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Optimizing Production Supply Chain With Markov Jump System for Logistics Collaboration

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ABSTRACT

This study employs a novel Markov jump system model to address complexities and uncertainties in modern logistics management, particularly in supply chain logistics information networks. It introduces dynamic memory to tackle issues in traditional static networks, enabling modeling and control of this intricate system. By assessing decision node importance, a novel strategy optimization method is devised. Through information exchange and decision adjustments among cooperating nodes, the overall decision system performance is enhanced, resulting in a comprehensive logistics information coordination mechanism for production supply chains based on the Markov jump system. The research demonstrates that this approach considers node interactions and information exchange, using dynamic memory to improve system adaptability and robustness, ultimately enhancing overall decision performance and stability. This has practical value for decision support and system optimization in production supply chain logistics information networks, offering fresh insights into Markov jump system control.

KEYWORDS

Information Collaboration Mechanism, Logistics Information, Markov Jump System, Optimization of Decision Control Strategies, Production Supply Chain

In the era of globalization and informatization, efficient collaboration of production and supply chain logistics has become an important guarantee for the competitiveness of enterprises (Guo et al., 2020). However, due to the complex connections and information asymmetry between various links in the supply chain, the difficulty of information collaboration increases, which in turn affects the operational efficiency and flexibility of the entire supply chain (Wang et al., 2022). To address this challenge, researchers have focused extensively on various logistics information collaboration mechanisms (Qin et al., 2021). This article focuses on a production supply chain logistics information collaboration mechanism based on Markov jump systems, aiming to use the theoretical model of Markov jump systems to explore their potential and advantages in improving the efficiency of supply chain logistics information collaboration.

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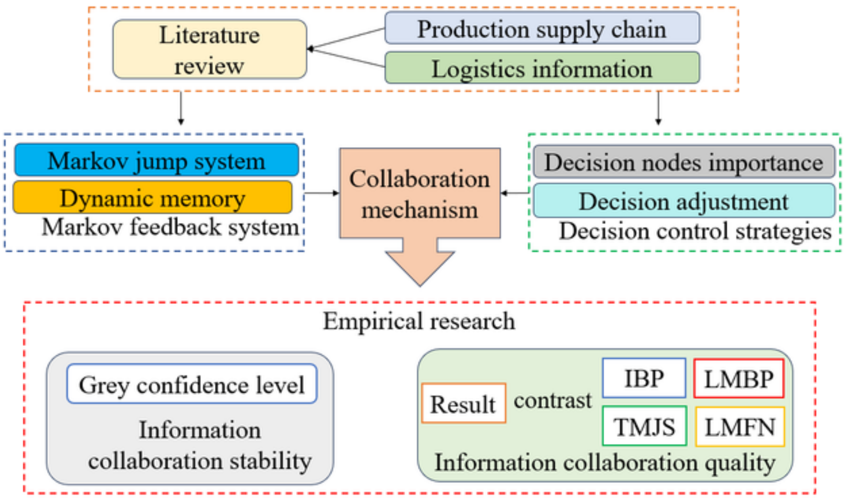
Figure 1. Research Framework



Although the use of Markov jump systems in the collaboration of production and supply chain logistics information is a popular research topic (Meng et al., 2022), this method relies on the estimation of historical data and state transition probabilities for modeling the system state, which may be affected by incomplete or inaccurate information, leading to challenges in the accuracy of the model (Gao et al., 2022). In addition, for complex supply chain network structures and dynamic environments, there are also problems such as difficulty in fully capturing the complexity and variability of the actual supply chain, as well as insufficient recognition and collaborative consideration of important decision-making nodes (Tang et al., 2023). In this regard, the aim of this study is to develop a new controllable Markov jump system by introducing the concept of dynamic memory, in order to improve the accuracy and efficiency of decision-making. This study constructs an effective decision-making node identification and collaborative mechanism to enhance the understanding and recognition of the importance of decision-making nodes in the supply chain logistics information network, more accurately grasp the key factors in the decision-making process, and optimize the selection and coordination of decision-making strategies to capture the influence of historical information and state transitions, thereby enhancing the decision-making ability of the model. The framework of this study is shown in Figure 1.

This study makes contributions to the literature in the following areas:

1. Using Markov jump systems to model the production supply chain and abstracting and describing the state transition process of each link in the supply chain, thereby providing a foundation for the subsequent design of collaborative mechanisms.
2. Introducing a Markov feedback system based on dynamic memory, fully considering the dynamic evolution of the system state, thus better adapting to the actual supply chain environment.
3. Utilizing the collaborative mechanism of this study to effectively improve the overall efficiency of the production supply chain, reduce the delay and cost of information transmission, improve the response speed and flexibility of the production supply chain, and thereby enhance the competitiveness of enterprises.
4. Combining the characteristics of Markov models and the demand for supply chain logistics information collaboration. The research results can provide support for production supply chain

management decisions and provide a new approach and method to solve the problem of supply chain logistics information collaboration.

LITERATURE REVIEW

In previous research, certain results were achieved in optimizing the logistics information collaboration mechanism of the production supply chain for enterprises to improve operational efficiency and reduce costs. For example, Mahdiraji et al. (2022) proposed an information sharing model based on Bayesian rules to address the information barriers faced by traditional supply chain management and designed an information sharing strategy to improve the efficiency and accuracy of information transmission between nodes in the supply chain. Hammad et al. (2023) proposed a production supply chain logistics information collaboration mechanism based on spatiotemporal flow and information sharing and verified the effectiveness of this mechanism through empirical cases. Wu et al. (2023) studied a production supply chain logistics information collaborative decision-making model based on intelligent optimization algorithms and applied it to practical cases to prove the effectiveness of the model in improving collaborative efficiency and reducing costs. Some scholars have also studied key issues in logistics management by constructing a production supply chain logistics information collaboration platform and proposed information sharing and security management methods based on blockchain technology (Liu et al., 2020).

In recent years, with the rapid development of the economy and society, many scholars have begun to apply Markov jump systems to logistics collaboration mechanisms. Jackson et al. (2023) found in their research that traditional logistics collaboration mechanisms often suffer from information lag and high costs, and Markov jump systems can effectively solve these problems. They designed a new logistics collaboration mechanism based on Markov jump systems and verified its effectiveness and feasibility through numerical simulations (2023). Sharma et al. (2023) proposed a decision control strategy based on state transition matrix by analyzing Markov jump systems and applied it to complex supply chain management. Experiments have shown that this method can significantly improve efficiency and stability in the supply chain. Wang et al. (2022) studied the optimization method of decision control strategy for Markov jump systems. By dynamically adjusting decision parameters, they achieved the optimization of process control and resource allocation in the production supply chain, improving production efficiency and supply chain flexibility (2022).

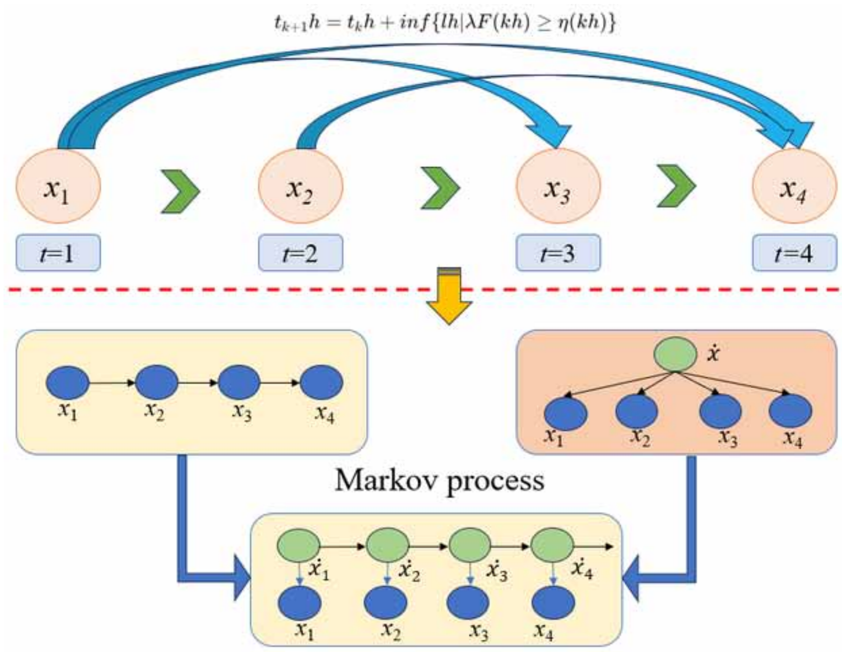
However, despite various measures being taken in the production supply chain, the collaborative efficiency and accuracy of logistics information still face significant challenges. This is mainly because each link in the production supply chain is full of uncertainty, complexity, and dynamic changes, which leads to an increase in the error of the model results. In the entire supply chain logistics information network, decision nodes are considered key points with significant influence in the system. To address this issue, this paper adopts a method based on Markov jump systems and introduces a dynamic memory mechanism to optimize the control strategy of decision nodes. By analyzing and modeling the dynamic memory of nodes, we can identify key factors that affect their importance and develop corresponding decision control strategies based on these factors. This will help optimize the node importance coordination mechanism in the supply chain logistics information network, thereby reducing uncertainty and risk in the system, and improving the efficiency and stability of the entire network.

MARKOV JUMP SYSTEM FOR PRODUCTION SUPPLY CHAIN

Markov Feedback Control Based on Dynamic Memory

Markov jump systems are mathematical models that describe the evolution of stochastic processes, characterized by the randomness of transitions between states (Gao et al., 2022). In other words, their

Figure 2. Markov Jump System



state is not fixed, but rather, it jumps and changes between different modes. This jump reflects the complex state transition process in the production supply chain, as shown in Figure 2. Information collaboration is crucial in the production supply chain. This study introduces Markov feedback control with dynamic memory, which can achieve dynamic regulation and optimization of information flow by comprehensively considering historical states (Sathyan et al., 2023). Specifically, it can predict potential state transitions in the future based on the past state and behavior of the system and take corresponding measures to adjust various links in the supply chain to maximize demand, improve efficiency, and reduce costs (Liang et al., 2019). Therefore, Markov feedback control based on dynamic memory provides a flexible and effective control strategy for the collaborative mechanism of logistics information in the production supply chain, which can better adapt to the complex and changing supply chain environment and improve the stability and resilience of the supply chain (Chen et al., 2022).

A class of continuous time Markov jump systems is considered in Equation 1.

$$\begin{cases} \dot{x}(t) = A_{r(t)}x(t) + B_{r(t)}u(t) + D_{r(t)}\omega(t) \\ \qquad\quad y(t) = C_{r(t)}x(t) \end{cases} \tag{1}$$

In Equation 1, $x(t)$, $u(t)$, and $y(t)$ represent the system state, control input, and measurement output, respectively. $\omega(t)$ represents external disturbances, $\{r(t), t>0\}$ represents non-homogeneous Markov processes, Ar(t), Br(t)$_{, Cr}$(t)$_{, Dr}$(t)$_{are}$ kn$_{own}$ matrices.

By using a dynamic variable, more transmission resources can be saved (Zhao et al., 2021). The triggering conditions are shown in Equation 2.

$$t_{k+1}h = t_k h + \inf_{l \in N^+}\left\{lh \mid \ddot{e}F(kh) \geq \varsigma(kh)\right\} \tag{2}$$

In Equation 2, tk is th$_e$ first transfer time; h, kh, tkh and h represent the sampling period, sampling time, and the latest triggering time, respectively. $\{tkh,\ k\in N+_{\}} \subseteq \{kh,\ h \in N+\}$. $\lambda>0$ is a given parameter.

Meanwhile, to better describe non-homogeneous Markov processes, the following definitions are given: tl represents $_t$he l-th transition time and Rl represents $_t$he Markov process, where the dwell time is Tl=tl-tl-1. Th_e $tr_a nsi_{tio}$n probability under the Markov chain Rl is shown in $E_q$uation 3.

$$\Pr\{R_{l+1} = j \mid R_l = i\} = \begin{cases} q_{ij}, i \neq j \\ 0, i = j \end{cases} \tag{3}$$

In Equation 3, i and j represent subsystem modes and {(Rl, tl), l ∈ $_N$} is a non-homogeneous Markov update process. Based on this description, when the system mode i is activated, Gi(·) represen$_t$s the probability distribution function calculated as shown in Equation 4.

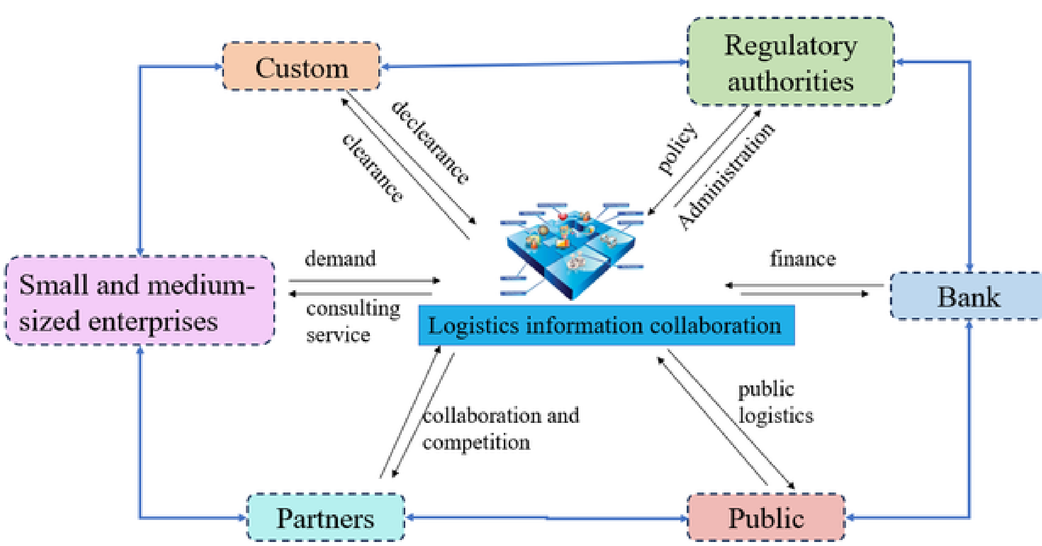
$$G_i(h) = \Pr\left\{T_{l+1} < h \middle| r(t_l) = i\right\} \tag{4}$$

In Equation 4, let $N(t)$=sup {l: tl ≤ t}. If $r(_t)$=RN (t), it is cal$_{led\ a}$ Markov process {$r(t)$, and t ≥ 0} is associated with the update process {(Rl, tl)} (Chen et al. 202$_0$).

Modern Multidimensional Logistics Information Collaboration System

Production supply chain logistics information collaboration refers to the use of information sharing and coordination methods to promote effective communication and cooperation between various links in the supply chain (Khoukhi et al., 2019). In modern logistics, multi-dimensional logistics information collaboration is crucial, which is reflected in the application of Internet of Things (IoT) technology. Lack of information collaboration will lead to the failure of other forms of collaboration (Jamrus et al., 2020). Therefore, the accuracy and timeliness of logistics information are crucial for the efficient operation of logistics systems. The modern logistics collaboration system aims to solve the problems of disharmony and information barriers between various logistics subsystems, thereby

Figure 3. Modern Multidimensional Logistics Information Collaboration System



achieving efficient transmission and sharing of information (Liu et al., 2021). Figure 3 shows the modern multi-dimensional logistics information collaboration system.

The modern multi-dimensional logistics information collaboration system aims to promote information sharing and smooth transmission among intelligent management departments within the enterprise, to ensure consistency in information collaboration (Liu et al., 2021). This system enables various management departments to update and share real-time information on procurement, supply, orders, finance, and transportation costs, thereby avoiding information duplication and accuracy issues, and significantly improving the efficiency of information processing (Gong et al., 2022). Of course, the functions of modern multi-dimensional logistics information collaboration systems are not limited to internal enterprises but also include information sharing with external partners (Li et al., 2022). By communicating and sharing information with upstream and downstream manufacturers, competitors, and cooperative allies, enterprises can better understand market demand, supply chain information, and the dynamics of competitors, thereby making early adjustments to strategies and maintaining market competitiveness (Liu et al., 2021). The benefits of this information sharing are obvious, but in order to ensure the collaborative operation of various information systems, it is necessary to use technical means such as data collection, transmission, publishing, sharing, and fusion. Through these technological means, it is possible to ensure timely and accurate sharing of information among various information systems, achieving collaborative operation (Ran et al., 2024).

Importance of Logistics Information Network Decision Nodes

In the logistics information network of the production supply chain, decision nodes refer to the key nodes responsible for formulating and executing logistics decisions. Through research based on Markov jump systems, the state transition probability and transition rate of each decision node are analyzed and its impact on the logistics information network is evaluated, the reliability and stability of decision nodes in the network are determined (Rukundo et al., 2022). In other words, logistics decision-making in the production and supply chain essentially relies on various data provided by logistics information network nodes to make decisions. Therefore, logistics information network decisions can be set as a decision information system (DIS), which is usually a binary: DIS=(U, AT) or DIS=(U, C ∪ D). Among them, C= {α1, α2, ..., αn} rep$_r$esents a set of conditional attributes, D={d} represents a set of decision attributes, and U={u1, u2, ..., un} rep$_r$esents a wide area (Gupta et al., 2022). If there are m decision objects (or samples), the decision matrix can be obtained, as shown in Equation 5.

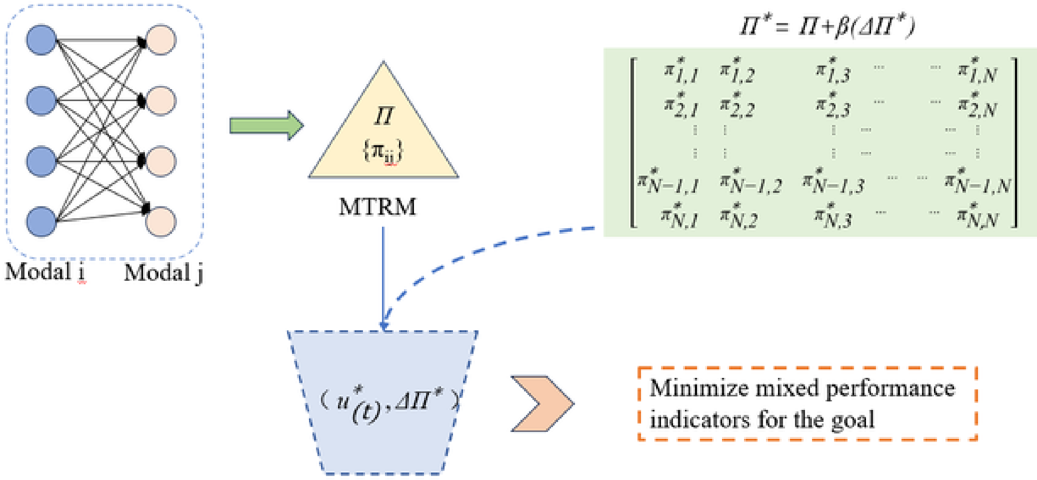
$$DIS = \begin{array}{c} \\ u_1 \\ \vdots \\ u_m \end{array} \begin{array}{c} \alpha_1 \cdots \alpha_n \; d \\ \begin{bmatrix} \alpha_1(1) & \cdots & \alpha_n(1) & d(1) \\ \vdots & \ddots & \vdots & \vdots \\ \alpha_1(m) & \cdots & \alpha_n(m) & d(m) \end{bmatrix} \end{array} \tag{5}$$

Equation 5 contains the conditions and decision information for each decision. In addition, in the Markov jump system, using the jump comprehensive correlation degree to measure the direct correlation degree of factors, the importance of decision nodes in the production supply chain logistics network is IMPfin (αi, *d)* $_{and}$ i*t can* be defined as the comprehensive degree of jump correlation between the information of each network node and logistics decisions (Yu et al., 2024), as shown in Equation 6.

$$IMP_{fin}(\alpha_i, d) = \omega_{0i} \tag{6}$$

The higher the importance value in the formula, the stronger the correlation between the logistics network node information of the production supply chain and logistics decisions, indicating that the network node information has a significant impact on logistics decisions.

Figure 4. Decision Control Strategy Optimization for Markov Jump Systems



OPTIMIZATION OF PRODUCTION SUPPLY CHAIN LOGISTICS INFORMATION COLLABORATION MECHANISM

Decision Control Strategy Optimization for Markov Jump Systems

In production supply chain logistics, the optimization of decision control strategies for Markov jump systems plays an important role. By optimizing state recognition prediction and decision-making, Markov jump models can improve the operational efficiency and collaboration of the production supply chain. In this process, the system's state can represent different stages or states, such as order processing, production, and transportation (Wei et al., 2023). The probability of system jumps between different modes directly affects the changes in system state, stability, and performance. The transition probability between these modes is usually described by the mode transition rate matrix (MTRM), which is closely related to the performance of Markov jump systems (Sathyan et al., 2023). By analyzing and optimizing MTRM, we can better understand the transition patterns between system states, thereby guiding decision-making and resource allocation. For example, adjusting the transition probability can reduce bottleneck links in the system, optimize supply chain processes, and improve overall efficiency and collaboration. This study introduces the controllability and mixed performance indicators of MTRM and designs an optimal decision control strategy based on MTRM. The optimization model is shown in Figure 4.

For the traditional jump linear quadratic Gaussian optimal control with a given MTRM, the MTRM is expressed as homogeneous as Π { π_{ij} }. The mode transition rate from mode i t*o* mode j *in* a continuous time Markov process often introduces performance metric J(Π*) to* measure the system cost of Markov jump systems, as shown in Equation 7.

$$J(\Pi) = E\left\{\int_{t_0}^{'} \left(x'\left(t\right) Q_{r(t)} x\left(t\right) + u'\left(t\right) R_{r(t)} u\left(t\right)\right) dt + x'\left(t_f\right) L_{t_f} \cdot x\left(t_f\right) \middle| \Pi\right\} \tag{7}$$

In Equation 7, *E* represents mathematical expectation, t_0 is the starting time, t_f is the termination time, $Q_{r(t)}$, $R_{r(t)}$ is the weight matrix and satisfies, and for any mode *i* satisfying $Q_i = Q_i^{'} > 0, R_i = R_i^{''}$ >0, based on this performance index, the current goal is to find the optimal decision control ($u_{(t)}^{*}$,

$\Delta\Pi^*$) pair to achieve the goal of minimizing the mixed performance index. However, there is a potential problem in the process of constructing the optimal control pair mentioned above, which is the coupling between the control quantity and the decision quantity (Piao et al., 2022). Equation 8 shows how to solve this problem by first assuming that the optimal decision $\Delta\Pi^*$ has been introduced into MTRM$\prod$, and after introducing the optimal decision, MTRM $\overset{*}{\prod}$ can be expressed as:

$$\overset{*}{\prod} = \prod + \beta(\Delta\Pi^*)$$
$$= \begin{bmatrix} \overset{*}{\pi}_{1,1} & \overset{*}{\pi}_{1,2} & \overset{*}{\pi}_{1,3} & \cdots & \cdots & \overset{*}{\pi}_{1,N} \\ \overset{*}{\pi}_{2,1} & \overset{*}{\pi}_{2,2} & \overset{*}{\pi}_{2,3} & \cdots & \cdots & \overset{*}{\pi}_{2,N} \\ \vdots & \vdots & \vdots & \cdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \cdots & \vdots \\ \overset{*}{\pi}_{N\text{-}1,1} & \overset{*}{\pi}_{N\text{-}1,2} & \overset{*}{\pi}_{N\text{-}1,3} & \cdots & \cdots & \overset{*}{\pi}_{N\text{-}1,N} \\ \overset{*}{\pi}_{N,1} & \overset{*}{\pi}_{N,2} & \overset{*}{\pi}_{N,3} & \cdots & \cdots & \overset{*}{\pi}_{N,N} \end{bmatrix} \tag{8}$$

Based on the optimal decision MTRM $\overset{*}{\prod}$, it is necessary to design a controller and introduce a Markov filter to estimate the system state, as shown in Equation 9.

$$\begin{cases} d\hat{x}(t) = \hat{A}_{r(t)}\hat{x}(t)\,dt + \hat{B}_{r(t)}dy(t) \\ u(t) = \hat{C}_{r(t)}\hat{x}(t) \end{cases} \tag{9}$$

In Equation 9, $\hat{x}(t)$ represents the estimation of the system, and the state estimation error $\psi(t) = x(t) - \hat{x}(t)$ is defined. For this type of Markov filter, we want to minimize the estimation error, that is, to minimize $E\left(\psi(t)^2\right)$ for any $t \in [t_0, t_f]$, where $\cdot$ represents a norm. Therefore, the structure in Equation 10 needs to be satisfied.

$$\begin{cases} d\hat{x}_{op}(t) = A_i\hat{x}_{op}(t)\,dt + B_i u(t)\,dt + \Gamma_i d\vartheta(t) \\ \hat{x}_{op}(t_0) = E\{x(t_0)\} = \overline{x}_0 \end{cases} \tag{10}$$

In Equation 10, *r(t)=i*, $\hat{x}_{op}(t)$ is the optimal state estimation value, and Γ_i represents the state estimation gain. Based on the above equation, the optimal state estimation error and state estimation covariance matrix can be obtained, thereby obtaining the optimal decision control and achieving the goal of minimizing mixed performance indicators.

Controllable Information Collaboration Mechanism Model Based on Markov Jump Systems

The controllable information collaboration mechanism model based on Markov jump systems is a research method used to improve the collaboration of supply chain logistics information. Its core idea is to combine the Markov jump system with the information collaboration mechanism to enhance the efficiency and controllability of the supply chain logistics system. In this model, the Markov jump system is used to describe the state transition and jump process of logistics information, and by designing and optimizing information collaboration mechanisms reasonably, the collaborative efficiency and operational controllability of the supply chain can be improved. This model can adaptively adjust collaborative strategies and methods according to different logistics needs and environmental conditions, to ensure the smooth operation of the supply chain system in different states.

By using a controllable information collaboration mechanism model based on Markov jump systems, we can achieve the following optimization effects:

1. Real time optimization: achieving real-time monitoring and adjustment of production and supply chain logistics information, making information transmission timelier and more effective, reducing information lag and delay, and improving the real-time performance of information collaboration.
2. Adapting to dynamic environments: dynamically evaluating and adjusting the importance of decision nodes to cope with the constantly changing supply chain logistics environment.
3. Improving the accuracy of system prediction: accurately modeling and predicting the status of various links in the production supply chain, thereby improving the accuracy and reliability of information, reducing errors and distortions in information transmission, and improving the accuracy of decision-making.
4. Improving resource utilization efficiency: achieving effective management and allocation of logistics information in the production supply chain, optimizing resource utilization, avoiding waste and idle resources, and improving production efficiency and overall operational efficiency of the supply chain.

This model provides a new method to study and optimize the logistics information collaboration of the production supply chain, which is of great significance to improve the performance and competitiveness of the supply chain. The pseudocode studied is shown in Table 1.

Table 1. Schematic Diagram of Pseudocode Research

```
Input: System state x(t), first transition time k, sampling period, sampling time, latest trigger time h, kh, t_k h,
probability distribution function G, conditional attribute α,Decision attribute d, external disturbance w
Markov feedback control with dynamic memory introduced
Calculate the triggering condition t_{k+1} h using eq-2
for all t= 1 to R do
        Gi(h)=Pr{T_l+1<h/r(t_l)=i}
Let N(t)=sup{l: t_l ≤t}
Calculate DIS using eq-5
for α=1: n
IMP_fin(α_i,d)=w_0i
if Q_i >0,R_i >0
x^(t_0)=E {x(t_0)}=x¯_0
    Obtain the optimal state estimate value
else
    Unable to obtain optimal decision control
end for
end for
```

Collaborative Quality Evaluation Methods

Collaborative quality is essentially a hierarchical and multi-dimensional concept. When conducting quality evaluation, the evaluation methods often vary depending on the evaluation objectives and objectives. The evaluation of logistics information collaboration quality in enterprise production supply chain is mainly based on just in time (JIT) and automation (Wang et al., 2022). The core concept of JIT is to produce the required products at the right time and in the right quantity, avoiding unnecessary inventory and waste, thereby improving production efficiency and quality and reducing costs. Therefore, the quality of logistics information collaboration in the production supply chain can be evaluated from the following three aspects.

Quantity

The ratio between the theoretical demand K_j for each material and the actual received quantity q_j is the material delivery rate θ (Piao et al., 2022), as shown in Equation 11.

$$\theta_j = K_j / q_j \tag{11}$$

In an ideal situation, θ_j=1, θ_j is actually within a certain control range, and the distribution of B values is random. That is to say, when the process is in a controlled state, the product quality characteristic values will follow a certain normal distribution $N (\mu, \sigma^2)$, so $\mu+3\sigma$ can be used as a control interval for θ, where CL, UCL, and LCL represent the mean, upper limit, and lower limit, respectively, as shown in Equation 12.

$$\begin{cases} CL = \mu \\ UCL = \mu + 3\sigma \\ LCL = \mu - 3\sigma \end{cases} \tag{12}$$

If θ_j is within this control range, it means that the actual amount of material received is the same as the theoretical material demand, and the collaborative quality is good in terms of quantity. However, it also indicates that there are quality issues in collaboration. The confidence probability of dynamic collaborative quality evaluation represented by $\mu+3\sigma$ is 99.73%, which can objectively evaluate the quality of collaboration.

Time

Both forward and backward delivery can have a negative impact on the supply chain, so the on-time delivery rate ρ_i of material x_i during a certain time period can evaluate the collaborative quality (Wang et al., 2024), as shown in Equation 13.

$$\rho_i = \frac{\sum_{j=1}^{n} N_{T_i^j}}{n} \tag{13}$$

In Equation 13, $N_{T_i^j}$ >0 represents that the actual arrival time is later than the standard arrival time, and $N_{T_i^j}$ is a binary expression of T_i^j. In an ideal situation, ρ_i =1, like the material delivery rate θ_j, needs to be within a certain control range to be able to evaluate the dynamic collaborative quality.

Comprehensive Evaluation

Information entropy is an important concept of probability distribution in space $X = [x_1, x_2, ..., x_i]$ (Li et al., 2022), as shown in Equation 14.

$$H\left(P\right) = -\sum_{i=1}^{n} P_i \ln P_i \tag{14}$$

In Equation 14, P_i represents the probability of the i-th element in the vector.

The comprehensive evaluation result LIQ_j of the j-th indicator is shown in Equation 15.

$$LIQ_j = \omega_j \theta_j + (1 - \omega_j)\rho_j \tag{15}$$

In Equation 15, w_j represents the weight coefficient of the j-th indicator. For a specific LIQ_j, if it is within the control range, this indicates that the collaborative quality is normal and the collaborative mechanism is good; however, there is also an abnormality, and appropriate measures need to be taken to improve the production logistics coordination quality of the material.

EMPIRICAL RESEARCH AND ANALYSIS

Experimental Data and Preprocessing

Experimental Data

This article takes the production supply chain of three different companies as an example and adopts JIT supply strategy to ensure smooth production. To achieve this goal, the company requires all suppliers to deliver materials on time. The company has established long-term cooperative relationships with all suppliers in the supply chain and requires them to provide fixed types of components. All companies have a sound foundation of informatization, with comprehensive coverage of their information systems. They can easily obtain the necessary relevant data from these systems to simulate and analyze the effectiveness and performance of supply chain logistics information collaboration mechanisms and help researchers evaluate and improve related algorithms and strategies. The following are the main data on the logistics information collaboration mechanism in the production supply chain:

Order data: information such as quantity, type, destination, and time limit of orders. These data can help understand production demand and logistics flow.

1. Transportation data: various parameters recorded during logistics transportation, such as transportation time, transportation cost, and transportation path. These data can be used to optimize logistics routes and select the best transportation methods.
2. Supplier data: supplier quality, delivery time, price, and other information. These data can be used to evaluate the performance of suppliers and select the optimal supply chain partners.
3. Customer demand data: customer demand, time limit, preferences, and other information. These data can help enterprises better understand customer needs and adjust production and logistics plans in a timely manner.
4. Supply chain network topology data: topology structure of the supply chain network, including the connection relationships between suppliers, manufacturers, distributors, and retailers, logistics flow, and inventory levels.
5. Jump system data: using Markov jump models for experiments, it is necessary to collect parameter data such as jump probability and state transition matrix.

Data Preprocessing

To better apply production supply chain data to various data analysis, modeling techniques, and model optimization, it is necessary to preprocess the experimental data mentioned above to improve data quality. The main steps of preprocessing include:

1. Data cleaning: deleting or repairing errors, missing, duplicate, or inconsistent parts of data, including filling in missing values, removing outliers, or fixing erroneous data.
2. Data integration: integrating data from different sources into a unified data storage for analysis and modeling. This may involve data merging, concatenation, and transformation.
3. Data conversion: transforming data to meet the requirements of analysis or modeling, including normalizing, standardizing, discretizing, or converting it to appropriate data types.
4. Feature engineering: creating new features or transforming existing features based on domain knowledge and analysis objectives to improve model performance.
5. Data reduction: reducing large datasets to reduce computational load and improve model training efficiency, including sampling, aggregating, or compressing data.

Evaluation of Information Collaboration Stability

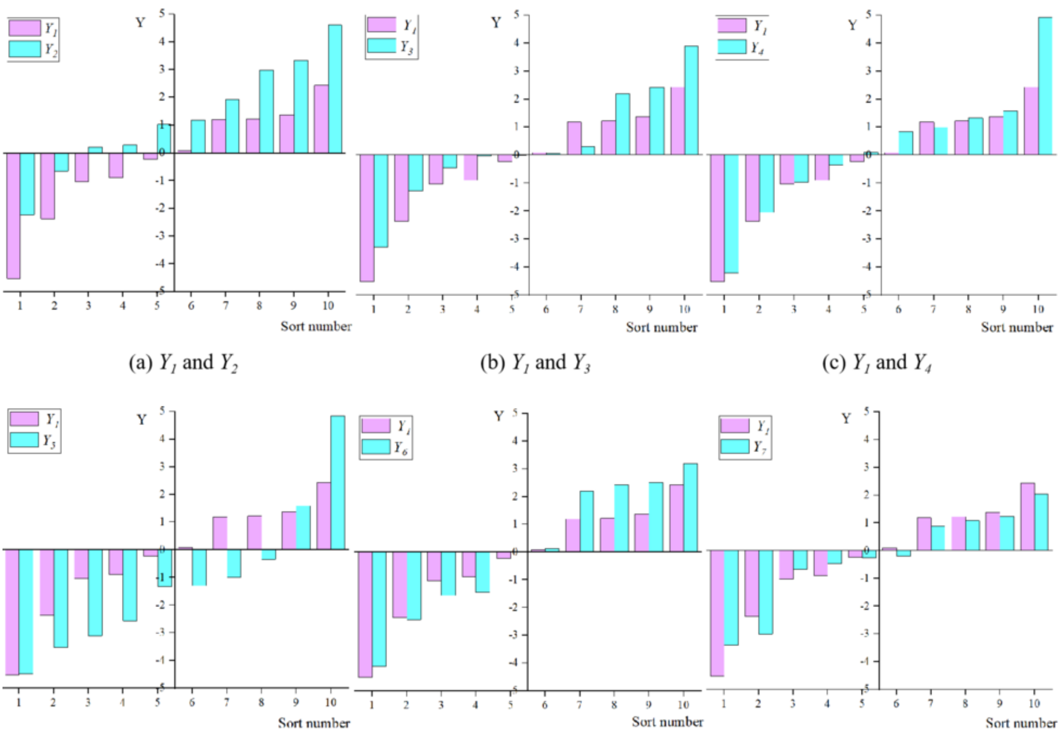
The instability of the logistics information collaboration mechanism in the production supply chain may lead to issues such as information delay and incompleteness. Therefore, to evaluate the stability of the production supply chain logistics information collaboration mechanism based on the Markov jump system constructed in this article, the calculation method of grey absolute correlation degree is adopted for stability evaluation analysis (Li et al., 2022). The grey absolute correlation degree between the first group of sample data and other sequences can be obtained. If the grey correlation degree is larger, the grey confidence level is higher, and the stability of the detailed production supply chain logistics collaboration mechanism is higher. If the system is stable, a data sequence based on the difference between the actual time received by the material procurement departments of three companies from the production sequence plan and the specified standard time (IT_i^j) is established and continuously extracted 70 times. For the convenience of display, this article selects one piece of the sample data shown in Table 2.

A computer simulation method was used to obtain 7 data sequences that follow the normal distribution (See Table 2). Each sequence contains 10 pieces of data, and the data sequence should

Table 2. Data of Logistics Information Sample

1	2	3	4	5	6	7
-1.03	1.93	-3.28	0.10	-1.33	-4.11	2.04
-2.37	1.18	0.05	-0.35	-2.56	0.02	-0.19
1.38	2.99	-0.01	0.99	1.59	2.19	0.89
1.22	-2.23	0.31	1.58	-4.49	0.13	-0.26
-0.89	1.03	-1.28	-4.21	-1.29	3.19	1.24
1.19	3.35	2.20	0.84	-0.34	-1.45	-0.46
2.43	-0.65	-0.02	-2.04	-3.54	-2.44	-0.66
-0.23	4.62	3.89	1.32	4.84	2.43	1.09
0.09	0.21	-0.46	4.92	-3.11	-1.56	-3.01
-4.52	0.28	2.41	-0.97	-1.00	2.51	-3.40

Figure 5. Comparison of Ranking Data Sequences for Y1 and Each Sequence



(a) Y_1 and Y_2 (b) Y_1 and Y_3 (c) Y_1 and Y_4

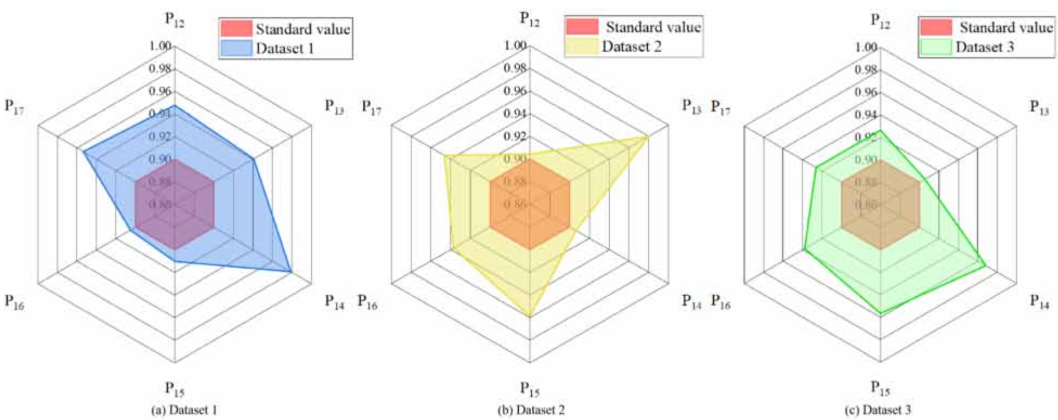
(d) Y_1 and Y_2 (e) Y_1 and Y_3 (f) Y_1 and Y_4

follow the normal distribution (assuming its mathematical expectation E and standard deviation are 0 and 0.1, respectively). The data are sorted to obtain the data sequences Y1~Y7, with Y1 as the key point of the network node. The comparison between Y1 and Y2~Y7 sorted data sequences is shown in Figure 5.

According to the results presented in Figure 5, it can be preliminarily considered that the system has good stability. In general, if the attribute weight based on the generalized grey correlation of two data sequences Y_1 and Y_j is f_{1j}=0.5, the judgment can be made based on the grey confidence level P_{1j}: If the grey confidence level is ≥ 90%, the collaborative process of production and supply chain logistics information is stable; if the gray confidence level is <90%, the information collaboration is unstable and corresponding measures need to be taken to eliminate the disturbance factors caused by the collaboration process. The calculation results of grey confidence level are shown in Figure 6.

According to the results in Figure 6, it can be seen that when the attribute weight of the generalized grey correlation based on two data sequences Y_1 and Y_j is f_{1j}=0.5, the grey confidence level results of the three datasets in this study all exceed 90%, indicating that the collaborative process of logistics information in each production supply chain is stable. Among them, dataset 1, two data sequences Y_1 and Y_4, have the highest gray confidence level, reaching 97.88%. The lowest gray confidence level of this dataset is also 90.53%. From this, it can be seen that the stability is good and can meet various requirements for logistics information in collaboration, thereby ensuring the integrity and accuracy of logistics information. This stability can support the establishment of an information sharing platform, enhance communication and collaboration efficiency among all parties involved, and facilitate the introduction of advanced information technology to enhance information collection and processing capabilities. In addition, the grey confidence level of the production supply chain in the other two

Figure 6. Calculation of Grey Confidence Level



datasets is also above 90%, indicating the stability of the collaborative mechanism, which will help improve the efficiency and competitiveness of the overall production supply chain logistics.

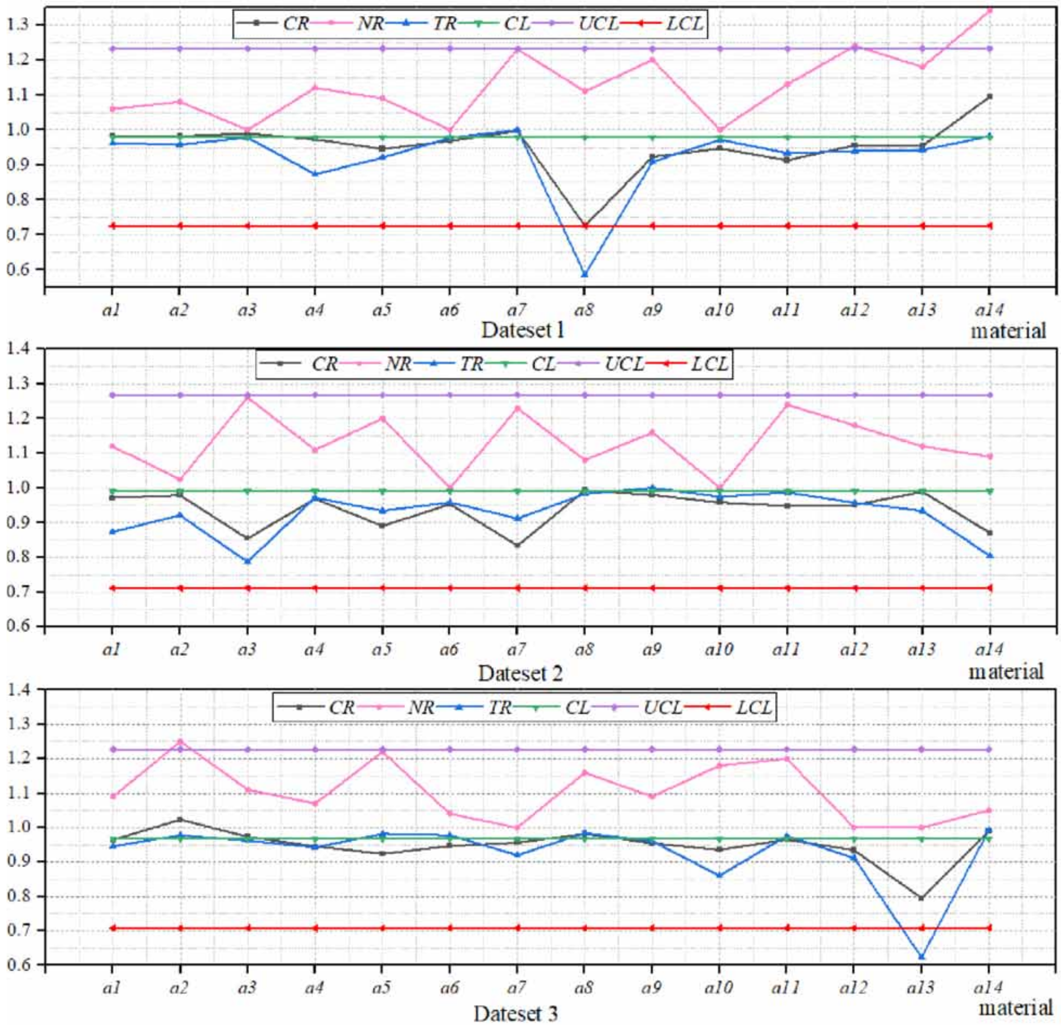
Collaborative Quality Results and Analysis

Based on the stability evaluation of information collaboration in the previous section, it can be seen that the stability of the controllable information collaboration mechanism model based on Markov jump system proposed in this study has been well verified. To further evaluate the quality of logistics information collaboration in the production supply chain, this study analyzed the quantity, time, and comprehensive evaluation aspects, and the results are shown in Figure 7.

First, taking 14 types of materials as examples, the material delivery rate was calculated by comparing the demand for enterprise materials with the actual quantity of materials received by the manufacturer. In three datasets, material delivery rates θ. The control ranges are (0.84, 1.45), (0.51, 1.83), and (0.74, 1.42), respectively. To ensure smooth production, a JIT supply strategy was adopted, and theoretically, the actual amount of materials received should be equal to the theoretical demand, that is θ= 1. However, in actual production supply chains, materials that exceed theoretical demand are often provided. Therefore, it is necessary to ensure that θ. If it is greater than or equal to 1, the quantity evaluation result (NR) of material information quality can be obtained. Second, the standard time and delivery frequency of 14 materials were calculated to obtain the on-time delivery rate of the materials ρ,thereby conducting a temporal material information quality evaluation (TR). Finally, we conducted a comprehensive evaluation (CR) based on the results of NR and TR. In the figure, CL, UCL, and LCL represent the mean, upper limit, and lower limit, respectively.

From the collaborative quality results in Figure 7, it can be seen that the comprehensive evaluation results in dataset 1 show that the collaborative quality of logistics information in the production supply chain of most materials is good and in a normal and stable state. Among them, there are quality issues with materials *a8* and *a14*, and the comprehensive evaluation results are 0.7275 and 1.0946, which are close to the lowest control range limit of 0.7264 and the highest control range limit of 1.2322, respectively. The production supply chain of material *a8* has a more serious quality problem of logistics information collaboration in the supply chain, while the problem of material *a14* is relatively mild. For material supply chains with good quality of logistics information collaboration based on Markov jump systems, it is recommended to continue maintaining the current logistics information collaboration strategy. For materials *a8* and *a14* with quality issues, certain measures need to be taken to improve the quality of logistics information collaboration in the production supply chain. In future production and supply chain logistics cooperation, more attention needs to be paid to the

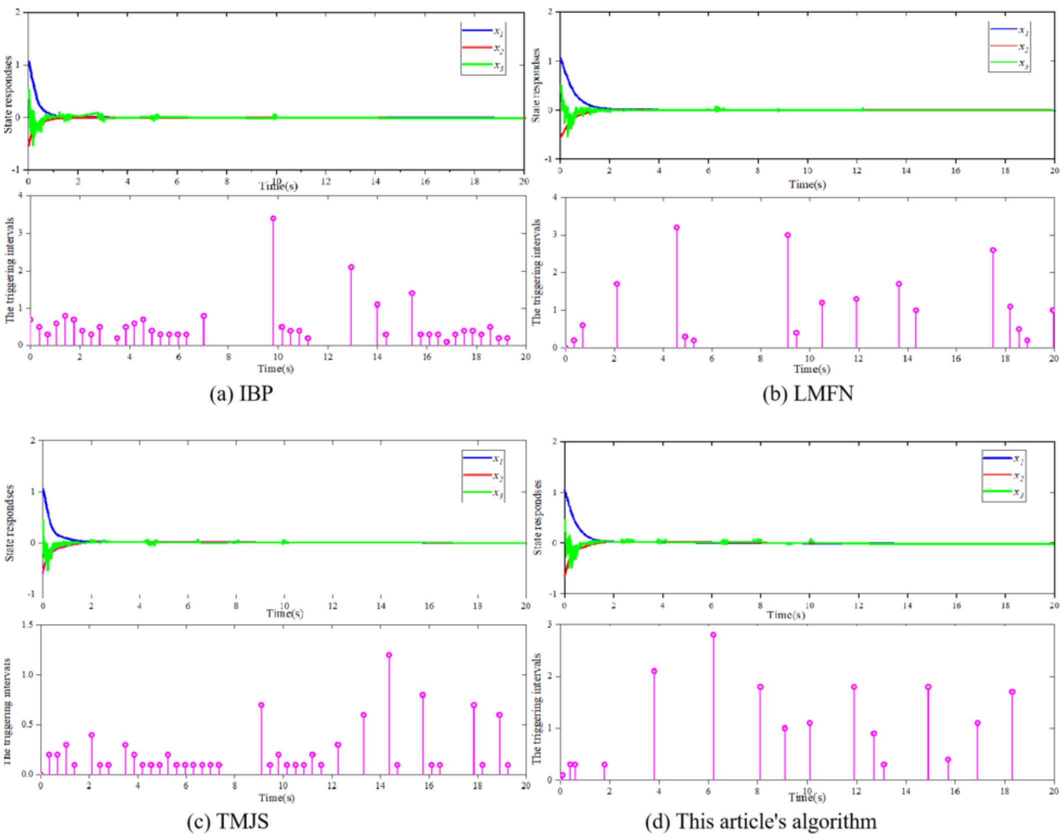
Figure 7. Collaborative Quality Results Chart



collaborative quality issues of material *a8* and material *a14*. The overall collaborative quality of the other two datasets is not an issue, with dataset 2 showing better material performance and fluctuating evaluation results between the median values, indicating no collaborative quality issues. Most of the materials in dataset 3 also meet the relevant requirements. In summary, the collaborative quality of the production supply chain logistics information collaboration mechanism based on Markov jump system is good and in a normal and stable state.

To further verify the effectiveness and superiority of the production supply chain logistics information collaboration mechanism based on Markov jump system in this study, a comparison of control performance was made with improved BP neural network (IBP) (Mahdiraji et al., 2022), LMBP feedback neural network algorithm (LMFN) (Jackson et al., 2023), and traditional Markov jump system (TMJS) (Sathyan et al., 2023) methods in terms of transmission data volume and logistics information triggering rate. The comparison results of the state trajectories, release times, and intervals of different methods in dataset 1 are shown in Figure 8.

Figure 8. System Trajectory and Trigger Time of Dataset 1 Under Different Methods



From Figure 8, it can be seen that the Markov jump system constructed in this study has superior control performance, thanks to its dynamic memory Markov feedback system. However, compared to IBP, LMFN, and TMJS, the triggering rate is significantly lower. High data transmission volume can lead to an increase in communication costs and may cause noise and confusion, thereby increasing the complexity of decision-making. Therefore, reducing the balance of data transmission can significantly reduce information exchange costs, meet changes in demand in the production supply chain, alleviate unnecessary pressure in operations, and improve overall operational collaboration efficiency. Compared with LMFN, although the model in this article transmits more data, it can stabilize more quickly, in other words, it has better control performance. From this, it can be seen that the Markov jump based system proposed in this article can achieve a balance between triggering rate and control performance, reduce information exchange costs, simplify decision-making processes, and ensure timely and smooth information exchange.

DISCUSSION

In production supply chain logistics, timely and accurate flow of information is crucial for ensuring the efficient operation of the supply chain. However, due to the uncertainty, complexity, and dynamic changes of each link, information collaboration often faces significant challenges. At this point, Markov jump systems can serve as an effective tool for modeling and optimizing decision control strategies. This study adopts a Markov feedback system based on dynamic memory to optimize relevant strategies in decision making. Because the Markov jump system allows system states to jump between different modes, each mode corresponds to a different operating state. Therefore, the process of state transition can be quantitatively described by utilizing the transition probability matrix between patterns. In the production supply chain logistics information collaboration mechanism, different operating states of the supply chain system can be considered as different modes, and corresponding transition probability matrices can be established to ultimately obtain a controllable information collaboration mechanism model based on Markov jump systems.

In addition, this research model can better establish a balance in triggering rate and control performance compared to algorithms such as IBP, LMFN, and TMJS, reduce information exchange costs, ensure timely and smooth communication of information, and produce certain effectiveness and superiority in decision results. The status of supply chain logistics information was divided into different modes and a transition probability matrix was constructed between modes. By monitoring and collecting real-time logistics information, the current status was observed and estimated. Based on the theory of Markov jump systems, the probability of jumping between different states can be described, and this method has great potential in studying information collaboration mechanisms in production supply chains. By modeling different states in the supply chain, we can better understand the way information is transmitted and shared and optimize the collaboration mechanism by adjusting the jump probability to improve the efficiency and adaptability of the supply chain. This will make a certain contribution to empirical research related to this type. First, the Markov jump system theory is introduced into the research of logistics information collaboration in the production supply chain in this study. Compared to traditional continuous system models, Markov jump systems can better describe the uncertainty and dynamic changes in the production supply chain. Second, the jump system modeling and analysis of the collaborative mechanism of logistics information in the production supply chain revealed the existence of nonlinear characteristics. This helps to gain a deeper understanding of the complexity of information flow in the production supply chain and provides a theoretical basis for developing more effective collaborative strategies. Furthermore, this article proposes a series of improvement strategies and algorithms, including dynamically adjusting information sharing strategies and flexibly adjusting collaborative nodes to cope with uncertainty and changes in the production supply chain. The application of these strategies and algorithms effectively improves the information collaboration efficiency of the production supply chain, reduces costs, and enhances the robustness and adaptability of the system. Finally, the successful application of this research method in practice will bring new ideas and methods to the field of supply chain management. This innovative development will promote the progress of supply chain management theory and practice, providing new theories and methods for improving the efficiency of production supply chains, reducing costs, enhancing the robustness and adaptability of systems.

CONCLUSION

In today's globalized and digitized business environment, logistics information collaboration in the production supply chain has become an important link for enterprises to improve operational efficiency and reduce costs. Based on the theory and method of Markov jump systems, this article proposes an innovative decision control strategy optimization model to improve the effectiveness of logistics information collaboration in the production supply chain and mitigate the impact of various uncertainty factors. This controllable information collaboration model established a Markov jump system model, abstracting the states of various nodes in the logistics network as states in the Markov chain, and describing the transition probabilities between different states through a transition probability matrix. Then, relevant indicators of the collaborative mechanism were introduced to evaluate the collaborative efficiency of the logistics network. Next, we improved the collaborative efficiency of the logistics network by optimizing control strategies. Finally, corresponding decision control strategies were designed for different system states to achieve the optimal path selection of information flow, improve information accuracy and feedback speed, and effectively improve the efficiency and accuracy of production and supply chain logistics information collaboration.

Research has shown that using Markov jump systems as the basis for collaborative mechanisms can effectively address the instability in the production supply chain. This mechanism can not only capture sudden changes in the system state, but also adjust collaborative strategies in real-time to adapt to environmental changes. By establishing more flexible and adaptable collaborative mechanisms, enterprises can better cope with market fluctuations, production changes, and logistics uncertainties, thereby improving the overall efficiency of the supply chain. It can be seen that this study provides useful theoretical guidance for the optimization and innovation of logistics information collaboration mechanisms in the production supply chain. In future research, we will further optimize this method and explore more information collaboration models applicable to the production supply chain, making greater contributions to the development of the logistics industry.

CONFLICTS OF INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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