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Predictive Control of Clustered Closed-Loop Supply Chains based on Multimodal Support Vector Machines

Haifeng Guo*, Qinwen Yang

School of Automation and Electrical Engineering, Shenyang Ligong University, Shenyang, China

*Corresponding author: ghf_1970@163.com

Abstract

To address inventory fluctuation and allocation coordination challenges faced by clustered closed-loop supply chains under demand uncertainty, this paper proposes an inventory allocation optimization method integrating demand forecasting with model predictive control (MPC) based on multimodal support vector regression. This approach utilizes numerical features such as historical sales data alongside sentiment features extracted from product reviews to establish a multimodal demand forecasting model. The forecast results are then embedded as exogenous inputs within an MPC control framework, enabling rolling optimization and coordinated allocation of inventory across multiple chains. Simulation comparisons with both basic MPC and unimodal SVR+MPC methods validate the improvements achieved by the multimodal SVR+MPC approach in demand forecasting accuracy, inventory fluctuation suppression, and system operational stability.

Keywords

Clustered Closed-loop Supply Chain; Multimodal Demand Forecasting; Support Vector Regression; Model Predictive Control; Cross-chain Inventory Coordination.

1. Introduction

As global supply chain networks continue to evolve toward multi-node collaboration, highly coupled information, and increased operational uncertainty, traditional supply chain management approaches-primarily based on empirical rules or static optimization-struggle to meet modern market demands for responsiveness, operational stability, and resource allocation efficiency. In Clustered Closed-Loop Supply Chains (CLSCs), systems typically comprise multiple interconnected production, sales, and recycling links, with frequent information exchange and inventory linkage across different product categories and channels. This highly coupled structure makes the system susceptible to inventory fluctuations and delayed allocation decisions during demand volatility, unstable returns, and cross-chain inventory coordination. This increases operational costs and undermines overall coordination efficiency.

In closed-loop supply chain research, Govindan et al.[1] systematically analyzed the coordination mechanisms between forward supply and reverse recovery from reverse logistics and system architecture perspectives. Disney and Towill [2] revealed the dynamic relationship between demand disturbances, information feedback, and the bullwhip effect from a control engineering perspective; Ivanov [3] further expanded the dynamic research framework for closed-loop supply chains from the perspective of resilience and uncertainty management. These studies laid an important foundation for the dynamic analysis and control of closed-loop supply chains.

In domestic research, Li and Liu et al.[4] introduced the concept of "cluster-based supply chains," emphasizing the systemic characteristics of parallel multi-chain and cross-chain coordination. Subsequently, Li Jizi et al.[5]conducted modeling and simulation studies on cross-chain inventory coordination and emergency complementarity, validating the effectiveness of multi-chain coordination mechanisms in reducing inventory fluctuations. With the introduction of dynamic systems theory, Model Predictive Control (MPC) has emerged as a vital tool for supply chain inventory regulation. He et al. [6] systematically summarized the applicability of predictive control methods in complex systems. Guo et al. [7] further integrated MPC into closed-loop supply chain dynamic systems, demonstrating that rolling optimization mechanisms enhance inventory stability.

In demand forecasting research, Support Vector Machines (SVM) and their regression variants (SVR) have gained widespread application due to their robust nonlinear modeling capabilities. Atsalakis and Valavanis [8] and Wu [9] validated the effectiveness of SVM in complex forecasting tasks. In recent years, with the rapid advancement of data-driven and artificial intelligence methods in supply chain management, Pietukhov et al. [10], Al Bashar et al. [11], and Beta et al. [12] have explored the application potential of data-driven approaches in inventory decision-making and supply chain resilience enhancement from predictive analytics and AI perspectives. Additionally, Fang and He's [13] multi-feature fusion modeling research provides valuable insights for integrating multi-source information in forecasting tasks.

However, existing research in clustered closed-loop supply chain scenarios still predominantly relies on single structured data for demand forecasting, with limited coupling mechanisms between forecasting models and MPC control strategies. In light of this, this paper proposes an inventory allocation optimization method for clustered closed-loop supply chains that integrates multimodal support vector regression with model predictive control. This method constructs a multimodal demand forecasting model by integrating structured data (e.g., historical sales) with sentiment features from customer reviews. The forecast results are then embedded into an MPC control framework to achieve rolling optimization and coordinated allocation of inventory across multiple chains. Simulation comparisons validate the proposed method's effectiveness in enhancing demand forecasting accuracy, suppressing inventory fluctuations, and improving system operational stability.

2. Clustered Closed-Loop Supply Chain System

Assume a clustered supply chain consists of three single chains, each being a five-tier supply chain handling a fully substitutable product. Downstream retailers place orders with upstream manufacturers periodically. Upon receiving orders, wholesalers ship products to retailers-this constitutes normal replenishment. When retailers face stockouts due to demand fluctuations and cannot be supplied by their immediate upstream or downstream links, retailers from other supply chains provide emergency replenishment, as illustrated in Figure 1.

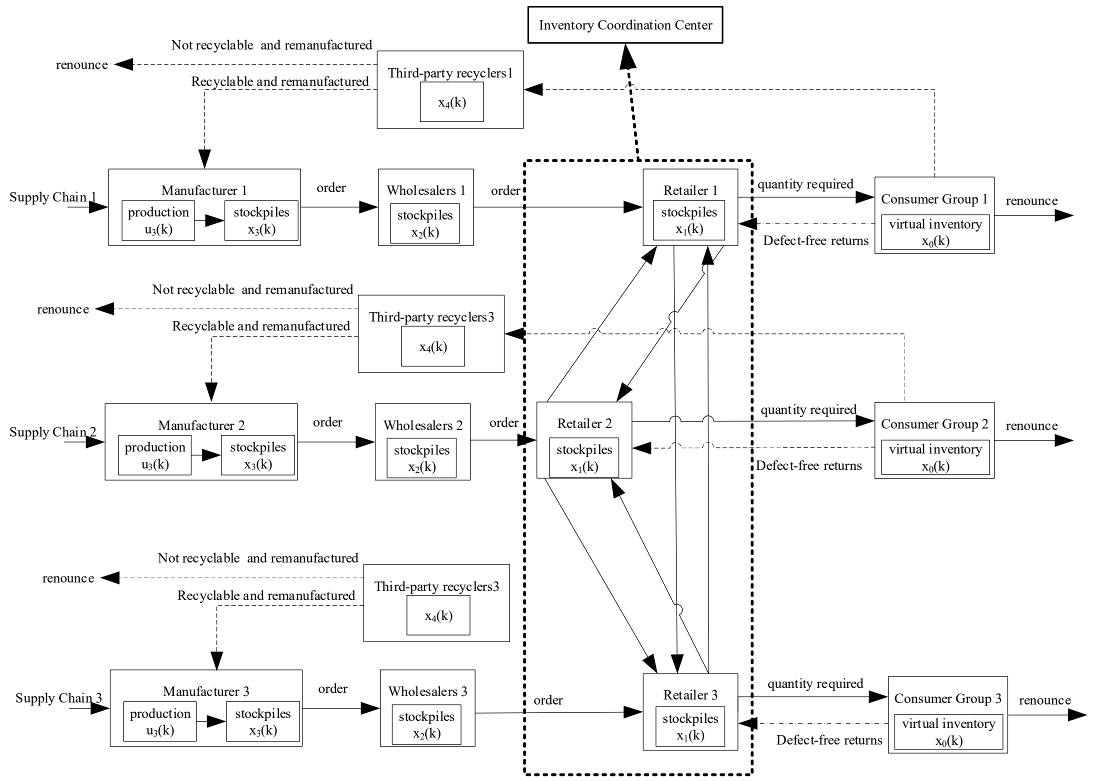

Figure 1. Clustered Closed-Loop Supply Chain Cross-Chain Inventory Collaboration Model Diagram

To model the system, this paper employs a state-space modeling approach. Inventory levels, order quantities, and external demand at each node are defined as state variables, control variables, and disturbance variables, respectively. The state-space equations for the system can be expressed as:

$$X(k+1) = Ax(k) + Bu(k) + Dd(k) \tag{1}$$

In the equation, $x(k)$ is the state vector representing inventory levels across all links; $u(k)$ is the control input vector representing order quantity, production quantity, and replenishment quantity; $d(k)$ is the external disturbance vector. A denotes the state transition matrix, B denotes the control input matrix, and D denotes the disturbance impact matrix. The main diagonal elements of matrix A describe the state vector, while the off-diagonal elements describe the coupled effects of remanufacturing, returns, and emergency replenishment. Matrix B defines the influence paths of control variables on inventory states.

Based on[14], treating consumer holdings of goods as virtual inventory, the inventory balance equations for each node are established according to the inventory balance principle as follows:

Consumer Group Inventory Balance Equation:

$$x_0^i(k+1) = (1-\mu_i-\beta_i-\gamma_i)x_0^i(k) + d^i(k) \tag{2}$$

Retailer Inventory Balance Equation:

$$x_1^1(k+1) = (1-b-e)x_1^1(k) + ax_1^2(k) + fx_1^3(k) + \beta_1 x_0^1(k) + u_1^1(k) - d^1(k) \tag{3}$$

$$x_1^2(k+1) = (1-a-c)x_1^2(k) + bx_1^1(k) + dx_1^3(k) + \beta_2 x_0^1(k) + u_1^2(k) - d^2(k) \tag{4}$$

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$$x_1^3(k+1)=(1-d-f)x_1^2(k)+cx_1^1(k)+ex_1^3(k)+\beta_3 x_0^1(k)+u_1^3(k)-d^3(k) \tag{5}$$

Wholesaler Inventory Balance Equation:

$$x_2^i(k+1)=x_2^i(k)+u_2^i(k)-u_1^i(k) \tag{6}$$

Manufacturer Inventory Balance Equation:

$$x_3^i(k+1)=x_3^i(k)+\delta_i x_4^i(k)+u_3^i(k)-u_2^i(k) \tag{7}$$

Recycler Inventory Balance Equation:

$$x_4^i(k+1)=(1-\delta_i-\lambda_i)x_4^i(k)+\mu_i x_0^i(k) \tag{8}$$

Where: $x_0^i(k)$ represents the consumer i inventory level at time k; $x_1^i(k)$ represents the retailer i inventory level at time k; $x_2^i(k)$ represents the wholesaler i inventory level at time k; $x_3^i(k)$ represents the manufacturer i inventory level at time k; $d^i(k)$ represents the consumer i group demand at time k; $u_1^i(k)$ represents the retailer i order quantity at time k; $u_2^i(k)$ represents the wholesaler i order quantity at time k; $u_3^i(k)$ represents the manufacturer i production quantity at time k; λ_i denotes the discard rate of third-party recyclers in single-chain i operations; β_i represents the defect-free return rate of products in the single chain i; δ_i represents the recyclable remanufacturing rate of third-party recyclers in the single chain i; $Wx_i^j(k)$ represents the emergency replenishment quantity from retailer j to retailer i, where $W=\{a,b,c,d,e,f\}$ is the emergency replenishment coefficient.

3. Multimodal Data Construction and Demand Forecasting Model Design

3.1. Data Sources and Preprocessing

This paper utilizes product sales and user review data from public e-commerce platforms to construct a multimodal demand forecasting dataset. The data includes structured numerical features such as product ratings, recommendation metrics, and positive review counts, alongside unstructured information like user review texts. This dataset reflects market demand trends from both behavioral and sentiment perspectives.

During data preprocessing, multimodal data construction follows the workflow: “numerical feature processing-text semantic extraction-temporal alignment-feature fusion.” First, numerical features undergo missing value removal and normalization to eliminate scale differences. Simultaneously, sales time series undergo smoothing and sliding window processing to mitigate the impact of random fluctuations on model training. Subsequently, the pre-trained BERT model is used to encode the comment text semantically. The [CLS] vector is extracted to obtain an overall representation of the semantic and emotional content for each comment.

To address temporal inconsistencies between structured behavioral data and review texts, a time-indexed rolling window method aligns both datasets, ensuring each sample contains both sales features and corresponding sentiment information within the same time period. The resulting multimodal feature data is stored in a unified format for subsequent training of the multimodal demand forecasting model.

3.2. Multimodal Feature Extraction and Fusion

The fusion of multimodal features is a critical step in constructing high-precision demand forecasting models. Its core lies in unifying the modeling of consumer behavior information with review semantic information. This paper employs an operational-level linking strategy to present structured numerical functions alongside unstructured semantic text functions. The entire process is illustrated in Figure 2.

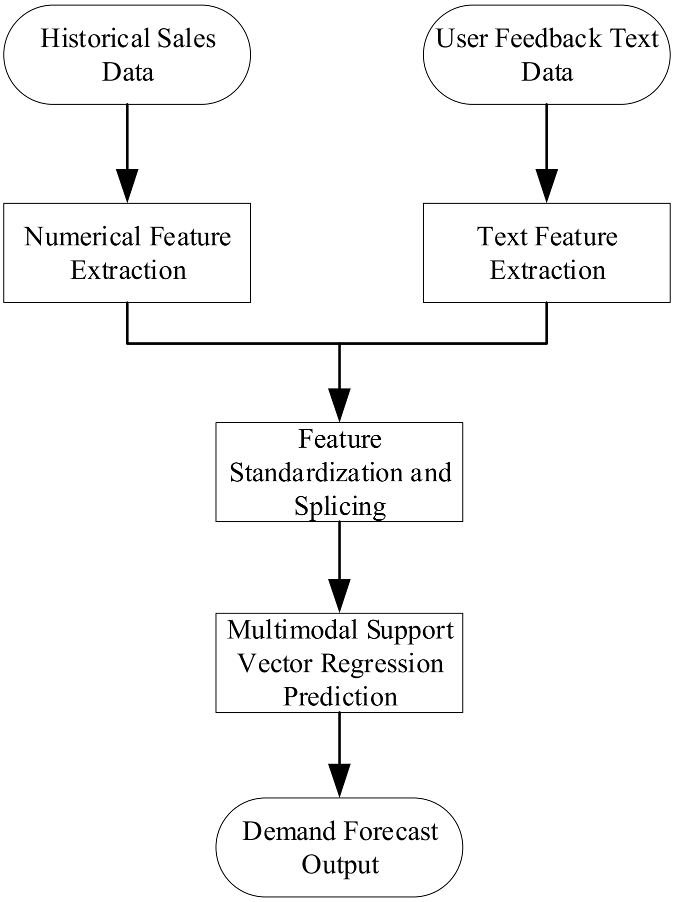

Figure 2. Flowchart of Multimodal Data Preprocessing and Feature Fusion

As shown in Figure 2, the multimodal feature construction process primarily consists of three steps: numerical feature processing, text semantic encoding, and feature fusion. First, numerical features in the raw sales data (such as sales volume, ratings, and recommendation metrics) undergo normalization to eliminate the impact of different feature scales on model training. Next, the raw review text data is fed into a pre-trained BERT model. By extracting its [CLS] vector, the overall semantic and sentiment representation of the review text is obtained, thereby mapping unstructured text into numerical feature vectors suitable for modeling.

After independently extracting these two feature types, feature-level fusion is applied at the input layer to concatenate numerical features with textual semantic features, constructing a unified multimodal feature representation. Let the numerical feature matrix be $X_{num} \in R^{n\times p}$ and the textual feature matrix be $X_{text} \in R^{n\times q}$. Then multimodal is defined as:

$$X_{mm} = [X_{num}, X_{text}] \tag{9}$$

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Among these, X_{mm} denotes the fused multimodal input matrix. This fusion approach not only preserves explicit features such as sales volume and feedback but also incorporates the latent influence of review semantics into the model. This enables the forecasting process to simultaneously account for the combined impact of consumer behavior and its associated opinion factors.

For model construction, Support Vector Regression is selected as the core algorithm for the multimodal demand forecasting model. SVR achieves modeling of multidimensional nonlinear features through kernel function mapping, demonstrating strong generalization capabilities and suitability for multimodal, high-dimensional input scenarios. By conducting grid search and cross-validation on model parameters, and comprehensively evaluating prediction error alongside model complexity, the optimal parameter combination is determined to construct the final multimodal SVR demand forecasting model.

3.3. Construction and Parameter Optimization of Multimodal Support Vector Machine Prediction Models

After completing data fusion, a multimodal demand forecasting model is established based on SVR. The model takes the fused feature matrix as input and historical demand as output, learning the relationship between input features and demand changes through a nonlinear mapping function:

$$f(x) = \omega^T \phi(x) + b \tag{10}$$

In the equation, denotes the mapping function from the input space to the high-dimensional space, while and represent the weights and bias terms of the mapping. Within the high-dimensional space, the best-fitting regression hyperplane minimizes the error between the input features and the output. The RBF is selected as the nonlinear mapping for training the nonlinear model, expressed as:

$$K(x_i, x_j) = \exp(-\gamma \left\| x_i - x_j \right\|^2) \tag{11}$$

In the formula, γ controls the smoothness of the kernel function. A smaller γ value indicates a larger influence range of the kernel function, suitable for sample distributions with smooth variations; a larger γ value makes the kernel function more sensitive to local differences, suitable for capturing nonlinear abrupt changes.

The training objective of the SVR model is to minimize prediction error while ensuring controllable model complexity. Its optimization problem can be expressed as:

$$\min\left(\frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n} \xi_i \right) \tag{12}$$

In the equation, ξ_i is the slack variable, which permits training errors within a certain range to enhance model robustness. C is the penalty coefficient, used to balance the relationship between prediction accuracy and model complexity.

For parameter optimization, this paper employs a combined grid search and cross-validation approach to jointly optimize the penalty coefficient C and kernel parameter γ. By evaluating prediction error metrics under multimodal feature inputs, the optimal parameter combination is selected to construct the final multimodal SVR demand forecasting model.

During the prediction phase, for a new input sample x_t, the model's predicted value is:

$$\hat{y}_t = \sum_{i=1}^{N_s} (\alpha_i - \alpha_i^*) K(x_i, x_t) + b \tag{13}$$

In the formula, N_s represent the number of support vectors, α_i and optimized Lagrange multipliers. is the kernel function. This prediction comprehensively reflects the influence of multi-source information-including historical sales data, consumer behavior, and review semantics-on future demand.

Compared to unimodal SVR models, multimodal SVR learns nonlinear coupling relationships between explicit behavioral features and implicit emotional features in high-dimensional feature spaces, demonstrating greater sensitivity to demand fluctuations and enhanced predictive stability. For MPC models, $\hat{y}_t$ is mapped to the demand disturbance sequence $\hat{d}(k)$ within the rolling time domain, serving as an external disturbance input to the control layer MPC module to forecast inventory adjustments in supply chain systems.

3.4. Multimodal SVR-MPC Cooperative Optimization Control Strategy

After obtaining demand forecast results from the multimodal SVR model, these are embedded into the MPC framework to achieve dynamic inventory allocation and coordinated control within a clustered closed-loop supply chain system. The demand forecasts provided by the multimodal SVR are treated as external disturbance inputs to the system, enhancing the MPC's ability to proactively respond to future demand fluctuations. The state update equation for the system in discrete time can be expressed as:

$$x(k+1) = Ax(k) + Bu(k) + D\hat{d}(k) \tag{14}$$

Here, $x(k)$ denotes the system inventory state vector at time k, $u(k)$ represents the control input vector (e.g., manufacturer production volume, wholesaler and retailer order quantities), and $\hat{d}(k)$ is the demand disturbance predicted by multimodal SVR.

At each decision time k, the MPC controller predicts future inventory changes over the next N_p time periods based on the current state $x(k)$, yielding the forecast sequence:

$$x(k+i) = A^i x(k) + \sum_{j=0}^{i-1} A^{i-1-j} (Bu(k+j) + D\hat{d}(k+j)) \tag{15}$$

Among these, $x(k+i)$ represents the predicted value of the inventory state at time $k+i$ under the information available at time k, used to determine the optimal control sequence. $x(k)$ denotes the actual value at time k, serving as the initial state update for the next step of rolling optimization.

The controller's optimization objective is to minimize inventory deviation and control change within a finite prediction horizon. The performance index function is defined as:

$$J = \sum_{i=1}^{N_p} \|x(k+i) - x_r\|_Q^2 + \sum_{i=0}^{N_c-1} \|u(k+i)\|_R^2 + \sum_{i=0}^{N_c-1} \|\Delta U(k+i)\|_{R_d}^2 \tag{16}$$

where x_r is the target inventory level, Q, R, and R_d are the weighted matrices for inventory deviation, control input, and control increment, respectively, and $\Delta u(k+i)=u(k+i)-u(k+i-1)$ represents the change in adjacent control variables. This performance metric maintains inventory stability while penalizing abrupt changes in control signals, thereby achieving smooth regulation and dynamic robustness.

The optimization task can be formulated as a quadratic programming problem with constraints:

$$\min_{U} J(U) \quad s.t. \ u_{\min} \le u(k+i) \le u_{\max}, x_{\min} \le x(k+i) \le x_{\max} \tag{17}$$

In the equation, $U=[u(k),u(k+1),\cdots,u(k+N_c-1)]^T$ represents the control variable sequence, with both control inputs and inventory states constrained by their physical upper and lower limits. At each time step, the optimization problem is solved using numerical algorithms to obtain the optimal control sequence, which is then executed through continuous implementation, thus creating a closed-loop control process that includes prediction, optimization, execution, and feedback.

Through the synergistic interaction of multimodal SVR and MPC, the prediction layer provides the control layer with more accurate and forward-looking demand information. Meanwhile, MPC continuously refines control decisions via feedback and rolling optimization, enabling the system's adjustment process to better align with the actual operating environment. Compared to prediction control methods based on single numerical features, the proposed multimodal SVR–MPC collaborative strategy demonstrates smoother inventory adjustment effects and stronger dynamic response capabilities when addressing demand fluctuations.

4. Quantitative Description of the Bullwhip Effect

In supply chain systems, quantifying the supply chain is necessary for a rational analysis of the bullwhip effect [15]. This paper employs the following methods to calculate the volatility of the overall supply chain, forward supply chain, and reverse supply chain.

The overall bullwhip effect measures the amplification of inventory fluctuations across all links in the supply chain relative to end-customer demand, and can be expressed as:

$$r_1=\frac{Var(X_{total})}{Var\left(D_{customer}\right)} \tag{18}$$

Among these, X_{total} denotes the total inventory or order volume at each node in the supply chain, $Var(\bullet)$ represents the variance operation, and $D_{customer}$ indicates consumer demand. This metric characterizes the propagation and amplification of disturbances throughout the supply chain, serving as a crucial reference for assessing the overall stability of the system.

The positive bullwhip effect, which refers to the amplification of fluctuations along the forward supply chain from consumers to manufacturers, can be calculated using the following formula:

$$r_2=\frac{Var(X_{forward})}{Var\left(D_{customer}\right)} \tag{19}$$

In the formula, $X_{forward}$ represents the inventory or order volume at each node along the forward supply chain. This metric measures the cumulative effect of fluctuations in order information as it propagates throughout the supply chain.

Reverse Bullwhip Effect: The reverse logistics bullwhip effect within a closed-loop supply chain indicates the sensitivity of remanufacturing control quantities to demand disturbances, expressed as:

$$r_3 = \frac{Var(X_{reverse})}{Var\left(D_{customer}\right)} \tag{20}$$

Among these, $X_{reverse}$ represents the inventory or return order volume at each node in reverse logistics. It measures the extent of fluctuation amplification within reverse logistics, reflecting the stability of the closed-loop supply chain.

5. Calculation Examples

To evaluate the performance of the proposed multimodal SVR–MPC collaborative predictive control strategy, three comparative strategies were established: basic MPC, single-modal SVR+MPC, and multimodal SVR+MPC. The prediction time horizon is set to 15 periods, the control horizon to 3 periods, and the simulation cycle to 100 periods. Initial inventory levels, target inventory levels, return rates, and remanufacturing rates are consistent across all chain nodes. Demand disturbances are driven by a dynamic sequence derived from historical sales data and sentiment analysis. The multimodal SVR model is jointly trained using sentiment vectors extracted from review texts and numerical features to generate future demand forecasts.

(2) Prediction Error Analysis

The accuracy of the forecasting model was evaluated using the mean absolute error , calculated between the forecasted and actual demand.:

$$E = \frac{1}{T}\sum_{k=1}^{T}\left|\hat{d}(t) - d(t)\right| \tag{21}$$

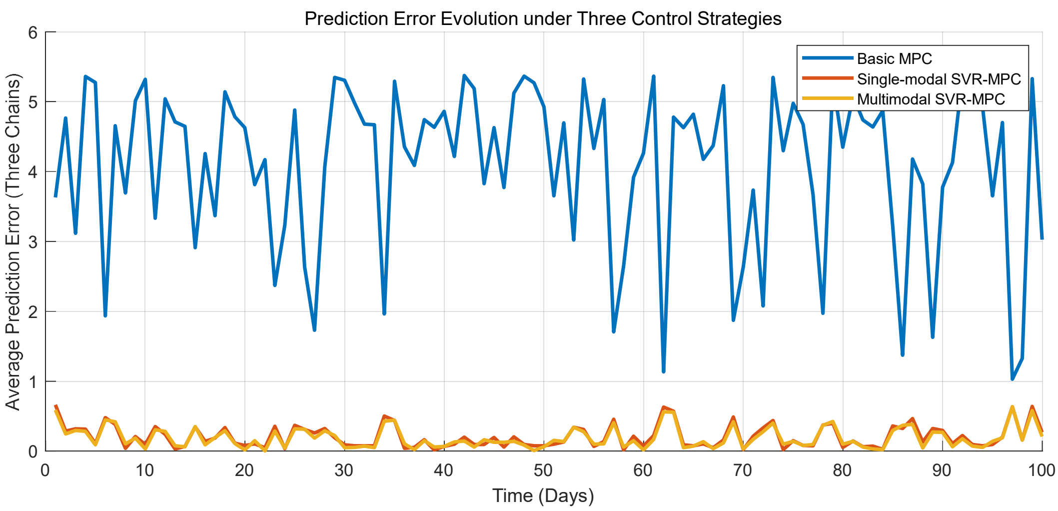

Figure 3. Predicted Trend Chart Under Three Control Strategies

Figure 3 shows the predicted variation curves under three control strategies. It can be observed that under the basic MPC strategy, the lack of demand feedforward information leads to significant fluctuations in prediction errors, with the average error remaining within the 3–5 range. This indicates that relying solely on state feedback is insufficient to handle complex demand disturbances. After introducing the unimodal SVR, the prediction error significantly decreases to below 1, and the fluctuation range noticeably converges. This demonstrates that nonlinear modeling based on historical sales data can effectively enhance prediction accuracy. Building upon this, the multimodal SVR–MPC strategy further reduces prediction errors, stabilizing the average error within the 0.3–0.5 range while producing a smoother error curve. This demonstrates that sentiment and public opinion embedded in review texts can anticipate demand trends in advance, endowing the predictive model with enhanced foresight.

(2) Analysis of Dynamic Inventory Response

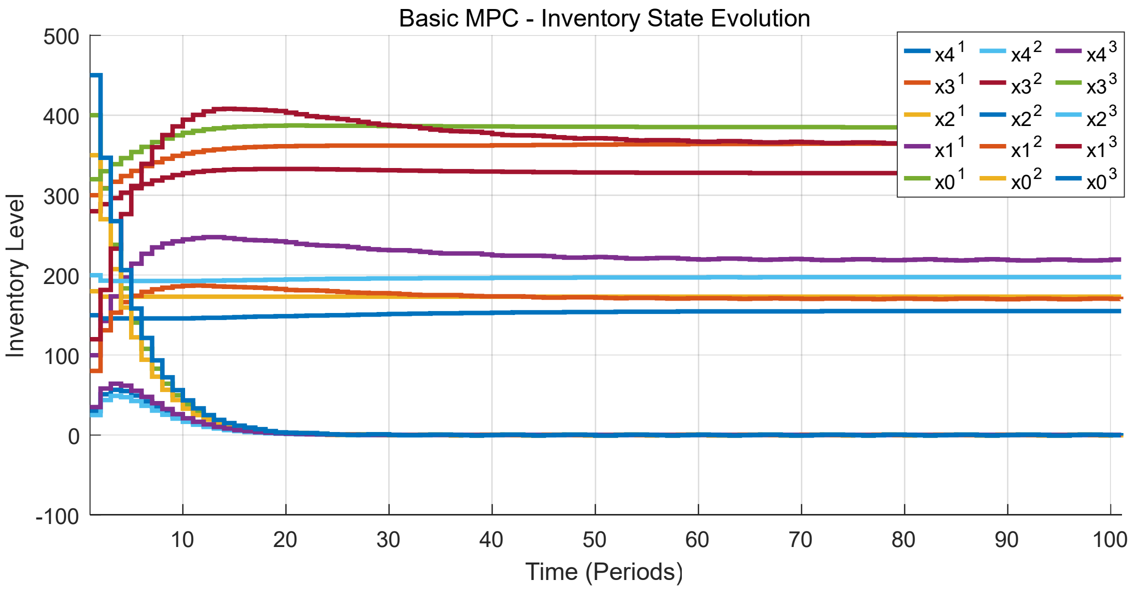

Figure 4. Inventory State Change Diagram for Basic MPC

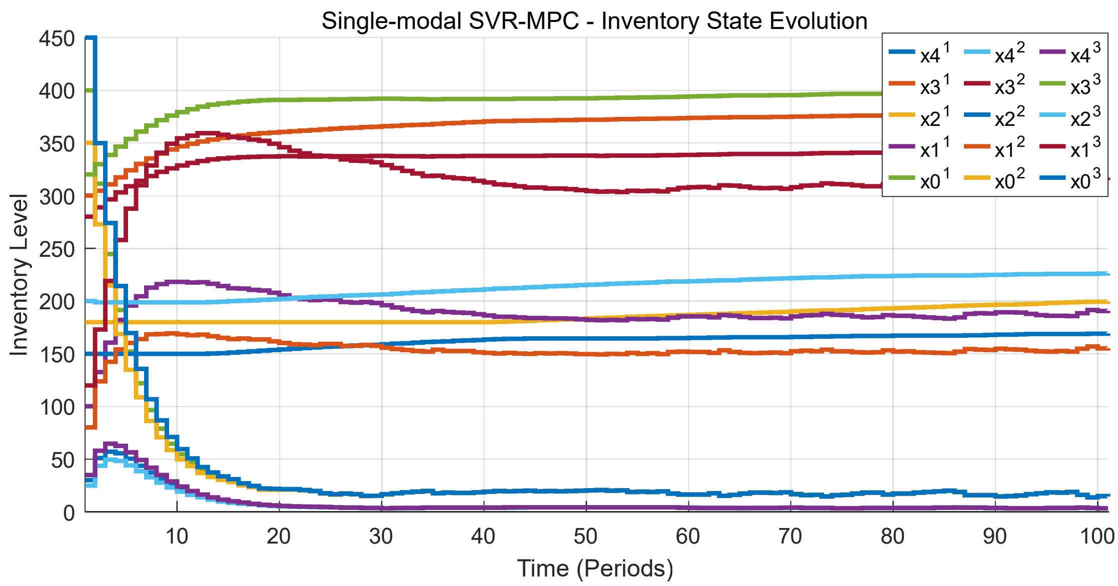

Figure 5. Inventory State Change Diagram of Single-Mode SVR and MPC Fusion

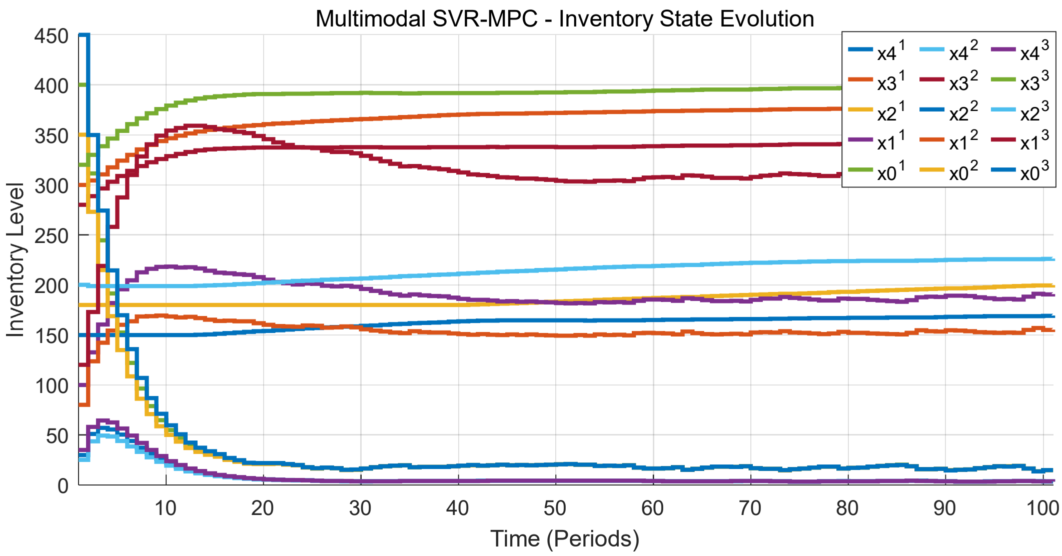

Figure 6. Multimodal SVR and MPC Fusion Inventory Status Change Diagram

Figures 4 to 6 illustrate inventory state changes under three control strategies.

Under basic MPC control (Figure 4), overall system inventory stabilizes but converges slowly. Initial inventory fluctuations are significant, with noticeable overshoot and undershoot at some nodes. This indicates that MPC control relying solely on historical state information has limited responsiveness under nonlinear demand disturbances.

After incorporating the single-mode SVR (Figure 5), inventory oscillations markedly decrease, and inventory levels at all nodes converge faster toward target levels. This demonstrates that integrating demand forecasting enhances the controller's feedforward adjustment capability. However, since the single-mode model utilizes only historical sales data, its sensitivity to emotional and sudden demand changes remains limited, resulting in high-frequency inventory oscillations persisting at some nodes.

In contrast, under the multimodal SVR-MPC strategy (Figure 6), inventory curves converged most rapidly, entering a stable range around 25 cycles with the smallest overall fluctuation amplitude. By incorporating review text and sentiment features, the multimodal fusion model makes forecasted demand more closely align with actual changes, thereby improving the accuracy of MPC optimization solutions and the stability of inventory adjustments.

(3) Analysis of Bullwhip Effect Suppression

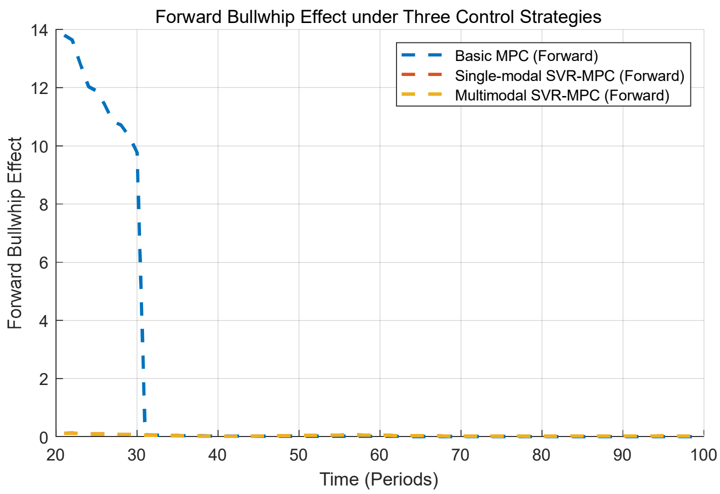

Figure 7. Comparison of Forward Bullwhip Effects Under Three Control Strategies

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Figure 7 presents a comparison of forward bullwhip effects under three control strategies. Under the baseline MPC strategy, the system exhibits delayed responses to demand fluctuations, with disturbances amplifying progressively through production and distribution stages. Inventory and production decisions become desynchronized, leading to pronounced system oscillations. After introducing single-mode SVR, the system's responsiveness to demand changes improves, aligning order and inventory variations and partially mitigating the forward bullwhip effect. The curve under the multimodal SVR–MPC strategy is the smoothest, exhibiting almost no noticeable oscillations. This indicates its ability to more accurately capture demand trend changes and achieve dynamic coordination in the forward link.

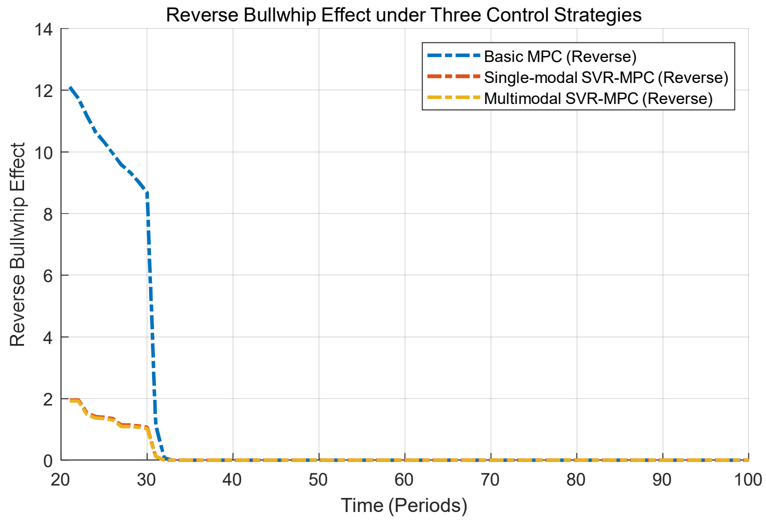

Figure 8. Comparison of Reverse Bullwhip Effects Under Three Control Strategies

Figure 8 illustrates the comparative results of the reverse bullwhip effect. The baseline MPC exhibits heightened sensitivity to demand disturbances, amplifying fluctuations in the return and remanufacturing stages. The unimodal SVR mitigates this issue to some extent. By incorporating implicit sentiment and return intent from review texts, the multimodal SVR–MPC enhances the accuracy of recycling stage predictions, thereby further reducing the bullwhip effect within the reverse supply chain.

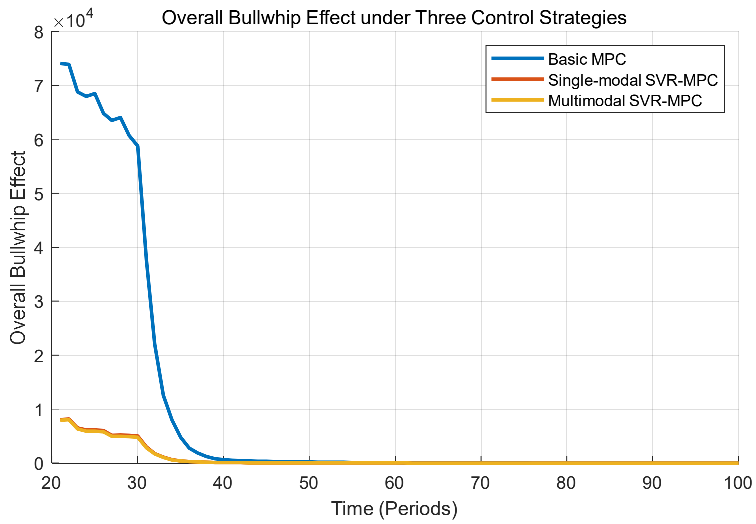

Figure 9. Comparison Chart of Overall Bullwhip Effects Under Three Control Strategies

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The overall bullwhip effect is illustrated in Figure 9. The baseline MPC exhibits pronounced oscillatory behavior during the early simulation phase, requiring a prolonged period for the system to reach a stable state. The single-modal SVR–MPC accelerates the convergence process and reduces oscillation amplitude. Under the multi-modal SVR–MPC strategy, the overall bullwhip effect is minimized, demonstrating the strongest suppression capability against demand disturbances.

Overall, the multimodal SVR–MPC strategy outperforms the comparison strategies in terms of prediction accuracy, inventory dynamic stability, and suppression of forward, reverse, and overall bullwhip effects.

6. Conclusion

This paper addresses the challenges of strong demand uncertainty, pronounced inventory fluctuations, and amplified bullwhip effects in clustered closed-loop supply chains by proposing a collaborative optimization method that integrates multimodal support vector regression with model predictive control. By integrating structured behavioral data (e.g., historical sales) with semantic sentiment features extracted from review texts, a multimodal SVR demand forecasting model is constructed. The forecast results are then fed as feedforward information into the MPC control framework, enabling rolling optimization and collaborative allocation across multi-chain inventories. Simulation results demonstrate that compared to basic MPC and single-modal SVR+MPC strategies, the proposed method exhibits significant advantages in demand forecasting accuracy, inventory dynamic stability, and suppression of forward, reverse, and overall bullwhip effects. The findings validate the effectiveness of multimodal information fusion and predictive control coordination in complex supply chain systems, offering a feasible modeling and control approach for intelligent inventory management in clustered closed-loop supply chains. Future work will further address model parameter uncertainty and online update mechanisms under real-world data conditions to enhance the method's engineering applicability.

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