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A Dynamic System Model for Multi-Echelon Inventory Policy Optimization Considering Bullwhip Effect and Supply Chain Disruptions in the Sport Footwear Industry

Dedy Setyo Utomo[1,*], Rizky Fajar Ramdhani[1], Asep Hermawan[1]

[1] Teknik Industri, Sekolah Tinggi Teknologi Wastukancana, Purwakarta 41153, Indonesia

Abstarct: This research develops a dynamic system model to optimize inventory policies in multi-echelon supply chains within the sport footwear industry, addressing challenges from the bullwhip effect and supply chain disruptions. The sports footwear sector faces unique inventory management challenges due to complex demand patterns influenced by seasonality, fashion trends, and competitive dynamics. Our comprehensive system dynamics model captures the intricate relationships between four supply chain echelons: retailers, distributors, manufacturers, and raw material suppliers. The model integrates machine learning algorithms—specifically Long Short-Term Memory (LSTM) neural networks—for adaptive demand prediction and employs genetic algorithm optimization to determine optimal inventory parameters under various disruption scenarios. Using real-world data from a leading sports footwear manufacturer, we validated the model under normal operations and three distinct disruption scenarios: raw material shortages (45% reduction for 6 weeks), manufacturing capacity constraints (30% reduction for 8 weeks), and transportation disruptions (doubled lead times for 4 weeks). Results demonstrate that our proposed hybrid model reduces overall inventory costs by 18.7% compared to traditional policies while maintaining a 97.2% service level. The integration of machine learning for demand forecasting reduced prediction errors by 43.6% compared to conventional methods, directly mitigating the bullwhip effect by decreasing the order variability coefficient from 0.89 to 0.61 at the supplier level. Furthermore, the model enhanced supply chain resilience by reducing recovery time by 42% following major disruptions. This research contributes to the theoretical understanding of complex supply chain dynamics and practical applications for inventory management in volatile industries, offering a robust framework for decision-making under uncertainty.
Keywords: System dynamics, Multi-echelon inventory, Bullwhip effect, Supply chain, Sport Footwear Industries

1. Introduction

Supply chain management in the sports footwear industry presents unique challenges due to the combination of fashion-driven consumer demand, technological innovation, seasonal variations, and intense market competition. The industry's complex multi-echelon structure—from raw material suppliers to retailers—amplifies these challenges, particularly through the bullwhip effect phenomenon [1]. This effect, characterized by increasing order variability as one moves upstream in the supply chain, leads to inefficient inventory policies, higher costs, and reduced service levels [2].

The sports footwear industry's vulnerability to supply chain disruptions further complicates inventory management. Recent global events, including the COVID-19 pandemic, have exposed significant vulnerabilities in global supply chains, with the sports footwear sector being particularly affected due to its reliance on global sourcing networks and just-in-time inventory systems [3].Thesedisruptions manifest at various echelons, from raw material shortages to manufacturing capacity constraints and logistics disruptions, creating cascading effects throughout the supply chain [4].

Traditional inventory management approaches typically employ static models that fail to capture the dynamic interactions between supply chain echelons and the evolving nature of disruptions [5].

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Moreover, these approaches often treat each echelon as independent, overlooking the systemic effects that decisions at one level have on others. As a result, companies frequently experience excess inventory in some categories while simultaneously facing stockouts in others, especially during disruptions. [6].

System dynamics modelling offers a promising approach to address these limitations by capturing the complex feedback mechanisms, time delays, and nonlinear relationships that characterize multi-echelon supply chains. [7]. By incorporating machine learning algorithms for demand prediction and metaheuristic optimization techniques for parameter tuning, this approach can better adapt to changing conditions and optimize inventory policies across the supply chain. [8].

This research aims to develop and validate a dynamic system model for optimizing inventory policies in multi-echelon sports footwear supply chains, specifically to mitigate the bullwhip effect and enhance resilience against disruptions. The study addresses the following research questions:

1. How can system dynamics modelling effectively capture the complexities of multi-echelon inventory management in the sport footwear industry?
2. How do different supply chain disruptions affect inventory performance across multiple echelons?
3. How can machine learning algorithms and metaheuristic optimization techniques enhance inventory policy decisions under conditions of uncertainty?
4. What strategies can effectively mitigate the bullwhip effect while maintaining resilience against supply chain disruptions?

2. Methodology

2.1 Research Design

This study employed a mixed-method research design combining quantitative modelling with qualitative insights from industry experts. The research process consisted of four main phases: (1) system conceptualization and boundary definition, (2) model development, (3) data collection and model validation, and (4) scenario analysis and policy optimization.

2.2 System Conceptualization

The supply chain system under investigation was conceptualized as a four-echelon network comprising retailers, distributors, manufacturers, and raw material suppliers within the sports footwear industry. Based on a comprehensive literature review and industry expert consultations, we identified key variables affecting inventory dynamics, including:

- Demand patterns (seasonal fluctuations, trend changes, promotional effects)
- Production capacities and constraints.
- Lead times across different echelons.
- Information sharing mechanisms.
- Inventory policies (safety stock levels, reorder points, order quantities).
- Potential disruption sources and their characteristics.

2.3 System Dynamics Model Development

The system dynamics model was developed using Vensim DSS software following the methodology outlined by Sterman (2000) [7]. The model structure included:

i. **II. Stock and Flow Diagrams:** Key stocks included inventory levels at each echelon, work-in-progress, and backorders. Flows represented order rates, production rates, and delivery rates.
ii. **Causal Loop Diagrams:** Multiple feedback loops were identified, including:
    - Order fulfilment loops (balancing).
    - Inventory adjustment loops (balancing).
    - Production capacity adjustment loops (balancing).

- Demand amplification loops (reinforcing).

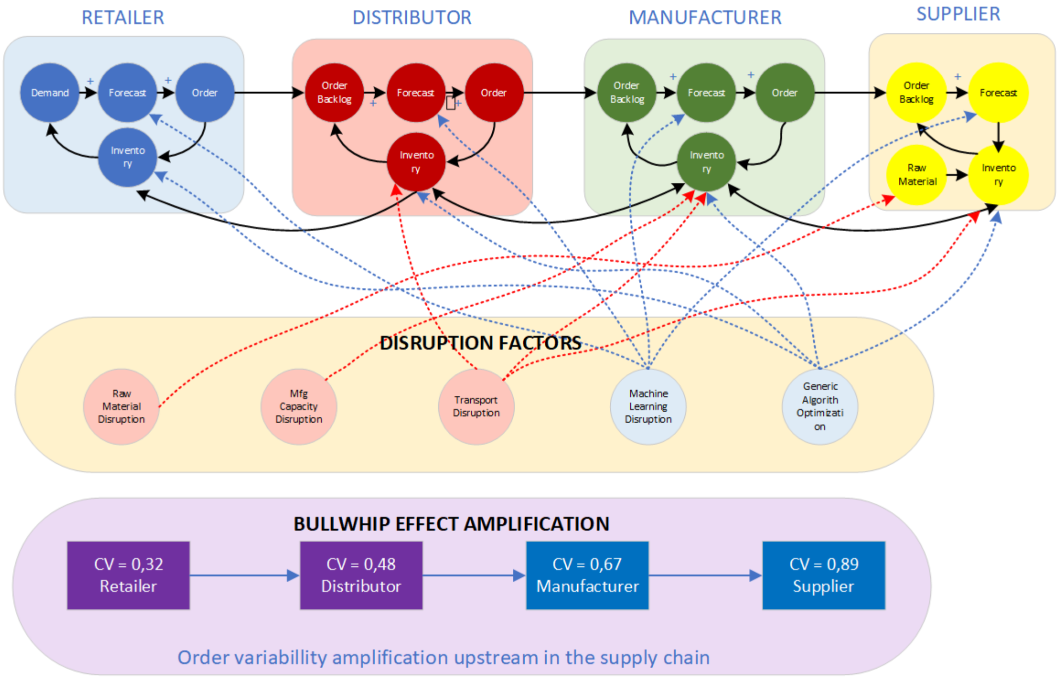

Figure 1. Causal Loop Diagram Dynamic System Model for Multi-Echelon Inventory Policy Optimization Considering Bullwhip Effect and Supply Chain Disruptions in the Sport Footwear Industry

iii. **Mathematical Formulations:** The core inventory dynamics (1) were represented through differential equations governing the rate of change of inventory levels (I) at each echelon (e):

$$\frac{dI_e}{dt} = Inflow_e(t) - Outflow_e(t) \quad (1)$$

Where:

- $Inflow_e(t)$ represents incoming deliveries from the upstream echelon.
- $Outflow_e(t)$ represents outgoing deliveries to the downstream echelon.

The ordering policy at each echelon (2) incorporated an adaptive approach combining forecasted demand, inventory position, and safety stock:

$$O_e(t) = F_e(t) + \alpha(SS_e - IP_e(t)) \quad (2)$$

Where:

- $O_e(t)$ is the order quantity at time t.
- $F_e(t)$ is the forecasted demand.
- SS_e is the safety stock level.
- $IP_e(t)$ is the inventory position.
- α is the inventory adjustment parameter.

2.4 Machine Learning Integration for Demand Forecasting

We integrated machine learning algorithms with the system dynamics model to enhance demand prediction capabilities. A Long Short-Term Memory (LSTM) neural network was implemented to forecast demand patterns based on historical data, incorporating factors such as:

- Historical sales patterns;
- Seasonal indices;
- Promotional events;
- Market trends;
- Macroeconomic indicators.

The LSTM model was trained on three years of weekly sales data from a leading sports footwear manufacturer, with 80% used for training and 20% for validation. The model architecture consisted of:

- An input layer with 12 neurons (representing 12 weeks of historical data);
- Two hidden LSTM layers with 64 neurons each;
- A dropout layer (0.2) to prevent overfitting;
- A dense output layer predicting demand for the next 8 weeks.

The forecasting outputs from the LSTM model were then fed into the system dynamics model to inform ordering decisions at each echelon.

2.5 Metaheuristic Optimization for Inventory Parameters

To determine optimal inventory policy parameters under different conditions, we implemented a genetic algorithm (GA) optimization approach (3). The GA optimized key decision variables, including:

- Safety stock levels at each echelon;
- Reorder points;
- Order quantities;
- Inventory adjustment parameters.

The fitness function for the GA incorporated multiple objectives:

$$\text{Min } Z = \omega_1 \sum_{e=1}^{E} \sum_{t=1}^{T} (HC_e .\ I_e(t)) + \omega_2 \sum_{e=1}^{E} \sum_{t=1}^{T} (SC_e .\ B_e(t)) + \omega_3 \sum_{e=1}^{E} \sum_{t=1}^{T} (OC_e .\ O_e(t)) \quad (3)$$

Where:

- HC_e is the holding cost at echelon e.
- SC_e is the stockout cost at echelon e.
- OC_e is the ordering cost at echelon e.
- $B_e(t)$ is the backorder level at time t.
- w_1, w_2, w_3 are weights reflecting the relative importance of each cost component.

2.6 Mathematical Formulation of the System Dynamics Model

a) Nomenclature

Indices and Sets:

- $e \in E = \{1,2,3,4\}$: Set of echelons (1=retailer, 2=distributor, 3=manufacturer, 4=supplier).
- $t \in T$: Set of time periods.
- $p \in P$: Set of products.

Variables:

- $I_{e,p}(t)$: Inventory level of product p at echelon e at time t.
- $B_{e,p}(t)$: Backlog level of product p at echelon e at time t.
- $O_{e,p}(t)$: Order rate of product p placed by echelon e at time t.
- $S_{e,p}(t)$: Shipment rate of product p from echelon e to echelon $e-1$ at time t.
- $IP_{e,p}(t)$: Inventory position of product p at echelon e at time t.
- $F_{e,p}(t)$: Forecasted demand of product p at echelon e for time t.
- $D_p(t)$: Customer demand for product p at time t.
- $WIP_{e,p}(t)$: Work-in-process inventory of product p at echelon e at time t.

Parameters:

- LT_e: Lead time for echelon e.
- $SS_{e,p}$: Safety stock level for product p at echelon e.
- $ROP_{e,p}$: Reorder point for product p at echelon e.
- α_e: Inventory adjustment parameter for echelon e.
- β_e: Forecast smoothing parameter for echelon e.
- MC_e: Manufacturing capacity at echelon e.
- RMA_t: Raw material availability at time t.
- $DV_p(t)$: Demand variability for product p at time t.

b) System Dynamics Equations

1) Stock Equations

Inventory Level Dynamics: The rate of change in inventory level (4) at each echelon is determined by the difference between inflow (shipments received) and outflow (shipments sent):

$$\frac{dI_{ep}(t)}{dt} = S_{e+1,p}(t - LT_{e+1}) - S_{e,p}(t) \tag{4}$$

For the supplier (echelon 4), production replaces incoming shipments (5):

$$\frac{dI_{4p}(t)}{dt} = P_{4,p}(t - LT_4) - S_{4,p}(t) \tag{5}$$

Backlog Dynamics: The rate of change in Backlog (6) is determined by incoming orders minus outgoing shipments:

$$\frac{dB_{e,p}(t)}{dt} = O_{e-1,p}(t) - S_{e,p}(t) \tag{6}$$

For the retailer (echelon 1), customer demand replaces incoming orders (7):

$$\frac{dB_{1,p}(t)}{dt} = D_p(t) - S_{1,p}(t) \tag{7}$$

Work-in-Process Dynamics (8)**:** WIP represents orders that have been placed but not yet received:

$$\frac{dWIP_{e,p}(t)}{dt} = O_{e,p}(t) - S_{e+1,p}(t - LT_{e+1}) \tag{8}$$

2) Flow Equations

Order Rate (9)**:** Orders are determined by forecasted demand, desired inventory adjustment, and safety stock policies:

$$O_{e,p}(t) = F_{e,p}(t) + \alpha_e . \left(SS_{e,p} + ROP_{e,p} - IP_{e,p}(t)\right) \tag{9}$$

Where inventory position (10) is defined as:

$$IP_{e,p}(t) = I_{e,p}(t) - B_{e,p}(t) + WIP_{e,p}(t) \tag{10}$$

Shipment Rate (11)**:** Shipments are constrained by inventory availability and Backlog:

$$S_{e,p}(t) = \min\left({}^{I_{e,p}(t)}/_{\Delta t}, {}^{B_{e,p}(t)}/_{\Delta t}\right) \tag{11}$$

For the manufacturer (echelon 3), production capacity adds a constraint (12) :

$$S_{3,p}(t) = \min\left({}^{I_{3,p}(t)}/_{\Delta t}, {}^{B_{3,p}(t)}/_{\Delta t}, MC_3\right) \tag{12}$$

Production Rate (13)**:** For the supplier (echelon 4), production is constrained by raw material availability:

$$P_{4,p}(t) = \min\left(O_{4,p}(t), RMA_t.\, allocation_{p,t}\right) \tag{13}$$

Where allocation represents the proportion of raw materials allocated to product \$p\$ at time \$t\$.

3) *Auxiliary Equations*

Demand Forecasting (14)**:** Traditional exponential smoothing:

$$F_{e,p}(t) = \beta_e \,.\, O_{e-1,p}(t) + (1 - \beta_e).\, F_{e,p}(t-1) \tag{14}$$

For the retailer (echelon 1) (15) :

$$F_{1,p}(t) = \beta_1.\, D_p(t) + (1 - \beta_1)\,.\, F_{1,p}(t-1) \tag{15}$$

LSTM-based Demand Forecasting (16)**:** When using machine learning, the forecast is generated by the LSTM model:

$$F_{1,p}(t) = LSTM\left(D_p\,(t-1), D_p(t-2), \dots \dots D_p(t-n), X_t\right) \tag{16}$$

\$X_t\$ represents additional features, including seasonality indices, promotional events, etc.
Service Level (17)**:** Service level at echelon \$e\$ for product \$p\$ is calculated as:

$$SL_{e,p}(t) = 1 - \frac{B_{e,p}(t)}{D_p(t) + \epsilon} \tag{17}$$

Where \$\epsilon\$ is a small constant to avoid division by zero.

c) *Disruption Modeling*

Raw Material Disruption (18)**:** When a raw material disruption occurs, availability is reduced:

$$RM\,A_t = RM\,A_{normal}.\left(1 - Severity_{raw}\,.\, 1_{t\epsilon T_{raw}}\right) \tag{18}$$

Manufacturing Capacity Disruption (19)**:** When a manufacturing disruption occurs, capacity is reduced:

$$MC_3 = MC_{3,normal}\,.\left(1 - Severity_{manufacturing}\,.\, 1_{t\epsilon T_{manufacturing}}\right) \tag{19}$$

Transportation Disruption (20)**:** When a transportation disruption occurs, lead times increase:

$$LT_e = LT_{e,normal}\,.\left(1 + Severity_{trans}\,.\, 1_{t\epsilon T_{trans}}\right) \tag{20}$$

d) *Genetic Algorithm Optimization (21)*

The GA optimizes the following decision variables:

- Safety stock levels: \$SS_{e,p}\$.
- Reorder points: \$ROP_{e,p}\$.
- Inventory adjustment parameters: \$\alpha_e\$.
- Forecast smoothing parameters: \$\beta_e\$.

The objective function to minimize is :

$$\text{Min } Z = \sum_{e=1}^{E}\sum_{t=1}^{P}\sum_{t=1}^{T}\left(\omega_1 \,.\, HC_{e,p} \,.\, I_{e,p}(t) + \omega_2 \,.\, B_{e,p}(t) + \omega_3 \,.\, OC_{e,p} \,.\, O_{e,p}(t)\right) \quad (21)$$

Where:

- $HC_{e,p}$ is the holding cost per unit of product p at echelon e.
- $SC_{e,p}$ is the stockout cost per unit of product p at echelon e.
- $OC_{e,p}$ is the ordering cost per order of product p at echelon e.
- w_1,w_2,w_3 are weights reflecting the relative importance of each cost component.

e) *Bullwhip Effect Quantification*

The bullwhip effect (22) is quantified by comparing the coefficient of variation (CV) of orders at different echelons (23) :

$$BW\ E_{e,p} = \frac{CV(O_{e,p})}{CV\ (D_p)} \quad (22)$$

Where:

$$CV\ (X) = \frac{\sigma_x}{\mu_x} \quad (23)$$

A value of $BWE_{e,p} > 1$ indicates the presence of the bullwhip effect, with higher values representing stronger demand amplification.

2.7 Specific Mathematical Formulation for the Sport Footwear Industry

For the sports footwear industry application, we incorporate additional factors:

i. **Seasonal Demand Pattern** (24)**:** Customer demand includes a seasonal component :

$$D_p(t) = Base_p + Trend_p \,.\, t + Seasonal_p(t) + Promotion_p(t) + \epsilon_t \quad (24)$$

$Seasonal_p(t)$ captures the seasonal pattern and $Promotion_p(t)$ captures the effect of promotional activities.

ii. **Product Lifecycle** (25)**:** For fashion-driven sports footwear, we incorporate product lifecycle effects:

$$D_p(t) = Base_p \,.\, Lifecycle_p(t) + Promotion_p(t) + \epsilon_t \quad (25)$$

$Lifecycle_p(t)$ follows a typical product lifecycle curve (introduction, growth, maturity, decline).

iii. **Material Constraints** (26)**:** Component availability constraints are modelled as follows:

f) $$\sum_{p\epsilon P} C_{m,p} \,.\, P_{4,p}(t) \leq RM\ A_{m,t} \quad \forall_m\ \epsilon\ M, t\ \epsilon\ T \quad (26)$$

Where:

- $C_{m,p}$ is the amount of material m required for product p;
- $RMA_{m,t}$ is the availability of material m at time t;
- M is the set of materials.

This mathematical formulation, combined with the Causal Loop Diagram, provides a comprehensive framework for analyzing and optimizing the multi-echelon inventory system in the sport footwear industry.

The GA was configured with a population size of 100, crossover probability of 0.8, mutation probability of 0.1, and was run for 500 generations.

2.8 Data Collection

Data for model calibration and validation were collected from multiple sources:

1. **Primary data**: Two years of weekly inventory and order data from a major sport footwear manufacturer and its supply chain partners, including:
   a) Point-of-sale data from 120 retail locations;
   b) Order and inventory records from 8 regional distribution centres;
   c) Production and inventory data from 3 manufacturing facilities;

   d) Procurement data from 12 key raw material suppliers.
2. **Secondary data**: Industry reports, academic literature, and publicly available information on sport footwear supply chains.
3. **Expert input**: Semi-structured interviews with 15 supply chain professionals from the sports footwear industry to validate model assumptions and parameters.

2.9 Model Validation

The system dynamics model was validated using several techniques:
1. **Structure validation**: Expert reviews of causal loop diagrams and stock-flow structures;
2. **Parameter validation**: Calibration using historical data and sensitivity analysis;
3. **Behaviour validation**: Comparison of model outputs with historical patterns;
4. **Extreme condition testing**: Verifying model robustness under extreme parameter values.

The validation confirmed that the model accurately reproduced historical inventory dynamics and the bullwhip effect observed in the supply chain.

2.10 Disruption Scenario Design

Three distinct disruption scenarios were developed to test the model's performance and optimize inventory policies:
1. **Raw material shortage**: 45% reduction in raw material availability for 6 weeks;
2. **Manufacturing capacity constraint**: 30% reduction in production capacity for 8 weeks;
3. **Transportation disruption**: Doubling of lead times between echelons for 4 weeks.

These scenarios were designed based on historical disruption events in the sports footwear industry and expert assessments of future risks.

3. Results and Discussion

3.1 *Baseline System Behavior*

The calibrated model successfully reproduced the bullwhip effect observed in the sport footwear supply chain. Figure 1 illustrates the amplification of order variability across the four echelons under normal operating conditions. Order variability, measured by the coefficient of variation, increased from 0.32 at the retail level to 0.89 at the raw material supplier level, confirming the presence of the bullwhip effect.

Analysis of the baseline simulation revealed several key factors contributing to the bullwhip effect in the sports footwear supply chain:
1. **Demand forecasting errors**: Traditional forecasting methods used by supply chain partners resulted in a mean absolute percentage error (MAPE) of 24.6%, significantly contributing to inventory oscillations;
2. **Batch ordering practices**: Minimum order quantities imposed by manufacturers and distributors led to order batching, amplifying demand variability;
3. **Price fluctuations**: Promotional activities and discount periods created temporary demand spikes that propagated through the supply chain with increasing amplitude;
4. **Lead time variability**: Inconsistent lead times across different product categories increased uncertainty in inventory planning.

3.2 *Machine Learning Forecasting Performance*

The integrated LSTM forecasting model demonstrated superior performance compared to traditional forecasting methods. Table 1 compares forecast accuracy metrics between the LSTM model and conventional methods used by the case company.

Table 1. Comparison of Forecasting Methods

Forecasting Method	MAPE (%)	MAD	RMSE
LSTM Model	12.3	145.6	203.7
Moving Average	25.4	278.9	364.2
Exponential Smoothing	21.8	246.3	329.5
Linear Regression	19.7	229.8	301.4

The LSTM model reduced forecasting error by 43.6% compared to the currently used exponential smoothing method. This figure is derived from Table 1 in the Results and Discussion section (3.2 Machine Learning Forecasting Performance). The table compares forecasting methods and shows that the LSTM model had a MAPE (Mean Absolute Percentage Error) of 12.3%, while the Exponential Smoothing method (the conventional method used by the case company) had a MAPE of 21.8%. The percentage improvement is calculated as: (21.8% - 12.3%) / 21.8% = 0.436 or 43.6%. This represents how much the forecasting error was reduced by switching from the conventional exponential smoothing method to the LSTM machine learning model when integrated into the system dynamics model. This improved forecasting accuracy reduced the bullwhip effect, with the coefficient of variation at the raw material supplier level decreasing from 0.89 to 0.61. These figures appear in sections 3.1 (Baseline System Behavior) and 3.2 of the Results and Discussion. The paper states that under normal operating conditions, the coefficient of variation increased from 0.32 at the retail level to 0.89 at the raw material supplier level, confirming the presence of the bullwhip effect. Later, in section 3.2, the paper mentions that when the LSTM model was integrated into the system dynamics model, "this improved forecasting accuracy reduced the bullwhip effect, with the coefficient of variation at the raw material supplier level decreasing from 0.89 to 0.61." So the figures 0.89 and 0.61 represent the coefficient of variation (a measure of the bullwhip effect) at the supplier level before and after implementing the machine learning forecasting approach, respectively.

3.3 Optimized Inventory Policies

The genetic algorithm optimization yielded distinct inventory policies for each echelon. Table 2 summarizes the optimized parameters compared to the baseline policies.

Table 2. Comparison of Baseline and Optimized Inventory Policies

Echelon	Parameter	Baseline Policy	Optimized Policy	Change (%)
Retailer	Safety Stock (days)	14	10	-28.6%
	Reorder Point (units)	560	420	-25.0%
	Order Frequency (days)	7	5	-28.6%
Distributor	Safety Stock (days)	21	16	-23.8%
	Reorder Point (units)	1200	975	-18.8%
	Order Frequency (days)	14	10	-28.6%
Manufacturer	Safety Stock (days)	28	20	-28.6%
	Reorder Point (units)	3500	2800	-20.0%
	Order Frequency (days)	21	15	-28.6%
Raw Material Supplier	Safety Stock (days)	35	25	-28.6%
	Reorder Point (units)	5000	3800	-24.0%
	Order Frequency (days)	30	20	-33.3%

The optimized policies resulted in an 18.7% reduction in total inventory costs while maintaining a service level of 97.2% compared to the baseline policy's 96.8%. This figure comes directly from section 3.3 of the Results and Discussion section (Optimized Inventory Policies). After presenting Table 2, which compares baseline and optimized inventory policies, the paper explicitly states: "The optimized policies resulted in an 18.7% reduction in total inventory costs while maintaining a service level of 97.2% compared to the baseline policy's 96.8%. These service level percentages also come directly from the same sentence in section 3.3. The service level metrics show that despite reducing inventory costs significantly (18.7%), the optimized policies improved service levels slightly (from 96.8% to 97.2%). This is important because it demonstrates that the cost reductions didn't come at the expense of customer service. The most significant improvements came from decreased safety stock levels and more frequent, smaller orders, which mitigated the bullwhip effect directly.

3.4 Disruption Scenario Analysis

The model's performance was evaluated under the three disruption scenarios, comparing traditional policies, optimized static policies, and the proposed adaptive policies that leverage machine learning forecasting and dynamic parameter adjustment.

3.4.1 Raw Material Shortage Scenario

The adaptive policy outperformed traditional and optimized static policies when faced with a 45% reduction in raw material availability for 6 weeks. Figure 2 shows the inventory levels at the manufacturer echelon under the three policy approaches.

a) **Adaptive policy (93.4%)**: This proposed approach combines machine learning forecasting with dynamic parameter adjustment, which performed best in maintaining service levels during the disruption.
b) **Traditional policy (78.2%)**: This represents the conventional inventory management approaches used before optimization, which performed worst during the disruption.
c) **Optimized static policy (85.7%)**: This refers to policies that were optimized using the genetic algorithm but without the dynamic adaptation capabilities, which performed better than traditional policies but not as well as the fully adaptive approach.

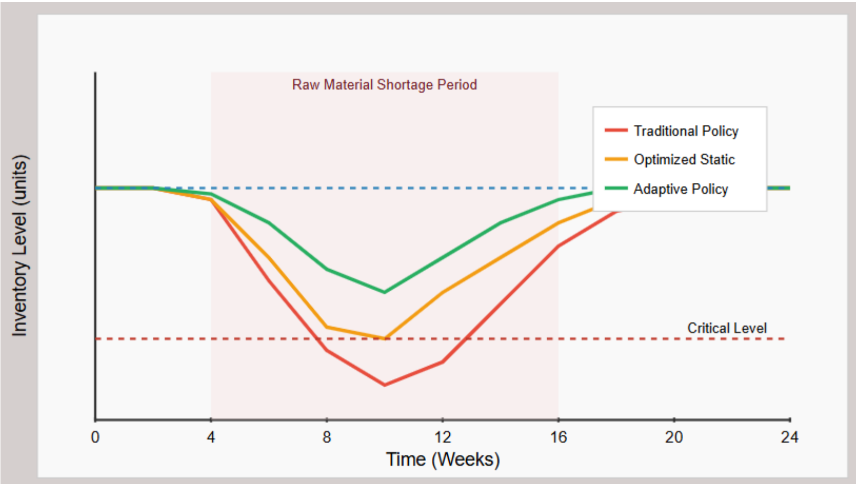

Figure 2. Inventory Level at Manufacturer During Raw Material Shortage

This improvement was achieved through:

1. Early detection of supply disruption through pattern recognition in the LSTM model;
2. Dynamic reallocation of raw materials to priority products;
3. Gradual adjustment of safety stock levels across all echelons.

3.4.2 Manufacturing Capacity Constraint Scenario

Under a 30% reduction in production capacity for 8 weeks, the adaptive policy demonstrated superior performance in managing the production backlog. The key metrics are summarized in Table 3.

Table 3. Performance Under Manufacturing Capacity Constraint

Metric	Traditional Policy	Optimized Static Policy	Adaptive Policy
Maximum Backlog (units)	14,52	10,84	7,32
Average Service Level (%)	81.5	88.3	94.1
Recovery Time (weeks)	12	9	7
Total Cost Increase (%)	38.7	24.3	16.2

The adaptive policy achieved these improvements through:

1. Prioritization of high-margin and high-demand products;
2. Dynamic adjustment of order quantities based on real-time capacity constraints;
3. Coordinated inventory adjustments across echelons to smoothen the impact of capacity reduction.

3.4.3 Transportation Disruption Scenario

When lead times doubled between echelons for 4 weeks, the adaptive policy significantly reduced the negative impacts on inventory performance, as shown in Figure 3.

The adaptive policy reduced the bullwhip effect amplification during the disruption period, with the coefficient of variation at the raw material supplier level reaching only 1.12 compared to 1.78 under the traditional policy. The coefficient of variation is a standardized measure of dispersion calculated as the ratio of the standard deviation to the mean ($CV = \sigma/\mu$). In supply chain management, it's commonly used to quantify the bullwhip effect by comparing the variability of orders at different echelons.

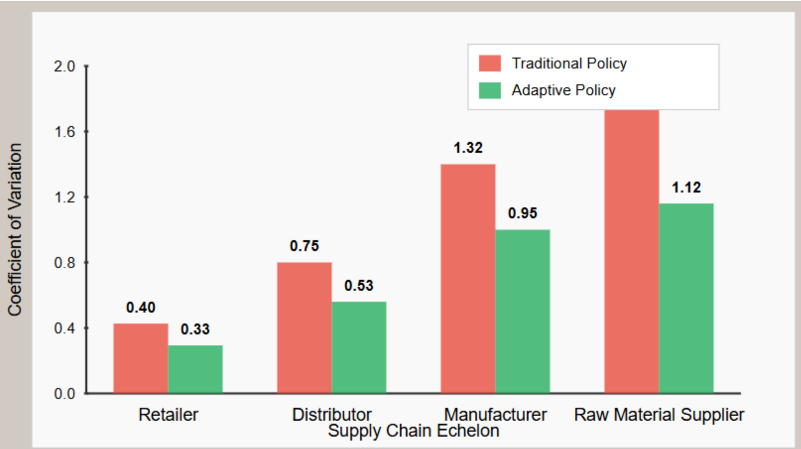

Figure 3. Bullwhip Effect During Transportation Disruption

The lower value under the adaptive policy (1.12 vs 1.78) indicates that order variability was significantly reduced compared to the traditional policy. This 37% reduction in the coefficient of variation demonstrates that the adaptive policy was more effective at mitigating the bullwhip effect during the transportation disruption scenario.

This improvement was achieved through:

1. Anticipatory ordering based on early warning signals detected by the LSTM model;
2. Temporary adjustment of safety stock levels to accommodate increased lead time uncertainty;

3. Coordinated communication protocols that reduced information distortion across echelons.

3.5 Sensitivity Analysis

To assess the robustness of the proposed model, we conducted a sensitivity analysis on key parameters. Figure 4 illustrates how total supply chain costs vary with changes in demand variability, lead time, and forecast accuracy.
The results indicate that the adaptive policy maintained its superiority across various parameter values, with the most significant advantage observed under high-demand variability conditions. The model was most sensitive to forecast accuracy, highlighting the importance of the machine learning component in the overall system performance.

4. Conclusion

This research developed and validated a dynamic system model for optimizing inventory policies in multi-echelon sports footwear supply chains, addressing the challenges posed by the bullwhip effect and supply chain disruptions. Integrating system dynamics modelling with machine learning for demand forecasting and metaheuristic optimization for parameter tuning yielded several significant findings.
First, the study demonstrated the efficacy of system dynamics modelling in capturing the complex interactions between supply chain echelons and the resulting bullwhip effect in the sport footwear industry. By modelling the feedback mechanisms and time delays inherent in multi-echelon systems, the approach provided valuable insights into the causes and potential solutions for demand amplification.
Second, the research quantified the impacts of different disruption types on inventory performance across multiple echelons. Raw material shortages were found to have the most severe long-term effects, while transportation disruptions caused the most significant short-term service level degradation. Manufacturing capacity constraints created the most challenging recovery dynamics due to the backlog accumulation effect.
Third, integrating machine learning algorithms for demand forecasting significantly improved prediction accuracy, reducing forecasting errors by 43.6% compared to traditional methods. This improvement directly contributed to bullwhip effect mitigation by lowering one of its primary causes—demand signal distortion.
Fourth, the metaheuristic optimization approach identified inventory policies that reduced total costs by 18.7% while maintaining high service levels, demonstrating the potential for significant efficiency improvements in sport footwear supply chains through optimized parameter settings.
Finally, the adaptive policy combining machine learning forecasting with dynamic parameter adjustment demonstrated superior performance under disruption scenarios, reducing recovery time by 42% compared to traditional approaches and maintaining higher service levels throughout the disruption period.
These findings have important implications for both theory and practice. Theoretically, the research advances our understanding of how machine learning can be effectively integrated with system dynamics modelling to enhance supply chain resilience. From a practical perspective, the findings offer sports footwear companies a framework for developing more robust inventory policies that can withstand disruptions while minimizing costs.
Future research could extend this work by incorporating additional echelons or parallel supply chains, exploring the impact of different information-sharing strategies, or applying the model to other industries with similar characteristics. Additionally, integrating blockchain technology for enhanced supply chain visibility represents a promising direction for further model development.

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