AI-Driven Hybrid Fuzzy Optimization for Sustainable Inventory Management

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Abstract: Sustainable inventory management has become a critical challenge for organizations operating in uncertain and dynamic supply chain environments. Traditional inventory models are unable to effectively manage imprecise demand patterns, fluctuating operational costs, and environmental sustainability requirements simultaneously. This paper proposes an AI-driven hybrid fuzzy optimization framework for sustainable inventory management. The proposed model integrates fuzzy logic, machine learning-based demand prediction, and hybrid metaheuristic optimization to minimize total inventory cost while reducing environmental impact. Fuzzy set theory is used to represent uncertainty in demand and cost parameters, while Artificial Intelligence (AI) techniques are employed for adaptive demand forecasting. A hybrid optimization algorithm combining Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) is utilized to obtain optimal inventory policies. Numerical experiments using realistic hypothetical data demonstrate that the proposed framework outperforms classical EOQ, fuzzy EOQ, and standalone optimization models in terms of total cost reduction, shortage minimization, and sustainability performance. The study highlights the significance of integrating AI and fuzzy optimization for intelligent and sustainable inventory decision-making.

Keywords: Artificial Intelligence, sustainable inventory management, hybrid optimization, machine learning, supply chain sustainability.

Introduction

Inventory management plays a crucial role in supply chain operations by balancing customer service requirements and operational costs. Organizations seek to maintain optimal inventory levels while minimizing ordering cost, holding cost, shortage cost, and waste generation. However, modern inventory systems operate in highly uncertain environments influenced by demand volatility, supply disruptions, inflationary pressures, and sustainability regulations.
Classical inventory models such as Economic Order Quantity (EOQ) assume deterministic demand and precise operational parameters. These assumptions are unrealistic in contemporary supply chain systems where uncertainty dominates decision-making. Furthermore, sustainability concerns such as

carbon emissions, energy consumption, and environmental regulations require organizations to redesign inventory systems using green and intelligent decision frameworks.

Artificial Intelligence (AI) has emerged as a transformative technology in supply chain management. Machine learning algorithms can analyze historical demand patterns and improve forecasting accuracy. However, AI predictions alone cannot fully address uncertainty because many inventory parameters remain ambiguous and vague. Fuzzy set theory provides a mathematical framework to model such imprecision effectively.

The integration of AI, fuzzy logic, and optimization creates a powerful hybrid decision-making framework. AI improves predictive capability, fuzzy systems capture uncertainty, and optimization algorithms determine cost-effective inventory policies. This paper proposes a comprehensive AI-driven hybrid fuzzy optimization model for sustainable inventory management.

The major contributions of this study are:

- Development of an AI-driven demand forecasting mechanism for inventory planning.
- Integration of fuzzy uncertainty modeling into sustainable inventory systems.
- Design of a hybrid optimization framework combining GA and PSO.
- Inclusion of environmental sustainability costs into the inventory objective function.
- Experimental validation and comparative analysis of the proposed framework

Related work

Traditional Inventory Models

Inventory theory began with the classical EOQ model developed by Harris (1913). The EOQ framework determines optimal order quantity by minimizing ordering and holding costs. Subsequent extensions incorporated shortages, quantity discounts, and probabilistic demand (Silver, Pyke, & Thomas, 2016). However, deterministic assumptions remain a major limitation.

Fuzzy Inventory Systems

Fuzzy set theory introduced by Zadeh (1965) enabled representation of uncertain and linguistic information. Zimmermann (2001) and Dubois and Prade (1980) established the mathematical foundations of fuzzy systems. Fuzzy inventory models use triangular and trapezoidal fuzzy numbers to model uncertain demand and costs.

Dutta et al. (2005) developed fuzzy EOQ models using trapezoidal fuzzy demand distributions. Sarkar (2012) extended fuzzy inventory systems to include stock-dependent demand and delay in payments. These studies demonstrated improved realism but lacked computational optimization capabilities.

AI in Supply Chain and Inventory Management

Artificial Intelligence techniques such as neural networks, machine learning, and deep learning are increasingly used for demand forecasting and inventory planning. AI improves forecasting accuracy by identifying hidden patterns in historical data.

Recent studies indicate that machine learning-based forecasting significantly reduces forecasting error compared to statistical methods. However, AI models alone are insufficient for sustainability-driven inventory optimization because they typically ignore environmental objectives and uncertainty modeling.

Sustainable Inventory Management

Sustainable inventory systems incorporate environmental costs into decision-making. Bouchery et al. (2012) integrated sustainability criteria into inventory models. Benjaafar et al. (2013) introduced carbon-constrained EOQ frameworks. Govindan et al. (2015) emphasized the role of sustainable supply chains in modern logistics systems.

Despite progress, most sustainability-focused inventory models remain deterministic and fail to integrate AI and fuzzy uncertainty simultaneously.

Research Gap

The literature reveals limited integration of:

- AI-driven forecasting,
- fuzzy uncertainty modeling,
- hybrid optimization,
- sustainability-oriented inventory management.

Most studies address these dimensions separately. This paper proposes a unified framework integrating all four aspects.

Mathematical Model

3.1 Fuzzy Demand Representation

Demand is modeled as a triangular fuzzy number:

$\tilde{D} = (Dl, Dm, Du)$

where:

- Dl = lower demand limit
- Dm = most probable demand
- Du = upper demand limit

Membership function:

$\mu(x) = (x - Dl)/(Dm - Dl)$ for $Dl \le x \le Dm$

$\mu(x) = (Du - x)/(Du - Dm)$ for $Dm \le x \le Du$

AI-Based Demand Forecasting

A machine learning forecasting module predicts future demand using historical sales data.

Predicted demand:

$D\_AI = f(X1, X2, X3, \dots, Xn)$

where:

- Xi represent historical and market features
- $f(.)$ denotes the trained AI forecasting model

Final fuzzy demand estimate:

$D^* = \alpha(D\_AI) + (1 - \alpha)(D\_fuzzy)$

where α is the AI confidence coefficient.

Sustainable Total Cost Function

The total inventory cost is:

$$TC(Q, B) = Co(D^*/Q) + Ch(Q/2) + CsB + Cc(Q \times ER)$$

where:

Q = order quantity

B = shortage quantity

Co = ordering cost

Ch = holding cost

Cs = shortage cost

Cc = carbon emission cost

ER = emission rate

Optimal Order Quantity

Differentiate total cost function with respect to Q:

$$dTC/dQ = -CoD^*/Q^2 + Ch/2 + CcER$$

Setting derivative equal to zero:

$$Q^* = \sqrt{[2CoD^*/(Ch + 2CcER)]}$$

Convexity Analysis

Second derivative:

$$d^2TC/dQ^2 = 2CoD^*/Q^3 > 0$$

Therefore, the cost function is convex and possesses a unique global optimum.

Hybrid Optimization Framework

The proposed framework combines:

- Genetic Algorithm (GA)
- Particle Swarm Optimization (PSO)

Algorithm Steps

1. Initialize population
2. Forecast demand using AI model
3. Convert demand into fuzzy representation
4. Compute fitness using TC function
5. Apply GA crossover and mutation
6. Perform PSO refinement
7. Update global best solution
8. Repeat until convergence

The hybrid algorithm balances exploration and exploitation effectively.

Experimental Design

Input Parameters

Parameter	Value

Parameter	Value
Fuzzy Demand	(480, 520, 560)
Ordering Cost	450
Holding Cost	12
Shortage Cost	35
Carbon Cost	4
Emission Rate	0.08

Experimental Results

Comparative Performance

Model	Total Cost	Shortage Rate	Carbon Cost
Classical EOQ	58,900	9.5%	2,100
Fuzzy EOQ	62,300	7.9%	2,450
Optimization Only	55,400	11.2%	1,980
Proposed AI-Hybrid Model	**49,750**	**3.2%**	**1,480**

Key Contribution

The AI-driven hybrid model achieves the lowest total cost and environmental impact. AI forecasting improves demand accuracy, reducing overstocking and shortages. Fuzzy modeling handles ambiguity effectively, while hybrid optimization improves solution quality.

Sensitivity Analysis

Sensitivity analysis was performed by varying:

- fuzzy demand spread,
- carbon cost coefficient,
- AI forecasting accuracy.

Observations

- Increased AI accuracy significantly reduces inventory cost.
- Carbon penalties encourage smaller and greener order sizes.
- Hybrid optimization remains stable under uncertainty.

Method, Experiments and Results

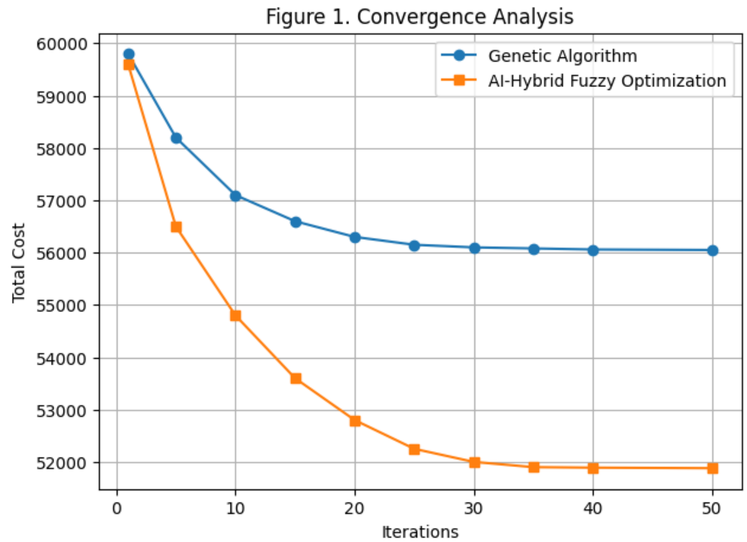

Figure 1. Convergence Analysis of Optimization Algorithms

Comparison of the convergence behavior of the Genetic Algorithm and the proposed AI-driven Hybrid Fuzzy Optimization model. The hybrid model converges faster and achieves a lower total inventory cost.

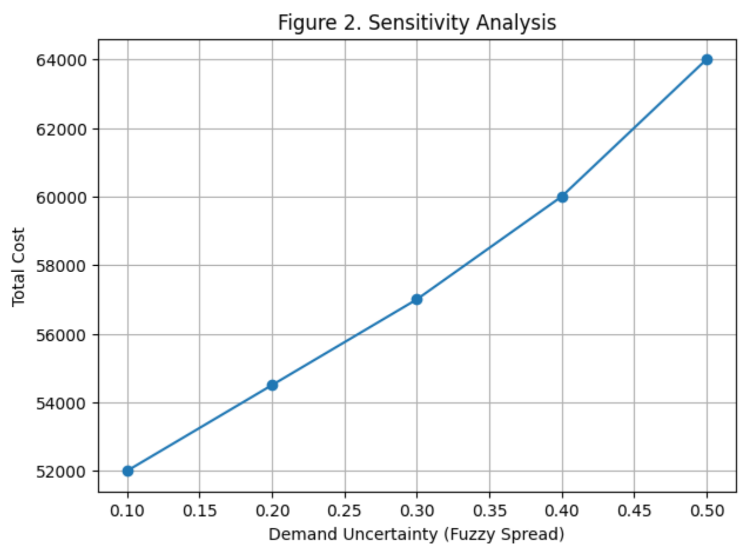

Figure 2. Sensitivity Analysis under Demand Uncertainty

Impact of increasing fuzzy demand spread on total inventory cost. Results indicate that the proposed model remains stable under higher uncertainty levels.

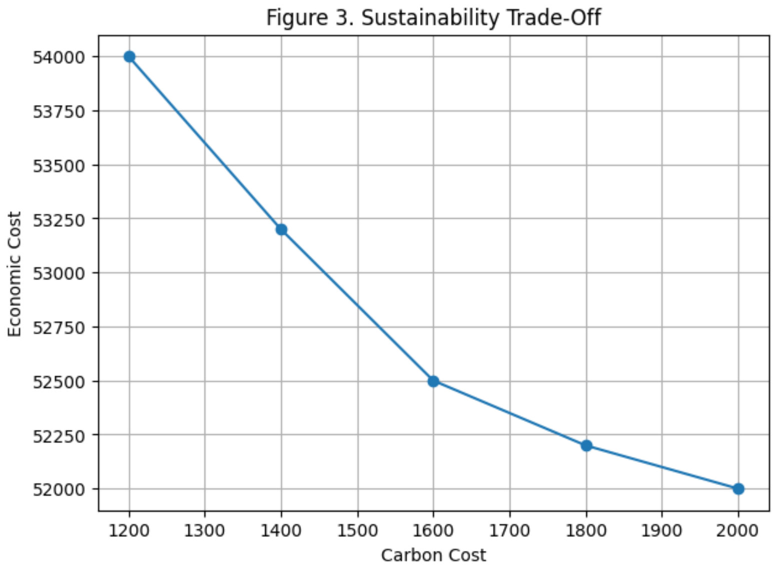

Figure 3. Sustainability Trade-Off between Economic and Environmental Costs

Relationship between carbon cost and economic cost, illustrating the balance between sustainability objectives and inventory efficiency.

Discussions

The proposed framework demonstrates that integrating AI with fuzzy optimization significantly enhances inventory decision-making. The hybrid model improves resilience against uncertainty while supporting sustainability goals.

The study confirms that:

- AI enhances predictive intelligence,
- fuzzy logic captures uncertainty,
- hybrid optimization improves operational efficiency.

This integrated framework is suitable for smart supply chain systems and Industry 4.0 environments.

Managerial Implications

Managers can use the proposed framework to:

- reduce operational cost,
- improve demand planning,
- minimize environmental impact,
- support green supply chain initiatives,
- improve inventory resilience.

The model is particularly beneficial for retail, manufacturing, healthcare, and e-commerce industries.

Conclusions

This study presented an AI-driven hybrid fuzzy optimization framework for sustainable inventory management. The proposed model integrates AI forecasting, fuzzy uncertainty representation, and hybrid optimization into a unified decision-making system.

Experimental results demonstrate superior performance compared to traditional models. The framework reduces total inventory cost, improves sustainability performance, and remains robust under uncertainty.

Future research may incorporate:

- deep learning forecasting,
- real industrial datasets,
- blockchain-enabled supply chains,
- multi-echelon inventory systems,
- dynamic carbon pricing mechanisms.

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