OPSEARCH
https://doi.org/10.1007/s12597-025-01005-w

THEORETICAL ARTICLE

Intelligent inventory demand forecasting: using chaos theory and optimization for supply chain resilience

T. Karpagavigneswari[1] · R. Kamali[1]

Received: 6 May 2025 / Accepted: 4 August 2025

Abstract

Supply chain inventory management is an essential yet demanding activity with parameters such as uncertain customer demand, time-varying lead times, and unexpected production or shipping disruptions. Traditional models like newsvendor and economic order quantity provide the basis for modeling strategies but are just insufficient when dealing with the real-world uncertainties. In this research, a cutting-edge demand forecasting model based on the Red Panda Optimizer with Logistic Mapping (RPO-LM) is proposed to support better inventory decisions. The methodology proposes three basic phases: data preparation, model training, and model evaluation. The prediction accuracy is improved by normalizing historical inventory data and splitting them into training and test datasets. The RPO-LM model is trained to reflect short-term fluctuation and long-term trends in demand to remain adaptive to dynamic inventory levels. To ascertain the accuracy of the predictions, performance analysis is carried out using metrics such as mean absolute percentage error and root mean squared error. The proposed model supports anticipatory inventory management, minimizing stockouts and overstocking, thereby maximizing supply chain effectiveness. Python simulations validate the effectiveness of the suggested strategy, demonstrating its superiority over more conventional approaches such as the least squares polynomial sinusoidal method and auto regressive integrated moving average. With a mean absolute percentage error of around 4 and a root mean squared error of about 6, the suggested approach has the highest forecast accuracy. Outcomes verify that proposed method greatly enhances prediction accuracy and economic efficiency, qualifying it as an optimal solution for contemporary inventory control systems.

Keywords Supply chain management · Demand forecasting · Logistic mapping · Inventory optimization · Stockout reduction · Economic order quantity · Overstock minimization

Extended author information available on the last page of the article

1 Introduction

A modern global economy is built on the foundation of supply chain (SC) efficiency, which enables information, goods, and services to flow freely between various industries within a market. The more markets are becoming connected, the more critical having the ability to supply the goods or services brings to the competitive and profitable arena [9, 18]. It is no longer, therefore, acceptable to believe that organizations streamlining their SC incur less cost and delay and bask less in enhanced customer satisfaction, especially with the ever-changing consumer demands and the unpredictable conditions in the market [29]. It has become formidable in the contemporary complex global landscape within which operations are done because some factors that discover vulnerabilities cause disruption in operations: geopolitical conflicts, natural disasters, pandemics, and climate-induced disruptions [23]. Furthermore, system fragmentation and manual processes, compounded by obsolete technology, have become additional inefficiency sources that cause delays and augmented operational overheads [20]. The COVID-19 pandemic exposed weaknesses in traditional SC, bringing into sharp focus the need for thinking out of the box solutions that could engender resilience and agility into the function [33]. The solution to the above problems is found in the transformation of SC activities into less efficient processes but more conducive to preemption of future risks. By following this principle, companies are in a better position not only to face the present challenges but also to nurture the groundwork for sustaining long-standing adaptability [19]. SC are, hardly, new buzzwords in business schools,every management student hears of such terms as Artificial Intelligence (AI, forecasting, demand planning, and others during their learning. By employing gains to rectify inefficiencies and improve decision-making, artificial intelligence has become a ground-breaking tool for optimizing SC [2, 28]. AI combines a number of cutting-edge technologies, including machine learning, predictive analytics, natural language processing (NLP), and autonomous systems, which together or separately help to open up a new way of thinking about how SC operations are carried out [25].

For instance, machine learning uses both historical and real-time data to forecast demand, manage inventory control, and anticipate any interruptions [16]. Predictive analytics deploys AI-based algorithms to inform a strategic decision by recognizing patterns and producing actionable insights [7, 8]. NLP identifies unstructured data sources such as emails and customer feedback to improve communication and coordination among SC stakeholders [7, 8]. Autonomous systems such as robots, self-driving vehicles, or drones, are changing logistics management by adding value through increasing operational efficiency, reducing human error, and speeding the movement of goods with little or no human involvement [32]. Today, when SC are expected to be flexible, effective, and sustainable, AI's unparalleled capacity to evaluate enormous amounts of data in real time, identify trends, and improve workflow optimization is crucial [17]. The integration of AI into SC management has become imperative for businesses in their quest for competitive advantage [6]. Apart from this, big data analytics as well improve logistics, cut downtime, and cut wastes [3]. These additions could give businesses, particularly those with the lowest margins, like oil and gas, significant competitive advantages [10]. Notably, big data analytics also assist in risk management by identifying possible threats and vulnerabilities even before they grow into crisis dimensions [11]. Continuous monitoring of such data and sources enables a company to spot and analyze anomalies for proactive mitigation [14].

1.1 Literature review

In a highly uncertain dynamic environment, Belhadi et al. [5] evaluate the direct and indirect effects of artificial intelligence (AI) on supply chain performance (SCP) and resilience (SCRs). The integration of AI into SC activities is also examined in this study in light of the Organizational Information Processing Theory (OIPT). In light of several causative circumstances (such as the adoption of digital technology, the supply of traceability, and the improvement of collaboration), Sezer et al. [27] sought to assess and investigate the resilience, sustainability, and intelligence of food SCs. The numerous and intricate links between result and causative variables are also examined in the study. Nuerk and Dařena [21] suggested combining enterprise architectural frameworks, AI-assisted business process optimization, and management science, specifically in strategic alignment. Azmat and Siddiqui [4] examined the pharmaceutical SCs complexity and various data characteristics. The research described a novel procedure for the identification of the most beneficial combination of demand forecasting models that ensure high accuracy through the use of deterministic factors by Mode and PERT analysis. Sepestanaki et al. [26] developed a finite-time global non-linear super-twisting sliding-mode controller while investigating the dynamic properties of a chaotic three-echelons SC system. This controller, designed through the technique of adaptive continuous barrier function, was developed to stabilize the system against external disturbances and model uncertainties.

In order to construct more resilient, intelligent, and adaptable SC into the industry 5.0 era, Williamson and Prybutok [31] introduced a revolutionary multidisciplinary framework that uses high-end approaches and strategies against critical obstacles. SCP was measured by AbouElaz et al. [1] using a classification control approach based on the Adaptive Neuro-Fuzzy Inference System (ANFIS). This was done in an effort to reduce expenses and increase overall production and efficiency. Rahman et al. [24] identified and developed effective recovery strategies with the objective of enhancing agility, resilience, and sustainability of SC while relieving from panic buying impacts during major catastrophes in core SC. Huang et al. [13] analyzed the Electric Vehicle (EV) SC network of China through a two-tier framework relying on the complex network approach of examining topological properties and resilience in general. In order to address the complexities of creating adaptable practices for resilient and sustainable SC through digital technologies for societal and economic development, Pandey et al. [22] use an integrated method that combines interpretive structural modeling, fuzzy, and ANFIS. The comparative table in terms of technique, goals, and results is shown in Table 1.

Table 1 Comparative table in terms of methodology, objectives, and outcomes

Authors (Year)	Methods used	Objectives	Outcomes
Belhadi et al. [5]	AI models, OIPT	Examine AI direct/indirect effects on SCR and SCP	Validated AI's significant role in improving SCR and SCP
Sezer et al. [27]	Causal analysis, digital tech, traceability	Assess resilience, sustainability, and smartness in food supply chains	Identified critical causal interdependencies for resilient SC
Nuerk and Dařena [21]	Strategic alignment, enterprise architecture, AI-assisted optimization	Optimize business process using AI to foster innovation and responsiveness	Framework shows how AI boosts adaptability under dynamic business needs
Azmat and Siddiqui [4]	PERT analysis, deterministic demand forecasting models	Improve demand forecasting accuracy in pharmaceutical SC	Achieved better forecasts using hybrid deterministic techniques
Sepestanaki et al. [26]	Chaotic SC modeling, super-twisting SMC, barrier function	Stabilize chaotic multi-echelon SC under external disturbances	Designed robust controller for SC resilience under non-linear chaos
Williamson and Prybutok [31]	Multidisciplinary framework, Industry 5.0 strategies	Address challenges in achieving intelligent and resilient SC	Strategic framework for SC in Industry 5.0 age
AbouElaz et al. [1]	ANFIS	Improve SC performance via fuzzy classification and control	Reduced inefficiencies and enhanced productivity in SC
Rahman et al. [24]	Scenario-based recovery strategy modeling	Improve agility and resilience post-catastrophes in SCs	Developed adaptive recovery measures for post-crisis SC
Huang et al. [13]	Complex network analysis of EV SC	Analyze resilience and topology of China's EV supply chain	Revealed structural resilience using two-tier network model
Pandey et al. [22]	ISM, fuzzy logic, ANFIS	Build flexible, tech-driven practices for sustainable SC	Enhanced SC sustainability through digital adaptability
Proposed Method (RPO-LM)	Red Panda Optimizer, Logistic Mapping, Python simulations	Improve inventory forecasting under uncertainty	Achieved MAPE ~ 4% and RMSE ~ 6; superior to ARIMA and LSP techniques

1.2 Research motivation

Effective demand forecasting for inventory becomes ever more prominent in ensuring the resilience of the SC in this fast-changing market environment. Nonlinear demand patterns and abrupt changes imposed on the SC by market uncertainty are difficult for traditional forecasting methods like the Auto Regressive Integrated Moving Average (ARIMA) and the Least Squares Polynomial Sinusoidal Model (LSPSM) to capture. Stockouts and overstocks are still common because traditional inventory models, including the Newsvendor and the Economic Order Quantity (EOQ) model, barely adjust to the constantly shifting conditions of lead time, supplier dependability, and demand fluctuation. With the increase in machine learning and metaheuristic optimization methods, the potential exists to improve forecasting precision by integrating adaptive models that consider chaotic and stochastic patterns of demand. Chaos theory when combined with optimization algorithms has the potential to enhance significantly demand forecasting by replicating intricate interactions in SC data. RPO-LM presents a new method of optimizing inventory forecast through a combination of chaotic behavior modeling and metaheuristic search methods. The aim of this study is to bridge the gap between modern adaptive optimization techniques and traditional demand forecasting restrictions. By combining RPO-LM with forecasting models, it aims to improve decision-making, minimize operational inefficiencies, and enhance SCR to uncertainties.

1.3 Contribution and organization

The following is a summary of this research's main contributions:

- Proposes a novel inventory forecasting framework based on RPO-LM, which is capable of dealing with uncertainties such as variable demand and dynamic lead times.
- Improves forecasting accuracy by explicitly modeling immediate demand shifts as well as trends.
- Outperforms classical forecasting methods and allows more proactive and efficient inventory management policies.

Section 2, Methodology, discusses data preparation, forecasting models (ARIMA, LSPSM), and implementing RPO-LM for identifying nonlinear demand fluctuations. Section 3, Results and Discussion, contrasts RPO-LM with conventional models, examining major SC parameters like demand volatility, supplier dependability, and inventory fluctuations. The research illustrates RPO-LM's advantage in minimizing forecasting errors and inventory inefficiencies. Section 4, Conclusion, outlines major findings, practical implications, and future research avenues, such as real-time data integration and reinforcement learning.

2 Methodology for demand forecasting and inventory decision process

Figure 1 describes the machine learning-based demand forecasting and inventory decision process. It starts with historical inventory and sales data, which is subjected to data processing and data preparation. The prepared data is then employed for Model Training, where preprocessing is done via the RPO-LM. Performance indicators such as RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error) showed that the model performed effectively. The assessment process also considers some parameters including historical sales, lead time, stock levels, demand variability, supplier reliability, inventory sales margins, and inventory costs. If YES, a demand forecast is created, resulting in proactive stock management for future stock optimization. If NO, comparative analysis is conducted on the model, and the system is reassessed. If required, the model is retrained and tuned prior to an inventory decision. Fig. 1 indicates an iterative process of optimizing forecasting accuracy to ensure effective inventory management through AI-based demand forecasting.

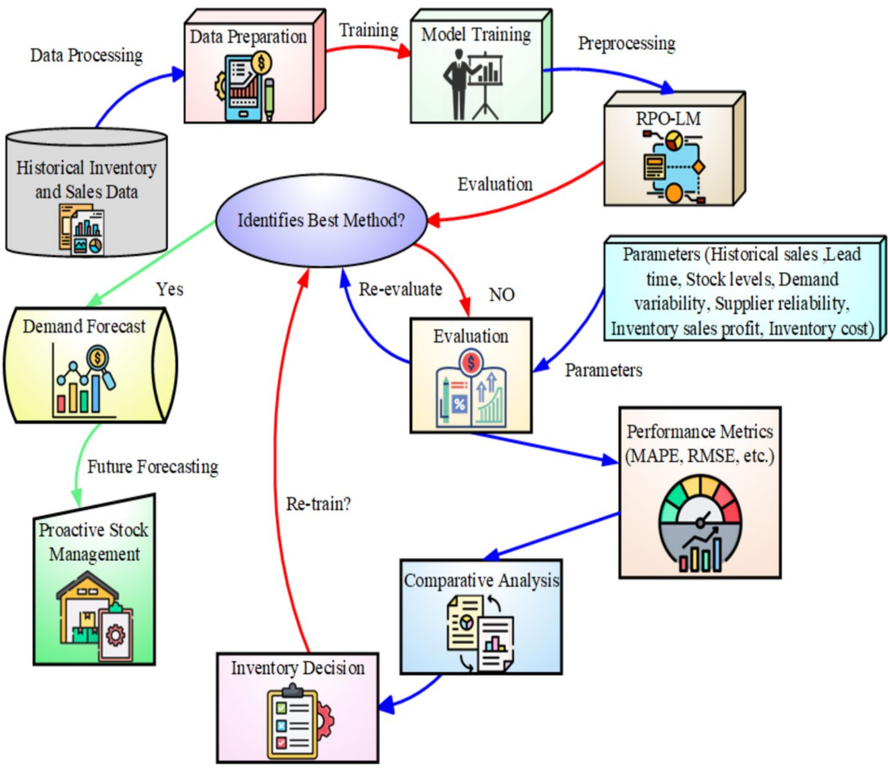


Fig. 1 Demand Forecasting and Inventory Decision Process

2.1 Data preparation

Data preparation plays a vital role in time series forecasting, wherein the model gets provided with neat, organized, and meaningful data to make appropriate predictions. Multiple steps are required to prepare data, such as collection of data, normalization of data, and addressing demand oscillation.

- *Collection of Historical Inventory and Sales Data*

Gathering historical inventory and sales records from several sources, including the Point of Sale (POS) system, the Enterprise Resource Planning (ERP) software, and the Warehouse Management Systems (WMS), is the first step in the data preparation process. Such records mainly contain essential details relating to transaction dates, product identifiers, sales quantities, inventory levels before and after sales, supplier restocking schedules, and seasonal demand trends. Thus, any data presented to the forecasting model should have no incompleteness and inaccuracies, as these are the key issues that diminish forecast quality.

- *Normalization and Partitioning into Training and Test Sets*

For consistency and to improve forecasting model performance, the data set needs to be standardized after collection. To bring all numerical values into range conformance, normalization procedures including log transformation, Z-score standardization, and min-max scaling are used. This keeps the model from being dominated by numerical discrepancies. Following normalization, the dataset ought to be divided into training and test sets, with the remaining 20–30% going toward testing and the remaining 70–80% going toward model training. In order to make sure the model generalizes effectively in real-time scenarios, it is essential to confirm the model's applicability on unseen data.

- *Handling Demand Variability and Stock Fluctuations*

Inventory and sales typically fluctuate due to seasonal demand, long-term trends, or sudden spikes because of promotions or SC disruptions. These fluctuations need to be managed so that it forecast accurately. Smoothing techniques such as moving averages and exponential smoothing filter out short-term noise while outlier detection techniques catch and repair abnormal spikes or missing data points. Besides, feature engineering to an outside factor such as weather conditions, economic indicators, or even special events that have an impact on demand also improve prediction ability. Above all, demand variability is handled by forecasting models to generate tightly defined stable and reliable inventory predictions.

2.2 Existing 1 (LSPSM)

LSPSM is a kind of hybrid mathematical model incorporated by the polynomial regressions and sinusoidal components for providing a proper representation of both linear and cyclic trends in inventory demands. It uses the least squares technique to formulate the minimization of errors and optimization of model parameters to be used where demand prediction patterns are seasonal, cyclic, and long-term trends. The LSPSM expresses inventory demand $D(t)$ as a polynomial trend complemented with the sinusoidal components:

$$D(t) = \sum_{i=0}^{n} a_i t^i + \sum_{j=1}^{m} b_j \sin(\omega_j t + \varphi_j) + \in \tag{1}$$

where, a_i represents the coefficients of the polynomial terms, t represents the time variable, b_j represents the amplitudes of the sinusoidal components, ω_j represents the frequency of sinusoidal components, φ_j represents the phase shifts, $\in$ represents the error term. The polynomial term captures the long-term trend, while the sinusoidal components capture seasonality and periodic fluctuations in demand.

2.3 Existing 2 (ARIMA)

ARIMA is a statistical technique used in forecasting a time series in different ways and angles in different industries, including finance, economics, energy, health, weather, and sales predictions. It uses historical trends, demand patterns, and seasonality to forecast future values from past observations. ARIMA would best fit data that typically have consistent statistical properties throughout time. In case of non-stationary time series, differencing is used to stabilize the series. The process is represented as [15]:

$$Y_t = X_t - X_{t-1} \tag{2}$$

where, Y_t represents the transformed time series, X_t denotes the original data points and X_{t-1} denotes the previous data point at time $t-1$. In order to forecast the value of Y_t,convert the differenced data back as follows:

$$X_t = Y_t + X_{t-1} \tag{3}$$

To calculate the MAE (Mean Absolute Error) for forecasting, consider the equation:

$$MAE = \frac{1}{N} \sum_{t=1}^{N} \left| \hat{X}_t - X_t \right| \tag{4}$$

where, N represents the total number of observations, $\hat{X}_t$ represents the predicted value at time t. The MEA quantifies the average magnitude of the forecast error, which provides an accurate measure without considering forecast direction.

2.4 Proposed RPO-LM

A recently proposed optimization method inspired by nature is the Red Panda Optimization (RPO) algorithm. It is employed to balance search space exploration and exploitation in order to effectively solve challenging optimization issues. RPO is chosen because it has a track record of striking a balance between exploration and exploitation, allowing for effective search over intricate solution spaces. Its lightweight design ensures faster convergence with reduced computational overhead, making it well-suited for real-time inventory forecasting. Unlike many recent metaheuristics, RPO adapts dynamically to changing data patterns, which is essential in handling uncertain demand and volatile supply chain environments. These characteristics collectively make RPO a robust and practical choice for the proposed forecasting framework. The best hyperparameters for the RPO-LM model are found by parameter tweaking utilizing grid search and cross-validation approaches to guarantee methodological robustness. Regularization during training, dropout mechanisms, and early quitting are ways to combat overfitting. The dataset was separated into training, validation, and testing sets, and k-fold cross-validation was used to improve model generalization. By doing this, the suggested approach as a whole guarantees that the model operates dependably on invisible data, enhancing its usefulness in dynamic, real-world inventory management situations. Fig. 2 gives a chronological outline of all sequential procedural steps in the RPO-LM through flowchart. The red panda position at the beginning of the optimization process is randomly initialized within the search space based on eqn. (5) [12].

$$Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_k \\ \vdots \\ Y_P \end{bmatrix}_{P\times q} = \begin{bmatrix} y_{1,1} & \cdots & y_{1,n} & \cdots & y_{1,q} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{k,1} & \cdots & y_{k,n} & \cdots & y_{k,q} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{P,1} & \cdots & y_{P,n} & \cdots & y_{P,q} \end{bmatrix}_{P\times q} \tag{5}$$

where, Y represents the transformed matrix of dimensions $P \times q$,Y_k represents an individual entity in the system, $y_{k,n}$ represents the element at the $k-th$ row and $n-th$ column in the matrix, P is the total number of observations or elements, q represents the number of features or attributes per entity. Each red panda's position represents a candidate solution, and the corresponding objective function values is organized into a matrix as in Eq. (6).

$$G = \begin{bmatrix} G_1 \\ \vdots \\ G_k \\ \vdots \\ G_P \end{bmatrix}_{P\times 1} = \begin{bmatrix} G(Y_1) \\ \vdots \\ G(Y_k) \\ \vdots \\ G(Y_P) \end{bmatrix}_{P\times 1} \tag{6}$$

where, G represents the transformed column vector of dimensions $P \times 1$, G_k represents a function evaluation at a specific input Y_k, $G(Y_k)$ denotes the function applied to each individual input Y_k, P represents the total number of observations or samples.

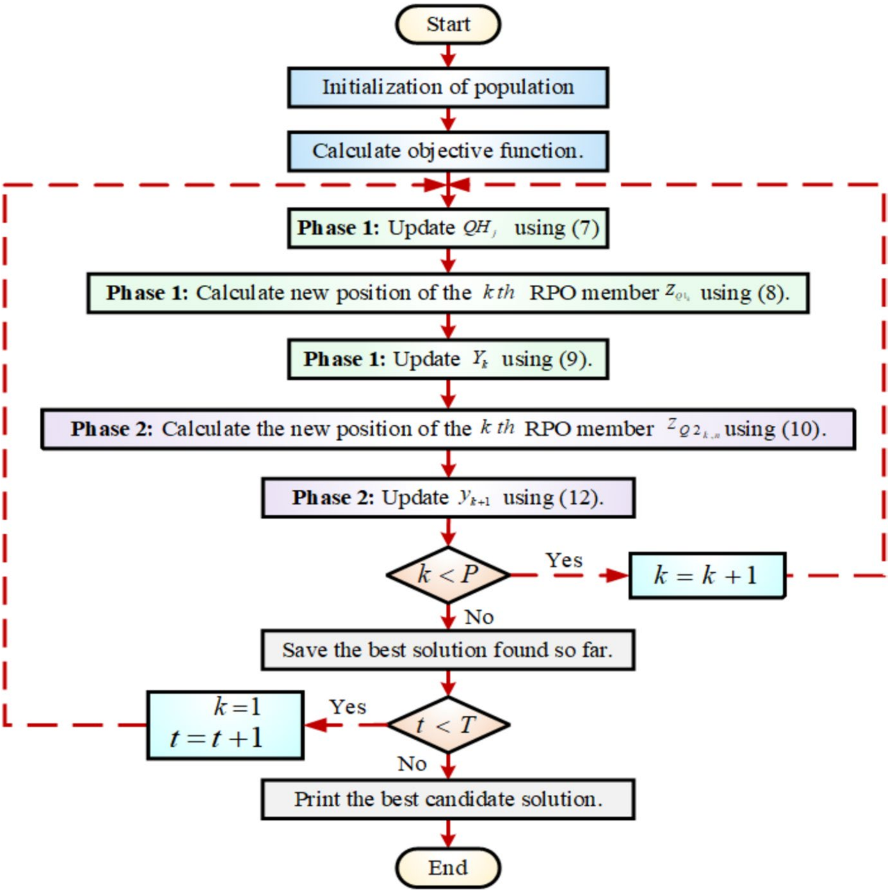


Fig. 2 Flowchart of the RPO-LM

Red Pandas use their keen senses to locate food, representing the optimal objective function, with allocations based on evaluations in (7).

$$QH_j = \left\{Y_r | r \in \{1, 2, \dots, P\}\, and\, G_r < G_j\right\} \cup \{Y_{opt}\} \tag{7}$$

where, QH_j represents the updated set based on a given condition, Y_r represents elements under evaluation, r represents the iteration from 1 to P, which is the total number of elements in the set, G_r represents the function value associated with each Y_r, G_j represents the reference function value used for comparison. Y_{opt} represents the best-performing element based on the criteria. Red pandas move toward the food source, enhancing exploration and global search, with position updates based on eqns. (8) and (9) if the objective function improves.

$$Z_{Q1_k} : z_{Q1_{k,n}} = y_{k,n} + \alpha \cdot (TR_k, n - \beta \cdot y_{k,n}) \tag{8}$$

$$Y_k = \begin{cases} Y_{Q1_k}, & if\ G_{Q1_k} < G_k; \\ Y_k, & otherwise. \end{cases} \tag{9}$$

where, Z_{Q1_k} represents the updated value after transformation, $z_{Q1_{k,n}}$ represents the individual element being updated, $y_{k,n}$ represents the original value before modification, α represents a random factor controlling the influence of the transformation, TR_k, n represents a reference value influencing the transformation, β represents a scaling factor modifying the original value $y_{k,n}$,Y_k represents the updated value after evaluation, Y_{Q1_k} represents the candidate value being tested, G_{Q1_k} represents the function evaluation of the candidate value, G_k represents the function evaluation of the current value. In the second phase of RPO, red pandas climb trees for rest, leading to small position changes that enhance local search, with updates based on (10) and (11) if the objective function improves.

$$z_{Q2_{k,n}} = y_{k,n} + \gamma_n + \alpha \quad k = 1, 2, \ldots, P, \quad n = 1, 2, \ldots, q, \quad and \quad t = 1, 2, \ldots, T \tag{10}$$

$$Y_k = \begin{cases} Y_{Q2_k}, & if\ G_{Q2_k} < G_k; \\ Y_k, & otherwise. \end{cases} \tag{11}$$

where, $z_{Q2_{k,n}}$ represents the updated value after transformation, γ_n represents a lower boundary adjustment factor, Y_{Q2_k} represents the newly proposed candidate value, G_{Q2_k} represents the function evaluation of the candidate value. The logistic map is a one-dimensional model that represents real-time systems in a very simple, nonlinear, discrete way, and it is defined through the recursive function stated as follows:

$$y_{k+1} = F(a, y_k) = a \cdot y_k \cdot (1 - y_k) \tag{12}$$

where, y_k represents the current value, y_{k+1} represents the next value, a represents the control parameter.

3 Results and discussions

This section presents optimizing techniques for demand forecasting and inventory management in highly complicated SC environments. The data for result analysis is taken from the dataset (https://www.kaggle.com/datasets/oscarm524/demand-forecast-for-optimized-inventoryplanning?select=orders.csv; https://www.kaggle.com/code/enjegodinez/supply-chain-demand-forecasting-prophet). The research builds efficiency and robustness in the SC through integrative demand modeling with predictive control and adaptive inventory control. Historical sales-related data, lead times, stock levels, variations in demand and supplier reliability have been optimized through python simulations to improve the quality of decision-making and minimize stockouts or overstocking. Chaos-based optimization applied through the RPO-LM ensures a high dynamism and adaptability in forecasting approaches for more precise and cost-effective inventory management.

Figure 3a shows forecasted production and sales values over six months from June to November by LSPSM model. The values of production are highly volatile, beginning at about 494.18 in June, decreasing -66.67 in September, increasing to about 330.90 in October before falling back. The forecasted values of sales are smoother and more progressively increasing, with a starting point of about 312.58 in June and an endpoint of about 986.06 in November. The high fluctuations in production reflect the volatility of demand and stock adjustment activities.

Figure 3b illustrates the forecasted production and sales figures based on the ARIMA model. This chart has minimal fluctuations, reflecting a more stable forecasting method. The forecasted production figures are relatively stable, varying slightly around 400. In contrast, the forecasted sales figures have a consistent pattern around 204.73 to 225.82, reflecting limited variation. This reflects that ARIMA offers a more conservative forecast, with stability in production and sales forecasts.

Figure 3c illustrates forecasted production and sales values with the Logistic Map model. The forecasted production begins at about 390 in June, increases to about 638.8 in July, decreases to almost 84.39 in August before it recovers to 652.32 in October and reduces again in November. The forecasted sales are similarly fluctuating but always retain slightly higher levels than production. This fluctuation mirrors the dynamic nature of the Logistic Map method, recording unpredictable demand changes while guaranteeing production to change in cycle.

Figure 3d illustrates the estimated production and sales values from the months of June to November by proposed model. The estimated production and estimated sales both trend in a steady positive direction. The values in both begin around 600 in June. In July, production comes up to about 750 and sales up to about 725. The pattern continues with the production reaching a value of close to 880 in September and over 1000 in November, followed very closely by the sales values. The tight production-to-sales gap indicates that there is good forecasting practice so that production captures demand effectively.

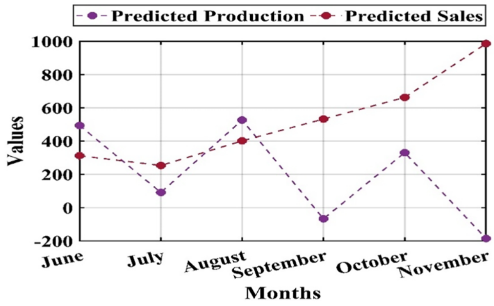
Figure 4a shows advancements in forecast accuracy, product availability, and savings in inventory carrying costs over eight months. Forecast accuracy increases from 0 to about 19%, product availability from 0 to about 7%, and savings in inventory carrying costs increase remarkably from $0M to about $42M, with an upward trend.

Figure 4b shows the percentage distribution of various SC areas of focus. Demand forecasting takes up 21%, performance measurement 11%, inventory management 10%, risk management 15%, supplier selection 20%, and other considerations 23%, indicating the well-balanced focus on various areas of SC management.

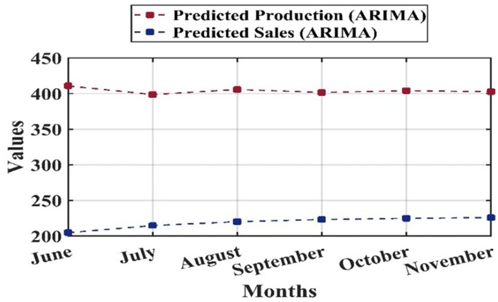
Figure 4c indicates values between 2011 and 2025, with increasing variations over time. The peak value occurs in 2017 at approximately 13, followed by variations. There is an increasing trend from 2020, with the value nearly reaching 13 by 2025, revealing a growth trend in recent years.

Figure 5a illustrates the efficiency of different forecasting models in stock replenishment. The ARIMA model begins at approximately 65%, LSPM enhances it to almost 72%, logistic mapping further enhances it to nearly 81%, and the proposed method provides the highest efficiency, approaching 89%, showing its better performance.

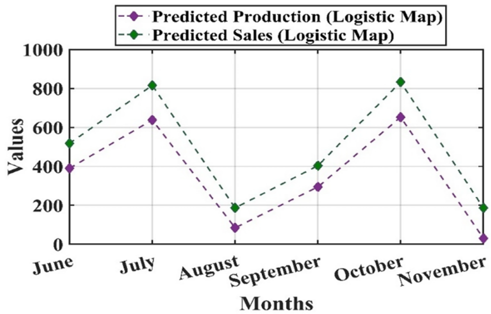
Fig. 3 Predicted production and sales trends using **a** LSPSM **b** ARIMA **c** logistic map model **d** proposed method



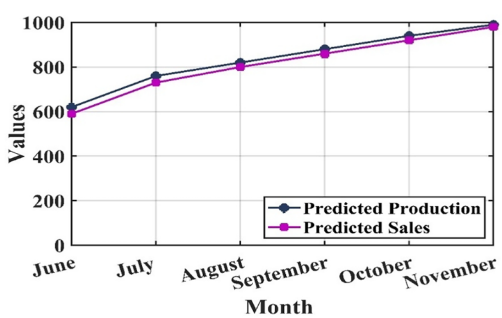
(a)



(b)



(c)



(d)

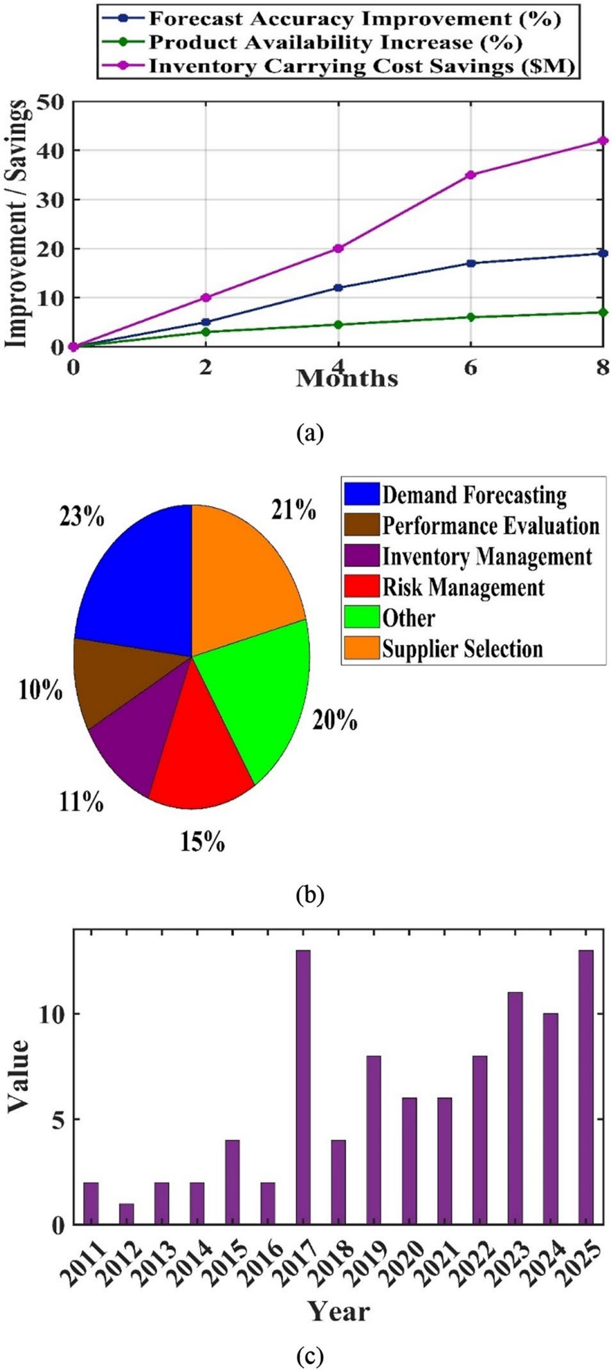


Fig. 4 Analysis of (**a**) Improvement and savings over time (**b**) Distribution of SC focus areas (**c**) Yearly value trends

Fig. 5 Analysis of (**a**) Stock replenishment efficiency across forecasting models (**b**) Comparative performance (**c**) MAPE and RMSE comparison (**d**) Stockouts and overstocks count across methods

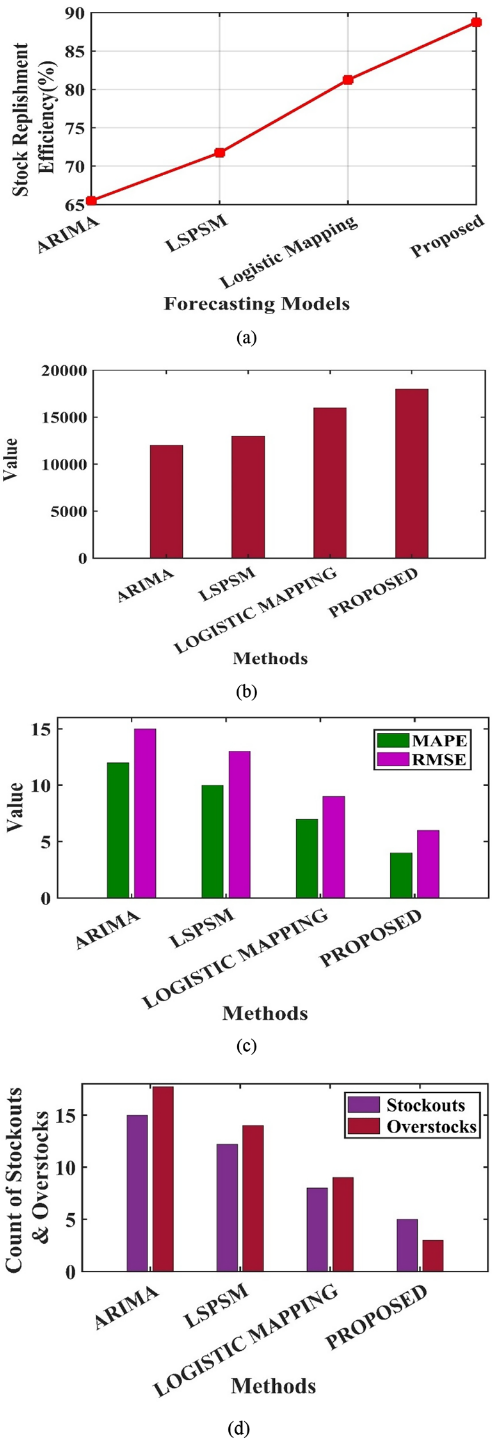


Figure 5b shows the comparison of performance of four forecasting techniques: ARIMA, LSPSM, logistic mapping, and the proposed method. The proposed method has the highest value, more than 18,000, followed by logistic mapping with approximately 16,500. LSPSM and ARIMA have lower values, about 13,000 and 12,500, respectively. The outcomes show that the proposed method is better than other methods in terms of numerical accuracy.

Figure 5c shows the MAPE and RMSE for four techniques. The ARIMA technique indicates the largest errors, with RMSE of about 15 and MAPE of about 12. LSPSM has slightly smaller values, with RMSE of about 13 and MAPE of about 10. Logistic Mapping is better, with RMSE and MAPE values lowered to about 9 and 7, respectively. The proposed method dramatically reduces errors to the tune of RMSE about 6 and MAPE nearly 4, showing it has better prediction accuracy.

Figure 5d compares the performances of various forecasting methods on stockout and overstock conditions. ARIMA results in the largest frequency of stockouts (around 15) and overstocks (around 18), and LSPSM lowers these somewhat to around 12 and 14, respectively. Logistic Mapping still further enhances inventory management with stockouts falling to around 8 and overstocks to about 9. The proposed method beats all the others with minimal stockouts (about 5) and overstocks (about 3), which indicates enhanced demand forecasting and inventory optimization.

Figure 6 displays correlations between main SC parameters. The historical sales proved that there is a very weak correlation between lead time (0.02), stock levels (− 0.03), and supplier reliability (− 0.19). Lead time had a very small correlation with stock levels (− 0.05) and supplier reliability (− 0.15). Stock levels are weakly related to demand variability (0.06) and reliability in suppliers (0.10). Demand

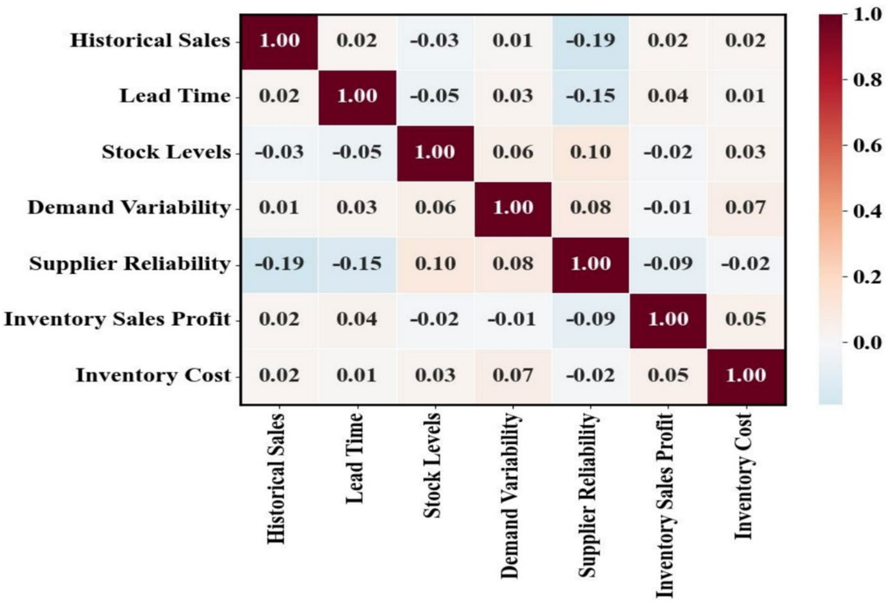


Fig. 6 Correlation matrix of SC parameters

variability has weak links with supplier reliability (0.08) and inventory cost (0.07). Overall, the results show that supplier reliability is negatively correlated to profit from inventory sales (− 0.09) and negatively correlated to inventory cost (− 0.02). Inventory sales profit as well as inventory cost had a weak correlation of 0.05. Hence overall, the relationship between these parameters generally remains weak.

Figure 7 compares the actual sales with the predicted demand through four techniques: ARIMA, LSPSM, Logistic Mapping and the proposed method. The actual sales pattern closely follows the forecast of the proposed method, illustrating its greater accuracy. The ARIMA prediction is fairly stable with negligible fluctuations, whereas LSPSM and Logistic Mapping are more responsive but still share deviations from the actual sales. The predicted demand ranges between 0 and 600 inventory units within the 10-month time frame, and the proposed method gets closest to actual sales patterns.

Figure 8 shows the annual value trends between 2018 and 2025, where previous years, a standout 2023 as an outlier, and the pink Line is an overall trend. The values are between 10 and 60, with 2023 being the highest peak at around 53. The trend Line goes up and down but has a general stability of around 20–30 across the years. The current period is noted at 2025, which is the most recent data point in the forecast. The visualization highlights the fluctuations in annual values, and 2023 is an outlier.

Table 2 shows comparison of different forecasting methods on the basis of MAE, Mean Square Error (MSE), RMSE, and R^2 values. The proposed system has been demonstrated to have the best performance in terms of lowest error rates (MAE=1.23, MSE=10.57, RMSE=3.5) with maximum R^2 values (0.94) pointing at high accuracy along with great variance explanation. Artificial Neural Network (ANN) comes in second with minimum errors (RMSE: 3.64, R^2: 0.88). Exponential

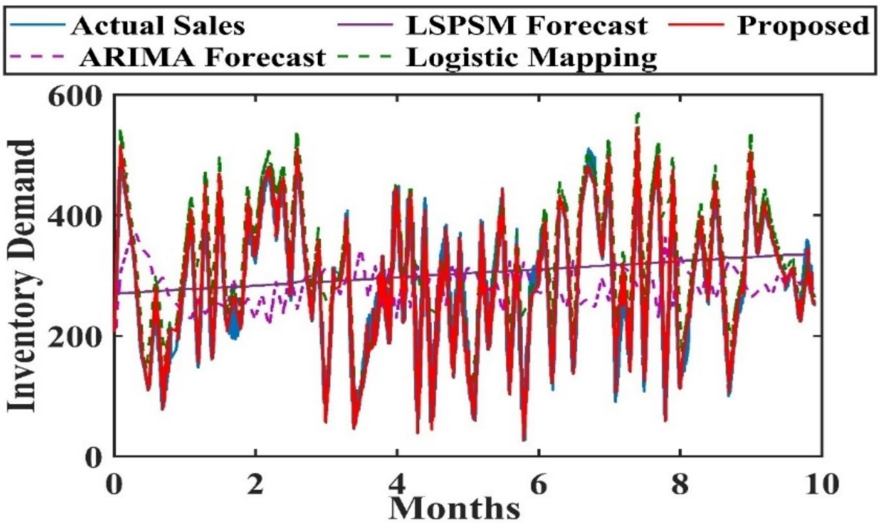


Fig. 7 Comparative forecasting of inventory demand over time

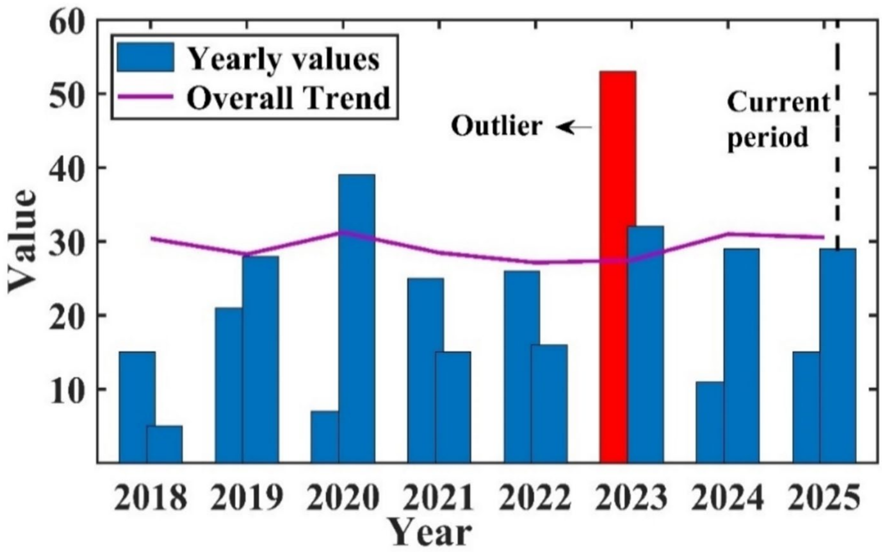


Fig. 8 Yearly value trends with forecasted growth

Table 2 Performance comparison of forecasting techniques

Technique	MAE	MSE	RMSE	R-Squared
Random forest [30]	7.79	88.60	9.41	0.70
DNN [30]	11.37	226.47	15.05	0.71
Multiple regression [30]	8.68	122.36	11.06	0.59
LS-SVM [30]	5.87	64.50	8.03	0.78
ELM [30]	15.17	473.02	21.75	0.68
Exponential GPR [30]	5.39	53.02	7.28	0.82
ANN [30]	2.50	14.88	3.64	0.88
Proposed	1.23	10.57	3.5	0.55

Gaussian Process Regression (GPR) and Least Squares-Support Vector Machines (LS-SVM) are moderately good, while Random Forest, Deep Neural Network (DNN), and Multiple Regression have maximum errors. Extreme Learning Machine (ELM) performs the poorest with RMSE of 21.75. The findings verify the proposed method as the best forecasting model. Table 3 shows the comparative analysis of forecasting techniques for production, sales, and inventory optimization.

3.1 Managerial implications and industry applications

The RPO-LM framework offers valuable insights for industries like Fast-Moving Consumer Goods (FMCG) and pharmaceuticals, where demand is unpredictable and lead-time management is crucial. In FMCG, where inventory cycles are short

Table 3 Comparative analysis of forecasting techniques for production, sales, and inventory optimization

Figure	Technique	Numerical outcomes & merits
Figure 3a	LSPSM Model	Production: 494.18 (June) → -66.67 (Sept) → 330.90 (Oct). Sales: 312.58 (June) → 986.06 (Nov). High production volatility; smoother sales increase
Figure 3b	ARIMA Model	Production stable (~400). Sales: 204.73—225.82. Offers conservative, stable forecasts
Figure 3c	Logistic Map	Production: 390 (June) → 638.8 (July) → 84.39 (Aug) → 652.32 (Oct). Sales fluctuate similarly. Captures dynamic, chaotic demand variations
Figure 3d	Proposed Model	Production: 600 (June) → 750 (July) → 880 (Sept) → 1000 + (Nov). Sales closely follow production. Ensures demand capture with minimal forecasting errors
Figure 4a	Forecast Accuracy	Accuracy: 0% → 19%, Availability: 0% → 7%, Inventory Savings: $0 M → $42 M. Significant improvements in forecasting efficiency and cost reduction
Figure 4b	SC Focus Areas	Demand Forecasting: 21%, Performance Measurement: 11%, Inventory Management: 10%, Risk Management: 15%, Supplier Selection: 20%, Others: 23%. Balanced SC management approach
Figure 4c	Value Trends (2011–2025)	Peak: 2017 (~13), 2025 (~13). Increasing trend post-2020, indicating market growth
Figure 5a	Forecasting Efficiency	ARIMA: ~65%, LSPSM: ~72%, Logistic Mapping: ~81%, Proposed: ~89%. Best stock replenishment efficiency with the Proposed Model
Figure 5b	Forecasting Performance	Proposed: 18,000 +, Logistic Map: 16,500, LSPSM: 13,000, ARIMA: 12,500. Proposed model shows superior numerical accuracy
Figure 5c	Prediction Errors (MAPE & RMSE)	ARIMA: RMSE ~ 15, MAPE ~ 12. LSPSM: RMSE ~ 13, MAPE ~ 10. Logistic Map: RMSE ~ 9, MAPE ~ 7. Proposed: RMSE ~ 6, MAPE ~ 4. Shows best prediction accuracy
Figure 5d	Stockouts & Overstocks	ARIMA: Stockouts ~ 15, Overstocks ~ 18. LSPSM: ~ 12 & ~ 14. Logistic Map: ~ 8 & ~ 9. Proposed: ~ 5 & ~ 3. Enhances demand forecasting and inventory optimization
Figure 6	SC Parameter Correlations	Weak correlations: Lead Time vs. Stock Levels (-0.05), Supplier Reliability (-0.15). Inventory Profit vs. Inventory Cost (0.05). Indicates minimal interdependence between SC factors
Figure 7	Predicted versus Actual Sales	ARIMA: stable but deviating. LSPSM & Logistic Map: responsive but less accurate. Proposed: Closest to actual sales, minimizing deviation
Figure 8	Annual Value Trends (2018–2025)	Fluctuating 10–60 range, peak in 2023 (~ 53). 2025 noted as most recent forecast point. Highlights annual value instabilities

and accurate demand estimation is essential to maintain product availability and shelf presence, RPO-LM can be integrated into existing Enterprise Resource Planning (ERP) or Inventory Management Systems to support real-time demand forecasting. This allows automated reorder point adjustments, reducing both stockout risks and excess inventory. In pharmaceuticals, where product shelf life and compliance are key concerns, the framework supports better inventory planning by anticipating demand surges due to seasonal trends or health initiatives. Improved forecasting helps maintain product availability while controlling storage costs through efficient inventory turnover. The model enables practical strategies such as real-time safety stock recalibration, flexible reorder scheduling, and demand-driven scenario analysis. When embedded as a decision-support tool in inventory processes, RPO-LM helps organizations improve cost efficiency, respond more effectively to demand changes, and boost customer satisfaction—fostering a more agile and resilient supply chain.

4 Conclusion

Supply chain inventory control is a dynamic and stochastic area that is affected by many stochastic parameters, such as changes in customer demand, uncertain lead times, and random supply disruptions. Conventional models such as the Newsvendor and EOQ give a structured background but fail to manage uncertainties of real-world scenarios. In this research, a new demand forecasting model using the RPO-LM is proposed to improve inventory decision-making. The research adopts a systematic approach to realizing data preparation, model training, and performance evaluation. The proposed RPO-LM model outperformed traditional forecasting methods such as ARIMA and LSPSM with respect to predictive accuracy in python simulations. The findings validate that RPO-LM successfully avoids stockouts and overstocking and optimizes SC processes through proactive inventory management. The proposed method achieves the best inventory optimization with minimal stockouts (≈ 5) and overstocks (≈ 3), ensuring superior demand forecasting. The research highlights the prospect of combining sophisticated optimization and chaos-based techniques in enhancing SC resilience, thus RPO-LM being a potential method for future inventory control systems. In order to improve forecasting accuracy and responsiveness in dynamic SC settings, future research will integrate real-time data streams with hybrid optimization techniques.

Acknowledgements None

Author contributions T. Karpagavigneswari: Conceptualization, Methodology, Validation R. Kamali: Project administration, Supervision, Investigation.

Funding This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Conflict of interest The authors declare that they have no potential conflict of interest.

Ethical approval All applicable institutional and/or national guidelines for the care and use of animals were followed.

Informed consent For this type of analysis formal consent is not needed.

References

1. AbouElaz, M.A., Alhasnawi, B.N., Sedhom, B.E., Bureš, V.: Anfis-optimized control for resilient and efficient supply chain performance in smart manufacturing. Results Eng. **25**, 104262 (2025). https://doi.org/10.1016/j.rineng.2025.104262
2. Al-kahtib, A., Alghababsheh, M., Khattab, M.: The role of organizational ambidexterity and frugal innovation in enhancing circular supply chains: the effect of artificial intelligence capabilities. Technol. Forecast. Soc. Change **210**, 123905 (2025). https://doi.org/10.1016/j.techfore.2024.123905
3. Attia, A.M.: Integrated risk management and maintenance planning in oil and gas supply chain operations under market uncertainty. Comput. Chem. Eng. **192**, 108879 (2025). https://doi.org/10.1016/j.compchemeng.2024.108879
4. Azmat, M., Siddiqui, R.: Enhancing supply chain efficiency: A holistic examination of hybrid forecasting models employing mode and PERT technique as deterministic factors. Int. J. Logist. Res. Appl. (2023). https://doi.org/10.1080/13675567.2023.2280094
5. Belhadi, A., Mani, V., Kamble, S.S., Khan, S.A.R., Verma, S.: Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation. Ann. Oper. Res. **333**(2), 627–652 (2024). https://doi.org/10.1007/s10479-021-03956-x
6. Chen, W., Choi, T.M., Dolgui, A., Ivanov, D., Pesch, E.: Digital manufacturing and supply chain: *creating* benefits through operations research and artificial intelligence. Ann. Oper. Res. **344**, 569–574 (2025). https://doi.org/10.1007/s10479-024-06450-2
7. Cheng, H., Huang, S.K., Lin, C.: Hybrid manufacturing logistics optimization scheduling algorithm based on intelligent supply chain management and artificial intelligence. Int. J. Adv. Manuf. Technol. (2025). https://doi.org/10.1007/s00170-025-15010-2
8. Cheng, M., Shen, B., Chan, H.L.: Implementing artificial intelligence consumer experience tools in supply chains. IEEE Trans. Eng. Manag. **72**, 717–729 (2025). https://doi.org/10.1109/tem.2024.3525412
9. Dolgui, A., Ivanov, D.: Internet of behaviors: conceptual model, practical and theoretical implications for supply chain and operations management. Int. J. Prod. Res. **63**(1), 1–8 (2025). https://doi.org/10.1080/00207543.2024.2372008
10. Egbumokei, P.I., Dienagha, I.N., Digitemie, W.N., Onukwulu, E.C., Oladipo, O.T.: Strategic supplier management for optimized global project delivery in energy and oil & gas. Int. J. Multidiscip. Res. Growth Eval. **5**(5), 2582–7138 (2024). https://doi.org/10.54660/.ijmrge.2024.5.5.984-1002
11. Ftiti, Z., Tissaoui, K., Boubaker, S.: On the relationship between oil and gas markets: a new forecasting framework based on a machine learning approach. Ann. Oper. Res. **313**(2), 915–943 (2020). https://doi.org/10.1007/s10479-020-03652-2
12. Givi, H., Dehghani, M., Hubálovský, Š: Red panda optimization algorithm: an effective bio-inspired metaheuristic algorithm for solving engineering optimization problems. IEEE Access **11**, 57203–57227 (2023). https://doi.org/10.1109/access.2023.3283422
13. Huang, Z., Zhou, Y., Lin, Y., Zhao, Y.: Resilience evaluation and enhancing for China's electric vehicle supply chain in the presence of attacks: a complex network analysis approach. Comput. Ind. Eng. **195**, 110416 (2024). https://doi.org/10.1016/j.cie.2024.110416

14. Jin, B., Xu, X.: Price forecasting through neural networks for crude oil, heating oil, and natural gas. Meas. Energ. **1**(1), 100001 (2024). https://doi.org/10.1016/j.meaene.2024.100001
15. Kumar, L., Khedlekar, S., Khedlekar, U.K.: A comparative assessment of Holt Winter Exponential Smoothing and autoregressive integrated moving average for inventory optimization in Supply Chains. Supply Chain Analytics **8**, 100084 (2024). https://doi.org/10.1016/j.sca.2024.100084
16. Lin, H., Lin, J., Wang, F.: An innovative machine learning model for supply chain management. J. Innov. Knowl. **7**(4), 100276 (2022). https://doi.org/10.1016/j.jik.2022.100276
17. Lokanan, M.E., Maddhesia, V.: Supply chain fraud prediction with machine learning and artificial intelligence. Int. J. Prod. Res. **63**(1), 286–313 (2025). https://doi.org/10.1080/00207543.2024.2361434
18. Mahapatra, A.S., Sengupta, S., Dasgupta, A., Sarkar, B., Goswami, R.T.: What is the impact of demand patterns on integrated online-offline and buy-online-pickup in-store (BOPS) retail in a smart supply chain management? J. Retail. Consum. Serv. **82**, 104093 (2025). https://doi.org/10.1016/j.jretconser.2024.104093
19. Maußner, C., Oberascher, M., Autengruber, A., Kahl, A., Sitzenfrei, R.: Explainable artificial intelligence for reliable water demand forecasting to increase trust in predictions. Water Res. **268**, 122779 (2025). https://doi.org/10.1016/j.watres.2024.122779
20. Modak, I., Bardhan, S., Giri, B.C.: Random pricing, product collection, and green investment strategies in a closed-loop supply chain with price dependent demand and remanufacturing. J. Clean. Prod. **486**, 144523 (2025). https://doi.org/10.1016/j.jclepro.2024.144523
21. Nuerk, J., Dařena, F.: Activating supply chain business models' value potentials through systems engineering. Syst. Eng. **26**(5), 660–674 (2023). https://doi.org/10.1002/sys.21676
22. Pandey, A.K., Daultani, Y., Pratap, S., Ip, A.W., Zhou, F.: Analyzing industry 4.0 adoption enablers for supply chain flexibility: impacts on resilience and sustainability. Glob. J. Flex. Syst. Manage. **26**(S1), 1–24 (2024). https://doi.org/10.1007/s40171-024-00396-x
23. Pournader, M., Ghaderi, H., Hassanzadegan, A., Fahimnia, B.: Artificial intelligence applications in supply chain management. Int. J. Prod. Econ. **241**, 108250 (2021). https://doi.org/10.1016/j.ijpe.2021.108250
24. Rahman, T., Paul, S.K., Agarwal, R., Shukla, N., Taghikhah, F.: A viable supply chain model for managing panic-buying related challenges: lessons learned from the covid-19 pandemic. Int. J. Prod. Res. **62**(10), 3415–3434 (2024). https://doi.org/10.1080/00207543.2023.2237609
25. Rai, R., Tiwari, M.K., Ivanov, D., Dolgui, A.: Machine learning in manufacturing and industry 4.0 applications. Int. J. Prod. Res. **59**(16), 4773–4778 (2021). https://doi.org/10.1080/00207543.2021.1956675
26. Sepestanaki, M.A., Rezaee, H., Soofi, M., Fayazi, H., Rouhani, S.H., Mobayen, S.: Adaptive continuous barrier function-based super-twisting global sliding mode stabilizer for chaotic supply chain systems. Chaos Solitons Fractals **182**, 114828 (2024). https://doi.org/10.1016/j.chaos.2024.114828
27. Sezer, M.D., Kazancoglu, Y., Mangla, S.K., Lafçı, Ç.: Smart, sustainable, and resilient food supply chains in disruptive events context. Bus. Strat. Environ. **33**(7), 6156–6171 (2024). https://doi.org/10.1002/bse.3801
28. Sjödin, D.R., Parida, V., Leksell, M., Petrovic, A.: Smart factory implementation and process innovation: a preliminary maturity model for leveraging digitalization in manufacturing moving to smart factories presents specific challenges that can be addressed through a structured approach focused on people, processes, and technologies. Res. Technol. Manag. **61**(5), 22–31 (2018). https://doi.org/10.1080/08956308.2018.1471277
29. Tseng, C.Y., Li, J., Lin, L.H., Wang, K., White, C.C., III., Wang, B.: Deep reinforcement learning approach for dynamic capacity planning in decentralised regenerative medicine supply chains. Int. J. Prod. Res. **63**(2), 555–570 (2025). https://doi.org/10.1080/00207543.2023.2262043
30. Vijai, P., Sivakumar, P.B.: Performance comparison of techniques for water demand forecasting. Procedia Comput. Sci. **143**, 258–266 (2018). https://doi.org/10.1016/j.procs.2018.10.394
31. Williamson, S.M., Prybutok, V.: Integrating human-centric automation and sustainability through the NATORM framework: a neuromorphic computing approach for resilient industry 5.0 supply chains. Int. J. Inf. Manag. Data Insights **4**(2), 100278 (2024). https://doi.org/10.1016/j.jjimei.2024.100278

32. Xu, J., Bo, L.: Optimizing supply chain resilience using advanced analytics and computational intelligence techniques. IEEE Access **13**, 18063–18078 (2025). https://doi.org/10.1109/access.2024.3523470
33. Yuan, D., Wang, Y.: Sustainable supply chain management: a green computing approach using deep Q-networks. Sustain. Comput. Inform. Syst. **45**, 101063 (2025). https://doi.org/10.1016/j.suscom.2024.101063

Authors and Affiliations

T. Karpagavigneswari[1] · R. Kamali[1]

✉ T. Karpagavigneswari
karpagavigneswarib@gmail.com

R. Kamali
kamali.sbs@vistas.ac.in

[1] Department of Mathematics, Vels Institute of Science, Technology and Advanced Studies (VISTAS), Pallavaram, Chennai, Tamil Nadu 600117, India