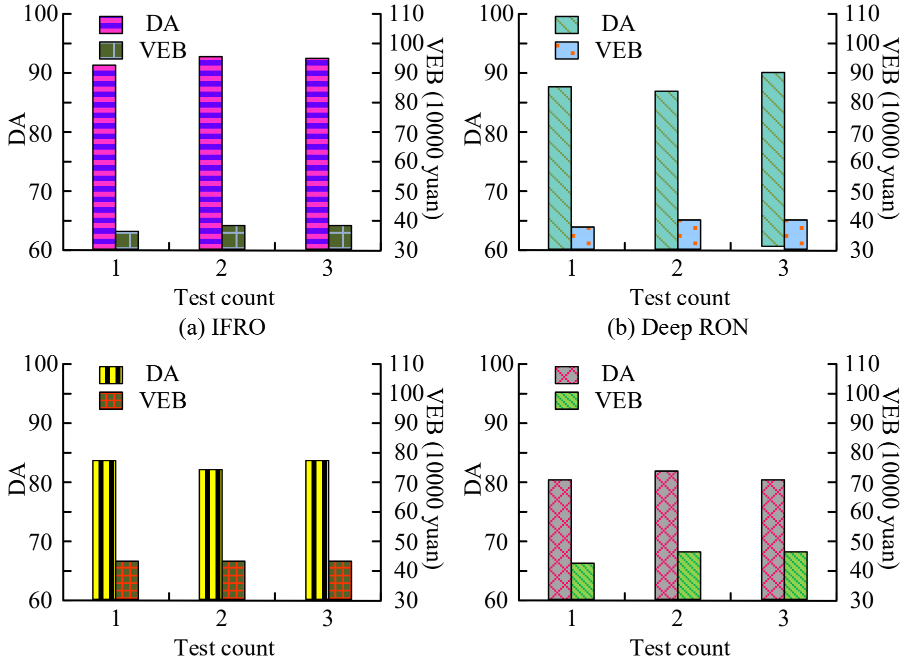
(a) IFRO (b) Deep RON (c) BFRO (d) TRO

Fig. 8. Comparison between PV and AV

As shown in Fig. 8(a), when IFRO predicted project risk, its PV closely matched the AV, resulting in a low prediction error. Fig. 8(b), 8(c), and 8(d) show that Deep RON, BFRO, and TRO predicted project risk with large discrepancies between PV and AV, indicating greater prediction error. Further analysis of its decision-making effectiveness is presented in Fig. 9.

Investment Decision Accuracy (DA) refers to the consistency ratio between the model's recommended decision and the actual optimal decision, while Value Evaluation Deviation (VEB) represents the average deviation between the project's valuation and its AV. As shown in Fig. 9(a), when making investment decisions based on the risks obtained from IFRO, the DA averaged 92.1%, while the VEB value was only 328,000 yuan. As shown in Fig. 9(b), 9(c), and 9(d), the DA values of

Deep RON, BFRO, and TRO are all below 90%, while their VEB values exceed 400,000 yuan. In conclusion, the IFRO method showed significant advantages across all indicators, validating its effectiveness and practicality in predicting the EBs of investment projects.

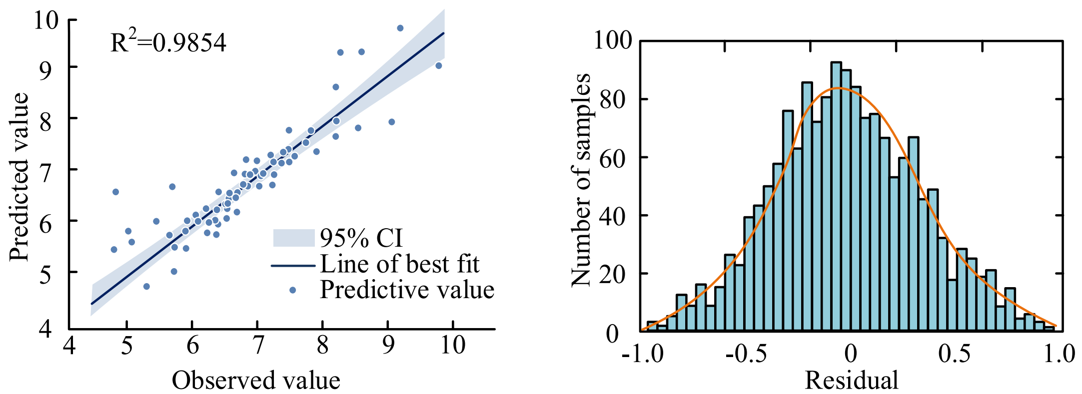


(a) IFRO (b) Deep RON (c) BFRO (d) TRO

Fig. 9. Decision validity

3.2. Performance Verification of EB Prediction Model for Investment Projects

After validating the effectiveness of IFRO, the actual performance of the comprehensive EB prediction model for investment projects based on IFRO-BLFC was then verified. The dataset and experimental environment used for verification were the same as those described above. First, the goodness-of-fit of the IFRO-BLFC prediction model was tested, and the results are presented in Fig. 10.



(a) Correlation of IFRO-BLFC (b) Residual of IFRO-BLFC

Fig. 10. IFRO-BLFC fitting results

As shown in Fig. 10(a), the IFRO-BLFC Predicted Values (PV) exhibit a highly linear correlation with the actual values, with an R^2 value of 0.9854 and an extremely narrow 95% confidence band. This indicates strong explanatory power and high stability of the model. As shown in Fig. 10(b), the model residuals follow a normal distribution, confirming that the risks of both overfitting and underfitting are low. Then, the performance of the IFRO-BLFC prediction model was analyzed against that of more advanced EB prediction models, including those grounded in Support Vector Machine-Machine Learning (SVM-ML), Particle Swarm Optimization-Radial Basis Function (PSO-RBF) and Sparrow Search Algorithm-LSTM (SSA-LSTM). The Trend Prediction Accuracy (TPA) of the four prediction models is analyzed first, and the outcomes are presented in Fig. 11.

As shown in Fig. 11(a), the TPA value of the IFRO-BLFC model can reach 97.3%. Fig. 11(b), 11(c), and 11(d) show that the TPA values of the SVM-ML, Particle Swarm Optimization-Radial Basis Function (PSO-RBF), and SSA-LSTM prediction models are 92.1%, 81.4%, and 80.2%, respectively, all lower than that of the IFRO-BLFC model. Further analysis of the project benefit prediction errors in the training and test sets after decision-making by the prediction models is presented in Fig. 12.

As shown in Fig. 12(a)-(d), the IFRO-BLFC achieves maximum benefit prediction errors of only 6.5% and 6.9% on the training and test sets, respectively, significantly lower than those of SVM-ML, PSO-BRF, and SSA-LSTM. This validates its superior predictive accuracy for investment benefits, providing reliable data support for investment benefit assessment. Analyzing this result, the reason the prediction error of the IFRO-BLFC model was lower than that of other methods was that traditional SVM-ML and PSO-RBF both used the original cash flow or yield sequence as the input, lacking explicit modeling of “cognitive uncertainty” such as policies, interest rates, and raw material prices. In the IFRO-BLFC model, IFRO first used trapezoidal fuzzy numbers to fuzzify key parameters, such as project costs and volatility, thereby condensing macro and micro risks into smooth, bounded sequences. This provided "denoising + enhancement" features for the subsequent network, enabling BiLSTM to no longer need to learn the risk transmission path from high-dimensional original economic variables, thereby significantly reducing prediction error. The response times and memory usage of each individual investment project by the four models were compared to determine the computational complexity of the models. The results are shown in Fig. 13.

In Figure 13(a), as the amount of data increases, both the prediction time and peak memory usage increase for the IFRO-BLFC prediction model when predicting the EBs of a single project. When the data volume reached 500, the model’s prediction time reached 67.8ms, and peak memory usage reached 103.5 MB. From Figure 13(b), it can be known that when the project EBs were predicted by the SVM-ML prediction model, at a data volume of 500, the prediction time and peak memory usage were 102.3ms and 76.9%, respectively. From Figures 13(c) and 13(d), when the data volume was 500, the prediction time and peak memory usage of the PSO-RBF and SSA-LSTM prediction models were both higher than those of the IFRO-BLFC model. From the above results, it can be concluded that the IFRO-BLFC prediction model proposed in this study had a shorter prediction time and lower memory usage when predicting projects. Analyzing this result, in IFRO-BLFC, the BiLSTM network was simplified, retaining only the minimum structure required for the prediction task, whereas SSA-LSTM often stacked the hidden layers to 2-3 to pursue accuracy, with parameter quantity growing exponentially, high computational complexity and high memory consumption. Moreover, both PSO-RBF and SSA-LSTM required 50-100 rounds of hyperparameter or weight optimization using metaheuristic algorithms before inference, resulting in significant CPU overhead. The FC layer of IFRO-BLFC performed only one matrix power iteration, and the MD calculation could be batched, transforming “repeated optimization” into “light matrix multiplication” and naturally saving substantial computing time and reducing computational complexity on the same hardware. Finally, the practical application effect of the economic prediction model was verified, and the outcomes are presented in Table 1.

Table 1 shows that the IFRO-BLFC prediction model exhibited the best performance across all aspects of the investment project. Its cost-benefit ratio, risk value prediction accuracy, and risk sensitivity analysis accuracy were 3.2%, 92.8%, and 94.3%, respectively, all higher than the other three comparative models. These results showed that the proposed IFRO-BLFC project EB prediction model accurately estimates EBs for investment projects, thereby reducing the investment payback period and improving the cost-benefit ratio. After adjusting the model parameters, the TPA of the IFRO-BLFC model was compared. This was done to assess the model’s parameter sensitivity. The results are shown in Table 2.

As shown in Table 2, the fluctuation range of the trapezoidal fuzzy number coverage degree and the hidden layer dimension within ±10% was only 1.2%, indicating a low-sensitivity zone. This indicated that once the front-end IFRO was determined, the subsequent network width had a limited impact on trend prediction. In engineering, SW and h can be set directly to “calibration value + 128” without online fine-tuning. Changes in the hidden-layer dimension of BilSTM and the number of clusters had trivial effect on the TPA value, so they did not need to be focused on. However, when the learning rate was -10%, the TPA dropped by 5.9%. Therefore, during model deployment, it was necessary to monitor and verify its learning rate in real time. Moreover, when the model was used for data prediction of other types, the IFRO layer only needed to replace the “risk parameter set.” The four endpoints of the trapezoidal fuzzy number can be automatically updated based on industry data, without modifying the fuzzy operation rules. The model has good scalability.

Table 1. Actual application effect

Predictive model	Cost-benefit ratio	Payback period	Accuracy of value at risk prediction	Accuracy of risk sensitivity analysis
IFRO-BLFC	3.2	2.3	92.8%	94.3%
SVM-ML	2.8	3.1	87.9%	89.2%
PSO-RBF	2.6	3.2	83.6%	86.7%
SSA-LSTM	2.5	3.5	80.8%	82.4%

Table 2. Actual application effect

Predictive model	-10%	-5%	+5%	+10%
Trapezoidal fuzzy number coverage degree	95.7%	96.5%	96.9%	96.3%
Hidden layer dimension of BilSTM	96.1%	96.8%	97.2%	97.3%
Learning rate	91.4%	95.1%	97.0%	96.2%
Number of clusters	94.8%	96.6%	97.1%	96.5%

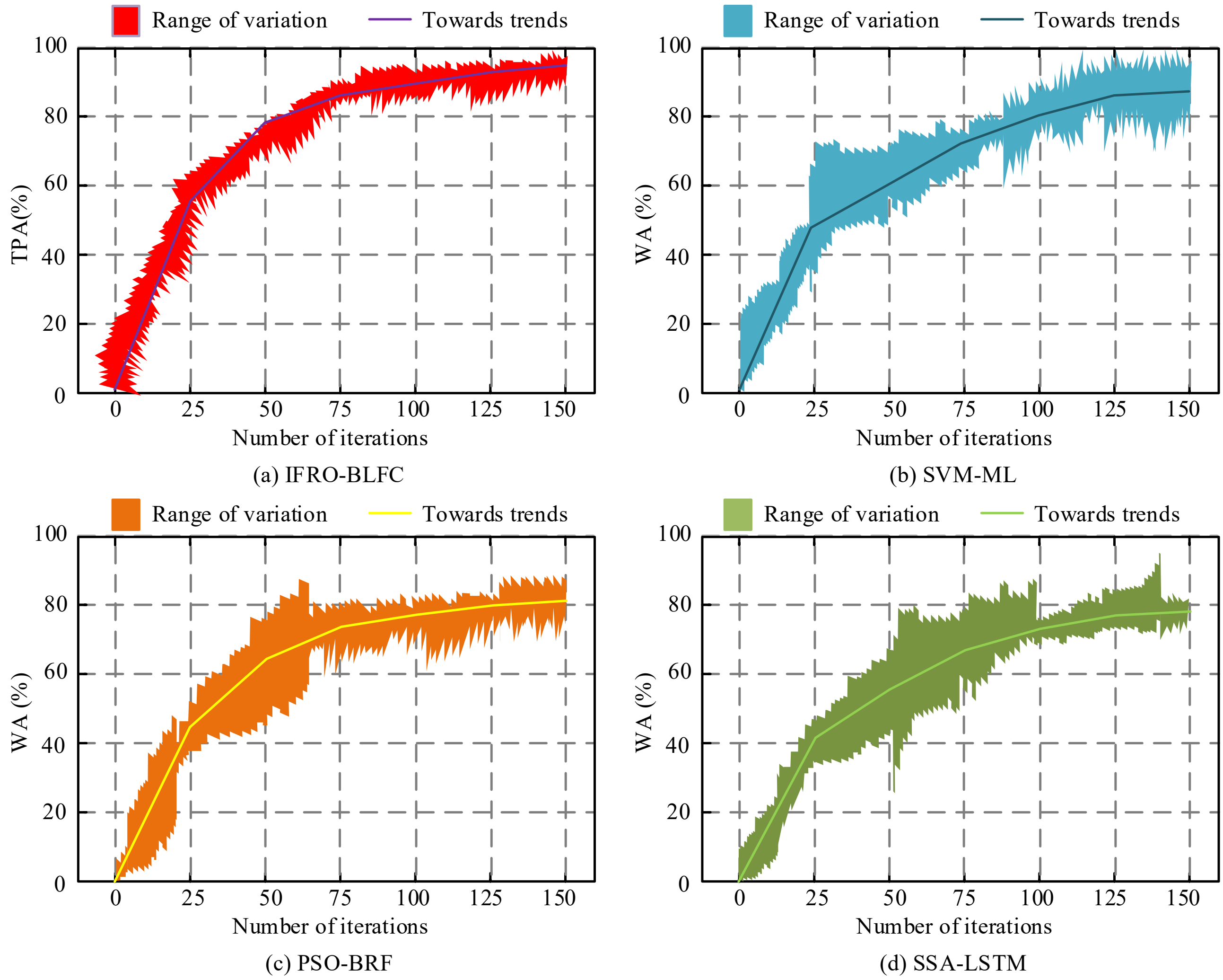
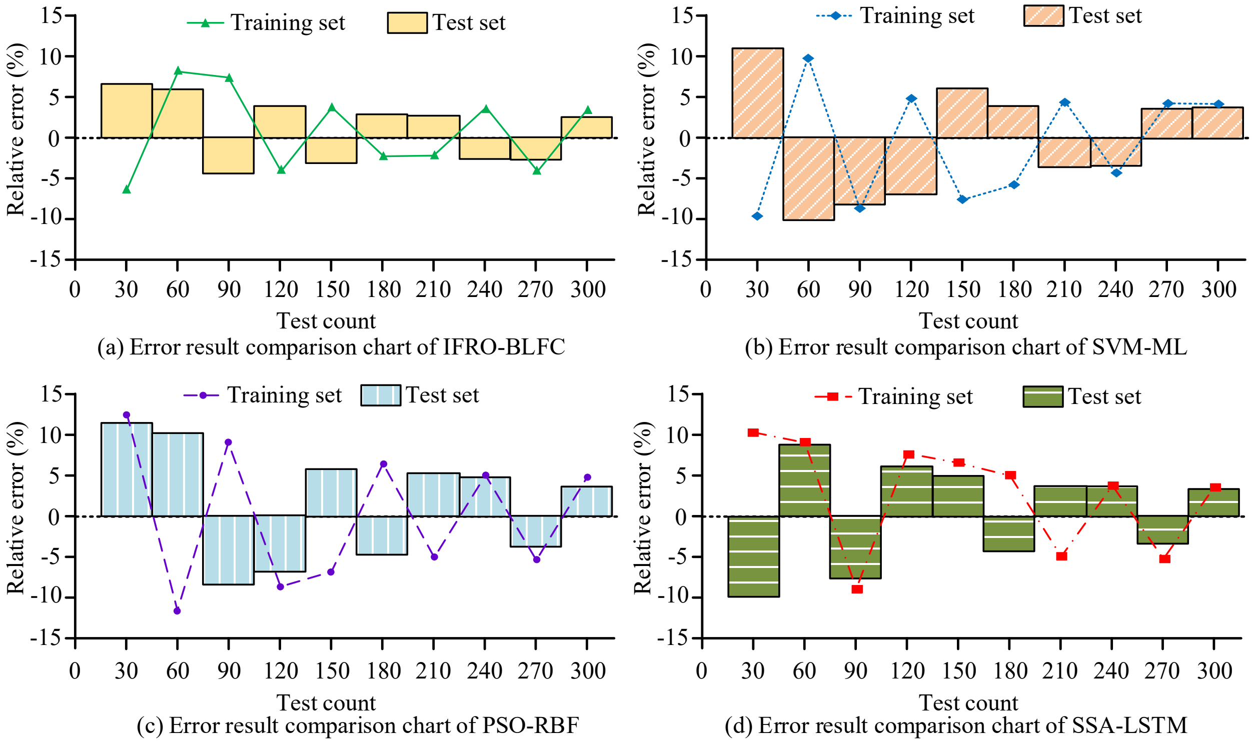


Fig. 11. Model TPA value

4. Conclusion

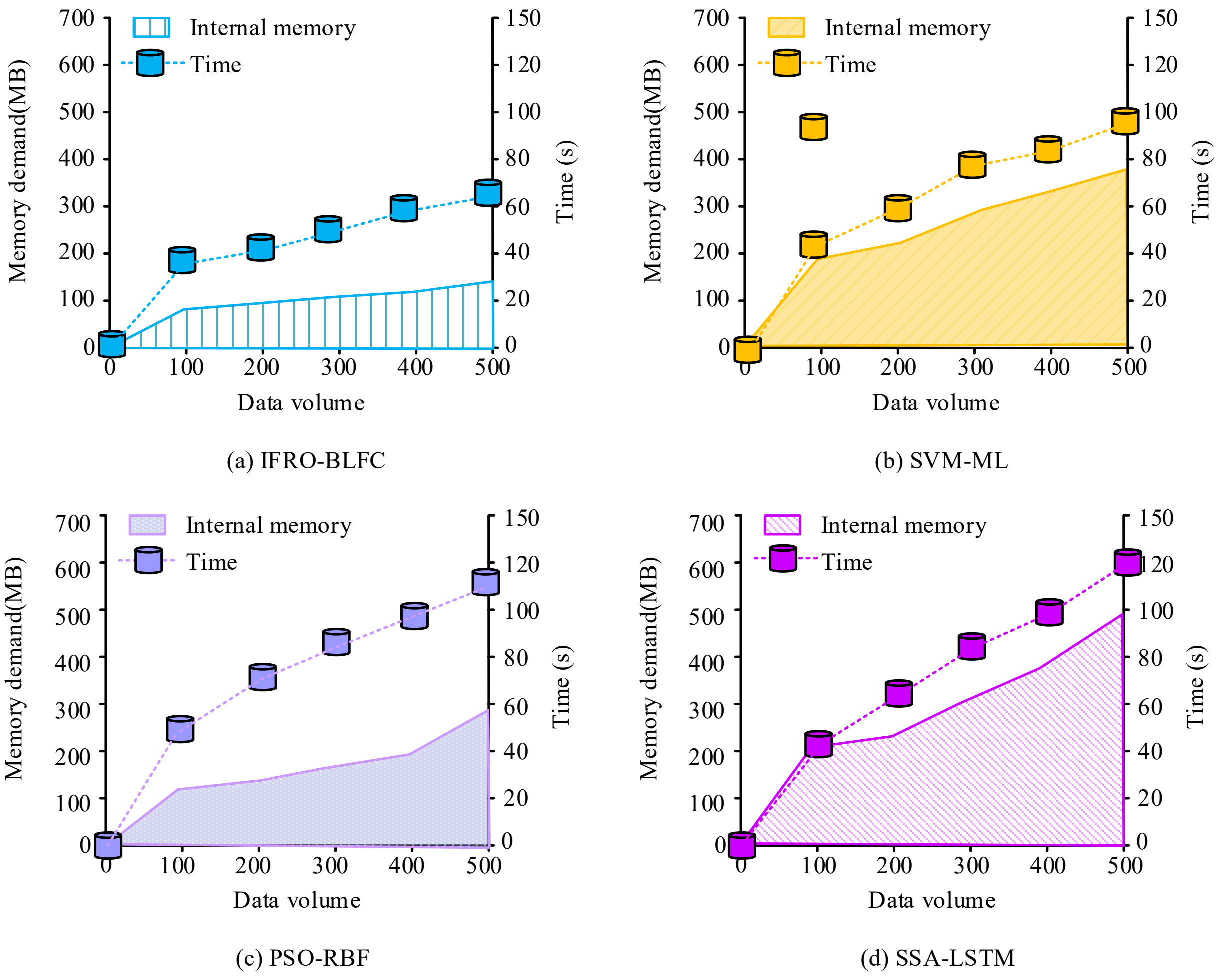
To predict the EBs of investment projects, reduce investment risks, and ensure the company's EBs, this study used the IFRO method to first calculate the ROs of investment projects, and then used BLFC to predict the EBs and risk levels of the projects based on the ROs, aiming to help relevant personnel make better decisions on investment projects through the prediction results. First, the effectiveness of the IFRO was analyzed, comparing it with Deep RON, BFRO, and TRO. The comparison findings demonstrated that IFRO had the lowest RMSE when predicting investment project uncertainty, averaging only 4.3, while Deep RON, BFRO, and TRO had RMSE values of 7.4, 9.8, and 13.2, respectively, higher than IFRO. Furthermore, IFRO's average DA value reached 92.1%, higher than those of other methods, while its VEB value was only 328,000 yuan, lower than those of other methods. These results indicated that the proposed IFRO method could analyze the uncertainty risk in the EBs of investment projects, providing accurate data support for subsequent EB risk prediction. The test results mentioned above were roughly similar to those reported by Esfandiari et al. (2024).



(a) Error result comparison chart of IFRO-BLFC (b) Error result comparison chart of SVM-ML

(c) Error result comparison chart of PSO-RBF (d) Error result comparison chart of SSA-LSTM

Fig. 12. Project revenue prediction error



(a) IFRO-BLFC (b) SVM-ML

(c) PSO-RBF (d) SSA-LSTM

Fig. 13. Peak single item prediction time and memory usage for four models

The validity of the IFRO-BLFC prediction model was analyzed. The performance of the IFRO-BLFC prediction model was compared with that of the SVM-ML, PSO-RBF, and SSA-LSTM prediction models. The findings demonstrated that when the IFRO-BLFC prediction model was used to predict investment projects, its TPA value reached 97.3% after 500 iterations, which was higher than those of the SVM-ML (92.1%), PSO-RBF (81.4%), and SSA-LSTM (80.2%) prediction models. Furthermore, after making decisions on projects based on the IFRO-BLFC model's prediction results, the cost-benefit ratio of the investment projects reached 3.2, which was higher than that of other prediction models. The above results indicated that the IFRO-BLFC economic prediction model accurately predicts the EBs of investment projects and can improve the cost-benefit ratio of projects based on these predictions. This result was similar to those of Zhang et al. (2024).

In summary, the proposed IFRO-BLFC forecasting model could accurately predict the EBs of investment projects. Based on the forecast results, relevant company managers could make decisions that are more beneficial to the company and improve the cost-effectiveness ratio of the projects. Although the bidirectional LSTM gating mechanism in IFRO-BLFC alleviated the gradient vanishing and exploding problems in traditional recurrent neural networks to some extent, it still struggled to fully retain information for extremely long sequences. In the future, attention mechanisms can be introduced to compute correlations across all positions in the sequence in parallel, addressing the problem of long sequence dependencies.

Author Contributions

Ting Wang contributed to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision, project administration, and funding acquisition. Yijing Liu contributed to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, visualization and supervision. Yu'na Si contributed to conceptualization, methodology, software, validation, analysis, investigation, data collection, supervision and project administration. Jingye Lyu contributed to conceptualization, data collection, draft preparation, manuscript editing, and visualization. Xianpeng Yuan contributed to conceptualization, methodology, software, analysis, manuscript editing, visualization, supervision and project administration.

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Institutional Review Board Statement

Not applicable.

Declaration of Artificial Intelligence (AI) Tools

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References

Alateeq, M. and Pedrycz, W. (2024). Multicontext fuzzy clustering: Toward interpretable fuzzy clustering. *IEEE Transactions on Fuzzy Systems,* 32(12), 6720-6730. doi: 10.1109/TFUZZ.2024.3460075

Ali, M. A. and Rafique, Q. (2024) Strategic Integration of Real Options for Enhanced Valuation and Optimization in Mining Project Planning under Uncertainty: A Comprehensive Review. *International Journal of Project Management,* 6(2), 26-50. doi: 10.47672/ijpm.2004

Barja-Martinez, S., Teng, F., Junyent-Ferré, A., and Aragüés-Peñalba, M. (2025). Personalized federated learning with cost-oriented load forecasting for home energy management systems. *IEEE Transactions on Industry Applications*, 61(1), 1410-1419. doi: 10.1109/TIA.2024.3462668

Ben, C., Peng, Y., Wang, Y., Zhang, Q. Y., Guo, L. T., and Lin, Y. (2025). Enhanced multi-band spectrum prediction using singular spectrum analysis and attention-based BiLSTM. *IEEE Transactions on Cognitive Communications and Networking*, 11(1), 118-126. doi: 10.1109/TCCN.2024.3415627

Cheng, L., Zang, H., Trivedi, A., Srinivasan, D., Wei, Z., and Sun, G. (2024). Mitigating the impact of photovoltaic power ramps on intraday economic dispatch using reinforcement forecasting. *IEEE Transactions on Sustainable Energy*, 15(1), 3-12. doi: 10.1109/TSTE.2023.3261444

Chen, H., Duan, Y., Nie, F., Wang, R., and Li, X. (2024). Fuzzy clustering from subset-clustering to fullset-membership. *IEEE Transactions on Fuzzy Systems*, 32(9), 5359-5370. doi: 10.1109/TFUZZ.2024.3421576

Elsisi, M., Ali, M. N., Aljohani, T. M., and Sharawy, M. (2025). A new variable step fuzzy logic control technique for minimum emission point tracking of ship microgrid. *IEEE Transactions on Transportation Electrification*, 11(1), 3323-3336. doi: 10.1109/TTE.2024.3439000

Esfandiari, S., Davari, M., Gao, W., Yang, Y., and Al-Haddad, K. (2024). A novel converter-based PV emulator control using Lambert W method and fractional-order fuzzy proportional-integral controller trained by Harris Hawks optimization for PV inverter-based resources. *IEEE Journal of Emerging and Selected Topics in Industrial Electronics,* 5(4), 1493-1507. doi: 10.1109/JESTIE.2024.3396140

Guo, L., Zhan, J., Zhang, C., and Xu, Z. (2024). A large-scale group decision-making method fusing three-way clustering and regret theory under fuzzy preference relations. *IEEE Transactions on Fuzzy Systems*, 32(9), 4846-4860. doi: 10.1109/TFUZZ.2023.3335965

Ji, X., Sun, J., Peng, J., Pang, Y., and Zhou, P. (2025). Clustering ensemble based on fuzzy matrix self-enhancement. *IEEE Transactions on Knowledge and Data Engineering,* 37(1), 148-161. doi: 10.1109/TKDE.2024.3489553

Li, Y., Vilathgamuwa, D. M., Quevedo, D. E., Lee, C. F., and Zou, C. (2023). Ensemble nonlinear model predictive control for residential solar battery energy management. *IEEE Transactions on Control Systems Technology*, 31(5), 2188-2200. doi: 10.1109/TCST.2023.3291540

Liu, C., Wang, C., Yao, W., and Liu, C. (2024). Distributed low-carbon economic dispatching for multiple park-level integrated energy systems based on improved Shapley value. *IEEE Transactions on Industry Applications*, 60(6), 8088-8102. doi: 10.1109/TIA.2024.3429068

Luo, N., Yu, H., You, Z., Li, Y., Zhou, T., and Han, N. (2023). Fuzzy logic and neural network-based risk assessment model for import and export enterprises: A review. Journal of Data Science and Intelligent Systems, 1(1), 2-11. doi: 10.47852/bonviewJDSIS32021078

Najafi, A., and Masih-Tehrani, M. (2025). Adaptive state of power estimation using fuzzy logic real driving patterns recognition based on error-effort tradeoff. *IEEE Transactions on Transportation Electrification*, 11(5), 11866-11877. doi: 10.1109/TTE.2025.3582631

Quadri, Z. F., Akhoon, M. S., and Loan, S. A. (2024). Epileptic seizure prediction using stacked CNN-BiLSTM: A novel approach. *IEEE Transactions on Artificial Intelligence*, 5(11), 5553-5560. doi: 10.1109/TAI.2024.3410928

Rubasinghe, O., Zhang, X., Chau, T. K., Chow, Y. H., Fernando, T., and Iu, H. H. C. (2024). A novel sequence-to-sequence data modelling based CNN-LSTM algorithm for three-years-ahead monthly peak load forecasting. *IEEE Transactions on Power Systems,* 39(1), 1932-1947. doi: 10.1109/TPWRS.2023.3271325

Sawangtong. P. and Najafi. A. (2025) Collocation method with Morgan-Voyce polynomials to solve the time fractional long memory Black-Scholes model with jump process. *Journal of Applied Mathematics and Computing.* 2, 71(6), 8123-61. doi: 10.1007/s12190-025-02604-y

Suryanarayanan, S., Puradbhat, S., Bhavaraju, V., Balasubramanian, P., Kapoor, A., and Zhang, L. C. (2024). The microgrid controller: An empowering technology at the grid edge—Realizing benefits from microgrids via sequential de-risking of controller technology. *IEEE Power and Energy Magazine,* 22(2), 78-89. doi: 10.1109/MPE.2023.3345276

Xiao, Y., Zhan, J., Xu, Z., and Martínez, L. (2024). Heterogeneous group consensus method with three-way decisions based on fuzzy social networks and manipulation behaviors under multiscale information systems. *IEEE Transactions on Fuzzy Systems,* 32(9), 5122-5135. doi: 10.1109/TFUZZ.2024.3414849

Xiao, Y., Zhan, J., Zhang, C., and Wu, W. Z. (2024). Three-way decision method within prospect theory via intuitionistic fuzzy numbers in multiscale decision information systems. *IEEE Transactions on Fuzzy Systems*, 32(9), 4820-4834. doi: 10.1109/TFUZZ.2023.3329486

Xiang, S. (2025) Research on Option Pricing Method Based on the Black-Scholes Model. *Economics and Management Innovation.* 2(1), 69-77. doi:10.71222/k8mkc798

Yang, A., Xie, B., Liu, Y., Wang, L., and Li, J. (2024). A network security situation prediction for consumer data in the Internet of Things using variational mode decomposition (VMD) and fused CNN-BiLSTM-attention. *IEEE Transactions on Consumer Electronics,* 70(1), 1122-1133. doi: 10.1109/TCE.2023.3323546

Yang, Y., Li, G., Li, D., Zhang, J., Hu, P., and Hu, L. (2025). Integrating fuzzy clustering and graph convolution network to accurately identify clusters from attributed graph. *IEEE Transactions on Network Science and Engineering*, 12(2), 1112-1125. doi: 10.1109/TNSE.2024.3524077

You, B., Rahim, M., Amin, F., Ahmad, S., and Asim, M. (2024). TOPSIS-based nonlinear programming method in cubic p, q–quasirung orthopair fuzzy environment: Application in green supplier selection. *IEEE Access,* 12, 114722-114734. doi: 10.1109/ACCESS.2024.3444605

Zhang, Q., Shukla, A., and Xie, L. (2024). Efficient scenario generation for chance-constrained economic dispatch considering ambient wind conditions. *IEEE Transactions on Power Systems*, 39(4), 5969-5980. doi: 10.1109/TPWRS.2023.3349237

Zhang, R., Duan, Y., Nie, F., Wang, R., and Li, X. (2024). Unsupervised deep embedding for fuzzy clustering. *IEEE Transactions on Fuzzy Systems, 32*(12), 6744-6753. doi: 10.1109/TFUZZ.2024.3462545

Zhang, T., Huang, Y., Liao, H., Gong, X., and Peng, B. (2024). Short-term power forecasting and uncertainty analysis of wind farm at multiple time scales. *IEEE Access,* 12, 25129-25145. doi: 10.1109/ACCESS.2024.3365493

Zhan, J., Cai, M., and Li, Q. (2025). Fuzzy clustering-based three-way asynchronous consensus for identifying manipulative and herd behaviors. *IEEE Transactions on Fuzzy Systems*, 33(10), 3529-3541. doi: 10.1109/TFUZZ.2025.3596689

Zhan, J., Deng, J., Xu, Z., and Martínez, L. (2023). A three-way decision methodology with regret theory via triangular fuzzy numbers in incomplete multiscale decision information systems. *IEEE Transactions on Fuzzy Systems*, 31(8), 2773-2787. doi: 10.1109/TFUZZ.2023.3237646

Zhou, Y., Wen, Q., Song, J., Cui, X., and Wang, Y. (2024). Load data valuation in multi-energy systems: An end-to-end approach. *IEEE Transactions on Smart Grid,* 15(5), 4564-4575. doi: 10.1109/TSG.2024.3392987

Zhu, J., Ma, X., Martínez, L., and Zhan, J. (2023). A probabilistic linguistic three-way decision method with regret theory via fuzzy c-means clustering algorithm. *IEEE Transactions on Fuzzy Systems,* 31(8), 2821-2835. doi: 10.1109/TFUZZ.2023.3236386

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