

Computer Aided Fuzzy Control Charts for Evaluating and Analyzing Variable Data

Reyam Raheem Jabbar¹, Ahmed Abdulrasool Ahmed Alkhafaji²

¹ M.Sc. Student, Mechanical Engineering Department, The University of Baghdad, Baghdad, Iraq.

² Professor of Manufacturing and Industrial Engineering, Mechanical Engineering Department, The University of Baghdad, Baghdad, Iraq.

ABSTRACT: One of the limitations of fuzzy control charts is the complexity of their mathematical relations, and there is no software built to draw and analyze the fuzzy control charts. This research presents a visual presentation of fuzzy control charts for variables ($\tilde{X} - R$, $\tilde{X} - S$, I-MR), using an integrated program built by MATLAB20 to draw and analyze fuzzy control charts. A real case study was conducted of data collected from the Al-Numan factory for a plastic connector product. The number of attempts to reach the approved control limits was less in the fuzzy charts, as well as the number of deleted samples in the fuzzy charts was less. It was also noted that the process capability indicators decreased after data fuzzing, they were equal to (3.049) and became equal to (3.013) after fuzzing. This is due to the increase in the standard deviation of the process.

KEYWORDS: Control Charts, Fuzzy Logic, Process Capability, Alpha-Cut, Alpha-Fuzzy, Quality Control.

1. INTRODUCTION

Recently, firms worldwide have made quality improvement a top priority. Setting greater standards has benefits such as growing income, output, customer happiness, and market share, to name a few. Experiment design, hypothesis testing, and statistical control are statistical procedures that are crucial to improving quality [1]. A quality control chart is a graph that largely originates from a normal distribution curve. On the y-axis, where the test value is expressed, is a quality feature or a particular characteristic of the product or process that is controlled and is indicated in units. Time Control Diagrams to Improve The x-axis is composed of either quality intervals or sample numbers. A central line is present, and it either depicts the nominal value or the average value of the substance under investigation. As a result, the upper control limit (UCL) is shown by the top border, and the lower control limit (LCL) is indicated by the lower boundary. The pattern visible on the chart is then examined after making sequential plots of the acquired data [2]. Control charts can be categorized into two main groups based on how the values were acquired. A numerical scale can be used to measure values, which can be done by counting, adding, subtracting, using a testing tool, or judging proportions. To determine if they are complying or not, one would look at the specific characteristics they need to have to make a case. When values were measured to obtain the values, control charts for variables were utilized. Characteristic control charts are ones where the values come from proportions. These charts can be used to evaluate various process-specific scenarios in

processes and are applicable to all of them [2]. Numerous characteristics can be measured and expressed numerically. For instance, a bearing's diameter can be measured using a micrometer and expressed in millimeters, or the processing time for an insurance claim might be specified in hours. A variable is a single qualitative characteristic that can be measured, like a dimension, weight, or volume. Control charts are frequently used for variables [3]. Control charts are typically created utilizing precise random data obtained from key quality criteria. However, some applications, such as the surface roughness of components, the speed at which some lights move through a material, and the coating thickness of industrial cutting tools, may not be accurately characterized by crisp data in practice because they cannot be precisely measured or recorded. In addition, assessments of whether a process is under control or out of control, as well as whether those outcomes are conforming or nonconforming, frequently require some degree of human subjectivity related to the knowledge and perspectives of the decision-makers. These issues render the measurement technique unclear, which causes the results to be viewed as fuzzy data [4]. Numerous properties can be expressed in terms of a numerical measurement, including length, width, weight, temperature, and volume. One can determine if a process is "in control" or "out of control" based on numerical observation data. There can never be too many process control limitations. The measurement system, which consists of the operators and gauges, as well as external influences, is the main source of uncertainty. Rational decision-making should take into

account human subjectivity rather than relying solely on objective probability calculations. The fuzzy set theory is the best instrument for explaining uncertainty (or imprecision) originating from mental events, which are neither random nor stochastic. Because they require specialized information and human subjectivity plays a large role in determining the quality requirements, the traditional control charts might not be applicable. Traditional process control yields a binary classification as "in-control" or "out-of-control," whereas fuzzy control charts can tolerate intermediate assessments

[5]. Fuzzy control charts must be utilized when there is uncertainty in the statistical data, ambiguity in the process information, or when human subjectivity is present. In the fuzzy situation, each sample or subgroup is represented by a trapezoidal fuzzy number (a, b, c, d) or a triangular fuzzy number (a, b, c), as illustrated in Figure. 1. In this paper, the triangular fuzzy number was used because it is widely used by previous research as well and the nature of the mean of the data for the production process is always located in a single point (b).

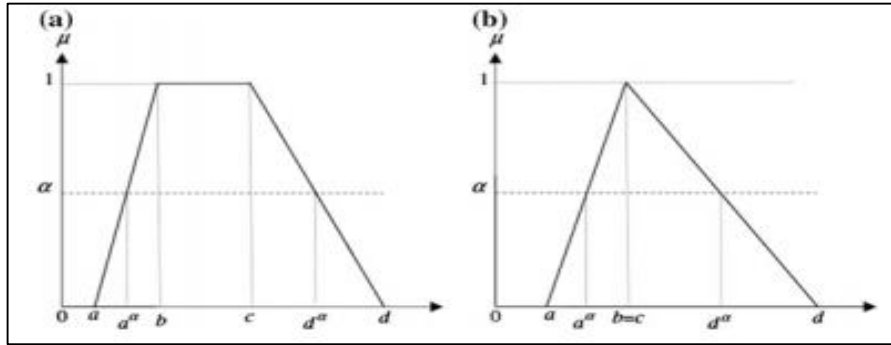


Figure 1. fuzzy representation of a sample, (a) trapezoidal fuzzy number, and (b) is a triangle fuzzy number [5]

This paper aims to construct a software where the variable fuzzy control charts can be drawn and analyzed. a real case study will be applied and the traditional control limits will also be calculated using the developed software to compare with the fuzzy control limits.

2. THEORETICAL PRINCIPLES

2.1 Fuzzification of the Data

The first step to attain the results was to convert the data from crisp values into fuzzy values by equations (1-3) [6].

$$X_a = X_b - \alpha X_b$$

$$(1)$$

$$X_b = X_i \tag{2}$$

$$X_c = X_b + \alpha X_b \tag{3}$$

Where:

X_a and X_c is the left- and right-hand sides of the sample, X_b is the original crisp sample and α is the uncertainty in the process ranging between (0-1%).

Previous studies failed to provide a precise value for the α -fuzzy. All in all, the researchers discovered that the value of the α -fuzzy was dependent on the experts' assumptions of a particular level of manufacturing process uncertainty. The quality expert in the manufacturing institution provided a value for the "fuzzy value" in the earlier research, and it was determined based on the process and measurement system uncertainty. According to equations (4) and (5), the methodology for this work was to select the α -fuzzy value based on the desired dimension, the actual dimension, and the kind of production process [7].

$$\bar{X}_j = \frac{\sum_{i=1}^n X_i}{n} \quad i = 1, 2, \dots, n \tag{4}$$

$$DNOM = \bar{X}_j - X_T \tag{5}$$

where (\bar{X}_j) is the sample mean, n is the sample size and X_T is the target dimension given by the designer.

Additionally, selecting the proper α -fuzzy depends on the process' standard deviation. The standard deviation of the procedure rises as a result of the fuzzification of the data, which accounts for the random differences that can occur between sample sizes. To make sure that it does not rise to an extremely high range during the fuzzification of the data, it is crucial to calculate the standard deviation of the procedure before and after the fuzzification. Equations (6) and (7) can be used to determine the standard deviation of the process both before and after fuzzification [8].

$$S_i = \sqrt{\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1}}, \bar{S} = \frac{\sum_{j=1}^m S}{m-1} \tag{6}$$

$$\bar{S} = \sqrt{\frac{\sum_{i=1}^n [(X_a, X_b, X_c) - (\bar{X}_a, \bar{X}_b, \bar{X}_c)]^2}{n}} \tag{7}$$

According to the sample size of the data used in the case under study, the fuzzy mean and range ($\tilde{\bar{X}} - R$) control charts and fuzzy mean and standard deviation control charts ($\tilde{\bar{X}} - S$) were used to monitor the process

2.2 Fuzzy $\tilde{\bar{X}} - R$ control charts

Let $X_i, X_{ija}, X_{ijb}, X_{ijc}, i = 1; 2; \dots, n, j = 1; 2; \dots, m$ be the fuzzy triangular representation of a quality characteristic of a sample with a size of m. The equations following can be used to calculate the mean of each subgroup and the overall average of the samples using fuzzy arithmetic [9].

$$\tilde{X}_j = \left(\frac{\sum_{i=1}^n X_{ija}}{n}, \frac{\sum_{i=1}^n X_{ijb}}{n}, \frac{\sum_{i=1}^n X_{ijc}}{n} \right) = (\bar{X}_{ja}, \bar{X}_{jb}, \bar{X}_{jc}); i=1, 2, \dots, n; j=1, 2, \dots, m \tag{8}$$

$$\bar{X} = \left(\frac{\sum_{j=1}^m X_{ja}}{m}, \frac{\sum_{j=1}^m X_{jb}}{m}, \frac{\sum_{j=1}^m X_{jc}}{m} \right) = (\bar{X}_a, \bar{X}_b, \bar{X}_c) \quad (9)$$

The fuzzy range of each subgroup can be represented in equation below:

$$R_{aj} = X_{\max;aj} - X_{\min;cj} \quad (10)$$

$$R_{bj} = X_{\max;bj} - X_{\min;bj} \quad (11)$$

And

$$R_{cj} = X_{\max;cj} - X_{\min;aj}; j=1,2,\dots,m \quad (12)$$

then the mean of the fuzzy range is calculated with the use of equation (13):

$$\bar{R}_a = \sum R_{a,j}/m, \bar{R}_b = \sum R_{b,j}/m, \bar{R}_c = \sum R_{c,j}/m \quad (13)$$

Fuzzy \bar{X} -R control chart limits can be obtained in a similar way to traditional R control charts, but they are represented by triangular fuzzy numbers as follows [10]

$$\bar{U}\bar{C}\bar{L}_x = \bar{C}\bar{L} + A_2 \bar{R} = (\bar{x}_a, \bar{x}_b, \bar{x}_c) + A_2 (\bar{R}_a, \bar{R}_b, \bar{R}_c) = \bar{U}\bar{C}\bar{L}_1, \bar{U}\bar{C}\bar{L}_2, \bar{U}\bar{C}\bar{L}_3 \quad (14)$$

$$\bar{C}\bar{L}_x = (\bar{x}_a, \bar{x}_b, \bar{x}_c) = \bar{C}\bar{L}_1, \bar{C}\bar{L}_2, \bar{C}\bar{L}_3 \quad (15)$$

$$\bar{L}\bar{C}\bar{L}_x = \bar{C}\bar{L} - A_2 \bar{R} = (\bar{x}_a, \bar{x}_b, \bar{x}_c) - A_2 (\bar{R}_a, \bar{R}_b, \bar{R}_c) = \bar{L}\bar{C}\bar{L}_1, \bar{L}\bar{C}\bar{L}_2, \bar{L}\bar{C}\bar{L}_3 \quad (16)$$

Where $\bar{U}\bar{C}\bar{L}_x$, $\bar{C}\bar{L}_x$ and, $\bar{L}\bar{C}\bar{L}_x$ is the upper, center and lower control limits of the fuzzy mean chart. A_2 is the control chart constant.

For R chart the control limits given by the following equations: [10]

$$\bar{U}\bar{C}\bar{L}_R = D_4 \bar{R} = D_4 (\bar{R}_a, \bar{R}_b, \bar{R}_c) \quad (17)$$

$$\bar{C}\bar{L}_R = (\bar{R}_a, \bar{R}_b, \bar{R}_c) \quad (18)$$

$$\bar{L}\bar{C}\bar{L}_R = D_3 \bar{R} = D_3 (\bar{R}_a, \bar{R}_b, \bar{R}_c) \quad (19)$$

Where $\bar{U}\bar{C}\bar{L}_R$, $\bar{C}\bar{L}_R$ and, $\bar{L}\bar{C}\bar{L}_R$ is the upper, center and lower control limits of the fuzzy range chart. D_4 and D_3 is the control chart constants.

2.3 Fuzzy \bar{X} - S control charts

Equations (20), (21), and (22) are used to determine the control limits of fuzzy \bar{X} charts based on standard deviation, with triangular fuzzy numbers acting as the upper and lower control limits [11].

$$\bar{U}\bar{C}\bar{L} = \bar{C}\bar{L} + A_3 \bar{S} = (\bar{X}_a, \bar{X}_b, \bar{X}_c) + A_3 (\bar{S}_a, \bar{S}_b, \bar{S}_c) = (\bar{X}_a + A_3 \bar{S}_a, \bar{X}_b + A_3 \bar{S}_b, \bar{X}_c + A_3 \bar{S}_c) \quad (20)$$

$$\bar{C}\bar{L} = (\bar{X}_a, \bar{X}_b, \bar{X}_c) \quad (21)$$

$$\bar{L}\bar{C}\bar{L} = \bar{C}\bar{L} - A_3 \bar{S} = (\bar{X}_a, \bar{X}_b, \bar{X}_c) - A_3 (\bar{S}_a, \bar{S}_b, \bar{S}_c) = (\bar{X}_a - A_3 \bar{S}_a, \bar{X}_b - A_3 \bar{S}_b, \bar{X}_c - A_3 \bar{S}_c) \quad (22)$$

where A_3 is the control chart constant.

The definition of a fuzzy (S) control chart is similar to that of a conventional (S) control chart. However, as shown below, they are created using a triangular fuzzy numbers approach [12].

$$\bar{U}\bar{C}\bar{L} = B_4 \bar{S} = B_4 (\bar{S}_a, \bar{S}_b, \bar{S}_c) = (B_4 \bar{S}_a, B_4 \bar{S}_b, B_4 \bar{S}_c) \quad (23)$$

$$\bar{C}\bar{L} = \bar{S} = (\bar{S}_a, \bar{S}_b, \bar{S}_c) \quad (24)$$

$$\bar{L}\bar{C}\bar{L} = B_3 \bar{S} = B_3 (\bar{S}_a, \bar{S}_b, \bar{S}_c) = (B_3 \bar{S}_a, B_3 \bar{S}_b, B_3 \bar{S}_c) \quad (25)$$

where B_3 and B_4 are the control chart constants.

2.4 Fuzzy transformation approach

There are basically four methods of fuzzy conversion, namely α -level fuzzy midrange, fuzzy average, fuzzy median, and fuzzy mode) for expressing the average (central tendency) of any given observation Due to its simplicity and prevalence in prior studies, the α -level fuzzy midrange transformation strategy was chosen for this article.

2.4.1 α -level fuzzy midrange transformation for (\bar{X} -R) control chart

The fuzzy \bar{X} control chart with an alpha-cut required selecting a value between 0 and 1 for the control limits. Therefore, the selection is based on the type or degree of the production process. The following is a possible rewriting of the " α -cut fuzzy \bar{X} control limits: [13]

$$\bar{U}\bar{C}\bar{L}_{mr-x}^\alpha = \bar{C}\bar{L}_{mr-x}^\alpha + A_2 \left(\frac{\bar{R}_a^\alpha + \bar{R}_c^\alpha}{2} \right) \quad (26)$$

$$\bar{C}\bar{L}_{mr-x}^\alpha = f_{mr-x}^\alpha = \frac{\bar{x}_a^\alpha + \bar{x}_c^\alpha}{2} \quad (27)$$

$$\bar{L}\bar{C}\bar{L}_{mr-x}^\alpha = \bar{C}\bar{L}_{mr-x}^\alpha - A_2 \left(\frac{\bar{R}_a^\alpha + \bar{R}_c^\alpha}{2} \right) \quad (28)$$

Where:

$$\bar{X}_a^\alpha = \bar{X}_a + \alpha (\bar{X}_b - \bar{X}_a) \quad (29)$$

$$\bar{X}_c^\alpha = \bar{X}_c + \alpha (\bar{X}_c - \bar{X}_b) \quad (30)$$

$$\bar{R}_a^\alpha = \bar{R}_a + \alpha (\bar{R}_b - \bar{R}_a) \quad (31)$$

$$\bar{R}_c^\alpha = \bar{R}_c + \alpha (\bar{R}_c - \bar{R}_b) \quad (32)$$

Where α -cut is a value ranging between (0-1) %.

The α -cut fuzzy R control limits can be rewritten as follows:

$$\widetilde{UCL}_{mr-R}^{\alpha} = \widetilde{CL}_{mr-R}^{\alpha} * D_4$$

(33)

$$\widetilde{CL}_{mr-R}^{\alpha} = f_{mr-R}^{\alpha} = \frac{\bar{R}_a^{\alpha} + \bar{R}_c^{\alpha}}{2}$$

(34)

$$\widetilde{LCL}_{mr-R}^{\alpha} = \widetilde{CL}_{mr-R}^{\alpha} * D_3$$

(35)

2.4.2 α -level fuzzy midrange transformation for (\bar{X} -S) control chart

The control limits for the α - cut fuzzy \bar{X} control chart based on standard deviation is as follows: [10]

$$\widetilde{UCL}_{mr-x}^{\alpha} = \widetilde{CL}_{mr-x}^{\alpha} + A_3 \left(\frac{\bar{S}_a^{\alpha} + \bar{S}_c^{\alpha}}{2} \right)$$

(36)

$$\widetilde{CL}_{mr-x}^{\alpha} = f_{mr-x}^{\alpha} = \frac{\bar{X}_a^{\alpha} + \bar{X}_c^{\alpha}}{2}$$

(37)

$$\widetilde{LCL}_{mr-x}^{\alpha} = \widetilde{CL}_{mr-x}^{\alpha} - A_3 \left(\frac{\bar{S}_a^{\alpha} + \bar{S}_c^{\alpha}}{2} \right)$$

(38)

where :

$$\bar{S}_a^{\alpha} = \bar{S}_a + \alpha(\bar{S}_b - \bar{S}_a)$$

(39)

$$\bar{S}_c^{\alpha} = \bar{S}_c + \alpha(\bar{S}_c - \bar{S}_b)$$

(40)

The control limits of the α - cut fuzzy standard deviation (S) control chart with the fuzzy midrange transformation approach is given in the equations below:

$$\widetilde{UCL}_{mr-S}^{\alpha} = \widetilde{CL}_{mr-S}^{\alpha} * B_4$$

(41)

$$\widetilde{CL}_{mr-S}^{\alpha} = f_{mr-S}^{\alpha} = \frac{\bar{S}_a^{\alpha} + \bar{S}_c^{\alpha}}{2}$$

(42)

$$\widetilde{LCL}_{mr-S}^{\alpha} = \widetilde{CL}_{mr-S}^{\alpha} * B_3$$

(43)

2.5 Process Capability Analysis

In the field of quality control, process capability is used to compare the output of a process with the specification limits of the product produced. The process capability index (PCI) is widely used to measure the inherent variability of a process and Process capability is a tool used in quality control to compare a process' output to the product's specified parameters. The process capacity index (PCI) is frequently used to gauge a process's intrinsic unpredictability and, consequently, its efficacy [14]. In fact, a number of common PCIs, including Cp, Cpk, Cpu, Cpl, Cpm, and Cpmk, are

frequently utilized. The Cp index solely represents the consistency of the product quality attributes because the total change in the process is relevant to the tolerability of the requirements. Cp can be mathematically represented as

$$Cp = \frac{USL - LSL}{6\sigma}$$

(44)

Where: USL and LSL = Two specification limits

σ = Standard deviation of process.

The pertinent equation below illustrates how the common indicator measures the distance between the average operation and the maximum specification using a half-distribution perspective (CPU). In a similar manner, Cpl, as shown in the equation, measures the distance between the average operation and the minimum requirements with half the distribution width. The fact that the process mean can be defined as follows is taken into account by Cpk. [15]

$$Cpu = \frac{USL - \mu}{3\sigma}$$

(45)

$$Cpl = \frac{\mu - LSL}{3\sigma}$$

(46)

$$Cpk = \min(Cpu, Cpl)$$

(47)

where: μ is the mean of the process

The means of the target value or departure operations are not taken into consideration by the Cp or Cpk indices. The following equation can be used to quantitatively express the CPM indices, which reflect the level of targeting of the process by include the departure process in their meta tags: [14]

$$Cpm = \frac{USL - LSL}{6\tau}$$

(48)

$$\tau = \sigma^2 + (\mu - T)^2$$

(49)

where T is the target dimension

For a power index that is more sensitive to the departure from the mean process than the target value, Pearn, Kotz, and Johnson (1992) introduced Cpmk [14], which combines the merits of the three basic indices (Cp, Cpk, and Cpm). Cpmk is defined as in the equation below [15]

$$Cpmk = \frac{\min(USL - \mu, \mu - LSL)}{3\sqrt{\sigma^2 + (\mu - T)^2}}$$

(50)

3. CONSTRUCTING THE SOFTWARE

One of the most important aims of the research and through the previous researches, there is no researcher constructed a program for this type of control charts. with the help of the

“Computer Aided Fuzzy Control Charts for Evaluating and Analyzing Variable Data”

available software (Excel 21 and Matlab20), the desired software was constructed to draw and analyze the fuzzy control charts and it is a new point and may be an original point added to the knowledge field in the application of the statistical fuzzy control charts. where any user can benefit from calculating the control limits for the variable fuzzy control charts ($\bar{X}-\bar{R}$, $\bar{X}-\bar{S}$, I-MR) and adopting their control limits after the comparison with the traditional control limits.

The software consists of the following tabs:

1. The first tab is the start page of the software and it is shown in Figure.2.

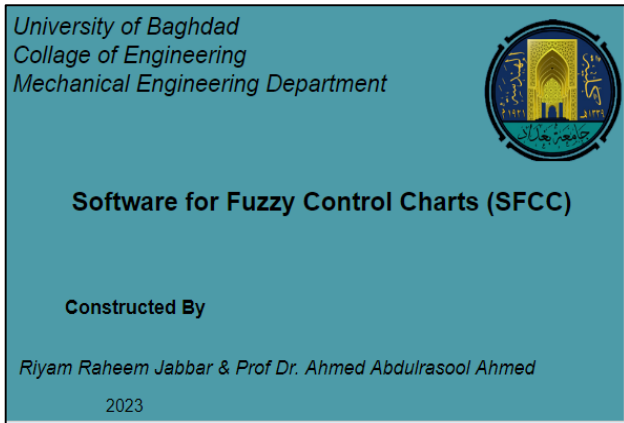


Figure. 2 The Start Page of the software

2. The second tab is the calculation tab and consists of the open file command which used to open the excel file that contain the data under study. the calculation tab also contains the main inputs required for the calculations of the control limits as well as the process capability (TD, Alpha-cut, USL, LSL). The run button in the calculation tab is used to run the program in order to get the results The calculation tab is shown in Figure.3.

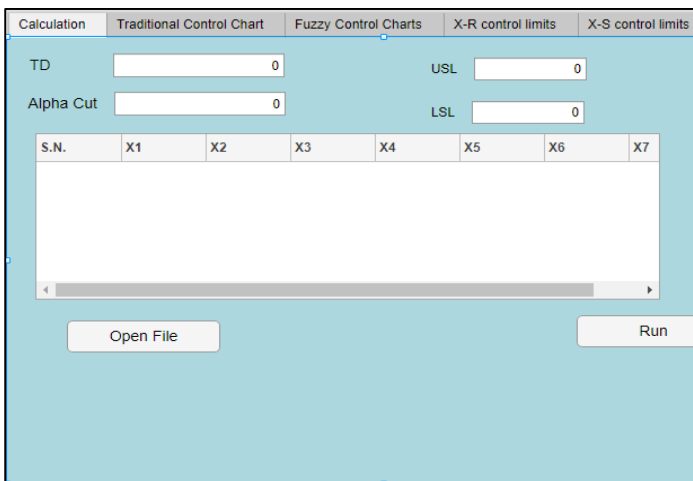


Figure 3. The Calculation Tab

If any error occurred during the input of the data the (please complete the input data) message is shown in the screen. when the program is done calculating and constructing the

results, the (The calculations are complete) message is shown on the screen.

3. The third tab is the traditional control charts. the traditional control charts were drawn for the purpose of verification of the program with the Minitab software results. Figure.4 shows the traditional control charts tab.

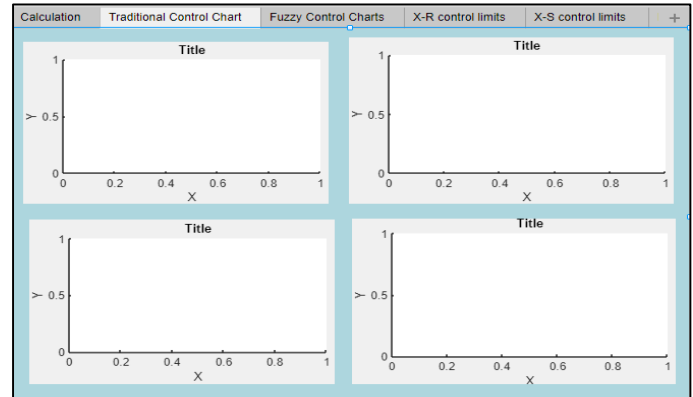


Figure 4. The traditional control Limits Tab

4. The fourth tab is the fuzzy control charts type where the fuzzy control charts are plotted and shown in Figure. 5.

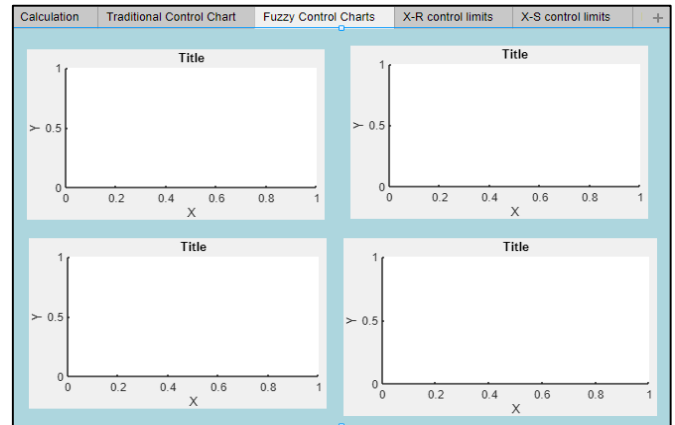


Figure 5. Fuzzy Control Charts Tab

5. The fifth, sixth and seventh tabs are the ($\bar{X}-R$, $\bar{X}-S$ and I-MR) control limits and it contains the traditional and fuzzy control limits. and are shown in Figs. from (6) to (8).

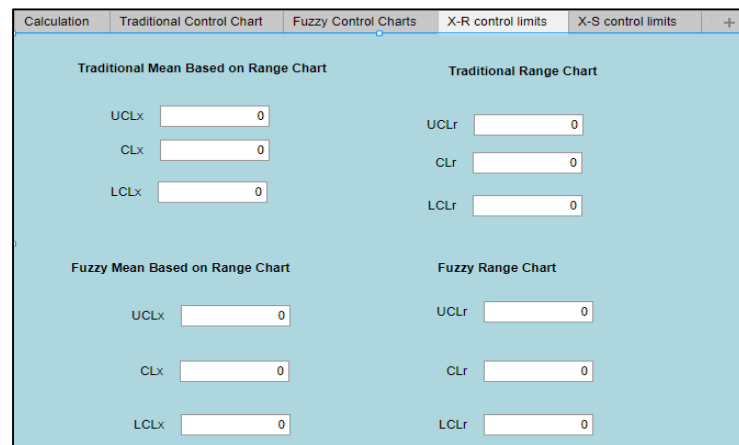


Figure 6. The $\bar{X}-R$ Control Limits

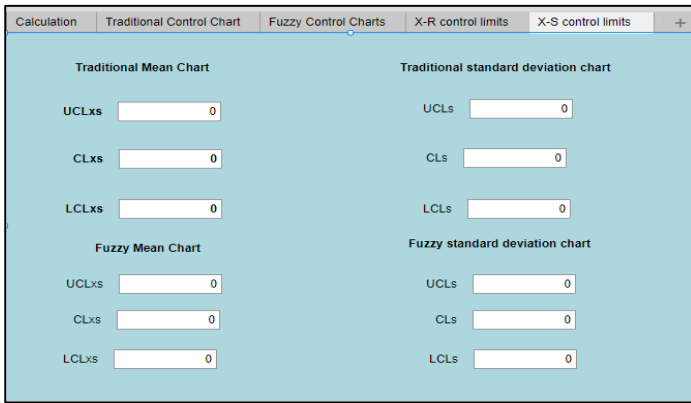


Figure 7. The \bar{X} -S Control Limits



Figure 8. The I-MR Control Limits

6. The next tab is the Analysis tab. This tab consists of the DNOM table, the alpha-fuzzy value, the standard deviation before the fuzzification (SD), the standard deviation for the fuzzified data and the process capability indices for the traditional and fuzzy data. Figure. 9 shows the Analysis tab.

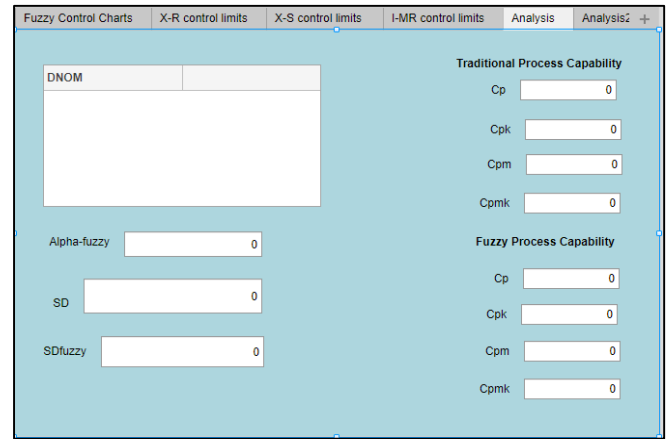


Figure .9 The First Analysis Tab

7. The last tab is the Analysis2 tab and it contains a plot for the relation between the alpha-fuzzy and the standard deviation for the process and a plot for the relation of the alpha-fuzzy and the mean of the process. Figure.10 shows the last tab.

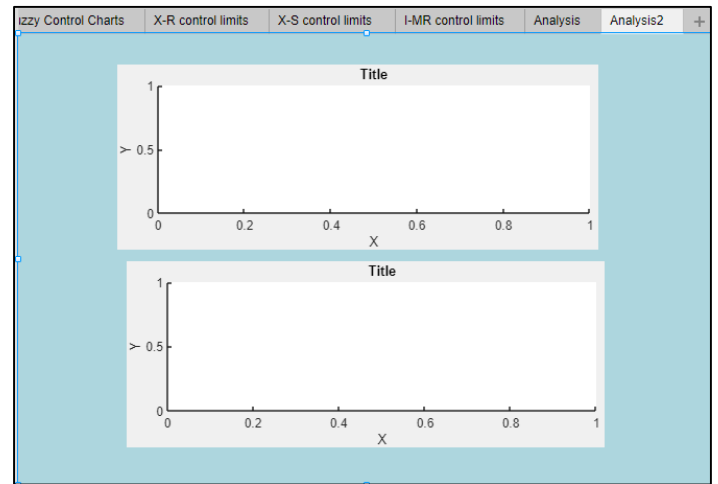


Figure. 10 The Second Analysis Tab

The following steps were used inside the code of the constructed software to obtain the results:

- I. Name the production process's kind. Include a target dimension definition in the specification. Determine the sample size's mean (\bar{X}). utilizing the formula (4).
- II. Determine the DNOM according to equation (5). Consider the sort of manufacturing process while choosing the α -fuzzy value. The highest negative value is selected as alpha-fuzzy if it is desired to approximate the upper specification limit and a negative value in the DNOM is undesirable. The smallest positive value is selected as the alpha-fuzzy value if there are no negative values present in the DNOM, and vice versa.
- III. By using the equations from (1) to (3), fuzzify the data.
- IV. Utilizing equations (6) and (7), determine the standard deviation of the process before and after fuzzification. The alpha-fuzzy value is reduced until the standard deviations are roughly equal if the

standard deviation following fuzzification differs significantly from the original data standard deviation.

- V. Using equations from (8) to (43), create the Fuzzy $\tilde{\bar{X}}$ - \tilde{S} and $\tilde{\bar{X}}$ - \tilde{S} , control charts using the fuzzified data.
- VI. Using the equations from (44) to (50), determine the process capability indices before and after the fuzzification.

4. CASE STUDY (AL-NUMAN FACTORY)

An armless plastic connector served as the case study. As a fitting component, this product is employed in irrigation systems. The product is seen in Figure (11) and was produced using an injection procedure. Since it is the most crucial component of the product, the internal diameter (73mm) was selected for monitoring. Vernier feet were used to measure the diameter. Table 1 displays the diameter for 25 measured objects. samples of size 5. The target dimension is (73 ± 0.07) mm. Raw data were generated at [AL-Numan Factory - Iraq]. Derived data supporting the findings of this study are available from the corresponding author [R.R.] on request.

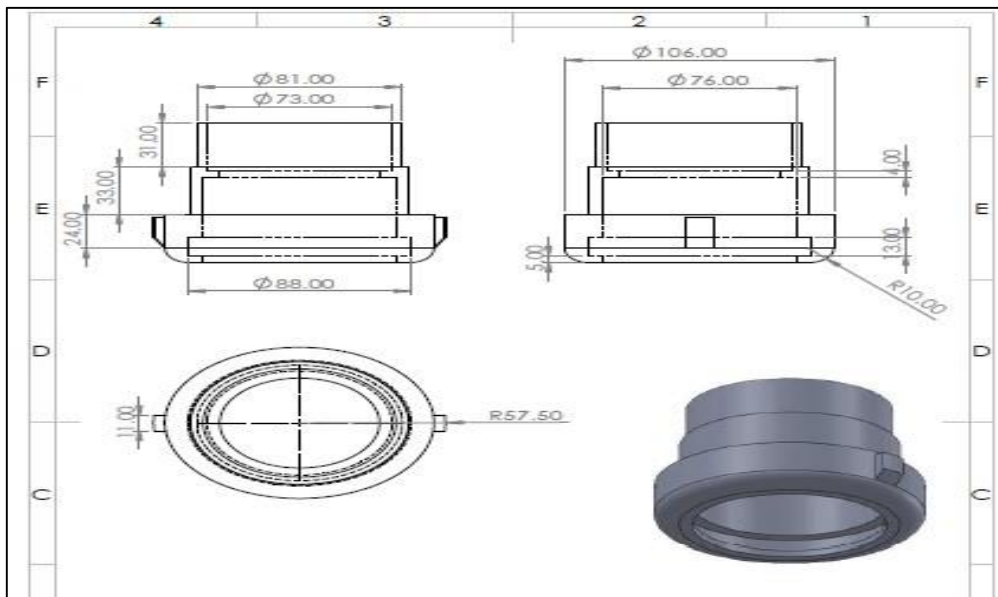


Figure (11) Plastic Connector Without Arms

Table (1): Data collected from Al-Noaman factory

sample no.	X ₁ (mm)	X ₂ (mm)	X ₃ (mm)	X ₄ (mm)	X ₅ (mm)
1	73.3	73.4	73.4	73.31	73.38
2	73.4	73.3	73.38	73.32	73.4
3	73.3	73.3	73.4	73.45	73.32
4	73.21	73.32	73.35	73.38	73.4
5	73.4	73.31	73.4	73.45	73.32
6	73.38	73.34	73.45	73.42	73.38
7	73.4	73.38	73.42	73.39	73.42
8	73.5	73.3	73.3	73.32	73.34
9	73.3	73.4	73.42	73.5	73.32
10	73.4	73.42	73.31	73.38	73.34
11	73.31	73.31	73.34	73.32	73.38
12	73.38	73.34	73.42	73.41	73.4
13	73.38	73.3	73.3	73.28	73.25
14	73.28	73.3	73.31	73.29	73.3
15	73.31	73.34	73.42	73.41	73.4
16	73.4	73.35	73.38	73.39	73.4
17	73.38	73.28	73.29	73.32	73.42
18	73.42	73.4	73.41	73.42	73.38
19	73.4	73.4	73.39	73.4	73.38
20	73.38	73.39	73.42	73.4	73.39
21	73.34	73.35	73.38	73.35	73.42
22	73.42	73.4	73.38	73.39	73.4
23	73.4	73.38	73.39	73.4	73.42
24	73.38	73.39	73.38	73.39	73.4
25	73.39	73.4	73.4	73.42	73.39

5. RESULTS AND DISCUSSION

As a first step, the traditional control charts were drawn using Minitab21 software. Depending on the sample size of the collected data (n=5, N=25) the appropriate control charts to monitor and control the manufacturing process are the mean and range (\bar{X} -R) and mean and standard deviation (\bar{X} -S) control charts.

Figure.12 shows the approved control limits of the (\bar{X} -R) control chart for the plastic connector. The control limits were

reached after the elimination of 6 samples in four trials. the maximum number of trials for control charts is three trials and the data need to be modified. in this research, the data were used for the purpose of comparison between the traditional and fuzzy control charts. In the first trial samples (13,14) were out of the lower control limit in the mean control chart and in the range control chart, samples (8,9) were out of the upper control limit. In the second trial, only sample (4) was out of the upper control in the range control chart. The third

trial showed that the sample (8) was out of the lower control limit in the main chart. In the fourth trial, the approved control

limit was obtained and all the remaining 19 samples were under control.

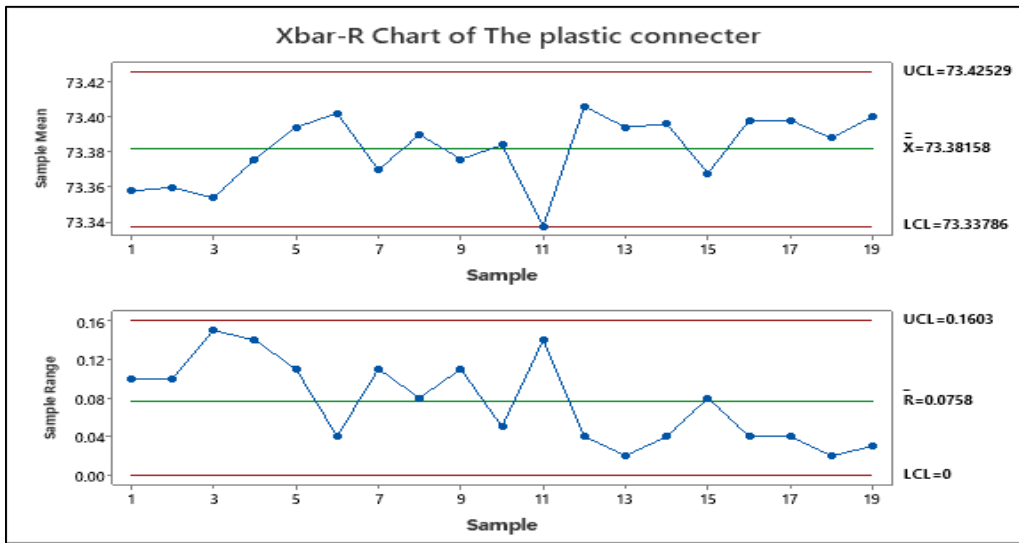


Figure 12. Traditional (\bar{X} -R) control chart for the plastic connector

Figure.13 shows the (\bar{X} -S) control charts drawn by Minitab. The approved control limits were obtained by dialing 10 samples in seven trials. The first trial showed that observations (13,14) in the mean chart and observations (8,9) in the standard deviation chart were out of control. In the second trial, sample 4 was out of control in the range chart. The third trial showed that sample (8) was out of control in

the main chart and sample (3) was out of control in the standard deviation chart. The fourth and fifth trials showed that samples (7,9) were out of control in the mean chart. The sixth trial showed an out-of-control sample (3) in the range chart. In the seventh trial, all samples were under control and the approved control limits were obtained.

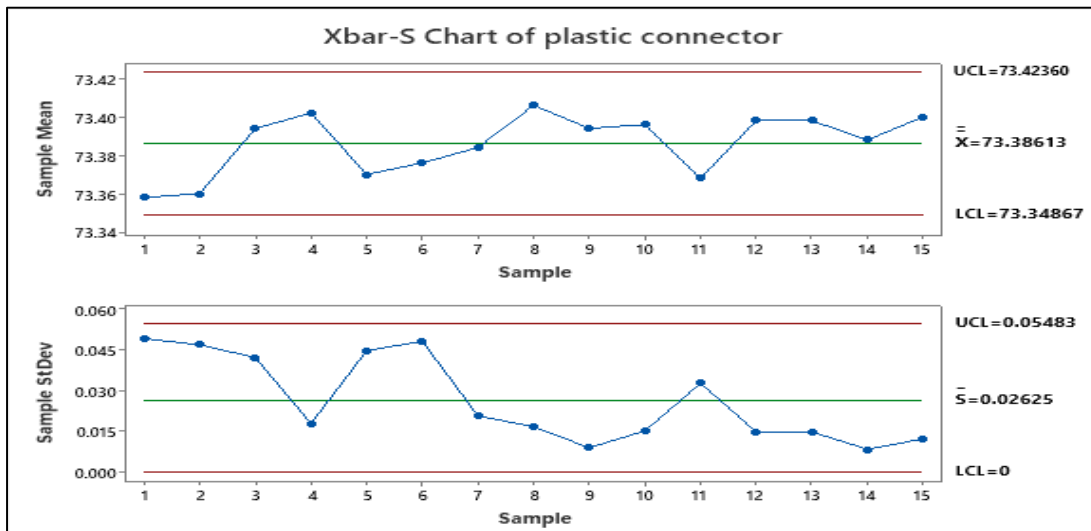


Figure 13. Traditional (\bar{X} -S) Control Chart for the Plastic Connector

The fuzzified data for the plastic connector product were used to construct the fuzzy mean and range as well as mean and standard deviation control charts. Figure.14 represents the approved \bar{X} -R and \bar{X} -S control chart with value of alpha-cut 0.65. this value of alpha-cut is the mostly used value in the production processes. the approved control limits were obtained in four trials. The first trial showed that samples

(13,14) were out of the control in the mean chart, while samples (8,9) were out of control in both range and standard deviation control charts. in the second trial, sample (4) was out of control in the range and standard deviation control charts. in the third trial, Sample 8 was out of the control in the mean chart and it was eliminated to obtain the approved control limits in the fourth trial.

“Computer Aided Fuzzy Control Charts for Evaluating and Analyzing Variable Data”

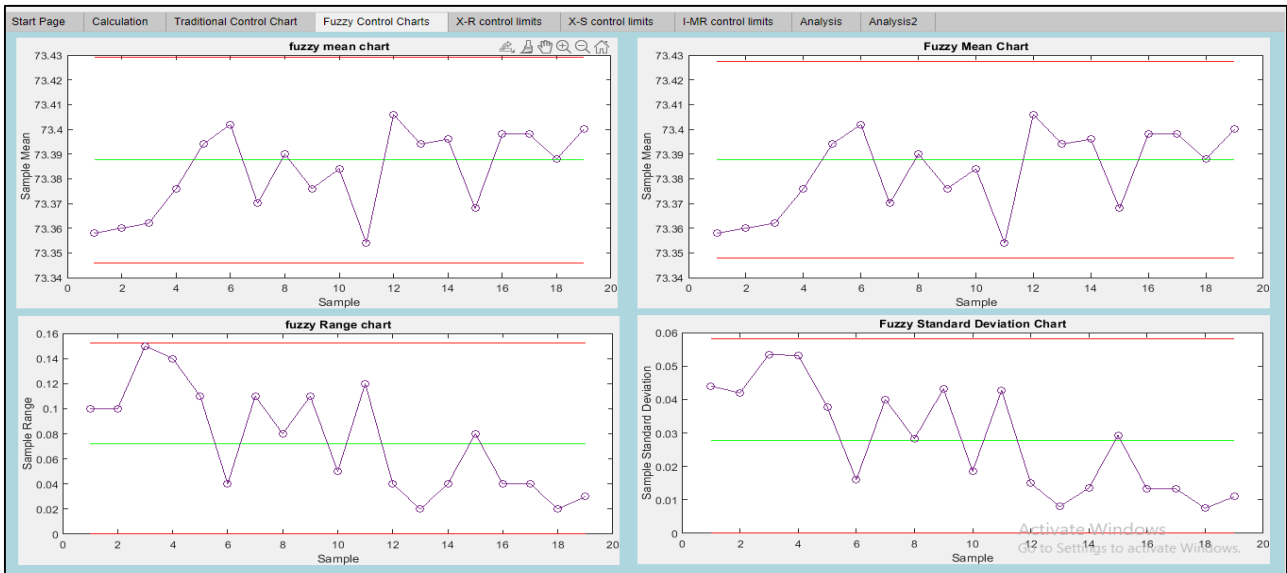


Figure 14. Fuzzy \bar{X} -R and \bar{X} -S Control Chart with α -cut=0.65

The developed software was designed to show the control limits for the drawn control charts for the traditional and fuzzy control charts in order to compare between the control limits and choose the appropriate ones to be the approved control limits depending on the specification limit of the

process as shown in Figs. from (15) to (18). For the mean chart based on range in Figure.15 and based on standard deviation in Figure.17, the fuzzy control limits increased by a value of 0.001 from the traditional control limits. This gives a flexibility to the process.

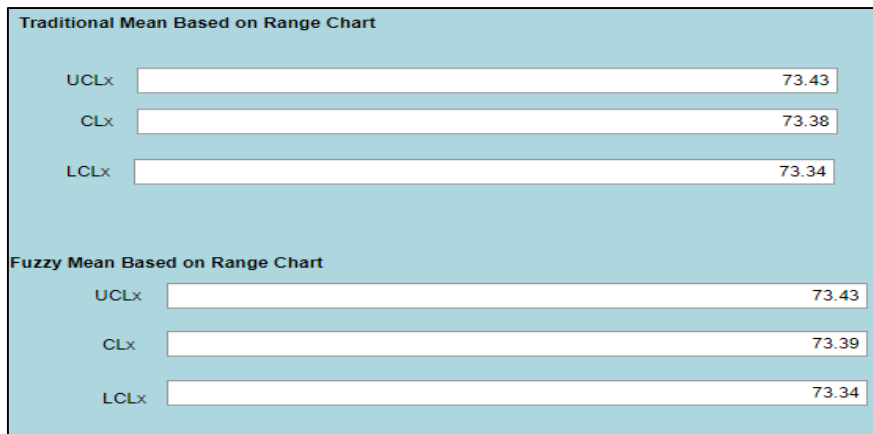


Figure 15. Traditional and Fuzzy Mean Based on Range Control Limits

The fuzzy range control limits in Figure.16 showed a significant decrement from the traditional control limits this

is due to the properties of the fuzzy logic in lowering and studying the differences between the sample sizes.

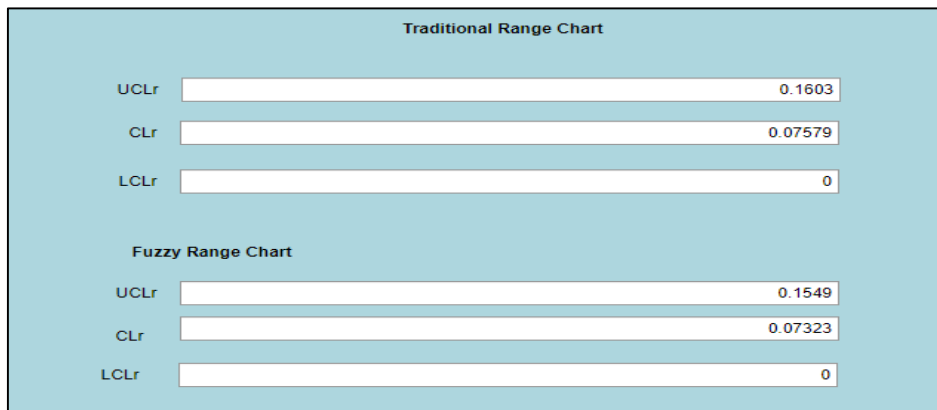


Figure 16. Traditional and Fuzzy Range Control Limits

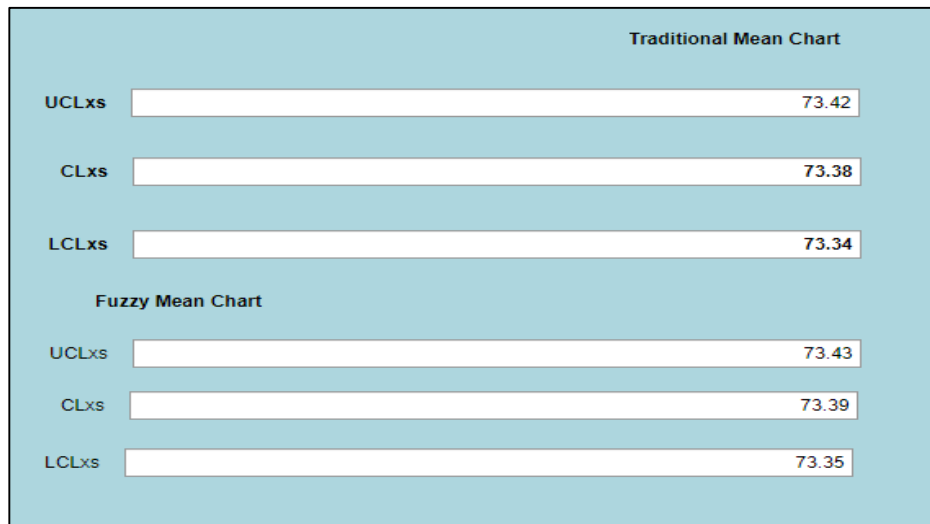


Figure 17. Traditional and Fuzzy Mean Based on Standard Deviation Control Limits

The fuzzy standard deviation control limits in Figure.18 did not change much as compared with the traditional control limits because the fuzzification of the data always takes into

consideration not to increase the standard deviation of the process.

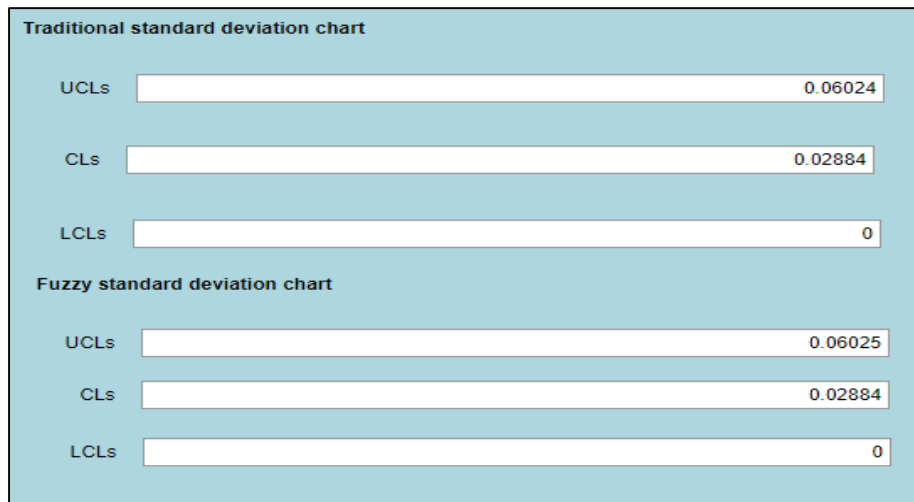


Figure.18 Traditional and Fuzzy Standard Deviation Control Limits

The software also has an analysis tab with the most important statistical indices. Figure.19 shows the analysis of the process. The standard deviation of the process increases by a value of 0.0044. The DNOM table showed that the value of

Alpha-fuzzy was chosen by the standard deviation condition. The process capability indices decreased after the fuzzification; this result can be considered by the designer to lower the specification limit if this is possible.

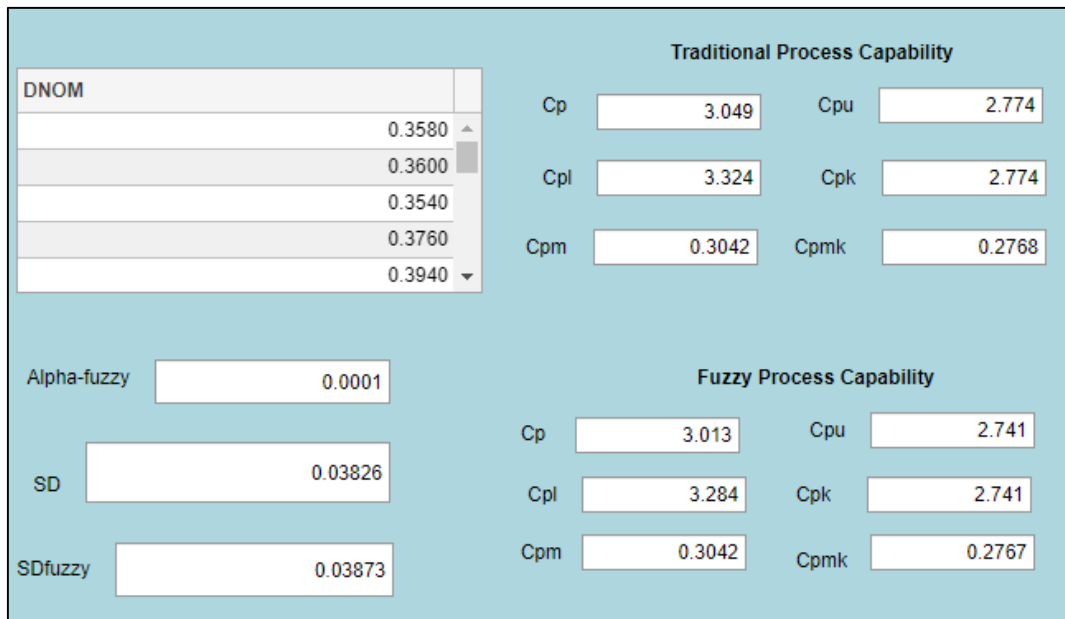


Figure.19 Process Capability Analysis

Figure.20 shows that the alpha-fuzzy increases the process’s standard deviation and has no effect noticeable effect on the mean of the process.

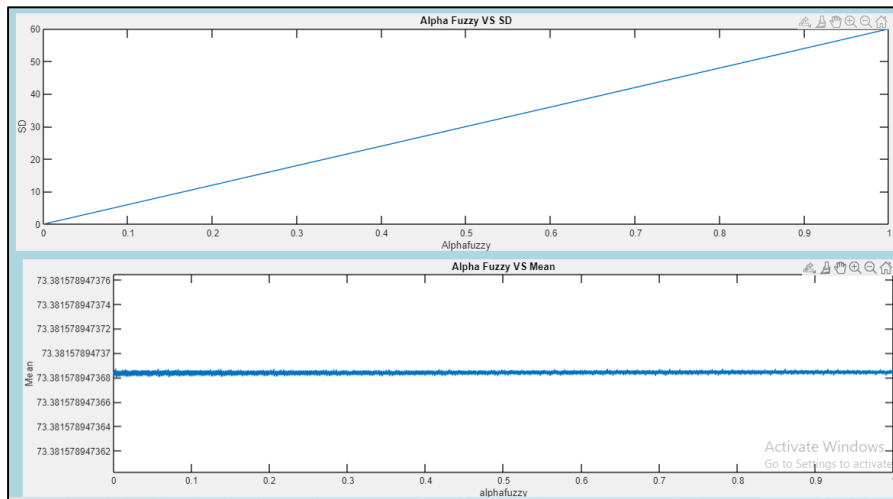


Figure 20. Alpha-Fuzzy with mean and standard deviation relations

6. CONCLUSION

The aim of this research was to develop a software that draw and analyze the fuzzy variable control charts as well as the ability of comparison with the traditional control charts. Practical application was applied from Al-Noaman factory for a plastic connecter product. From The applied methodology the following can be concluded:

- 1- The fuzzy control limits have flexibility over the traditional control limits.
- 2- The fuzzy control charts the number of trials as well as the number of deleted samples are lowered.
- 3- The developed software was a new point in the field of knowledge.

- 4- The developed software eases the complex calculation of the fuzzification of the data and the control charts calculations.
- 5- The process capability indices decreases with the fuzzified data due to the increase of the standard deviation of the process.
- 6- The increase in the alpha-fuzzy value increases the standard deviation of the process as it diverges between the mean and the left- and right-hand sides from the mean.
- 7- The fuzzification of the data has no effect on the mean of the process.

DATA AVAILABILITY STATEMENTS

Raw data were generated at [AL-Numan Factory - Iraq]. Derived data supporting the findings of this study are available from the corresponding author [R.R.] on request.

REFERENCES

1. Alakoc N. P.; Apaydin A., (2018), “A Fuzzy Control Chart Approach for Attributes and Variables”, *Engineering, Technology & Applied Science Research*, Vol. 8, No. 5, pp. 3360-3365.
2. ÖZDAĞOĞLU A.; ÖZDAĞOĞLU G.; GÜLER M. E., (2018), “Developing Quality Control Charts for the Control Points of A Food Product”, *International Journal of Contemporary Economics and Administrative Sciences*, Vol.8, No. 2, pp.89-113.
3. Montgomery D., (2013), “Introduction to Statistical Quality Control”. seventh edition. *Arizona State University*.
4. Enad F. H.; Jaber A. G., (2020), “Using Kernel Density Estimator to Determine the Limits of Multivariate Control Charts”. *Journal of Economics and Administrative Sciences*, Vol.26, No. 124,pp. 443-459.
5. Kahraman C.; Kabak Ö., (2016), “Fuzzy Statistical Decision-Making Theory and Applications”. *Studies in Fuzziness and Soft Computing, Springer Nature, Switzerland*.
6. Hamada A. A; Melik H. N.; Raheem S.H, (2020), “The Use of Fuzzy Logic Theory in Control Charts (A Comparative Study)”. *International Journal of Innovation Creativity and Change*, Vol.11, No.7,pp. 389-402.
7. Al obeidy N. Q.; Alkhafaji A. A., (2018), “Improving the Statistical Process Control Chart by Applying a DNOM Chart for Multiprocessor Products”. *2nd International Conference on Engineering Sciences*.
8. Mustafa H.; Asmaa F.; Jaber G., (2021), “Comparison of Some Non-Parametric Quality Control Methods”. *Journal of Economics and Administrative Sciences*, Vol.27, No.130, pp. 197-209.
9. Akeem A.A., (2018), “Performance of fuzzy control chart over the traditional control chart”. *Benin Journal of Statistics*, Vol.1, No.2018, pp.101-112.
10. Zafirah N.A.; Basri A.; Rusiman S.; Roslan R.; Mohamad M.; Khalid K., (2016), “Application of Fuzzy \bar{X} -S Charts for Solder Paste Thickness”. *Global Journal of Pure and Applied Mathematics*. Vol.12, No.5, pp. 973-1768.
11. Senturk S.; Erginel N., (2009), “Development of fuzzy \bar{X} -R and \bar{X} -S control charts using α -cuts”. *Information Sciences*, Vol.179, pp. 1542–1551.
12. Dilipkumar R.; Nanthakumar C.,(2019), “Construction of Fuzzy Mean Using Standard Deviation \bar{X} - S Control Chart with Process Capability” *International Journal of Recent Technology and Engineering*, Vol. 8, No.4, pp. 5390-5396.
13. Kaya I.; Erdogan M.; Yildez C., (2017), “Analysis and control of variability by using fuzzy individual control charts”. *Applied Soft Computing Journal*. Vol.51, pp.370-381.
14. Alwan N. Q.; Ahmed A. A.,(2018), “Comparison Between (\bar{X} – R) Charts in Traditional and Deviation Nominal Methods with Usage Process Capability Analysis”. *Association of Arab*
15. Al -Khafaj A.A.; AL -Mendwi K. A.; Al-saad D.M.H.,(2012), “Adjusting off-centering process for a blow molded plastic product by use of WINQSB software”. *Journal of Engineering*, Vol.18, No.4, 2012, 518-534.