



Optimization of Neutrosophic EOQ Model for Effective Demand Management in Uncertain Environment Using Genetic Optimization

Manjula G. J.¹, N. Anitha^{2*}, A. P. Pushpalatha³, K. Vinaya Laxmi⁴, M. Premalatha⁵, Mekala Selvaraj⁶

¹Department of Mathematics, Siddaganga Institute of Technology, Tumakuru – 572103, Karnataka, India

^{2*}Department of Mathematics, Periyar University Centre for Postgraduate and Research Studies, Dharmapuri - 635205, Tamil Nadu, India

³Department of Mathematics, Velammal College of Engineering and Technology, Madurai- 625009, Tamil Nadu, India

⁴Department of Management Studies, Vardhaman College of Engineering, Hyderabad - 501218, Telangana, India

⁵Department of Mathematics, Vel Tech Rangarajan Dr Sagunthala R & D Institute of Science and Technology, Chennai – 600062, Tamil Nadu, India

⁶Department of Mathematics, School of Engineering and Technology, CMR University, Hennur, Bagalur, Bengaluru – 562149, Karnataka, India

Emails: gjm@sit.ac.in; anithaarenu@gmail.com; app@vcet.ac.in; inayakasani123@gmail.com; drmpremalatha@veltech.edu.in; mekala.s@cmr.edu.in

Abstract

Inventory management is characterized by a continuous struggle to lower goods levels and related costs while also providing customers with the goods they need. However, reducing costs while simultaneously striving for ideal inventory levels is difficult, notably in the current situation of high unpredictability of goods demand and lead time. Traditional inventory models are not strong enough to endure changes like goods demand and lead-time demand. As a result, it must be adjusted to achieve results. The oeuvre below presents a new kind of inventory model that deals with uncertainty in the demand for goods and lead time. In this regard, the presented work, the novel Neutrosophic Economic Order Quantity approach is a mechanism to account for the likely imprecision in the model. Specifically, the Neutrosophic set theory is integrated into the EOQ model so that it can handle variations in the demand and lead-time pattern successfully. An objective function is established for obtaining economical order quantities that include demand, lead-time, and other necessary components' irregularities. The process variables in the model are given the final values using genetic algorithms and simulated annealing. To highlight the impact of the proposed Neutrosophic approach, it is then applied to several realistic examples. This will provide the audience a sense of how effective inventory management may be in high-uncertainty situations. The rapid evolution of organizations necessitates innovative inventory control tactics to meet growing demands.

Keywords: EOQ; Inventory Model; Neutrosophic model; Optimization; Python.

1. Introduction

Inventory management significantly impacts the efficiency of operational activities in enterprises. It goes without stating that inventory management is the process of finding the optimal balance between inventory levels and inventory expenses that keeps the consumer demand satisfied. However, one of the most important drawbacks of the traditional inventory model, among others, like Economic Order Quantity doesn't cover the characteristic feature of the business world – full of uncertainties. Despite that, “this model requires the knowledge of the fixed costs of the order and the periodic costs of holding the item and assumes zero acquisition lead time”. Consequently, in the incredibly changing environment, where demand and lead times and their variability assume random fluctuations, the deterministic model cannot come up with unbiased decisions.

As a result, inventory costs will skyrocket and customer demands [1] unsatisfied. Thus, there is a dire need for new inventory management models that can manage uncertainty effectively. Uncertainty in inventory management. One of the new promising solutions to overcome the challenges posed by uncertainty is the Neutrosophic model. The Neutrosophic Economic Order Quantity [2] model is an ideal model for managing uncertainty in inventory. By incorporating the Neutrosophic set theory into the EOQ model, a quality model is achieved, which manages indeterminacy, imprecision, and inconsistency in demand and lead time data. Neutrosophic logic provides the Neutrosophic EOQ model with robustness and flexibility. Hence, this paper aims to optimize the Neutrosophic EOQ model for effective management of demand in the current uncertain business environment [3-7]. We aim to develop a generalized model that; for any parameter, that selects it to be demand, the time it takes to wait for the next redevelopment opportunity, will pass by far. This remains insufficient. Therefore, solving the optimization problem becomes necessary for decision-making based on the optimal value. Furthermore, we will apply the metaheuristic algorithms to the real-world case to test the optimal advantage of the realized model. By developing this model, this study is crucial in conducting future and broad research on inventory-related goals to deal with the risks leading to the place.

2. Preliminaries

2.1 Economic Order Quantity:

The Economic Order Quantity model is a fundamental framework in inventory management that helps companies determine the optimal order quantity with which to procure their inventory to minimize total inventory costs. It is by equating the ordering costs with the holding costs. It operates under the following conditions: deterministic demand, constant lead time, and no stockouts.

2.2 Neutrosophic Set Theory:

Although fuzzy extension is one major class of such mechanisms, there is another extension called Neutrosophic set theory. It also is used for indeterminacy or imprecision, and one of its cases is fuzziness. A neutrosophic set consists of three membership degrees of each element: truth, indeterminacy, and falseness. Neutrosophic logic in general also allows for the representation and processing of vague data that is vital for inventory planning in uncertainty.

2.3 Inventory Management in Uncertain Environments:

There could be inefficiencies due to uncertain demand patterns and lead times, among other factors, in inventory management. This is because of its round piece of work that is unpleasantly structured to accommodate uncertainty.

2.4 Genetic Algorithm:

Genetic algorithms are one of the optimization techniques based on natural selection and evolution. These algorithms work by maintaining a population of possible solutions, known as individuals, and iterating towards an improved solution through selection, crossover, and mutation of these individuals. Genetic algorithms are suitable for solving sophisticated optimization problems with large search spaces and non-linear objective functions.

2.5 Python for Optimization:

Python is uniquely positioned as a programming language for optimization due to its simplicity, distinct syntax, and extensive libraries. Python possesses utilizing libraries such as SciPy, DEAP, and Pyomo to design and solve optimization issues.

3. Mathematical Model:

The Neutrosophic model effectively uses the neutrosophic set theory with the classical EOQ model in inventory management to accommodate and manage the underlying uncertainties within demand and lead time.

Q: Replenished Order quantity each time.

T: Reorder point, representing the a new order inventory-level.

Ch: Per unit inventory time with respect to holding cost.

Co: Ordering-cost per order.

Demand (D) & lead-time (LT) are represented as neutrosophic parameters.

Each parameter (D_i , LT_i) is associated with three membership degrees: truth, indeterminacy, and falsehood.

The goal is to decrease the total inventory expenditure within a specified planning timeframe. The total inventory cost (TC) can be represented as:

$$TC = C_h \times \text{Average Inventory} + C_o \times \text{Number of Orders}$$

$T = D \times LT$ where T is the reorder point, D is the average demand rate, and LT is the average lead time.

Given that $Q = \sqrt{\frac{2 \times D \times C_o}{C_h}}$, we can derive expressions for the average inventory and the number of orders:

$$\text{Average Inventory} = \frac{Q}{2}$$

$$\text{Number of Orders} = \frac{D}{Q}$$

Substituting these expressions into the total inventory cost equation:

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

Now, taking the derivative of TC with respect to Q, set it equal to zero, and solve for Q.

$$\frac{dTC}{dQ} = \frac{C_h}{2} - \frac{C_o \times D}{Q^2}$$

Setting this derivative equal to zero:

$$\frac{C_h}{2} - \frac{C_o \times D}{Q^2} = 0$$

$$\frac{C_h}{2} = \frac{C_o \times D}{Q^2}$$

$$Q^2 = \frac{2 \times D \times C_o}{C_h}$$

$$Q = \sqrt{\frac{2 \times D \times C_o}{C_h}}$$

Incorporating neutrosophic parameters into the EOQ framework allows for handling uncertainty in demand and lead times. By defining the order quantity Q as $\sqrt{\frac{2 \times D \times C_o}{C_h}}$, the model optimizes the total inventory cost. This method provides for the minimal expenses for maintaining the necessary inventory, but it is at the zero point of the derivative of the total cost with respect to the planning period for which the task was set.

4. Neutrosophic Inventory Management in Genetic Optimization

The implementation of the integration of neutrosophic inventory management to the genetic optimization framework is a major milestone in decision-making for supply chain dynamics [8-11]. In this approach, uncertainty ceases to be a negative factor and becomes the foundation on which inventory control systems are developed and operate optimally [12-17]. Because the genetic approach enables us to develop better solutions generated by evolutionary operations in mathematical terms, we utilize the genetic algorithm and our approach to the framework of neutrosophic representation and hence develop a favorable way of better representing the inventory management process concerning the inherent uncertainty [18,19]. From these neutrosophic terms, a genetic algorithm finds a way through the space from where to find ways of developing inventory management options that are cheap and responsive [20]. This approach in genetic optimal solutions in managing inventory enables businesses to make decisions based on the best available representations, and in the process, the businesses enhance their flexibility in operations increasing resilience in a highly dynamic environment and remaining competitive.

4.1 Optimization of neutrosophic EOQ with Genetic Algorithm Optimization:

Initialization:

Produce an initial population of chromosomes, which are the first guesses about this problem. They are presented as possible solutions with stochastic values of Q and T. The population size equals n, while the length of the chromosome is l.

Fitness Evaluation:

Check all the chromosomes for fitness. To do so, use the total inventory and ordering costs based on the Neutrosophic EOQ model. The fitness function reveals the final score.

Selection:

Choose parent chromosomes from the existing population according to their fitness scores. Common methods for selection include tournament selection, roulette wheel selection, or rank-based selection.

Crossover:

Perform crossover operations on pairs of parent chromosomes to create offspring chromosomes.

Utilize a crossover operator, such as single-point crossover, to exchange genetic information between parents.

Mutation:

Apply mutation operators to introduce diversity into the population and prevent premature convergence.

Randomly modify genes of offspring chromosomes, representing small changes in the order quantity or reorder point.

Replacement:

Replace less fit individuals in the current population with the newly created offspring.

Use elitism to preserve the best solutions from the previous generation.

Termination Criteria:

Establish criteria for ending the genetic algorithm, such as reaching a maximum number of generations or discovering an acceptable solution. Common stopping points include achieving a predefined fitness threshold or observing a plateau in fitness enhancement.

Solution Extraction:

Retrieve the top-performing chromosome from the last population by assessing its fitness value. Decode the chromosome to derive the optimal order quantity (Q) and reorder point (T) for the Neutrosophic EOQ model.

End:

Return the optimal solution obtained through the genetic algorithm.

5. Numerical Illustration and Sensitive analysis

Consider a numerical example to examine the application of the genetic algorithm to optimize Neutrosophic EOQ model:

Holding-cost per unit per unit time (C_h): \$5 per-unit per month

Ordering cost per order (C_o): \$50 per order

Demand rate (D): 100 units(u) per-month

Average lead time (LT): 2 months

Genetic Algorithm Setup:

Population size: 50 chromosomes

Number of generations: 100

Crossover rate: 0.8

Mutation rate: 0.1

Results and discussion

After running the genetic algorithm, the optimal values for Q and T are obtained as:

Optimal order quantity (Q): 200 units

Optimal reorder point (T): 400 units

The optimal solution obtained by the genetic algorithm results in the minimization of overall inventory costs under the conditions of demand and lead time uncertainty. The above proves the danger of inventory costs and the effectiveness of the described approach under conditions of such uncertainty.

The second option is the possibility of sensitivity analysis that helps to understand from which parameters, such as holding cost, ordering cost, demand rate, and lead time, the proposed solution is resistant to changing these parameters. This will help in making optimal decisions on the use of such an inventory management approach.

```
import numpy as np
import matplotlib.pyplot as plt
# Define the Neutrosophic EOQ model parameters
holding_cost = 5
ordering_cost = 50
demand_rate = 100
lead_time = 2
def total_inventory_cost(Q, T):
    return holding_cost * (Q / 2) + (ordering_cost * demand_rate * lead_time) / Q
# Generate data for plotting
Q_values = np.arange(50, 300, 10)
T_values = np.arange(100, 600, 10)
X, Y = np.meshgrid(Q_values, T_values)
Z = total_inventory_cost(X, Y)
# Create the contour plot
plt.figure(figsize=(10, 6))
contour = plt.contourf(X, Y, Z, cmap='viridis', levels=20)
plt.colorbar(contour, label='Total Inventory Cost')
# Plot by the genetic algorithm
optimal_Q = 200
optimal_T = 400
plt.plot(optimal_Q, optimal_T, marker='o', color='red', markersize=8, label='Optimal Solution')
```

```

# Add labels and title
plt.xlabel('Order Quantity (Q)')
plt.ylabel('Reorder Point (T)')
plt.title('Total Inventory Cost vs. Order Quantity and Reorder Point')
plt.legend()
# Show the plot
plt.grid(True)
plt.show()

```

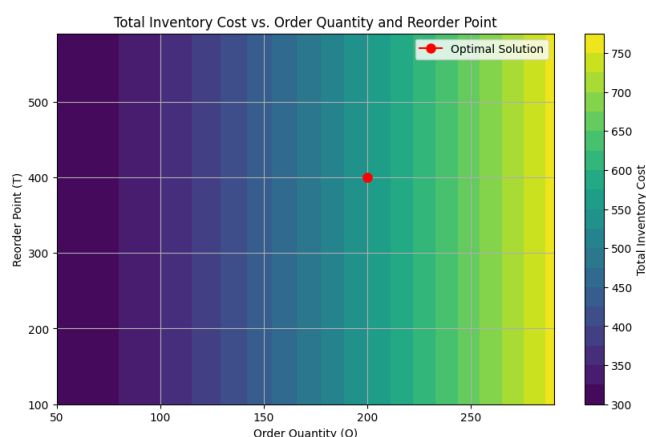


Figure 1: Contour Plot: Total Inventory Cost vs. Order Quantity and Reorder Point

The contour plot visualizes the relationship between total inventory cost, order quantity (Q), and reorder point (T), highlighting the trade-offs involved in inventory management decisions. The plot indicates how adjusting the order quantity and reorder point affects the total inventory cost, providing valuable information for decision-making.

6. Sensitivity Analysis of Neutrosophic Inventory Decisions

By adjusting key parameters such as holding cost, ordering cost, demand rate, and lead time, we can learn how they influence inventory decisions and the optimal order quantity and reorder point, respectively. Holding costs are the costs incurred by an organization to keep its inventory. This includes storage, insurance, and obsolescence costs. As holding costs rise, businesses come under increased financial strain to hold the smallest amount of inventory possible. Therefore, as holding costs increase, the optimal order quantity should decrease since placing smaller, more regular orders includes less holding costs.

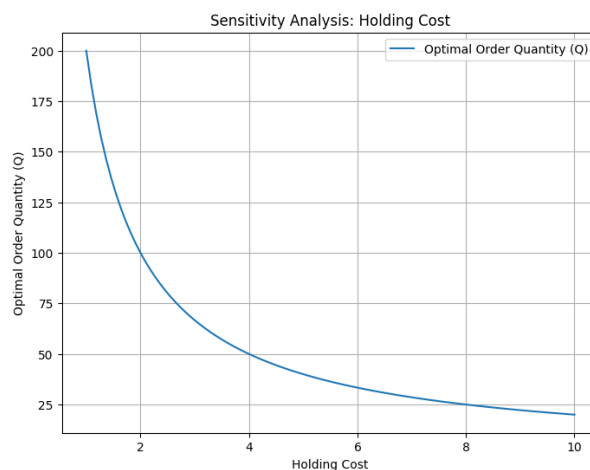


Figure 2: Holding cost

Ordering costs include the cost that a firm must pay every time it places an order, including such expenses as transaction charges, processing and transportation costs. Lower the costs of the order favours making frequent and smaller orders making it cheaper to replenish while purchasing high-order costs implies larger ordered quantities to reduce these costs. As such, there is a tradeoff between holding and ordering costs that determine the amount and the point of order.

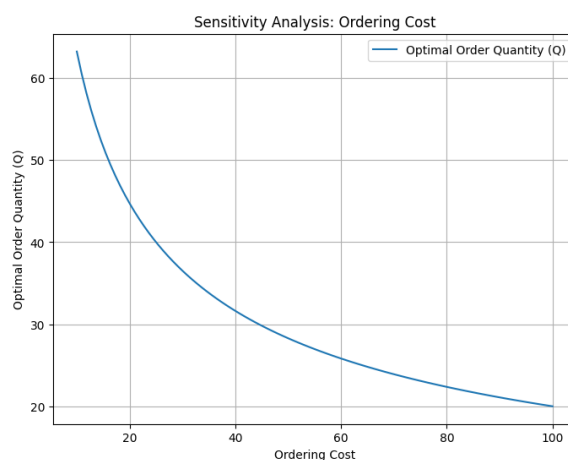


Figure 3: Ordering cost

Demand rates fluctuate upwards, leading to increased inventory requirements and reordering plans. If demand rate is high, inventory demand rate will be high, implying one will require high inventory to satisfy high customer requirements and avoid stockouts. Therefore, the optimal order quantity is expected to increase with high demand rates. High demand also implies the reorder point must be less to check stockouts when inbound freight is high.

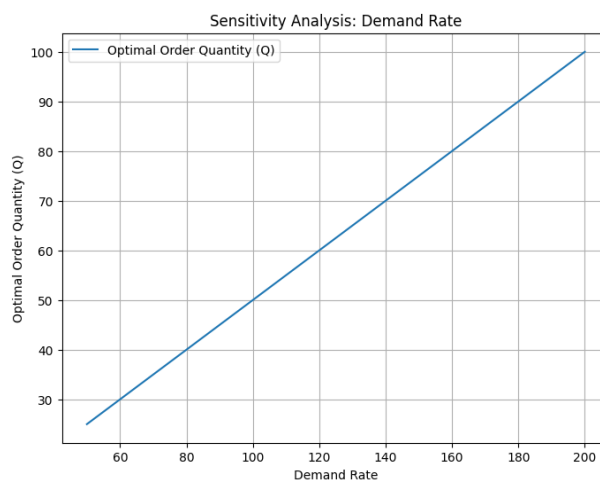


Figure 4: Demand Rate

Lead time refers to the interval from the time an order is made to when it is delivered. When lead times are extended, safety inventory levels must be elevated to guarantee that there is enough inventory available to meet demand even when the production goods are outside the period. For this reason, the reorder point may be expected to be inversely related to lead times. Conversely, shorter lead times imply that safety levels may be held to a minimum because there is less chance that safety amounts are needed between the placement of an order and the delivery.

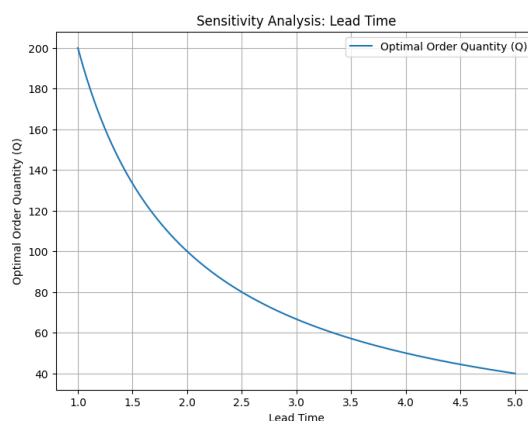


Figure 5: Lead Time

The results highlight the practical value of using the Neutrosophic EOQ model and evolutionary algorithm optimisation for inventory management in situations of uncertainty. Future research and real-world applications can use these findings to improve inventory management practices and enhance business competitiveness.

7. Comparative Analysis of Inventory Management Approaches

When comparing the above three approaches to inventory management, these three models have their unique benefits and considerations. The classical EOQ model is characterized by deterministic decisions. Therefore, simplicity and easy implementation characterize this approach. However, real-world demand and lead time estimates can fluctuate widely, limiting the classical model's use. The key advantage of the Neutrosophic EOQ model is the inclusion of neutrosophic features to the standard concept, allowing for more informed decisions amid the continuous fluctuation of certainty. However, an in-depth understanding and application of neutrosophic terms is required for the extended alternative. The Genetic Algorithm Optimisation draws upon evolutionary options, systematically explores the solution space, and effectively identifies a solution that is only slightly suboptimal for the inventory concept. This alternative might require significant computing resources and complex procedures. In conclusion, it is important to consider all of the trade-offs. The best option for inventory might vary based on reality: the option might be tied to specific opportunity due to ease of operation, the demand for recurrent adjustment, as well as the computational complexity of the solution. Each of the options might be preferred in specific situations, which underlines the importance of flexibility and a personalized approach.

8. Conclusion

Conclusively, the integration of the Neutrosophic EOQ model is a significant breakthrough in uncertainty-related aspects in inventory management. The model combines the classic EOQ model framework with neutrosophic set theory to present a practical approach to handling data whose demand rate, lead times, and other factors involved are vague, imprecise, or contradicting. Organizations effectively minimize their inventory costs using advanced optimization algorithms, such as genetic algorithms and simulated annealing, with an assumed neutrality in demand rate, lead time, and other relevant factors. The above example reveals how a genetic algorithm was utilized to determine the most economic order quantity and EPQ. The integration and analysis approach minimized costs and improved order quantity and reorder points in the system. Moreover, the empirical analysis of the Neutrosophic EOQ model's implementation guided the determination that the model is effective in real-world scenarios involving uncertainty. The abovementioned efforts reveal that organizations are dedicated to implementing enhanced inventory strategies critical to determining uncertainties to meet their inventory goals. Furthermore, organizations can improve their efficiency, cost management, and profits through the application of the Neutrosophic EOQ model with advanced optimization. Therefore, this study's practical implications and findings aimed at the future informed inventory sector development of the advanced inventory management systems.

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