Journal of Engineering Research

Volume 7 | Issue 2 Article 7

2023

# Forecasting of Service Parts Based on Fuzzy Reliability of the Product

Maha El-Sakka,

Journal of Engineering Research (ERJ)
Vol. 7 – No. 2, 2023
©Tanta University, Faculty of Engineering
ISSN: 2356-9441
https://erjeng.journals.ekb.eg/
e ISSN: 2735-4873

# Forecasting of Service Parts Based on Fuzzy Reliability of the Product

Maha A. El-sakka[1, *], Ahmed El-Kassas[1], Eman El-Ghamry[2], Ahmed A. Hawam[1]

[1]Department of Production Engineering and Mechanical Design, Faculty of Engineering, Tanta University, Gharbia, Egypt
[2]Department of Mathematics and Physics, Faculty of Engineering, Tanta University, Tanta, Gharbia, Egypt
*Email: maha.ahmed@f-eng.tanta.edu.eg , ORCiD: 0000-0002-6953-7338

***Abstract-*** **This paper presents a forecasting model that depends on the reliability of the product and the failure of its parts to forecast the required quantity of spare parts. Fuzzy logic is integrated with the forecasted model to treat the uncertainty that may exist around defining the values of the parameters. Fuzzification of the product reliability is constructed using alpha cut and triangular fuzzy number. The effect of the fuzzy process on the forecasted required demand of spare parts will be studied in three cases: 1) fuzzification of the mean of the product reliability, 2) fuzzification of the standard deviation of the product reliability, and 3) fuzzification of both the mean and standard deviation of the product reliability. Four suggested defuzzification methods (mean-max, centroid, signed distance, and graded mean integration representation) were used to figure out the difference between the crisp and the fuzzy forecasted demand with its related costs and to save the stock with the suitable production ranges. From the results, the maximum deviation between the crisp and the fuzzy forecasted demand resulted from the fuzzification of both the mean and the standard deviation with a percentage range from 2.06 up to 5.45 which would save the non-stock out of crisp forecasting.**

***Keywords-*** **Reliability, Failure Rate, Spare Parts, Demand, Triangular fuzzy number**

## I. INTRODUCTION

Industries that have long-life products exceeding 10 years, usually require extended support warranty that includes spare parts as well as technical and service support. In such cases, providing spare parts is essential for the continuity of the product; nevertheless, it requires efficient inventory management to be provided in the right place with sufficient quantities at the right time without excess holding or shortage costs [1].

In practice, the economic supply of spare parts requires a highly accurate forecast of the demand. The low accurate forecast would probably increase the capital losses due to excess holding cost or shortage cost resulting from over or under-demand estimation respectively [2].

Traditional forecasting methods such as moving averages and exponential smoothing [3] are commonly applied for spare parts management. The moving average method gives equal weight to all the data used by taking the average or the mean of the previous data. The exponential smoothing method is used to detect significant changes in data by using a random smoothing parameter which is considered a weighting factor that is given to the most recent data. These methods are simple and widely used for a long time, but they assume a certain stability in the environment, this is what makes them biased towards the most recent data and the trends of future demand cannot be forecasted well. At the same time, they are suitable for small forecast horizons to guarantee a sufficient degree of accuracy. Synthetic and Boylan approximation [4] tries to deal with biased of these methods by changing the weighted factor, but choosing the appropriate smoothing parameter is still difficult and not suitable for all demand types. Bootstrapping approach [5] offers a non-parametric alternative by using the probability of the demand instead of the demand intervals.

Due to the stochastic nature of spare parts demand, traditional forecasting methods do not give the most accurate results because they are dependent mainly on the history of the demand. Therefore, other forecasting models that are based on other parameters more related to the product and its parts become popular in the past decades. These parameters are based on perspectives such as product life cycle cost [1], condition monitoring data [6], maintenance [7], installed base information [8], and reliability of the product with its parts [9], [10].

In practice, the demand for spare parts is subjected to uncertainty which makes the use of deterministic forecasting models infeasible. In such cases, using other forecasting models that have a stochastic nature can predict a reasonable range of demand instead of a specific value.

The stochastic forecasting models are based on random variables. Mathematically dealing with a random variable may be accomplished by applying the theory of probability. Nevertheless, defining the random variables by specifying the crisp values of their parameters may be impractical in real-life situations due to uncertainty. In such a case, considering the defining parameters of a random variable as a fuzzy number can represent a more reasonable solution [11].

Recently, the fuzzy concept is used for forecasting in a wide range of applications to deal with their inherent uncertainty nature. An accurate forecast is necessary for inventory control and management of the supply chain process of spare parts. M. Hu and J. Ruan [12] proposed a fuzzy inventory model to predict the optimum required storage quantity using of trapezoidal fuzzy number and Graded Mean Integration Representation (GMIR) method for the defuzing process. F. L. Chen [13] applied a moving fuzzy neuron network with other tools to forecast the required quantity of critical spare parts. LES M. SZTANDERA [14] proposed a fuzzy system to

DOI: 10.21608/ERJENG.2023.199925.1163

Journal of Engineering Research (ERJ)
Vol. 7 – No. 2, 2023
©Tanta University, Faculty of Engineering
ISSN: 2356-9441 https://erjeng.journals.ekb.eg/ e ISSN: 2735-4873

estimate the number of spare parts based on the type of failure and take the reliability of the part into account. C. H. Hsieh [15] proposed an optimization production inventory model of fuzzy parameters to calculate the better quantity of the model by using trapezoidal for fuzzy parameters and the GMIR method for defuzing the fuzzy inventory model. N. Kumar and S. Kumar [16] used a triangular fuzzy number to fuzzy parameters of the inventory model for deteriorating parts with shortages under backlogging. GMIR, Centroid (C), and Signed Distance methods (SD) were used for defuzing the total cost function. Sahidul Islam and A. K. Biswas [17] proposed economic order quantity of exponential demand rate, deterioration of Weibull Distribution with shortage and partial backlogging. Triangular Fuzzy Numbers (TFN) and the GMIR method were used.

In this paper, a forecasting technique is proposed based on the product reliability and failure rate of its parts which can deal with the stochastic nature of the demand. The fuzzification process of the proposed forecasting model is considered the contribution of this paper.

This research aims to deal with the uncertainty of defining the parameters of the probability forecast and treating the instability of the environment surrounding the product with its parts. Also, estimate a range of reasonable forecasting quantities that would save stock and avoid excessive costs resulting from over or underestimation of the required demand.

## II. Production Policy

Usually, the production of any product does not last forever. In practice, the production scheme includes two stages; 1) The period in which the product is continued to be produced as well as a specified margin of its spare parts. 2) The survival period of the product in the market after its production is discontinued. The production of spare parts does not represent a problem in the first period as it planned to cover accidental failures, however, in the second period the production of spare parts needs an accurate forecast to cover the increasing rate of its demand until the end of the product life cycle without excess holding or shortage costs.

The assumptions of spare parts production planning and inventory control are suggested as follows:

1. The system is in a steady state, and the production lot size is constant.
2. The produced parts are sent to market at the beginning of their period without a holding period as inventory.
3. There are no deteriorated parts so, there are no shortage costs or salvage values.
4. The setup cost related to spare parts production is increased in stage two after the production of the product is discontinued.
5. The production cost related to spare parts production is increased in stage two after the production of the product is discontinued.
6. The demand is a dynamic probabilistic (stochastic).
7. Spare parts are available for satisfying demand after the product is discontinued.

The production is usually having a monthly plan; consider that the production has a monthly plan that extends from period 1 to period M during the first stage; where $M$ is the number of periods (months) during which the production of the considered product (will be referred as related product) is continued. Stage 2 extends from period $M$+1 to period $N$; at this stage, another product (will be referred to as an unrelated product) is active while the related product is discontinued.

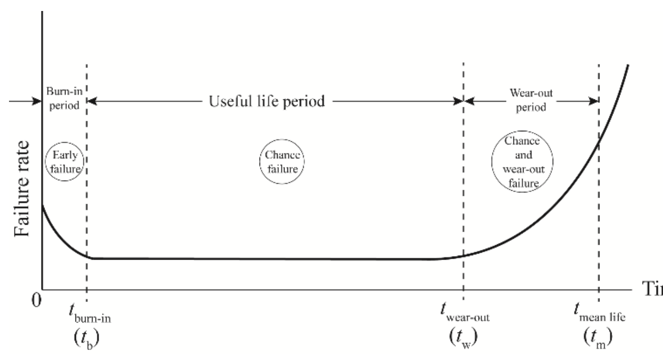


**Figure 1. Failure rate curve.**

The periodical setup cost of spare part $S_J$ at period $i$ can be calculated as follows:

$$C(s_J(i)) = A^L_{S_J} * Q(i) \quad ,$$

$$L = \begin{cases} L = 1 & , \quad i = 1, 2, 3, \ldots\ldots, M \\ L = 2 & , \quad i = M + 1, \ldots\ldots, N \end{cases}$$

The periodical production cost of spare part SJ at period i can be calculated as follows:

$$P(s_J(i)) = p^L_{S_J} * Q(i) \quad ,$$

$$L = \begin{cases} L = 1 & , \quad i = 1, 2, 3, \ldots\ldots, M \\ L = 2 & , \quad i = M + 1, \ldots\ldots, N \end{cases}$$

Total periodical cost = $C(s_J(i)) + P(s_J(i))$ (1)

Where $C$ ($s_J(i)$) total periodical setup cost of the required spare parts at period $i$, $A^L_{S_J}$ is the unit setup cost of spare part $S_J$, $P(s_J(i))$ total periodical production cost of the required spare parts at period $i$, $p^L_{S_J}$ is the unit production cost of spare part $S_J$. $L$ represents the related and unrelated product, and $Q$ ($i$) is the production quantity of the required number of spare parts that should be produced through period $i$ where $i$=1, 2, 3, …, $N$. This quantity requires to be determined by using a suitable forecasting technique.

## III. Spare Parts Forecasting

### A. Crisp Forecasting

When products are exposed to operation in an environment, the accumulation of stress cause the failure of its parts. Figure

DOI: 10.21608/ERJENG.2023.199925.1163

Journal of Engineering Research (ERJ)
Vol. 7 – No. 2, 2023
©Tanta University, Faculty of Engineering
ISSN: 2356-9441 https://erjeng.journals.ekb.eg/ e ISSN: 2735-4873

1 shows the failure rate curve of spare parts that have a long life cycle. The curve consists of three regions; Region 1) the Burn-in period, Region 2) the useful life period, and Region 3) Wear out Period. Region 1 starts with the entry of the product to the service (time *t=0*), along this region, the failure starts with a high rate due to manufacturing defects and decreases gradually until it reaches the burn-in point (time $t = t_{\text{burn-in}}$) at which the failure rate would be stable. In region 2, the chance failure region starts at $t = t_{\text{burn-in}}$ and through it, the failure rate is still constant until it reaches the wear-out point ($t=t_w$). Region 3, the wear-out region, starts at ($t = t_w$), the failure rate would increase due to the wear-out of the part until the end of the product life. As an approximation to the failure rate curve shown in Figure 1, Region 1 can be considered a Weibull distribution, Region 2 can be considered an exponential distribution, and Region 3 can be considered a truncated normal distribution. This approximated curve shown in Figure 2 is given in (Eq.2)

$$f(t)=\frac{\alpha}{b}\,k\,t^{k-1}\,e^{\frac{-t^k}{b}}+(1-\alpha)\frac{1}{a_f\sigma_f\sqrt{2\pi}}\,e^{\frac{-(t-\mu_f)^2}{2\sigma_f{}^2}} \qquad (2)$$

where $f(t)$ is the failure rate of the part at period $t$. $\alpha$ is the Weibull weight, b is the scale parameter, $k$ is the shape parameter, $a_f$ is the normalization factor of failure rate function, $\mu_f$ is the part means, $\sigma_f$ is the part standard deviation.

The suggested applied forecasting model [9] assumed that the required forecast demand can be calculated from (Eq.3).

$$d(i)=\sum_{t=1}^{t=i-1} s(i-t)R(i-t)P_r(t) \qquad (3)$$

where $d(i)$ represents the required forecasted demand of spare part at the $i^{th}$ period, $s(i)$ represent the probability that the product which contains part $S_J$ is still in use after the $i$ period and the part $S_J$ needs a spare part at $i^{th}$ period and depend on the failure rate of the part (Eq. 2), $R(t)$ represents the reliability of the product Figure 3 which contains part $S_J$ until period $i$ and can be calculated from (Eq. 5), $P_r$ represents the production quantity at period $i$.

$$s(i)=\sum_{t=1}^{t=i} s(i-t)f(t) \qquad (4)$$

$$R(t)=1-\frac{1}{a_r\sigma_r\sqrt{2\pi}}\,e^{\frac{-(t-\mu_r)^2}{2\sigma_r{}^2}} \qquad (5)$$

where $a_r$ represent the normalization factor of the reliability function, $\mu_r$ and $\sigma_r$ is the product mean and standard deviation respectively.

For clarification

$$d(2) = s(1)R(1)P_r(1)\ ,\ s(1)= f(1)\ ,$$

So,

$$d(2)= f(1)R(1)P_r(1)$$

$$d(3) = s(2)R(2)P_r(1) + s(1)R(1)P_r(2)\ ,$$

$$s(2)= s(1)f(1) + f(2)$$

So,

$$d(3) = f(1)f(1) + f(2))R(2)P_r(1) + f(1)R(1)Pr(2)$$

And so on…..

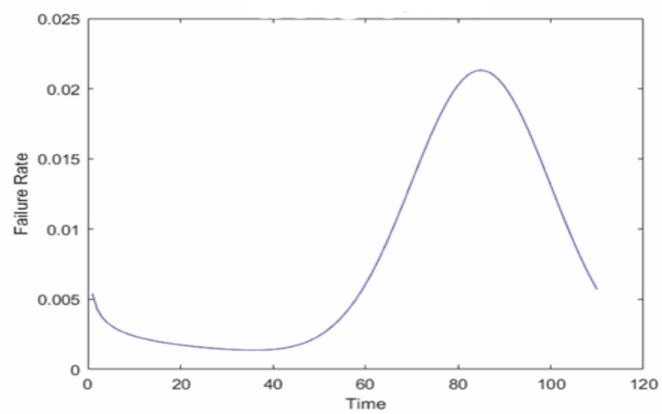


**Figure 2. Crisp failure rate of the part**

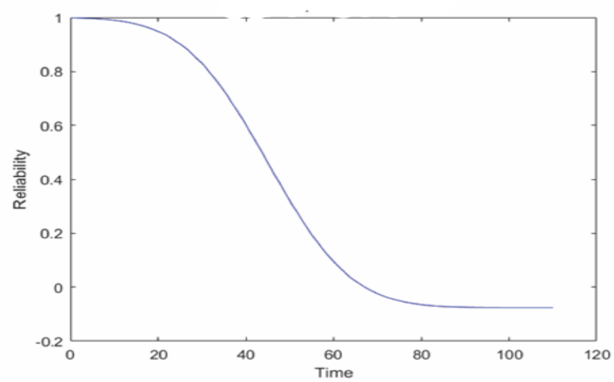


**Figure 3. Crisp reliability of the part**

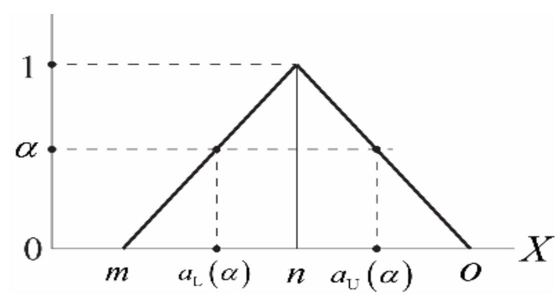


**Figure 4. Alpha cut of a triangular fuzzy number**

## *B. Fuzzy Forecasting*

A fuzzy system (FS) is considered a nonlinear mapping of a set of input data to a scalar set of output data. The FS comprises four main processes: Fuzzification (Fuzzifier) process, Rules, Inference engine, and Defuzzification (Defuzzifier) process.

DOI: 10.21608/ERJENG.2023.199925.1163

Journal of Engineering Research (ERJ)
Vol. 7 – No. 2, 2023
©Tanta University, Faculty of Engineering
ISSN: 2356-9441 https://erjeng.journals.ekb.eg/ e ISSN: 2735-4873

### *B. I. Basic Fuzzy Rules*

- A crisp set is a group of definite elements from the universal set X and its characteristics function is {0,1}. If x ∈ X or x ∈ A where A is a subset from X the characteristics function is 1, otherwise x ∉ X and the characteristics function is 0. But if subset A does not contain a fixed boundary and there was an element existing on this boundary, then the possibility of the element dependency may vary over 0-1. This is known as a fuzzy set $\tilde{A}$ which is denoted by (Eq.6), and is characterized by the membership function which represents the mapping from the universal set X in [0,1].[18]
  $\tilde{A}$ ={ (x, $\mu_{\tilde{A}}$(x))/x ∈X , $\mu_{\tilde{A}}$(x) ∈[ 0,1]} (6)
  Where $\mu_{\tilde{A}}$(x) is the membership function of x ∈ X.

- The fuzzy set $\tilde{A}$ is called a fuzzy number $\tilde{a}$ under certain conditions [19]. There are different shapes of fuzzy numbers that are widely used such as Triangular (TFN), Trapezoidal (TrFN), and Gaussian (GFN). The TFN in Figure .4 is preferred when fuzziness exists around a single value on both sides, and it is characterized by not having complex computation. The membership function of triangular fuzzy number $\tilde{a}$ is represented by (Eq.7) TFN $\tilde{a}$= (m,n,o) where m < n < o, and x,m,n, and o ∈ ℜ .

$$\mu_{\tilde{a}}(x) = \begin{cases} \frac{x-m}{n-m} & if\ m \le x \le n \\ 1 & if\ x = n \\ \frac{o-x}{o-n} & if\ n \le x \le o \end{cases} \quad (7)$$

- α-cut is used to make a shift from the crisp set towards a fuzzy set and it is considered the crisp set associated with the fuzzy number $\tilde{a}$ . Figure 4 shows the graphical representation of the α-cut concept as denoted by (Eq.8).
  $a_\alpha = \{ x \in U : \mu_{\tilde{a}}(x) \ge \alpha\}$; α ∈ [0,1] (8)
  Then the TFN $\tilde{a}$= (m,n,o) can be represented by a fuzzy interval (Eq.9) which represents the confidence interval using an α-cut concept.
  $\tilde{a} = a_\alpha$ = [$a_L(\alpha)$, $a_U(\alpha)$]
  =[m+α(n−m), o−α (o−n)] (9)

  where *L* is the lower value and *U* is the upper value.

The above-mentioned points are considered the basic fuzzy rules that are required for performing the fuzzification process.

### *B.2. Defuzzy*

The defuzzification process is the inverse of the fuzzification process. It is a transformation process of a fuzzy output through a fuzzy inference system into a crisp output. There are many defuzzy methods widely applied such as aggregation, a center of gravity, weighted average, mean-max [18], centroid, signed distance, and the graded mean integration representation method [16]. The suggested applied methods in this study are *Mean-Max* (*M-M*), *Centroid* (*C*), *Signed Distance* (*SD*), *and the Graded Gean Integration Representation* (*GMIR*) method. Let a* be the crisp output obtained from the defuzzy process of the TFN $\tilde{a}$= (m,n,o). The mathematical expression of the suggested applied methods is denoted as follows:

$$\text{M-M } a^* = \frac{a_L(\alpha) + a_U(\alpha)}{2},\ \text{C } a^* = \frac{m+n+o}{3},\ \text{SD } a^* = \frac{m+2n+o}{4},\ \text{GMIR } a^* = \frac{m+4n+o}{6}$$

### *B.3. Fuzzy Reliability Using Alpha Cut and Triangular Fuzzy Number*

From the proposed forecasted model, product reliability (Eq. 5) will be studied in a fuzzy environment. The product reliability is controlled by two parameters: the mean and the standard deviation of the product. Let these parameters be defined by two TFN as follows [20]; TFN $\widetilde{\sigma_r}$ = (a1, b1, c1), and TFN $\widetilde{\mu_r}$= (a2, b2, c2) and the alpha-cut fuzzy number of the two parameters are defined as follows; $\sigma_r \in \sigma_r[\alpha]$, $\mu_r \in \mu_r[\alpha]$

where $\sigma_r[\alpha]$ = [ a1 + α(b1 – a1), c1 − α(c1 – b1) ] and $\mu_r[\alpha]$= [ a2 + α(b2 – a2), c2 − α(c2 – b2) ].

Then, the reliability of the product (Eq.5) can be expressed by alpha cut fuzzy number as represented in (Eq.10) and (Eq.11)

$$R(t)[\alpha]=[R(t)_L[\alpha] , R(t)_U[\alpha]] \quad (10)$$

where *L* is the lower value, and *U* is the upper value

$$R(t)[\alpha]=\{ 1- \frac{1}{a_r(a_1+\alpha(b_1-a_1))\sqrt{2\pi}} e^{\frac{-(t-(a_2+\alpha(b_2-a_2)))^2}{2(a_1+\alpha(b_1-a_1))^2}} , 1- \frac{1}{a_r(c_1-\alpha(c_1-b_1))\sqrt{2\pi}} e^{\frac{-(t-(c_2-\alpha(c_2-b_2)))^2}{2(c_1-\alpha(c_1-b_1))^2}} \} \quad (11)$$

If the alpha cut is assumed 0, 0.5, 1 the fuzzy reliability curve is illustrated in Figure 5.

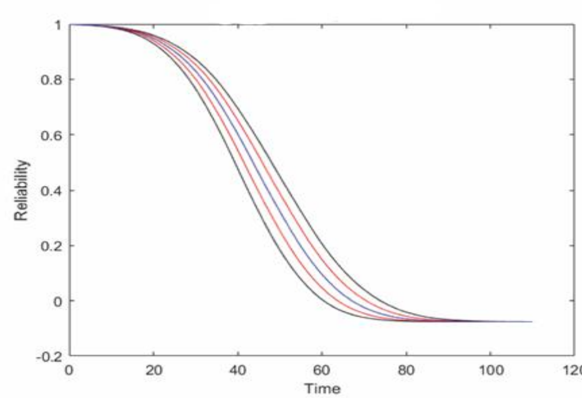


**Figure 5. Fuzzy reliabilities at alpha cut 0,0.5, and 1**

DOI: 10.21608/ERJENG.2023.199925.1163

Journal of Engineering Research (ERJ)
Vol. 7 – No. 2, 2023
©Tanta University, Faculty of Engineering
https://erjeng.journals.ekb.eg/
ISSN: 2356-9441 e ISSN: 2735-4873

Table 1. Crisp values of all parameters

| | | | |
|---|---|---|---|
| $\alpha$ | 0.24 | B | 30 |
| K | 0.7 | $a_f$ | 0.98 |
| $\sigma_f$ | 15 | $\mu_f$ | 85 |
| $a_r$ | 0.93 | $\sigma_r$ | 15 |
| $\mu_r$ | 45 | $P_r$ | 1000 |
| A1 | 1 | A2 | 2 |
| P1 | 2 | P2 | 4 |
| M | 50 | N | 110 |
| T | 0:110 | | |

## IV. CASE STUDY

The forecasting of the required demand for spare parts will be achieved in two stages. The first stage is the forecasting of the required demand for spare parts with crisp parameters. Stage two is the forecasting of the required demand for spare parts with the fuzzy reliability function of the product. The second stage is divided into three cases; 1) Fuzzification of product reliability mean and crisp standard deviation. 2) Fuzzification of product standard deviation and crisp mean. 3) Fuzzification of both the product reliability mean and standard deviation. To clarify the effects of each fuzzy case, a comparison will be introduced between crisp and fuzzy forecasting using four different defuzzification methods which are mean-max, centroid, signed distance, and graded mean integration representation. The percentage of deviation between the crisp and fuzzy cases would be calculated for the required demand and its corresponding costs.

### *A. Crisp Forecasting of Required Demand for Spare Parts*

All parameters crisp values of the product reliability function and the part failure rate function are in table 1. Figure 6 represents the forecast curve of required demand and Figure 7 illustrates the corresponding costs.

From the cost curve, the cost of demand increases gradually with the increase of the volume of forecasting demand until period 50. At this period the production of the first product is ended but continues producing its spare parts which cover the needs until the end of its life with the production of another product. So, from period 51, the total cost is doubled due to the presence of a new setup of another product. This increase in cost is continued until period 67 where there is the maximum forecasting demand value and the maximum cost.

### *B. Fuzzy Forecast of Required Demand of Spare Parts*

#### *B.1. The Effect of Mean Fuzzification on the Reliability Function of the Product*

When the mean of the reliability function of the product is fuzzified, there are different results in the required forecasted demand of spare parts from each defuzzy method. From period 1 to period 60 the crisp state is higher than the fuzzy state.

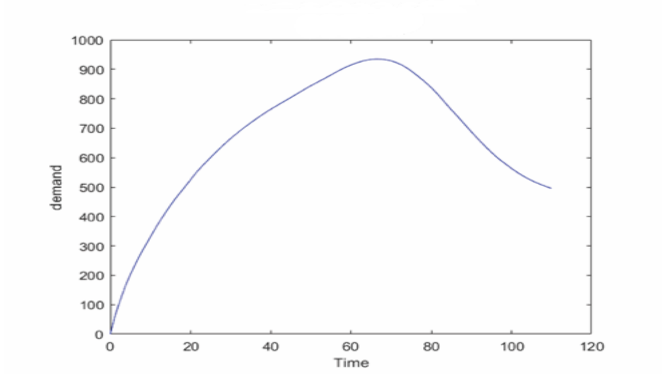


Figure 6. Crisp forecasted demand.

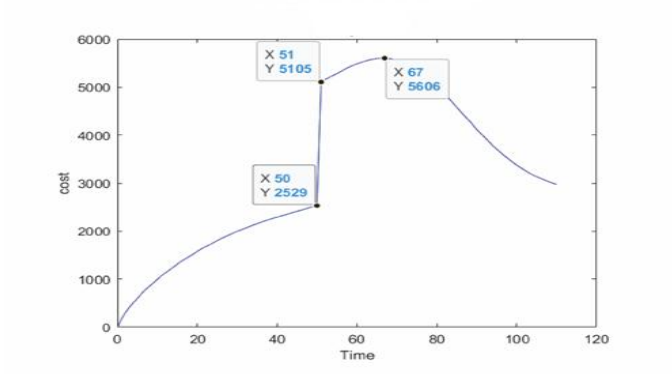


Figure 7. Cost of crisp forecasted demand

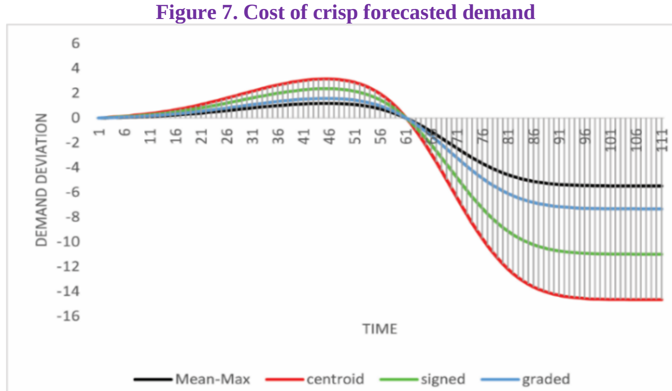


Figure 8. Demand deviation of different defuzzification methods for the fuzzy mean of reliability

From period 61 to 110 the fuzzy state is higher than the crisp state.In this case, the deviation in demand is from 1 to 5 parts in the mean-max method, 1 to 7 parts in the graded mean representation method, 1 to 11 parts in the signed distance method, and from 1 to 15 parts in the centroid method. Figure 8 and Figure 9 illustrate the deviation line of the forecasted demand and the corresponding cost of all defuzzification methods for the fuzzified mean parameter of the reliability function of the product. The corresponding deviation percentage is presented in Table 2.

DOI: 10.21608/ERJENG.2023.199925.1163

Journal of Engineering Research (ERJ)
Vol. 7 – No. 2, 2023
©Tanta University, Faculty of Engineering
ISSN: 2356-9441 https://erjeng.journals.ekb.eg/ e ISSN: 2735-4873

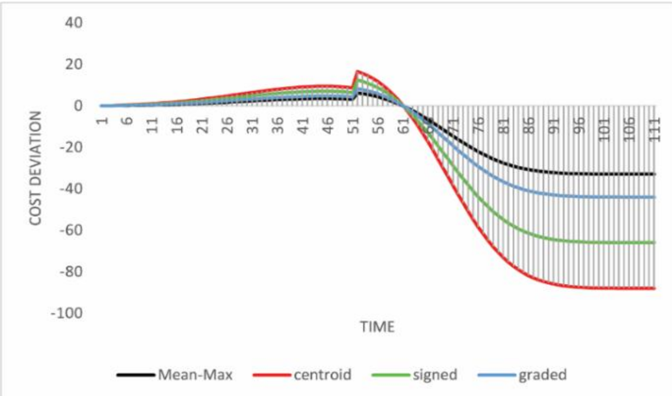


**Figure 9. Cost deviation of different defuzzification methods for fuzzy mean of reliability.**

**Table 2. Deviation percentage of the fuzzy mean of reliability**

| Defuzzification Method | Deviation Percentage % |
|---|---|
| Mean-Max | 1.1065 |
| Graded | 1.4777 |
| Signed | 2.2165 |
| Centroid | 2.9553 |

**Table 3. Deviation percentage of the fuzzy standard deviation of reliability**

| Defuzzification Method | Deviation Percentage % |
|---|---|
| Mean-Max | 0.159 |
| Graded | 0.212 |
| Signed | 0.317 |
| Centroid | 0.423 |

### *B.2.The Effect of Standard deviation Fuzzification on the Reliability Function of the Product*

When the standard deviation of the reliability function of the product is fuzzified, we find that from period 1 to period 75 the crisp state is higher than the fuzzy state. From period 76 to 110, the fuzzy state is higher than the crisp state. Through the horizon, 1 to 75, the demand curve and the corresponding cost curve increase gradually from period o to 23 then decrease gradually up to period 45 then increase gradually up to 68 finally decrease up to period 75. Figure 10 and Figure 11 illustrates the deviation line of the forecasted demand and the corresponding cost of all defuzzification methods for the fuzzified standard deviation parameter of the reliability function of the product. The deviation percentage is presented in table 3.

### *B.3. The Effect of Mean and Standard Deviation Fuzzification on the Reliability Function of the Product*

When the mean and the standard deviation of the reliability function of the product are fuzzified. We find that from period 1 to period 63, the crisp state is higher than the fuzzy state. From periods 64 to 110 the fuzzy state is higher than the crisp state. The deviation in demand is from 1 to 10 parts in the mean-max method, 1 to 13 parts in the graded mean representation method, 1 to 20 parts in the signed distance method, and from 1 to 27 parts in the centroid method. Figure 12 and Figure 13 illustrate the deviation line of the forecasted demand and the corresponding cost of all defuzzification methods for fuzzy mean and standard deviation parameters of the reliability function of the product. The deviation percentage is presented in Table 4.

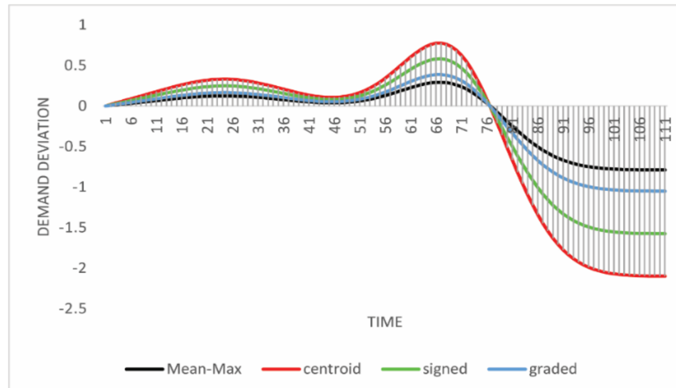


**Figure 10. Demand deviation of different defuzzification methods for a fuzzy standard deviation of reliability.**

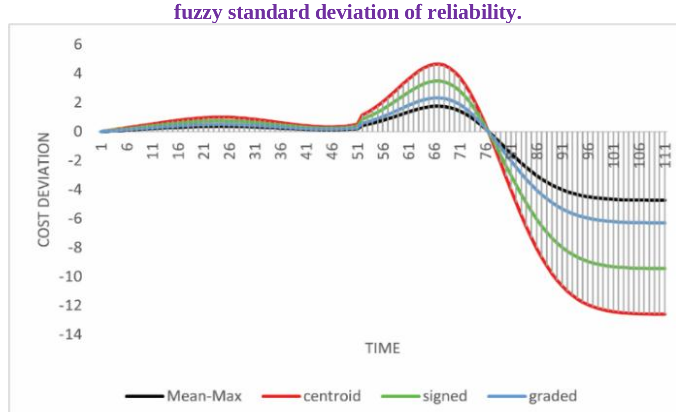


**Figure 11. Cost deviation of different defuzzification methods for fuzzy the standard deviation of reliability.**

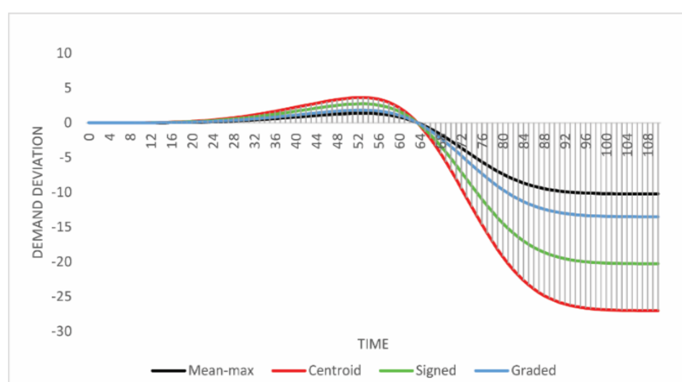


**Figure 12. Demand deviation of different defuzzification methods for fuzzy mean and standard deviation of reliability.**

DOI: 10.21608/ERJENG.2023.199925.1163

Journal of Engineering Research (ERJ)
Vol. 7 – No. 2, 2023
©Tanta University, Faculty of Engineering
ISSN: 2356-9441 https://erjeng.journals.ekb.eg/ e ISSN: 2735-4873

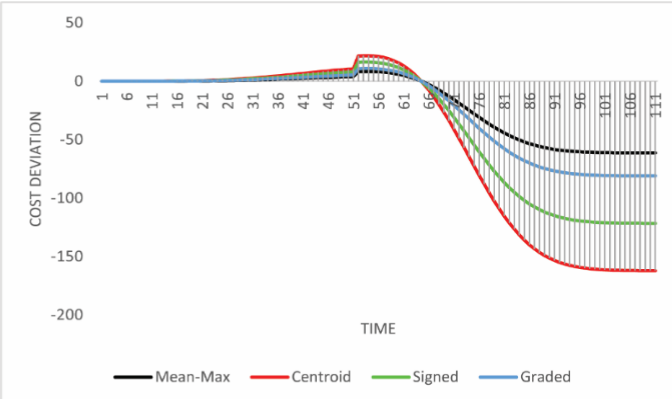


Figure 13. Cost deviation of different defuzzification methods for fuzzy mean and standard deviation of reliability.

Table 4. Deviation percentage of the fuzzy mean and standard deviation of reliability

| Defuzzification Method | Deviation Percentage % |
|---|---|
| Mean-Max | 2.0608 |
| Graded | 2.7224 |
| Signed | 4.0836 |
| Centroid | 5.4481 |

## V. Analysis of Results

As introduced previously when the product reliability is fuzzified, the effect of each fuzzy parameter on the forecasted demand for spare parts is explained clearly. The data results of each case are shown in Table 5 and Figure 14 can be summarized as follows:

- When the product reliability is fuzzified, not all fuzzy parameters have the same effect on the output demand and its related cost. The maximum deviation between the crisp and fuzzy cases is obtained from the fuzzification of both the mean and standard deviation compared with the fuzzification of the mean and the standard deviation of each parameter separately.
- Each defuzzy method gives a different deviation percentage. Mean-max gives the minimum deviation percentage from 0.159 to 2.06 %, Graded mean gives from 0.212 to 2.72 %, Signed-distance gives from 0.317 to 4.08 %, and Centroid gives the maximum deviation percentage from 0.423 to 5.45 %.
- The effect of the fuzzy environment on the time series is not the same for each fuzzy case: 1) In the case of the mean fuzzification the maximum deviation at period 44 and the turning point at period 60 then increase gradually up to the end of production, 2) In case of the standard deviation fuzzification the maximum deviation at period 66 and the turning point at period 75 then increase gradually up to the end of production, 3) In case of the mean and the standard deviation fuzzification together the maximum deviation at period 53 and the turning point at period 63 then increase gradually up to the end of production.
- Before the turning point, the crisp forecast is greater than the fuzzy forecast, and after the turning point, the opposite occurs.

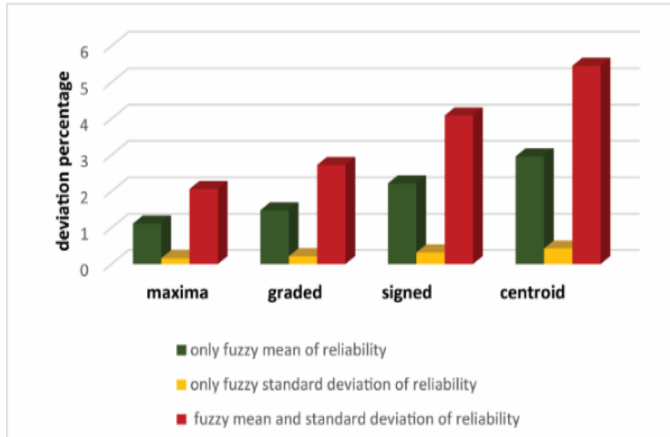


Figure 14. Deviation percentage of different defuzzy methods of fuzzy reliability case

## IV. Discussion

From the proposed case study, the real life of the product is represented by the fuzzy state of high certainty, as the product faces a lot of changes every day should be taken into account for an accurate forecast. And the theoretical or actual life is represented by the crisp state of low certainty due to inaccurate values of the parameters. Between the real and the actual, there is a range of forecasted demand that would keep stocks not running out.

From the proposed three cases of fuzzy reliability, there are three different estimated ranges of the forecasted demand. In the case of the fuzzy mean of the product reliability only, the expected deviation is from 1.1% to 2.95%. 2) In the case of the fuzzy standard deviation of the product reliability only, the expected deviation is from 0.16 % to 0.42%. 3) In the case of the fuzzy both the mean and the standard deviation of the product reliability, the expected deviation is from 2.06 % to 5.45%. To combine theoretical or actual and real study, the life span of the product is divided into four sections based on the highest deviation obtained from the fuzzification of both the mean and the standard deviation of the product; 1) From the start up to standard deviation value, this interval represents highest reliability of the product and low part failure rate this require to provide the market with minimum quantities that would be enough in case of accidental failure, therefore the output forecasted quantity obtained from mean-max method is suggested. 2).

DOI: 10.21608/ERJENG.2023.199925.1163

Journal of Engineering Research (ERJ)
Vol. 7 – No. 2, 2023
©Tanta University, Faculty of Engineering
ISSN: 2356-9441 https://erjeng.journals.ekb.eg/ e ISSN: 2735-4873

**Table 5. Difference between fuzzy reliability cases.**

| Fuzzified Parameter | Defuzzified Method | Crisp High | | | Fuzzy High | | | Deviation Percentage |
|---|---|---|---|---|---|---|---|---|
| | | Max Dev. Point | Max Demand Dev. | Max Cost Dev. | Turning Point | Max Demand Dev. | Max Demand Dev. | |
| $\mu_r$ | M-M | 44 | 1.1857 | 6.2299 | 60 | 5.4884 | 32.9305 | 1.107 |
| | GMIR | | 1.5748 | 8.289 | | 7.3297 | 65.9676 | 1.478 |
| | SD | | 2.3622 | 12.4335 | | 10.9946 | 43.9784 | 2.217 |
| | C | | 3.1496 | 16.578 | | 14.6595 | 87.9567 | 2.955 |
| $\sigma_r$ | M-M | 66 | 0.2931 | 1.7585 | 75 | 0.7887 | 4.7321 | 0.159 |
| | GMIR | | 0.3882 | 2.3294 | | 1.0492 | 6.2953 | 0.212 |
| | SD | | 0.5823 | 3.4941 | | 1.5738 | 9.443 | 0.317 |
| | C | | 0.7765 | 4.6588 | | 2.0985 | 12.5907 | 0.423 |
| $\mu_r$ & $\sigma_r$ | M-M | 53 | 1.3836 | 8.3019 | 63 | 10.22 | 61.3343 | 2.0608 |
| | GMIR | | 1.822 | 10.9322 | | 13.5041 | 81.0247 | 2.7224 |
| | SD | | 2.7331 | 16.3984 | | 20.2562 | 121.537 | 4.0836 |
| | C | | 3.6441 | 21.8645 | | 27.0082 | 162.0493 | 5.4481 |

From the standard deviation up to the mean value, through this interval the product reliability is considered decreased from one to half, but the failure rate of the part is considered constant and the chance of failure may occur through this interval. In such case, the required spare parts may be increased slightly, therefore the output forecasted quantity obtained from a graded mean method is suggested. 3) From the mean up to the turning point value, in this interval the product reliability is considered low and the failure rate is increased due to the wear-out of the part. In this case, the required spare parts are increased before, therefore the output forecasted quantity obtained from the signed distance is suggested. 4) From the turning point value up to the end of life, the product with its parts starts aging and this required high quantities of spare parts, therefore the output forecasted quantity obtained from the centroid method is suggested.

## VII. Conclusion

According to the results obtained in this study, the crisp forecast is applied in case of high certainty and it is difficult to get this level. Determining the required number of spare parts is suggested based on the fuzzy reliability of the product with its parts failure rate to deal with the stochastic nature of spare parts demand and treat uncertainty around defining the parameters of the probability forecasting model.

By applying the four different defuzzy methods it was found that the Mean-Max method gives the lowest forecasted quantities and the Centroid method gives the highest value. The highest range of the forecasted quantities and the corresponding costs is about 2.06 % to 5.45%.

From the suggested fuzzy reliability cases, the effect on the forecasted demand differed from the forecasted quantities. And from using different defuzzy methods there is a forecasted range of the required demand that is considered reasonable for saving stock from running out and avoiding excessive costs resulting from an underestimation of demand that cause a shortage, penalty, or loss of customers, and overestimation of demand that leads to high inventory costs or deteriorated parts.

**Funding statement:** The authors did not receive any financial support for the research, authorship, and/ or publication of this article.

**Declaration of conflicting interest statement:** There are no potential conflicts of interest concerning the research, authorship, or publication of this article.

## References

[1] O. Durán, A. Carrasco, P. S. Afonso, and P. A. Durán, “Evolutionary optimization of spare parts inventory policies: A life cycle costing perspective,” IFAC-Papers Online, vol. 52, no. 13. ScienceDirect, IFAC PapersOnLine 52-13, pp. 2243–2248, 2019. doi: 10.1016/j.ifacol.2019.11.539.

[2] N. A. Lelo, P. S. Heyns, and J. Wannenburg, “Forecasting spare parts demand using condition monitoring information,” J Qual Maint Eng, vol. 26, no. 1, pp. 53–68, 2020, doi: 10.1108/JQME-07-2018-0062.

[3] H. H. Hameed, “Smoothing Techniques for Time Series Forecasting,” Eastern Mediterranean University, no. July. Master of Science in Applied Mathematics and Computer Science, Eastern Mediterranean University, 2015.

Journal of Engineering Research (ERJ)
Vol. 7 – No. 2, 2023
©Tanta University, Faculty of Engineering
ISSN: 2356-9441 https://erjeng.journals.ekb.eg/ e ISSN: 2735-4873

[4] R. Henkelmann, “A Deep Learning based Approach for Automotive Spare Part Demand Forecasting,” Is.Ovgu.De. Otto-von-Guericke-Universität Magdeburg, pp. 1–163, 2018.
[5] J. E. Boylan and A. A. Syntetos, “Spare parts management: A review of forecasting research and extensions,” IMA Journal of Management Mathematics, vol. 21, no. 3, pp. 227–237, 2010, doi: 10.1093/imam/dpp016.
[6] ANTON OTTOSSON; OLOF WIREKLINT, “Forecasting of Spare Parts Based on Vehicle Condition Monitoring Data.” Chalmers university of Technology, Gothenburg, Sweden, p. E 2018:010, 2018.
[7] S. Zhu, W. van Jaarsveld, and R. Dekker, “Spare parts inventory control based on maintenance planning,” Reliab Eng Syst Saf, vol. 193, 2020, doi: 10.1016/j.ress.2019.106600.
[8] S. Van der Auweraer, R. N. Boute, and A. A. Syntetos, “Forecasting spare part demand with installed base information: A review,” Int J Forecast, vol. 35, no. 1, pp. 181–196, 2019, doi: 10.1016/j.ijforecast.2018.09.002.
[9] M. Sharaf, “study on the service parts control,” Japan, no. Ph.D.thesis, 1989.
[10] Nataša Kontrec and Stefan Panić Additional, “Spare Parts Forecasting Based on Reliability,” in tech open since open minds, 2017, pp. 112–128.
[11] E. Baloui Jamkhaneh, “Analyzing System Reliability Using Fuzzy Weibull Lifetime Distribution,” 2014.
[12] M. Hu and J. Ruan, “Application of fuzzy forecast of inventory management in the auto company,” ICLEM 2010: Logistics for Sustained Economic Development - Infrastructure, Information, Integration - Proceedings of the 2010 International Conference of Logistics Engineering and Management, vol. 387, pp. 4441–4446, 2010, doi: 10.1061/41139(387)621.
[13] F. L. Chen, Y. C. Chen, and J. Y. Kuo, “Applying Moving back-propagation neural network and Moving fuzzy-neuron network to predict the requirement of critical spare parts,” Expert Systems with Applications, vol. 37, no. 9. pp. 6695–6704, 2010. doi: 10.1016/j.eswa.2010.04.037.
[14] LES M.SZTANDERA, “Spare parts allocation - fuzzy systems approach,” Recent Researches in Computer Science, pp. 245–249, 2011.
[15] C. H. Hsieh, “Optimization of Fuzzy Backorder Inventory Models,” Inf Sci (N Y), vol. 146, pp. 29–40, 2002.
[16] N. Kumar and S. Kumar, “An inventory model for deteriorating items with partial backlogging using linear demand in fuzzy environment,” Cogent Business and Management, vol. 4, no. 1. Cogent Business & Management, 2017. doi: 10.1080/23311975.2017.1307687.
[17] Sahidul Islam and A. K. Biswas, “A Fuzzy Inventory Model having Exponential Demand with Weibull Distribution for Non-Instantaneous Deterioration, Shortages under Partially Backlogging and Time-Dependent Holding Cost,” International Journals of Advanced Research in Computer Science and Software Engineering, vol. 7, no. 6-2277–128X, 2017, doi: DOI: 10.23956/ijarcsse/V7I6/0184.
[18] S. Chakraverty, D. M. Sahoo, and N. R. Mahato, “Concepts of Soft Computing: Fuzzy and ANN with Programming,” Springer Nature Singapore Pte Ltd. pp. 1–195, 2019. doi: 10.1007/978-981-13-7430-2.
[19] P. KUMAR, “a Study of Reliability Models Based on Fuzzy Set Theoretic Approach.” G. B. Pant University of Agriculture & Technology Pantnagar – 263145 (U. S. Nagar), Uttarakhand, INDIA By, pp. 1–204, 2016.
[20] A. Kumar and M. Ram, “System reliability analysis based on Weibull distribution and hesitant fuzzy set,” International Journal of Mathematical, Engineering and Management Sciences, vol. 3, no. 4, pp. 513–521, 2018, doi: 10.33889/ijmems.2018.3.4-037.

DOI: 10.21608/ERJENG.2023.199925.1163