Journal of Computer Science and Artificial Intelligence
ISSN: 3078-8242 (Print), ISSN: 3078-2309 (Online) | Vol. 5, No. 1, 2025

Construction and Application of AI-Based Intelligent Evaluation Model for DRP Level

Botao Liu *

Bachelor of Science in Information and Computing Science, Xi'an Jiaotong Liverpool University, Suzhou, China

* **Corresponding author**: (Email: botao-liu123@outlook.com)

Abstract: As a crucial component of enterprise supply chain management, Distribution Requirements Planning (DRP) directly impacts product distribution efficiency, inventory control levels, and customer responsiveness. Traditional DRP rating evaluation methods, which predominantly rely on expert experience and static analysis, exhibit issues such as excessive subjectivity and poor dynamic adaptability, making them inadequate for modern complex supply network demands. To address these challenges, this study proposes an AI-powered intelligent DRP rating evaluation model. By integrating machine learning algorithms with multidimensional data features, the model establishes an evaluation index system and achieves dynamic rating determination. Through training and testing on multiple real-world corporate datasets, the results demonstrate that this evaluation system outperforms traditional methods in accuracy, stability, and practicality. In practical applications, the study explores the model's specific value in inventory optimization, distribution node configuration, and supply chain collaboration, providing theoretical foundations and practical pathways for enterprises to implement intelligent supply management. This research aims to drive the evolution of DRP system evaluation from static, subjective approaches toward intelligent, real-time methods, thereby enhancing the responsiveness and resource allocation efficiency of overall supply chain systems.

Keywords: DRP level, artificial intelligence, evaluation model, supply chain management, intelligent decision making.

1. Introduction

With the accelerated evolution of global supply chain systems and intensifying competition, enterprises are demanding more refined and intelligent management of distribution processes. Distribution Resource Planning (DRP), serving as the bridge between manufacturing schedules and market demands, plays a pivotal role in achieving inventory balance, transportation coordination, and supply responsiveness. DRP level evaluation serves as a critical tool for companies to diagnose distribution system performance, optimize resource allocation, and enhance supply efficiency. However, traditional assessment methods suffer from limitations such as single-dimensional data, vague evaluation criteria, and delayed responses, failing to meet the demands for dynamic, real-time, and precise assessments in evolving environments. Against this backdrop, artificial intelligence (AI) technology has demonstrated growing advantages in data mining, pattern recognition, and predictive modeling, providing innovative approaches and technical support for intelligent DRP level evaluation. In recent years, an increasing number of enterprises have integrated AI into supply chain systems, using historical data to train models that enable intelligent classification of logistics nodes and risk alerts. Nevertheless, systematically constructing a self-learning and adaptive DRP level evaluation model tailored to operational realities remains a challenging yet valuable research topic. This paper explores model construction, algorithm selection, data acquisition, and practical applications, aiming to bridge theoretical foundations with engineering implementation.

2. Traditional mode and limitations of DRP level evaluation

In the context of increasingly complex modern supply chain and increasingly data-driven trend, the traditional distribution resource planning (DRP) level evaluation system is facing many challenges and needs to be reformed and upgraded.

2.1. Overview of Traditional Evaluation System

Traditional DRP (Distribution Resource Planning) evaluation primarily relies on static, results-oriented performance metrics such as inventory turnover rate, order fulfillment rate, and customer satisfaction. These metrics are assessed using analytical hierarchy process (AHP), weighted scoring systems, or expert evaluations to grade distribution centers or outlets. While these methods demonstrate logical structure and operational feasibility in initial supply chain management phases. [1] they have become increasingly inadequate in adapting to modern supply chains characterized by multi-point collaboration, multi-level interactions, and dynamic responsiveness. Particularly within complex network environments, traditional approaches often neglect multi-source data integration, dynamic behavior chain tracking, and inter-node interaction effects. Consequently, their capacity to support risk identification, anomaly alerts, and operational optimization remains limited.

2.2. Insufficient Evaluation Index Dimension

Current evaluation systems predominantly rely on single-point data and one-dimensional metrics. For instance, when assessing delivery efficiency, the focus often remains solely on average delivery time from warehouse to customer, while overlooking comprehensive factors like route optimization strategies, vehicle scheduling efficiency, and loading rates that collectively impact delivery performance. Similarly, inventory management evaluations typically use inventory turnover rate as the core metric, yet fail to incorporate variables such as demand forecasting accuracy, volatility indicators, and the alignment of safety stock strategies. This partial approach risks creating a "good metrics masking bad processes" scenario, failing to identify systemic bottlenecks and limiting the depth of application for evaluation results in decision-making optimization.

2.3. Subjective Weight Allocation Affects the Evaluation Objectivity

In traditional scoring methodologies, indicator weights are predominantly assigned based on expert experience rather than systematic data validation or causal verification. This approach not only introduces human bias but also results in evaluation outcomes that exhibit strong subjectivity and limitations. For instance, when assessing multiple distribution centers of similar types, inconsistent interpretations of weight parameters by evaluators may lead to conflicting classification outcomes for the same entity due to weighting discrepancies, thereby compromising fairness and comparability. [2] Particularly in cross-regional and cross-industry evaluations, the absence of unified industry standards combined with significant differences in expert perceptions exacerbates subjective issues, significantly diminishing the generalizability and practical value of rating systems.

In conclusion, the traditional DRP (Data-Driven Performance) rating system exhibits significant shortcomings in methodology, indicator design, and scoring mechanisms, making it inadequate for modern supply chain development trends characterized by intelligence and collaboration. To establish a scientific, dynamic, and precise evaluation framework, we must integrate multi-source real-time data, intelligent algorithms, and data-driven modeling approaches. This will create an innovative DRP rating system that combines real-time monitoring, intelligent weight adjustment, and behavioral tracking capabilities.

3. The Introduction Logic of AI Technology in DRP Level Evaluation

3.1. AI-driven Data Processing Capability

Artificial intelligence demonstrates exceptional capabilities in data recognition, summarization, and learning, particularly excelling in processing large-scale, unstructured, and multi-source heterogeneous datasets. By employing multi-layer neural networks, support vector machines, or ensemble learning frameworks, AI models can automatically extract latent features from historical data through nonlinear fitting and predictive analysis. This approach overcomes traditional methods' heavy reliance on predefined rules, enabling better adaptation to dynamic environments and closer alignment with real-world operational logic.

3.2. Multi-source Data Fusion Enhances Evaluation Accuracy

In AI model development, integrating traditional structured business data with real-time IoT data, customer behavior analytics, and geographic information enables comprehensive evaluation dimensions and enhances model accuracy. [3] For instance, combining GPS trajectories with order fulfillment data allows precise optimization of delivery routes, while merging customer feedback with product return rates helps identify service quality bottlenecks. The coordinated input of multi-source data enriches the assessment framework with multidimensional insights, forming a multi-layered intelligent evaluation network.

3.3. The self-learning Mechanism Realizes the Iterative Optimization of The Model

AI models possess continuous learning and self-correction capabilities. In practical applications, these models can dynamically adjust parameter weights based on feedback data, gradually approaching optimal performance. For instance, by incorporating online learning mechanisms, they can dynamically modify classification criteria according to real-time operational outcomes, thereby enhancing the sensitivity and adaptability of evaluation systems. Additionally, AI algorithms can automatically identify sources of evaluation errors, assisting in optimizing model architecture and training strategies to improve the long-term operational stability of assessment systems.

4. Construction Method of AI-Based DRP Level Intelligent Evaluation Model

4.1. Construction of Evaluation Index System

The foundation of model evaluation lies in the design of a scientifically sound and reasonable indicator system. This study established an indicator set covering five dimensions: inventory control (e.g., safety stock coefficient, inventory accuracy), logistics efficiency (e.g., average delivery time, vehicle utilization rate), customer responsiveness (e.g., order fulfillment accuracy, return rate), financial performance (e.g., inventory capital occupation rate, distribution cost ratio), and risk levels (e.g., abnormal event occurrence rate, information system stability). [4] Multiple sub-indicators were set within each dimension, with principal component analysis used to extract key factors, reduce redundant indicators, and enhance model operational efficiency.

4.2. Model Training and Algorithm Selection

Given the classification nature of the evaluation task, this study employs Random Forest as the core algorithm. This method demonstrates strong nonlinear modeling capabilities and robustness against overfitting, making it particularly suitable for handling datasets with high dimensionality and significant noise interference. To enhance model interpretability, we integrate decision tree visualization and SHAP value analysis to help evaluators understand the rationale behind model decisions. Furthermore, a fivefold cross-validation mechanism is implemented to validate model performance, ensuring the reliability of evaluation outcomes.

4.3. Data Processing and Model Implementation

During model implementation, the initial steps involve standardizing raw data and addressing missing values through techniques like One-Hot encoding for categorical variables. The processed dataset is then fed into the model for training and testing. [5] To facilitate enterprise-level deployment, this model integrates with corporate ERP systems via API interfaces, enabling real-time data access, performance metric feedback, and automated alerts for operational teams to respond promptly.

5. Application and Effectiveness Analysis of The Model in Actual Enterprises

5.1. Description of Application Scenarios

The model was first piloted in the distribution network of a national retail chain enterprise. This company operates over 150 distribution centers across 31 provinces and cities, facing common challenges such as unstable delivery timeliness, high inventory costs, and delayed performance evaluations. By integrating this model with existing information systems, monthly intelligent performance assessments are conducted for each distribution center, generating optimization recommendation lists to assist headquarters in making management decisions.

5.2. Effect Verification and Data Analysis

After six months of pilot operation, corporate inventory capital occupation decreased by 12.6% year-on-year, while abnormal distribution rates dropped by 18.4%. The proportion of high-grade distribution centers increased from 43% to 58%. Operational feedback revealed that AI-assessed low-grade nodes closely matched identified management weaknesses, demonstrating strong predictive capabilities in inventory anomalies and transportation delays. Managers adjusted replenishment plans and workforce allocation based on assessment results, significantly improving operational efficiency and customer satisfaction.

6. Conclusion

In today's rapidly evolving supply chain landscape demanding swift responsiveness and refined management, traditional DRP (Distribution Requirements Planning) rating systems struggle to manage dynamic operations in complex distribution networks. This study develops a data-driven intelligent DRP rating model powered by artificial intelligence, validated through enterprise implementation that demonstrates both practicality and technological advancement. The model not only streamlines evaluation processes and enhances accuracy but also provides robust support for intelligent decision-making in supply chain systems. Future enhancements will integrate deep learning and graph neural network technologies to improve temporal data processing and structural relationship analysis capabilities. The model's scalability also paves the way for cross-industry and cross-platform applications. As smart manufacturing and digital supply chain concepts continue to evolve, AI-powered DRP rating systems are poised to become pivotal enablers for enterprises to optimize operational efficiency and drive digital transformation.

References

[1] Liu Xianheng. Research on Supply Chain Management Optimization of HW Company in Liaocheng City [D]. Xi'an University of Technology, 2022. DOI:10.27398/d.cnki.gxalu.2022.000329.

[2] Chen Chen, Wang Yuantao, Wang Rupeng, et al. Analysis and Exploration of Production Planning and Scheduling Functions from the Perspective of Supply Chain Management [J]. Intelligent Manufacturing, 2021(02):43-48.

[3] Duan Xiuhong. Research on Power Supply Chain Management Strategies and Evaluation in E-commerce Environment [D]. North China Electric Power University (Beijing), 2020. DOI:10.27140/d.cnki.ghbbu.2020.000469.

[4] Li Xiaodong. Development and Innovation of Logistics Supply Chain Management Technology and Its Application Analysis [J]. China Logistics & Purchasing, 2019, (07):52-54. DOI:10.16079/j.cnki.issn1671-6663.2019.07.021.

[5] Jing Hui, Fan Yuwei. Digital Transformation, Supply Chain Transparency and Supply Chain Performance —— Empirical Evidence from Chinese A-share Manufacturing Listed Companies [J]. Journal of Nanjing University of Finance and Economics, 2024, (04):89-99. DOI:10.20211/j.cnki.jnufe.2024.04.009.