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FUZZY LOGIC TEST IN DRAWING AND CALCULATING DEFECTIVE RATIO CONTROL CHARTS IN INDUSTRIES COMPANY

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ABSTRACT

For businesses to remain competitive in the market today, the quality of their products must either be improved upon or maintained. Therefore, creating a fresh strategy that might make more use of data from the production process has turned into a necessary program for every organization looking to boost quality. Fuzzy attribute control charts were created in the current study to track the manufacturing process. The triangle membership function was used to get the fuzzy numbers, and the recommended ranking function was then applied to turn them into a conventional sample. Fuzzy control charts have the potential to mitigate uncertainty stemming from incomplete, ambiguous, and/or confusing information, also the inherent uncertainty originating from measurement randomness in quality characteristics. Through data collection from the Al-Mamon facility and comparison with the conventional Shewhart control charts, a case study at the state corporation for vegetable oils in Iraq was used to validate the suggested fuzzy control charts. This study compares the use of fuzzy logic with the traditional way when adopting variable cases through the arrangement function to attain the control limits for faulty percentages and quality control for all samples using (w=0.6, 0.8, 0.9) and (λ = 0.7, 0.9). The results showed that a fuzzy control chart manages manufacturing quality more quickly, cheaply, and accurately. It makes it easier to find defective units during the manufacturing process, which helps to quickly ascertain whether or not production is under control. It also offers quality enhancements that are advantageous to the company.

KEYWORDS

Statistical Process, Attributes Control, P-chart, Fuzzy Sets Theory, Ranking function.

1. INTRODUCTION

Lately, companies everywhere have turned their attention to improving quality. Raising standards has several advantages, including higher market share, revenue, productivity, and customer happiness. Statistical techniques such as experiment design, hypothesis testing, and statistical process control are essential for enhancing quality. The primary instruments in statistical process control, quality control charts, were first introduced by Walter A. Shewhart (Montgomery, D.C., 2020). Statistical process control (SPC) ensures the predictability of the process and is used to check process stability. The Statistical Process Control (SPC) process was created by Shewhart in the 1924s and is still in use today, especially in industrial production processes. It includes observation, assessment, diagnosis, and decision-making. One of the essential SPC tools for quality improvement is the control chart (Zabihinpour, S.M., Ariffin, M.K.A., Tang, S.H., Azfanizam, A.S. and Boyer, O., 2014, Abdulghafour, A.B., Omran, S.H., Jafar, M.S., Mottar, M.M. and Hussein, O.H., 2021). A control chart is a graphic depiction of a quality attribute that compares a time or sample number to a measured or computed sample. Control charts are powerful tools because they may be used to identify abnormal circumstances in the process and detect shifts in the process (Hassoon, O.H., Ibrahim, B. and Albaghdadi, B., 2020). Even if it isn't the original control chart that is given, statistical process control, or SPC, is an essential tool for carrying out quality improvement initiatives in many manufacturing environments (Montgomery, D.C., 2020).

One of the most popular statistical techniques for tracking changes that arise throughout the stages of the product process is the control chart. Its use depends on the observation made from the sampled data, which establishes the process's statistical accuracy (Ahmad, M. and Cheng, W., 2022, Amjad, B., Hussien, S., Ghulam, Z.J. and Rashed, M.K., 2017). Products are divided into conformed and non-conforming categories in traditional P-control charts. With multiple intermediate levels and the need to use a mathematical tool to improve control chart performance, binary classification may not be suitable in many circumstances. Because of this, fuzzy control charts have recently been used to assess data that is linguistically defined or that is unclear, ambiguous, and incomplete (Sogandi, F., Mousavi, S.M. and Ghanaatian, R., 2014). A fuzzy set is a class of things that have a range of membership grades. Such a collection is characterized by a membership (characteristic) function that assigns a membership grade to each item, ranging from zero to one (Zadeh, 1965; Zadeh, L.A., 1965).

The aim of this essay is to apply the product whose constant simple size and triangular membership function are available into both crisp control and fuzzy charts. Finally, the quality control of the attributes is determined using ranking technique in case of $w = 0.5$, $\lambda = 0.5$, $w =$

0.6, λ = 0.7, and w = 0.2, λ = 0.9. Section 2 illustrates the development of control charts and presentation through a mathematical form. Part 3 provided me with examples of how to make and use numbers. In Part 4, results and dissociation are shown. Section 5 presents the findings.

2. LITERATURE SURVEY

Numerous academics try to apply fuzzy set theory to control charts and SPC. To ascertain the process condition, all of these methods convert fuzzy control limits and fuzzy observations into a crisp value; however, this process may obliterate valuable process information, and it appears preferable to ascertain the process condition directly and without any transformation (Thamer, E.D. and Hussein, I.H., 2021, Alakoc, N.P. and Apaydin, A., 2018, Khan, M.Z., Khan, M.F., Aslam, M., Niaki, S.T.A. and Mughal, A.R., 2018). Salah et al. examined several frequently used control chart styles for features in this paper, including the synthetic chart, np chart, exponential moving average chart (EWMA), cumulative sum chart (CUSUM), and the Sequential Likelihood Ratio Test (SPRT) scheme. Additionally, a generic model for the best layout of trait control methods is put forth. To get the greatest overall performance in this study, independent and dependent graph parameters were tuned using a thorough search technique. Using an objective function that was susceptible to the same false alarm rate as a straightforward and trustworthy search technique, the average number of defects (AND) was chosen for the design and comparison of the graphs. Through quantitative comparison, the researchers in this study concluded that the newly generated graphs significantly increased the efficacy of detection. Specifically, the np-CUSUM scheme and Curt CUSUM schemes are the fastest CUSUM graphs for p-transformation detection; the Syn-np scheme is the most efficient Shewhart-type scheme for traits in the current SPC literature; and the optimized SPRT scheme can double the overall detection speed when compared to the base SPRT scheme. Although the optimum schemes for SPRT, np-CUSUM, Syn-np, and Curt CUSUM have more complex designs and take slightly more effort to implement than its counterpart schemes, the notable improvement in performance validates the application of the novel schemes developed in this study. Under some circumstances, it was discovered that the new AFV scheme employing basic trait screening performed better overall than the X&R and X&S variable schemes concerning performance. One shortcoming of the AFV system is that it cannot identify shifts with diminishing variance. Furthermore, keeping an eye on the parameters of processes that alter often is not acceptable (Thamer, E.D. and Hussein, I.H., 2021).

Esraa et al. employed statistical techniques to identify quality control schemes for properties using actual data from the Iraqi Baghdad Soft Drinks Company. Fuzzy numbers were obtained by applying the triple membership function, which was followed by a conversion to a conventional model using the proposed ranking function. A comparison of the clear and fuzzy theme quality settings (Alakoc, N.P. and Apaydin, A., 2018). Nilufer and associates introduced a novel method for fuzzy control methods. This is in line with how fuzzy theory and Shewhart control diagrams are learned. They created the curriculum in a way that allows the methodology to be used in a range of procedures. The following are the primary characteristics of the suggested method: Fuzzy control systems come in a variety of forms that are not restricted to variables or attributes. The method can be readily adjusted for various activities and fuzzy numbers by decision-makers through assessment or judgment. They created the approach to a fuzzy quality control diagram, and an example diagram is displayed, to fully explain the approach technique. The Shewhart C graph and the fuzzy C graph performance were both analyzed and contrasted. The outcomes demonstrated that the suggested strategy performs better and offers an effective method for identifying process changes (Khan, M.Z., Khan, M.F., Aslam, M., Niaki, S.T.A. and Mughal, A.R., 2018).

To monitor processes with fuzzy data, Muhammad et al. suggested a novel fuzzy control strategy for EWMA. This was accomplished by using fuzzy data gathered from the cooking oil sector and the recently created FEMWA control scheme, which demonstrated its efficacy. When fuzzy trapezoidal numbers are employed in place of rectangular ones in the future, the same analysis can be applied. It is necessary to compare the effectiveness of fuzzy and traditional EWMA charts concerning the ARL criterion. (Saravanan, A. and Alamelumangai, V., 2014). Saravanan et al. have developed feature charts for the standard deviation of variable data for process optimization, including the p plot, the CUSUM plot, and the fuzzy α cutoff control plot. To monitor processes with fuzzy data, Muhammad et al. suggested a novel fuzzy control strategy for EWMA. This was accomplished by using fuzzy data gathered from the cooking oil sector and the recently created FEMWA control scheme, which demonstrated its efficacy. When fuzzy trapezoidal numbers are employed in place of rectangular ones in the future, the same analysis can be applied. It is necessary to compare the effectiveness of fuzzy and traditional EWMA charts concerning the ARL criterion. (Saravanan, A. and Alamelumangai, V., 2014). Saravanan et al. have developed feature charts for the standard deviation of variable data for process optimization, including the p plot, the CUSUM plot, and the fuzzy α cutoff control plot. To monitor processes with fuzzy data, Muhammad et al. suggested a novel fuzzy control strategy for EWMA. This was accomplished by using fuzzy data gathered from the cooking oil sector and the recently created FEMWA control scheme, which demonstrated its efficacy. When fuzzy trapezoidal numbers are employed in place of rectangular ones in the future, the same analysis can be applied. It is necessary to compare the effectiveness of fuzzy and traditional EWMA charts concerning the ARL criterion. (Saravanan, A. and Alamelumangai, V., 2014). Saravanan et al. have developed feature charts for the standard deviation of variable data for process optimization, including the p plot, the CUSUM plot, and the fuzzy α cutoff control plot. The control strategy based on Markov Chain Theory (MC) known as the Transfer Probability Control (TPCC) scheme compares its output performance to that of the control scheme based on the membership approach known as the Fuzzy Control scheme (FCC) (Thaga, K. and Sivasamy, R., 2015).

This study uses recommended control systems to show statistically if the FCC is more effective at regulating the quality attributes of the production process than the TPCC. It is concluded that the FCC outperforms the TPCC (Ahmad, M. and Cheng, W., 2022) if the sample point in period k = 4th is a true alarm for some assignable cause. Otherwise, the TPCC operates similarly. Mohammad et al. investigated the fuzzy control approach based on fuzzy process ability indices (FCPI) using triangular fuzzy numbers (TFNs). In an industrial context, statistical quality control of fuzzy processes has been implemented using the concept of alpha clipping. This study is divided into five sections that focus on the control approach using power indicators. We used the previously mentioned method on the numerical case. This study improved our understanding of the manufacturing system's data and demonstrated the use of fuzzy control techniques. It also demonstrated that the process should be controlled using cut-off TFNs, which are appropriate when data shows uncertainty and can also be used to fix levels at steady state values by using the fuzzy control charts that are recommended (Kaya, İ., Karaşan, A., İlbahar, E. and Cebeci, B., 2020). Ihsan et al aimed to extend this CC using Intuitive Fuzzy Sets (IFS). When compared with available studies, it allows the use of IFSs for frequency representation in the design stages of p and np control schemes. To achieve this goal, in this paper, two types of ACCs based on IFS were redesigned to improve their sensitivity and flexibility. Additionally, IF-based extensions of p and np control schemes are suggested, and a detailed presentation of the architecture of these CCs is provided. Additionally, control limits and center lines were recast using IFs, and the applicability of the suggested method was examined through the presentation of a descriptive example. To address uncertainty, community centers may be designed and evaluated more effectively with integrated finance strategies, according to a summary of the research findings. When compared to the traditional p-control system, the suggested approach yields insightful and thorough outcomes. They advise that in order to compare the findings, similar research should be conducted in the future utilizing actual case application data. It is also possible to create other kinds of fuzzy groups that can be used to indicate uncertainty and frequency in comparison. (Gülbay, M. and Kahraman, C., 2006).

Sogandi and colleagues created an innovative fuzzy control system to track trait quality attributes using a fuzzy mean-range technique at the α level. Next, using Monte Carlo simulation, the effectiveness and comparative outcomes of the suggested fuzzy control scheme are expressed in terms of average run length (ARL). They came to the conclusion that the suggested strategy performed well and could identify changes in the process more quickly than the conventional control system through comparison utilizing the ARL criterion. They advise that to compare the findings, similar research should be conducted in the future utilizing actual case application data. It is also possible to create other kinds of fuzzy groups that can be used to indicate uncertainty and frequency in comparison. (Gülbay, M. and Kahraman, C., 2006).

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The purpose of Reyam Raheem et al. study was to compare fuzzy control charts to regular control charts for short-run production. In the conventional scenario, the software Minitab 21 was used to process the data that were gathered. It was discovered that when figuring out the control limits of the machine under study, fuzzy control charts were more accurate and adaptable (Jabbar, R.R. and Alkhafaji, A.A.A., 2023). To ascertain the extent of samples outside or within the bounds of quality control, Faraza, A. and Shapiro, A. developed a fuzzy quality control chart, which was an extension of conventional quality control charts (Shewhart $\bar{X}$-S) (Faraz, A. and Shapiro, A.F., 2010). A multistage technique was provided by Engin, O. et al. to address the issue of fuzziness for an Attribute Control Chart (ACC), and genetic algorithms were used to tackle the problem (Engin, O., Çelik, A. and Kaya, İ., 2008). M. Hungshu and H. Chung Wu. used p-control charts to keep an eye on samples that don't correspond during production. By utilizing fuzzy set theory in conventional p-control charts, fuzzy-control charts have been utilized to produce linguistic judgments that disclose the number of samples that are under or out of control (Shu, M.H. and Wu, H.C., 2010). S. Sorooshian experimented with a fuzzy set theory-based method for tracking attribute quality attributes that takes ambiguity and uncertainty into account. It was discovered that, in comparison to existing relevant methodologies, the suggested approach performs better and identifies anomalous shifts in the process more quickly, particularly in tiny shifts and small sample sizes (Sorooshian, S., 2013).

It is possible to use linguistic variable directly or to transform them into fuzzy numbers to build fuzzy control charts. A fuzzy number is an extension of a conventional real number and is characterized as connected array of possible values instead of a single value (Sorooshian, S., 2013). The findings of the control scheme, such as defective sample may be detected during the creation of the sample and the error can be cured the soonest possible time and can eliminate the error in the subsequent samples, makes fuzzy control appear faster and more accurate. The fuzzy statistical control systems should include an appropriate design that can be used within the working limits that the samples to be produced are acceptable. They can be processed directly or executed as a fuzzy number to make fuzzy control chart. A fuzzy number is an extension of a conventional real number (Sorooshian, S., 2013) that is a fuzzy number refers to a linked universe of the possible values rather than a single value.

Fuzzy control shows itself to be faster and more accurate because its findings of control scheme disclose the error, cure it as early as possible during the creation of the defective sample, and thus avoid the error in the subsequent samples. The fuzzy statistical control systems should be given an appropriate design in the working limitations, which pertains to the samples that are going to be produced. Patterns form rules with options of variation, and solution is realized with creating such schemes through the methods of artificial intelligence such as the fuzzy logic and the neural networks (Cheng, C.B., 2005, Dale H. Biesterfield, 2009) to monitor and improve the production quality. Several simulations have been run to improve production quality through the use of monitoring techniques and sample data that is both clear and fuzzy from real sources. An order function between 0 and 1, such as (w = 0.4, λ = 0.7), can be proposed and used as the basis for the control.

3. CHART OF CONTROL FOR THE PERCENTAGE OF NONCONFORMING GOODS (P-CHARTS):

Different forms of control charts, based on various statistical distributions, are used in response to the following kinds of attributes:

a) Units that are either conforming or non-conforming; these could include ball bearings, invoices, employees, and so forth. Each of these categories could be fully characterized as acceptable or faulty, failing or not failing, present or not present, etc.

b) Non-conformities or conformities, which can be used to characterize a good or service; examples include the number of flaws, mistakes, or problems, as well as positive metrics like sales calls, truck deliveries, and goals, scored (Ravi, V., 2015).

P-charts are used to express the proportion of a sample that contains errors. The binomial distribution can be used to get this figure. The center line and the upper and lower control limits are computed similarly to how the other types of control charts are computed. The average fraction faulty in the population, or ˥P, is used to compute the center line. This is done by randomly selecting multiple observation samples and calculating the average value of p for each sample (Rubens, N., 2006).

In the conventional method, the following equations were used to compute the upper and lower bounds of P-control charts based on clean data (Shuraiji, A.L. and Shneen, S.W., 2022, Salman Hussein Omran , 2012);

Calculate the fraction defective (P) for each subgroup

$$P = \frac{D}{p} \tag{1}$$

P , proportion of defective: D, Total of defective in a subgroup: p, Number of items inspected in a subgroup.

Calculate the average fraction defective (p^{-})

$$\text{the Central Line } (CL) = \bar{p} = \frac{\sum P}{g} = \frac{\textit{Total number of defective in a period}}{\textit{The total number of samples}} \tag{2}$$

3-Determine upper control limits and lower control limits for the p-chart

$$\text{Upper control limit } (UCL) = CL + 3\sqrt{\frac{p^{-}(1-p^{-})}{m}} \tag{3}$$

$$\text{Lower control limit } (LCL) = CL - 3\sqrt{\frac{p^{-}(1-p^{-})}{m}} \tag{4}$$

m is the number inspected in a subgroup (sample size)

The production process is out of control limit when the number of the defect proportions exceeds the upper and lower control limits. It is different how the production process runs. The Ranking function and the Fuzzy set are used in Eqs. 5 and 6. To apply fuzzy logic, it is essential to designate a distinct sample group and to find the expression of this fuzzy group in terms of a fuzzy set. In the address of the group, the connection is between ordered pairs. The name of another group is membership. Both groups state that A is the obscure or fuzzy and X is the clear. Hence, the function may be written as follows (Thamer, E.D. and Hussein, I.H., 2021) in the form of fuzzy logic to write the fuzzy group's membership:

$$\mu_A(x) = \begin{cases} \dfrac{\lambda(x-a)}{(b-a)} & a \le x \le b \\ \lambda & x = b \\ \dfrac{\lambda(c-x)}{(c-b)} & b \le x \le c \end{cases} \tag{5}$$

The fuzzy sums can be represented by fuzzy logical elements. The ideals of Trigone are taken up and shown in ($\tilde{A}$)= (a, b, c), which may be contained in the following equation:

$$R(\tilde{A}) = \frac{\lambda(2b+a+c)+w(2b-a-c)}{\lambda(\lambda+w)} \tag{6}$$

4. NUMERICAL MODEL TRAINING SAMPLES OF PRODUCTION AND IMPLEMENTATION

In this section two stets are shown in the sections below:

4.1. Production's samples

One of the big producers provided the data, and the first was the production, which was shown to have flaws in each sample in two months, the Al-Mamon factory, and the state firm responsible for producing vegetable oils in Iraq. As indicated in Table, a sample of 450 cans per day for 30 days was chosen to identify the rejected goods (1).

Table 1. Product Outcomes [33]

N	No. of defectives	Sample size	N	No. of defectives	Sample size	N	No. of defectives	Sample size
1	8	450	11	1	450	21	5	450
2	5	450	12	0	450	22	4	450
3	2	450	13	0	450	23	0	450
4	3	450	14	0	450	24	4	450
5	0	450	15	2	450	25	3	450
6	0	450	16	4	450	26	4	450
7	18	450	17	2	450	27	4	450
8	3	450	18	0	450	28	4	450
9	2	450	19	1	450	29	0	450
10	3	450	20	3	450	30	3	450

The determination of (p) is done in Table 1 after making use of attribute control charts of each sample to get (p), Eq.1 will be used to determine that (p) = the proportion of defective samples for each sample in Table 2. In the second phase determine the control limits given by Eqs.(2-4) as well. Attributes control charts Fig.1 have been created using the Minitab (21) software using the controls pertaining with this project. As an example, sample one is:

$$P = \frac{D}{p} = \frac{8}{450} = 0.0177777778 \qquad (1)$$

$$the\ CL = \bar{p} = \frac{\sum P}{n} = \frac{1.639337}{30} = 0.00659 \qquad (2)$$

$$UCL = CL + 3\sqrt{\frac{p^{-}(1-p^{-})}{m}} = 0.01804 \qquad (3)$$

, at m=450

$$(LCL) = CL - 3\sqrt{\frac{p^{-}(1-p^{-})}{m}} = 0 \qquad (4)$$

Table 2. Proportion of defective value

N	P	N	P	N	P
1	0.0177777778	11	0.0022222222	21	0.0111111111
2	0.0111111111	12	0	22	0.0088888889
3	0.0044444444	13	0	23	0
4	0.0066666667	14	0	24	0.0088888889
5	0	15	0	25	0.0066666667
6	0	16	0.0088888889	26	0.0088888889
7	0.04	17	0.0044444444	27	0.0088888889
8	0.0066666667	18	0	28	0.0088888889
9	0.0044444444	19	0.0022222222	29	0
10	0.0066666667	20	0.0066666667	30	0.0066666667

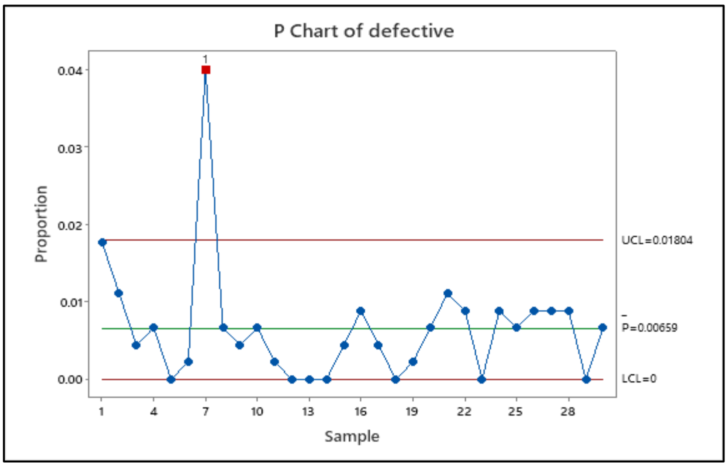

Fig.1. A p-chart in case of constant subgroup size.

4.2. Numerical implementation

Taking Eq.5 and considering that (a, b, c) = ($all\ samples - \bar{x}, all\ samples, all\ samples + \bar{x}$) [25], as indicated in Table 3. The Fuzzy numbers may be generated considering the values of w, λ where they are in the range of zero to one, w, λ ∈ (0,1). For the current work, three cases were chosen, and they included the following:

Now let's use λ=0.9 and w=0.9 to calculate a new ranking function.

Next, use Eq.6 to find the ranking function.

Table 3: Defective samples when λ=0.9 and w=0.9 using the fuzzy ranking method

N	Defective	N	Defective	N	Defective
1	17.77777778	11	2.222222222	21	11.11111111
2	11.11111111	12	0	22	8.888888889
3	4.444444444	13	0	23	0
4	6.666666667	14	0	24	8.888888889
5	0	15	4.444444444	25	6.666666667
6	0	16	8.888888889	26	8.888888889
7	40	17	4.444444444	27	8.888888889
8	6.666666667	18	0	28	8.888888889
9	4.444444444	19	2.222222222	29	0
10	6.666666667	20	6.666666667	30	6.666666667

When λ = 0.9 and w = 0.9, all samples are now subjected to attributes control charts. To begin with, as table shown, we first decide to find (p) in the Eqs. 1 and 4.

$$P = \frac{D}{p} \quad = \frac{17.77777778}{450} = 0.039506173$$

Eq.2 is then used to find the middle limit of the attribute control.

$$CL = \bar{P} = \frac{\sum_{i=1}^{30} P_i}{30} = 0.01448$$

Table 4. P-fuzzy for λ= 0.*9*, w= 0.*9*

N	Defective	N	Defective	N	Defective
1	0.039506173	11	0.004938272	21	0.024691358
2	0.024691358	12	0	22	0.019753086
3	0.009876543	13	0	23	0
4	0.014814815	14	0	24	0.019753086
5	0	15	0.009876543	25	0.014814815
6	0	16	0.019753086	26	0.019753086
7	0.088888889	17	0.009876543	27	0.019753086
8	0.014814815	18	0	28	0.019753086
9	0.009876543	19	0.004938272	29	0
10	0.014814815	20	0.014814815	30	0.014814815

Thereupon, use equation to get the maximum control of attributes (3).

$$UCL = CL + 3 \times \sqrt{\frac{p^{-}(1-p^{-})}{m}} = 0.0313$$

Eq.4 is used to determine the lower bound of the attribute control.

$$LCL = CL - 3 \times \sqrt{\frac{p^{-}(1-p^{-})}{m}} = -0.002411 \approx 0$$

Last, Figure reveals that the quality control charts are founded on the characteristics control charts (2).

Then, according to Table Next, using w and λ as above, find a fresh ranking function, λ=0.7 w=0.6, and then compute the ranking function with the aid of Eqs.5 and 6.

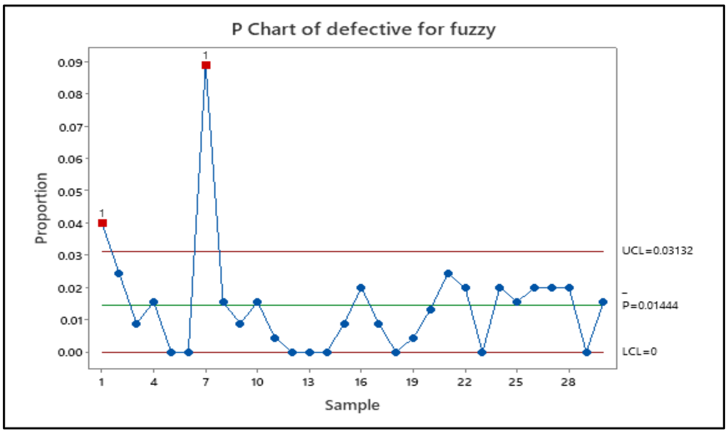

Fig.2. Fuzzy P Control Chart for λ=0.9, w =0.9

Table 5: Using the fuzzy ranking method to identify defective samples when λ=0.7 and w=0.6

N	Defective	N	Defective	N	Defective
1	21.0989011	11	5.714285714	21	13.18681319
2	13.18681319	12	0	22	10.54945055
3	5.274725275	13	0	23	0
4	7.912087912	14	0	24	10.54945055
5	0	15	11.42857143	25	7.912087912
6	0	16	22.85714286	26	10.54945055
7	47.47252747	17	11.42857143	27	10.54945055
8	7.912087912	18	0	28	10.54945055
9	5.274725275	19	5.714285714	29	0
10	7.912087912	20	17.14285714	30	7.912087912

This is done for all samples with w = 0.6 and λ = 07. In Table, first find (p) in Eqs.1 and 6.

$$P = \frac{D}{p} = \frac{21.0989011}{450} = \quad 0.046886447 \quad \text{and so that}$$

Table 6: Value of P when λ=0.7 and w=0.6 for Fuzzy ranking function.

N	Defective	N	Defective	N	Defective
1	0.046886447	11	0.005860806	21	0.029304029
2	0.029304029	12	0	22	0.023443223
3	0.011721612	13	0	23	0
4	0.017582418	14	0	24	0.023443223
5	0	15	0.011721612	25	0.017582418
6	0	16	0.023443223	26	0.023443223
7	0.105494505	17	0.011721612	27	0.023443223
8	0.017582418	18	0	28	0.023443223
9	0.011721612	19	0.005860806	29	0
10	0.017582418	20	0.017582418	30	0.017582418

Then, Eq.2 is used to find the middle limit of the attribute control.

$$CL = \bar{P} = \frac{\sum_{i=1}^{30} P_i}{30} = \ 0.017192$$

That is where the upper amortize of attribute control is arrived, using Eq.3.

$$the\ UCL = CL + 3 \times \sqrt{\frac{p^{-}(1-p^{-})}{m}} = 0.0358$$

Third, we determine the lower bound of the attribute control through Eq.4.

$$\mathrm{LCL} = \mathrm{CL} - 3 \times \sqrt{\frac{\mathrm{p}^{-}(1-\mathrm{p}^{-})}{\mathrm{m}}} \ = 0.000$$

Lastly, in Figure, the quality control charts are premised on characteristics control charts (3).

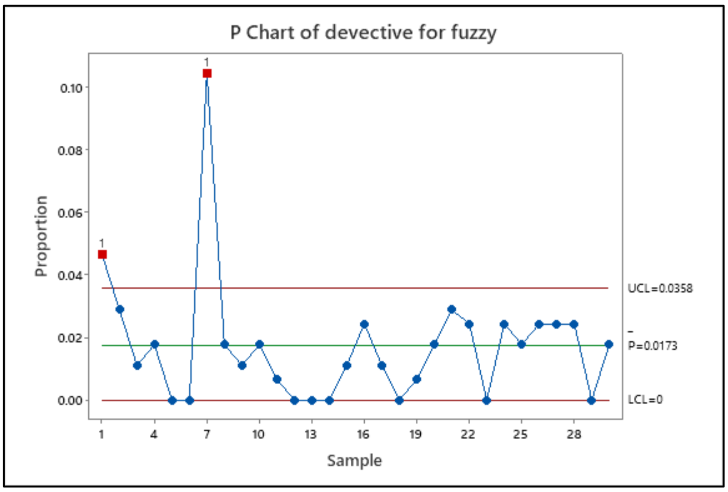

Fig. 3. P Chart for λ=0.7, w= 0.6

Creating a new ranking function for w=0.8 and λ=0.9 as the values of w and λ. After that, use Eq.6 to determine the ranking function, as shown in Table 7.

Table7: Using the fuzzy ranking method to identify defective samples when λ=0.9 and w=0.8

N	Defective	N	Defective	N	Defective
1	18.81190995	11	2.352941176	21	11.76470588
2	11.76470588	12	0	22	9.411764706
3	4.705882353	13	0	23	0
4	7.058823529	14	0	24	9.411764706
5	0	15	4.705882353	25	7.058823529
6	0	16	9.411764706	26	9.411764706
7	42.35294118	17	4.705882353	27	9.411764706
8	7.058823529	18	0	28	9.411764706
9	4.705882353	19	2.352941176	29	0
10	7.058823529	20	7.058823529	30	7.058823529

When λ=0.9 and w=0.8, apply attributes control charts to all samples. In Eq.1, calculate (p) first in Table. 8.

$P = \frac{D}{p} = \frac{18.81190995}{450} = \quad 0.071111111$ and so that

Table 8: Value of P when λ=0.9, w=0.8 for Fuzzy rank function

N	Defective	N	Defective	N	Defective
1	0.041804244	11	0.005228758	21	0.026143791
2	0.026143791	12	0	22	0.020915033
3	0.010457516	13	0	23	0
4	0.015686275	14	0	24	0.020915033
5	0	15	0.010457516	25	0.015686275
6	0	16	0.020915033	26	0.020915033
7	0.094117647	17	0.010457516	27	0.020915033
8	0.015686275	18	0	28	0.020915033
9	0.010457516	19	0.005228758	29	0
10	0.015686275	20	0.015686275	30	0.015686275

Then you look for Eq.2 to get the middle limit of the attribute control.

$CL = \bar{P} = \frac{\sum_{i=1}^{30} P_i}{30} = 0.15337$, second, we apply this computation to acquire upper bound of attribute control (3).

$UCL = CL + 3 \times \sqrt{\frac{p^{-}(1-p^{-})}{m}}$ = 0.0325, compute the lower limit of attribute control in Eq.4.

$LCL = CL - 3 \times \sqrt{\frac{p^{-}(1-p^{-})}{m}}$ = 0.000, Finally, the charts of quality control depend on the attributes control charts as shown in Fig.4.

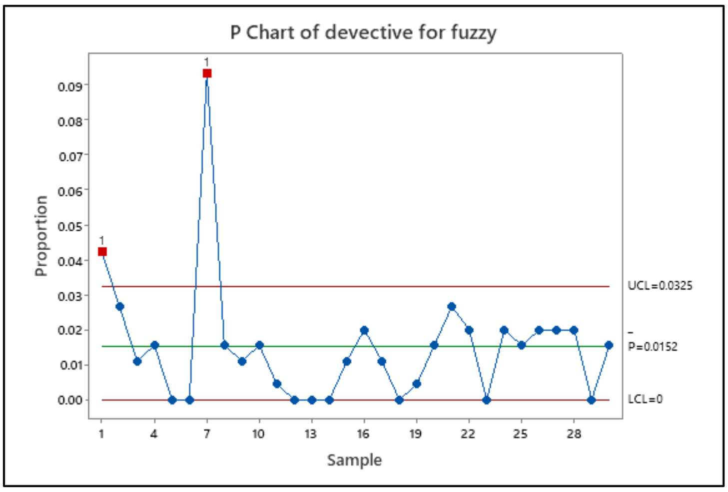

Fig. 4. Fuzzy P Chart for λ=0.9, w= 0.8

5. RESULTS AND DISCUSSION

With the MINITAB 21 program, the results of the following are obtained, following the completion of the necessary calculations and the creation of the conventional and fuzzy P-chart and fuzzy chart for thirty industrial product samples (state firm for vegetable oils in Iraq – Al-Mamon factory):

Fig.1 shows the limit values of the faulty proportions chart P control CHART. From the zero sample (7) the upper limit of the line is obtained as lower control limit is 0.000, center limit 0.0065 and higher control limit 0.018.

Figure indicates control limits values of Fuzzy Chart with λ = 0.9 and w= 0.9. Values in the line are as follows: Upper Control Limit=0.0313, Center Limit=0.0014 and Lower Control Limit= 0.00, two samples (1 and 7) give the upper limit of the line.

Values of the limits of fuzzy chart's control are displayed in Fig.3. Two samples (1 and 7) output the upper limit of the line and the number that lower control applied to the samples. The 0.000 is lower control limit, 0.0173 is center, and 0.0358 is higher.

Fuzzy Chart's control limit values for λ=0.9 and w = 0.8 are displayed in Fig.4. The two samples (1 and 7) output the upper limit of the line and the number of samples applied lower control limit. Upper limit = 0.0325, Center = 0.0152, Lower = 0.000. as displayed in the Table 9.

Only two samples are outside the higher limit of control in the p-chart through the aforementioned four points, however the number of samples applied below the lower control limit is displayed in Figs. (2,3, and 4), indicating that they were more susceptible to changes in product quality. We found that the sample size constant had its quality changes better identified by the Fuzzy Control Chart than the other charts. It is all the product levels as opposed to only those accepted or not accepted. This type of control chart is therefore required in order to divide the resulting product into levels according to specialists and to control quality.

Table9: Test at different values of w& λ with results for UCL, CL &LCL

<table>
<tr><td>W / λ</td><td colspan="2">0.6</td><td rowspan="4">0.8</td><td rowspan="7">0.9</td></tr>
<tr><td rowspan="3">0.7</td><td>UCL</td><td>0.0358</td></tr>
<tr><td>CL</td><td>0.0173</td></tr>
<tr><td>LCL</td><td>0</td></tr>
<tr><td rowspan="3">0.9</td><td>UCL</td><td colspan="2">0.0325</td></tr>
<tr><td>CL</td><td colspan="2">0.0152</td></tr>
<tr><td>LCL</td><td colspan="2">0</td></tr>
<tr><td rowspan="3">0.9</td><td>UCL</td><td colspan="3">0.0313</td></tr>
<tr><td>CL</td><td colspan="3">0.0144</td></tr>
<tr><td>LCL</td><td colspan="3">0</td></tr>
</table>

6. CONCLUSIONS

The attribute quality control chart is used to find the proportion of each sample's defects at the start of employment, the approximate numbers of defective of each sample are determined by using and triangle membership function. Then, the fuzzy number is calculated and obtained by three repetitions of the suggested ranking function to every sample (w=0.9, λ=0.9), (w=0.6, λ=0.7), (w=0.8, λ=0.9), respectively. Second, fuzzy quality control is used to determine the percentage of faulty samples for all samples. This is followed by comparing all production samples on crisp and fuzzy charts, and findings indicated that the fuzzy chart is more precise and can more quickly and economically control production quality in order to detect defective units at any stage of production process to identify errors at an early stage. The use of fuzzy set based control charts proved to be more accurate and practical in the analysis of the data. Fuzzy control chart charts produced by fuzzy set theory is much more accurate to show the uncertainty than Shewhart control chart. The contribution of this paper is the development of a fuzzy method that combines fuzzy set theory with Shewhart control chart principles. In addition, the fuzzy and Shewhart c control charts comparisons are made, and the fuzzy control chart's efficacy is analyzed.

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