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DEVELOPMENT OF AN ATTRIBUTE CONTROL CHART BASED ON THE INVERSE KUMARASWAMY DISTRIBUTION

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Abstract

This article presents the development of an attribute control chart designed for products with lifespans following the inverse Kumaraswamy distribution, using the distribution's mean as the quality metric. The study assumes one distribution parameter is known while varying the other to design the control chart. The chart's performance is evaluated using Average Run Length (ARL), with adjustments to parameter values determining ARL in out-of-control conditions. The proposed control chart is assessed through simulations. A comparative analysis with other similar charts is conducted based on ARL values, and the findings are discussed in detail.

Keywords: Attribute control chart, variable control chart, Inverse Kumaraswamy distribution, average run length, control limits.

I. Introduction

A control chart is an essential tool in statistical process control used to improve process quality. It is used in manufacturing and non-manufacturing settings to reduce variability by identifying special causes of variation. This ultimately leads to improved products and services and increased profit margins. Control charts (CCs) monitor process quality and identify deviations. The visual representation of data collected by CCs makes it easy to detect process variability and take necessary measures to eliminate the source of variation. A process is considered under control when all data points fall between the upper control line (UCL) and lower control line (LCL) within the CCs. Conversely, an out-of-control state is identified when any data point falls outside the control limits.

There are two main types of CCs for process monitoring: attribute and variable CCs. A process is considered variable if it relies on continuous data. There are several variable CCs designed to monitor the state of the process. Among these, Shewhart x bar CCs are the most popular due to their simplicity. Page [18] proposed the cumulative sum CCs, a graphical technique showing the cumulative sums of deviations of sample values related to a quality characteristic. In a study that compared the effectiveness of Shewhart x bar CCs and cumulative sum CCs in identifying slight changes in process averages, Hawkins and Olwell [10] concluded that the former was more effective. Abbas et al. [1] investigated process location monitoring using the nonparametric adaptive cumulative sum CCs method. Robert [21] also introduced exponentially weighted moving average CCs with average run lengths (ARL), studied the characteristics of CCs tests based on moving averages, and described a process for creating geometric moving averages. Jing-Er Chiu and Tsen-I Kuo [13] developed the MP chart, a multivariate Poisson count data control chart. A new control chart, the np S2 control chart, was developed by Linda and Quinino [16] to monitor process variance instead of using S2 or R control charts. Based on the findings of an attribute inspection, this control chart's primary contribution is the assessment of process variability status.

Conversely, CCs are categorized as attribute CCs when the product's compliance with specific requirements determines the quality rating. Processes with non-normal distributions are best supervised by attribute CCs. Aslam and Jun [6] demonstrated that attribute CCs can successfully monitor the lifespan of high-quality products in the literature on single sampling schemes. To accommodate the Weibull distribution, they created attribute CCs. When the process is stable, the test's duration and the parameters of the recommended CCs are set up to guarantee that the average run length stays near the intended goal. The CCs were found to be highly flexible and appropriate for monitoring the lifespans of high-quality products. For processes that generate count data, Ahangar and Chimka [4] introduced attribute control charts with optimal limits. The chart's objective is to lower the overall cost related to its errors, which are represented linearly by Type I and Type II errors. Poisson, geometric, and negative binomial distributions can all be represented by the proposed chart, indicating that it can detect both quality improvement and degradation. Baklizi and Ghannam [7] explored attribute CCS based on the inverse Weibull distribution during their discussion of the use of CCS in industry. A quality indicator for the product was the quantity of failures that occurred during the life testing. The Average Run Length (ARL) values when the process deviates from control for different shift coefficient values are computed to evaluate the CCs. The truncation coefficient and control limit coefficients were also calculated for various sample sizes and target average run lengths. An example was provided to demonstrate how they explained the application of this CCS. Rao [19] created characteristic CCs for the exponentiated half Logistic distribution calculated dispersion with either a known or vague shape parameter, noticing a drift in ARL values. They concluded that the proposed control outline is appropriate for covering non-conforming items. Rao et al. [20] moreover proposed CCs for the Dagum distribution. These CCs can be utilized to track the continuances of quality items. The chart execution is detailed in terms of ARLs, showing that ARL values increase with bigger sample sizes and drop with progressed dissemination of shape parameters. Adeoti and Ogundipe [2] evaluated the execution of CCs utilizing a generalized exponential distribution. They studied the plan based on the assumption that the shape parameter is known and the scale parameter is varied. Srinivasa Rao et al. [23] created an attribute control chart by presuming the item's lifetime adheres to the Exponentiated Inverse Kumaraswamy distribution within the framework of a time-truncated life test. The operation of the formulated control chart is analyzed using the average run length (ARL) values. The devised chart is subsequently evaluated by the ARLs obtained from simulation studies for various sample sizes. Sriramachandran et. al., [24] constructed a CC for a repetitive sampling plan if the product life follows the Lindley distribution.

Many authors studied the properties of different forms of the Kumaraswamy distribution such as log-Kumaraswamy distribution, Ishaq et. al., [12], Transmuted Exponentiated Kumaraswamy Distribution, Joseph and Ravindran [14], exponentiated Kumaraswamy distribution, Lemontea et. al., [15], Odd Lindley-Kumaraswamy Distribution, Samson et. al., [22], Type II Half Logistic Kumaraswamy Distribution, El-Sayed et. al., [9], Generalized Odd Maxwell-Kumaraswamy Distribution, Ishaq et. al., [11] and many more. Based on our review of the literature, it appears that no research has been done on the attribute control chart for the life span of items that follow the Inverse Kumaraswamy distribution. This study's remaining sections are arranged in the following deliberate manner. Section 2 defines the Inverse Kumaraswamy distribution as studied by Daghistani et al. [8] Both the CC design and its implementation strategy are explained in Section 3. Section 4, compares the efficacy of the suggested CC to other CC that are available in the literature. Section 5 studies the proposed CC using simulated. Section 6 studies the proposed CC using a real application. In Section 7, conclusions are provided.

II. Inverse Kumaraswamy Distribution

One of the most significant lifetime distributions, the Kumaraswamy distribution (KD) was introduced in Kumaraswamy and has a range of [0, 1]. Because of its properties such as unimodal, increasing, decreasing, or constant—it makes a good substitute for beta dissemination. AL-Fattah, et al.,[3] studied some of the properties of the inverse Kumaraswamy distribution (IKD). This distribution has several applications in various fields, such as medical research, life-testing problems, and stress-strength analysis. In addition, the IKD can be used to model failure rates in reliability and biological studies. Areej and AL-Zaydi [5] and Daghistani et al. [8] proposed a new version of the IKD based on the transformation $X = Z^{-1}$. The PDF and CDF of their proposed IKD are

$$f(x) = \theta\beta x^{-(\theta+1)}\left(1 - x^{-\theta}\right)^{\beta-1}, x > 1, \theta, \beta > 0 \tag{1}$$

$$F(x) = \left(1 - x^{-\theta}\right)^{\beta}, x > 1, \theta, \beta > 0 \tag{2}$$

The mean of the IKD is defined as

$$\mu = \beta B\left(1 - \frac{1}{\theta}, \beta\right) \tag{3}$$

where B(..) is the beta function.

III. Design of The Proposed Control Chart

The design of an np-Control Chart (np-CC) for the Inverse Kumaraswamy Distribution (IKD) under a time-truncated life test based on the failure count in each subgroup can be summarized as follows:

- A random sample of size n is selected and subjected to the life test.
- The test is terminated at a pre-specified time $t_0 = a.\mu_0$, where μ_0 is the mean of the distribution, and a is the control chart coefficient determining the termination time.
- Count the number of failures, D, observed during the test.
- If the failure count satisfies LCL ≤ D ≤ UCL, the process is in control.
- if D > UCL or D < LCL, the process is declared out-of-control.
- The number of failures, D, is modelled by a binomial distribution with parameters n (sample size) and with p_0 (probability of failure within the time t_0).
- The Upper Control Limit (UCL), Central Line (CL), and Lower Control Limit (LCL) for the proposed control chart are calculated using the binomial distribution and expressed as:

$$UCL/LCL = CL \pm K\sqrt{np_0q_0} \tag{4}$$

where n- sample size, p_0 - failure probability before time t_0, $q_0 = 1 - p_0$, $CL = np_0$ and K- coefficient of control limit. For unknown failure probability p_0, the control limits for the mean number of failures (MNF) is

$$UCL/LCL = MNF \pm K\sqrt{MNF\left(1 - \frac{MNF}{n}\right)} \tag{5}$$

As the number of items that failed in a production process may vary, implementing *CC* is complicated due to varying sample sizes. Hence the CC is designed based on *ARL*. Here *ARL* for the in-control process is denoted as ARL_0 and ARL for the out-of-control process is denoted as ARL_1. Let r_0 be the specified ARL_0. Then the in-control *ARL* is given as

$$ARL_0 = \frac{1}{1-P_{in}^0} \quad (6)$$

where p_{in}^0 is the probability that a production process is under control and can be obtained

$$P_{in}^0 = P(LCL \le f \le UCL) = \sum_{f=LCL+1}^{UCL} \binom{n}{f} {p_0}^f (1-p_0)^{n-f}, \text{where } p_0 = \left(1-(a.\mu_0)^{-\theta}\right)^{\beta} \quad (7)$$

If the process is declared out of control when the scale parameter is shifted to $z_1 = cz_0$ then

$$P_{in}^1 = P(LCL \le f \le UCL) = \sum_{f=LCL+1}^{UCL} \binom{n}{d} {p_1}^f (1-p_1)^{n-f}, \text{ where } p_1 = \left(1-(c.\mu_0)^{-\theta}\right)^{\beta} \quad (8)$$

The out-of-control - ARL_1 is given as

$$ARL_1 = \frac{1}{1-P_{in}^1} \quad (9)$$

For the target $\text{ARL}_0 = 200, 250, 300 \text{ and } 370$, shape parameter $\beta_0 = 0.5, 0.7, 0.9, 1.0, 1.2$ the sample size n=20, a, k, UCL, and LCL are determined using eqn (5). By substituting the values in the eqn (9), the ARL_1 for shifts c= 0.9, 0.8, 0.7... 0.1 are obtained and the values obtained are tabulated in Tables 1 to 4.

Table 1: *CC Parameters for ARL_0=200 and ARL_1 for different shifts when n=20 and* $\theta = 3$

β	0.5	0.7	0.9	1.0	1.2
UCL	16	17	16	18	18
LCL	3	4	3	6	5
a	0.8371	0.8518	0.8706	0.9242	0.9498
L	2.9132	2.9214	2.9354	2.9502	2.9754
Shift c	ARL_1				
1	201.97	200.64	200.52	200.31	201.32
0.9	23.32	60.29	75.45	83.09	92.82
0.8	3.43	5.35	9.3	14.04	21.68
0.7	1.51	2.59	2.75	4.29	5.58
0.6	1.11	1.42	1.53	2.05	2.35
0.5	1.02	1.1	1.24	1.34	1.43
0.4	1	1.02	1.03	1.09	1.12
0.3	1	1	1	1.02	1.02
0.2	1	1	1	1	1
0.1	1	1	1	1	1

From Table 1 to 4, the following trends are noticed: As β increases from 0.5 to 1.2, the ARL_1 values increase, i.e. from Table 4, for the shift c=0.9, the ARL_1 values are 16.29, 32.08, 64.35, 98.08, and 104.95 when $\beta = 0.5, 0.7, 0.9, 1.0$ and 1.2 respectively.

- The control chart coefficient a and also the coefficient of control limit K increase as β changes from 0.5 to 1.2
- As shift c moves from 1 to 0.1, the ARL_1 decreases which is represented in Figure 1.

Table 2: *CC Parameters for ARL0=250 and ARL1 for different shifts when n=20 and* $\theta = 3$

β	0.5	0.7	0.9	1.0	1.2
UCL	17	17	16	18	16
LCL	4	4	3	5	3
a	0.8612	0.8768	0.8958	0.9292	0.9512
L	2.9031	2.9035	2.9058	2.9065	2.9139
Shift c	ARL1				
1	251.5	250.22	250.61	250.82	252.87
0.9	39.39	40.78	67.15	88.11	93.99
0.8	5.55	7.77	13.83	15.87	18.56
0.7	2.06	2.5	2.98	5.67	7.29
0.6	1.29	1.4	1.52	2.36	3.3
0.5	1.07	1.09	1.18	1.43	1.5
0.4	1.01	1.02	1.08	1.12	1.2
0.3	1	1	1.04	1.08	1.14
0.2	1	1	1.01	1.03	1.05
0.1	1	1	1	1	1.01

Table 3: *CC Parameters for ARL0=300 and ARL1 for different shifts when n=20 and* $\theta = 3$

β	0.5	0.7	0.9	1.0	1.2
UCL	16	17	16	16	18
LCL	3	4	3	3	5
a	0.8437	0.8617	0.8807	0.9286	0.9562
L	2.9039	2.9053	2.9055	2.9061	2.9065
Shift c	ARL1				
1	300.08	302.99	301.87	302.33	302.02
0.9	19.2	43.01	60.74	92.27	87.44
0.8	3.19	5.26	7.44	18.57	12.87
0.7	1.47	2.42	3.92	6.28	8.75
0.6	1.1	1.38	1.45	3.52	5.39
0.5	1.02	1.09	1.21	1.56	2.44
0.4	1	1.02	1.12	1.15	1.18
0.3	1	1	1.01	1.1	1.09
0.2	1	1	1	1.05	1.02
0.1	1	1	1	1.01	1

IV. Comparative Study

The out-of-control Average Run Length (ARL) values are utilized to evaluate and compare the performance of the proposed control charts against other similar control charts. Specifically, Table 5 at ARL_0=370 and ARL_0=300 illustrates the comparative analysis of out-of-control ARL values for the proposed control charts with those based on the Exponentiated Inverse Kumaraswamy Distribution by Srinivasa Rao et. al., [23], Inverse Weibull Distribution by Baklizi and Ghannam [7], and Inverse Rayleigh Distribution by Nanthakumar, and Kavitha [17]. The analysis reveals that the proposed control chart demonstrates superior performance, consistently achieving smaller out-of-control ARL

Table 4: *CC Parameters for ARL_0=370 and ARL_1 for different shifts when n=20 and $\theta = 3$*

β	0.5	0.7	0.9	1.0	1.2
UCL	16	17	16	15	16
LCL	3	4	3	2	3
a	0.8497	0.8684	0.8392	0.8024	0.8361
L	2.9045	2.904	2.9032	2.8023	2.8067
Shift c	ARL 1				
1	372.27	372.68	371.03	372.08	370.11
0.9	16.29	32.08	64.35	98.08	104.95
0.8	2.99	8.85	16.64	22.48	32.08
0.7	1.44	1.83	4.32	8.62	10.08
0.6	1.09	1.19	1.36	4.12	6.25
0.5	1.01	1.03	1.08	1.84	2.25
0.4	1	1	1.01	1.2	1.14
0.3	1	1	1	1.14	1.18
0.2	1	1	1	1.08	1.10
0.1	1	1	1	1.02	1.04

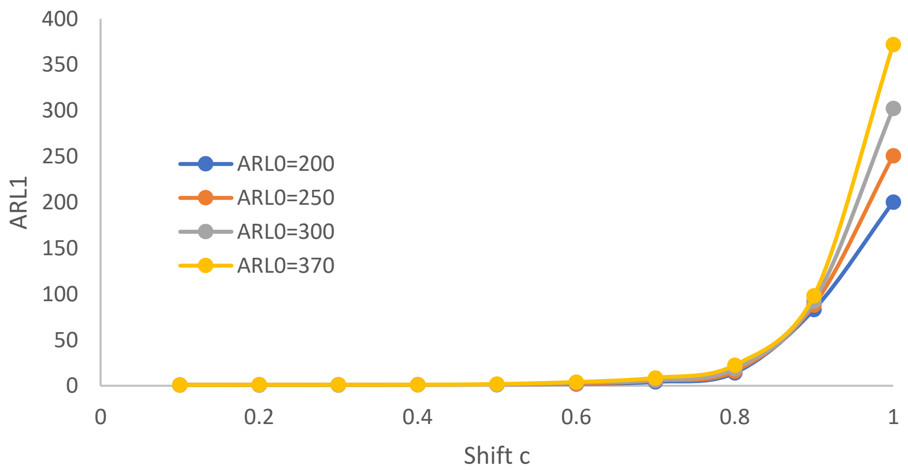

Figure 1: *ARL1 values for different shift c when $\beta = 1, \theta = 3$ when n=20*

values than the other charts. This is significant because control charts with lower out-of-control ARL values are more effective at quickly detecting shifts in the process, making them better suited for maintaining quality control.

Table 5: *Comparative analysis of out-of-control ARL values of similar CC*

Shift c	ARL_0=370			ARL_0=300		
	Exponentiated Inverse Kumaraswamy CC	Inverse Weibull CC	Proposed CC	Inverse Rayleigh CC	Exponentiated Inverse Kumaraswamy CC	Proposed CC
0	370.89	370.11	372.27	300.04	300.37	300.08
0.9	178.75	261.72	16.29	152.82	119.55	19.2
0.8	71.21	10.36	2.99	45.04	46.68	3.19
0.7	28.76	1.89	1.44	14.34	19.16	1.47
0.6	12.29	1.08	1.09	5.37	8.45	1.1
0.5	5.66	1	1.01	2.46	4.09	1.02
0.4	2.89	1	1	1.44	2.23	1
0.3	1.69	1	1	1.09	1.42	1
0.2	1.76	1	1	1.01	1.09	1
0.1	1.01	1	1	1	1	1

V. Study on Simulated Data

A simulated dataset was used to demonstrate the effectiveness of the proposed control charts. Specifically, two sets of 20 samples each, with a subgroup size of n=40, were randomly generated from an IKD to showcase the in-control and out-of-control performance of the control charts. These samples were generated using a target ARL_0=370, with a truncated life test time of t_0 = 0.8024(1.5) = 72 sec (approximately). The number of failed items was recorded in each subgroup and denoted as D and it is tabulated in Table 6. Based on Equation (5) from the study, the calculated control limits for the control charts are LCL=2 and UCL=15. The observed results are illustrated in Figure 2, which plots the number of failed items (D) against the subgroup index. The first 20 subgroups are in control, whereas the subsequent 20 subgroups reflect an out-of-control process due to a shift in the underlying distribution. The proposed control charts successfully detect the shift, with out-of-control signals observed at the 24^{th} and 25^{th} subgroups. These findings highlight the effectiveness of the proposed control charts in detecting process shifts, showcasing their reliability in identifying changes in quality within a timely manner.

VI. Real-Life Application

Suppose that a producer wants to enhance the quality of a product. It is known that the failure time of the product follows the IKD with shape parameter 3 and the scale parameter $\beta = 1.2$ and the target mean life is 1 hour and ARL_0=370, with the failure probability p_0 = 0.3254 from Eq. (7). Also, from Table 4, the control charts parameters such as sample size n = 20, LCL = 3, UCL = 16, a=0.8361 and L=2.8067 are obtained. Thus, the testing time t_0 =50 min.

Therefore, the proposed charts work as follows:

1. Randomly select 20 samples from each group.
2. Test the samples for t_0 =50 min.
3. Observe the MNF.
4. If $3 \leq MNF \leq 16$, declare the process as under control, otherwise, declare it as out of control.

***Table 6:** Simulated Data*

Sample No	No. of Defectives (D)	Sample No	No. of Defectives (D)	Sample No	No. of Defectives (D)	Sample No	No. of Defectives (D)
1	11	11	11	21	7	31	5
2	8	12	5	22	6	32	14
3	4	13	12	23	5	33	8
4	6	14	5	24	17	34	13
5	12	15	11	25	16	35	9
6	14	16	9	26	11	36	7
7	4	17	5	27	10	37	8
8	2	18	15	28	13	38	9
9	6	19	5	29	13	39	11
10	3	20	5	30	14	40	12

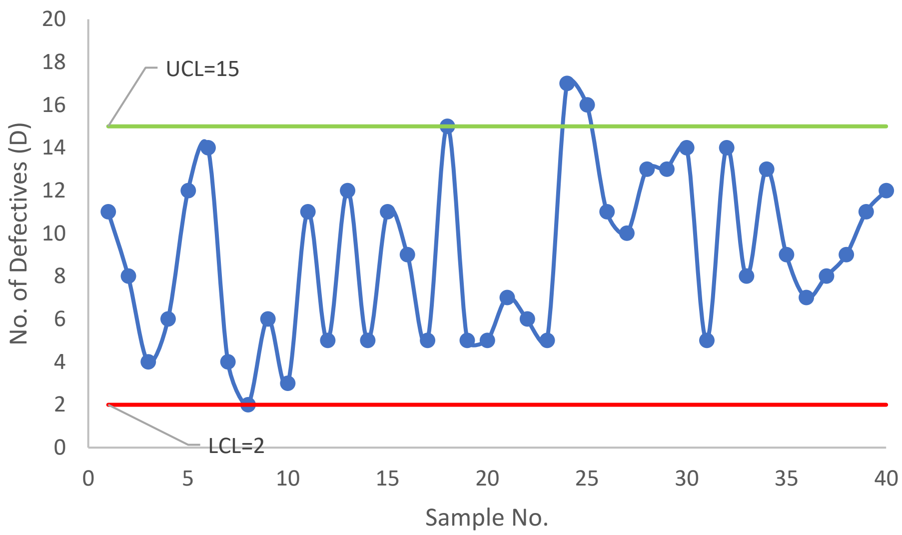

Figure 2: *Control chart for simulated data*

VII. Conclusions

This article proposes a new attribute control chart based on the Inverse Kumaraswamy distribution (IKD). The mean value of the IKD is used as the quality parameter to monitor the process. The scale parameter of the IKD is adjusted to accommodate various values, enabling the design of flexible control charts for different scenarios. The failure probability is calculated for the process shifts (c), and the corresponding out-of-control Average Run Length (ARL_1) is determined. Results for different process conditions are tabulated and compared to assess the chart's performance. Simulated data is used to evaluate the performance of the proposed control chart. The results demonstrate the chart's effectiveness in detecting shifts, as evidenced by the data and its ability to signal out-of-control conditions promptly. The applicability of the control chart is explained in real-life applications. This showcases its ability to monitor the lifespan of products that follow the IKD. The new control charts are suitable for industries that need to track product lifespans and ensure quality control, particularly for processes characterized by the IKD. The study suggests potential extensions, such as: employing the proposed control charts in repetitive sampling schemes to improve efficiency in monitoring processes, incorporating neutrosophic statistics to handle uncertainty and imprecision in data, and further enhancing the applicability of the control charts in complex real-world scenarios. The proposed IKD-based control charts provide a robust tool for process monitoring, with proven efficacy in detecting shifts through both simulated and real-world data. This study lays the groundwork for future research in applying these charts to advanced sampling schemes and integrating statistical methods to handle uncertain environments. These advancements can enhance their utility in diverse industrial applications.

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