Decision Making Advances

Journal homepage: www.dma-journal.org
ISSN: 2956-2384

Fuzzy Inventory Implementation of Minimum Value unused Storing Profitable by Executing Python

Kalaiarasi Kalaiselvan[1,2,*]

[1] Department of Mathematics, Cauvery College for Women (Autonomous),(Affiliated to Bharathidasan University), Tiruchirappalli, Tamil Nadu, India
[2] Srinivas University, Surathkal, Mangaluru, Karnataka, India

ARTICLE INFO

Article history:
Received 30 November 2023
Received in revised form 10 April 2024
Accepted 10 August 2024
Available online 15 August 2024

Keywords:
Fuzzy inventory; Economic Order Quantity; Total cost.

ABSTRACT

Stock management holdings would be required in this scenario to reduce losses and increase profits. In light of this, we propose in this article that you build a model by combining time series data with machine learning machines using algorithms and employing the Lagrangian method. Combinatorial optimization is used to discover opportunities for acquiring stock at a more affordable cost and sell a portion of the unused stock to make more money for the corporation. To guarantee production, we use time series and machine learning models to forecast stock prices and demand forecasts. The Inventory Management system can be employed to oversee shop merchandise and keep appraised of every product in stock, as well as to verify the store's previous purchases. We then incorporate these projections into a combinatorial optimization algorithm to aid in the decision-making process (buy, sell, or hold), and we additionally determine the exact amounts to buy or sell in the appropriate sequence. By minimizing the sharp model in fuzzy optimization via Python programming.

1. Introduction

There are three different categories of manufacturing inventories: finished goods, work-in-progress, and raw materials. Inventory management's goals are to meet consumer demand, increase revenue, and assure the proper managing the business. It is essential to the company's ability to complete. The cost of the stocks' existence outweighs their value as operating values that must be handled. The corporation faces the prospect of a stock-out that could halt operations when supplies are not as crucial. In addition to adding costs, this disruption could harm the company's reputation. On the other hand, if the supplies are too crucial, they become fixed assets and raise the price.

Inventory control is used to meet customer demand, increase revenue, and make sure the blessing is managed effectively. It is essential to the company's ability to complete. The costs of the

* *Corresponding author.*
E-mail address: kalaishruthi1201@gmail.com

https://doi.org/10.31181/dma31202524

© 2025 by Scientific Oasis | Creative Commons License: CC BY-NC-ND

stock's existence outweigh their value as operating values that must be handled. The model inventory serves as a repository for findings linked to the model's known parameters and limitations. This repository may contain everything that's related to the model, such as model methodology historical records and endorsement reports, as well as proof of important events that occurred on the model. (e.g., bias treatment approvals). More broadly, maintaining a model inventory proves to be critical to supporting the entire model management comprehend, with the primary goal of identifying and managing model risk.

A Comparison Inventory management is a database which presents a description of all kinds of models that are accessible within an organization at any given moment. It usually includes model influencers and their respective duties; The corporation faces the prospect of a stock-out that could halt operations when supplies are not as crucial. In addition to adding costs, this disruption could harm the company's reputation. However, when suppliers become overly crucial, they become fixed assets, which raises the cost price and throws off the cash flow balance. This is why inventory management in supply chain management is a difficult issue. The back-order fuzzy inventory model was proposed by Shan-Huo Chen *et.al*. [1] and Covert *et. al* [2]. Inventory management software allows the business to better manage its funds and maximize the turnover of merchandise and profits. Customers are happier because inventory management improves purchase fulfilment and delivery times.

A classical set's fuzzy generalization, the fuzzy set was introduced by Zadeh *et al* [3]. In the fuzzy context, Bellman *et al* [4] used fuzzy principles to decision-making. Kaufmann [5] discovered the best solution for fuzzy nonlinear programming problems with inequality constraints. The fuzzy linear programming approach was put forth by Zimmermann [6]. Solving fuzzy nonlinear programming was published by Lalitha *et al* (7).

Taha [8] described how to use the Lagrangian conditioned to resolve an inequality-constrained nonlinear programming issue. In order to secure the manufacture and delivery of the finished goods, inventory management entails locating and procuring from suppliers the inventories that are necessary for the activity at the best possible price and timing. The listing any object are resource that the organization uses.

Some of the research related to the dependability elements in inventory control are Sarker et. al [9,10], Manna et al. [11], Singh and Sharma [12], Rahman et al. [13], Guchhait et al. [14], and Singh et al. [15]. Kalaiarasi et al., introduced the idea of machine learning with python in recent years [16, 17,18,19].

To resolve inequality restrictions and identify optimal solutions, the fuzzy total cost, an extension of the Lagrangian approach, and the Kuhn Tucker method are used as arithmetic operations. Uncertain Economic Order each fuzzy inventory model's total number. The annual integrated total cost is defuzzied using graded mean integration. The numerical example serves as an illustration of how the developed model is solved. Monitoring the infiltration, storage, and evacuation of inventory effectively is essential to the company's financial performance. Customers can place orders with trust when inventory management is done correctly, stock levels are kept at optimal levels, waste is reduced to a minimum, and sales increase.

2. Preliminaries

2.1 Crisp Set

Typically, a collection of finites, countable, or over countable items or objects is referred to as crisp set $y \in Y$. $A \subseteq Y$ is a group of components that may or may not be related to one another. In the first statement "y belongs to A" is correct, however in the second it is incorrect.

2.2 Fuzzy Set

If X is a set of universally signed objects, then J in X is a set of ordered pairs $\tilde{J} = \left\{\left(x, \mu_{\tilde{J}}(x)\right) | x \in X\right\}$, $\mu_{\tilde{J}}(x)$ is the membership function of x in $\tilde{J}$ that maps X to the membership space M and $\tilde{J}$ is the same as a nonfuzzy set's characteristic function.

2.3 Trapezoidal Fuzzy Number (TFN)

TFN A is defined as $A = (d_1, d_2, d_3, d_4)$ the membership function of this Fuzzy Number will be interpreted as follows

$$\mu_A(x) = \begin{cases} 0, & x < d_1 \\ \dfrac{x - d_1}{d_2 - d_1}, & d_1 \leq x \leq d_2 \\ 1, & d_2 \leq x \leq d_3 \\ \dfrac{d_4 - x}{d_4 - d_3}, & d_3 \leq x \leq d_4 \\ 0, & x > d_4 \end{cases}$$

2.4 Operations using Fuzzy Arithmetic under the Function Principle:

The Function Principle was initially mentioned by S.H. Chen [20]. The following TFN of Fuzzy Arithmetical Algorithms make use of the function concept.

Suppose $\tilde{R} = (R_1, R_2, R_3, R_4)\ and\ \tilde{S} = (s_1, s_2, s_3, s_4)$ are TFN. Then

$(i)\ \tilde{R} \oplus \tilde{S} = (r_1 + s_1, r_2 + s_2, r_3 + s_3, r_4 + s_4)$

$(ii)\ \tilde{R} \otimes \tilde{S} = (r_1 s_1, r_2 s_2, r_3 s_3, r_4 s_4)$

$(iii) \tilde{R} \ominus \tilde{S} = (r_1 - s_4, r_2 - s_3, r_3 - s_2, r_4 - s_1)$

$(iv)\ \tilde{R} \oslash \tilde{S} = \left(\frac{r_1}{s_4}, \frac{r_2}{s_3}, \frac{r_3}{s_2}, \frac{r_4}{s_1}\right)$

$(v)\ Let\ Z \in \mathcal{R}, then$

$(i)\ Z \geq 0, Z \otimes \tilde{G} = (ZG_1, ZG_2, ZG_3, ZG_4)$

$(ii)\ Z \leq 0, Z \otimes \tilde{G} = (ZG_4, ZG_3, ZG_2, ZG_1)$

2.5 Graded Mean Integration Representation Method (GMI)

The integral value of the graded mean h-level of a generalized Fuzzy Number is used for defuzzification. A's GMIRM is defined as follows:

$$J(\tilde{A}) = \int_0^{w_A} h\left(\frac{L^{-1}(h) + R^{-1}(h)}{2}\right) dh \Big/ \int_0^{w_A} hdh,$$

The GMIRM of $\widetilde{D}$ is

$$P(\widetilde{D}) = \int_0^1 h\left(\frac{d_1 + d_4 + (d_2 - d_1 - d_4 + d_3)h}{2}\right) dh\ \int_0^1 hdh = \frac{d_1 + 2d_2 + 2d_3 + d_4}{6}.$$

3. Methodology

A mathematical relationship that describes a situation in real life is known as a mathematical model. A mathematical model uses equations to try to simulate how a real-world object would behave. To investigate what happens when measurements, temperatures, and costs change, we can experiment with the equations. Mathematical models are used to tackle many real-world problems.

3.1 Notation Applied

Symbols	Description	unit
I	Inventory system with cost	$/Unit
P	Production cost	$/Unit
A	Quantity cost saving	$/Unit
S	Storage cost	$/Unit
Qu	Quality cost	$/Unit
E	Existence cost	$/Unit
D	Disruption cost	$/Unit

The total cost is given by,

$$TC = \frac{2PE}{Qu} + \frac{2SIA}{Qu} + \frac{2QuI}{S} + \frac{2PQu}{A}$$

Differentiating with respect to Qu and $\frac{\partial TC}{\partial Qu} = 0,$ we get

$$Qu^* = \sqrt{\frac{2SA(PE + SIA)}{2IA + 2PS}}$$

3.2. Fuzzy Inventory Model of storing profit

3.2.1 Crisp model:

For crisp production, a representation of the inventory with fuzzy constants is provided.
Here we consider $\tilde{I} = (I_1, I_2, I_3, I_4)$ and $\tilde{P} = (P_1, P_2, P_3, P_4)$ as fuzzy parameters.

$$P(J\tilde{T}C(Qu)) = \frac{1}{6}\left\{\begin{array}{l} \left[\frac{2P1E}{Qu} + \frac{2SI1A}{Qu} + \frac{2QuI1}{S} + \frac{2P1Qu}{A}\right] + \\ 2\left[\frac{2P2E}{Qu} + \frac{2SI2A}{Qu} + \frac{2QuI2}{S} + \frac{2P2Qu}{A}\right] + \\ 2\left[\frac{2P3E}{Qu} + \frac{2SI3A}{Qu} + \frac{2QuI3}{S} + \frac{2P3Qu}{A}\right] + \\ \left[\frac{2P4E}{Qu} + \frac{2SI4A}{Qu} + \frac{2QuI4}{S} + \frac{2P4Qu}{A}\right] \end{array}\right\}$$

Let $\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu} = 0$, we get

$$Qu^{*}=\sqrt{\frac{SA\left\{\begin{array}{l}[2P_1E+2SI_1A]+2[2P_2E+2SI_2A]+\\2[2P_3E+2SI_3A]+[2P_4E+2SI_4A]\end{array}\right\}}{\begin{array}{l}[2I_1A+2P_1S]+2[2I_2A+2P_2S]+\\2[2I_3A+2P_3S]+[2I_4A+2P_4S]\end{array}}}$$

Now we have Qu* value for crisp model. The entire total cost of my model determines the value.

3.2 Lagrangian model for minimizing the value

We change the crisp values into fuzzy values for that we apply the graded mean integration representation of P(JT̃C(Qu)) is

$$P(J\tilde{T}C(Qu))=\frac{1}{6}\left\{\begin{array}{l}\left[\frac{2P_1E}{Qu_4}+\frac{2SI_1A}{Qu_4}+\frac{2Qu_1I_1}{S}+\frac{2P_1Qu_1}{A}\right]+\\2\left[\frac{2P_2E}{Qu_3}+\frac{2SI_2A}{Qu_3}+\frac{2Qu_2I_2}{S}+\frac{2P_2Qu_2}{A}\right]+\\2\left[\frac{2P_3E}{Qu_2}+\frac{2SI_3A}{Qu_2}+\frac{2Qu_3I_3}{S}+\frac{2P_3Qu_3}{A}\right]+\\\left[\frac{2P_4E}{Qu_1}+\frac{2SI_4A}{Qu_1}+\frac{2Qu_4I_4}{S}+\frac{2P_4Qu_4}{A}\right]\end{array}\right\}$$

Lagrangian method to find solutions of Qu_1, Qu_2, Qu_3, Qu_4.

Step 1: To find the min P(JT̃C(Qu)), P(JT̃C₁(Qu)) the derivatives of must be discovered with respect to Qu_1, Qu_2, Qu_3, Qu_4.

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_1}=\frac{1}{6}\left[\frac{2I_1}{S}+\frac{2P_1}{A}-\frac{2P_4E}{Qu_1{}^2}-\frac{2SI_4A}{Qu_1{}^2}\right]$$

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_2}=\frac{2}{6}\left[\frac{2I_2}{S}+\frac{2P_2}{A}-\frac{2P_3E}{Qu_2{}^2}-\frac{2SI_3A}{Qu_2{}^2}\right]$$

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_3}=\frac{2}{6}\left[\frac{2I_3}{S}+\frac{2P_3}{A}-\frac{2P_2E}{Qu_3{}^2}-\frac{2SI_2A}{Qu_3{}^2}\right]$$

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_4}=\frac{1}{6}\left[\frac{2I_4}{S}+\frac{2P_4}{A}-\frac{2P_1E}{Qu_4{}^2}-\frac{2SI_1A}{Qu_4{}^2}\right]$$

Equate to zero for the above partial derivatives and solve Qu_1, Qu_2, Qu_3, Qu_4

Let $\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_1}=0$, then $Qu_1=\sqrt{\frac{SA(2P_4E+2SI_4A)}{2I_1A+2P_1S}}$

Let $\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_2}=0$, then $Qu_2=\sqrt{\frac{SA(4P_3E+4SI_3A)}{4I_2A+4P_2S}}$

Let $\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_3} = 0$, then $Qu_3 = \sqrt{\frac{SA(4P_2E + 4SI_2A)}{4I_3A + 4P_3S}}$

Let $\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_4} = 0$, then $Qu_4 = \sqrt{\frac{SA(2P_1E + 2SI_1A)}{2I_4A + 2P_4S}}$

It does not satisfy the constraint 0<Qu_1>Qu_2>Qu_3>Qu_4>Q. Because the above values are Q_1>Qu_2>Qu_3>Qu_4. Therefore, move to Step 2.

Step 2: Change the inequality restriction $Qu_2 - Qu_1 \geq 0$ into equality constraints $Qu_2 - Qu_1 = 0$ by the Lagrangian method. We have the Lagrangian method as L (Qu_1, Qu_2, Qu_3, Qu_4, λ) = P(J$\tilde{T}$C(Qu)) - λ($Qu_2 - Qu_1$).

Differentiate partially L (Qu_1, Qu_2, Qu_3, Qu_4, λ) with respect to Qu_1, Qu_2, Qu_3, Qu_4, λ to find minimization of L (Qu_1, Qu_2, Qu_3, Qu_4, λ).

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_1} = \frac{1}{6}\left[\frac{2I_1}{S} + \frac{2P_1}{A} - \frac{2P_4E}{Qu_1^{\ 2}} - \frac{2SI_4A}{Qu_1^{\ 2}}\right] + \lambda$$

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_2} = \frac{2}{6}\left[\frac{2I_2}{S} + \frac{2P_2}{A} - \frac{2P_3E}{Qu_2^{\ 2}} - \frac{2SI_3A}{Qu_2^{\ 2}}\right] - \lambda$$

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_3} = \frac{2}{6}\left[\frac{2I_3}{S} + \frac{2P_3}{A} - \frac{2P_2E}{Qu_3^{\ 2}} - \frac{2SI_2A}{Qu_3^{\ 2}}\right]$$

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_4} = \frac{1}{6}\left[\frac{2I_4}{S} + \frac{2P_4}{A} - \frac{2P_1E}{Qu_4^{\ 2}} - \frac{2SI_1A}{Qu_4^{\ 2}}\right]$$

$$\frac{\partial L}{\partial \lambda} = -(Qu_2 - Qu_1)$$

Equate all the derivatives to zero. We get,

$$Qu_1 = Qu_2 = \sqrt{\frac{SA[(2P_4E + 2SI_4A) + (4P_3E + 4SI_3A)]}{(2I_1A + 2P_1S) + (4I_2A + 4P_2S)}}$$

$$Qu_3 = \sqrt{\frac{SA(4P_2E + 4SI_2A)}{4I_3A + 4P_3S}}$$

$$Qu_4 = \sqrt{\frac{SA(2P_1E + 2SI_1A)}{2I_4A + 2P_4S}}$$

It does not satisfy the constraint 0<Qu_1>Qu_2>Qu_3>Qu. Because the above result shows that Qu_2 > Qu_3.

Therefore, move to Step 3.

Step 3: Change the inequality restriction $Qu_2 - Qu_1 \geq 0$, $Qu_3 - Qu_2 \geq 0$ restrictions on equality $Qu_2 - Qu_1 = 0$ and $Qu_3 - Qu_2 = 0$ and optimize P (J$\tilde{T}$C(Qu)) subject to $Qu_2 - Qu_1 = 0$, $Qu_3 - Qu_2 = 0$. We have the Lagrangian method as, L (Qu_1, Qu_2, Qu_3, Qu_4, λ_1, λ_2)=P(J$\tilde{T}$C(Qu)) – λ_1($Qu_2 - Qu_1$) - λ_2($Qu_3 - Qu_2$).

Differentiate partially L(Qu_1, Qu_2, Qu_3, Qu_4, λ_1, λ_2) with respect to Qu_1, Qu_2, Qu_3, Qu_4, λ_1, λ_2 to find the minimization of L(Qu_1, Qu_2, Qu_3, Qu_4, λ_1, λ_2) and equate all the derivatives to zero to get the values of Qu_1, Qu_2, Qu_3, Qu_4.

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_1} = \frac{1}{6}\left[\frac{2I_1}{S} + \frac{2P_1}{A} - \frac{2P_4E}{Qu_1^{\ 2}} - \frac{2SI_4A}{Qu_1^{\ 2}}\right] + \lambda_1 = 0$$

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_2} = \frac{2}{6}\left[\frac{2I_2}{S} + \frac{2P_2}{A} - \frac{2P_3E}{Qu_2^{\ 2}} - \frac{2SI_3A}{Qu_2^{\ 2}}\right] - \lambda_1 + \lambda_2 = 0$$

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_3} = \frac{2}{6}\left[\frac{2I_3}{S} + \frac{2P_3}{A} - \frac{2P_2E}{Qu_3^{\ 2}} - \frac{2SI_2A}{Qu_3^{\ 2}}\right] - \lambda_2 = 0$$

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_4} = \frac{1}{6}\left[\frac{2I_4}{S} + \frac{2P_4}{A} - \frac{2P_1E}{Qu_4^{\ 2}} - \frac{2SI_1A}{Qu_4^{\ 2}}\right] = 0$$

$$\frac{\partial L}{\partial \lambda_1} = -(Qu_2 - Qu_1) = 0 = 0$$

$$\frac{\partial L}{\partial \lambda_2} = -(Qu_3 - Qu_2) = 0$$

$$Qu_1 = Qu_2 = Qu_3 = \sqrt{\frac{SA[(2P_4E + 2SI_4A) + (4P_3E + 4SI_3A) + (4P_2E + 4SI_2A)]}{(2I_1A + 2P_1S) + (4I_2A + 4P_2S) + (4I_3A + 4P_3S)}}$$

$$Qu_4 = \sqrt{\frac{SA(2P_1E + 2SI_1A)}{2I_4A + 2P_4S}}$$

It does not satisfy the constraint $0<Qu_1>Qu_2>Qu_3>Qu$. Because the above result shows that $Qu_3>Qu_4$. It is not a local optimum as a result. Similar results can be obtained by choosing any other inequality constraint to be an equality constraint, so it able to move for Step 4.

Step 4: The inequality constraints are converted into $Qu_2 - Qu_1 \geq 0$, $Qu_3 - Qu_2 \geq 0$, $Qu_4 - Qu_3 \geq 0$ into equality constraints $Qu_2 - Qu_1=0$, $Qu_3 - Qu_2=0$, $Qu_4 - Qu_3=0$ and optimize P(J$\tilde{T}$C(Qu)) subject to $Qu_2 - Qu_1=0$, $Qu_3 - Qu_2=0$, $Qu_4 - Qu_3=0$.

We have the Lagrangean method as, L (Qu_1, Qu_2, Qu_3, Qu_4, λ_1, λ_2, λ_3) = P(J$\tilde{T}$C(Qu)) – λ_1(Qu_2 – Qu_1) - λ_2(Qu_3 - Qu_2) – λ_3(Qu_4 – Qu_3).

Differentiate partially L (Qu_1, Qu_2, Qu_3, Qu_4, λ_1, λ_2, λ_3) with respect to Qu_1, Qu_2, Qu_3, Qu_4, λ_1, λ_2, λ_3 to find the minimization of L(Qu_1, Qu_2, Qu_3, Qu_4, λ_1, λ_2, λ_3) and equate all the derivatives to zero to get the values of Qu_1, Qu_2, Qu_3, Qu_4.

Then,

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_1} = \frac{1}{6}\left[\frac{2I_1}{S} + \frac{2P_1}{A} - \frac{2P_4E}{Qu_1^{\ 2}} - \frac{2SI_4A}{Qu_1^{\ 2}}\right] + \lambda_1 = 0$$

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_2} = \frac{2}{6}\left[\frac{2I_2}{S} + \frac{2P_2}{A} - \frac{2P_3E}{Qu_2^{\ 2}} - \frac{2SI_3A}{Qu_2^{\ 2}}\right] - \lambda_1 + \lambda_2 = 0$$

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_3} = \frac{2}{6}\left[\frac{2I_3}{S} + \frac{2P_3}{A} - \frac{2P_2E}{Qu_3^{\ 2}} - \frac{2SI_2A}{Qu_3^{\ 2}}\right] - \lambda_2 + \lambda_3 = 0$$

$$\frac{\partial P(J\tilde{T}C(Qu))}{\partial Qu_4} = \frac{1}{6}\left[\frac{2I_4}{S} + \frac{2P_4}{A} - \frac{2P_1E}{Qu_4^{\ 2}} - \frac{2SI_1A}{Qu_4^{\ 2}}\right] - \lambda_3 = 0$$

$$\frac{\partial L}{\partial \lambda_1} = -(Qu_2 - Qu_1) = 0$$
$$\frac{\partial L}{\partial \lambda_2} = -(Qu_3 - Qu_2) = 0$$
$$\frac{\partial L}{\partial \lambda_3} = -(Qu_4 - Qu_3) = 0$$

We get,

$$Qu_1 = Qu_2 = Qu_3 = Qu_4 = \sqrt{\frac{SA[(2P_4E + 2SI_4A) + (4P_3E + 4SI_3A) + (4P_2E + 4SI_2A) + (2P_1E + 2SI_1A)]}{(2I_1A + 2P_1S) + (4I_2A + 4P_2S) + (4I_3A + 4P_3S) + (2I_4A + 2P_4S)}}$$

Because the above equation $\tilde{Q}u=(Qu_1, Qu_2, Qu_3, Qu_4)$ satisfies all inequality constraints. Since the above solution is feasible solution. Thus, the inventory model's optimal solution for the fuzzy production quantity.

Let $Qu_1=Qu_2=Qu_3=Qu_4=\tilde{Q}u^*$. Consequently, the ideal quantity of fuzzy creation is $\tilde{Q}u^*=(Qu_1, Qu_2, Qu_3, Qu_4)$.

$$Qu^* = \sqrt{\frac{SA[(2P_4E + 2SI_4A) + (4P_3E + 4SI_3A) + (4P_2E + 4SI_2A) + (2P_1E + 2SI_1A)]}{(2I_1A + 2P_1S) + (4I_2A + 4P_2S) + (4I_3A + 4P_3S) + (2I_4A + 2P_4S)}}$$

For a fuzzy model, this is the Qu value. The Qu value was calculated using Lagrange conditions, and it is identical to the Qu value of crisp model.

4. Numerical example data of crisp and fuzzy

To show how the model works and how the section's numerical component's function.

A. Lagrange Method:

Crisp Model:

The crisp values are, I = 80, P = 50, A = 2, S = 5, E = 7, D = 9, Qu^*= 5.2961, TC = 868.5620.

Fuzzy Model:

The fuzzy values are, A = 2, S = 5, E = 7, D = 9, $\tilde{I} = [I_1, I_2, I_3, I_4]$ = [78, 79, 81, 82], $\tilde{P} = [P_1, P_2, P_3, P_4]$ = [48, 49, 51, 52], Qu^*= 5.2961 TC = 868.5620.

Results for both models are presented in Table 1.

Table 1
Total cost for both crisp and fuzzy model

S	Crsip $\tilde{Qu}$	Crisp TC	Fuzzy $\tilde{Qu}$	Fuzzy TC
5	3.2961	968.0746	3.2861	965.075
10	4.2961	887.6495	4.2861	885.65
15	5.2961	868.562	5.2961	868.562
20	6.2961	881.5825	6.3061	885.583
25	7.2961	913.5171	7.3061	916.517

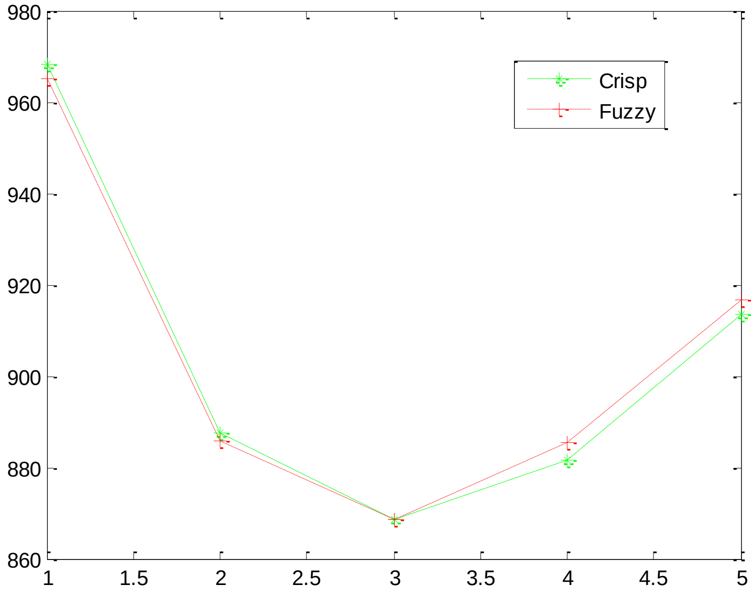

Fig. 1. Crisp Vs Fuzzy

For minimizing inventory expenses such as purchase cost, carrying cost, storage cost, and other associated costs. To keep materials expenses under control because they help to lower production costs. Figure 1 shows the crisp values and fuzzy values are merely equal.

Python Code:

```
import matplotlib.pyplot as pyplot
S = [5,10,15,20,25]
Q =[3.29,4.29,5.29,6.29,7.29]
TC =[968,887,868,881,913]
pyplot.plot([],[], color='G', label = 'Q', linewidth=5)
pyplot.plot([],[],color = 'G', label='TC', linewidth=5)
pyplot.stackplot(S, Q, TC, colors = ['c', 'g'])
pyplot.xlabel('S')
pyplot.ylabel('Q')
pyplot.title('TC')
pyplot.legend()
# Print the chart
pyplot.show()
```

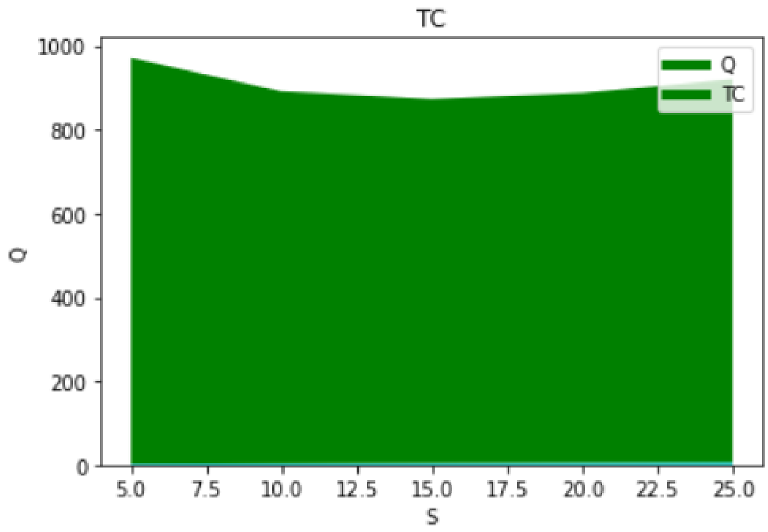

Fig. 2. Crisp model in fuzzy optimization in matplot programming

The Matplotlib module for Python provides a complete toolset for creating static, adaptive, and group visualization tools (Figure 2). Matplotlib makes both difficult problems and straightforward things possible. Create designs suitable for distribution. Stimulate positive charts with magnifying and modify the options. Matplotlib is a graphical interface and graphic charting library for Python and its quantitative expansions NumPy. A tool for visualising the numerical data, Matplotlib is a graph charting framework created through the Python programming.

5. Python executing for data optimizing process

```
import matplotlib.pyplot as plt
import numpy as np
# Use numpy to generate a bunch of random data in a bell curve around 5.
n = 5 + np.random.randn(868)
m = [m for m in range(len(n))]
plt.bar(m, n)
plt.title("Data of Inventory model")
plt.show()
plt.hist(n, bins=20)
plt.title("Inventory of Histogram  ")
plt.show()
plt.hist(n, cumulative=True, bins=20)
plt.title("Cumulative Histogram of fuzzy inventory optimization")
plt.show()
```

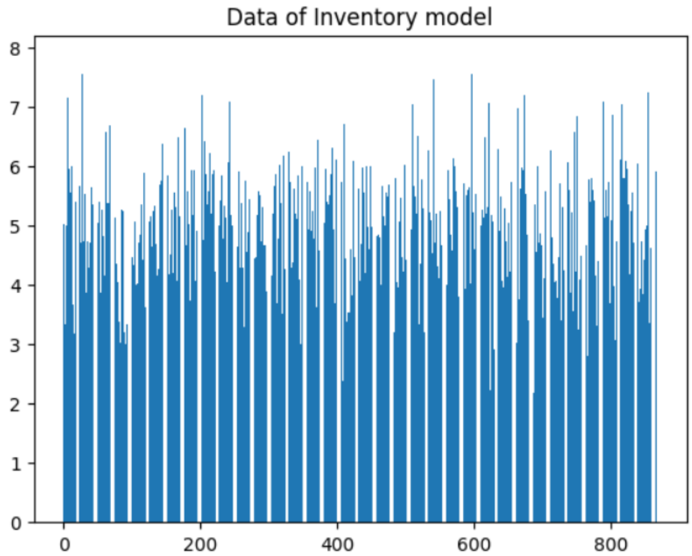

Fig. 3. Data of inventory model

A histogram is a type of graph that is used to summarise discontinuous or continuous data. It visualises numerical data by displaying a certain number of indications which reside within a given range of values. It resembles an organizational hierarchy bar graph. Figure 3 defines the data of fuzzification in the optimization of fuzzy model.

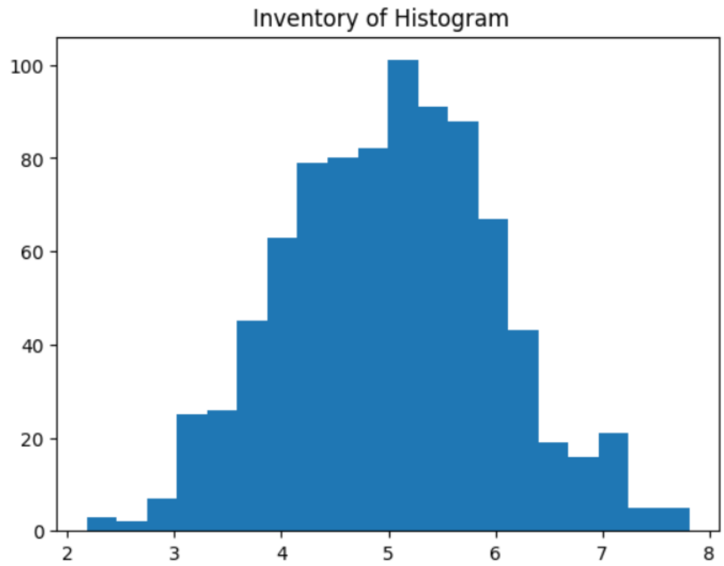

Fig. 4. Inventory model optimization level with Histogram

It has designed and solved an inventory method that includes unit manufacturing cost, time-dependent holding cost, and no shortages. Figure 4 represents the optimizing the level with creisp model and fuzzy model. We considered a singular objective inventory model here. Because the intent and constraint functions of the decision-making process are specific in most real-world situations, the coefficients, which indices, intention function, and restrictive objectives have been determined here in a fuzzy environment.

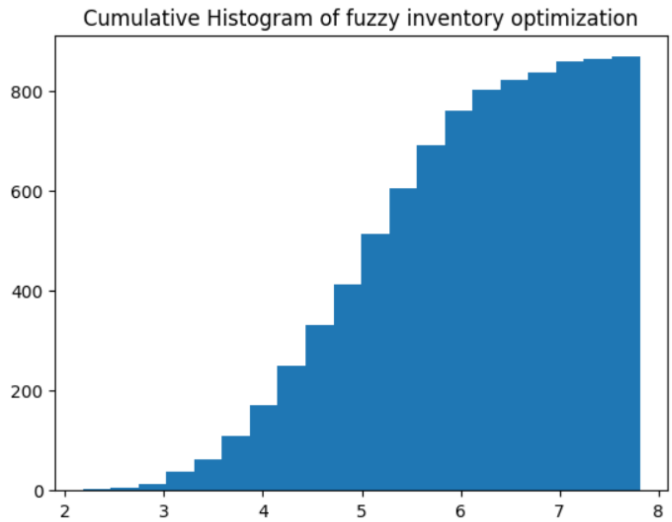

Fig. 5. Step by Step reduction of crisp model through fuzzy

An inventory option making is one that seeks to minimize total average expense or maximize total average profit. It depends on different interpretations and generalizations. Figure 5 depends on the step-by-step reduction of crisp model with the fuzzy model in the inventory modulizations.

6. Conclusion

Any business that controls inventories will benefit from implementing this decision support tool. A well-managed inventory can be maintained, and the risk of stock-outs can be reduced with the use of demand forecasting. Additionally, it helps to prevent overstocking, which drives up the cost of purchases. To optimize profits, the combinatorial optimization models tell us whether to buy or sell unneeded inventory. Finding purchasers for the excess merchandise and implementing this new inventory management strategy continue to be challenges. The paper represents the matplotlib diagram through python coding in crisp and fuzzy optimization variances.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Chen, S. H., Wang, C. C., & Arthur, R. (1996). Backorder fuzzy inventory model under function principle. *Information sciences*, *95*(1-2), 71-79. https://doi.org/10.1016/S0020-0255(96)00085-0

[2] Covert, R. P., & Philip, G. C. (1973). An EOQ model for items with Weibull distribution deterioration. *AIIE transactions*, *5*(4), 323-326. https://doi.org/10.1080/05695557308974918

[3] Bellman, R. E., & Zadeh, L. A. (1970). Decision-making in a fuzzy environment. *Management science*, *17*(4), B-141. https://doi.org/10.1287/mnsc.17.4.B141

[4] Zimmerman, H. J. (1983). Using fuzzy sets in operational research. *European journal of operational research*, *13*(3), 201-216. https://doi.org/10.1016/0377-2217(83)90048-6

[5] Kaufmann, M., & Gupta, M. (1985). Introduction to Fuzzy Arithmetic Theory and Applications. Van Nostrand, Reinhold, New York, USA.

[6] Zimmermann, H. J. (1975). Description and optimization of fuzzy systems. *International journal of general System*, *2*(1), 209-215. https://doi.org/10.1080/03081077508960870

[7] Lalitha. M., & Loganathan, C. (2018). Solving Nonlinear Programming Problem in Fuzzy Environment. International Journal of Pure and Applied Mathematics, 118(7), 491-49.

[8] Hamdy, A. T. (2008). Operations Research Introduction, 8th ed., Pearson Publisher, London, UK.

[9] Sarkar, B., Mandal, P., & Sarkar, S. (2014). An EMQ model with price and time dependent demand under the effect of reliability and inflation. *Applied Mathematics and Computation*, *231*, 414-421. https://doi.org/10.1016/j.amc.2014.01.004

[10] Sarkar, B., Gupta, H., Chaudhuri, K., & Goyal, S. K. (2014). An integrated inventory model with variable lead time, defective units and delay in payments. *Applied mathematics and computation*, *237*, 650-658. https://doi.org/10.1016/j.amc.2014.03.061

[11] Rahman, M. S., Manna, A. K., Shaikh, A. A., & Bhunia, A. K. (2020). An application of interval differential equation on a production inventory model with interval-valued demand via center-radius optimization technique and particle swarm optimization. *International Journal of Intelligent Systems*, *35*(8), 1280-1326. https://doi.org/10.1002/int.22254

[12] Singh, S. R., & Sharma, S. (2017). A production reliable model for deteriorating products with random demand and inflation. *International Journal of Systems Science: Operations & Logistics*, *4*(4), 330-338. https://doi.org/10.1080/23302674.2016.1181221

[13] Das, S. C., Zidan, A. M., Manna, A. K., Shaikh, A. A., & Bhunia, A. K. (2020). An application of preservation technology in inventory control system with price dependent demand and partial backlogging. *Alexandria Engineering Journal*, *59*(3), 1359-1369. https://doi.org/10.1016/j.aej.2020.03.006

[14] Guchhait, P., Maiti, M. K., & Maiti, M. (2013). Production-inventory models for a damageable item with variable demands and inventory costs in an imperfect production process. *International Journal of Production Economics*, *144*(1), 180-188. https://doi.org/10.1016/j.ijpe.2013.02.002

[15] Singh, S., Gupta, V., & Gupta, P. (2013). Three stage supply chain model with two warehouse, imperfect production, variable demand rate and inflation. International Journal Industrial Engineering Computations, 4(1), 81-92. https://doi.org/10.5267/j.ijiec.2012.10.005

[16] Kalaiarasi, K., Sumathi, M., & Mary Henrietta, H. (2020). Optimizing EOQ using geometric programming with varying fuzzy numbers by applying Python. *Journal of Critical Reviews*, *7*(18), 596-603.

[17] Kalaiarasi, K., Sabina Begum, M., & Sumathi, M. (2021). Optimization of unconstrained multi-item (EPQ) model using fuzzy geometric programming with varying fuzzification and defuzzification methods by applying python, Materials today: Proceedings https://doi.org/10.1016/j.matpr.2020.10.588

[18] Kalaiarasi, K., Soundaria, R., Kausar, N., Agarwal, P., Aydi, H., & Alsamir, H. (2021). Optimization of the average monthly cost of an EOQ inventory model for deteriorating items in machine learning using PYTHON. *Thermal Science*, *25*(SpecialIssue 2), S347-S358. https://doi.org/10.2298/TSCI21S2347K

[19] Kausar, N., Munir, M., Agarwal, P., & Kalaiarasi, K. (2022). The characterization of fuzzy and anti fuzzy Ideals in AG-groupoid. *Thai Journal of Mathematics*, *20*(2), 653-667.

[20] Chen, S. H., & Hsieh, C. H. (1999). Graded mean integration representation of generalized fuzzy number. Journal of Chinese Fuzzy Systems, 5(2), 1-7.