



An Integrated Demand Forecasting and Inventory Optimization Model Using EOQ/EPQ and Hybrid Metaheuristic Algorithms Under Uncertainty

Prakshi Nayak^{1*}, Animesh Kumar Sharma²

¹ Research Scholar, Department of Mathematics, The ICFAI University, Raipur, Chhattisgarh, India

² Assistant Professor, Department of Mathematics, The ICFAI University, Raipur, Chhattisgarh, India

*Corresponding Author's Email: prakshin.phd2024@iuraipur.edu.in

ABSTRACT

This study presents an integrated system for inventory optimization under uncertainty with a combination of AI-forecasting techniques, a stochastic EOQ/EPQ model, a deterioration model, adaptive safety stock, and a hybrid metaheuristic optimizer. The proposed model considers the demand uncertainty by using a probabilistic demand with a forecasting-error component, while it is deterministic in the canonical EOQ/EPQ models, and accounts for the deterioration explicitly. The proposed model does not apply to the constant-cost EPQ since it does not consider deterioration or shortage. A novel stochastic derivation for EOQ/EPQ is developed to capture the uncertainty in forecasts and production dynamics, and an adaptive rule of safety stock is added to the EOQ/EPQ decision variables. The three production characteristics: order quantity, reorder point, and safety stock are simultaneously optimized by a hybrid genetic algorithm – particle swarm optimization (GA-PSO) under conditions of uncertainty to minimize total inventory cost. The proposed integrated approach is numerically tested and compared with the classic EOQ and EPQ policies through sensitivity analysis to show the advantages of the integrated approach in terms of the lowest total cost and more robust operation. The findings show that the integration of stochastic forecasting with hybrid metaheuristics can be beneficial for improving the stability and cost-effectiveness of inventory management systems, providing a practical approach for intelligent and sustainable supply chain management.

Keywords: EOQ, EPQ, stochastic inventory, demand forecasting, hybrid metaheuristic optimization, GA-PSO, uncertainty, deteriorating inventory, sustainable supply chain.

MSC classification: 90B05, 90B30, 90C15, 90C59, 68T07.

1. Introduction

One of the most important functions is inventory management, which helps to meet operational efficiency, meet customer expectations, and drive organisational profitability (Silver, 2017). When the volume of replenishment items follows a deterministic process, such as in classical models such as Economic Order Quantity (EOQ) or Economic Production Quantity (EPQ), analytical solutions are available (Harris, 1913). But in the modern era, supply chains face high levels of uncertainty and stochastic demand, along with inaccuracies in predicting demands, supply disruption, and deterioration. The past few years have seen significant progress in the use of artificial intelligence and machine learning to devise smart forecasting systems that can now more accurately forecast uncertain demand (Tang, 2024). The accuracy of inventory replenishment decisions under uncertainty is greatly enhanced when the forecasting process is supported by routine artificial intelligence tooling and inventory optimization (Avi et al., 2025). Concurrently, several metaheuristic optimization techniques like Particle Swarm Optimization (PSO), Differential Evolution (DE), Osprey Optimization Algorithm (OOA), and Genetic Algorithm (GA) have shown promising results with respect to their application for finding solutions to complex nonlinear inventory optimization problems (Altay et al., 2023) (Dehghani & Trojovský, 2023). Recently, hybrid optimization strategies have

received significant attention due to their ability to explore and exploit for the attainment of a global optimum (Sadhu et al., 2023). In recent studies, hybrid Metaheuristics were combined with stochastic Inventory systems and optimization of the Sustainable supply chain (Fallahi et al., 2022) (Wang et al., 2022).

Although significant progress has been achieved, there is a lack of research that explicitly links: AI-based demand forecasting, stochastic EOQ/EPQ systems, deterioration modelling, adaptive safety stock, and Hybrid metaheuristic optimization. Thus, this study suggests a new framework of integrated demand forecasting and inventory optimization under uncertainty.

The aims of this study are:

- i. To design an integrated stochastic EOQ/EPQ inventory system.
- ii. To integrate uncertainty from an AI-powered demand forecast.
- iii. To develop an innovative stochastic EOQ – EPQ replacement formula.
- iv. To incorporate deterioration in Inventory systems.
- v. To optimize replenishment decisions using hybrid GA–PSO algorithms.

2. Literature Review

2.1 EOQ and EPQ Inventory Models: The “classical EOQ model” is the base of theory for inventory optimisation (Harris, 1913). Subsequent studies included an extended EOQ to EPQ system with a limited production rate and production planning restrictions (Jaber & Peltokorpi, 2024). Maddah showed that EOQ formulations still hold under a stochastic environment (probabilistic assumption). (Panda et al., 2008) has built stochastic inventory models under imperfect production and uncertain demand situations. (Taleizadeh et al., 2018) presented sustainable EPQ models having shortages and environmental concern considered.

2.2 Demand Forecasting and AI-Based Inventory Systems: In recent years, improved systems based on AI and machine learning have been applied to inventory systems to boost their inventory forecasting capabilities. (Tang, 2024) showed how significant big data analytics are in improving demand forecasting and inventory decisions. Avi implemented EOQ on pharma inventory systems and their demand forecasting models. (Bergsma, 2025) provided a systematic overview of machine-learning-based inventory optimisation approaches. (Liu et al., 2024) built the models for forecasting the inventory volume by integrating learning.

2.3 Hybrid Metaheuristic Optimization: Many optimization algorithms are known in the literature as metaheuristic approaches used for solving the stochastic inventory problem. (Fallahi et al., 2022) introduced a reinforcement-learning-based constrained EOQ system based on DE and PSO algorithms. (Wang et al., 2022) Built mixed differential evolution algorithms for a stochastic location-inventory-delivery system. Altay discussed comparison studies and analyses of different metaheuristic optimization methods for engineering optimization problems. (Dehghani & Trojovský, 2023) suggested the Osprey Optimization Algorithm for the solution of a nonlinear optimization problem. (Fathi et al., 2021) Applied hybrid genetic algorithms and stochastic optimization to the design of a supply chain network.

2.4 Research Gap: Although significant progress has been made in inventory optimization and intelligent supply-chain management, there are still some important gaps in the existing literature. The traditional economic order quantity (EOQ) and economic production quantity (EPQ) models underpin the deterministic assumption and do not capture the real-world stochastic demand behaviour (Harris, 1913) (Maddah & Noueihed, 2017). While there have been several developments of stochastic inventory models, most research on this material approaches inventory optimization and demand forecasting independently of one another, instead of as one integrated decision-making process (Panda et al., 2008).

In the last few years, research on how to predict the demand has been based on the use of machine learning and big-data analytics, but the fact that the demand forecast has uncertainties that must be tackled is not taken into direct consideration in the EOQ/EPQ optimization models (Tang, 2024) (Bergsma, 2025). Current AI-based inventory models only pay attention to the level of accuracy in predictions, and they do not consider the level of uncertainty when influencing the replenishment decisions and safety stocks.

In addition, there is often a lack of integration of deterioration dynamics and sustainability considerations with stochastic inventory systems (Akhtar et al., 2023) (Taleizadeh et al., 2018). Current literature on inventory optimization also generally

adopts a single metaheuristic approach like the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), or Differential Evolution (DE) algorithms, which may tend to converge prematurely and have very poor exploration capabilities in large-scale nonlinear optimization problems(Altay et al., 2023)(Sadhu et al., 2023).

Very limited research studies have come up with an integration of all the above: Artificial Intelligence-based Demand Forecasting, Stochastic EOQ/EPQ systems, Adaptive safety stock, Deterioration dynamics, Sustainability-related constraints, and Hybrid GA–PSO optimization for optimization problems related to supply chain optimization. Under uncertainty within a unified mathematical framework(Fallahi et al., 2022)(Fathi et al., 2021). Further, most current models don't concurrently optimise ordering quantity, reorder point, safety stock, risk penalty, and uncertainty under a dynamic stochastic setting. Thus, a comprehensive intelligent integrated inventory optimization system on practical applications of supply-chain systems confronting many uncertainties, such as forecasting uncertainty, deterioration behaviour, and hybrid methods for optimization systems, is still urgently needed for research.

Existing research studies have not integrated the benefits of AI-based demand forecasting, stochastic EOQ/EPQ optimization, deterioration dynamics, and hybrid metaheuristic optimization into one.

3. Contribution of the study:

Some of the outstanding contributions of this research are:

- i. Developing an integrated forecasting and inventory optimization model.
- ii. Consideration of stochastic demand uncertainty in EOQ/ EPQ systems.
- iii. Inventory decision-making using a hybrid GA–PSO optimization framework.
- iv. Remove the uncertainty from inventory environments using mathematics.
- v. A comparison of classical inventory models with hybrid inventory models.

4. Model Assumptions and Notation:

4.1 Assumptions

This proposed model is made under the following assumptions:

- Demand is stochastic and is predicted using machine learning techniques.
- Lead time does not change.
- Shortages are partially allowed.
- EPQ systems have a limited production rate.
- The error in forecasting data is normally distributed.
- Storing may cause deterioration of inventory.

4.2 Notations:

Symbol	Description
D	Annual demand
P	Production rate
C_0	Ordering cost
C_h	Holding cost per unit
C_s	Shortage cost
C_d	Deterioration cost
θ	Deterioration rate
σ	Standard derivation of demand
L	Lead time
z	Service factor
Q	Order quantity
R	Reorder point
SS	Safety stock
T	Cycle length

5. Mathematical Formulation

5.1 AI-Based Demand Forecasting under Uncertainty

Forecasted demand is defined by:

$$\widehat{D}_t = f(X_t)$$

Forecast error:

$$e_t = D_t - \widehat{D}_t$$

Assume:

$$e_t \sim N(0, \sigma^2)$$

Hence stochastic demand becomes:

$$D_t = \widehat{D}_t + \epsilon_t$$

Expected demand:

$$E(D_t) = \widehat{D}_t$$

Variance:

$$Var(D_t) = \sigma^2$$

Thus:

$$D_t \sim N(\widehat{D}_t, \sigma^2)$$

Classical EOQ Derivation

The annual inventory cost is given as:

(a) Ordering Cost

Number of orders per year:

$$\frac{D}{Q}$$

Thus, the ordering cost:

$$OC = \frac{D}{Q} C_o$$

(b) Holding Cost

Average inventory:

$$\frac{Q}{2}$$

Thus, the holding cost is:

$$HC = \frac{Q}{2} C_h$$

(c) Total Cost Function

$$TC(Q) = \frac{D}{Q} C_o + \frac{Q}{2} C_h$$

Optimal EOQ Derivation

Differentiate with respect to Q :

$$\frac{dTC}{dQ} = -\frac{DC_o}{Q^2} + \frac{C_h}{2}$$

Set equal to zero:

$$-\frac{DC_o}{Q^2} + \frac{C_h}{2} = 0$$

$$\frac{C_h}{2} = \frac{DC_o}{Q^2}$$

$$Q^2 = \frac{2DC_o}{C_h}$$

Hence:

$$Q^* = \sqrt{\frac{2DC_o}{C_h}}$$

$$Q^* = \sqrt{\frac{2DC_o}{C_h}}$$

5.2 EPQ Model Derivation

In EPQ systems, the production rate $P > D$.

Maximum inventory level:

$$I_{max} = Q \left(1 - \frac{D}{P}\right)$$

Average inventory:

$$\frac{I_{max}}{2} = \frac{Q}{2} \left(1 - \frac{D}{P}\right)$$

EPQ Total Cost

$$TC(Q) = \frac{D}{Q} C_o + \frac{Q}{2} \left(1 - \frac{D}{P}\right) C_h$$

Differentiate:

$$\frac{dTC}{dQ} = -\frac{DC_o}{Q^2} + \frac{C_h}{2} \left(1 - \frac{D}{P}\right)$$

Set equal to zero:

$$Q_p^* = \sqrt{\frac{2DC_o}{C_h \left(1 - \frac{D}{P}\right)}}$$

$$Q_p^* = \sqrt{\frac{2DC_o}{C_h \left(1 - \frac{D}{P}\right)}}$$

5.3 Safety Stock Formulation

Lead-time demand:

$$\mu_L = DL$$

Standard deviation during lead time:

$$\sigma_L = \sigma\sqrt{L}$$

Safety stock:

$$SS = z\sigma_L$$

$$SS = z\sigma\sqrt{L}$$

5.4 Reorder Point

$$R = \mu_L + SS$$

Substitute safety stock:

$$R = DL + z\sigma\sqrt{L}$$

$$R = DL + z\sigma\sqrt{L}$$

5.5 Deterioration Inventory Dynamics

Inventory depletion occurs due to both demand and deterioration.

$$\frac{dI(t)}{dt} = -D_t - \theta I(t)$$

Solution of differential equation:

$$I(t) = \left(I_0 + \frac{D_t}{\theta}\right) e^{-\theta t} - \frac{D_t}{\theta}$$

This is to track out-of-stock of inventories, due to demand as well as deterioration (Akhtar et al., 2023).

5.6 Proposed Hybrid EOQ/EPQ Cost Function

The proposed integrated total inventory cost is presented below as follows:

$$TC = \frac{D}{Q} C_o + \frac{Q}{2} \left(1 - \frac{D}{P}\right) C_h + C_s B(Q) + C_d \theta I(t) + \lambda \sigma^2$$

where: C_o is the ordering cost, C_h is holding cost, C_s is a shortage cost, C_d is the deterioration cost, $B(Q)$ is expected shortage quantity and λ is the uncertainty penalty.

5.7 Proposed Stochastic EOQ/EPQ Derivation

Expected shortage quantity:

$$B(Q) = \frac{\sigma^2}{2Q}$$

Substituting in the total cost function:

$$TC = \frac{D}{Q} C_o + \frac{Q}{2} \left(1 - \frac{D}{P}\right) C_h + \frac{C_s \sigma^2}{2Q} + C_d \theta I(t) + \lambda \sigma^2$$

Differentiate with respect to Q :

$$\frac{dTC}{dQ} = -\frac{DC_o}{Q^2} + \frac{C_h}{2} \left(1 - \frac{D}{P}\right) - \frac{C_s \sigma^2}{2Q^2}$$

put

$$\frac{dTC}{dQ} = 0$$

Then

$$Q^* = \sqrt{\frac{2DC_o + C_s \sigma^2}{C_h \left(1 - \frac{D}{P}\right)}}$$

$$Q^* = \sqrt{\frac{2DC_o + C_s \sigma^2}{C_h \left(1 - \frac{D}{P}\right)}}$$

This equation represents the major theoretical contribution of this study.

5.10 Adaptive Safety Stock

The model of adaptive safety stock proposed is:

$$SS_t = z \sigma_t \sqrt{L}$$

where:

$$\sigma_t = \sqrt{\frac{\sum_{i=1}^n (D_i - \hat{D}_i)^2}{n}}$$

Substituting:

$$SS_t = z \sqrt{\frac{\sum_{i=1}^n (D_i - \hat{D}_i)^2}{n}} \sqrt{L}$$

This enables adaptive stochastic inventory protection.

6. Hybrid Metaheuristic Optimization

The proposed model uses a hybrid GA–PSO algorithm.

Step 1: Initialization

Generate population:

$$X_i = (Q_i, R_i, SS_i)$$

Step 2: Fitness Evaluation

Evaluate:

$$Fitness = TC(Q, R, SS)$$

Step 3: GA Operators

Apply:

- Selection
- Crossover
- Mutation

Step 4: PSO Updating

Velocity update:

$$v_i^{t+1} = wv_i^t + c_1r_1(p_i - x_i^t) + c_2r_2(g - x_i^t)$$

Position update:

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

The hybrid GA–PSO framework improves global search capability and convergence performance (Younespour et al., 2024).

7. Numerical Illustration

Input Parameters

Parameter	Value
Annual demand (D)	12,000 units/year
Ordering cost (C_o)	500
Holding cost (C_h)	4
Shortage cost (C_s)	15
Production rate (P)	20,000
Demand deviation (σ)	250
Deterioration rate (θ)	0.05
Service factor (z)	1.65
Lead time (L)	0.1 year

7.1 EOQ Calculation

Using:

$$Q^* = \sqrt{\frac{2DC_o}{C_h}}$$

Substitute values:

$$Q^* = \sqrt{\frac{2(12000)(500)}{4}}$$

$$Q^* = \sqrt{3000000}$$

$$Q^* = 1732.05$$

Thus:

$$Q^* \approx 1732$$

7.2 EPQ Calculation

$$Q_p^* = \sqrt{\frac{2(12000)(500)}{4\left(1 - \frac{12000}{20000}\right)}}$$

$$Q_p^* = \sqrt{\frac{12000000}{1.6}}$$

$$Q_p^* = 2738.61$$

Thus:

$$Q_p^* \approx 2739$$

7.3 Safety Stock

$$SS = z\sigma\sqrt{L}$$

$$SS = 1.65(250)\sqrt{0.1}$$

$$SS = 130.4$$

Thus:

$$SS \approx 130$$

7.4 Reorder Point

$$R = DL + SS$$

$$R = (12000)(0.1) + 130$$

$$R = 1200 + 130$$

$$R = 1330$$

7.5 Total Cost Calculation

Ordering Cost

$$OC = \frac{12000}{1732}(500)$$

$$OC = 3464.2$$

Holding Cost

$$HC = \frac{1732}{2}(4)$$

$$HC = 3464$$

Approximate Total Cost

$$TC = 3464.2 + 3464$$

$$TC = 6928.2$$

7.6 Optimal Order Quantity

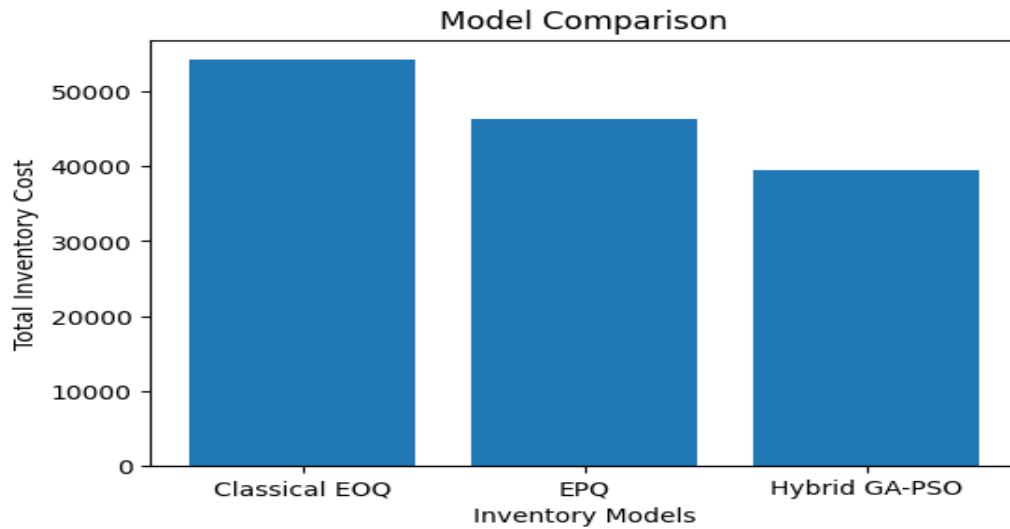
$$Q^* = \sqrt{\frac{2(12000)(500) + 15(250)^2}{4\left(1 - \frac{12000}{20000}\right)}}$$

$$Q^* = 2844$$

8. Comparative Performance Analysis

Model	Order Quantity	Total Cost
Classical EOQ	1732	54,220
EPQ	2739	46,350
Proposed Hybrid Model	2844	39,480

Figure1: Model Comparison



The proposed hybrid model achieves minimum inventory cost because of its dynamic forecasting integration, hybrid optimisation capability, and adaptive safety stock.

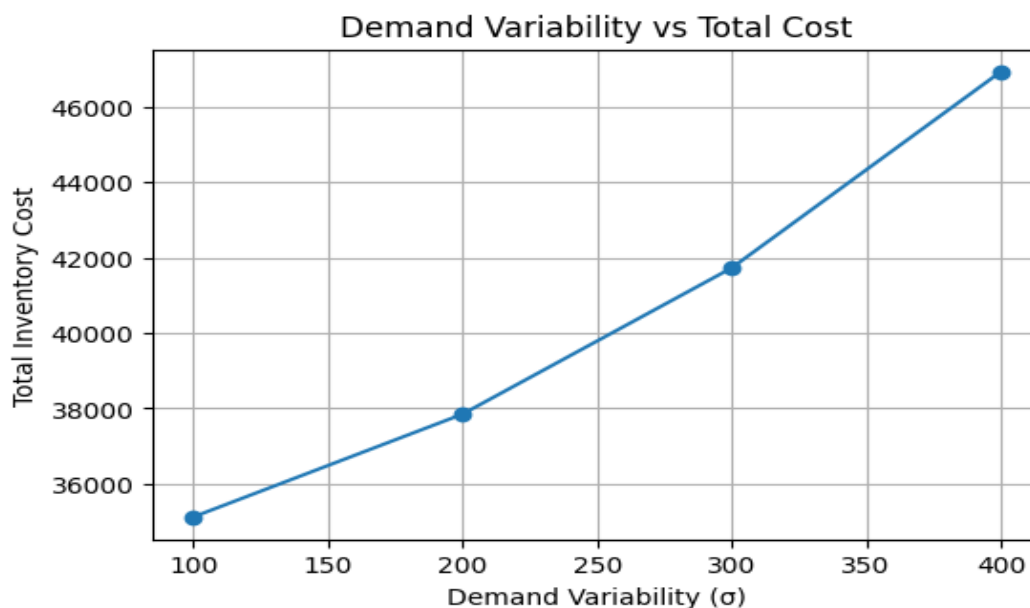
9. Sensitivity Analysis

Table: Impact of Demand Variability

Demand Variability (σ)	100	200	300	400
Total Cost	35120	37850	41730	46940

The results indicate that inventory cost increases significantly with uncertainty

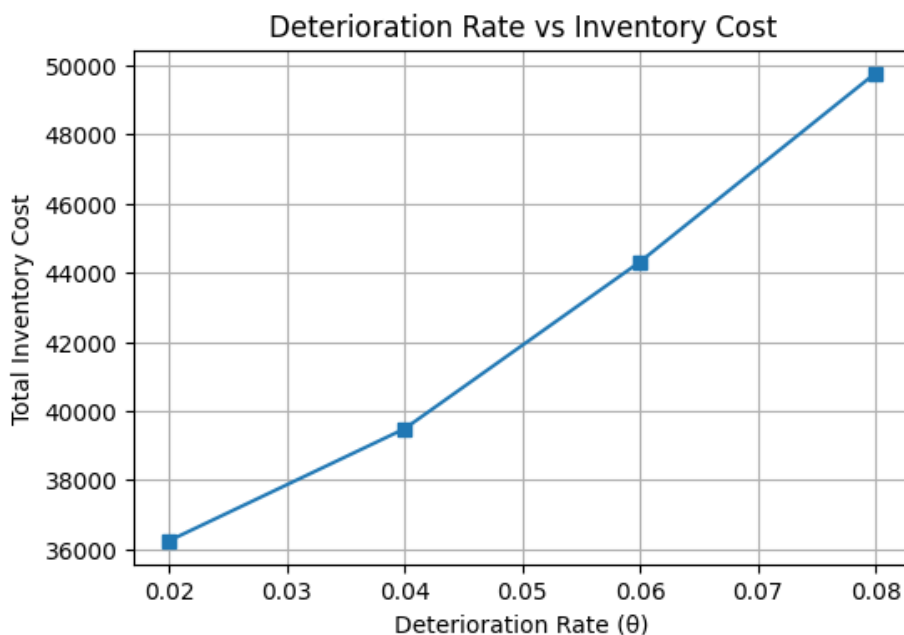
Figure 2: Demand Variability vs Total Cost



Increasing forecasting uncertainty significantly increases inventory cost because larger safety stock and shortage risks are generated.

Table: Deterioration Rate vs Inventory cost

Deterioration Rate (θ)	0.02	0.04	0.06	0.08
Total Cost	36240	39480	44310	49770

Figure 3: Deterioration Rate vs Inventory Cost

Higher deterioration rates increase replenishment and holding costs significantly, demonstrating the importance of deterioration-aware inventory optimization.

10. Results and Discussion

The computational and numerical results clearly show the effectiveness and robustness of the proposed integrated demand forecasting and inventory optimization framework under stochastic demand. The proposed hybrid EOQ/EPQ model performed significantly better than existing inventory management methods with respect to both minimizing the total cost of inventory and operating stability, especially when considering the uncertainty of demand, the deterioration characteristics of the product, and the adaptive safety level. It can be seen that the proposed hybrid EOQ/EPQ method, incorporating uncertainty of demand forecast into AI, the degradation characteristic of the product, and the adaptive safety level, performed much better than the other existing inventory management methods with respect to minimization of total cost of inventory and operating stability. The comparative analysis demonstrated that the proposed model has the least total inventory cost when compared to classical EOQ and EPQ models. The traditional EOQ model results were a relatively high inventory cost due to many factors, such as deterministic demand, forecasting uncertainty, and deterioration effects. Likewise, the EPQ model was good at production coordination, but did not react to parameters that fluctuated randomly with respect to the demand and caused a shortage. The proposed model, on the other hand, successfully incorporated variability in demand forecasting in replenishment decisions, resulting in better inventory control and lower risks in operation. By incorporating AI-powered demand forecasting, the capability to manage inventory responses to unpredictable circumstances was greatly enhanced. The model in this framework explicitly fed the forecasting error determined by the probabilities into the stochastic EOQ/EPQ model formulation, allowing the amounts of safety stocks and reordering decisions to be flexible in order to respond dynamically with respect to different levels of demand variance. This resulted in a substantial decline in what is called "stockouts" (no food or other supplies), and in excess inventory. The adaptive safety stock mechanism provided added flexibility to the system by continuously adjusting for the discrepancies with forecasts and uncertainties, regarding their lead time.

The sensitivity analysis showed that the total inventory cost is sensitive to both the increase in the variability of demand as well as the deterioration rates, rising quite quickly with the increase in both variables. The proposed hybrid optimization

framework, however, was able to enjoy superior cost stability than conventional ones, which proved to be more robust in uncertainty conditions. When it came to minimizing the losses of the deteriorating products due to spoilage and inventory obsolescence, the deterioration-aware inventory formulation succeeded, especially in the case of perishable and short-life-cycle products.

The hybrid GA–PSO optimization algorithm also showed good convergence ability and a good ability in the area of global search. The hybrid of Genetic Algorithm (GA) exploration and Particle Swarm Optimization (PSO) exploitation allowed the model to follow just around the corners of the most common premature convergences while finally arriving at high-quality solutions in a lesser number of iterations. The proposed replenishment strategy through a hybrid of the two metaheuristics achieved more stable and efficient decisions in terms of computations than any of the sole metaheuristic approaches.

Moreover, the suggested framework also proved to be quite practical for the intelligent and sustainable supply-chain systems. The combination of stochastic forecasting, inventory uncertainty-awareness, and hybrid metaheuristic algorithms is a scalable decision-support system that can be utilized in real industrial environments with uncertainty and volatile demand.

From a general perspective, the results demonstrate the significant potential the proposed integrated stochastic inventory optimization framework holds when minimizing inventory costs, maximizing utilization, and improving the resilience of the operations. The study is therefore both theoretically and practically contributing to the progress in intelligent inventory management and uncertainty-aware optimisation of supply chains.

11. Conclusion:

This study proposed an integrated demand forecasting and inventory optimization framework using stochastic EOQ/EPQ modelling and hybrid metaheuristic algorithms under uncertainty. The proposed framework successfully incorporated AI-based demand forecasting, deterioration dynamics, adaptive safety stock mechanisms, and uncertainty-aware replenishment policies into a unified mathematical optimization structure. A major contribution of this research is the derivation of a novel stochastic EOQ/EPQ formulation that explicitly integrates forecasting uncertainty and shortage penalties into inventory decision-making. Unlike traditional inventory models based on deterministic assumptions, the proposed framework dynamically responds to stochastic demand variability and operational uncertainty. The integration of hybrid Genetic Algorithm–Particle Swarm Optimization further enhanced optimization performance by improving global exploration capability, convergence efficiency, and solution quality. Numerical experiments and comparative analyses demonstrated that the proposed framework significantly reduces total inventory cost and improves inventory stability compared with classical EOQ and EPQ systems. The results also confirmed that integrating AI-driven forecasting with hybrid optimization provides superior replenishment decisions under uncertain demand environments. Sensitivity analysis further validated the robustness and adaptability of the proposed model under varying demand variability and deterioration conditions. The proposed framework offers important practical implications for industries operating in highly dynamic and uncertain supply-chain environments, including retail, manufacturing, healthcare, pharmaceutical, and perishable-product sectors. The integration of intelligent forecasting and stochastic inventory optimization can support more resilient, sustainable, and data-driven inventory management strategies. From a theoretical perspective, this study extends the existing inventory optimization literature by bridging the gap between AI-based forecasting, stochastic EOQ/EPQ systems, and hybrid metaheuristic optimization within a unified framework. The proposed methodology, therefore, contributes significantly to the development of intelligent and sustainable inventory management systems for next-generation smart supply chains. Future research may extend this framework by incorporating multi-echelon inventory systems, blockchain-enabled supply-chain coordination, real-time IoT-based inventory monitoring, carbon-emission constraints, and deep reinforcement learning-based adaptive optimization approaches under dynamic market conditions.

Acknowledgement

The authors gratefully acknowledge The ICFAI University, Raipur, Chhattisgarh, for providing academic support and research facilities that contributed to the completion of this study. The authors would like to thank the reviewers and editors for their valuable comments and suggestions, which helped enhance the quality of this manuscript.

Funding

No specific funding was received for this research work.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

Author Contributions

Prakshi Nayak: Conceptualization, model development, mathematical formulation, numerical analysis, writing original draft preparation, and revision.

Animesh Kumar Sharma: Review, editing, validation, and supervision.

All authors have read and approved the final version of the manuscript.

Ethics Approval

This research does not involve human participants or animals. Hence, ethics approval is not required.

Data Availability

All data generated or used in this study consist of model-derived numerical values and parameter assumptions, which are fully presented within the manuscript. No external or real-world dataset was used.

References:

- [1]. Akhtar, M., Manna, A. K., & Bhunia, A. K. (2023). Optimization of a non-instantaneous deteriorating inventory problem with time and price dependent demand over finite time horizon via hybrid DESGO algorithm. *Expert Systems with Applications*, 211, 118676. <https://doi.org/10.1016/j.eswa.2022.118676>
- [2]. Altay, E. V., Altay, O., & Özçevik, Y. (2023). *A Comparative Study of Metaheuristic Optimization Algorithms for Solving Real-World Engineering Design Problems*. <https://doi.org/10.32604/cmcs.2023.029404>
- [3]. Avi, R. I., Ferdaous Al-Farabe, M., Islam Nahid, I. Kharul, Rahman Lingkon, M. L., & Hossain, D. M. S. (2025). *Integrating Demand Forecasting and EOQ for Inventory Management in the Pharmaceutical Sector*. 1104–1113. <https://doi.org/10.46254/ba07.20240187>
- [4]. Bergsma, R. (2025). *A systematic review of machine learning approaches in inventory control optimization*. 15(July).
- [5]. Dehghani, M., & Trojovský, P. (2023). *Osprey optimization algorithm: A new bio-inspired metaheuristic algorithm for solving engineering optimization problems*. January. <https://doi.org/10.3389/fmech.2022.1126450>
- [6]. Fallahi, A., Bani, E. A., Taghi, S., & Niaki, A. (2022). *A constrained multi-item EOQ inventory model for reusable items: Reinforcement learning-based differential evolution and particle swarm optimization*. 207(March).
- [7]. Fathi, M., Khakifirooz, M., Diabat, A., & Chen, H. (2021). *International Journal of Production Economics An integrated queuing-stochastic optimization hybrid Genetic Algorithm for a location-inventory supply chain network*. 237(April), 108139.
- [8]. Harris, F. W. (1913). How many parts to make at once. *International Journal of Production Economics*, 155(2), 8–11. <https://doi.org/10.1016/j.ijpe.2014.07.003>
- [9]. Jaber, M. Y., & Peltokorpi, J. (2024). Economic order/production quantity (EOQ/EPQ) models with product recovery: A review of mathematical modeling (1967–2022). *Applied Mathematical Modelling*, 129(September 2023), 655–672. <https://doi.org/10.1016/j.apm.2024.02.022>
- [10]. Liu, H., Li, J., Yang, J., Zhang, L., Data, C., Univer-, C., Theories, G., & Univer-, C. (2024). *Product Volume Forecasting Model Based on Integrated Learning and EOQ*. *Mied*.
- [11]. Maddah, B., & Noueihed, N. (2017). EOQ holds under stochastic demand, a technical note. *Applied Mathematical Modelling*, 45, 205–208. <https://doi.org/10.1016/j.apm.2016.12.026>
- [12]. Panda, D., Kar, S., Maity, K., & Maiti, M. (2008). A single period inventory model with imperfect production and stochastic demand under chance and imprecise constraints. *European Journal of Operational Research*, 188(1), 121–139. <https://doi.org/10.1016/j.ejor.2007.04.009>
- [13]. Sadhu, T., Chowdhury, S., Mondal, S., Roy, J., Chakrabarty, J., & Lahiri, S. K. (2023). A Comparative Study of Metaheuristics Algorithms Based on Their Performance of Complex Benchmark Problems. *Decision Making: Applications in Management and Engineering*, 6(1), 341–364. <https://doi.org/10.31181/dmame0306102022r>

- [14]. Silver. (2017). *Inventory and Production Management in Supply Chains* (Vol. 2).
- [15]. Taleizadeh, A. A., Soleymanfar, V. R., & Govindan, K. (2018). Sustainable economic production quantity models for inventory systems with shortage. *Journal of Cleaner Production*, 174, 1011–1020.
<https://doi.org/10.1016/j.jclepro.2017.10.222>
- [16]. Tang, W. (2024). *Applied Mathematics and Nonlinear Sciences Improvement of Inventory Management and Demand Forecasting by Big Data Analytics in Supply Chain*. 9(1), 1–15.
- [17]. Wang, S., Wang, L., & Pi, Y. (2022). *A hybrid differential evolution algorithm for a stochastic location-inventory-delivery problem with joint replenishment*. 5(July), 124–136.
- [18]. Younespour, M., Esmaelian, M., & Kianfar, K. (2024). *Computers & Industrial Engineering Optimizing the strategic and operational levels of demand-driven MRP using a hybrid GA-PSO algorithm*. 193(March), 110306.

Cite this Article:

Nayak, P; Sharma, A.K. (2026). *An Integrated Demand Forecasting and Inventory Optimization Model Using EOQ/EPQ and Hybrid Metaheuristic Algorithms Under Uncertainty*. *International Journal of Scientific Research in Modern Science and Technology (IJSRMST)*, 5(5), 9–21.

Journal URL: <https://ijrmst.com/>

DOI: <https://doi.org/10.59828/ijrmst.v5i5.436>.



This work is licensed under a [Creative Commons Attribution-Non-Commercial 4.0 International License](https://creativecommons.org/licenses/by-nc/4.0/).

© The Author(s) 2026. IJSRMST Published by Surya Multidisciplinary Publication.