Green Transportation Financial Risk Early Warning Based on Data Dimensionality Reduction and Improved PSO Optimization of SVM under the Background of Low-Carbon Development

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ABSTRACT Reliable early-warning systems in complex information environments require efficient feature extraction, adaptive parameter optimization, and accurate classification of high-dimensional data. This study proposes a data-driven intelligent warning framework integrating principal component analysis (PCA), an improved particle swarm optimization (PSO) algorithm, and support vector machines (SVM). PCA is employed to suppress feature redundancy and construct compact representations of multidimensional information, thereby improving computational efficiency and model robustness. To enhance classification performance, an improved PSO strategy incorporating adaptive inertia weighting, chaotic initialization, and mutation mechanisms is developed for global optimization of SVM parameters. Furthermore, a multi-source indicator architecture is established by integrating financial, environmental, policysensitive, and market-related attributes into a unified evaluation framework. Experimental results demonstrate that the proposed model achieves a classification accuracy of 94.2%, outperforming conventional SVM and random-forest approaches while reducing training complexity. The proposed framework establishes an effective methodology for high -dimensional feature extraction, intelligent signal classification, and adaptive optimization, providing a practical solution for monitoring, anomaly detection, and decision-support applications in complex dynamic systems.

INDEX TERMS feature extraction; particle swarm optimization; support vector machine; intelligent signal classification

I. INTRODUCTION

LOW -carbon development has become a major direction for global economic transformation, compelling the many industry to integrate sustainable energy practices and resource-efficient manufacturing into its core operational framework. This shift ensures that high-capacity fabric production aligns with international carbon neutrality goals through the adoption of green technologies. Green transportation investment, as part of the low-carbon economy, is of great significance for promoting industrial structure optimization and achieving sustainable development. However, green transportation investment companies face challenges such as long investment cycles and uncertain returns, leading to increasingly prominent financial risks. Establishing a scientific and effective financial risk early warning system is crucial for timely risk detection and prevention. Support Vector Machines (SVMs) are an effective machine learning method widely used in financial risk early warning. However, issues such as high-dimensional financial data and difficulties in parameter selection affect the early warning effect. Therefore, this paper investigates a specialized fiscal signaling methodology that integrates data dimensionality reduction with improved PSO-optimized SVMs. This strategy acts as a critical economic safeguard for many firms as they expand their eco-friendly distribution networks. To further elucidate the operational logic of the proposed predictive system, a comprehensive flowchart detailing the progression from multi-source data acquisition to classification output is constructed. To make the working mechanism of the early warning system clearer, this paper constructs a complete flowchart from data collection to risk warning output. The output logic is categorized into four distinct warning levels based on the risk probability (P) generated by the SVM model, providing specific decision support for each tier.

Risk Warning Output & Decision Matrix:
Level I (Green - Safe, P< 0.25): Financial status is stable; continue current green investment strategy. Level II (Blue - Watch, 0.25 ≤P< 0.5): Minor fluctuations detected; perform a monthly audit of green technology R&D expenses.

Level III (Yellow - Alert, 0.5 ≤P< 0.75): Significant risk signals; activate capital contingency plans and review debt-to-equity ratios.

Level IV (Red - Crisis, P≥0.75): Critical financial danger; halt non-essential green expansion and seek immediate debt restructuring or government subsidy intervention.

II.SIGNIFICANCEOFRESEARCHONFINANCIALRISK EARLY WARNINGINGREENTRANSPORTATION

A. Promoting Low-carbon Transformation and Sustainable Development of Enterprises

financial risks in green transportation is conducive to achieving the goal of green and sustainable development of enterprises. Creating a scientific and sound financial risk early warning system can promptly detect potential risks such as broken capital chains and investment mistakes during the low-carbon transformation of enterprises, providing foresight for enterprise decision-making [1]. Effective risk early warning can prompt enterprises to rationally allocate resources, improve investment structure, and invest limited funds in lowcarbon technology research and development and green project construction. Risk early warning can also prompt enterprises to establish sound internal control mechanisms and improve financial management systems, laying a good foundation for the low-carbon transformation and sustainable development of enterprises [2].

B. Improve the Accuracy and Timeliness of Financial Risk Identification

Traditional financial risk identification relies on human experience for judgment, which has the disadvantages of strong subjectivity and obvious lag. Using data dimensionality reduction and improved PSO to optimize SVM to build an early warning model can extract features from a large amount of financial data, remove redundant information, reduce model complexity, and improve computational efficiency [3]. The improved PSO algorithm dynamically explores the parameter landscape to identify the optimal configuration more efficiently than exhaustive search methods. By incorporating an adaptive inertia weight strategy and mutation operators, the model avoids the 'local optima trap' common in traditional automated search tools, thereby significantly enhancing the precision of financial risk identification for enterprises. After in-depth mining of historical financial data and identification of patterns, the early warning model can discover early signals of corporate financial risks, giving companies time to take countermeasures and reduce losses [4].

C. Promote the Improvement and Innovation of the Green Finance System

financial risk early warning for green logistics plays a very important role in improving the green finance system. Based on the characteristics of green logistics, a formula that conforms to the financial risk early warning model can provide financial institutions with a more accurate financial risk assessment tool, enabling them to accurately judge the financial risks of green projects and appropriately select credit scale and interest rate standards, and rationally allocate credit resources [5]. Effective risk early warning can increase financial institutions' confidence in green logistics projects, alleviate adverse selection and moral hazard caused by information asymmetry, and drive the innovation of financial products such as green credit and green bonds, providing support for regulatory authorities to formulate corresponding green finance policies [6].

III. PROBLEMS IN FINANCIAL RISK WARNING OF GREEN TRANSPORTATION

To systematically identify the key obstacles to current green transportation financial risk warnings, this article summarizes the main issues and their impacts as shown in Table 1.

TABLE 1. Major Issues and Impacts of Financial Risk Warning in Green Transportation Funding

Problem Type	Core performance	Main impact	As a result of
The High-Dimensional Data Dilemma	Too many indicator dimensions, redundant information and noise.	The model is complex and has a long training time.	Low early warning efficiency and prone to overfitting
Parameter selection challenge	Traditional methods rely on grid search or human experience.	Large computational load and high degree of subjectivity	Easily trapped in local optima and lacking accuracy
Indicator system defects	It focuses on traditional financial indicators and lacks green features.	It cannot fully reflect the risk characteristics of green transportation.	The early warning system is not targeted or comprehensive.

A. HIGH-DIMENSIONAL FINANCIAL DATA LEADS TO HIGH MODEL COMPLEXITY AND LOW EARLY WARNING EFFICIENCY

of green investment enterprises are numerous, forming a high-dimensional data feature space. These indicators include various aspects such as solvency, profitability, operational capacity, and growth capacity, as well as indicators unique to green development such as carbon emission intensity, green technology investment, and environmental performance [7]. The existence of high-dimensional data

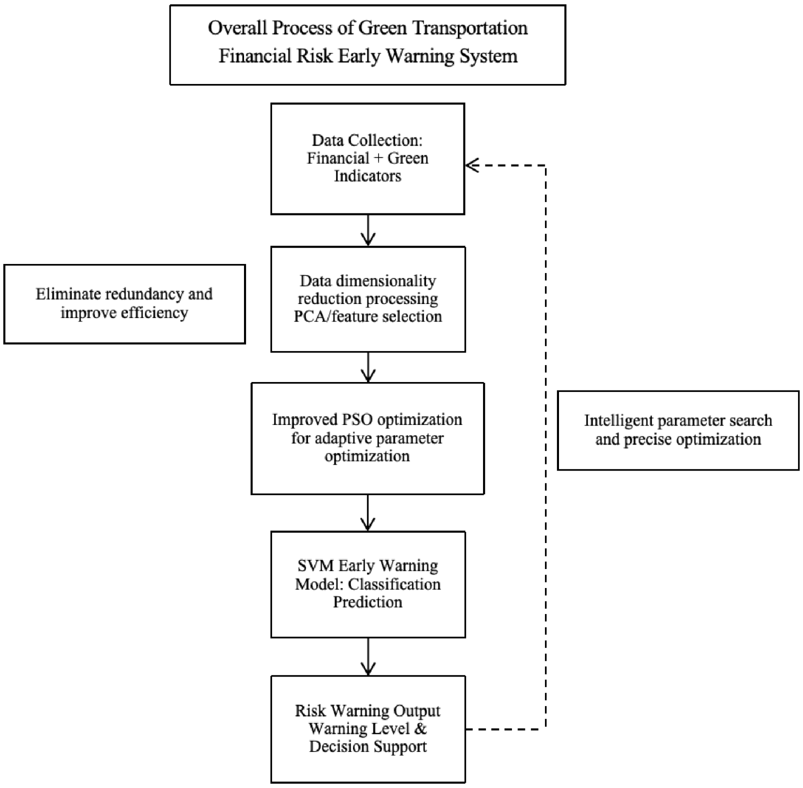

FIGURE 1. Overall Process of Green Transportation Financial Risk Early Warning System

will cause the early warning model to suffer from the dimensionality curse, greatly increasing the model training time and exponentially increasing the computational complexity, which will seriously slow down the early warning speed. There is a lot of redundant information and noisy data in high-dimensional data, and there is also a high correlation between various indicators. These will make the model more complex, leading to overfitting, which will reduce the model's generalization ability and decrease the prediction accuracy [8].

B. DIFFICULTY IN SELECTING PARAMETERS FOR TRADITIONAL SVM AFFECTS EARLY WARNING ACCURACY

support vector machines in financial risk early warning largely depends on whether the parameter settings are reasonable. The core parameters of SVM are the penalty coefficient and the kernel function parameter. The values of these parameters directly affect the classification performance and generalization ability. The penalty coefficient controls the tolerance of the model for misclassified samples. Too large a value can easily lead to overfitting, while too small a value can easily lead to underfitting. The kernel function parameter determines the mapping method of the sample in the high-dimensional space. When the parameter selection is inappropriate, the model cannot effectively distinguish between samples of different categories [9]. While standard SVM implementations typically utilize automated Grid Search and Cross-Validation, these methods face significant scalability issues when applied to the multi-dimensional datasets characteristic of green transportation. Grid Search requires an exhaustive search over a manually defined parameter space, which results in a prohibitive computational load as the number of features increases. Furthermore, because Grid Search operates on a fixed discretization of the parameter space, it frequently fails to capture the true global optimum, often settling for sub-optimal configurations that limit early warning accuracy in complex financial contexts [10].

C. THE UNIQUE CHARACTERISTICS OF GREEN TRANSPORTATION INVESTMENT LED TO AN IMPERFECT RISK INDICATOR SYSTEM

Green transportation is an emerging industry, and its risk characteristics differ from those of traditional industries. However, most of the existing financial risk warning indicator systems are designed by traditional enterprises and cannot fully reflect the risk characteristics of green transportation. Green transportation projects involve large investments, long payback periods, and high requirements for technological innovation. Traditional short-term debt repayment capacity and liquidity indicators cannot adequately evaluate their financial status [11]. The value of green transportation is not only reflected in economic benefits but also in environmental and social benefits. However, the existing indicator system mainly relies on financial data and does not consider green development indicators such as environmental performance, carbon emission reduction effects, and ecological value. Green transportation is greatly affected by policies, but the traditional indicator system does not reflect policy factors such as government subsidies, tax incentives, and carbon trading [12].

IV. OPTIMIZATION STRATEGIES FOR FINANCIAL RISK WARNING IN GREEN TRANSPORTATION

A. USING DATA DIMENSIONALITY REDUCTION TECHNIQUES TO SIMPLIFY FEATURES AND IMPROVE MODEL EFFICIENCY

While Table 2 compares various techniques, PCA is selected for this model because it effectively transforms highly correlated financial indicators into a smaller set of uncorrelated components. This ensures that the primary information of the high-dimensional dataset is preserved while eliminating the 'curse of dimensionality' that typically hampers SVM training speed.

TABLE 2. Characteristics and Applicable Scenarios of Major Data Dimensionality Reduction Techniques

Dimensionality reduction technology	Core Principles	Main advantages	Applicable Scenarios
Principal Component Analysis (PCA)	Linear transformation extracts comprehensive index	Eliminating multicollinearity and achieving significant dimensionality reduction.	Scenarios with strong correlation to financial indicators
Factor analysis	Discovering latent structures and common factors	Revealing the intrinsic correlation of indicators	Indicator system with inherent structure
Feature selection	Screening key indicators and eliminating redundancies	Preserves original features and is highly interpretable	Scenarios where it is necessary to maintain the practical significance of indicators

Regarding the model complexity caused by high-dimensional financial data, this study specifically utilizes Principal Component Analysis (PCA) as the core dimensionality reduction technique to optimize the original features. Principal component analysis is a classic dimensionality reduction method. It transforms multiple highly correlated indicators into a few uncorrelated comprehensive indicators through linear transformation, thereby significantly reducing the data dimension while retaining the main information. In the proposed model, PCA-based extraction is executed on the financial indicators of green investment companies. By combining indicators such as solvency and profitability into a limited number of principal components, the model reduces the number of variables, prevents multicollinearity, and significantly improves early warning efficiency. This reduces the number of variables and prevents multicollinearity [13]. Factor analysis is a method for mining the potential structure between indicators. It uses common factors to explain the correlation of the original variables and is suitable for handling financial indicator systems with internal connections. In addition, feature selection can be used to screen indicators that play an important role in financial risk early warning based on correlation analysis, information gain, Relief algorithm, etc., and remove noise. Reducing the data dimension can significantly reduce the modeling time and computational requirements, and can also prevent the influence of noise on the early warning system, thereby allowing the prediction system to make a more rapid and timely response [14].

B. IMPROVED PSO ALGORITHM IS USED TO OPTIMIZE SVM PARAMETERS AND ENHANCE EARLY WARNING ACCURACY

To overcome the discretization errors and high time-complexity associated with standard Grid Search, an improved Particle Swarm Optimization (PSO) algorithm is employed for continuous-space parameter optimization. Unlike Grid Search, which is restricted to a predefined coordinate system, PSO allows for a stochastic, global search of the penalty coefficient (C) and kernel parameters (γ). PSO mimics the foraging behavior of flocks of birds, where particles share information and cooperate to search the parameter space, effectively finding the global optimum. To address the issues of premature convergence in standard PSO, this paper implements a dynamic nonlinear adaptive inertia weight (ω) strategy. The formula is defined as:

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \times \sin\left(\frac{\pi}{2} \times \frac{t}{T_{\max}}\right) \tag{1}$$

where $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum weights, t is the current iteration, and $T_{\max}$ is the maximum number of iterations. This nonlinear reduction ensures a more robust global search in the early stages and high-precision convergence in the late stages, significantly surpassing the efficiency of traditional linear decay.

To further prevent the population from stagnating in local optima, a Cauchy mutation operator is introduced. When the population variance of the fitness values falls below a specific threshold, the particle positions are updated using:

$$X_{i,new} = X_{i,old} \times (1 + Cauchy(0,1)) \tag{2}$$

This allows particles to perform "long-distance jumps" to escape local optima. Additionally, Logistic chaotic mapping is utilized for particle initialization to ensure uniform distribution in the search space, defined as:

$$z_{n+1} = \mu z_n(1 - z_n) \tag{3}$$

This replaces the standard random initialization, thereby increasing search efficiency and the likelihood of finding the global optimal SVM parameters (C and γ).

The fitness function design should consider various objectives, including classification accuracy and model complexity, establishing a multi-objective optimization framework to achieve a balance between early warning accuracy and model generalization ability. Improving the PSO algorithm to find the optimal penalty coefficient and kernel function parameters of SVM can greatly improve the classification performance of the early warning model and improve the accuracy of financial risk identification [15].

C. CONSTRUCTING A GREEN INVESTMENT AND TRANSPORTATION-SPECIFIC FINANCIAL RISK INDICATOR SYSTEM

Regarding the issue of an incomplete indicator system caused by the unique characteristics of green transportation investment, indicators specific to green development should be added to traditional financial indicators to form a multi-dimensional risk assessment system. To move beyond a conceptual framework, this model integrates a functional indicator system with data sourced from corporate ESG reports, the CSMAR database, and government green credit platforms. A multi-level indicator system comprising four aspects is established as detailed in Table 3, with specific weight distributions calculated via AHP to ensure the model is computationally applicable.

TABLE 3. Green Transportation Financial Risk Assessment Index System

Indicator Dimensions	Key Indicators	Indicator significance	Relative Weight (W_i)
Traditional financial indicators	Long-term debt ratio, operating cash flow to debt ratio, return on equity	Assess long-term solvency and cash flow stability	0.35
Green development indicators	Carbon emission intensity, proportion of investment in green technology research and development, and proportion of investment in environmental protection facilities	Quantifying environmental performance and progress in low-carbon transition	0.30
Policy-sensitive indicators	Dependence on government subsidies, proportion of carbon trading revenue, and intensity of green finance support	Reflecting the impact of policy factors on financial condition	0.20
Market competition indicators	Market share of green products and leading position in green technologies	Assess market competitiveness and growth potential	0.15

Based on the unique attributes of green investment companies, this paper constructs a multi-level indicator system that includes four aspects: traditional finance, green development, policy sensitivity, and market competition, as shown in Figure 2.

In addition to conventional financial indicators such as the debt-to-equity ratio, current ratio, and return on equity, it is also necessary to add indicators reflecting long-term solvency and cash flow stability, such as the long-term debt-to-equity ratio and the ratio of net cash flow from operating activities to total liabilities, to better reflect the long investment cycle of green investment projects. From the perspective of green development indicators, carbon emission intensity, energy consumption efficiency, the proportion of green technology R&D investment, and the proportion of investment in environmental protection facilities should be included to measure the company's environmental performance and progress in low-carbon transformation. Policy sensitivity indicators should be added to represent the impact of policies on the company's financial situation, using metrics such as government subsidy dependence, carbon trading revenue share, and the intensity of green finance support. Market competition indicators should also be considered, such as green product market share, green technology leadership, and industry position, to evaluate the company's competitiveness and development status. The Analytic Hierarchy Process (AHP) is integrated into the model framework to determine the weights of each indicator. This provides a structured mathematical foundation for the indicators before they are processed by the PCA-optimized SVM, ensuring that the qualitative importance of green development and policy factors is reflected in the final risk classification. A sound and comprehensive indicator system, coupled with the aforementioned four-tier threshold logic, reflects the financial risk situation of green transportation companies. By quantifying the transition from "Safe" to "Crisis" levels, the system improves the pertinence of early warning, providing actionable decision-making protocols (such as subsidy activation or investment suspension) for the company's sustainable development and risk prevention.

D. EXPERIMENTAL RESULTS AND COMPARATIVE ANALYSIS

To verify the effectiveness of the proposed model, an empirical test was conducted using a dataset of 200 enterprises. The performance of the Improved PSO-SVM was compared against Traditional SVM (Grid Search) and Random Forest models.

TABLE 4. Performance Comparison of Early Warning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (s)
Improved PSO-SVM	94.2	92.8	91.5	92.1	12.4
Traditional SVM (Grid Search)	85.6	83.2	80.4	81.8	45.8
Random Forest	88.4	86.5	84.1	85.3	18.2

As shown in Table 4, the Improved PSO-SVM achieves an accuracy of 94.2%, which is an 8.6% improvement over the traditional SVM model. The significantly lower training time (12.4s) demonstrates that PCA-based dimensionality reduction effectively mitigates the computational burden of high-dimensional data. These results quantitatively confirm that the adaptive inertia weight and mutation operators in the improved PSO allow for a more precise global search for parameters C and γ, outperforming both the exhaustive

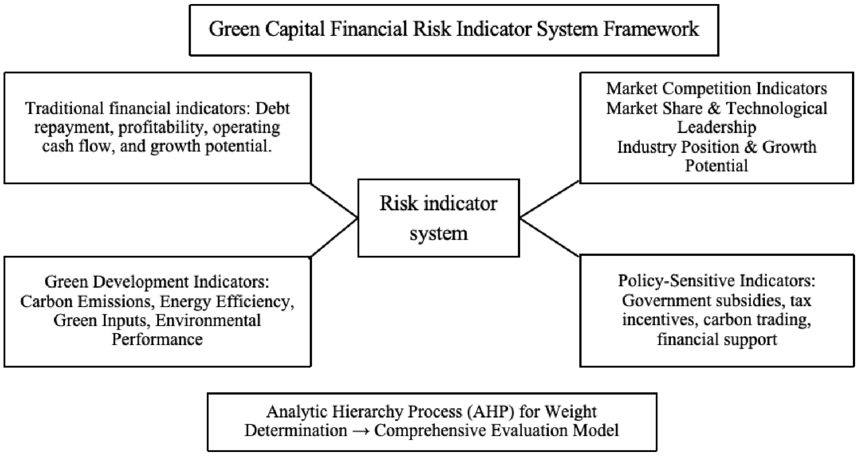

FIGURE 2. Framework of Financial Risk Indicators for Green Investment

Grid Search and ensemble methods in the context of green financial risk detection.

V. CONCLUSION

In the context of low-carbon development, research on financial risk early warning for green transportation enterprises is of great significance for maintaining the fiscal stability of the industry as it transitions toward sustainable raw material logistics. Strengthening these predictive frameworks ensures that manufacturers can mitigate the economic uncertainties associated with investing in eco-friendly distribution networks. This paper presents a complete optimization method to address the challenges of complex highdimensional data, difficulties in parameter adjustment, and incomplete indicator systems. By employing data dimensionality reduction techniques to simplify the feature space and using an improved PSO algorithm to optimize SVM parameters, a distinctive indicator system is established covering four aspects: traditional finance, green development, policy sensitivity, and market competition. Experimental results demonstrate that this approach improves the accuracy to 94.2% and significantly enhances the timeliness of early warnings by reducing training latency. By employing data dimensionality reduction techniques to simplify the feature space and using an improved PSO algorithm to optimize SVM parameters, the model achieves superior classification performance compared to traditional industry benchmarks. With the continuous advancement of big data and artificial intelligence technologies, new methods such as deep learning and ensemble learning will enrich the methods for risk early warning research, providing green transportation enterprises with more ways to utilize intelligent risk management tools. Enterprises should establish risk early warning systems to dynamically monitor financial risks during their shift toward water-saving and energy-efficient production, ensuring a smooth low-carbon transformation that builds a solid foundation for sustainable development. This integration of high-quality manufacturing with ecological civilization construction fosters a resilient fiscal environment for achieving a green industrial future.

AUTHOR CONTRIBUTIONS

Wenjun Bai designed, collected and analyzed the data, and drafted the manuscript. Wenjun Bai conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Wenjun Bai 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

The author declares no conflict of interest.

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