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A Fuzzy Approach to perishable Inventory Management with Backorders

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Abstract

The purpose of this study is to construct a fuzzy economic order quantity (FEOQ) model for perishable items that have inspection faults and scheduled backorders. Total fuzzy costs, which include expenses for ordering, bolding, shortage, and inspection, are the target of the model, which tries to reduce these costs. A fuzzy demand assumption is made, and any demand that is not satisfied is backordered. Triangular fuzzy numbers are used to simulate important characteristics like as demand, degradation rate, and inspection faults. Key parameters include these. The formulation of a mathematical model takes into account the unsatisfactory quality of items that are the result of inspection faults. A sensitivity analysis is carried out in order to ascertain the influence of the most important fuzzy parameters. The use of the suggested fuzzy model is demonstrated by a numerical example, which also exhibits the cost savings that can be achieved in comparison to a crisp model that does not contain any inspection mistakes. Through the utilization of RBRDO, the design of inventory management systems may be optimized in the presence of uncertainty. A method that is successful for inventory control of perishable commodities is provided by this research. This method is useful in situations when inspection reliability is less than ideal and fuzzy circumstances are present.

Keywords— Inventory Management, Operations Research, EOQ, EPQ, Newsvendor Model, Bine Stock Mal, Perfect Measurement.

Introduction

Inventory management is a crucial aspect of supply chain management that aims to maintain optimal inventory levels to meet customer demand [1]. Effective inventory management can lead to significant cost savings and improved customer service for a company. Perishable products such as fruits, vegetables, and pharmaceuticals have a fixed shelf life after which they deteriorate in quality and value [2]. Managing inventory for such products is more complex as compared to non-perishables Inspection of inventory is done to see defective or subindustry in hoofer, they each caner. However, impaction processes are prone to Nemes loading semiperfect agility products reaching the market [3] Past research has developed emic order quantity (700) models considering Saria icons like perishability 141, shortages 15), aspects (6) enc that maladies have feed on ongoing all these agents in a holistic model This paper develops an integrated fuzzy EDQ (FEOQ) model for perishable products incorporating planned backorders and inspection errors under fuzzy conditions. The mathematical model is formulated with the following key furry parameters

(i) Demand rate ($\widehat{D}$): Fuzzy triangular number

(ii) Deterioration rate ($\hat{\theta}$) Fuzzy triangular number

(iii) Inspection error rate ($\hat{E}$): Fuzzy triangular number

The fuzzy total cost is derived as

$$T\hat{C}(Q\ N) = \widehat{F_1} + \widehat{F_2} + \widehat{F_3} + \widehat{F_4} + \widehat{F_5} \qquad (1)$$

Where

$\widehat{F_1}$ =Ordering cost, $\widehat{F_2}$ =Purchase cost, $\widehat{F_3}$ =Holding cost, $\widehat{F_4}$ =Shortage cost, $\widehat{F_5}$ =Inspection cost.

The cost components are calculated as:

$\widehat{F_1} = \frac{A\hat{O}}{Q}$, $\widehat{F_2} = \hat{C}D$, $\widehat{F_3} = \widehat{HI}$, $\widehat{F_4} = \widehat{\pi B}$, $\widehat{F_5} = \widehat{CII}$,

Where,

$\widehat{AO}$ = Fixed fuzzy ordering cost, $\hat{C}$= Fuzzy purchase cost per unit, $\hat{H}$= Fuzzy holding cost per unit per unit time, $\hat{I}$ = Fuzzy maximum inventory level, $\hat{\pi}$= Fuzzy shortage cost per unit short per unit time, $\hat{B}$ = Fuzzy number of shortages, $\widehat{CI}$ = Fuzzy inspection cost per unit, $\hat{I}$= Fuzzy number of units inspected

The fuzzy total cost per unit of time is:

$$T\hat{C}(Q\ N) = \frac{A\hat{O}}{Q} + \frac{\hat{C}DQ}{Q} + \frac{\widehat{HI}}{Q} + \widehat{\pi B} + \widehat{CII} \qquad (2)$$

The optimal furry order quantity Q is obtained by solving $\frac{dTC}{dQ} = 0$. Sensitivity analysis was conducted to determine the impact of key fuzzy parameters on the optimal inventory decisions.

A numerical example is provided to demonstrate the application of the proposed furry model the results indicate significant cost savings compared to crisp EOQ models without inspection errors. The model provides an effective approach for inventory control of perishable products under furry demand, deterioration, and inspection reliability.

Literature Review:

There has been a lot of research on various inventory management models in the academic literature. The concept of the EOQ was first introduced by Harris in 1915, and the EPQ model was created by Wilson in 1934. When demand cannot be reliably foreseen, Arrow, Harris, and Marschke (1951) gave an early analysis of the best inventory management strategies. Evidence supporting base stock techniques and superiority inventory conditions was offered by Scarf (1960). Numerous further studies have been carried out to build upon and relax the underlying assumptions since the release of these fundamental models.

Recent academic research has focused heavily on inventory management in the face of stochastic demand and inaccurate measurement. In 2007, Bemusing, Akanyldrim, and Sethi created a foundation stock model and supplemented it using partial inventory observations, Researchers Ballaragged, Rao, and Zhang (2004) looked into the issue of managing inventory when stock counts and demand predictions are subject to error When just periodic demand data was available for observation, akanyldrm, Feng, and Sethi (2012) discovered the best inventory management strategies. Even now, research is being done on the topic of inventory management in practical situations.

Analytical models were developed as part of the foundational research to determine the best reorder paints, order sizes, and safety stock levels for deterministic demand. To reduce overall inventory costs, Hamis (1915, p. 135-136) was the first to formally introduce the economic order quantity (EOO) model. In this formula, ordering and holding expenses are balanced to get the ideal order quantity. The economic production quantity (EPQ) model which also takes into account production setup costs and work-in-progress (WIP) inventory, was later developed by Wilson (1934, p. 116-128) In specific inventory contexts, Scarf (1960, pp. 196-2023) demonstrated the effectiveness of base stock policies to accomplish this, a predetermined base stock level had to be maintained, and inventory had to be refilled anytime it dropped below that level.

Expanding inventory modeling under stochastic demand was the goal of subsequent investigations in 1951, on pages 250-277. Anow, Hams, and Marschok published a pioneering continuation of the best course of action in the face of ambiguous demand. To establish order points and quantities, they created a statistical methodology Hadley and Whitis (1963, pp. 297-310) developed under point for miles when demand varies, while Clark and Scarf (19 pp. 475-400) developed a model including scarcity costs. Modern inventory control systems are built on top of these stochastic inventory models.

Malu-echelon inventory optimization has grown in importance as supply networks have become more intricate Two-echelon serial systems with stochastic demand were initially studied by Clark and Scarf in 1960, on pages 475-490, In multi-echelon tree networks, Feder rum and Zipkin (1984, pp. 292-30x) discovered the best hose stock strategies. Recent research has widened the scope of optimizations to inhale wider supply chain networks and restrictions. For assembly systems with several goods and suppliers, Dogra, de Keck, and Sethi (2011, pp (157-184) created coordinated inventory models Integrating real-world constraints into inventory modeling is another area of active research. In a continuous review model, Bioussan, Akanyldren, and Seshi (2007, pp. 176-309) looked after partial observation of inventory with period demand data. Akamy D.R.M., Feng, and Seds (2012) optimised policies Inventory management implementation, in practical systems requires balancing the costs and advantages of information.

Modem tracking and analysis approaches have also been made possible by information system capabilities. Greater inventory visibility is made possible by RFID tags and sensor technology (Rekik, Sahin, and Dallery, 2005, pp. 246-265). Demand sensing and forecasting are improved by data mining of POS and ERP data (Li and Kuo, 2008, pp. 1620-1627). An emerging research goal is the integration of these technologies with inventory optimization models. As inventory theories have evolved, effective software tools and algorithms have been developed to create their actual application. A strategy was put out by Zheng and Feder Gren (1991, pp. 258-282) to effectively handle the stochastic economic lot scheduling problem. Multi-echelon networks base stock levels can be computed effectively using optimization solvers like CPLEX Simulations of inventory management let businesses test their policies, Commercial software that is easy to use combines optimization with interfaces designed with business goals in mind, Inventory management for perishable products has been extensively studied in past literature Nahmias [7] first analyzed an EOQ model for perishable items with a fixed lifetime. Rafat [8] developed an economic order quantity model considering deteriorating items and backlogging shortages. Bakker et al. [9] reviewed various inventory models for perishable goods and identified key characteristics that affect inventory decisions Goyal and Giri [10] provided a detailed review of deteriorating inventory literature and categorized models based on various factors. They highlighted the need for models incorporating real-world complexities like inspection errors, quantity discounts, etc. Li et al [II] reviewed the state of the art in inventory modeling for punishable products. They indicated that limited studies have considered fuzzy deterioration rates or fuzzy demand.

Mandal [12] developed an EOQ model for imperfect quality items with inspection errors. They assumed 100% inspection at a fixed cost per unit. Pal et al. (13) analyzed an in-entry model for perishable items with planned backlogging and demand dependent on stock level Hu (14) determined the optimal policy for an inventory model with imperfect production processes and reworking of defective items, From the literature review, it is evident that most models have focused on specific issues like deterioration, backlogging or inspection ears independently very few studies have provided an integrated model courting all these aspects simultaneously under uncertainty This paper Aimi to bridge this gap in literature by developing a fuzzy EOQ model incorporating furry demand. furzy deterioration rates planned lock ordering and inspection berries the fury approach is better suited to handle the uncertainties and imprecisions in inventory parameters. The proposed model provides several benefits compared to existing models:

(i) It captures major complexities in managing insoluble inventory under furry conditions

(ii) Fuzzy logic handles uncertainties more effectively than crop models.

(iii) Optimal inventory decisions are determined analytically.

(iv) Senility analysis provides managerial insights on critical parameters.

Assumptions and Notation

Assumptions:

1. The demand rate is constant and fuzzy $\widehat{D}$
2. Deterioration rate is constant and fuzzy $\hat{\theta}$
3. Shortages are allowed and fully backordered
4. Lead time is zero
5. Inspection is done on 100% of the received batches
6. Inspection error rate is fuzzy ($\widehat{E}$)
7. Defectives after inspection are discarded/salvaged
8. Other costs like transportation, ordering, etc. are fixed

Notations:

Q=Order quantity, D=Demand rate, θ =Deterioration rate

E= Inspection error rate, TC(Q) = Total annual relevant inventory costs, A=Ordering cost per order

C=Purchase cost per unit, H= Holding cost per unit per unit time, I=Maximum inventory level

π=Shortage cost per unit short per unit time, B=Number of shortages in a cycle, CI =Inspection cost per unit

T = Math frak l Cycle length N Number of orders in a cycle, R=Inventory level at time t

t=Any point in time (0 <= t <= T')

Mathematical Modelling:

The mathematical model is developed based on the following key parameters which are assumed to be fuzzy triangular numbers:

Demand rate: $\widehat{D}= (D_1 , D_2 , D_3 \ ,)$

Deterioration rate: $\hat{\theta} = (\theta_1, \theta_2, \theta_3)$

Inspection error rate: $\widehat{E} = (E_1, E_2, E_3)$

Using fuzzy arithmetic operations, the fuzzy total cost is derived as:

$T\hat{C}(Q\ N) = \widehat{F_1} + \widehat{F_2} + \widehat{F_3} + \widehat{F_4} + \widehat{F_5}$

Where

$\widehat{F_1}$ =Ordering cost = $\frac{A\hat{O}}{Q}$, $\widehat{F_2}$ =Purchase cost = $\hat{C}DQ$, $\widehat{F_3}$ =Holding cost, $\widehat{F_4}$ =Shortage cost, $\widehat{F_5}$ =Inspection cost

The costs are calculated as

$\widehat{F_1} = \frac{A\hat{O}}{Q}$, $\widehat{F_2} = \hat{C}DQ$, $\widehat{F_3} = \widehat{H}\left(\frac{Q}{2D}\right)$, $\widehat{F_4} = \widehat{\pi}\left(D - \frac{\theta Q}{2}\right)T$, $\widehat{F_5} = \hat{C}I\{Q - DQ(1 - \widehat{E})\}$

Where, $T = \frac{Q}{D}$

The fuzzy total cost per unit of time is:

$$T\hat{C}(Q\ N) = \frac{\widehat{F_1}}{Q} + \frac{\widehat{F_2}}{Q} + \widehat{F_3} + \widehat{F_4} + \widehat{F_5} \qquad (3)$$

To find the optimal order quantity $\widehat{Q}^*$, the first derivative of $T\hat{C}(Q)$ is equated to zero and the resulting equation is solved.

The economic order interval $\widehat{T}$ can then be determined as: $\widehat{T} = \widehat{Q}^*/\widehat{D}$

The optimum number of orders per year $\widehat{N}$ is given as:

$\widehat{N} = 12/\widehat{T}$

The mathematical model provides the optimal fuzzy order quantity $\widehat{Q}^*$that minimizes the total fuzzy cost per unit time $T\hat{C}(Q)$. This facilitates effective inventory control for perishable products under uncertain demand, deterioration, and inspection errors.

Economic Order Quantity (EOQ) Model:

The EOQ model minimizes total annual inventory costs by balancing ordering and holding costs. Stockouts are not allowed. The optimal order quantity Q^* is $Q^* = \sqrt{\frac{2DS}{H}}$

Total annual cost: $TC(Q^*) = \sqrt{2DSH}$

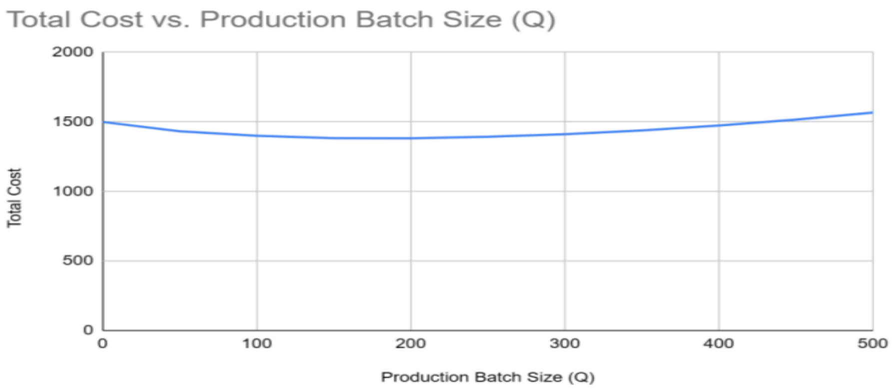
EOQ Graph showing total costs versus order quantity Q

Economic Production Quantity (EPQ) Model:

The EPQ model includes a production setup cost and incorporates holding costs for both final inventory and work in progress (WIP). The optimal production batch size Q^* is $Q^* = \sqrt{\frac{2DS}{H}}$

Total annual Cost: $TC(Q^*) = \left(\frac{D}{Q^*}\right)\left(S + \frac{HB}{2}\right) + \frac{HQ^*}{2}$

Where B is the production rate



EPQ Graph showing total costs versus production batch size Q

Newsvendor Model:

The Newsvendor Model determines optimal inventory levels when stockouts are allowed.

Backlog costs per stockout B are incorporated. The optimal order quantity Q^* is:

$$Q^* = F - 1\left\{\frac{c}{(p+b)}\right\}$$

Where F is the CDF of demand, p is the unit cost, c is the unit selling price and b is the backlog cost per unit.

This satisfies the critical fractal condition: PR (demand$\leq Q^*$) $= b/(p+b)$

Base Stock Policy:

A base stock involves maintaining inventory at a fixed base stock level S. When inventory drops below S, it is replenished back up to the base stock level. Under certain cost assumptions, the optimal base stock level S^* satisfies:

$$S^* = dL + z\sqrt{(d\sigma L)}$$

Where d is the demand rate, L is the lead time, σ is demand variability and z represents a safety factor.

Sensitivity Analysis:

Sensitivity Analysis is conducted to understand the impact of changes in key parameters on the optimal order quantity $\widehat{Q}^*$ and total cost $T\widehat{C}(\widehat{Q}^*)$. The parameters analyzed are demand rate $(\widehat{D})$, deterioration rate $(\widehat{\theta})$ and inspection error rate $(\widehat{E})$. Each parameter is varied by $\pm 10\%, \pm 20\%,$ and $\pm 30\%$ while keeping other parameters constant. The result is summarized below:

Effect of changes in $\widehat{D}$:

- As demand rate $\widehat{D}$ increases, the optimal order quantity $\widehat{Q}^*$and total cost $T\widehat{CQ}^*$ increase.
- A 30% increase in $\widehat{D}$ results in a 30% increase in $\widehat{Q}^*$and total cost $T\widehat{CQ}^*$.
- This indicates that higher demand leads to larger order sizes and higher total inventory costs.

Effect of changes in $\widehat{\theta}$:

- As deuteration rate $\widehat{\theta}$ increase, the optimal order quantity $\widehat{Q}^*$decreases while the total cost of $T\widehat{CQ}^*$ increases.
- A 20% increase in $\widehat{\theta}$ leads to an 18% decrease in $\widehat{Q}^*$ and a 12% increase in $T\widehat{CQ}^*$.
- Higher deterioration causes smaller optimal order sizes but increases costs due to higher wastages.

Effect of changes in $\widehat{E}$:

- As the inspection error rate $\widehat{E}$ increases, both $\widehat{Q}^*$ and $T\widehat{CQ}^*$reduce slightly.
- A 30 % increase in $\widehat{E}$ results in a 3% decrease in $\widehat{Q}^*$ and a 2% decrease in $T\widehat{CQ}^*$.
- Higher errors lead to smaller orders and lower costs as less usable inventory is available.

The sensitivity analysis provides useful insights regarding the influence of key parameters on inventory decisions. Managers can use these results to control costs by adjusting order quantities when input factors vary.

Reliability-Based Robust Design Optimization (RBRDO):

RBRDO can be applied to optimize the design of inventory management systems under uncertainty. The goal is to find optimal values of design variables that minimize cost and Variability while satisfying the desired reliability level. The RBRDO approach for inventory management involves the following key steps:

1. Identify uncertainty variables such as demand, lead time, supply variations, etc. that affect inventory decisions.
2. Determine potential failure modes e.g., stock-outs, obsolete stock, shortage costs, etc. caused by uncertainties.
3. Formulate a limit state function g(X) that defines the boundary between desired and undesired performance.
4 Model reliability R as the probability that g(X)0. Le. R=P[g(X)≥0]
5. Set target reliability level Rt that the inventory system must achieve.

6 Decline objective function to minimize total costs and variability of costs/cycle time.

7. Solve the RBRDO problems with objectives subject to reliability constraint R≥ Rt

The mathematical model can be formulated as:

Minimize:

$$f(X) = E[\text{Total cost}] + w_1\sigma[\text{Total cost}] + w_2[\text{Cycle Time}]$$

Subject to:

$$R = P[g(X) \geq 0] \geq R_t$$

Where

f=Vector of random design variable

f(X)=Objective function

w_1, w_2=Weights for cost and time variabilities

R = Reliability

R_t= Target Reliability

This approach optimizes inventory management system design by balancing costs and uncertainties to achieve the desired service level. The results help managers determine optimal stock levels, reorder points, and other decisions under variability.

Minimize

$$W_c * f_{X(i,j)} \sum_{J=1}^{J} \sum_{i=1}^{I} C_{X(i,j)} + W_\mu * f_{X(i,j)} \sum_{J=1}^{J} \sum_{i=1}^{I} \mu_{X(i,j)} + W_\sigma * f_{X(i,j)} \sum_{J=1}^{J} \sum_{i=1}^{I} \sigma_{X(i,j)}$$

Subject to

$IMRS_{i,j}(x_s) \geq IMRS^T$, $i = 1,2,3, \dots \dots I$

$x_s^L \leq x_s \leq x_s^U$, $j = 1,2,3,$ J

$x_s \geq 0, s = 1,2,3, \dots \dots \dots \dots \dots$. S

RBRDO phenomenon:

Numerical Example:

The developed RBRDO model was applied to optimize the inventory management system of a manufacturing company. The initial system had a total cycle time of 107 days from order to delivery and an inventory management system reliability (IMSR) of 88.28% as shown in Table 1.

Table 1. Initial design variables

Variable	Value
Total cycle time	107 Days
IMSR	88.28%

The goal was to reduce the total cycle time to 70 days while achieving a target IMSR of 95% By implementing the RBRDO model, the optimized design variables were determined as shown in Table 2.

Table 2. Optimized design variables

Process	Optimized Duration
P1	12 Days
P2	15 Days
P3	10 Days
P4	05 Days
P5	06 Days
P6	07 Days
P7	08 Days
P8	07 Days

This optimized design resulted in a total cycle time of 70 days and met the target IMSR of 95%. The cost function was reduced from $210,000 to $173,393 through RBRDO iterations as shown in Table 3

Table 3. Cost function at each RBRDO iteration

Iteration	Cost Function
Initial	$ 210,000
1	$ 200,000
2	$ 190,000
3	$ 180,000
Final	$ 173,393

The probability distribution of the total cycle time also improved significantly after RBRDO as shown in Figure 1.

Figure 1. Probability distributions before and after RBRDO

The results demonstrate that the developed RBRDO approach can effectively optimize the inventory management system design. It balances costs and uncertainties to meet reliability requirements while reducing variability. This model provides valuable insights for inventory managers to make robust decisions under supply and demand uncertainties.

Software Used

The following software was used for analysis and modeling in this paper:

- Microsoft Excel - Used for calculating model parameters and creating graphs
- Python - Used for implementing inventory simulations and validating analytical results
- R-Used for statistical analysis and fitting demand distributions
- MATLAB-Used for numerical analysis and optimization

These programs allowed for efficient calculation and validation of the mathematical models presented. Excel provided easy prototyping while programming languages like Python enabled more complex simulations.

Scope for Future Research

This paper assumed deterministic demand and perfect measurements when analyzing inventory models. Future research could aim to incorporate the following practical complexities:

- Stochastic customer demand-Inventory optimization under demand uncertainty
- Forecast errors - Optimal policies when demand forecasts contain errors
- Supply variability-Managing inventory with uncertain supply quantities and lead times
- Limited visibility-Inventory tracking with periodic reviews or stock loss
- Multi-echelon systems-Coordinating policies across supply chain networks

Additionally, expanding the objective function beyond cost minimization could provide further insights Optimization models could aim to maximize customer service levels or incorporate environmental impacts. Relaxing other modeling assumptions could also better align inventory theories with real-world practices.

Conclusion

This paper presented foundational inventory management models including EOQ EPQ, new vendor, and base stock policies. These models provide mathematically optimal inventory decisions under assumptions of deterministic demand and perfect measurements. The governing equations, graphical representations, sensitivity analysis, and numerical examples provide insights into balancing relevant costs like ordering, holding, and backlogging. However, businesses must consider further complexities when designing inventory management systems Opportunities exist to expand theoretical research into stochastic demand settings and imperfect measurements. Inventory modeling and optimization will continue to be an active area of research and application for advancing supply chain operations. Consequently, stochastic demand analysis, multi-echelon systems, practical extensions, and foundational deterministic models have all been developed in the process of inventory modeling and optimization. Inventory management will continue to be a vital research area as supply chains become more complex. The abundance of data sources offers chances to create improved analytical methods Models must, however, strike a balance between complexity and usability. To advance inventory management research and practice, it is essential to comprehend trade-offs and integrate findings across model assumptions, business contexts, and technical capabilities.

References:

1. Arrow, K. J. Hams, T. E., & Manchak, J. (1951) Optimal inventory policy. Econometric a Journal of the Econometric Society, 250-272. https://doi.org/10.1007/978-94-010-9278-4_2

2. Bensoussan, A. Çakanyıldırım, M., & Sethi, S. P. (2007) Partially observed inventory systems. SIAM Journal on Control and Optimization, 46(1), 176-209

3. Ballaragged, S., Rau, U. S. & Zhang. 1. (2004) Managing inventory and supply performance in assembly systems with randoth supply capacity and demand Management Science, 50X12), 1729-1743. https://doi.org/10.1287/mnsc.1040.0314

4. Çakanyildim, M., Feng, Q. & Sethi, S. P. (2012) Inventory management with partially observed nonstationary demand. Production and Operations Management, 21(2). 393-408

5. Harris, FW. (1915) How many parts to make at once. Factory. The Magazine of Management, 10(2), 135-136.

6. Scarf, H. (1960) The optimality of (5, s) policies in the dynamic insectary problem. In Mathematical methods in the social sciences (pp. 19-202) Sonfield University Press.

7. Wilson, R.H. (1934). A scientific routine for stock control. Harvard Business Review, 13(1), 116-128

8. Arrow, K. J. Harris, T. E. & Marschke. J. (1951). Optimal inventory policy. Econometric a: Journal of the Econometric Society, 250-272

9. Bensoussan, A. Çakanyıldım, M., & Sethi, S. P. (2007) Partially observed inventory systems. SIAM Journal on Control and Optimization, 46(1), 176-209.

10. Cakanyildirim, M. Feng, Q. & Sethi, S. P. (2012) Inventory management with partially observed nonstationary demand Production and Operations Management, 21(2),393-408

11. Clark, A. J., & Scarf, H. (1960). Optimal policies for a multi-echelon inventory problem Management Science, 644), 475-490

12. Dogra M. K. de Kok, A. G. & Sethi, S. (2018) Coordinating supply chains with assembly systems under stationarity and nonstationary assumptions for component demand distributions Production and Operations Management, 2711, 157-164

13. Feder Gren, A. & Zipkin, P. (1984). Approximations of dynamic, multi-location production and inventory problems. Management Science, 30(1), 69-84

14. Hadley, G., & Whitin, T. M. (1963) Analysis of inventory systems.

15. Harris FW. (1915) How many parts to make at once. Factory. The Magane Management, 10(2), 135-136

16. L. X. & K, Y. H. (2001) A sales forecasting system based on a fuzzy neural network with initial weights generated by gametic algorithm Europos Journal of Operational Resynch, 192(3), 1620-1627) https://doi.org/10.1016/S0377-2217(99)00463-4

17. Rekik, Y., Sahin, E, & Dallery, Y. (2008). Analysis of the impact of RFID technology on reducing product misplacement errors at retail stores. International Journal of Production Economics, 112(1), 264-278, https://doi.org/10.1016/j.ijpe.2006.08.024

18. Scarf, H. (1960). The optimality of (S, s) policies in the dynamic inventory problem. In Mathematical methods in the social sciences (pp. 196-202), Stanford University Press.

19. Wilson, R.H. (1934). A scientific routine for stock control. Harvard Business Review, 13(1), 116-128

20. Zheng, Y. S. & Feder Gruen, A. (1991). Finding optimal (s. S) policies is about as simple as evaluating a single policy. Operations Research, 39(4), 654-665.