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Data-Driven Blood Inventory Optimization Using Fuzzy Demand Forecasting in Healthcare Systems

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Abstract
Blood supply chain management is important and effective in providing timely availability of blood and blood products there is an emergency and critical healthcare delivery. The problem of hospitals is that they have to deal with demand fluctuations, the perishability of blood products and logistical inefficiencies which cause shortages, wastage or delays and, inevitably, affect patient outcomes. The present study, an inventory model is developed for managing blood supplies, which are inherently spoilable and sensitive to demand fluctuations. We have considered a model, which accounts for time dependent and uncertain demand represented in both triangular fuzzy and cloud fuzzy environments, which better reflect real-word uncertainties in blood utilization rates. A deterioration rate influenced by preservation technology investment is incorporated, emphasizing the critical role of refrigeration and storage protocols in mitigating blood wastage. The total inventory cost includes setup, procurement, holding, deterioration, shortage, and preservation costs over a finite planning horizon. A non-linear optimization framework is formulated to minimize the total cost by jointly determining the optimal inventory depletion time and investment in preservation technology. The model is particularly applicable to healthcare systems and blood banks aiming to balance cost-efficiency with life-saving service levels. Defuzzification techniques such as Yager's ranking index are used for decision-making under fuzzy demand scenarios, offering a more realistic and adaptable decision-support system for the blood supply chain. The model is illustrated by a numerical example. Sensitivity analysis is also performed.

Keywords: - *Blood Supply Chain, Hospitals, Data-Driven Strategies, Inventory Management.*

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I. Introduction

Blood supply chain management is an integral part of a healthcare system, keeping the lifesaving blood and blood products flowing where it is needed. Hospitals struggle to optimize their management of blood products as supply is affected with fluctuating demand, a limited shelf life and unpredictable emergencies. These complexities frequently perplex traditional methods, leading to shortages, waste, or delays that can influence patient results unfavorably. However, the integration of data driven strategies, to overcome these challenges is a transformative approach in blood supply chain management. Through the use of data analytics, hospitals can better manage inventory levels, forecast demand patterns, and refine distribution channels to ensure supplies are readily available when needed without creating wastage.

This paper proposes a mathematical inventory model for a single deteriorating item — in this case, blood — under uncertain, time-dependent demand. The model incorporates both triangular fuzzy and cloud fuzzy representations of demand to manage imprecision and partial knowledge effectively. Importantly, it integrates the impact of preservation technology investments on the deterioration rate, acknowledging the critical role of refrigeration and controlled storage in extending blood shelf-life.

Shortages are permitted and assumed to be fully backlogged, reflecting situations where emergency requests are delayed but not denied. The model includes the total cost associated with the system: setup cost, procurement cost, inventory holding cost, deterioration loss, shortage cost, and the cost of preservation technology. The optimization problem is formulated to minimize the total inventory cost (TIC) with respect to cycle time and preservation technology expenditure, offering valuable insights for decision-makers in blood banks and hospital supply departments.

II. Literature Review

Nayeri, S., et al (2023). In adapting to the ever-changing paradigm of quality of care in healthcare industry, a data driven model for sustainable and resilient supplier selection and order allocation tackles critical hurdles in supply management in such a responsive healthcare supply chain. This kind of model integrates sustainability criteria such as environmental, social, and economic criteria with resilience measures, to maintain supply chain continuity in case of disruptions. The model analyzes historical data, Realtime data and predictive analytics to evaluate the potential suppliers on their level of reliability, ability to comply towards ethical practices, risk mitigation & environmental compliance. Further it optimizes a match of an order allocation that minimizes carbon footprint while considering the cost efficiency, delivery time and capacity constraints. In the case of healthcare with immediate need for timely availability of critical supplies such as medicines and medical equipment, this approach aligns operational demand with longer term sustainability goals to improve decision making. Through advanced technology like machine learning and blockchain, it resolves challenges like data integration, supplier collaboration and changing regulations. The model is then utilized as a case study in the healthcare system to show the risks can be mitigated, costs reduced, and supply chain agility enhanced during emergencies such as pandemics.

Bhatia, A., et al (2019). A healthcare supply chain driven by big data is transformative in that it utilizes data of massive volume to enable efficiency, resilience and responsiveness. Big data analytics helps in real time tracking of medical supplies, predictions around demand patterns and optimization of inventory level to avoid shortage or overstocking. Healthcare organizations can forecast disruptions (such as pandemics or natural disasters) by analyzing historical and real time data, and proactively develop strategies to maintain supply chain continuity. Machine learning and AI are some of the advanced techniques that allow trends to be identified and therefore better decisions to be made, and to allocate resources cost—effectively. Big data ensures visibility of the supply chain embarking upon all the stakeholders such as suppliers, distributors and healthcare providers. Strategic solutions like adopting in cloud-based platforms with data governance, and ensuring good data governance becomes a strategic imperative to address the challenge of data silos, security and integration challenges of track and trace. Its potential lies in an ability to personalize the supply chain processes to address the custom demand, for example, rapid delivery of crucial medicines or conformity to regional healthcare needs. In addition to streamlining operations, a big data driven approach enables better patient care, cuts down on waste and promotes sustainability – representing a major change of course toward smarter, more efficient healthcare supply chain management.

Delen, D., et al (2019). By integrating geographical and spatial data, GIS-based analytics has great transformative potential for improving management of the blood supply chain, optimizing collection, storage and distribution. Geographic Information Systems (GIS) serve as real time map of the donor locations, blood bank inventory and healthcare facility, and improve deployment decision through better resource allocation. Using population density, healthcare demands and transportation networks patterns GIS can spot the right areas to start blood collection drives and storage facilities. It allows routing of the logistics, reduce delays and fast delivery of blood products, especially in case of emergency. GIS based systems can predict demand taking into account seasonal fluctuations and regional health challenges and thereby reinforce proactive inventory management so that the perishable blood products are not wasted. And they improve coordination between blood banks, hospitals and emergency services by centralizing location specific data. With targeted investments and capacity-building initiatives such investments can address challenges in data integration, maintaining real-time accuracy and personnel training in GIS tools. Healthcare systems can improve the efficiency, responsiveness and sustainability of the blood supply chain through the utilization of GIS analytics, resulting in better patient outcomes and saving lives.

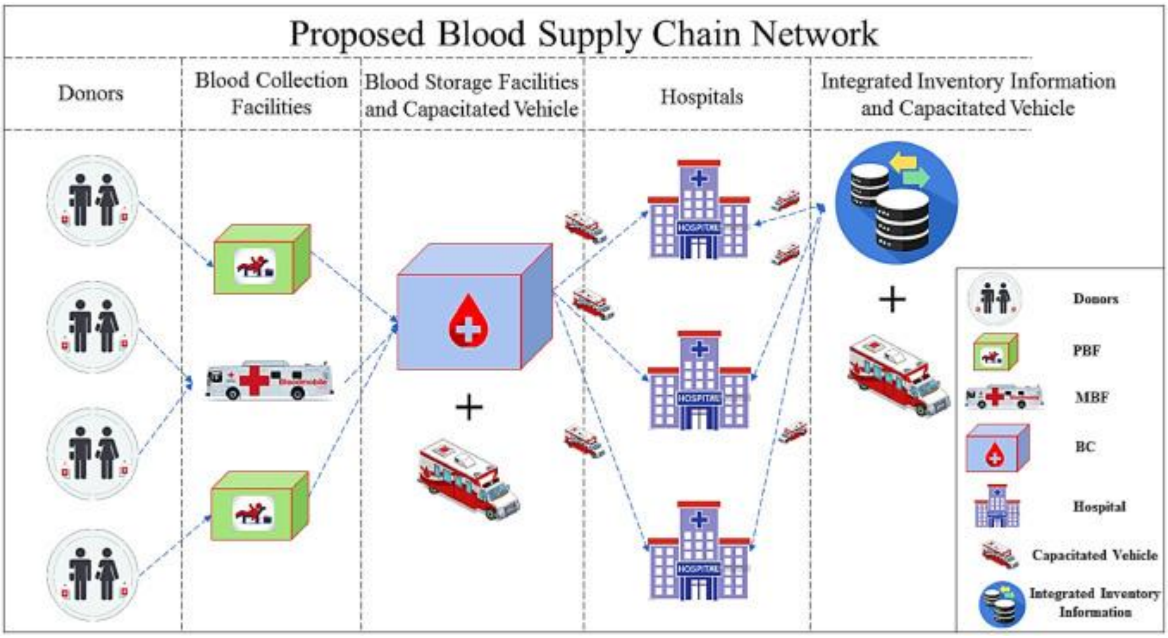
Lotfi, R., et al (2022). By leveraging the uncertainty modeling of fuzzy theory and the emerging advanced data analytic approaches, a hybrid fuzzy and data driven robust optimization approach can improve resilience and sustainability in healthcare supply chains. The utilization of fuzzy logic in a supply chain system enables the handling of uncertain and ambiguous data required to manage products subject to fluctuating demand, supply disruptions and emergency incidents of a healthcare supply chain. Data driven methods—through integration with the existing tools—provides real time insight and predictive capabilities for inventory, supplier management, and other times where decisions are based on forecast. This system is further enhanced through such a vendor managed inventory (VMI) approach, whereby inventory control is handed over to suppliers, who are thus made responsible for timely replenishments and relieving healthcare providers of inventory burdens. This hybrid model can become more responsive by adapting dynamically to new conditions and with preference for sustainability in waste minimization and transportation routing to reduce environmental impacts. This is a case of robust optimization, making sure that the supply chain runs on the worst case, always preserving the continuity for availability of critical medical supplies. While faced with system complexity and integration costs, the combined approach increases the efficiency, reliability, and sustainability of the healthcare supply chain to reinforce better patient care and system resilience during emergencies.

Abbasi, B., et al (2020). A cutting edge approach of using machine learning (ML) to predict solutions for large scale optimization problems in the blood supply chain management to improve efficiency and nimbleness. Blood product supply chain is inherently complex, including dynamic demand, perishable products, and importance of timely delivery. Using ML models trained on real time and historic data, we can predict such solutions for donor scheduling, inventory management and distribution route management on a supply chain. Predictive analytics can be used to ML to forecast demand patterns, anticipate potential shortages and allocate resources as effectively as possible — even in emergency scenarios. These models can work with huge datasets and factor in demographics of population, seasonal factors, some transportation impediments etc. ML is able to solve such complex problems instantaneously (or near instantly), at a much lower computational complexity, also resulting in resources being saved. While issues like data quality, model effectiveness, and implementation expenses exist, ML driven optimization is highly encouraging. This approach to blood supply chain management reduces waste, lifts service levels, and improves decision making under uncertainty providing the most critical resources when and where they are needed most. This then sets the way for the development of a smarter, more resilient healthcare system.

Abouee-Mehrizi, H., et al (2022). The potential for transformative changes in how healthcare systems utilize the blood supply chain is also possible with a smart platform for blood bank data management that uses machine learning to predict demand. Blood inventory management is an important, yet highly difficult, function to perform, characterized by perishable blood products and unpredictable demand. Using a platform that is based on machine learning, historical data, donor patterns, seasonal trends, healthcare demands and so on can be analyzed to provide a precise forecast of the requirements of blood from one region to the other. This capability enables the prediction of shortages in addition to wastage due to overstocking — an efficient utilization of resources. They could also automate the donor outreach, identifying the ideal times to run the drives and predicting potential shortages in their donating systems well in advance. Using real time data integration at several blood banks, unites a network to track availability, distribution, demand alignment. A challenge lies in securing data, getting rid of historical data biases, and convincing blood bank employees to adopt the tool. However, this technology can greatly improve the decision making, streamline the operations of the supply chain, and improve blood delivery reliability in both emergency and routine situations, as long as there is proper design and implementation. The smart blood bank management platform not only optimizes the utilization of resources but provides a backup to better patient care and life saving interventions through the more resilient and responsive supply chain.

III. Methodology

In hospitals, blood supply chain optimization necessitates data driven strategies to address intrinsic complexities in blood supply chain, for example, volatile demand, perishable inventory and logistical challenges. Analyzing historical data, analyzing seasonal trends and demographic factors, forecasting blood demand is a thing that is done by predictive analytics and it plays a vital role. Access to blood traceability provides hospitals and blood banks the ability to anticipate shortages, plan procurement proactively, and prevent the wastage caused by overstocking. Additionally, inventory management exploits algorithms to follow blood product lifecycles, optimize its stock level, and give a higher priority to the usage of blood products nearing to expiry. These systems make available supplies meet real time demand and also minimize spoilage risk.



The image of the proposed blood supply chain network initially considers donors, blood collection facilities, storage facilities, hospitals, and real-time inventory management using capacitated vehicles. Blood is donated by donors to collection facilities, followed by transport with vehicles to blood storage centers for storage. They collect and distribute blood as it is needed to hospitals. Optimized transportation efficiency is achieved with capacitated vehicles and real time blood stock and logistics tracking can be done using an integrated inventory system. This system reduces the waste and maximizes the collaboration of the stakeholders in order to decrease the cost of a given healthcare organization and improve the working of supply chain and in accomplishing this process.

Supply chain visibility is enhanced by Real Time monitoring and tracking systems during the blood product collection, storage and distribution phases, which providing stakeholders the ability to track blood products throughout this process. Temperature fluctuations and delays can be alerted through these systems thus complying with quality standards and reducing loss. Technology powered collaborative frameworks like blockchain or cloud-based platforms enable smooth coordination among blood banks, hospitals and logistic provider. Compared to more traditional communication platforms, these platforms facilitate transparent communication, efficient resource allocation and quick response to emergencies, e.g. re-distribution of surplus stock when there are shortages of the same in different regions. All combined, these strategies establish a resilient, efficient blood chain that can reliably meet patient needs, minimize wastage, and support cost effective operations. Integrating data driven tools transforms the blood supply chain from being proactive on the one end and adaptive on the other, which improves healthcare outcomes and better resource management.

IV. Mathematical Model

The below mentioned notations and assumptions are used to develop the mathematical model

Notations:

a. $I(t)$ is the on hand inventory at any time t
b. The demand rate function $D(t)$ is assumed to be a function of time in a polynomial form: $D(t) = \beta t^{\gamma-1}$ with $\gamma > 1$ for increasing demand, $\gamma < 1$ for decreasing demand and $\gamma = 1$ for constant demand and β is a positive constant.
c. $\widetilde{D_f}$ is the triangular fuzzy demand rate
d. $\widetilde{D_c}$ is the cloud fuzzy demand rate
e. $\theta(\xi)$ is the preservation technology cost dependent Deterioration rate which is defined as $\theta(\xi) = \theta_0 e^{-\delta\xi}$ where $0 < \theta_0, \delta < 1, \theta_0 =$ initial deterioration rate.
f. T is the total cycle time
g. A is the Set up cost per cycle
h. h_r is the Inventory holding cost per unit per unit time

i. d_r is the Deterioration cost per unit per unit time
j. p is the purchasing cost per unit
k. s is the Shortage cost per unit per unit time
l. Q is the initial inventory level
m. TIC is the total cost per unit time
n. $\widetilde{TIC_f}$ is the fuzzy total cost per unit time
o. $\widetilde{TIC_c}$ is the cloud fuzzy total profit per unit time

Assumptions:

a. Demand rate is uncertain in character.
b. Single deteriorating type of product is considered over a finite planning horizon T.
c. The deterioration rate θ is depending on the preservation technology investment cost ξ.
d. There is no repair or replacement of deteriorated products during cycle time T.
e. Shortages are allowed and completely backlogged.
f. Lead time is zero.

Crisp mathematical Model

The initial inventory level is Q at time $t = 0$. The inventory level gradually depletes to zero at time $t = t_1$ due to demand and deterioration. Now shortages occur and accumulate to the level I_s at time $t = T$. Then the cycle repeats thereafter.

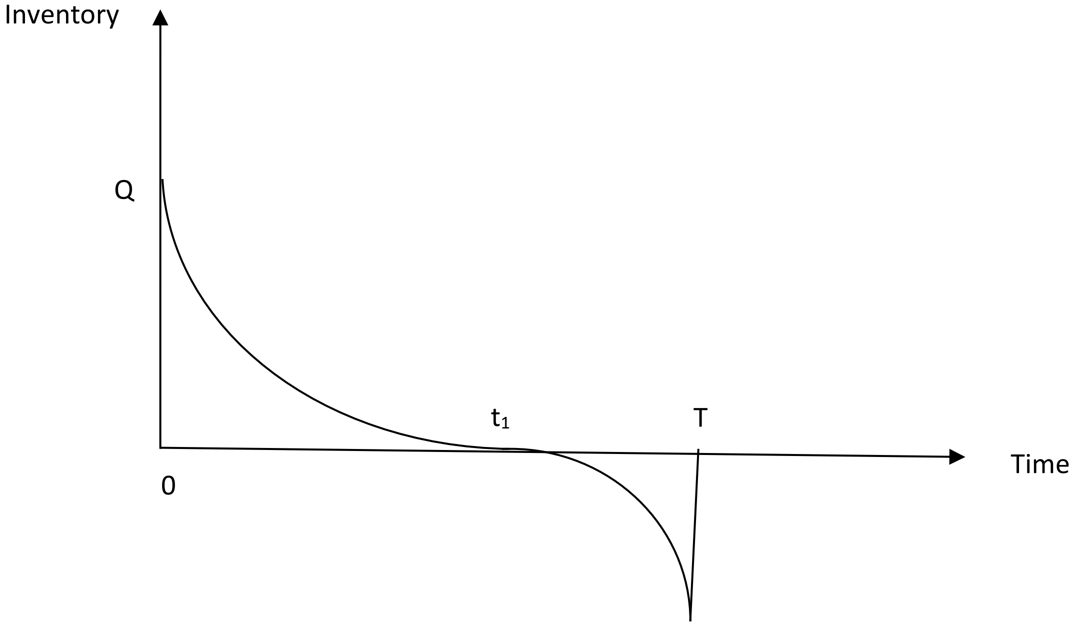


Fig. 1: Graphical representation of the inventory system

The mathematical formulation of the model is given by

$$\frac{dI(t)}{dt} + \theta(\xi)I(t) = -\beta t^{\gamma-1}, \quad 0 \leq t \leq t_1 \tag{1}$$

$$\frac{dI(t)}{dt} = -\beta t^{\gamma-1}, \qquad t_1 \leq t \leq T \tag{2}$$

With the boundary conditions:

$$I(0) = Q, \quad I(t_1) = 0, I(T) = -I_s \tag{3}$$

Solving (1) and (2) we get

$$I(t) = \beta\left\{\frac{1}{\gamma}({t_1}^{\gamma} - t^{\gamma}) + \frac{\theta(\xi)}{(\gamma+1)}({t_1}^{\gamma+1} - t^{\gamma+1})\right\}e^{-\theta(\xi)t} \tag{4}$$

$$I(t) = \frac{\beta}{\gamma}\{{t_1}^{\gamma} - t^{\gamma}\} \tag{5}$$

Now from (4) and the boundary condition $I(0) = Q$ we get

$$Q = \beta\left\{\frac{1}{\gamma}{t_1}^{\gamma} + \frac{\theta(\xi)}{(\gamma+1)}{t_1}^{\gamma+1}\right\} \tag{6}$$

Set up cost in the cycle T is

$$Su_c = A \quad (7)$$

Purchasing cost in the cycle T is

$$P_c = Q.p = p\beta\left\{\frac{1}{\gamma}{t_1}^{\gamma} + \frac{\theta(\xi)}{(\gamma+1)}{t_1}^{\gamma+1}\right\} \quad (8)$$

Holding cost in the cycle T is

$$H_c = h_r\int_0^{t_1} I(t)dt$$

$$= \beta h_r\left\{\frac{1}{(\gamma+1)}{t_1}^{\gamma+1} + \frac{\theta(\xi)}{2(\gamma+2)}{t_1}^{\gamma+2}\right\} \quad (9)$$

(Neglecting higher powers of (ξ))

Deterioration cost in the cycle T is

$$D_c = d_r\int_0^{t_1}\theta(\xi)I(t)dt$$

$$= \beta d_r\theta(\xi)\left\{\frac{1}{(\gamma+1)}{t_1}^{\gamma+1} + \frac{\theta(\xi)}{2(\gamma+2)}{t_1}^{\gamma+2}\right\} \quad (10)$$

Preservation technology cost in the cycle T is

$$Pr_c = \xi t_1 \quad (11)$$

Shortage cost in the production cycle T is

$$S_c = s\int_{t_1}^{T}\{-I(t)\}\,dt$$

$$= s\frac{\beta}{\gamma}\left\{{t_1}^{\gamma}T - \frac{1}{(\gamma+1)}T^{\gamma+1} - \frac{\gamma}{(\gamma+1)}{t_1}^{\gamma+1}\right\} \quad (12)$$

Therefore, the total inventory cost of the system is

$$TIC(t_1,\xi) = Su_c + P_c + H_c + D_c + Pr_c + S_c$$

Hence from the relations (7) - (12) we get,

$$TIC(t_1,\xi) = A + p\beta\left\{\frac{1}{\gamma}{t_1}^{\gamma} + \frac{\theta(\xi)}{(\gamma+1)}{t_1}^{\gamma+1}\right\} + \beta\big(h_r + d_r\theta(\xi)\big)\left\{\frac{1}{(\gamma+1)}{t_1}^{\gamma+1} + \frac{\theta(\xi)}{2(\gamma+2)}{t_1}^{\gamma+2}\right\} + \xi t_1 + \frac{s\beta}{\gamma}\left\{{t_1}^{\gamma}T - \frac{1}{(\gamma+1)}T^{\gamma+1} - \frac{\gamma}{(\gamma+1)}{t_1}^{\gamma+1}\right\} \quad (13)$$

(Where $\theta(\xi) = \theta_0 e^{-\delta\xi}$)

Then the problem is described as follows:

$Minimize\ TIC(t_1,\xi), Subject\ to\ t_1 > 0, 0 \le \xi \le \bar{\xi}$

Our aim is to obtain the minimum total inventory cost $TIC(t_1,\xi)$ with respect to the time interval t_1 and the cost of preservation technology ξ. The objective function is non-linear and continuous function of two variables. The necessary condition for existence of the solution is $\frac{\partial TIC}{\partial t_1} = 0$ and $\frac{\partial TIC}{\partial \xi} = 0$ provided it satisfies

$$\begin{vmatrix} \frac{\partial^2 TIC}{\partial {t_1}^2} & \frac{\partial^2 TIC}{\partial t_1 \partial \xi} \\ \frac{\partial^2 TIC}{\partial \xi \partial t_1} & \frac{\partial^2 TIC}{\partial \xi^2} \end{vmatrix} > 0$$

Fuzzy Mathematical Model

In real-life scenario, it is observed that the demand rate cannot be predicted precisely. Hence, to formulate the fuzzy model we assumed demand rate as fuzzy number.

Let us consider the demand parameter β as triangular fuzzy number $\widetilde{\beta_f}$ as $\widetilde{\beta_f} = \langle \beta_1, \beta_2, \beta_3 \rangle$

Hence the total fuzzy profit function reduces to (fuzzifying (13))

$$\widetilde{TIC_f}(t_1,\xi) = A + p\widetilde{\beta_f}\left\{\frac{1}{\gamma}{t_1}^{\gamma} + \frac{\theta(\xi)}{(\gamma+1)}{t_1}^{\gamma+1}\right\} + \widetilde{\beta_f}\big(h_r + d_r\theta(\xi)\big)\left\{\frac{1}{(\gamma+1)}{t_1}^{\gamma+1} + \frac{\theta(\xi)}{2(\gamma+2)}{t_1}^{\gamma+2}\right\} + \xi t_1 + \frac{s\widetilde{\beta_f}}{\gamma}\left\{{t_1}^{\gamma}T - \frac{1}{(\gamma+1)}T^{\gamma+1} - \frac{\gamma}{(\gamma+1)}{t_1}^{\gamma+1}\right\} \quad (14)$$

Hence, the membership function for the fuzzy cost under triangular fuzzy number is

$$\mu(TIC) = \begin{cases} \frac{TIC - TIC_1}{TIC_2 - TIC_1}, TIC_1 \le TIC \le TIC_2 \\ \frac{TIC_3 - TIC}{TIC_3 - TIC_2}, TIC_2 \le TIC \le TIC_3 \\ 0, \quad Otherwise \end{cases} \quad (15)$$

Where TIC_i , $i = 1,2,3$ can be obtained by replacing $\widetilde{\beta_f}$ with $\beta_i, i = 1,2,3$ in equ. (14) and expressed as

$$TIC_i(t_1,\xi) = A + p\beta_i\left\{\frac{1}{\gamma}{t_1}^{\gamma} + \frac{\theta(\xi)}{(\gamma+1)}{t_1}^{\gamma+1}\right\} + \beta_i\big(h_r + d_r\theta(\xi)\big)\left\{\frac{1}{(\gamma+1)}{t_1}^{\gamma+1} + \frac{\theta(\xi)}{2(\gamma+2)}{t_1}^{\gamma+2}\right\} + \xi t_1 + \frac{s\beta_i}{\gamma}\left\{{t_1}^{\gamma}T - \frac{1}{(\gamma+1)}T^{\gamma+1} - \frac{\gamma}{(\gamma+1)}{t_1}^{\gamma+1}\right\} \quad (16)$$

Now, left α- cut of $\mu(TIC)$ is $L(\alpha) = TIC_1 + \alpha(TIC_2 - TIC_1)$
and right α- cut of $\mu(TIC)$ is $R(\alpha) = TIC_3 - \alpha(TIC_3 - TIC_2)$
By using the Yager's ranking index method for defuzzification, the defuzzified value of the fuzzy objective function is

$$I(\widetilde{TIC_f}) = \frac{1}{2}\int_0^1 \{L(\alpha) + R(\alpha)\}d\alpha$$
$$= A + p\frac{(\beta_1+2\beta_2+\beta_3)}{4}\left\{\frac{1}{\gamma}t_1{}^{\gamma} + \frac{\theta(\xi)}{(\gamma+1)}t_1{}^{\gamma+1}\right\} + \frac{(\beta_1+2\beta_2+\beta_3)}{4}\left(h_r + d_r\theta(\xi)\right)\left\{\frac{1}{(\gamma+1)}t_1{}^{\gamma+1} + \frac{\theta(\xi)}{2(\gamma+2)}t_1{}^{\gamma+2}\right\} + \xi t_1 + \frac{s}{\gamma}\frac{(\beta_1+2\beta_2+\beta_3)}{4}\left\{t_1{}^{\gamma}T - \frac{1}{(\gamma+1)}T^{\gamma+1} - \frac{\gamma}{(\gamma+1)}t_1{}^{\gamma+1}\right\} \quad (17)$$

Then the objective function under fuzzy model is described as follows:
$Minimize \quad \widetilde{TIC_f}(t_1,\xi), Subject\ to \quad t_1 > 0, 0 \le \xi \le \bar{\xi}$

Cloud Fuzzy Model

To formulate the cloud fuzzy model, let us assume the demand parameter β as a cloud triangular fuzzy number.
$\widetilde{\beta_c} = \langle b\left(1 - \frac{\rho}{1+t}\right), b, b\left(1 + \frac{\sigma}{1+t}\right)\rangle$ for $0 < \rho, \sigma < 1, t > 0$
The total cloud fuzzy cost function is given by

$$\widetilde{TIC_c}(t_1,\xi) = A + p\widetilde{\beta_c}\left\{\frac{1}{\gamma}t_1{}^{\gamma} + \frac{\theta(\xi)}{(\gamma+1)}t_1{}^{\gamma+1}\right\} + \widetilde{\beta_c}\left(h_r + d_r\theta(\xi)\right)\left\{\frac{1}{(\gamma+1)}t_1{}^{\gamma+1} + \frac{\theta(\xi)}{2(\gamma+2)}t_1{}^{\gamma+2}\right\} + \xi t_1 + \frac{s\widetilde{\beta_c}}{\gamma}\left\{t_1{}^{\gamma}T - \frac{1}{(\gamma+1)}T^{\gamma+1} - \frac{\gamma}{(\gamma+1)}t_1{}^{\gamma+1}\right\} \quad (18)$$

Again the membership function for the fuzzy objective function under cloud triangular fuzzy number is

$$\omega(TIC,t) = \begin{cases} \frac{TIC - TIC_1}{TIC_2 - TIC_1}, TIC_1 \le TIC \le TIC_2 \\ \frac{TIC_3 - TIC}{TIC_3 - TIC_2}, TIC_2 \le TIC \le TIC_3 \\ 0, \quad Otherwise \end{cases} \quad (19)$$

Where TIC_i , $i = 1,2,3$ can be obtained by replacing $\widetilde{\beta_c}$ with $b\left(1 - \frac{\rho}{1+t}\right), b, b\left(1 + \frac{\sigma}{1+t}\right)$ in equation (18) and expressed as

$$TIC_1(t_1,\xi) = A + p\,b\left(1 - \frac{\rho}{1+t}\right)\left\{\frac{1}{\gamma}t_1{}^{\gamma} + \frac{\theta(\xi)}{(\gamma+1)}t_1{}^{\gamma+1}\right\} + b\left(1 - \frac{\rho}{1+t}\right)\left(h_r + d_r\theta(\xi)\right)\left\{\frac{1}{(\gamma+1)}t_1{}^{\gamma+1} + \frac{\theta(\xi)}{2(\gamma+2)}t_1{}^{\gamma+2}\right\} + \xi t_1 + \frac{s}{\gamma}b\left(1 - \frac{\rho}{1+t}\right)\left\{t_1{}^{\gamma}T - \frac{1}{(\gamma+1)}T^{\gamma+1} - \frac{\gamma}{(\gamma+1)}t_1{}^{\gamma+1}\right\} \quad (20)$$

$$TIC_2(t_1,\xi) = A + pb\left\{\frac{1}{\gamma}t_1{}^{\gamma} + \frac{\theta(\xi)}{(\gamma+1)}t_1{}^{\gamma+1}\right\} + b\left(h_r + d_r\theta(\xi)\right)\left\{\frac{1}{(\gamma+1)}t_1{}^{\gamma+1} + \frac{\theta(\xi)}{2(\gamma+2)}t_1{}^{\gamma+2}\right\} + \xi t_1 + \frac{sb}{\gamma}\left\{t_1{}^{\gamma}T - \frac{1}{(\gamma+1)}T^{\gamma+1} - \frac{\gamma}{(\gamma+1)}t_1{}^{\gamma+1}\right\} \quad (21)$$

And

$$TIC_3(t_1,\xi) = A + pb\left(1 + \frac{\sigma}{1+t}\right)\left\{\frac{1}{\gamma}t_1{}^{\gamma} + \frac{\theta(\xi)}{(\gamma+1)}t_1{}^{\gamma+1}\right\} + b\left(1 + \frac{\sigma}{1+t}\right)\left(h_r + d_r\theta(\xi)\right)\left\{\frac{1}{(\gamma+1)}t_1{}^{\gamma+1} + \frac{\theta(\xi)}{2(\gamma+2)}t_1{}^{\gamma+2}\right\} + \xi t_1 + \frac{s}{\gamma}b\left(1 + \frac{\sigma}{1+t}\right)\left\{t_1{}^{\gamma}T - \frac{1}{(\gamma+1)}T^{\gamma+1} - \frac{\gamma}{(\gamma+1)}t_1{}^{\gamma+1}\right\} \quad (22)$$

Now, left α- cut of $\omega(TIC,t)$ is $L(\alpha,t) = TIC_1 + \alpha(TIC_2 - TIC_1)$
and right α- cut of $\omega(TIC,t)$ is $R(\alpha,t) = TIC_3 - \alpha(TIC_3 - TIC_2)$
By using the extension of Yager's ranking index method for defuzzification, the defuzzified value of the cloud fuzzy objective function is

$$I(\widetilde{TIC_c}) = \frac{1}{2T}\int_{\alpha=0}^{\alpha=1}\int_{t=0}^{t=T}\{L(\alpha,t) + R(\alpha,t)\}dt\,d\alpha$$
$$= A + pb\left\{1 + \frac{(\sigma-\rho)}{4}\frac{\log(1+T)}{T}\right\}\left\{\frac{1}{\gamma}t_1{}^{\gamma} + \frac{\theta(\xi)}{(\gamma+1)}t_1{}^{\gamma+1}\right\} + b\left\{1 + \frac{(\sigma-\rho)}{4}\frac{\log(1+T)}{T}\right\}\left(h_r + d_r\theta(\xi)\right)\left\{\frac{1}{(\gamma+1)}t_1{}^{\gamma+1} + \frac{\theta(\xi)}{2(\gamma+2)}t_1{}^{\gamma+2}\right\} + \xi t_1 + \frac{s}{\gamma}b\left\{1 + \frac{(\sigma-\rho)}{4}\frac{\log(1+T)}{T}\right\}\left\{t_1{}^{\gamma}T - \frac{1}{(\gamma+1)}T^{\gamma+1} - \frac{\gamma}{(\gamma+1)}t_1{}^{\gamma+1}\right\} \quad (23)$$

Then the objective function under cloud fuzzy model is described as follows:
$Minimize \quad \widetilde{TIC_c}(t_1,\xi), Subject\ to \quad t_1 > 0, 0 \le \xi \le \bar{\xi}$

V. Numerical Analysis

In this Section, we have calculated optimal time interval length t_1^*, and cost of preservation technology ξ^* and the minimum total cost TIC^* for Crisp model, $\widetilde{TIC_f}^*$ for fuzzy model and $\widetilde{TIC_c}^*$ for Cloud fuzzy model over cycle time T for given values of other parameters by considering example.

Example:
The following numerical values of the parameters have been considered in appropriate units to evaluate the models
For Crisp model, $A = 100, \beta = 5, \gamma = 0.8, \ \theta_0 = 0.2, \delta = 0.5, h_r = 2, d_r = 5, p = 15, s = 13, T = 5$ in appropriate units.
For fuzzy model, $\widetilde{\beta_f} = \langle \beta_1, \beta_2, \beta_3 \rangle = \langle 3.5,5,6.5 \rangle$ and keep other parameters as in crisp model.
For cloud fuzzy model, $\rho = 0.12, \sigma = 0.65, \ b = 5$ and keep other parameters as in crisp model.

Table 1. Optimal solutions under different environments

Environment	t_1^*	ξ^*	Optimal Cost
Crisp	3.28	1.8	TIC^* =1287.35
Fuzzy	3.36	2.1	$\widetilde{TIC_f}^*$ = 1103.71
Cloud Fuzzy	3.52	2.4	$\widetilde{TIC_c}^*$ =1062.39

- From Table 1, we observe that Cloud Fuzzy model is the most profitable policy compared to the other policy. In this model we get the minimum cost of the inventory system is 1062.39 along with the time is 3.52 and the preservation technology investment cost is 2.4.
- The degree of fuzziness under a fuzzy environment can be calculated using the formula $D_f = \frac{U-L}{2M}$, where U and L are upper bound and lower bound of triangular fuzzy number, respectively, and $M = 3(median) - 2(mean)$ is the mode of the triangular fuzzy number. The degree of fuzziness under cloud fuzzy environment known as the cloud index can be obtained using the formula $I_c = \frac{\log(1+T)}{T}$. We have a fuzzy demand parameter $\widetilde{\beta_f} = \langle 3.5,5,6.5 \rangle$. Therefore, upper bound is $U = 6.5$ and lower bound is $L = 3.5$. The median of $\tilde{\beta}$ is 5, and mean is 5; therefore, mode $M = 5$ and degree of fuzziness $D_f = 0.3$. Since the cycle time under the cloud fuzzy environment is $T = 5$ and cloud index $I_c = 0.08$, which proves that ambiguity associated with cloud fuzzy environment is less than in the fuzzy environment.

VI. Sensitivity Analysis

Sensitivity analysis under different environments is conducted by changing one of , θ_0 , δ, A , $h_r, d_r, p,\ s$ and keeping others parameters fixed.

Table 2: Impact of θ_0 on optimal cost under different environments

Change value		Crisp Model			Fuzzy Model			Cloud Fuzzy Model		
		t_1^*	ξ^*	TIC^*	t_1^*	ξ^*	$\widetilde{TIC_f}^*$	t_1^*	ξ^*	$\widetilde{TIC_c}^*$
θ_0	0.30	3.1	1.64	1321.57	3.23	1.82	1246.21	3.39	2.10	1173.26
	0.25	3.19	1.72	1292.32	3.31	2.04	1183.05	3.46	2.26	1119.71
	0.15	3.32	1.89	1259.15	3.39	2.22	1056.31	3.55	2.49	1010.23
	0.10	3.39	1.96	1207.26	3.45	2.29	1002.53	3.63	2.61	963.57

Fig. 2 Impact of θ_0 on Total inventory Cost under different environments

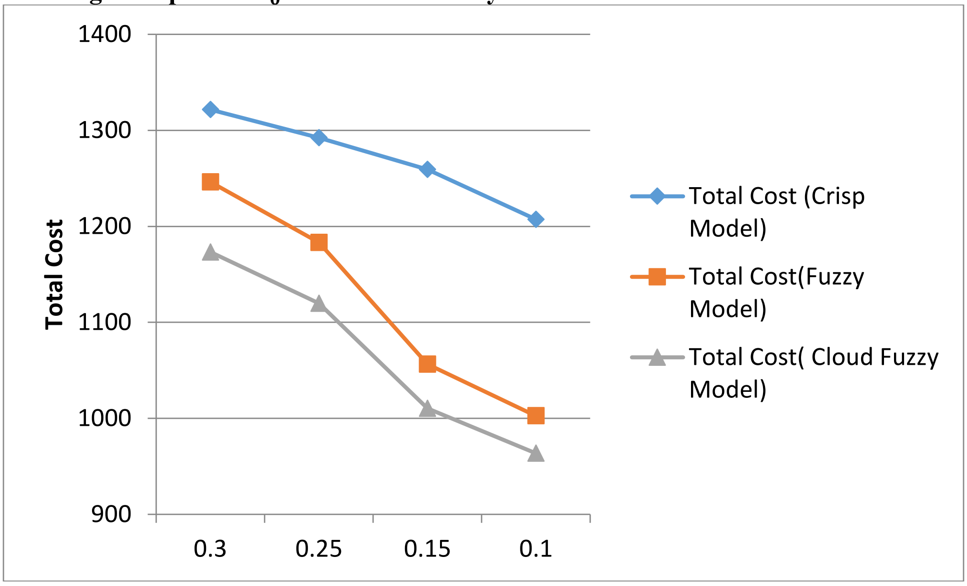


Table 3: Impact of δ on optimal cost under different environments

Change value		Crisp Model			Fuzzy Model			Cloud Fuzzy Model		
		t_1^*	ξ^*	TIC^*	t_1^*	ξ^*	$\widetilde{TIC_f}^*$	t_1^*	ξ^*	$\widetilde{TIC_c}^*$
δ	0.7	3.38	1.98	1208.42	3.46	2.3	1047.25	3.64	2.62	985.47
	0.6	3.31	1.87	1269.76	3.41	2.25	1139.22	3.56	2.50	1059.36
	0.4	3.18	1.73	1297.47	3.32	2.14	1194.65	3.47	2.29	1120.39
	0.3	3.09	1.61	1345.92	3.25	1.95	1216.26	3.41	2.06	1194.14

Fig. 3 Impact of δ on Total inventory Cost under different environments

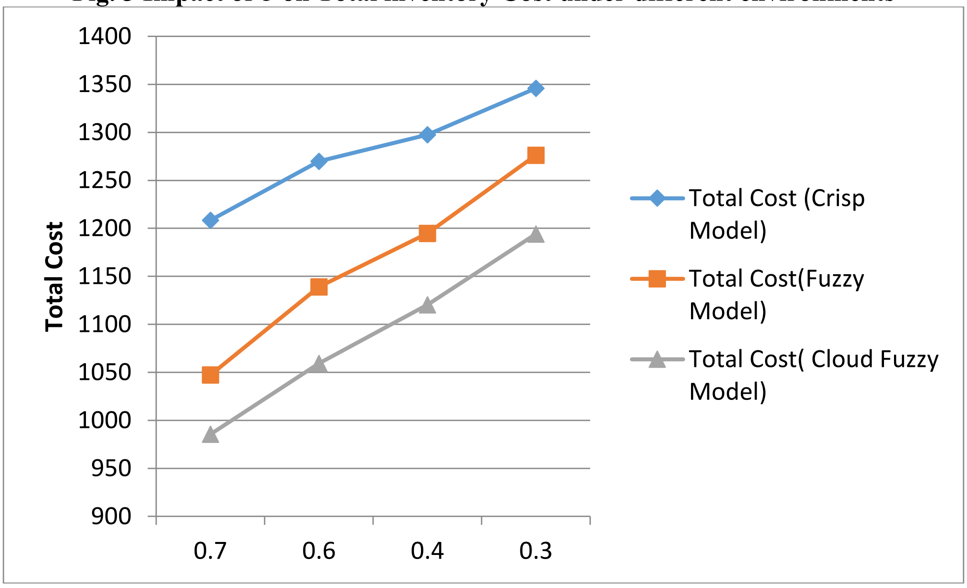


Table 4: Impact of A on optimal cost under different environments

Change value		Crisp Model			Fuzzy Model			Cloud Fuzzy Model		
		t_1^*	ξ^*	TIC^*	t_1^*	ξ^*	$\widetilde{TIC_f}^*$	t_1^*	ξ^*	$\widetilde{TIC_c}^*$
A	150	3.28	1.95	1310.21	3.36	2.22	1153.50	3.52	2.52	1126.83
	125	3.28	1.88	1298.53	3.36	2.15	1126.33	3.52	2.47	1089.65
	75	3.28	1.69	1263.45	3.36	1.93	1067.36	3.52	2.35	1027.76
	50	3.28	1.51	1236.76	3.36	1.87	1027.97	3.52	2.29	982.23

Fig. 4 Impact of *A* on Total inventory Cost under different environments

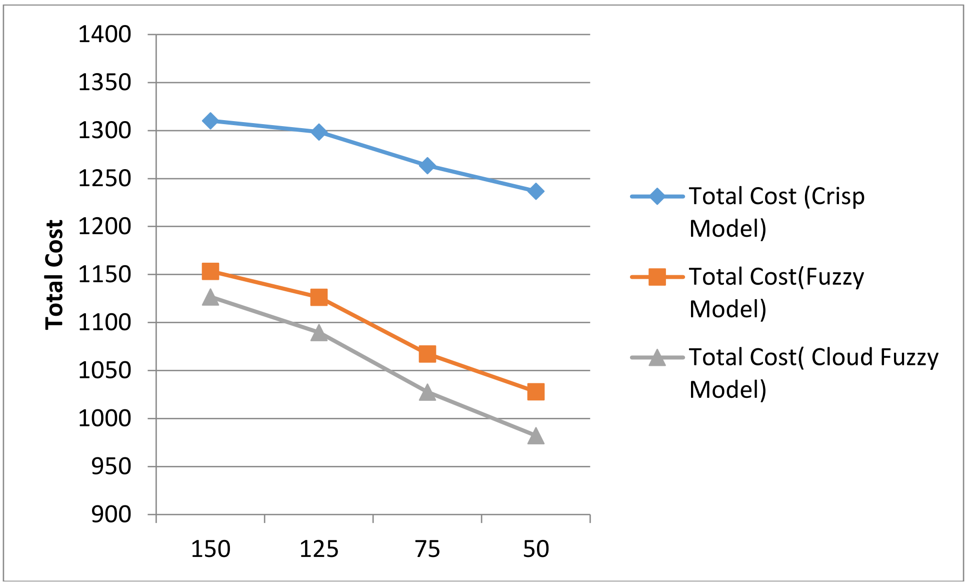


Table 5: Impact of h_r on optimal cost under different environments

Change value		Crisp Model			Fuzzy Model			Cloud Fuzzy Model		
		t_1^*	ξ^*	TIC^*	t_1^*	ξ^*	$\widetilde{TIC_f}^*$	t_1^*	ξ^*	$\widetilde{TIC_c}^*$
h_r	3	3.23	1.94	1334.26	3.31	2.23	1191.62	3.45	2.53	1136.37
	2.5	3.26	1.87	1296.87	3.33	2.16	1154.41	3.49	2.48	1102.46
	1.5	3.29	1.68	1258.27	3.38	1.94	1085.87	3.55	2.36	1022.39
	1	3.31	1.52	1247.60	3.41	1.88	1032.31	3.58	2.31	996.81

Fig. 5 Impact of h_r on Total inventory Cost under different environments

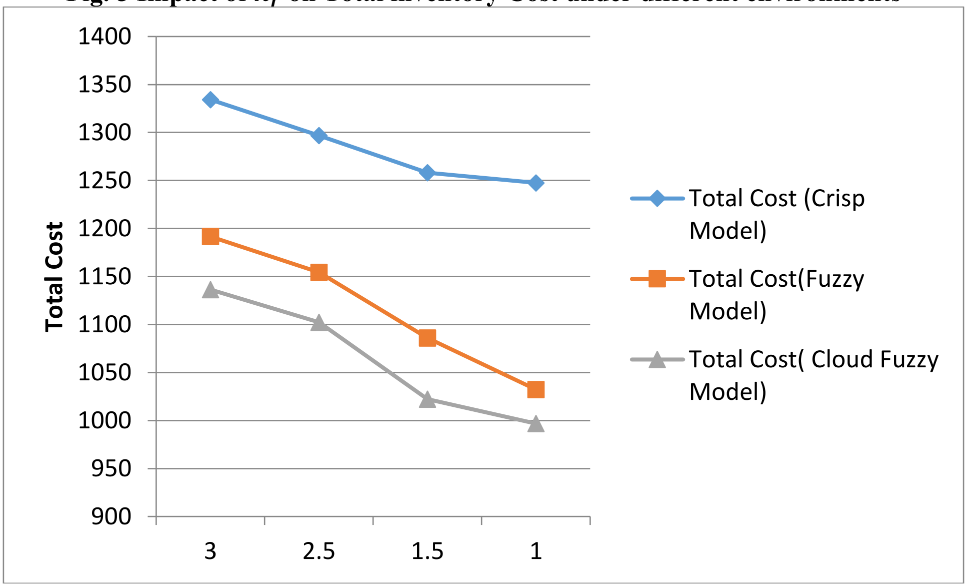


Table 6: Impact of d_r on optimal cost under different environments

Change value		Crisp Model			Fuzzy Model			Cloud Fuzzy Model		
		t_1^*	ξ^*	TIC^*	t_1^*	ξ^*	$\widetilde{TIC_f}^*$	t_1^*	ξ^*	$\widetilde{TIC_c}^*$
d_r	7	3.25	1.93	1356.29	3.32	2.24	1196.54	3.46	2.55	1148.32
	6	3.27	1.86	1306.31	3.34	2.17	1173.87	3.48	2.49	1119.71
	4	3.29	1.67	1276.11	3.39	1.95	1092.46	3.54	2.37	1047.26
	3	3.33	1.53	1256.74	3.42	1.89	1053.19	3.57	2.33	1024.47

Fig. 6 Impact of d_r on Total inventory Cost under different environments

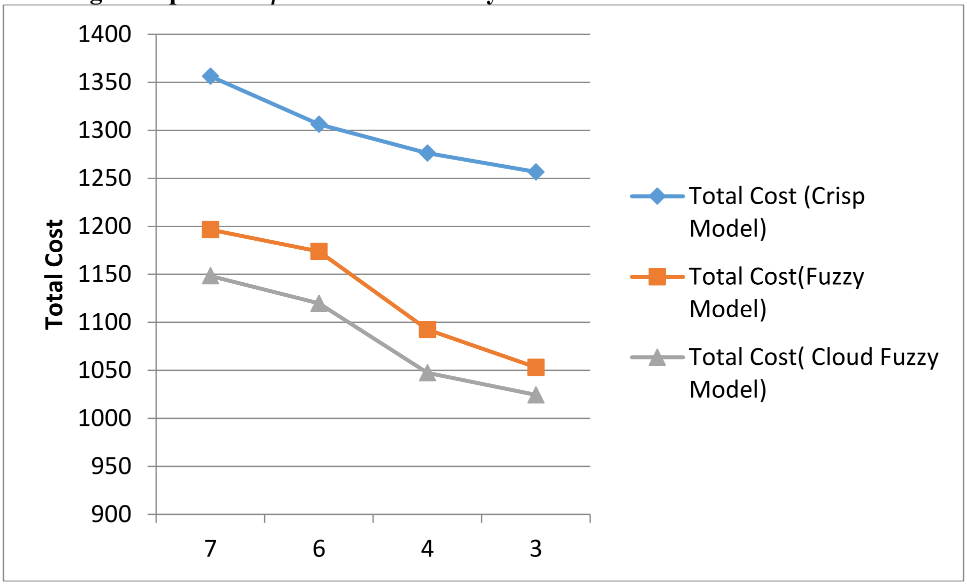


Table 7: Impact of p on optimal cost under different environments

Change value		Crisp Model			Fuzzy Model			Cloud Fuzzy Model		
		t_1^*	ξ^*	TIC^*	t_1^*	ξ^*	$\widetilde{TIC_f}^*$	t_1^*	ξ^*	$\widetilde{TIC_c}^*$
p	19	3.22	1.39	1331.98	3.31	1. 68	1213.09	3.45	2.01	1148.47
	17	3.27	1.45	1293.23	3.33	1.72	1155.27	3.49	2.18	1106.30
	13	3.31	1.79	1257.58	3.38	2.16	1096.75	3.55	2.49	1039.35
	11	3.38	1.91	1246.27	3.41	2.31	1031.27	3.58	2.57	979.19

Fig. 7 Impact of p on Total inventory Cost under different environments

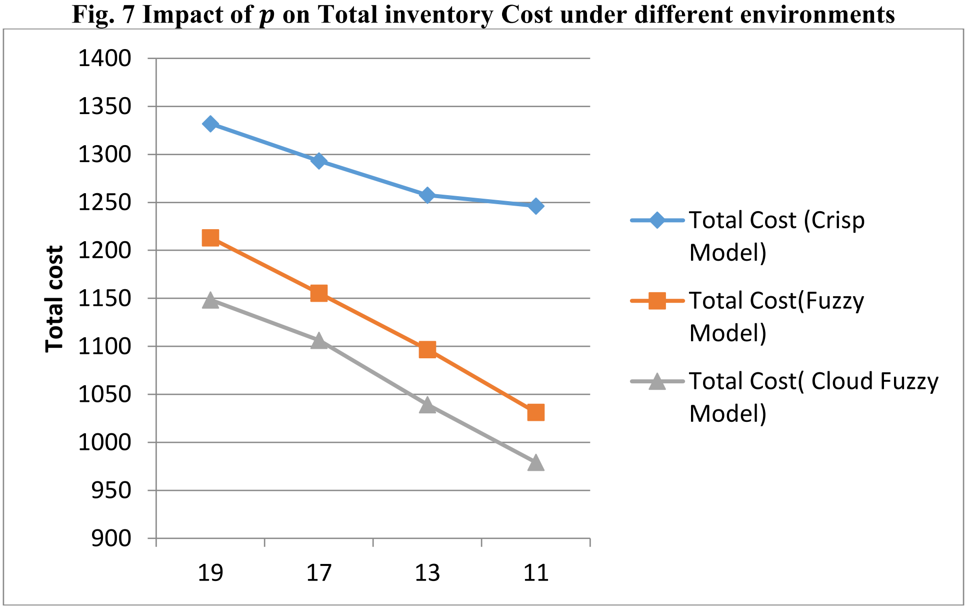
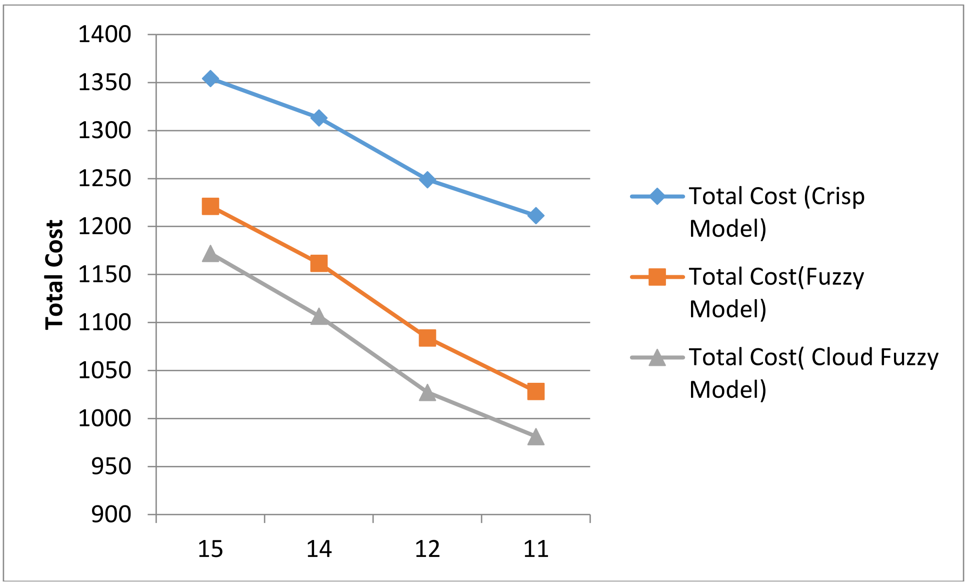


Table 8: Impact of s on optimal cost under different environments

Change value		Crisp Model			Fuzzy Model			Cloud Fuzzy Model		
		t_1^*	ξ^*	TIC^*	t_1^*	ξ^*	$\widetilde{TIC_f}^*$	t_1^*	ξ^*	$\widetilde{TIC_c}^*$
s	15	3.32	1.95	1354.29	3.42	2.45	1221.19	3.56	2.78	1172.02
	14	3.29	1.88	1313.23	3.39	2.27	1161.67	3.48	2.57	1106.57
	12	3.24	1.37	1248.88	3.32	1.70	1083.89	3.46	2.01	1027.19
	11	3.22	1.11	1211.36	3.29	1.59	1028.27	3.42	1.78	981.43

Fig. 8 Impact of s on Total inventory Cost under different environments



VII. Observations

It is observed from the tables (2) – (8) that:

i. With the increase (or decrease) of θ_0 , A , h_r, d_r, p, s, the total inventory cost under different environments TIC, TIC_f and TIC_c increases (or decreases) monotonically. Further, TIC, TIC_f and TIC_c are highly sensitive towards the parameters θ_0, h_r, d_r, p, s but moderately sensitive towards A.

ii. For different environments, with the decrease (or increase) of δ, the total inventory cost TIC, TIC_f and TIC_c increases (or decreases) monotonically. Further, TIC, TIC_f and TIC_c are moderately sensitive to the parameter δ.

iii. When parameters δ , A , h_r, d_r, p, s increase, preservation technology investment cost ξ increases (for the three models). With the decreasing values of the parameter θ_0, preservation technology investment cost ξ increases (for the three models). The preservation technology investment cost ξ is moderately sensitive to θ_0, δ , A , h_r, d_r, p, s.

iv. Following the increase of parameters δ, s, the timew period t_1 increases (for the three models). However, when the parameters θ_0, h_r, d_r, p decrease, the time period t_1 increases (for the three models). Particularly the production period t_1 changes nothing when the parameter A increases or decreases (for all models).

VIII. Conclusion

The proposed model offers a realistic and adaptable framework for managing blood inventory systems, addressing both the perishable nature of blood and the uncertainty in its demand. By employing fuzzy and cloud fuzzy environments, the model captures the ambiguity inherent in medical supply chains more effectively than traditional crisp models. The integration of preservation technology cost as a control variable introduces a practical trade-off between operational cost and blood wastage, highlighting the importance of investing in infrastructure to extend shelf life. The non-linear, two-variable optimization provides a flexible yet robust structure for identifying the cost-optimal cycle time and preservation investment. The use of Yager's ranking index and α-cut methods for defuzzification ensures that decision-makers are supported with actionable insights under uncertainty. In application, this model can greatly benefit blood banks, hospitals, and healthcare policymakers aiming to reduce costs, minimize blood wastage, and ensure timely availability of blood products. Future extensions could explore multi-item scenarios**,** different blood types, and the impact of random supply disruptions to enhance the model's utility in real-world scenarios.

IX. Future Work

In turn, future research on data driven strategies of efficient blood supply chain management in hospitals will cover several crucial issues aimed to achieve greater efficiency and resilience. Among them, the introduction of advance machine learning algorithms and Artificial Intelligence (AI) to assist in improving the accuracy of prediction of demand and optimizing the logistics are one key area. These technologies can process complex, real-time data to predict demand patterns, detect anomalies and make adaptive strategies recommendations in emergency situations.

Another important direction is development and setup of blockchain based frameworks for supply chain transparency and traceability. With blockchain, data security is improved and trust among stakeholders is established, improving collaboration and accountability between stakeholders increase.

Future work should examine the use of the Internet of Things (IoT) to monitor conditions during blood storage and transportation. Sensors that are at IoT can offer real time updates on temperature, location and other key parameters providing guarantees that safety standards are being met and that wastage is being minimized.

Another promising area is for the implementation of decision-support systems for hospitals and blood banks. Actionable insights, arising out of these systems can be used to manage inventory, plan logistics, and allocation of resources for better supply chain efficiency.

Studies can be done looking at the socio-economic impact for those taking up data driven strategies in the low resource part of the world and creating a level playing field when it comes to accessing the most advanced solutions everywhere. But his directions will mean innovation and a more resilient healthcare system.

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