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Control Chart Recognition Patterns Using Fuzzy Rule-Based System

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Abstract
Control Chart Patterns (CCPs) recognition is one the most important concepts in control chart application. Relating the patterns exhibited on the control chart to assignable causes is an ambiguous and vague task especially when multiple patterns co-exist. In this study, a fuzzy rule-based system is developed for $\bar{X}$ control charts to prioritize the control chart causes based on the accumulated evidence. To demonstrate the reasonable performance of the proposed fuzzy rule-based system, the case studies are performed and the results are analyzed.

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INTRODUCTION

Statistical Process Control (SPC) techniques have been widely used for many years to control the quality characteristic of a process. These techniques are not limited to their context. Many statistical process control techniques have the potential to be developed with separate research in other fields, such as Data Envelopment Analysis (Alinezhad, Makui, & Kiani Mavi, 2007; Mirmozaffari, & Alinezhad, 2017), Supply Chain (Sarrafha, Kazemi, & Alinezhad, 2014), etc., which has been researched in recent years (Jain, Triantis, & Liu, 2011; Metzner et al., 2019). SPC techniques have played a crucial role in process monitoring and quality control since the 1920s (Lu, Wang, & Dai, 2020). Statistical process control chart or control charts are the representation of a process in the form of a graph. It shows how a process changes over time. Control charts are used to routinely monitor quality of a process. Typically, A single quality characteristics is calculated and plotted in the control chart with respect to the sample number or time (Chowdhury, & Janan, 2020). Statistical signals in science of SPC are able to find variations in manufacturing process, recognize the source of variation, efficiency development and to keeping the process in a highlevel quality. As a signifcant tool for the SPC a control chart plays an important role in the manufacturing quality control, wherein it is widely used to monitor whether the machining process is in control or not (Zan et al., 2020). Control chart, as a primary tool in statistical process control, is utilized to monitor the production process in complex manufacturing and service industries. It is built on the statistical hypothesis test principle, recording and monitoring the production process by the fuctuations of the main quality characteristics. Control chart patterns (CCPs) recognition is benefcial to explore the causes of the abnormal patterns and develop a corresponding treatment program (Zhang et al., 2020). Adequate recognition of CCPs is a crucial task since abnormal or irregular patterns displayed in a CCP collaborate with specific attributable factors influencing the process (Kalteh, & Babouei, 2019). Control charts are one of the most practical tools in SPC that was first time proposed in 1920s by Shewhart. Control charts are used as a tool to monitor the variation of process. These variations have two causes: 1. Random causes and 2. Assignable causes that refer a specific reason in process that should be recognized and removed until variations remain between control limits. Abnormal patterns of Control chart can able to detect assignable cause variations. Western-Electric (1956) and Nelson rules (1984) are traditional sensitizing rules for checking abnormal pattern in control charts. Existences an abnormal pattern in control chart can be associated with specific assignable causes adversely affecting the process stability and they must be recognized and removed (Montgomery, 2015). Control charts are provided and performed in two phases. In first phase data is gathered from producing process and determined initial control limits. After depicting samples data in control charts, if the process was out of control, outward spots must be removed and new control limits calculated. In the second phase, final calculated control limits are used for controlling process situation. In second phase, using sensitizing rules can reduce the probability of wrong alarms and Average Run Length (ARL). Each abnormal pattern in control charts has a set of separate assignable causes. Avoid using sensitizing rules reduce ability of CCPs recognition.

In practice cases, recognition of multiple CCPs simultaneously in a control chart and identify related assignable causes would be so difficult. However, recognition of abnormal CCPs is jointed with uncertainty and ambiguity Therefore, quantifying the uncertainty to indicate the measure of each abnormal patterns and the degree of each associated cause can be valuable for decision making. Because of that many researchers suggested fuzzy logic for solving this problem in CCPs recognition area. Fuzzy logic presented in middle 1990s.

RESEARCH BACKGROUND

Kahraman et al. (1995) implemented triangular membership functions for defining different abnormal patterns. Zalila et al. (1998) proposed a fuzzy supervision method for SPC which by using visual signals alerts operators on the process condition. They designed visual signals by using fuzzy logic. Tannock (2019) used two fuzzy sets namely centered fuzzy set and random fuzzy sets to recognize three common patterns namely shift, trend and cyclical pattern. Senturk and Erginel (2019) developed fuzzy control limits in control charts ($\bar{X}$,R) and ($\bar{X}$,S). Zarandi et al. (2018) increased sensitivity of control charts with using hybrid fuzzy sampling and run rules. In aforesaid research fuzzy logic was used for analyzing process condition by CCPs recognition and detecting of source of assignable cause has not been considered. But it is valuable and important to diagnosis and prioritizes the assignable causes from the existence patterns in control charts. Hsu and Chen (2011) developed a hybrid method of fuzzy logic and genetic algorithm to identify source of assignable causes. Many researches hybridized fuzzy logic and other concepts such as artificial neural networks (ANNs) (Tontini, 1996; Tontini, 1998; Wang, & Rowlands, 2017) in order to assignable cause diagnosis. Some research attempted to use Computational Intelligence techniques for CCPs recognition problem. Lu et al (2018) hybridized independent component analysis (ICA) and Support Vector Machine (SVM) for CCPs recognition. Du et al. (2019) developed a hybrid approach of integrating wavelet transform and improved particle swarm optimization-based support vector machine (P-SVM) for on-line recognition of CCPs. Ebrahimzadeh et al. (2013) proposed a hybrid intelligent method for CCPs recognition problem. Their method included the feature extraction module, the classifier module and optimization module modules. Addeh et al. (2013) investigated an efficient system that includes feature extraction module and classifier module modules. And then a hybrid heuristic based on Cuckoo Optimization Algorithm (COA) algorithm to improve the generalization performance of the classifier was introduced. Ebrahimzadeh et al. (2018) used Control chart pattern recognition using K-MICA clustering and neural networks for CCPs recognition. Gu et al. (2015) proposed an approach based on Singular Spectrum Analysis (SSA) and learning vector quantization network to identify concurrent CCPs. Bag et al (2018) proposed an expert system for CCPs recognition with using decision three techniques for extracting rules.

ANNs are powerful tools for classifying data and pattern recognition. However, for applying them, large number of real data is required.

As previous mentioned one of Shewhart control chart's disadvantage was recognition of abnormal patterns from control charts and diagnosis source of assignable causes. In practice several abnormal patterns may exist simultaneously in a control chart, therefore CCPs recognition and intensity estimation of each pattern hold in uncertainty condition. As each CCP has own assignable causes, thus in order to reform process to in control state, estimation of each abnormal intensity is necessary.

In this paper an integrated fuzzy system based on fuzzy rules for CCPs recognition is developed and prioritization of assignable causes is applied.

RESEARCH METHODOLOGY

When a process is in-control, depicted data in a control chart are following a random pattern based on a normal distribution. When a process is out-of-control, normal behavior of data on the chart change and some of abnormal patterns appear on the control chart. Following is the list of some remarkable ab normal patterns:

1. Out of Control (OCL): One or more point falling beyond 3σ control limits.

This is the conventional rule for concluding that process has gone out-of-control. For a normal distribution curve, 99.73% of all points fall within 3σ limits. Hence, the probability of a point falling beyond 3σ control limits is 0.0027.

2. Freak: this pattern is divided into two parts.

2.1. FR1: four out of five consecutive points fall beyond 1σ limit on the same side of the center line.

From the properties of normal distribution curve, the probability of observing a point beyond on 1σ is 0.16. Hence, the probability of observing four out of five consecutive points beyond 1σ is given by:

$$Pr(4 \text{ out of } 5 \text{ beyond } 1\sigma)= 5(0.16\times0.16\times0.16\times0.16\times0.84) =0.0028$$

2.2. FR2: two out of three consecutive points fall beyond 2σ limits on the same side of center line.

From the properties of normal distribution, the probability of observing one point beyond 2σ limits, is 0.023. Hence, the probability of observing two out of three consecutive points beyond 2σ limits is given by:

Pr (2 out of 3 beyond 2σ)=
3(0.023×0.023×0.997)=0.0016

3. Run (R): Eight or more consecutive points on one side of centerline.

From the properties of normal distribution curve, the probability of observing a point on one side of centerline is 0.5. Hence, the probability of observing eight consecutive points beyond on one side of centerline is given by:

Pr (8 points on one side)=$(0.5)^8$
=0.0039

4. Trend (T): Sven or more points continually increasing or decreasing.

The probability of seven consecutive points increasing (or decreasing) can be calculated as follows:

Pr (7 increasing)=Pr $(1^{st}$*>based point)*
$\times$*Pr* $(2^{nd}>1^{st}) \times \ldots \times$ *Pr* $(7^{th}>6^{th})$
Where,Pr (1^st>based point)<0.5,
Pr $(2^{nd}>1^{st})<0.5$ *and*
finally Pr $(7^{th}>6^{th})<0.5$
Therefore,Pr (7 increasing)<$(0.5)^7$
=0.008

5. Cycle: Repetitive forms of patterns observed on the control chart over a period of time.

This kind of pattern exhibits systematic changes in the process. There is an indication of an assignable cause because a characteristic of a random pattern is that it does not repeat.

In this paper, OCL, FR1, FR2, Run and Trend patterns as most commonly used pattern have been considered for modeling. Since, there is no generally definition for some patterns like cycle, instability, etc. and modeling of them is difficult then we do not have considered them in our model.

When the pattern is not natural, something is existent in the process that has an effect on the control chart pattern. All unnatural patterns need to be investigated to determine the causes. Each unnatural pattern exhibits presence of certain set of causes. The relation between assignable causes and chart patterns is established by classifying the domain of assignable causes based on the each, cause influence on the process mean. The effect of the causes to make certain patterns has been collected by (Smith, 2014; Doty, 1996; Montgomery, 2015). Accordingly, assignable causes are categorized in to three divisions based on three modes of shift exhibited by the unnatural patterns. They are:

1) Isolated causes:

It is happened when a single sample will be fluctuated intensely and specially one point fallen outside the control limits such as an OCL pattern. The possible causes that comes under this category are:

• A mistake in measurement, recording or plotting.
• Damage in handling.
• Defect in raw-material used for that unit alone.
• False alarm.

2) Shift causes:

When a considerable shift in the process mean is occurred, shift causes must be considered. Most influence patterns in shift causes are Freaks and Run patterns on the control chart. They show some assignable causes have been occurred in process that caused a sudden shift in the mean. These shifts may result from the some, causes are:

• Tool break.
• Change in raw-material or supplier.
• Change in inspection methods or standards.
• Adjustments made in machine settings.
• Introduction of new workers or inspectors.
• change in either the skill, attentiveness, or motivation of the operators.

3) Gradual causes:

Gradual causes are defined as a long series of points that lack a change of direction. There is a continuous movement of points up or down this chart. Points will be on one side of the centerline, followed by points on the other side. Gradual causes are identified by the trend pattern. Typical causes of trend patterns are:

- Gradual introduction of new raw-material.
- Loosening fixtures.
- Operator fatigue.
- Machine tool wear.
- Gauge wear.
- Environmental changes.
- settling or separation of the components of a mixture in chemical processes.
- seasonal influences, such as temperature.

assignable causes can be modeled as Fig. 1.

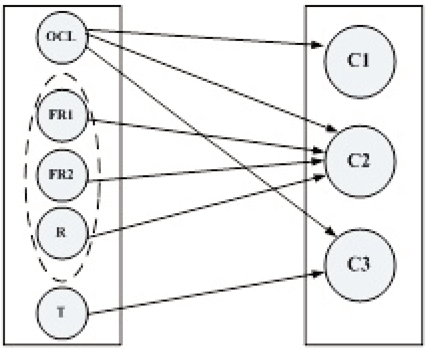

Fig. 1. Relationship chart between abnormal pattern and assignable causes

Based on Fig. 1, we can find out OCL pattern indicates isolated causes (C1), FR1, FR2 and Run patterns indicate shift causes and T pattern indicates gradual causes. OCL patterns, in addition to C1, it also affects on C2 and C3.

Proposed fuzzy system

In this section, a fuzzy system based on fuzzy rules is designed. Fuzzy system is applied for CCPs recognition and then intensity estimation and Prioritization of assignable cause are performed. In order to design proposed fuzzy system following stage are carried out:

Input and output variations

In this paper four abnormal pattern including 1) Out of control (OCL), 2) Freak (FR1, FR2), 3) Run (R) & 4) Trend (T) are considered. In order to design proposed fuzzy system, Fig. 1 as a relationship chart between abnormal patterns and assignable causes is used.

Proposed fuzzy system includes 5 input variables can be measured from control chart and also includes 3 output variables, can be exhibited quantized intensity of each assignable causes.

Input variables are:

1) OCL: indicates the intensity of out-of-control abnormal pattern and is calculated as:

$$OCL = \frac{|\bar{x}_i - \mu|}{\sigma} \quad (1)$$

Where, $\bar{x}_i$ is the mean of ith sample measurement plotted on the control chart, μ and σ denote the mean and standard deviation respectively. It is noticeable about OCL variable that, this variable can influence simultaneously in C1, C2 and C3. But it is realizable from fig.1 that that presence of OCL pattern indicates isolated causes (C1). However, but presence of OCL alone cannot confirm the presence of C2 or C3.

Then, fuzzy set of OCL variable should be designed as: when $|x_i\text{-}\mu|$ is greater than or equal 3σ, OCL would have the most influence in C1.

However, Influence of OCL on C2 and C3 would be about 0.6 (Demirli & Vijayakumar, 2017). Therefore, two separated variables called "OCL_C1" and "OCL_C2,C3" for OCL are introduce to support different influence of OCL on C1 and also on C2 and C3.

Thus, OCL_C1 input must have the highest membership function for OCL_C1≥3 and for smaller than 3 the amount of related function must be decreased (Fig. 2). Also OCL_C2,C3 input for OCL_C2,C3≥3 must be around 0.6 and for smaller than 3 the amount of related function must be decreased (Fig. 3).

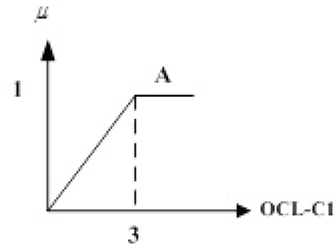

Fig. 2. Fuzzy membership function of OCL_C1

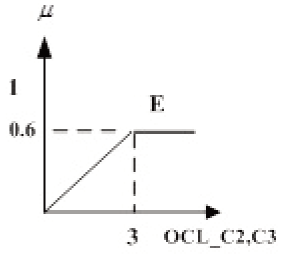

Fig. 3. Fuzzy membership function of OCL_C2,C3≥3

2) FR1: Number of data of 5 consecutive data in a control chart which are beyond the 1σ in same side of central line. Whenever four data of five consecutive spots locate beyond 1σ then related assignable cause will have the most strength. So fuzzy membership function (Fig. 4) of the FR1 variable must be designed to have highest amount for FR1≥4 and decrease for smaller amounts.

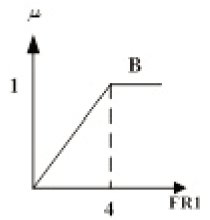

Fig. 4. Fuzzy membership function of FR1

3) FR2: Number of Data of 3 consecutive data that fall beyond 2σ in same side of central line. Whenever 2 data of 3 consecutive data fall beyond 2σ in same side of central line, related assignable cause will have the most strength. Therefor fuzzy membership function of FR2 must have the biggest amount for FR2≥2 as Fig. 5 and for amounts smaller than 2, membership function should be decreased.

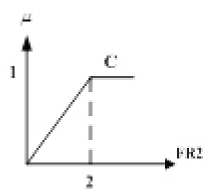

Fig. 5. Fuzzy membership function of FR2

3) FR2: Number of Data of 3 consecutive data that fall beyond 2σ in same side of central line. Whenever 2 data of 3 consecutive data fall beyond 2σ in same side of central line, related assignable cause will have the most strength. Therefor fuzzy membership function of FR2 must have the biggest amount for FR2≥2 as Fig. 5 and for amounts smaller than 2, membership function should be decreased.

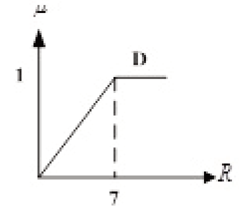

Fig. 6. Fuzzy membership function of R

Whenever 7 consecutive data are increased or decreased, then related assignable cause will have the most strength. So, the related fuzzy membership function must be designed as Fig. 7 to have the biggest amount for T≥7 and should decrease for smaller than 7.

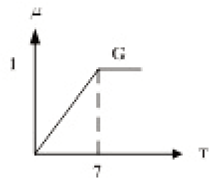

Fig. 7. Fuzzy membership function of T

Considered output variables for proposed fuzzy system are C1, C2 and C3. These variables express the effect of isolated cause, shift causes and gradual causes respectively. Fuzzy membership functions of output variables are designed as Fig 8.

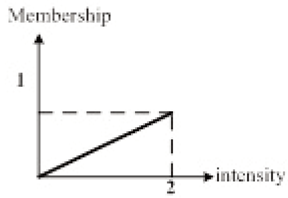

Fig. 8. Membership function of output variables

In this membership function, if the membership degrees of input variables have highest value (means the amount of 1); then, it will have the highest defuzzified intensity in output variables (means the amount of 1). To do so, a customized defuzzification method is developed. In this method area of fuzzy membership function that is based on involved membership degree of inputs is considered and calculated as crisp amount of output. As indicated in Fig. 9-a, it is confirmed that the highest value of output variable is 1. The other example is shown as Fig. 9-b.

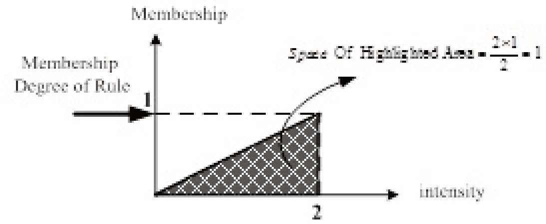

Fig. 9-a. an example of defuzzification

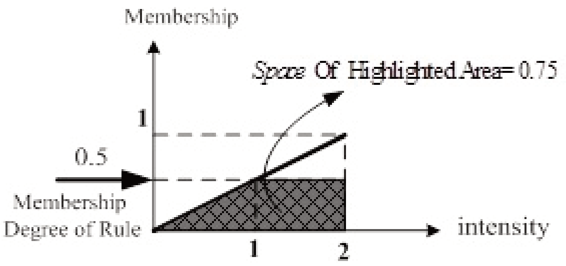

Fig. 9-b. an example of defuzzification

Proposed fuzzy rule-based and fuzzy inference

As it was indicated in Fig. 1, each of C1, C2 and C3 variables are influenced by some abnormal patterns. With using relations between abnormal patterns and assignable causes (Fig. 1), a fuzz system including 3 fuzzy rules is developed. In this fuzzy system each fuzzy rule is designed to estimate the intensity of each assignable cause, namely C1, C2 and C3.

Rule 1: This rule is established for estimating intensity of isolated cause (C1). As it is denoted in Fig. 1, C1 was only connected to OCL abnormal pattern. As mentioned in previous subsection, input variable of OCL_C1 was considered for this connection. Therefore, rule1is designed as:

Rule 1:

if (OCL-C1 is A) Then (C1 is I)

Implication of *Rule1* is pictorially represented in Fig. 10. In the Fig.10 amount of μ_{OCL_C1} is calculated as:

$$\mu_{OCL\_C1} = \begin{cases} \frac{OCL\_C1}{3} & ; 0 \leq OCL \leq 3 \\ 1 & ; OCL \geq 3 \end{cases} \tag{2}$$

Rule 2: This rule is established for estimating intensity of shift cause (C2). As shown in Fig. 1, C2 is affected by some abnormal patterns including FR1, FR2, R and also OCL. *Rule 2* is designed as:

Rule 2:
if (FR1 is B) or (FR2 is C) or (R is D) then (C2 is I)

Fig. 11 demonstrates the implication of Rule 2. $\mu_{FR1}, \mu_{FR2}, \mu_R, \mu_{FOCL\_C2,C3}$ are calculated as following equations:

$$\mu_{FR1} = \begin{cases} \frac{FR1}{4} & ; 0 \leq FR1 < 4 \\ 1 & ; FR1 \geq 4 \end{cases}$$

$$\mu_{FR2} = \begin{cases} \frac{FR2}{2} & ; 0 \leq FR2 < 2 \\ 1 & ; FR2 \geq 2 \end{cases}$$

$$\mu_{R} = \begin{cases} \frac{R}{7} & ; 0 \leq R < 7 \\ 1 & ; R \geq 7 \end{cases}$$

$$\mu_{OCL} = \begin{cases} 0.2 \times OCL\_C2 & ; 0 \leq OCL\_C2 < 3 \\ 0.6 & ; OCL\_C2 \geq 3 \end{cases} \tag{3}$$

In order to calculate the final membership degree of *Rule 2*, a customize method is proposed as Eq.4 that is contained logical relation indicated in Fig. 1.

$$\mu_{C2} = Max\,(\mu_{FR1}, \mu_{FR2}, \mu_R) \oplus \mu_{OCL\_C2,C3}$$
$$\text{Where, } a \oplus b = a + b - ab \tag{4}$$

As it is specified in *Rule 2*, relation between input variable is type of "*OR*", thus a t-norm operator is applied. As presence of abnormal patterns of FR1, FR2 and R alone can confirm the presence of C2; therefor firstly max operator is applied between them.

In addition, presence of abnormal pattern of OCL can provides additional evidence to presence of C2. Then this evidence also has to be added to confirm presence of C2. Hence algebraic sum operator (⊕) is used to aggregate the evidence from OCL_C2, C3 and Max of FR1, FR2 and R.

Rule 3: This rule is established for estimating intensity of gradual cause (C3). As shown in Fig. 1, C3 is affected by some abnormal patterns including T and also OCL. Rule 3 is designed as:

Rule3:
If (T is G) OR (OCL-C2,C3 is A)
Then (C3 is I)

Performance and implication of *Rule 3* is demonstrated in Fig. 12.

In this rule μ_T is calculated similar to μ_R. Also, like to reasons that mentioned for μ_{C2}, similarly μ_{C3} is calculated as:

$$\mu_{C3}=\mu_T \oplus \mu OCL\_C3 \qquad (5)$$

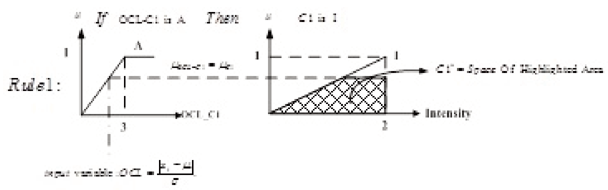

Fig. 10. Implication method in *Rule 1*

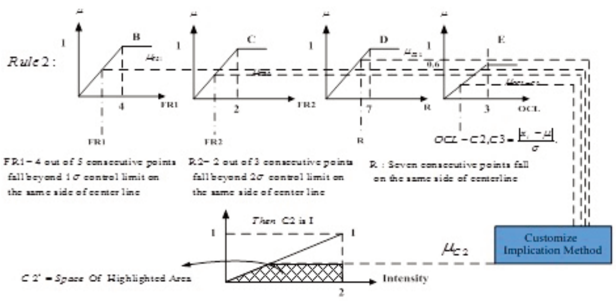

Fig. 11. Implication method in *Rule 2*

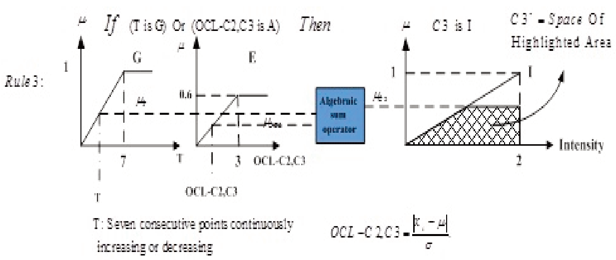

Fig. 12. Implication method in *Rule 3*

RESULTS

In order to evaluate and vindicate our proposed method, in this section we present a case study as Fig. 13 in phase II of control charts. In this process mean is 50, Standard deviation is 1 and sample size is 5 to depict $\bar{X}$ chart.

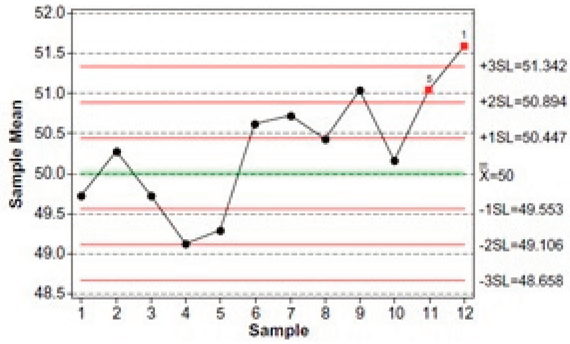

Fig. 13. A case study of $\bar{X}$ control chart

Results of prioritize of assignable cause for sample number 8-12 in shown in Table 1.

In order to apply proposed method, firstly value of input variables should be calculated. Then propose fuzzy system is carried out to achieve intensity value of C1, C2 and C3. Then C1, C2 and C3 are sorted in descending order toward its intensity value. Therefore, looking for source of assignable cause is done. Finally, to CCP recognition we will follow this process. If C1 is the biggest one, abnormal pattern would be out of control pattern (OCL). If C2 has biggest value, membership degree of μ_{FR1}, μ_{FR2}, μ_R must be checked. Each on them that consist highest value, its related pattern would have the highest effect. If C3 the biggest one, then R pattern would happen.

For instance, we explain the computations of 10th sample. First, we should calculate OCL, FR1, FR2, R and T input variables based on control chart that are 0.35, 3, 1, 5 and 1 respectively. For example, to calculate FR1 we consider 6th, 7th, 8th, 9th and 10th samples and the number of spots that placed beyond 1σ will be counted and would be considered as FR1. After calculation input variable from control chart, calculated values are involved into fuzzy rule-based system. Thus, value of OCL that are 0.35 is involved into *Rule1* and μ_{OCL_C1} calculated as μ_{C1}=0.12 that is membership degree of *Rule 1*. Then, μ_{C1}=0.12 is imported into related output of *Rule 1*, namely, C1 and highlighted area (similar to Fig. 10) is obtained as C1*=0.22. Next, for calculating C2* value of input variables *Rule 2* are involved into their fuzzy sets and membership degree of each input are calculated as μ_{FR1}=0.75 ,μ_{FR2}=0.5 ,μ_R=0.71 and μ_{OCL_C2}=0.07. Then μ_{C2} would be calculated by Eq.4 to do so Max (0.75,0.5,0.71)=0.75 is obtained and then μ_{C2}=0.75+0.07-0.75×0.07=0.767 is calculated. Finally, μC2=0.767 is imported into output variable of C2 and highlighted area (similar Fig. 11) is calculated equal to C2*=0.94. Ultimately, *Rule 3* is applied to calculate intensity value of C3*. To do so, like to *Rule 2*, μ_T=0.14 and $\mu_{OCL\_C2,C3}$=0.07 are calculated and then with using Eq.5 μ_{C3}=0.14+0.07-0.14×0.07=0.20 is obtained.

Finally, obtained value of μ_{C3} is imported into output variable of C3 and highlighted area (similar to Fig. 12) is calculated and equal to C3*=0.25 as crisp value of intensity. The So, we have C1= 0.22, C2=0.94 and C3=0.25 and priority of assignable causes will be as C2 >> C3 >> C1. Therefore, assignable cause of C2 as shift cause will have the most priority and isolated cause as C1 will have the least one. Now, to remove source of variation should be focus on detailed causes of shift cause. In order to more analysis of results, 9 other examples are considered as Fig. 14 and numerical results are summarized as table 2 in appendix.

Table 1: Results of applied proposed method

Sample Number		8	9	10	11	12
Input variables	OCL	0.96	2.34	0.35	2.34	3.58
	FR1	2	3	3	3	3
	FR2	0	1	1	2	2
	R	3	4	5	6	7
	T	1	1	1	1	2
Membership Degree of Each Input variables	μ_{OCL-C1}	0.32	0.78	0.12	0.78	1
	μ_{FR1}	0.5	0.75	0.75	0.75	0.75
	μ_{FR2}	0	0.5	0.5	1	1
	μ_R	0.43	0.57	0.71	0.86	1
	μ_{OCL-C2}	0.19	0.46	0.07	0.46	0.6
	μ_T	0.14	0.14	0.14	0.14	0.29
	μ_{OCL-C3}	0.19	0.46	0.07	0.46	0.6
Out puts	C1*	0.537	0.951	0.219	0.951	1
	C2*	0.836	0.982	0.945	1	1
	C3*	0.443	0.757	0.258	0.757	0.885
Cause priority		C2 C1 C3	C2 C1 C3	C2 C3 C1	C2 C1 C3	C1,C2,C3
recognized Pattern		FR1	FR1	FR1	R	OCL,FR2,R

CONCLUSION

Control charts in addition to determine presence of abnormal, can present useful information to identify type of variation with using happened patterns in manufacturing process. It is possible that some abnormal patterns presence simultaneously in a control chart, therefore CCPs recognition and the most intensity assignable cause are dealt with uncertainty and ambiguity.

Because if that a fuzzy system method based on relationship between abnormal patterns and assignable causes has been proposed. Three fuzzy rules are used in proposed fuzzy system that each of them can be used to estimate the intensity of assignable causes. In this proposed fuzzy system intensity of each assignable cause is calculated based on abnormal patterns presence in control chart. When manufacturing process become out-of-control, attempt for finding the variation source is started. In order to increase accuracy, proposed fuzzy system prioritizes most intensity of assignable cause and recognizes related CCP. The So, we would search source of causes that have most intensity instead of all. For future research other abnormal patterns such as cyclic can be considered in proposed fuzzy system.

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APPENDIX

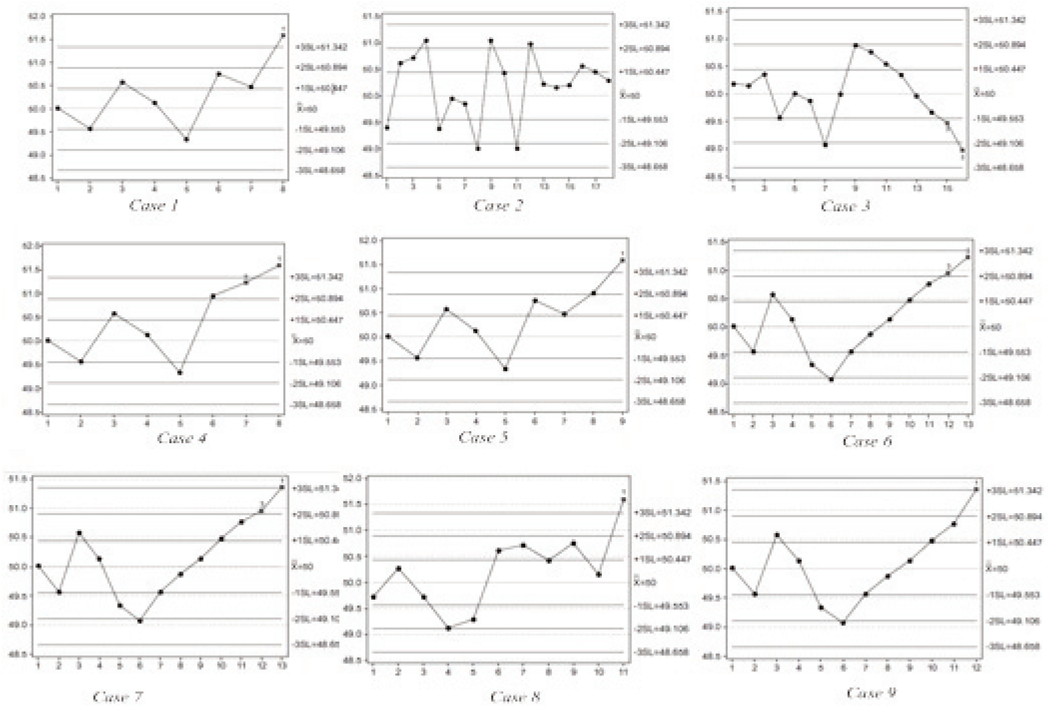

Fig A1. Applied more cases of control charts (Demirli and Vijayakumar, 2017)

Table A1: Results of other applied examples

Case Number		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Input Variables	OCL	3.58	0.64	2.30	3.58	3.58	2.75	3.02	3.58	3.02
	FR1	3	2	2	3	4	4	4	3	3
	FR2	1	0	1	3	2	2	2	1	1
	R	3	7	4	3	4	5	5	6	4
	T	1	2	7	3	2	7	7	1	6
Out puts	$C1^*$	1	0.38	0.94	1	1	0.99	1	1	1
	$C2^*$	0.99	1	0.94	1	1	1	1	0.99	0.99
	$C3^*$	0.88	0.61	1	0.91	0.91	1	1	0.88	0.997
Cause priority		C1 C2 C3	C2 C3 C1	C3 C1,C2	C1,C2 C3	C1,C2 C1	C2,C3 C3	C1,C2,C3	C1 C2 C3	C1 C3 C2
Recognized Pattern		OCL	Run	Trend	OCL, FR2	OCL, FR1, FR2	FR1, FR2, Trend	OCL, FR1, FR2, Trend	OCL	OCL, Trend