CSCC CHART FOR BINOMIAL PARAMETERS UNDER INSPECTION ERROR

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ABSTRACT
In this paper an attempt has been made to construct CSCC under inspection error for Binomial Parameters when underlying distribution is Poisson. We have investigated distance d and angle ϕ along with ARL of CUSUM chart under inspection error.

KEYWORDS: CSCC, Inspection Error, ARL, Binomial Distribution, Poisson distribution.

MSC: 62N25

RESUMEN
En este trabajo intentamos construir un plan CSCC pare el error de inspección para parámetros Binomiales cuando la distribución subyacente es Poisson. Hemos investigado la distancia d y el ángulo ϕ junto con ARL para cartas de calidad CUSUM bajo error en la inspección.

1. INTRODUCTION

Principal purpose of inspection is to separate product that conform to the specification. The inspections of raw materials or in process products or to end products are the important parts of quality guarantee. Quality characteristics obtained from inspections are drawn in the control charts in order to monitor and control product process. However, the traditional control chart methods assume that inspection process have no mistake, but in actually inspection error is very difficult to avoid whatever using visual or mechanical detection. Montgomery (2005) also pointed out that inspection error was usually caused by the inspector, and perhaps the inspector equipments standard scale divisions are not suitable. Also, Laterolla and Prabhu (2000) researched the detail human error styles of inspectors. In addition, many researchers have investigated influences of inspection error on sampling plan and control charts. The influences of inspection error on sampling plans have been considered by Ferrell and Chhoker (2002) and Markowski and Markowski (2002). Wang (2007) extended the inspection model to consider two types of inspection error in order to facilitate the adaption of the economic model to real world applications. Chen et al. (2011) pointed out the application of multinomial control charts for inspection error.
In the last several years, nonparametric control charts have attracted much attention from researchers. Johnson (1961) showed that the CUSUM control charts can be interpreted as a modified form of a pair of Sequential Probability Ratio Test (SPRT) treated simultaneously and gave mathematical procedures for constructing the CUSUM charts. Johnson and Leone (1962) constructed CUSUM charts for controlling the means of the Binomial and Poisson distributions. Hawkins and Olwell (1998) gave a comprehensive overview of CUSUM charts for numerous distributions. CUSUM control charts are widely used monitoring processes with the objective of improving process quality and productivity (Luceno and Puig-Pey, 2000). The pioneering work on CUSUM control charts is attributed to Page (1954,1961). Lucas (1985) described the design and implementation procedure for count data through CUSUM chart to detect increase or decrease in the count level. Han et al. (2007) developed Multi-Charts for Detecting a Range of Mean Shifts for CUSUM and EWMA multi-charts. Qiu (2008) discussed a multivariate process for a distribution-free based log-linear modeling. New approximation of ARL in CUSUM control chart provided by Hanif et al. (2012). EGER and TSOY (2009); CHAKRABORTY and KHURSHID (2011) and Cheng and Yu (2013) also studied the CUSUM control chart. Recently, Saghir, and Lin (2014) proposed the study of three kinds of CUSUM control chart based on either the rate parameter, dispersion parameter or both to detect shift.
Several different types of control charts based on Poisson distribution are available in the literature. Singh and Sayyed (2001) suggested the technique of CSCC for Poisson variable under inspection error. Singh et al. (2002) investigated CSCC for proportion under inspection error. Wu; Zhu and Wang (2009) discussed the construction of an upward CUSUM chart in the presence of inspection error. Eger (2010) presented a corresponding direct method of computation of ARL of a CUSUM test for discrete monitoring of the intensity of a Poisson process. Chakraborty and khurshid (2011) constructed CSCC for Binomial parameters when the underlying distribution is Poisson. Wei; Lianjie and Kwok (2011) suggested weighted CUSUM control

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charts for monitoring Poisson processes when the Sample Sizes varying. A zero inflated Poisson process for CUSUM chart monitored by He et al. (2012). Mei (2008); Pollak (2008); Mei et al. (2011) and Sayyed and Singh (2013) also studied the Poisson process and effect of inspection error on CUSUM chart. He et al. (2014) combined CUSUM Charts for monitoring a zero-inflated Poisson process**.**

The purpose of this paper is, therefore to determine and illustrate the effect of inspection error on CSCC for controlling the different parameters of the distribution under study and to obtain ARL for detecting the shift of the process parameters for Binomial parameter. The Poisson distribution is well suited to model many processes in a broad variety of fields such as agriculture, ecology, biology, medicine, commerce, industrial quality control and particle counting when the control charts for ratio of two Poisson means (Sahai and Khurshid, 1993) need to be constructed. In such situation Binomial distribution being derived based on the ratio of two Poisson can be used to develop the CUSUM chart.

2. BINOMIAL DISTRIBUTION

Let λ and μ are the parameters of two independent Poisson variates X and Y respectively then the conditional distribution of x given X+Y follows a Binomial distribution (Lehmann and Romano, 2005), thus

$$P[X = x/(X+Y=n)] = \frac{P[X = x \cap Y = n-x]}{[P(X+Y) = n]}$$

$$= \binom{n}{x}\left(\frac{\lambda}{\lambda+\mu}\right)^{x}\left(\frac{\mu}{\lambda+\mu}\right)^{n-x} \qquad (2.1)$$

Where x = 0,1,2,…,n.

Table-2.1: Values of d for controlling the parameter λ

When μ = 0.5 and n=24																
		(r,λ_f)= (1,0)					**(r,λ_f)= (1,2)**					**(r,λ_f)= (.8,2)**				
		A					**α**					**A**				
λ0	**λ1**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**
0.4	**0.43**	3.807	4.688	5.852	6.733	8.778	20.450	25.182	31.437	6.733	47.1549	24.611	30.305	37.833	43.5271	56.7490
0.4	**0.46**	1.934	2.382	2.973	3.421	4.460	10.256	12.629	15.766	3.421	23.6492	12.336	15.191	18.964	21.8186	28.4463
0.4	**0.49**	1.31	1.613	2.013	2.316	3.020	6.858	8.445	10.543	2.316	15.8138	8.245	10.153	12.675	14.5824	19.0120
0.4	**0.52**	0.997	1.228	1.533	1.764	2.300	5.159	6.353	7.931	1.764	11.8961	6.199	7.634	9.530	10.9642	14.2947
0.4	**0.55**	0.81	0.997	1.245	1.432	1.867	4.139	5.097	6.364	1.432	9.5454	4.972	6.122	7.643	8.7933	11.4644
When μ = 0.6 and n=20																
		(r,λ_f)= (1,0)					**(r,λ_f)= (1,2)**					**(r,λ_f)= (.8,2)**				
		A					**α**					**A**				
λ0	**λ1**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**
0.4	**0.43**	4.223	5.200	6.492	7.469	9.737	20.866	25.694	32.076	36.904	48.114	25.027	30.817	38.472	44.263	57.708
0.4	**0.46**	2.142	2.638	3.293	3.789	4.940	10.464	12.885	16.086	18.507	24.129	12.544	15.447	19.284	22.186	28.926
0.4	**0.49**	1.448	1.784	2.227	2.562	3.340	6.997	8.616	10.756	12.375	16.134	8.384	10.323	12.888	14.828	19.332
0.4	**0.52**	1.101	1.356	1.693	1.948	2.540	5.263	6.481	8.091	9.308	12.136	6.303	7.762	9.689	11.148	14.535
0.4	**0.55**	0.893	1.100	1.373	1.580	2.059	4.223	5.199	6.492	7.469	9.737	5.055	6.225	7.771	8.940	11.656
When μ = 0.6 and n=24																
		(r,λ_f)= (1,0)					**(r,λ_f)= (1,2)**					**(r,λ_f)= (.8,2)**				
		A					**α**					**A**				
λ0	**λ1**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**
0.4	**0.43**	5.067	6.240	7.790	8.962	11.685	25.039	30.833	38.491	44.284	57.737	30.032	36.981	46.167	53.116	69.250
0.4	**0.46**	2.571	3.165	3.952	4.546	5.927	12.557	15.462	19.303	22.208	28.955	15.053	18.536	23.141	26.624	34.711
0.4	**0.49**	1.738	2.140	2.672	3.074	4.008	8.396	10.339	12.907	14.850	19.360	10.060	12.388	15.465	17.793	23.198
0.4	**0.52**	1.321	1.628	2.032	2.338	3.048	6.316	7.777	9.709	11.170	14.563	7.564	9.314	11.628	13.378	17.441
0.4	**0.55**	1.072	1.320	1.648	1.895	2.471	5.067	6.239	7.789	8.962	11.685	6.066	7.4696	9.325	10.728	13.987

Table-2.2: Values of ARL for controlling the parameter λ

When μ = 0.5 and n=24																
		(r,λ_f)= (1,0)					**(r,λ_f)= (1,2)**					**(r,λ_f)= (.8,2)**				
		A					**A**					**A**				
λ0	λ1	0.05	0.025	0.01	0.005	0.001	0.05	0.025	0.01	0.005	0.001	0.05	0.025	0.01	0.005	0.001

0.4	0.43	192.40	236.92	295.77	340.28	443.65	6472.59	7970.21	9949.95	11447.57	14924.93	9429.50	11611.28	14495.44	16677.22	21743.16
0.4	0.46	51.35	63.23	78.94	90.82	118.41	1638.01	2017.01	2518.02	2897.02	3777.02	2381.39	2932.40	3660.78	4211.78	5491.17
0.4	0.49	24.31	29.93	37.36	42.99	56.05	736.87	907.37	1132.76	1303.25	1699.13	1069.12	1316.49	1643.49	1890.86	2465.24
0.4	0.52	14.53	17.89	22.34	25.69	33.50	419.51	516.57	644.88	741.95	967.33	607.43	747.98	933.77	1074.32	1400.66
0.4	0.55	9.86	12.14	15.15	17.44	22.74	271.71	334.58	417.68	480.55	626.53	392.649	483.49	603.60	694.45	905.40
When μ = 0.6 and n=20																
		(r,λf)= (1,0)					**(r,λf)= (1,2)**					**(r,λf)= (.8,2)**				
		A					**A**					**A**				
λ0	**λ1**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**
0.4	**0.43**	197.09	242.70	302.98	348.58	454.47	6479.21	7978.36	9960.13	11459.28	14940.19	9436.22	11619.55	14505.76	16689.1	21758.65
0.4	**0.46**	52.39	64.51	80.54	92.66	120.81	1639.42	2018.75	2520.19	2899.51	3780.28	2382.82	2934.16	3662.98	4214.32	5494.47
0.4	**0.49**	24.70	30.42	37.98	43.69	56.96	737.39	908.01	1133.55	1304.17	1700.33	1069.64	1317.13	1644.30	1891.79	2466.45
0.4	**0.52**	14.71	18.12	22.62	26.02	33.93	419.74	516.85	645.24	742.35	967.86	607.66	748.26	934.13	1074.73	1401.19
0.4	**0.55**	9.95	12.26	15.30	17.60	22.95	271.82	334.71	417.85	480.74	626.77	392.76	483.63	603.76	694.64	905.64
When μ = 0.6 and n=24																
		(r,λf)= (1,0)					**(r,λf)= (1,2)**					**(r,λf)= (.8,2)**				
		A					**A**					**A**				
λ0	**λ1**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**
0.4	**0.43**	236.51	291.23	363.57	418.30	545.36	7775.06	9574.03	11952.15	13751.1	17928.23	11323.46	13943.46	17406.92	20026.92	26110.38
0.4	**0.46**	62.87	77.42	96.64	111.19	144.97	1967.30	2422.50	3024.22	3479.42	4536.34	2859.39	3520.99	4395.58	5057.18	6593.37
0.4	**0.49**	29.64	36.50	45.57	52.43	68.36	884.87	1089.61	1360.26	1565.00	2040.39	1283.57	1580.56	1973.16	2270.15	2959.74
0.4	**0.52**	17.66	21.74	27.14	31.23	40.71	503.68	620.22	774.28	890.82	1161.43	729.20	897.92	1120.96	1289.68	1681.43
0.4	**0.55**	11.94	14.71	18.36	21.12	27.54	326.18	401.65	501.42	576.89	752.13	471.31	580.36	724.51	833.56	1086.77

For the above distribution (2.1), the mean and variance are given by

$E(X) = \frac{n\lambda}{\lambda+\mu}$ *and* $V(X) = \frac{n\mu\lambda}{(\lambda+\mu)^2}$

Table-2.3: Values of ϕ for controlling the parameter λ

When μ = 0.5 and n=24															
	(r,λf)= (1,0)					**(r,λf)= (1,2)**					**(r,λf)= (.8,2)**				
Λ0/λ1	**0.43**	**0.46**	**0.49**	**0.52**	**0.55**	**0.43**	**0.46**	**0.49**	**0.52**	**0.55**	**0.43**	**0.46**	**0.49**	**0.52**	**0.55**
0.4	84.75	84.84	84.93	85.01	85.08	85.15	85.17	85.18	85.19	85.21	85.17	85.18	85.19	85.20	85.21
0.3	84.31	84.42	84.52	84.61	84.69	85.10	85.11	85.13	85.14	85.16	85.12	85.14	85.15	85.16	85.17
When μ = 0.6 and n=20															
	(r,λf)= (1,0)					**(r,λf)= (1,2)**					**(r,λf)= (.8,2)**				
Λ0/λ1	**0.43**	**0.46**	**0.49**	**0.52**	**0.55**	**0.43**	**0.46**	**0.49**	**0.52**	**0.55**	**0.43**	**0.46**	**0.49**	**0.52**	**0.55**
0.4	84.18	84.29	84.40	84.49	84.58	85.05	85.07	85.08	85.10	85.12	85.08	85.09	85.11	85.12	85.14
0.3	83.66	83.79	83.91	84.02	84.12	84.99	85.02	85.03	85.05	85.06	85.04	85.05	85.07	85.08	85.09
When μ = 0.6 and n=24															
	(r,λf)= (1,0)					**(r,λf)= (1,2)**					**(r,λf)= (.8,2)**				
Λ0/λ1	**0.43**	**0.46**	**0.49**	**0.52**	**0.55**	**0.43**	**0.46**	**0.49**	**0.52**	**0.55**	**0.43**	**0.46**	**0.49**	**0.52**	**0.55**
0.4	83.02	83.16	83.28	83.40	83.50	84.07	84.09	84.11	84.13	84.14	84.11	84.12	84.14	84.15	84.17
0.3	82.40	82.56	82.70	82.83	82.95	84.01	84.02	84.04	84.06	84.08	84.06	84.07	84.09	84.10	84.12

3. CSCC FOR POISSON VARIABLE WITHOUT INSPECTION ERROR:

The hypothesis under test is $H_0 : \lambda = \lambda_0$ Vs $H_1 : \lambda = \lambda_1 (>\lambda_0)$ assuming μ Known, we use the likelihood ratio

$$\frac{f(x_1, x_2, x_3, .., x_m/\lambda_1, \mu)}{f(x_1, x_2, x_3, .., x_m/\lambda_0, \mu)} = \left(\frac{\lambda_1}{\lambda_0}\right)^{\sum_{i=1}^{m} x_i} \left[\frac{\lambda_0 + \mu}{\lambda_1 + \mu}\right]^{mn}$$

The continuation region of the SPRT discrimination between the two hypothesis $H_0 : \lambda = \lambda_0$ Vs $H_1 : \lambda = \lambda_1 (>\lambda_0)$ has the continuation region

$$log\left(\frac{\beta}{1-\alpha}\right) < \sum_{i=1}^{m} x_i \log\left(\frac{\lambda_1}{\lambda_0}\right) + mn \log\left(\frac{\lambda_0+\mu}{\lambda_1+\mu}\right) < \log\left(\frac{1-\beta}{\alpha}\right) \quad (3.1)$$

where

α = probability of accepting H_1 when H_0 is true.

β = probability of accepting H_0 when H_1 is true.

If we plot points (m, X_m) with $X_m = \sum_{i=1}^{m} x_i$, the boundary line between the continuation region and the acceptance region n for H_1, has the equation

$$X_m < \frac{-\log\alpha + nm\, log\left(\frac{\lambda_1+\mu}{\lambda_0+\mu}\right)}{log\left(\frac{\lambda_1}{\lambda_0}\right)} \quad (3.2)$$

Then the control limits for CSCC for Poisson Variables are

$$d = -log\alpha \left[n \log\left(\frac{\lambda_1+\mu}{\lambda_0+\mu}\right)\right]^{-1} \quad (3.3)$$

$$\emptyset = tan^{-1} \left[\frac{\left[n \log\left(\frac{\lambda_1+\mu}{\lambda_0+\mu}\right)\right]}{\left[\log\left(\frac{\lambda_1}{\lambda_0}\right)\right]}\right] \quad (3.4)$$

Following Johnson (1961), the approximate formula for ARL detecting a shift for the parameter λ from λ0 to λ1 Is given by

$$ARL = (-log\ \alpha) \left[\frac{n\lambda_1}{\lambda_1+\mu} \log\left(\frac{\lambda_1}{\lambda_0}\right) + n \log\left(\frac{\lambda_0+\mu}{\lambda_1+\mu}\right)\right]^{-1} \quad (3.5)$$

4. CSCC FOR POISSON VARIABLE WITH INSPECTION ERROR

Let r be the probability that a non inconformity is correctly noted by the inspector. We note that r is assumed to be a constant over different values of λ and μ. In one study reported by Harris and Chaney r varies from 0.58 to 0.8 where as λ and μ varies from 0.0025 to 0.16. However, this variability among different inspectors, since different inspectors were used for different values of μ. Therefore, the assumption of a constant r does not seen to be too seriously violated, especially noting the large spread in values of λ and μ. If λ_f and μ_f are the average no. of false alarms per item and λ and μ are the true average number of non-conformities per part and μ' and λ' are the average number per part observed by the inspector, then

$$\lambda_0' = r\lambda_0 + \lambda_{0f} \quad (4.1)$$

$$\lambda_1' = r\lambda_1 + \lambda_{1f} \quad (4.2)$$

$$\mu' = r\mu + \mu_f \quad (4.3)$$

with both r and μ_f estimated. Every effort should be made to estimate both types of errors, i.e. to get r close to one and μ_f close to zero. If μ is the target value then the control limits and ARL under inspection error for CSCC on Poisson variable is obtained by (3.3), (3.4) and (3.5) as follows

$$d = -log\alpha \left[n \log\left(\frac{\lambda_1'+\mu'}{\lambda_0'+\mu'}\right)\right]^{-1} \quad (4.4)$$

$$\emptyset = tan^{-1} \left[\frac{\left[n \log\left(\frac{\lambda_1'+\mu'}{\lambda_0'+\mu'}\right)\right]}{\left[\log\left(\frac{\lambda_1'}{\lambda_0'}\right)\right]}\right] \quad (4.5)$$

and

$$ARL = (-log\ \alpha) \left[\frac{n\lambda_1'}{\lambda_1'+\mu'} \log\left(\frac{\lambda_1'}{\lambda_0'}\right) + n \log\left(\frac{\lambda_0'+\mu'}{\lambda_1'+\mu'}\right)\right]^{-1} \quad (4.6)$$

5. DISCUSSION OF RESULTS AND CONCLUSION:

In this paper we have investigated distance d and angle ф along with ARL of CUSUM chart under inspection error. For the effect of inspection error we have considered three cases (r, μ_f) = (1,0) ,(1,2) and (0.8,2). The first case corresponds to CSCC without inspection error while the other two correspond to different inspection error. The lead distance d and angle ф of the V-mask for CUSUM chart computed for the different values of λ, μ, n and α for controlling the parameter λ.

It has been observed from the table 2.1 for fixed α, the values of d decreases as the difference (λ_1- λ_0) increases, whereas for the same difference (λ_1- λ_0), the value of d increases as α decreases. It can also be seen from table 2.2 that the angle of the mask increases as the ratio (λ/μ) increases and angle of the mask decreases as n is decreased. It is evident from table 2.3 that for fixed α, the ARL decreases as the shift from λ_0 to λ_1 increases and for fixed changed from λ_0 to λ_1, the ARL increases as the initial region α decreases but for fixed ratio and α, the ARL increases if the parameter decreases.

We conclude that both type of error i.e. failing to note a nonconformity and noting one where none exists, seriously affect the control limits d, and ARL from that which would be obtained under error free inspection. This statement is especially true when one is setting up CSCC on Poisson variable based on a target value of μ. In any situation, every effort should be made to minimize both types of inspection errors. Here we have assumed a constant r (and μ_f) for the entire inspection scheme but in a reality, r (and μ_f) could vary by inspector, type of nonconformity, shift, etc. Further one should not increase false alarms to compensate for missed non conformities since the cost for such a scheme is high. Both types of errors are to be avoided, but one should not attempt to eliminate one at the cost of the others.

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