

Dynamic Monitoring System Design for Enterprise Financial Liquidity Risk Based on Multimodal Data Fusion

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Abstract

The traditional monitoring system for enterprise finance relies on a single structured financial data, which has a lag problem. This article proposes a design scheme for a dynamic monitoring system of enterprise financial liquidity risk that integrates multimodal data, and conducts theoretical analysis from the system architecture, multimodal data fusion model, and dynamic risk monitoring model. By comparing the theoretical adaptability of different data fusion strategies and risk assessment models, the advantages of combining hybrid fusion strategies with temporal neural networks are clarified. This system can integrate structured and unstructured text data as well as real-time transaction data, achieve dynamic perception and early warning of risks, and provide theoretical support for enterprise liquidity risk management.

Keywords Financial Liquidity Risk; Data Fusion; Risk Assessment Model; Multimodal Dynamic Monitoring

1 Introduction

In the complex and ever-changing market environment, financial liquidity risk has become the core risk that restricts the survival and development of enterprises [1-2]. Traditional enterprise financial liquidity risk monitoring is mainly based on structured financial statement data such as balance sheets and income statements, and evaluated through static indicators such as current ratios and quick ratios. However, the financial statement data of such methods have periodic lag and cannot reflect the real-time cash flow status of the enterprise, resulting in omissions in risk monitoring [3-4].

The development of multimodal data fusion technology provides the possibility to break through the bottleneck of traditional monitoring. Multimodal data encompasses structured financial data, unstructured text data, semi-structured data, and real-time streaming data. By integrating multidimensional and multi type data, a more comprehensive portrait of enterprise liquidity risk can be constructed, achieving a transition from static post evaluation to dynamic real-time monitoring [5-7]. Therefore, designing a dynamic monitoring system for enterprise financial liquidity risk that integrates multimodal data has important theoretical and practical significance for improving the accuracy of risk monitoring and early warning of potential risks.

Currently, relevant scholars have conducted research on enterprise financial risk monitoring. Static evaluation methods based on traditional financial indicators, such as Altman Z-score model and ZETA credit risk model, rely on structured data and have strong model stability but poor dynamic adaptability. Some scholars have also studied dynamic monitoring based on big data technology, and some have attempted to introduce a single unstructured data to assist risk assessment, but a system framework for deep integration of multimodal data has not yet been formed. From this, it can be seen that in financial risk monitoring scenarios, the heterogeneity of multimodal data makes fusion difficult, and the adaptability of existing fusion models needs to be further studied. In addition, there is controversy over the selection of dynamic risk monitoring models. Models such as temporal neural networks and dynamic Bayesian networks have their own advantages in handling temporal data, but the optimal model architecture for multimodal financial data scenarios has not yet been determined.

The main research contributions of this paper are as follows: a design scheme for a dynamic monitoring system of enterprise financial liquidity risk that integrates multimodal data is proposed, and theoretical analysis is conducted from aspects such as the system architecture, multimodal data fusion model, and dynamic risk monitoring model.

2 Overall System Architecture Design

The enterprise financial liquidity risk dynamic monitoring system that integrates multimodal data adopts a layered architecture design, with the application layer, monitoring layer, fusion layer, and data layer arranged from top to bottom. The various layers are coordinated and linked through data interfaces to ensure smooth data flow and real-time monitoring.

2.1 Data Layer

The data layer is the foundation of the system, and its core function is to achieve comprehensive collection and standardized preprocessing of multimodal data, including structured financial data, unstructured text data, and real-time streaming data.

(1) Collect structured financial data. It comes from enterprise ERP systems, financial software, and financial statements disclosed by regulatory departments, including asset liability data, profit data, cash flow data, debt repayment ability indicators, etc. The data formats are numerical and tabular.

(2) Unstructured text data. Including internal financial report notes, management discussion and analysis texts, external news and public opinion, supply chain cooperation agreement texts, credit rating reports, etc., all data formats are text based.

(3) Real time streaming data. Originating from enterprise fund management systems, bank transaction systems, and supply chain trading platforms, including real-time fund transfer records, order payment data, accounts receivable collection data, etc., the data has high-frequency and real-time characteristics.

The preprocessing stage mainly solves the problem of heterogeneity in multimodal data, including the cleaning and normalization of structured data; Word segmentation, stop word removal, and word vector conversion of unstructured text data; The timing alignment and denoising processing of real-time streaming data ultimately convert all data into feature vectors in a unified format, providing standardized data input for subsequent fusion layers.

2.2 Fusion Layer

The fusion layer is the core component of the system, responsible for effectively fusing preprocessed multimodal data and extracting comprehensive features for risk monitoring. Design a multimodal data fusion model based on a hybrid fusion strategy, taking into account the heterogeneity characteristics of financial data. This model integrates the advantages of early and late fusion and is divided into two sub stages: feature level fusion and decision level fusion.

2.3 Monitoring layer

The monitoring layer constructs a dynamic risk assessment model based on the comprehensive feature vector output by the fusion layer, achieving real-time evaluation and early warning of financial liquidity risks in enterprises. The model needs to have the ability of temporal analysis and be able to capture the dynamic changes in the flow status of enterprise funds. At the same time, multi-level risk warning thresholds are set, and when the risk assessment results exceed the corresponding threshold, the warning mechanism is automatically triggered.

2.4 Application Layer

The application layer is aimed at enterprise management, financial personnel, and regulatory departments, providing visual display and decision support functions for risk monitoring results. Specifically, it includes real-time risk indicator dashboard, risk trend curve, multi-dimensional risk profile, warning information push, and risk management suggestion generation, achieving a closed-loop management of "monitoring warning decision-making".

3 Theoretical Analysis and Comparison of Models

The fusion strategy includes three types: early fusion, late fusion, and hybrid fusion. This article compares and analyzes the three strategies from three dimensions: theoretical adaptability, advantages,

and limitations, and clarifies the optimal fusion strategy applicable to the monitoring scenario of enterprise financial liquidity risk. The core idea of early fusion strategies is to directly concatenate the feature vectors of different modal data into a unified high-dimensional feature vector after data preprocessing is completed, and then input it into the risk assessment model. This can fully preserve the original feature information of each modal data, achieve deep complementarity at the feature level, and avoid information loss. For financial liquidity risk monitoring, it is possible to simultaneously capture the quantitative characteristics of enterprise financial indicators and the qualitative characteristics in textual data. However, due to the significant differences in feature dimensions and scales among different modal data, it increases the difficulty and computational cost of model training. In addition, if there is noise in a modal data, it will directly affect the quality of fusion features and reduce the monitoring accuracy. The core idea of the late stage fusion strategy is to construct independent risk assessment models for different modal data, obtain the corresponding risk assessment results for each modal data, and then fuse multiple assessment results through weighted voting, Bayesian inference and other methods to obtain the final risk assessment conclusion. The model architecture can be selected according to different data types to reduce the difficulty of model design. At the same time, the noise of a certain modal data will not directly affect the output of other modal models, and the system is more stable. The independent training of each modal model makes it impossible to make full use of the complementary information between different modal data, which may lead to information fragmentation. The hybrid fusion strategy integrates the advantages of early fusion and late fusion, adopting a two-level fusion architecture of "feature level fusion+decision level fusion": the first level is feature level fusion, which concatenates features of modality data with high correlation; The second level is decision level fusion, which combines the results of feature level fusion with independent evaluation results of other modal data to obtain the final risk assessment conclusion. The theoretical comparison and summary of the three fusion strategies are shown in Table 1.

Table 1. Theoretical comparison of fusion strategies

Fusion Strategy	Theoretical Adaptability	Advantages	Limitations
Early Fusion	Suitable for scenarios with highly correlated modal data and low dimensions; moderate adaptability	Retains original feature information and achieves in-depth complementarity	Prone to the curse of dimensionality and weak noise resistance
Late Fusion	Suitable for scenarios with strongly independent modal data and much noise; moderate adaptability	Simple model design and strong system stability	Information isolation, failing to fully utilize complementary information
Hybrid Fusion	Suitable for complex scenarios with large differences in modal data correlation; optimal adaptability	Balances information complementarity and system stability, avoiding the curse of dimensionality	Complex model architecture, requiring reasonable division of fusion layers

4 Theoretical Analysis and Comparison of Dynamic Risk Monitoring Models

The financial liquidity risk of enterprises has obvious temporal characteristics, so the dynamic risk monitoring model needs to have the ability to process temporal data. The current models suitable for time series risk assessment mainly include Time Series Neural Network (TSN), Dynamic Bayesian Network (DBN), and Support Vector Machine (SVM) dynamic extension models (such as Time Series Support Vector Machine TS-SVM). Temporal neural network is a deep learning based temporal data processing model that can capture long-term dependencies in temporal data by introducing structures such as recurrent neural network (RNN), long short-term memory network (LSTM), gated recurrent unit (GRU), etc. In the monitoring of financial liquidity risk in enterprises, the TSN model can use the fused multimodal temporal feature vectors as input, and learn the historical changes of fund flow status through LSTM/GRU units to predict the risk trend in the future. Having strong temporal feature extraction capabilities, it can automatically mine hidden temporal correlations in multimodal data, meeting the real-time monitoring requirements. However, the high demand for data quality is not conducive to the understanding of the core basis of risk assessment by enterprise management.

Dynamic Bayesian network is a temporal extension model of Bayesian network, which describes the evolution of risk factors over time by constructing a network structure with multiple time slices. In

financial liquidity risk monitoring, the DBN model can use current ratio, cash flow, public opinion risk level, etc. as nodes to calculate the probability of risk occurrence at different time intervals through probabilistic inference, achieving dynamic risk assessment. The model is based on probability and statistics theory, with strong interpretability and the ability to clearly demonstrate causal relationships between various risk factors. However, it is difficult to handle high-dimensional multimodal fusion features and has weak inclusiveness towards feature dimensions.

TS-SVM is a dynamic extension model of support vector machine, which introduces a temporal kernel function into traditional SVM to map temporal data to a high-dimensional feature space, achieving classification and prediction of risk states. This model can take the temporal sequence of multimodal fusion features as input and capture the trend of risk state changes through the temporal kernel function. The model has strong generalization ability and performs well in small sample and high-dimensional data scenarios; The computational complexity is lower than that of TSN model, and the training efficiency is high; The temporal kernel function can be flexibly adjusted to adapt to the risk change patterns of different periods. The ability to extract temporal features is weaker than the TSN model. The theoretical comparison and summary of dynamic risk monitoring models are shown in Table 2.

Table 2. Comparison of dynamic risk monitoring models

Model Type	Theoretical Basis	Temporal Processing Capability	Adaptability
Temporal Neural Network (TSN)	Deep learning and temporal neural network structure	Strong, capable of capturing long-term temporal dependencies	Optimal, adaptable to multimodal temporal data and supports real-time monitoring
Dynamic Bayesian Network (DBN)	Probability statistics and Bayesian inference	Moderate, dependent on time slice division	Moderate, suitable for scenarios with small samples and the need to explain risk causal relationships
Temporal Support Vector Machine (TS-SVM)	Statistical learning and temporal kernel function	Weak, difficult to capture long-term dependencies	General, suitable for scenarios with small samples and low-dimensional temporal data

Comprehensive analysis shows that the TSN model outperforms Dynamic Bayesian Networks and Temporal Support Vector Machines in terms of temporal processing capability, multimodal data adaptability, and real-time performance. Therefore, the dynamic risk monitoring system designed in this paper adopts the TSN model as the core evaluation model, combined with the feature output of the hybrid fusion strategy, to achieve dynamic monitoring of enterprise financial liquidity risk.

5 Conclusion

The study proposes a design scheme for a dynamic monitoring system of enterprise financial liquidity risk that integrates multimodal data. Through theoretical analysis and model comparison, the following conclusions are drawn:

(1) The system adopts a hierarchical architecture design, with the data layer implementing the collection and preprocessing of multimodal data, the fusion layer using a hybrid fusion strategy to solve the problem of data heterogeneity, the monitoring layer using a TSN model to achieve dynamic risk assessment, the application layer providing visualization and decision-making support, and each layer working together to ensure the comprehensiveness and real-time monitoring;

(2) Comparing three multimodal data fusion strategies, the hybrid fusion strategy balances information complementarity and system stability, and is the most suitable fusion solution for enterprise financial liquidity risk monitoring scenarios;

(3) Comparing three dynamic risk monitoring models, the TSN model has significant advantages in temporal processing capability, multimodal data adaptability, and real-time performance, making it suitable as a core evaluation model for the system.

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Conflicts of Interest

The authors declare no conflicts of interest.

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融合多模態數據的企業財務流動性風險動態監測系統設計

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摘要：傳統企業財務管理依賴單一結構化數據，導致存在滯後性問題。本文提出一種融合多模態數據的企業財務流動性風險動態監控設計方案，從系統架構、多模態數據融合、動態風險監控三個方面展開理論分析，通過對比不同數據融合策略與風險評估模型的理論適配性，闡明瞭混合融合策略結合時序神經網絡的優勢。研究表明，該方案可融合結構化與非結構化文本數據及實時交易數據，實現風險的動態感知與預警，為企業風險管理提供理論支撐。

關鍵詞：多模態數據；財務流動性風險；動態監控；數據融合；風險評估模型

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