Mathematical Forum ISSN: 0972-9852

Vol. 31, 2023

Model with unsatisfactory quality items and random fuzzy Economic Order Quantity

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Received on: 16/06/2023

Accepted on: 03/09/2023

Abstract

In this study, the amount of bad goods in every lot is christened a random fuzzy variable, and the cost to set up each lot is studied as part of an economic order quantity (EOQ) problem. The examination budget of every unit article and the field budget of every unit article each day are separately referred to as "fuzzy variables." Using a chance fuzzy EOQ model, the projected long-run average profit is maximised. A particle swarm optimization (PSO) approach created continuously the random fuzzy (RF) reproduction is created because it is nearly impossible to discover an analytical technique for solving the given model. Ultimately, a numerical example demonstrates the design algorithm's usefulness.

Keywords: · Fuzzy model, Inventory, Probability Measurements, EOQ model

1. Introduction

Unique of the presumptions in the traditional EOQ model is that completely units restocked or created remain of high excellence (Waters 1994). Even so, subpar-quality items frequently show up in replenishment or production lots due to lax process control, natural calamities, harm or breakage in transportation, etc. As a result, when choosing an economical lot size, the cost associated with quality must be taken into consideration. Over the past 20 years, several scholars have created the EOQ and EPQ models with items of variable quality. Shafali et al. (2021) his paper explores a combined inventory model (IM) when the collapse rate shadows histrionic movement under conversation acclaim. Chaudhary et al. (2023) determine the model's robustness; sensitivity analysis has also been done on the effect ive parameters. Shafali et al. (2021) the focus of the study would be to identify different types of waste generated and to suggest ways as to what measures can be adopted to reduce waste and save the environment. De and Mahata (2019) discussed the cloud models, in combination with their new techniques, are a ways more profitable than deterministic models. Kumar et al. (2020) studied on the Inventory Control Policy aimed at Imperfect Manufacture Procedure on Numerous Demand. Kumar et al. (2020) optimised the batch size and backordering quantity to reduce the overall inventory cost. To optimise the lot size and backorder amount, numerical examples are employed. One is implementing Kwakernaak's fuzzy random theory (1978). A calculable function after likelihood space to the assortment of FV is what is devoted to by way of a RF variable. Thomas and Kumar (2022) in the context of single sampling plans with inspection mistakes, a fuzzy EOQ model is developed in this study. The model counts on misclassifications happening occasionally. We propose an inventory system in which orders are subjected to acceptance sampling, backorders are removed, and defectives are segregated from the stock. Poswal et al. (2022) the goal of the effort is to identify upcoming research recommendations and acquire an on-going, thorough assessment of the body of literature. In a time of limited resources, this review aids other scholars in formulating a conclusion. The other is Liu's proposed RF theory (2002a). A mapping from option planetary to a group of accidental variables is the description of a chance fuzzy variable. The estimation of the proportion of faulty goods in an inventory organization through products of variable quality is fully known, with the exception of the overall mean. Defective items may be included in each delivered lot. Due to a lack of trustworthy data, management can only designate a recess in which the indefinite mean is prospective to lay. It makes sense to describe the part of sub-standard products in each lot as a RFV if the mean value is given as a FV. In an inventory organization, the expressions "holding budget is possible amid 21 and 41% of element cost" and "system cost comes to an interlude thru an association degree" are frequently used to describe the inspection cost, operational expenses, and setup cost. It makes more sense to refer to these expenses as "relevant fuzzy variables." In fact, a number of scholars have raised the issue of cost in these areas. The initial expense, cost factors, and screening expense are all referred to as "fuzzy variables," and the proportion of faulty goods in every set is meant to be a random fuzzy variable. This study takes into account an inventory decision-making issue with products of partial quality. Maximizing the predicted long-run average profit is the goal of determining the appropriate lot size. One such article's remaining sections are divided into different sections: Section 2 has some introductory details. In Section 3, a RF EOQ model with items of varying quality is constructed. In Section 4, a PSO method is industrialised to address this issue by a random fuzzy model. A numerical example in Section 5 illustrates the design algorithm's performance.

2. Preliminaries

This section will discuss some ideas and findings about accidental fuzzy variables that are fuzzy. If is a nonempty established, P(Θ) is its power established, and Pos stands an option amount, before let (Θ, P(Θ), Pos) remain a likelihood interplanetary. The trustworthiness metric on behalf of A is given via Cr{A} = $\frac{1}{2}$ (Pos{A} + 1 Pos{Ac}), if A stays an element in P. Liu (2005, 2006) look at the believability metric in depth.

Definition 1. (Liu, 2005) A uncertain variable is described as a purpose since the set of actual numbers to the opportunity space (Θ,P(Θ), Pos). If ξ remains a fuzzy adjustable defined on (P(Θ), Pos), before μ(x) = Pos{ɵ ϵ Θ | ξ (ɵ) = x}, x ϵ is used to generate the probability measurement's membership function.

Definition 2 (Liu, 2005) Let's ξ represent a fuzzy inconstant in the galaxy of possibilities (P(Θ), Pos). If unique of the binary integrals is finite, the predictable assessment E[ξ] is distinct as

$$E[\xi] = \int_0^{+\infty} Cr\,\{\xi \geq r\}dr \text{ - } 0\ Cr\ \{\xi \geq r\}dr \qquad (1)$$

In specific, if is a nonnegative FV, E[ξ] = $\int_0^{+\infty} Cr\{\xi \geq r\}dr$.

Definition as 3 (Liu, 2006) If and solitary if

$$Pos\{\xi i \in Bi,\ I = 1, 2,..., n\} = \min Pos\{\xi_i \in B_i\} \qquad (2)$$

on behalf of sets of B1, B2,..., or Bn, the FV ξ1, ξ2,..., ξn remain supposed to remain independent.

Definition 4 (Liu, 2006) If besides individual if

$$Pos\ \{\xi i \in B\} = Pos\ \{\xi i \in B\},\ \text{and}\ \ i,j = 1, 2,..., n \qquad (3)$$

on behalf of one set B of fuzzy variables, then the FV are ξ1, ξ2,..., ξn are supposed to have the same distribution.

Definition as 5 (Liu, 2005) A RFV is a planning after the likelihood space (Θ,P(Θ), Pos) near a group of arbitrary variables, Some RFV that are widely used in applications are provided in the examples that follow.

Example 1, p: $\xi \sim u$ (p,p +1), wherever p stands a FV. Before, ξ stays a RFV with a "uniformly spread variable u (p,p +1)".

Example 2: Accept that Ϛ is a FV distinct in the likelihood space (Θ,P(Θ), Pos) and that is a RV. Following that, ξ = n+Ϛ remains a RFV distinct by $\xi(^{\theta})$ = n+Ϛ $(^{\theta})$,

Definition 6: Let B be a RFV and a Borel established of real statistics. The probability of a random fuzzy incident, B, stays then definite as

Ch(B) = sup Cr(A) inf (A) Pr(B), (4)

which is a function from [0, 1] to [0, 1].

Definition 7 (Li 2006): The RFV ξ1, ξ2,..., ξn distinct continuously the likelihood space (Θ,P(Θ), Pos) are supposed to stand self-determining if ξ1(ɵ),ξ 2(ɵ),..., ξn(ɵ) stand independent indiscriminate variables on behalf of every of the possibilities.

Definition 8 (Li & Liu, 2006)

$Ch(\xi \in B)(\alpha) = Ch\{n \in B(\alpha)$ (5)

the random fuzzy variables per the same dispersal, for each (0, 1) and Boral set B of real statistics.

Resolution 1: Let f remain a measurable function, and let and be two randomly distributed FV with the same distribution. Before, f() and f() are randomly circulated FV with the same distribution.

Definition 9 (Liu 2005) Let's start with a fuzzy RV. After that, assuming that at minimum individual of binary integrals is determinate, anticipated value E[ξ] remains defined as $E[\xi] = \int_0^{+\infty} Cr\ E[\xi(^{\theta})] \geq\ r\}\ dr - \int_0^{+\infty} Cr\ E[\xi(^{\theta})] \geq\ r\}\ dr$ (6)

3. **Model developments**:

Generally, the major goal of the EOQ model via defective substances is to regulate the best lot size at which the yield margin attains its highest level during the time frame. The notations that were rummage-sale in the paper remain following:

D	demand daily
x	lot size apiece cycle
c	buying price of all unit element
hi	holding cost of all unit element apiece day, i = 1, 2, ...
di	assessment cost of every unit element, i = 1, 2, ...
pi	percentage of faulty substances, i = 1, 2, ...
Ki	setup total, i = 1, 2, ...
Ti(x)	measurement of ith cycle, i = 1, 2, ...
Vi(x)	overall returns, i = 1, 2, ...
Ci(x)	overall cost, i = 1, 2, ...
Fi(x)	overall profit, i = 1, 2, ...

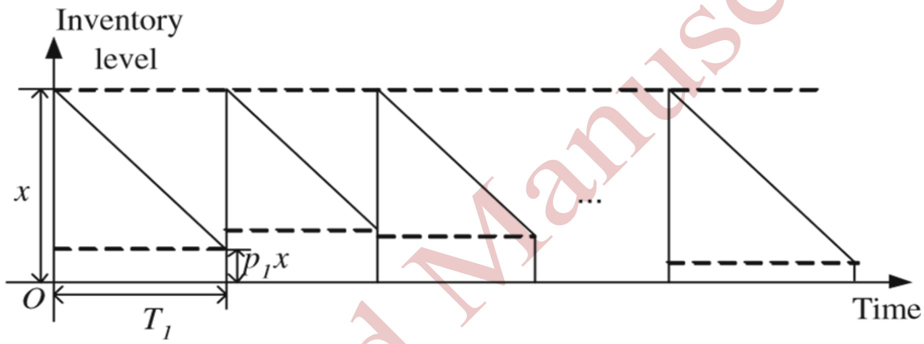

Fig. 1: Inventory level behaviour across the planned horizon

Cogitate an inventory organization in which products are removed from inventories by outside buyers and replaced by an external supplier. When the inventory equal drips to nil, an instruction is processed, and the replacement is transported right away at batch size x. The delivery time is also nil. Although the likelihood dispersal of the proportion of damaged goods is well recognized, their average is not. Each delivery lot may contain some products of different quality. As a result, it makes sense to refer to the proportion pi of damaged goods in the ith lot as a fuzzy RV. The maximum tolerance for the proportion of damaged products in every lot is 50%, that is, $0 \leq pi \leq \frac{1}{2}$; it was also assumed that pi, I = 1, 2,... remain distributed independently and identically. Given the deterministic demand D for high-quality items each day, a 100% examination of the lot is performed at a rapid pace to avoid a scarcity of excellent quality goods. The faulty products are reserved in stock up to the delivery of the subsequent delivery, after which they are sent back to the manufacturer at a rate of r each item. A common pattern of the inventory equal as period progresses is seen in Fig. 1. According to the relationship between r and c and s, the unit marketing price s of high-quality substances, unit frequent worth r of low-quality items, and the unit obtaining charge c of every single article are fixed for each lot. However, it is difficult to characterise the assessment cost di, holding cost hi, and start-up cost Ki accurately in qualitative terms. Therefore, it makes sense to refer to di, i = 1, 2,..., hi and Ki, i = 1, 2,... as nonnegative iid fuzzy variables. Furthermore, di, hi, Ki, and pi (i = 1, 2,...) are supposed to stay independent of one another and distinct on the likelihood space (P(Θ), Pos).

$V_i(x) = sx\,(1- p_i) + rxp_i,\ i= 1,2$ (7).

where i = 1, 2,... 8, and sx(1-pi) is the entire amount of high-quality products sold, whereas rxpi has been the amount of money paid to the manufacturer. The ith cycle's duration is

$Ti(x) = \frac{x(1-pi)}{D}$, where i = 1, 2 (8)

Additionally, the ith cycle's total cost is

$Ci(x) = Ki + cx + d_ix + \frac{1}{2}\ h_ix(1- p_i)\ Ti(x) + h_i,p_i,x,T_i(x)$, where i = 1, 2, (9)

Ki is In the same cycle, the overhead expenses for high-quality products are hi,x (1 pi) Ti(x), whereas those for low-quality products are hi,pi,x,Ti(x). Cx represents the expenses, cx the purchase price, dix the evaluation cost, and 1 2 hi,x(1 pi) Ti(x).The overall profit Fi(x) in the ith series dismiss stand expressed by way of an accidental fuzzy economic order quantity classical thru poor quality substances, as is evident from (7) through (9) 145. Fi(x)=Vi(x) - Ci(x)

$= \frac{x(s-c-d-\frac{K)}{x}}{(1-e)} + \frac{hx}{2}[(s-r)e)\text{- } k_1$ (10)

Ti(x), I = 1, 2,... are iid RF variables as a result of (8), Explanation 7, and Intention 1.Pi, i = 1, 2,... are thus iid RFV. Additionally, we can infer that Fi(x), I = 1, 2,..., stay iid RFV since (10), Definitions 7 and 8, and Proposition 1 since di, hi, and Ki, I = 1, 2,..., are each iid FV, and di, hi, Ki, and pi are independent of one another. Fi (x) and Ti (x) are not independent; rather, it is obvious that they are connected to pi. We evaluate the complete profit F1(x) and duration T1(x) in the initial cycle without losing generality, and we are aware that for every, E[F1(x)(ɵ)] and E[T1(x)(ɵ)] stand FV. They have the following values:

$E[F_1(x)(ɵ)] = \frac{x(s-c-d-\frac{K)}{x}}{(1-e)} + \frac{hx}{2}[(s-r)e) + Var[p] + e - 1)\ (s-r)E[p_1(ɵ_{4)}$ (11)

The corresponding values are

$$E[T_1(x)(\theta)] = \frac{x(1-E[p1(\theta)])}{D} \tag{12}$$

For ease of use, let 1 and 1 stand for E[F1(x)(ɵ)] besides E[T1(x)(ɵ)], individually. Next, we must

$$\frac{\xi_1}{n_1} = \left(\frac{D}{1-E[p1(\theta 4)]}\right)^{nt} = \left(s - c - d1(\theta 1) - \frac{K_{1(\theta_3}}{x}\right)^{nt} - (s-r)E[p_1(\theta_{4)} \tag{13}$$

For a given, p1(4) is a random variable, and d1(ɵ1), h1(ɵ2), and K1(ɵ3) are crisp integers because p1 is a haphazard fuzzy variable and d1, h1, and K1 are fuzzy variables. In order to make notation easier, we'll denote d1, h2, K3, and p as d, h, K, and p, individually. We also distinguish that

$$E[p^2] = Var[p] + (E[p])^2 \tag{14}$$

Everyplace Var[p] is p's adjustment. Additionally, use e to represent E[p] and think of p's expected value as a function defined on As a result, (13), where 1 is a purpose of e, dismiss be inscribed as f(e) = for a given.

$$f(e) = \frac{D(s-c-d-\frac{K)}{x}}{(1-e)} + \frac{hx}{2}[(s-r)e) + Var[p] + e - 1) \tag{15}$$

Furthermore,

$$\frac{dVar[p]}{de} = 0 \tag{16}$$

is present. Lemma 1 (Liu & Li, 2006) Let p remain a RV that has an expected value of e and accepts values in the range [a, b], nonetheless whose probability circulation is otherwise random.

Lemma 1 states that Var[p] e on behalf of a RV p with values in [0, 1] has an predictable assessment e and a modification Var[p].

$$Var[p] \leq e\left(\frac{1}{2} - e\right)^{nt} \tag{17}$$

Lemma 2 Let f(e) stand a purpose of e by the appearance (15), everyplace r, c, d, h, and K stay nonnegative real values. Then f(e) becomes smaller in relation to e. Because f(e) = 1.

$$\frac{df(e)}{de} = \frac{D(s-c-d-\frac{K)}{x}}{(1-e)} + Var[p] + e - 1) \quad (18)$$

Additionally, since 0 r c, 0 e 1 2, and D, x, d, h, and K stand nonnegative material values, it follows from (16)-(18) that df(e) de = D

$$\frac{df(e)}{de} = \frac{D(r-c-d-\frac{K)}{x}}{(1-e)} + \frac{hx}{2}[2e(1-e) + Var[p] + e - 1)$$

$$\frac{df(e)}{de} \leq \frac{D(r-c-d-\frac{K)}{x}}{(1-e)} + \text{1-e+p} \quad (19)$$

The evidence is complete because function f(e) is dwindling by deference to e. Because f(e) decreases with esteem to e, casual fuzzy restitution reward proposition (Zhao 2006) is now too believed on behalf of the situation in this work. Based on the characteristics of the accidental fuzzy restitution progression (Zhao 2006), we must

$$\lim_{t\to\infty} \frac{E\{\,the\ total\ profit\ in\ [0,t]\}^n}{t} = \frac{E[\xi 1]}{E[n1]} \quad (20)$$

where ξ1 and n1 are FV with values E[F1(x)(ɵ)] plus E[T1(x)(ɵ)], individually. A haphazard fuzzy EOQ model dismisses be created as surveys if the pronouncement maker wants to maximise predicted long-run typical profit, provided that:

$$\begin{cases} \max E\left[\frac{\xi 1}{n1}\right] \\ subject\ to: \\ x > 0, \end{cases} \quad (21)$$

where x is the choice variable.

Comment 1 If the cost parameters di, hi, and Ki in equations (8) as well as (10) decadent to sharp quantities d, h, and K, individually, proportion pi of damaged goods reprobates to a RV, I = 1, 2,..., then equation (20) convert to the conservative outcome in the stochastic circumstance,

$$\lim_{t\to\infty} \frac{E\{\,the\ total\ profit\ in\ [0,t]\}^n}{t} = \frac{E[F1(x)]}{E[T1(x)]} \quad (22)$$

Additionally, the form of the perfect (21) is changed to the subsequent:

$$\{\max(\text{ s-c-d-}\frac{K}{x} - \text{(s-r) E [p1]+}\frac{hx(E[p_1^2}{2D}] - 1) \quad (23)$$

where x is the deciding factor, It is obvious that

$$x^{*} = \sqrt{\frac{2DK}{h(1-E\,[p_1^2}} \tag{24}$$

is the only possible value for the objective meaning in model (23) to reach its maximum value. Additionally, (24) becomes the conventional EOQ formulation, x = 2DK h, if p1 = 0. The chief work of the planned model in this study contains fuzzy variables and a random FV, which is the primary distinction amid the random fuzzy record problem, defined overhead and additional inventory optimization glitches in the works. Due to the inability to determine the gradient of the impartial function then the difficulty in calculating the objective function's value for a given decision, this aspect is the main challenge encountered though cracking the model (21) using general approaches. In the following section, a hybrid intelligence algorithm motivation is created to explain the model that has been presented.

4. Hybrid intelligent algorithms

Aimed at broad decision-making difficulties in accidental fuzzy surroundings, Liu (2005) and Liu & Liu (2006) respectively, provide a range of random fuzzy probable assessment models (EVM) and random fuzzy DCP. Hybrid intelligent approaches that integrate the RFS and GA stay developed to address such mathematical modelling techniques. The problem being studied in this paper, however, has several aspects in common, including a single limitation and a decision variable. In command to answer the model (21), the RFS is combined with the PSO algorithm, which is then rummage-sale to find the best possible explanation. The RFS is used to figure out how much the target function is likely to be worth. This hybrid intelligent algorithm is developed in light of such characteristics.

Random Fuzzy Simulation

The RFS was first proposed by Liu and Liu (2006). Here, the objective purpose value is calculated using the random fuzzy simulation that follows. E s c d1 (1, 1), K1 (3, x s r) E[p1(4)] h1(2)x(E[p2 1(4)] plus1) 2D, For a given x, D 1E [p1(4)] in model (21). In the following sections, we'll refer to this objective function as E[f(x, d1, h1, K1, p1)].

Step 1: Determine k = 1 and λ = 0.

Step 2: Generate k in such a way that Pos(θ_k) > ϵ , wherever ϵ is a satisfactorily minor integer and vk equals Posk, i.e., θ_k = (ɵk1,ɵk2, k3, k4) from Θ.

Step 3: Run a Monte Carlo reproduction to estimate the anticipated significance of the haphazard variable f(x, d1(ɵk1), h1(ɵk2), K1(ɵk3), and p1(ɵk4), E[f(x, d1(ɵk1), h1(ɵk2), K1(ɵk3), and p1(ɵk4)].
Step 4: Repeat Step 2 per k + 1 in place of k up until k equals N, which is a big enough number.
Step 5: define a = E[f(x, $d_1(ɵ_{11})$, $h_1(ɵ_{12})$, $K_1(ɵ_{13})$, and $p1(ɵ_{14})$].
Step 6: Create r' at random using [a, b].
Step 7: If r'≥ 0
Step 8 Repeat steps 6 and 7 as required.
Step 9 Yield E[f(x, d1, h1, K1, p1)] = a∨0 + b∧ 0 + λ.(b-a)/N.

The RFS-based PSO method

Kennedy and Eberhart created the PSO method, a random search algorithm, with inspiration from simulations of social behaviour (1995). The inhabitants are devoted to as a "swarm" in the PSO algorithm, and all member of the swarm is referred to as a "particle." All particle explorations the variable planetary through a speed and communicates its location to the rest of the swarm. P-best refers to the earlier best location of particle I, while g-best refers to the prior prime location of all components. Every particle modifies its speed and location toward the p- and g-best places at each iteration. Furthermore, the PSO method just needs to determine the objective function's value using basic mathematical operations; it is not required to know the objective function's gradient. As a result, it is simple to apply. By joining the RFS and PSO method, the arbitrary fuzzy simulation-based PSO algorithm is created for resolving the model (22), and its stages are as shadows:

Step1: set k to be 1.
Step 2: For the particle I, generate a random initial position from the range (0, M), where i = 1, 2,... N.M is the maximum range of positions that can be chosen for each particle, and N is the integer of particles in the swarm. Then, at random, choose a velocity on behalf of the particle i from the range [0, v], wherever v is the highest possible velocity on behalf of the particle i.
Step 3: Assume that p_i^k is the particle's position is a value that may be computed using the random fuzzy replication described in Section 4.1. p_g^k is referred to as the g-best particle.
Step 4: Calculate Vk+1 as follows everyplace w is the torpor weight, c1 too c2 are spurt coefficients, and r1 and r2 are rotational constants (Eberhart & Shi, 2001).

Step 5: Make $x_i^{k+1} = x_i^k + v_i^{k+1}$.
Step 6: enter k = k + 1.
Step 7 Continue as of Steps 3 to 6 up to the specified repetitions have been completed.
Step 8: Provide the value of P_g^k as the best answer.

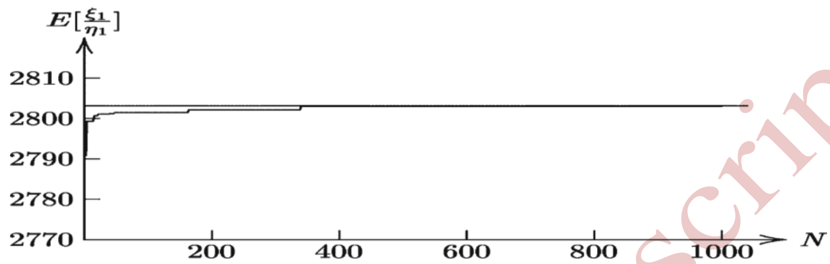

Fig. 2 shows how the PSO algorithm's $E[\frac{\xi_1}{n_1}]$ varies with the iterations number N.

Fig. 2 shows how the profit generated by the PSO algorithm changes with N, the number of rounds. Last but not least, we employ a GA using the RFS to solve the identical numerical case. This is a shortened version of the hybrid intelligence technique created by Liu and Liu (2005). The strictures of the GA remain set as surveys: the size of inhabitants is 20, the likelihood of cross-over is 0.2, and likelihood of alteration is 0.2. Additionally, a binary coding system is used to characterize answers in GA as DNAs. After successively the GA built on the RF reproduction for 11,00 cycles, during which the RFS repeats 4,000 eras, the maximum lot size is determined to be $x^* = 107.954$ by a profit of $2,802.98 a day. By contrasting such two results, we can demonstrate that the PSO method, which is focused on the RFS, performs just as well as the GA approach. This is because the maximum speed of each particle is sometimes changed so that it can be in as many places as possible.

5. A monetary illustration

Even though not all of the products are of the same quality standard, imagine stock levels where the stock is automatically refreshed by batch size x units. The percentage pi of flawed products in the ith portion, i = 1, 2,..., is determined by iid accidental fuzzy variables in this system, where pi = U(i, I + 0.03) and I = (0, 0.03, 0.05). The results for the following criteria are shown: The single sale value for premium goods is $60 per unit, the unit purchase price for every product is $26, and the unit exchange charge for defective goods is $24. Every day, the claim rate D is

135 U. Additionally, in the ith sequence, I = 1, 2,... with di = (0.4, 0.55, 0.6), hi = (3, 3.5, 5, 6), and Ki = (195, 200, 210), respectively. Additionally, each lot comprises a maximum of 2,000 units, as determined by the capacity of the machine. Decision-maker seeks to identify an ideal lot extent x at which the anticipated long-run typical revenue is at its highest level. As a result, the construction of a random vague EOQ models dismiss be accomplished as tracks:

$$\begin{Bmatrix} \max & g(x, \theta) \\ & subject\ to: \\ & 0 < x \leq 2000, \end{Bmatrix} \tag{25}$$

Where g(x,ɵ)

$$= \left[\left(\frac{135}{1 - E[p_1(\theta 4)} \right) \left(25 - \frac{K_{1(\theta 3}}{x} - 25E[p1(\theta 4)] + \frac{h1(\theta 2)x(E[p2-1)}{270} - d1(\theta 1) \right] \right.$$

The random fuzzy simulation from Section 3 is carried out by the PSO method on behalf of answering the model (25), in which the overall population of the group is 30, the highest speed of each particle is 30, the disinterest weight is 1, speed variables are b1 = b2 = 3, the inertia weight is 1, and r1 and r2 stay binary random quantities in the assortment [0, 1]. 3,000 iterations of the random fuzzy reproduction are performed however the developed algorithm is conducted 1000 times. The best lot size is thus determined to be x* = 108.696, with a daily profit of $2,803.01.

6. Conclusions

The inquiry cost, inventory cost, and setup cost are similarly uttered as FV, as is the proportion of goods with subpar performance in every set. This study looked into the issues with EOQ stock and products with poor performance under a variety of conditions. The projected long-run average profit has been maximised using a random fuzzy expected value model. Analytical solutions to the given model are challenging; hence, a PSO method that uses random fuzzy simulation has been created. A fascinating new area of study will be the evolution of the inventory problem involving deficits and an unknowable quantity supplied. It should also be noted that the demand rate is stable, and gaps are not permitted in this analysis.

Acknowledgement: We are thankful to the unknown reviewer for constructive as well as creative suggestions.

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