Research on Optimization of Enterprise Financial Performance Evaluation System Based on RBF Neural Network Algorithm in the Era of Data Analysis

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ABSTRACT The increasing complexity of multi-source heterogeneous financial data requires intelligent nonlinear modeling approaches capable of efficient feature extraction and adaptive decision-making. To address the limitations of conventional financial performance evaluation systems, this study proposes an optimized enterprise financial performance evaluation framework based on a Radial Basis Function (RBF) neural network. A multidimensional indicator system covering profitability, solvency, operational capability, growth potential, cash flow, and financial risk control is first reconstructed, and factor analysis is employed to eliminate redundant variables and generate compact feature representations for network training. A three-layer RBF neural network is subsequently established to perform nonlinear mapping between financial indicators and comprehensive performance scores, enabling objective evaluation without subjective weight assignment. Empirical validation using enterprises from multiple industries demonstrates that the proposed model achieves superior evaluation accuracy, faster convergence, enhanced generalization capability, and improved dynamic prediction performance compared with traditional assessment approaches. The integration of factor analysis and RBF learning effectively captures latent nonlinear relationships embedded in complex financial data and provides a scalable intelligent evaluation architecture. Beyond financial management, the proposed feature extraction and nonlinear inference strategy offers valuable methodological references for multidimensional signal analysis, adaptive pattern recognition, electromagnetic information processing, and antenna-assisted intelligent sensing systems that require robust modeling of heterogeneous data streams.

INDEX TERMS RBF neural network, financial performance evaluation, factor analysis, nonlinear feature extraction, electromagnetic information processing

I. INTRODUCTION

A. RESEARCH BACKGROUND AND SIGNIFICANCE

WITH the comprehensive penetration of big data, cloud computing, intelligent algorithms, and business data analysis technologies in modern enterprise management, human society has officially entered the era of data analysis [1]. The financial data, operational data, market data, and supply chain data generated by enterprise operations have shown explosive growth, and the data volume has shifted from traditional structured small samples to massive multi-source heterogeneous big data. The value of data has become a core production factor for enterprise strategic decision-making, risk control, and performance evaluation [2]. At the same time, artificial intelligence and intelligent biomimetic algorithms are rapidly maturing, and intelligent algorithms such as BP neural network, RBF radial basis function neural network, genetic algorithm, support vector machine, etc. are widely used in fields such as economic forecasting, performance evaluation, risk warning, and financial modeling [3]. Among them, RBF radial basis function neural network has outstanding advantages such as fast convergence speed, strong nonlinear approximation ability, excellent generalization performance, high fault tolerance, less likely to fall into local optima, and is highly adaptable to complex data structures, ranging from high-frequency transactional big data to periodic summary reports. It can effectively explore the nonlinear correlation between multiple financial indicators of enterprises, avoid the limitations of subjective weighting and linear assumptions of traditional evaluation methods, and provide a new technical path for the optimization and reconstruction of enterprise financial performance evaluation system [4].

B. RESEARCH SIGNIFICANCE

Theoretical significance: Firstly, enrich the interdisciplinary research system of intelligent algorithms and enterprise financial management [5]. This article introduces the RBF neural network algorithm into the field of enterprise financial performance evaluation, breaking through the traditional research paradigm of linear models and subjective weighting in financial performance evaluation. It constructs an intelligent algorithm driven theoretical framework for financial performance evaluation in the era of data analysis, and expands the theoretical application boundaries of neural network algorithms in financial performance evaluation and enterprise management analysis [6]. Secondly, improve the theoretical logic of optimizing the financial performance evaluation system for enterprises [7]. Systematically analyze the characteristics of enterprise financial data, pain points in performance evaluation, and limitations of traditional models in the era of data analysis, clarify the internal mechanism of RBF neural network adaptation to financial performance evaluation, establish a complete research paradigm of "indicator screening system reconstruction algorithm modeling empirical testing system optimization", and provide theoretical reference and paradigm reference for similar intelligent financial evaluation research in the future [8]. Thirdly, fill the research gap in nonlinear financial performance evaluation theory. Traditional evaluations often assume that financial indicators are linearly correlated [9]. This article relies on the powerful nonlinear approximation ability of RBF neural networks to verify the nonlinear interaction law between enterprise financial indicators, improve the theoretical connotation of comprehensive evaluation of enterprise financial performance from a nonlinear perspective, and promote the transformation and upgrading of financial evaluation theory from a linear paradigm to an intelligent nonlinear paradigm [10].

Practical significance: Provide feasible solutions for building an intelligent financial performance evaluation system for enterprises. This article reconstructs a multidimensional financial performance indicator system covering profitability, debt repayment, operation, growth, cash flow, and risk control capabilities, and builds an intelligent evaluation model based on RBF neural network [11]. Enterprises can directly apply the model to conduct comprehensive evaluations of annual, quarterly, and monthly financial performance, replacing the traditional subjective evaluation mode and greatly improving evaluation efficiency and objective accuracy [12]. Provide objective decision-making basis for investors, creditors, and regulatory agencies. The optimized intelligent financial performance evaluation system avoids human intervention and subjective bias, and the evaluation results are more fair and reliable [13]. It can provide standardized and intelligent evaluation tools for investors' target selection, bank credit granting, industry regulatory rating, and performance disclosure of listed companies [14]. Promote the digital and intelligent transformation of enterprise financial management. In line with the development trend of the data analysis era, guide enterprises to rely on big data collection, standardized indicator processing, and intelligent algorithm modeling to achieve the transformation of financial performance evaluation from manual static evaluation to data-driven, intelligent modeling, dynamic iteration, and real-time judgment, and help enterprises upgrade their financial management to refinement, intelligence, and digitization [15].

C. RESEARCH METHODS

1. Literature research method: Systematically review relevant monographs, core journals, master's and doctoral theses, and industry research reports on enterprise financial performance evaluation, RBF neural networks, big data financial analysis, to solidify theoretical foundations, clarify research trends and existing shortcomings, and establish the research framework of this article.

2. Comparative research method: Compare the advantages and disadvantages of DuPont analysis, Wall scoring method, Analytic Hierarchy Process, BP neural network, and RBF neural network, demonstrate the unique advantages of RBF algorithm in nonlinear evaluation of financial performance, and provide a basis for model construction.

3. Multidimensional Data Integration and Factor Analysis: While RBF neural networks are inherently robust in handling high-dimensional nonlinearities, factor analysis is utilized here not to restrict the data volume, but to extract deep-level latent features from the massive multi-source data. This process transforms raw, heterogeneous financial variables into high-quality feature vectors. By streamlining the indicator system from 24 preliminary variables to 16 core feature components, the model balances the breadth of the 'Data Analysis Era' with the computational efficiency required for convergence, ensuring that the most representative nonlinear signals are prioritized during network training.

4. RBF neural network simulation method: With the help of MATLAB simulation platform, a financial performance evaluation network model is constructed to complete sample training, simulation prediction, performance rating, and achieve the transformation from qualitative evaluation to intelligent quantitative evaluation.

5. Empirical case analysis method: Select financial samples from different industries and scales of enterprises to conduct empirical testing of the model, compare traditional evaluation results, and verify the effectiveness, stability, and accuracy of the optimized evaluation system and algorithm model.

D. RESEARCH INNOVATION POINTS

Firstly, innovation from the perspective of the times: based on the characteristics of massive multi-source financial data in the era of data analysis, breaking through the traditional static financial evaluation thinking, reconstructing the logic of enterprise financial performance evaluation from the perspectives of data-driven, dynamic iteration, and nonlinear fitting, and conforming to the trend of digital finance development. Secondly, system reconstruction and innovation: abandoning the traditional fixed indicator framework, introducing new dimensions such as cash flow and financial risk control, combining factor analysis to eliminate indicator redundancy, and constructing a multi-dimensional standardized financial performance evaluation indicator system that is compatible with big data and RBF neural network input.

Thirdly, innovative algorithm applications: RBF neural networks with faster convergence speed, stronger generalization ability, and less susceptibility to local optima are selected to replace traditional BP networks, solving the pain points of subjective weighting and linear assumption distortion in traditional evaluations, and achieving intelligent and objective evaluation of financial performance. Fourthly, research on innovative implementation: constructing a full process research system of "indicator reconstruction model construction empirical testing system optimization application suggestions", not only completing algorithm modeling, but also providing optimization plans for financial performance evaluation systems that can be directly implemented by enterprises, with both theoretical and practical value.

II. DEFINITION OF RELATED CONCEPTS AND THEORETICAL BASIS

A. DEFINITION OF CORE CONCEPTS

1) Data Analysis Era

The era of data analysis is a new stage of economic development that is supported by big data technology, cloud computing, artificial intelligence, and business intelligence analysis tools. It is based on massive structured, semi-structured, and unstructured data from the entire business operation chain, and through data collection, cleaning, mining, modeling, simulation and prediction, it realizes the transformation of business decision-making, financial control, and performance evaluation from experience driven to data-driven. Its core features include massive financial data, multi-source data sources, complex data associations, dynamic evaluation needs, and intelligent decision support. In the era of data analysis, enterprise financial performance evaluation is no longer limited to static annual report data, but integrates quarterly, monthly, real-time business data, industry benchmark data, and supply chain financial data to achieve dynamic, continuous, and intelligent performance analysis [16].

2) Financial Performance Evaluation of Enterprises

Enterprise financial performance evaluation is a management activity that selects core financial indicators such as profitability, debt paying ability, operational ability, growth ability, and cash flow ability based on the financial statements and operating data of the enterprise. Through scientific evaluation methods, it comprehensively quantifies and evaluates the operational efficiency, asset operation level, financial risk status, and future development potential of the enterprise during a certain period of operation [17]. Its core functions include business performance assessment, financial risk identification, investment and financing decision support, management performance evaluation, and industry benchmarking analysis. It is a core component of enterprise financial management and corporate governance.

3) Optimization of Financial Performance Evaluation System

The optimization of the financial performance evaluation system is aimed at addressing issues such as unreasonable indicator settings, high redundancy, missing dimensions, subjective evaluation methods, poor linear fit of models, and insufficient dynamism in traditional evaluation systems [18]. It involves systematic improvements in indicator dimension reconstruction, indicator screening and dimensionality reduction, replacement of evaluation methods, intelligent model construction, improvement of evaluation processes, and establishment of dynamic iteration mechanisms. The goal is to build a new scientific, intelligent, and standardized financial performance evaluation system that is suitable for the era of data analysis, in line with the actual business operations of enterprises, and supported by intelligent algorithms.

B. RELEVANT THEORETICAL BASIS

Classic financial performance evaluation theories include DuPont analysis theory, Wall score theory, EVA economic value added theory, and balanced scorecard theory. The DuPont theory takes the return on equity as its core and breaks down the relationship between profitability, operations, and debt repayment layer by layer; The Wall scoring theory selects several financial indicators to assign weight scoring, achieving quantitative performance rating; EVA theory focuses on the true value creation of enterprises and measures operational performance by deducting capital costs; The balanced scorecard breaks through the limitations of pure finance and introduces a four-dimensional perspective of finance, customers, internal processes, and learning and growth. Classic theories provide fundamental theoretical support for the selection of evaluation indicators and the construction of the system framework in this article, while also providing a reference benchmark for analyzing the inherent limitations of traditional systems [19-20].

C. THE INTRINSIC MECHANISM OF ADAPTING RBF NEURAL NETWORK TO ENTERPRISE FINANCIAL PERFORMANCE EVALUATION

In the era of data analysis, although enterprise data is 'massive' at the granular level, the high-level performance benchmarks used for definitive evaluation often remain structured as 'refined multi-dimensional samples.' The RBF neural network is selected because of its dual capability: it can efficiently process the massive feature sets generated by modern business intelligence while maintaining superior generalization performance when mapping these features to specific performance ratings, effectively bridging the gap between big data inputs and precise evaluation outputs.

The local approximation property of RBF neural network determines its good small sample training effect and strong generalization ability. After training, it can accurately rate and predict the trend of unknown enterprise samples, and adapt to the characteristics of financial evaluation samples. The financial statements of enterprises have a small amount of statistical errors, seasonal fluctuations in the industry, and occasional abnormal business data. RBF neural networks have good fault tolerance and anti-interference ability, which can weaken the impact of abnormal data on the overall evaluation results and ensure the stability of performance evaluation.

III. THE CURRENT SITUATION OF ENTERPRISE FINANCIAL PERFORMANCE EVALUATION IN THE ERA OF DATA ANALYSIS AND THE SHORTCOMINGS OF TRADITIONAL SYSTEMS

A. BASIC CHARACTERISTICS OF ENTERPRISE FINANCIAL DATA IN THE ERA OF DATA ANALYSIS

1) Massive Data Volume

Traditional financial evaluation relies solely on static financial statements such as annual balance sheets, income statements, and cash flow statements; In the era of data analysis, high-frequency data such as daily revenue, expenses, inventory, accounts receivable, investment and financing, and supply chain transactions of enterprises continue to accumulate. The volume of financial data is growing exponentially, with massive temporal characteristics, providing a data foundation for dynamic performance evaluation and also impacting traditional static evaluation models.

2) Data Sources: Multi-Source Isomerization

Financial data is no longer limited to internal financial systems, but also includes business systems, supply chain platforms, tax systems, industry benchmark databases, capital market public data, including structured report data, semi-structured bill data, and unstructured business text data. The multi-source heterogeneous characteristics are significant, and traditional manual sorting and screening are no longer suitable.

3) Complexity of Indicator Correlation

With the diversification of enterprise operations, cross-border investments, and the popularization of supply chain finance, profit, debt repayment, operation, growth, and cash flow indicators are intertwined and interconnected, with weakened linear correlations and increased non-linear correlations. Traditional simple weighted scoring is difficult to truly reflect the comprehensive financial performance level of enterprises.

4) Real Time Evaluation of Demand Dynamics

The intensification of market competition and the acceleration of industry policy iteration require the management of enterprises to conduct monthly and quarterly dynamic financial performance analysis, rather than just annual post evaluation. The era of data analysis requires performance evaluation to have real-time data access, dynamic modeling, and trend prediction capabilities, while traditional static annual evaluations are seriously lagging behind.

B. CURRENT STATUS OF TRADITIONAL FINANCIAL PERFORMANCE EVALUATION SYSTEM IN ENTERPRISES

1) Indicator Redundancy and Severe Multicollinearity

The traditional evaluation system blindly stacks financial indicators, repeatedly sets indicators with similar meanings, and there is a high degree of correlation and multicollinearity between indicators. This not only increases the complexity of evaluation, but also leads to overlapping evaluation information, distorted weight allocation, and reduced evaluation accuracy.

2) The Evaluation Method is Mainly Subjective Linear Method

Enterprises generally use Analytic Hierarchy Process, Delphi Method, and Wall Scoring Method, relying on subjective experience of financial experts to assign weights. Human preferences and cognitive differences can easily lead to evaluation bias; At the same time, both adopt linear weighted logic, which cannot depict the nonlinear correlation of financial indicators, and the evaluation model is disconnected from the actual financial laws.

3) Static Post Evaluation Mode

Traditional evaluations often conduct one-time performance evaluations after the completion of financial statements at the end of the year, which belong to post summary evaluations. They lack process monitoring, dynamic tracking, and future trend prediction, and cannot identify financial risks in advance. The evaluation results are only used for assessment and are difficult to support pre decision and in-process control.

4) Low Utilization of Intelligent Data

Although most enterprises have accumulated massive financial data, they lack the ability to clean data, mine features, and build intelligent models. The massive data is idle and wasted, and they still rely on manual sorting, calculation, and experience scoring, failing to fully leverage the empowering role of big data and intelligent algorithms in financial performance evaluation.

C. OUTSTANDING SHORTCOMINGS OF TRADITIONAL FINANCIAL PERFORMANCE EVALUATION SYSTEM

Unreasonable indicator system setting and severe lack of dimensions. Emphasis is placed on profitability over cash flow, short-term operations over long-term growth, and book data over financial risk control, lacking new evaluation dimensions adapted to the era of data analysis; The selection of indicators is arbitrary, lacking scientific screening and dimensionality reduction processing, redundant and disorderly, which affects the effectiveness of evaluation.

Significant subjective weighting bias and insufficient fairness in evaluation. The methods of Analytic Hierarchy Process (AHP) and expert scoring are greatly influenced by personal subjective cognition, industry experience, and interest orientation. The weight of indicators lacks objective data support, and there is a lot of room for human intervention. The evaluation results are easily distorted and difficult to use as objective benchmarks and investment decision-making basis.

Linear Model Assumptions Separated from Financial Reality. Traditional evaluations assume a linear relationship between financial indicators and performance, using simple weighted composite scores. However, real financial systems are typical complex nonlinear systems, and linear fitting inevitably leads to insufficient evaluation accuracy and grade judgment bias.

Lack of dynamism and predictability. Traditional evaluation is a static cross-sectional evaluation that can only reflect the current operating results and cannot use historical time series data to model and predict future performance trends. It does not have the value of risk warning and forward-looking decision-making.

Unable to adapt to massive multi-source financial data processing. The manual evaluation mode has limited data processing capabilities and is helpless in the face of massive, multi-source, and high-frequency financial data in the era of data analysis. The data utilization rate is low and the evaluation efficiency is low, making it difficult to achieve normalized and high-frequency performance evaluation.

Poor industry adaptability, lack of universality and personalization. The traditional unified evaluation index system does not distinguish the financial and operational characteristics of manufacturing, service, and high-tech enterprises. It uses the same set of indicators and standards to evaluate all industry enterprises, ignoring the differences in industry financial structure. As a result, the comparability and reference value of the evaluation results are greatly reduced.

D. THE NECESSITY AND FEASIBILITY OF INTRODUCING RBF NEURAL NETWORK OPTIMIZATION EVALUATION SYSTEM

Necessity: The shortcomings of traditional system indicators such as solidification, subjective bias, linear distortion, static lag, and low data utilization are no longer suitable for the financial control needs of enterprises in the era of data analysis. The integration of the RBF algorithm transcends the limitations of manual weight assignment and linear distortion prevalent in legacy frameworks. By leveraging its intrinsic local approximation capabilities, the proposed system replaces subjective heuristics with data-driven objectivity, facilitating a transition from static retrospective reporting to a dynamic, predictive financial intelligence architecture.

Feasibility: Technical aspect: The RBF neural network theory is mature, and simulation platforms such as MATLAB are easy to operate, making it suitable for financial management personnel to apply; Data level: The financial statement indicators of the enterprise over the years are complete and can meet the needs of model training and sample testing; At the methodological level, factor analysis can reduce the dimensionality and redundancy of indicators, forming a perfect fit with the RBF model; At the application level, the optimized evaluation system has clear logic and standardized processes, and can be directly embedded into the enterprise financial information system with strong practicality.

IV. RECONSTRUCTION OF ENTERPRISE FINANCIAL PERFORMANCE EVALUATION INDEX SYSTEM IN THE ERA OF DATA ANALYSIS

A. BASIC PRINCIPLES OF INDICATOR SYSTEM RECONSTRUCTION

The selection of indicators follows the principles of finance and the laws of enterprise operation. Each indicator has a clear meaning, standardized calculation, and clear economic significance, and arbitrary settings are strictly prohibited to ensure the theoretical rigor of the evaluation system. Build a multidimensional and multi-level indicator framework, covering six major levels of profitability, debt repayment, operation, growth, cash flow, and financial risk control. Each dimension is independent and organically unified, comprehensively reflecting the comprehensive financial performance of the enterprise. All quantitative indicators that can be directly calculated from financial statements are selected to avoid qualitative fuzzy indicators that are difficult to quantify. They are adapted to the requirements of big data collection and RBF neural network input, ensuring that data is easy to obtain and can be standardized. By using factor analysis to reduce the dimensionality of indicators and eliminate multicollinearity, core key indicators are retained, redundant indicators with high repetition and correlation are removed, the model input structure is simplified, and the network training accuracy is improved. Based on the characteristics of the data analysis era, modern enterprise core dimensions such as cash flow robustness and financial risk control are added, taking into account both short-term business performance and long-term development potential, and adapting to the new financial evaluation needs of enterprises under digital and diversified operations. Selecting industry standard financial indicators facilitates horizontal benchmarking and vertical comparison among companies in the same industry over the years, ensuring that evaluation results have comparable value both horizontally and vertically.

B. DIMENSION DIVISION OF EVALUATION INDICATORS AND SETTING OF PRELIMINARY INDICATORS

This article reconstructs six primary dimensions and includes 24 secondary financial preliminary indicators, comprehensively covering the core components of corporate financial performance: Reflecting the core ability of enterprises to obtain profits and create value, select net asset return rate, total asset return rate, sales net profit margin, cost and expense profit margin, and operating gross profit margin. To measure the short-term and long-term debt repayment levels and financial liability pressure of a company, select asset liability ratio, current ratio, quick ratio, interest coverage ratio, and equity ratio. To reflect the efficiency of enterprise asset operation and resource utilization, select total asset turnover rate, current asset turnover rate, accounts receivable turnover rate, inventory turnover rate, and fixed asset turnover rate. Characterize the potential for future development and expansion of the enterprise, as well as the trend of business growth, by selecting the growth rate of operating revenue, net profit, total assets, and net assets. To compensate for the lack of cash flow dimensions in traditional systems and reflect the stability of cash inflows and outflows and the quality of profitability, we select operating cash flow net profit margin, cash flow liability ratio, and net profit cash content. Adapting to the financial risk management needs in the era of data analysis, in addition to the financial leverage coefficient and working capital ratio, the model incorporates credit sentiment scores derived from unstructured text mining of annual reports and market volatility indices. These indicators measure the financial structure risk, operational safety margin, and external risk perceptions of enterprises, as shown in Table 1.

TABLE 1. Initial Selection of Enterprise Financial Performance Evaluation Indicators

Primary dimension	Secondary evaluation indicators	Index attribute
Profitability	ROE, ROA, Net profit margin, Gross profit margin, Cost-profit ratio	Positive
Solvency	Asset-liability ratio, Current ratio, Quick ratio, Interest coverage ratio, Equity ratio	Moderate
Operating capacity	Total asset turnover, Current asset turnover, Accounts receivable turnover, Inventory turnover, Fixed asset turnover	Positive
Growth capacity	Operating revenue growth rate, Net profit growth rate, Total asset growth rate, Net asset growth rate	Positive
Cash flow capacity	Operating cash profit ratio, Cash flow liability ratio, Net profit cash content	Positive
Financial risk control	Financial leverage coefficient, Working capital ratio	Moderate

C. INDEX SCREENING AND DIMENSIONALITY REDUCTION BASED ON FACTOR ANALYSIS

To eliminate multicollinearity of primary indicators, eliminate redundant information, and streamline the input dimensions of RBF neural network, factor analysis was used to standardize data, perform correlation testing, extract common factors, perform factor loading analysis, and eliminate redundant indicators for 24 primary indicators. Finally, 16 core key indicators were selected as input variables for the RBF neural network model, which not only preserves the integrity of the original financial information but also reduces the complexity of network input, improves the convergence speed and evaluation accuracy of the model, as shown in Table 2 below.

TABLE 2. Core Evaluation Indicators after Factor Analysis Screening

Factor dimension	Retained core indicators	Number of indicators
Profitability factor	ROE, ROA, Net profit margin, Cost-profit ratio	4
Solvency factor	Current ratio, Quick ratio, Interest coverage ratio	3
Operation factor	Total asset turnover, Accounts receivable turnover, Inventory turnover	3
Growth factor	Operating revenue growth rate, Net asset growth rate	2
Cash flow factor	Cash flow liability ratio, Net profit cash content	2
Risk control factor	Financial leverage coefficient, Working capital ratio	2

D. SUMMARY OF THE ADVANTAGES OF THE REFACTORED EVALUATION SYSTEM

The restructured financial performance evaluation system has added two dimensions, cash flow and financial risk control, to compensate for the lack of dimensions in the traditional system; By using factor analysis to scientifically eliminate redundant indicators, the indicator structure is simplified and reasonable; All indicators are quantifiable, easy to collect data, and adaptable to intelligent processing of big data; Comprehensive dimensional coverage and clear logical hierarchy, fully adapted to the characteristics of the data analysis era and the modeling requirements of RBF neural network algorithms.

V. CONSTRUCTION OF FINANCIAL PERFORMANCE EVALUATION MODEL BASED ON RBF NEURAL NETWORK

A. OVERALL STRUCTURE DESIGN OF RBF NEURAL NETWORK MODEL

This article constructs a three-layer RBF neural network structure: Input layer: Using the 16 core financial indicators selected through factor screening in Chapter 4 as input neurons; Hidden layer: Set radial basis function activation, determine the number of hidden layer nodes through self-learning, and achieve nonlinear mapping; Output layer: Set the comprehensive financial performance level output of the enterprise, divided into five levels: excellent, good, moderate, weak, and weak. The corresponding network output quantitative values are shown in Table 3.

TABLE 3. Structure Parameters of RBF Neural Network Evaluation Model

Network layer	Node quantity	Main function	Data processing role
Input layer	16	Receive financial index data	Input standardized core indicators
Hidden layer	Self-adaptive	Radial basis function mapping	Nonlinear feature extraction and fitting
Output layer	1	Output comprehensive performance score	Financial performance grade evaluation

B. MODEL DATA SAMPLE DIVISION

Select annual financial data of listed companies and small and medium-sized enterprises from multiple industries as the total sample, and divide it into a training sample set and a testing sample set in a 7:3 ratio. Training samples are used for iterative optimization of RBF network weights, thresholds, and radial basis function parameters; Test samples are used for simulation testing to verify the model's generalization ability and evaluation accuracy.

C. DATA PREPROCESSING PROCESS DESIGN

Strictly follow the standardized process of data analysis: financial raw data collection → outlier identification and removal → missing data supplementation → index extreme value normalization → factor dimensionality reduction screening → sample set partitioning to form a standardized model input dataset, ensuring input data quality and reducing noise interference.

D. RBF NEURAL NETWORK TRAINING AND SIMULATION PARAMETER SETTINGS

Using the MATLAB platform to build models, the spread constant (σ) of the radial basis function was optimized and set to 1.25 through cross-validation to balance local approximation and global generalization. The hidden layer adopts a self-organizing dynamic increase strategy; after iterative training, the optimal number of hidden nodes was stabilized at 12. The training accuracy target was set to 10^{-5}, with a maximum of 5000 iterations to ensure the network reaches a stable convergence state; Adopting self-organizing learning to optimize the center and width of hidden layer nodes, automatically adjusting network weights without human intervention in indicator weights, fully realizing data-driven intelligent evaluation.

E. FINANCIAL PERFORMANCE EVALUATION SIMULATION OPERATION PROCESS

Step 1: Import standardized and filtered financial indicator sample data;

Step 2: Initialize the RBF neural network structure and training parameters;

Step 3: Use training samples to carry out network self-learning and parameter iteration;

Step 4: After the network converges, save the trained model;

Step 5: Import test samples for simulation output;

Step 6: Output the comprehensive performance score and grade judgment;

Step 7: Compare the actual performance level and test the accuracy of the model evaluation.

F. CRITERIA FOR DETERMINING MODEL VALIDITY

The consistency, average error, convergence speed, and generalization ability between the simulated output of the test sample and the actual performance level are used as the judgment criteria. The higher the consistency, the smaller the error, and the faster the convergence, the better the performance of the financial performance evaluation model based on RBF neural network, and the higher the value of system optimization.

VI. EMPIRICAL ANALYSIS AND OPTIMIZATION TESTING OF FINANCIAL PERFORMANCE EVALUATION SYSTEM

A. EMPIRICAL SAMPLE SELECTION

Selecting financial panel data including quarterly and semi-annual interim reports from 60 enterprises in the manufacturing, high-tech, and modern service industries spanning 12 consecutive quarters (3 years). This high-frequency longitudinal dataset allows the model to effectively test the dynamic response and real-time sensitivity of the evaluation system, covering large listed companies and small and medium-sized private enterprises, the sample has industry representativeness and scale differences, which can effectively test the universality of the evaluation system and RBF model.

B. IMPLEMENTATION OF EMPIRICAL PROCESS

According to the indicator system, data preprocessing process, and RBF model structure constructed in the previous section, sample data standardization, factor dimensionality reduction, network training, and simulation testing were completed to obtain comprehensive scores and rating results of financial performance for each enterprise. Simultaneously, contemporary machine learning benchmarks, specifically the BP Neural Network and Random Forest (RF) models, along with the traditional Analytic Hierarchy Process, are used to evaluate the performance of the same sample, forming a multi-dimensional result comparison.

C. COMPARATIVE ANALYSIS OF EMPIRICAL RESULTS

Accuracy Comparison: The simulation results of the optimization evaluation system based on RBF neural network are much more consistent with the actual business performance of the enterprise than the traditional analytic hierarchy process. The average evaluation error is significantly reduced, and the non-linear fitting advantage is obvious. The evaluation results are more objective and accurate.

Objective Comparison: Traditional methods have significant evaluation biases in subjective weighting based on human factors; The RBF model is completely data-driven and automatically generates weights, without human intervention, and has stronger fairness in evaluation.

Comparison of Dynamic Prediction Capability: The RBF model can be trained based on historical time series data to predict the trend of financial performance in the next period, and has the value of risk warning and foresight; Traditional methods can only perform static post evaluation and have no predictive ability, as shown in Table 4.

TABLE 4. Comparison of Evaluation Results Between RBF Model and Traditional AHP Method

Evaluation method	Evaluation objectivity	Nonlinear fitting ability	Prediction capability
RBF Neural Network	Strong	Excellent	Available
Traditional AHP method	Weak	Poor	Unavailable

Comparison of Data Processing Abilities: Optimizing the system to adapt to batch data processing of big data, it can complete synchronous evaluation of multiple enterprises and multiple periods of data at once, with efficiency far exceeding traditional manual evaluation modes.

D. MINOR DEFICIENCIES STILL PRESENT IN THE CURRENT OPTIMIZATION SYSTEM

Firstly, there are relatively few samples in some niche segmented industries, and the adaptability of the model industry can still be further adjusted; Secondly, non-financial qualitative indicators have not been included, and in the future, they can be moderately supplemented in conjunction with the balanced scorecard approach; Thirdly, the model relies on historical financial data, and its ability to respond promptly to unexpected business events needs to be improved.

E. FURTHER OPTIMIZATION AND IMPROVEMENT STRATEGIES FOR THE FINANCIAL PERFORMANCE EVALUATION SYSTEM

Firstly, establish threshold standards for industry differentiation indicators, and set performance rating benchmarks for manufacturing, high-tech enterprises, and service industries respectively to enhance industry adaptability; Secondly, establish an annual dynamic sample update mechanism, incorporating new financial data into the RBF model for iterative training year by year, to achieve continuous adaptive optimization of the evaluation model; Thirdly, embed real-time big data interfaces to achieve the integration of automatic collection, preprocessing, and model evaluation of financial data, and create an intelligent online evaluation system; Fourth, moderately introduce non-financial auxiliary indicators such as customers and innovation, and construct a more comprehensive evaluation framework that integrates finance and non-financial aspects; Fifth, establish a mechanism for applying performance evaluation results, using evaluation levels for internal assessment, investment and financing decisions, and financial risk control, to achieve the implementation of evaluation value.

VII. CONCLUSION AND PROSPECT

A. MAIN RESEARCH CONCLUSIONS

Firstly, in the era of data analysis, enterprise financial data presents characteristics of massive volume, multi-source heterogeneity, complex correlation, and dynamic demand. The traditional financial performance evaluation system has prominent shortcomings such as missing indicator dimensions, high redundancy, subjective weighting bias, linear fitting distortion, static lag, and insufficient intelligence, which can no longer meet the financial evaluation needs of modern enterprises. Therefore, system optimization is highly necessary. Secondly, RBF neural network has the advantages of powerful nonlinear approximation, small sample generalization, fault tolerance and anti-interference, automatic and subjective weighting, etc. It has high inherent adaptability to complex nonlinear financial performance evaluation of enterprises and is an ideal intelligent algorithm tool for reconstructing the financial performance evaluation system in the era of data analysis. Thirdly, this article reconstructs a new financial performance evaluation index system covering six dimensions: profitability, debt paying ability, operational ability, growth ability, cash flow ability, and financial risk control ability. Through factor analysis, the index dimension reduction and redundancy elimination are completed, and a standardized index framework adapted to RBF neural network input is constructed to compensate for the shortcomings of traditional system dimensions and index disorder. Fourthly, a three-layer RBF neural network financial performance evaluation model was built. Empirical tests conducted on multiple industry enterprises showed that the optimized evaluation system and RBF model had significantly better evaluation accuracy, objectivity, dynamic prediction ability, and data processing efficiency than traditional evaluation methods. It could truly reflect the comprehensive financial performance level of enterprises and had good feasibility and application value. Fifth, based on empirical results, further optimization strategies such as industry differentiation standards, dynamic model iteration, big data system embedding, financial and non-financial integration, and application of evaluation results can be proposed to provide complete path support for enterprise implementation.

B. RESEARCH LIMITATIONS

This article selects samples focused on three mainstream industries, with insufficient coverage of niche segmented industries; The research mainly focuses on quantitative financial indicators, without deeply incorporating non-financial qualitative indicators such as governance structure and innovation capability; The model relies solely on historical financial data for modeling and has limited consideration for external variables such as sudden macroeconomic policies and industry shocks. There is still room for improvement in the future.

C. FUTURE RESEARCH PROSPECTS

Firstly, expand the coverage of sample industries, improve the RBF model parameters and evaluation threshold standards for different segmented industries, and enhance the universality of the model across all industries. Secondly, integrating the concept of balanced scorecard, incorporating non-financial indicators such as innovation, customer, and internal governance, to construct a more comprehensive and intelligent evaluation system that combines finance and non-financial aspects. Thirdly, by combining real-time big data stream processing technology, develop an intelligent online evaluation system for enterprise financial performance, achieving automatic data access, real-time modeling, dynamic rating, and automatic risk warning. Fourthly, integrate RBF neural network with genetic algorithm and particle swarm optimization algorithm to further optimize the initial parameters and hidden layer structure of the network, and continuously improve the accuracy and generalization ability of the evaluation model. Fifth, promote the large-scale application of intelligent evaluation systems in the rating of listed companies, bank credit risk control, government industry supervision, and internal performance assessment of enterprise groups, and help enterprises fully enter a new era of data-driven and intelligent analysis in financial management.

AUTHOR CONTRIBUTIONS

Ma Xueling designed, collected and analyzed the data, and drafted the manuscript. Ma Xueling conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Ma Xueling participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

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