

RESEARCH ARTICLE

Control charts to monitor rates and proportions

Linda Lee Ho¹  | Fidel Henrique Fernandes² | Marcelo Bourguignon²

¹Production Engineering, Universidade de São Paulo, São Paulo, Brazil

²Statistics, Universidade Federal do Rio Grande do Norte, Natal, Brazil

Correspondence

Linda Lee Ho, Production Engineering, Universidade de São Paulo, São Paulo, Brazil.

Email: lindalee@usp.br

Funding information

Conselho Nacional de Desenvolvimento Científico e Tecnológico, Grant/Award Number: 304670/2014-6

Abstract

In this paper, we call attention for monitoring proportions and rates when they are not results of Bernoulli experiments. To deal with this problem, usually control charts based on Beta distributions are built as this distribution is a well-known one. However, in practice, there are other distributions to be considered as Simplex and Unit Gamma distributions. The impact of the speed to signal a shift in the average proportion in terms of out-of-control average run length is measured when the control limits determined under a Beta distribution is equivocally used to monitor individual rates from Simplex or Unit Gamma distributions or vice versa.

KEYWORDS

average run length, Beta distribution, Simplex distribution, Unit Gamma distribution

1 | INTRODUCTION

Control charts have been the most used tool to monitor the stability of process parameters (like mean, variance, or nonconforming fraction). It is desirable that the goods/products/items are being manufactured to meet the client's requirements and in absence of special/assignable causes. Most recently, their applications have been extended to other areas than manufacturing. For example, they have been used to verify the stability of a service quality or the price of stock or the surveillance of a disease to declare if the epidemic level is reached or not, and so.

In many practical situations, there is interest in monitoring rates/proportions of components in a product. When they are results from Bernoulli experiments, the np and p charts may be applied to monitor the stability of nonconforming proportion.¹ Good review papers about attribute charts can be found in the literature as these written by Szarka and Woodall² and Woodall.³ Some recent contributions on np or p charts varying estimator, sampling, or decision scheme can be cited.⁴⁻⁷ For a single quality characteristic normally distributed, many contributors have proposed “pure” attribute charts based on the results of

classifications of the values of the quality characteristic by a gauge to monitor process parameters as mean⁸⁻¹² or variance.^{13,14} Its extensions to monitor bivariate process parameters can be found in the literature: for monitoring a vector of mean¹⁵ and covariance-variance matrix.¹⁶ Other authors have combined attribute (as results of gauge classification) and variable charts¹⁷⁻²⁰ to improve the performance in signaling out-of-control state. Attribute charts have also been used to monitor parameters of Weibull and^{21,22} exponential²³ distributions.

However, there are situations that rates or proportions are not results from Bernoulli experiments although assume values in the range (0, 1). For example, the monitoring of the proportion of the drug components (of a medicine) in pharmaceutical industries is essential to assure its effectiveness. Or the proportion of components in a casting product or the monitoring of the unemployment rate to drive the resources in public politics. Thus, the former mentioned control charts cannot be applied for this purpose.

The well-known probability distribution that deals with this type of random variable is Beta distribution, and a Shewhart-type control chart considering this baseline distribution was developed by SantAnna and ten

Caten.²⁴ Recently, Bayer et al²⁵ extended considering beta regression control chart to monitor proportions and rates. However, other probability functions modelling rates/proportions in the range (0, 1) are available in the literature like Simplex²⁶ or Unit Gamma²⁷ distributions.

The aim of this paper is to measure the impact of the speed to signal shifts in the average proportion measured in terms of usual performance metrics, as out-of-control average run length (ARL_1), out-of-control median run length (MRL_1), and out-of-control standard deviation run length ($SDRL_1$) when control limits determined under a Beta distribution are inappropriately used to monitor rates/proportions from other distributions than Beta like Simplex or Unit Gamma distributions or vice versa.

This paper is organized as follows: this introductory section. In section 2, a brief review of the main probability distributions for modelling proportions or rate in the unit interval is presented. The Shewhart-type control charts to monitor proportions are the subject of section 3. The performance of the control charts (for Beta, Simplex and Unit Gamma) are determined for a set of shifts. Additionally, the impact in the speed to signal changes in the average proportion when the control limits obtained under a baseline distribution are misused for others distributions. These results are discussed in section 4. Applications to a real data set are presented in section 5, and conclusion remarks are outlined in Section 6.

2 | SOME DISTRIBUTIONS FOR MODELLING RATES AND PROPORTIONS

In what follows, we shall briefly present three different distributions that can be used to model data that assume values in the unit interval, namely, the Beta, Simplex, and Unit Gamma distributions.

2.1 | Beta distribution

A random variable Y follows a Beta distribution with shape parameters $\delta > 0$ and $\gamma > 0$, denoted by $Y \sim B(\delta, \gamma)$, if its cumulative distribution function is given by

$$F(y|\delta, \gamma) = I_y(\delta, \gamma), \quad 0 < y < 1, \quad (1)$$

where $I_x(\delta, \gamma) = \frac{B_x(\delta, \gamma)}{B(\delta, \gamma)}$ is the incomplete beta function ratio, $B_x(\delta, \gamma) = \int_0^x \omega^{\delta-1}(1-\omega)^{\gamma-1}d\omega$ is the incomplete function, $B(\delta, \gamma) = \frac{\Gamma(\delta)\Gamma(\gamma)}{\Gamma(\delta+\gamma)}$ is the beta function, and $\Gamma(\delta) = \int_0^\infty \omega^{\delta-1}e^{-\omega}d\omega$.

The probability density function (pdf) associated with 91) is

$$f(y|\delta, \gamma) = \frac{y^{\delta-1}(1-y)^{\gamma-1}}{B(\delta, \gamma)}, \quad 0 < y < 1. \quad (2)$$

The mean and variance associated with (2) are given by

$$E(Y) =: \mu = \frac{\delta}{\delta + \gamma} \quad (3)$$

and

$$\text{Var}(Y) = \frac{\delta\gamma}{(\delta + \gamma)^2(\delta + \gamma + 1)}, \quad (4)$$

respectively. Let, in (2)

$$\delta = \mu\phi \quad \text{and} \quad \gamma = (1 - \mu)\phi. \quad (5)$$

From (5), the Beta density in (2) can be written as

$$f(y|\mu, \phi) = \frac{y^{\mu\phi-1}(1-y)^{(1-\mu)\phi-1}}{B(\mu\phi, (1-\mu)\phi)}, \quad 0 < y < 1. \quad (6)$$

Thus, under this parameterization, it follows from Equations 3 and 4 that

$$E(Y) = \mu \quad \text{and} \quad \text{Var}(Y) = \frac{\mu(1-\mu)}{\phi + 1}.$$

2.2 | Simplex distribution

A random variable Y follows a Simplex distribution,²⁶ denoted by $Y \sim S(\mu, \sigma^2)$ if its pdf is given by

$$f(y|\mu, \sigma^2) = \{2\pi\sigma^2[y(1-y)]^3\}^{-\frac{1}{2}} \exp\left[-\frac{1}{2\sigma^2}d(y; \mu)\right], \quad 0 < y < 1, \quad (7)$$

where

$$d(y; \mu) = \frac{(y - \mu)^2}{y(1-y)\mu^2(1-\mu)^2}$$

is the deviance function, $0 < \mu < 1$, and $\sigma^2 > 0$. The Simplex distribution has a unimode if $\sigma \leq 4/\sqrt{3}$; otherwise, it yields multimodes.

The mean and variance of Y are given by

$$E(Y) = \mu$$

and

$$\text{Var}(Y) = \frac{1}{\sqrt{2\sigma^2}} \exp\left\{\frac{1}{2\sigma^2\mu^2(1-\mu)^2}\right\} \Gamma\left(\frac{1}{2}, \frac{1}{2\sigma^2\mu^2(1-\mu)^2}\right),$$

respectively, where $\Gamma(a, b)$ is the incomplete gamma function defined by $\Gamma(a, b) = \int_b^\infty t^{a-1}e^{-t}dt$.

2.3 | Unit gamma distribution

The last distribution we shall present is the Unit Gamma model proposed by Grassia.²⁷ The random variable Y follows a Unit Gamma distribution with parameters θ and τ , denoted by $Y \sim \text{uGA}(\theta, \tau)$, if its pdf is given by

$$f(y|\theta, \tau) = \frac{\theta^\tau}{\Gamma(\tau)} y^{\theta-1} \left[\log\left(\frac{1}{y}\right) \right]^{\tau-1}, \quad 0 < y < 1,$$

where $\theta > 0$ and $\tau > 0$. The mean and variance are given by

$$E(Y) = \mu = \left[\frac{\theta}{\theta + 1} \right]^\tau$$

and

$$\text{Var}(Y) = \left[\frac{\theta}{\theta + 2} \right]^\tau - \left[\frac{\theta}{\theta + 1} \right]^{2\tau},$$

respectively.

Mousa et al.²⁸ considered a new parameterization for the Unit Gamma distribution. Let $\theta = \frac{\mu^{1/\tau}}{(1 - \mu^{1/\tau})}$, from this new parameterization, the Unit Gamma density can be written as

$$f(y|\mu, \tau) = \frac{\left[\frac{\mu^{1/\tau}}{1 - \mu^{1/\tau}} \right]^\tau}{\Gamma(\tau)} y^{\frac{\mu^{1/\tau}}{1 - \mu^{1/\tau}} - 1} \left[\log\left(\frac{1}{y}\right) \right]^{\tau-1}, \quad 0 < y < 1, \quad (8)$$

where $0 < \mu < 1$ and $\tau > 0$. Thus, the mean and variance are given by

$$E(Y) = \mu \quad \text{and} \quad \text{Var}(Y) = \mu \left[\frac{1}{(2 - \mu^{1/\tau})^\tau} - \mu \right].$$

3 | CONTROL CHARTS TO MONITOR INDIVIDUAL OBSERVATIONS OF RATES AND PROPORTIONS

Usually, to monitor nonconforming proportions in the production process, the p and np control charts have been employed for such purposes. In this case, the proportions, most of them, are results of Bernoulli experiments. Due to its discreteness nature (of the binomial distribution) and depending on the sample size, the symmetric control limits (used in Shewhart-type control chart) determined by the approximated normal distribution may not reach the desired values of ARL_0 like 370. Thus, procedures have been proposed by many researchers to improve the performance of np or p charts.²⁹⁻³⁶

When the monitored proportions are not results of Bernoulli experiments, control charts can also be built using distributions with the random variable defined in the range $(0, 1)$ like Beta or Simplex or Unit Gamma distributions.

Fixed the type I error α , the lower and upper probability control limits LCL_B and UCL_B for Beta chart are determined such that

$$P(Y < LCL_B | \mu_{0B}, \phi_0) = P(Y > UCL_B | \mu_{0B}, \phi_0) = \alpha/2$$

$$\int_0^{LCL_B} f(y|\mu_{0B}, \phi_0) = \int_{UCL_B}^1 f(y|\mu_{0B}, \phi_0) = \alpha/2,$$

where μ_{0B} and ϕ_0 , respectively, are the in-control average proportion and dispersion parameter of Beta chart and $f(y|\mu_{0B}, \phi_0)$ expressed in (6). The probability control limits LCL_S and UCL_S for Simplex chart are similarly calculated as

$$P(Y < LCL_S | \mu_{0S}, \sigma_0^2) = P(Y > UCL_S | \mu_{0S}, \sigma_0^2) = \alpha/2$$

$$\int_0^{LCL_S} f(y|\mu_{0S}, \sigma_0^2) = \int_{UCL_S}^1 f(y|\mu_{0S}, \sigma_0^2) = \alpha/2,$$

with μ_{0S} and σ_0^2 , respectively, the in-control average proportion and precision parameter of Simplex chart, $f(y|\mu_{0S}, \sigma_0^2)$ in (7), and finally, the probability control limits LCL_G and UCL_G for Unit Gamma chart are obtained as

$$P(Y < LCL_G | \mu_{0G}, \tau_0) = P(Y > UCL_G | \mu_{0G}, \tau_0) = \alpha/2$$

$$\int_0^{LCL_G} f(y|\mu_{0G}, \tau_0) = \int_{UCL_G}^1 f(y|\mu_{0G}, \tau_0) = \alpha/2,$$

with μ_{0G} , τ_0 , respectively, the in-control average proportion and precision parameter of Unit Gamma control chart and $f(y|\mu_{0G}, \tau_0)$ in (8).

The power $(1 - \beta)$ of these control charts can be calculated as

$$1 - \beta = P(Y < LCL_i | \Theta_1) + P(Y > UCL_i | \Theta_1),$$

$i = B, S, G$, with $\Theta_{1i} = \{(\mu_{1B}, \varphi_1), (\mu_{1S}, \sigma_1^2), (\mu_{1G}, \tau_1)\}$, respectively, the out-of-control parameters of Beta, Simplex, and Unit Gamma control charts. Usually, the out-of-control average proportion μ_{1i} is expressed in terms of in-control average proportion as $\mu_{1i} = \mu_{0i} + k\sqrt{\text{Var}(Y)}$ or $\mu_{1i} = \mu_{0i} + \Delta_i$ or $\mu_{1i} = \mu_{0i}\Delta_i$ depending on the context of interest. In this paper, we consider shifts only on the average proportion and no shifts on the dispersion parameters.

In case of unilateral control charts, the control limits UCL_i or LCL_i are similarly calculated with $P(Y < LCL_i | \Theta_0) = \alpha$ or $P(Y > UCL_i | \Theta_0) = \alpha$, $i = B, S, G$ with $\Theta_0 = \{(\mu_{0B}, \varphi_0), (\mu_{0S}, \sigma_0^2), (\mu_{0G}, \tau_0)\}$, respectively, the in-control parameters of Beta, Simplex, and Unit Gamma control charts. And the power $(1 - \beta)$ is obtained as $1 - \beta = P(Y < LCL_i | \Theta_1)$ or $1 - \beta = P(Y > UCL_i | \Theta_1)$, $i = B, S, G$ with $\Theta_1 = \{(\mu_{1B}, \varphi_0), (\mu_{1S}, \sigma_0^2), (\mu_{1G}, \tau_0)\}$, respectively, the out-of-control parameters of Beta, Simplex, and Unit Gamma control charts.

In the production processes, the performance of the control chart is usually measured in terms of the number of samples (the run length) until a signal is observed and the

most used metric is the average run length (ARL). In the current context, the observations y_i are independent as at every sampling interval, a single proportion is observed, and a decision is taken on the production process (stops or continues). Thus, the run length follows a geometric distribution with parameter p . When the process is in-control, $p = \alpha$ and the process is out-of-control, $p = (1 - \beta)$. As the run length is high asymmetrically distributed, other metrics than $ARL = 1/p$ as the standard deviation of the run length, ($SDRL = \sqrt{(1-p)/p^2}$) or the median run length, ($MRL = \ln(0.5)/\ln(1-p)$) are also considered. When the process is in-control, large values of $ARL_0 = 1/\alpha$ is desirable, but in a case of out-of-control low values of $ARL_1 = 1/(1 - \beta)$ is preferable.

4 | PERFORMANCE OF CONTROL CHARTS

In this section, the performance (measured in terms of ARL_1 , MRL_1 , $SDRL_1$) of the three control charts to detect

different sizes of shifts are obtained. In addition, the impact in the speed to detect the shifts in the average proportion if a set of control limits determined under distribution “A” is wrongly used to monitor proportions under distribution “B” or vice versa. All results presented in this section are obtained considering as in-control average proportion $\mu_{0B} = \mu_{0S} = \mu_{0G} = 0.2$ and out-of-control $\mu_{1B} = \mu_{1S} = \mu_{1G} = 0.2 \pm \epsilon$, $\epsilon = \{0.02, 0.04, 0.06, 0.08\}$. Four levels of dispersion/precision are chosen for each distribution such that they present similar probability distribution function. The dispersion/precision parameters are shown in Table 1, where the cases 1 (–) and 4 (+) denote, respectively, the cases with lower and higher variances. Probability density functions of cases 2 and 4 are shown in Figure 1. The other cases also have similar probability density functions and are not shown here.

Table 2 presents the performance of the control charts (in terms of ARL , $SDRL$, and MRL) when the average proportion shifts in two directions (increase and decrease) using error type I $\alpha = 0.0027$ to yield $ARL_0 = 370$. The results are organized in three blocks of nine columns. The first block (columns 3–11) is related to Beta control chart, the second to Simplex control chart, and the last to Unit Gamma control chart. At every block, the first three columns are the performance metrics when the correct control limits are used (Beta/Simplex/UGamma-true), and other six columns are the metrics when incorrect control limits are employed. For example, columns 3 to 5 are the true performance of Beta chart (that is, the Beta control limits are correctly used). Columns 6 to 8 and columns 9 to 11 are, respectively, the performance metrics employing

TABLE 1 Dispersion parameters

Case	Beta ϕ	Simplex σ^2	Unit Gamma τ
1 (–)	290	0.37	1.55
2	148	0.5	96
3	80	0.71	51
4 (+)	31	1.2	20

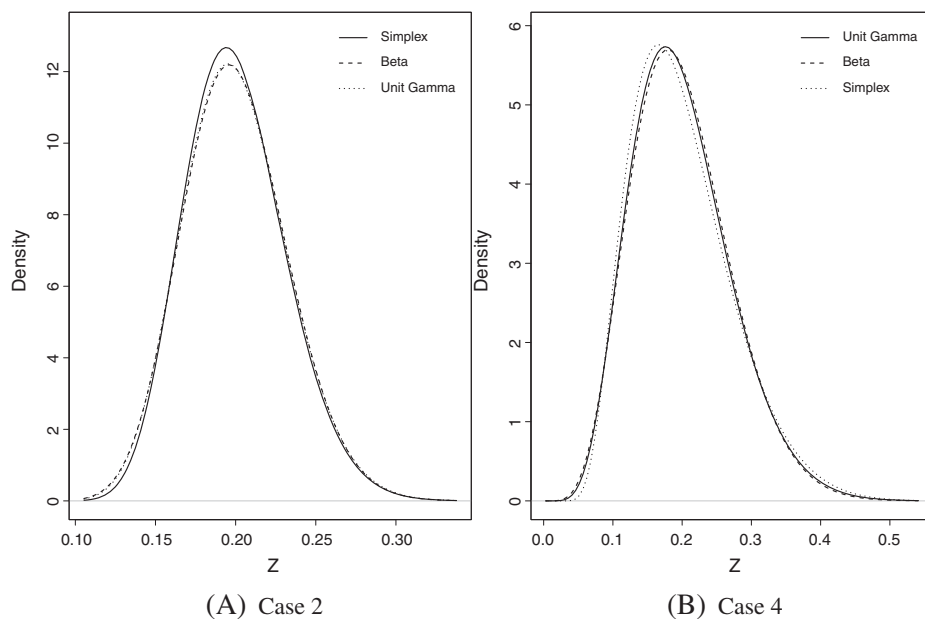


FIGURE 1 Beta, Simplex, and Unit Gamma probability density function (pdf) of cases 2 and 4

TABLE 2 Comparing the performance of the control charts-bidirectional

μ	Beta - True				Simplex				UGamma				Simplex - True				Beta				UGamma				UGamma - True				Beta				Simplex			
	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL			
Case 1: $\phi = 290$ $\sigma = 0.37$ $\tau = 155$	0.12	1.26	0.57	0.44	1.21	0.5	0.4	1.39	0.74	0.55	1.09	0.31	0.28	1.13	0.38	0.32	1.25	0.56	0.43	1.4	0.75	0.55	1.28	0.6	0.46	1.23	0.53	0.41	0.12	1.26	0.57	0.44	1.21	0.5	0.4	
	0.14	2.34	1.77	1.24	2.1	1.52	1.07	2.99	2.44	1.7	2.15	1.57	1.11	2.5	1.94	1.36	3.56	3.02	2.1	2.85	2.3	1.6	2.28	1.71	1.2	2.07	1.49	1.05	0.16	8.04	7.52	5.22	6.6	6.08	4.22	
	0.16	8.04	7.52	5.22	6.6	6.08	4.22	12.49	11.98	8.31	9.34	8.83	6.12	12.32	11.81	8.19	22.95	22.44	15.56	10	9.49	6.58	6.8	6.28	4.36	5.7	5.18	3.59	0.18	54.6	54.1	37.5	40.35	39.85	27.62	
	0.18	54.6	54.1	37.5	40.35	39.85	27.62	105.26	104.76	72.61	70.24	69.74	48.34	103.42	102.92	71.34	242.45	241.95	167.71	63.21	62.71	43.47	35.72	35.22	24.41	27.37	26.87	18.62	0.2	370.37	369.87	256.37	333.95	333.45	231.13	
	0.2	370.37	369.87	256.37	333.95	333.45	231.13	1028.5	1028	712.56	370.46	369.96	256.44	371.34	370.84	257.05	1080.23	1079.73	748.41	370.3	369.8	256.33	155.73	155.23	107.6	146.39	145.89	101.12	0.22	69.71	69.21	47.97	91.56	91.06	63.12	
	0.22	69.71	69.21	47.97	91.56	91.06	63.12	178.02	177.52	123.05	55.04	54.54	37.8	43.89	43.39	30.07	95.21	94.71	65.65	90.28	89.78	62.23	41.69	41.19	28.55	52.04	51.54	35.72	0.24	12.26	11.75	8.15	15.05	14.54	10.08	
	0.24	12.26	11.75	8.15	15.05	14.54	10.08	24.7	24.19	16.77	10.52	10.01	6.94	8.97	8.46	5.86	15.43	14.92	10.34	17.82	17.31	12	9.85	9.34	6.47	11.72	11.21	7.77	0.26	3.71	3.17	2.21	4.26	3.73	2.59	
	0.26	3.71	3.17	2.21	4.26	3.73	2.59	6.01	5.49	3.81	3.71	3.17	2.21	3.34	2.8	1.95	4.81	4.28	2.97	5.36	4.83	3.36	3.51	2.97	2.07	3.97	3.43	2.39	0.28	1.78	1.18	0.84	1.93	1.34	0.95	
	0.28	1.78	1.18	0.84	1.93	1.34	0.95	2.38	1.81	1.27	1.98	1.39	0.99	1.85	1.25	0.89	2.34	1.77	1.24	2.36	1.79	1.26	1.81	1.21	0.86	1.95	1.36	0.96	LCL	0.135	0.138	0.135	0.131	0.135	0.138	
	UCL	0.275	0.278	0.278	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	UCL	0.275	0.278	0.275	0.285	0.275	0.278	
Case 2: $\phi = 148$ $\sigma = 0.5$ $\tau = 96$	0.12	2.36	1.79	1.26	1.88	1.29	0.91	2.24	1.67	1.17	1.87	1.28	0.91	2.73	2.17	1.52	2.5	1.94	1.36	2.23	1.66	1.16	2.35	1.78	1.25	1.86	1.26	0.9	0.12	2.36	1.79	1.26	1.88	1.29	0.91	
	0.14	5.72	5.2	3.61	3.9	3.36	2.34	5.26	4.73	3.29	5.72	5.2	3.61	11.14	10.63	7.37	9.6	9.09	6.3	5.36	4.83	3.36	5.85	5.33	3.7	3.93	3.39	2.36	0.16	5.72	5.2	3.61	3.9	3.36	2.34	
	0.16	20.11	19.6	13.59	11.52	11.01	7.63	17.84	17.33	12.02	24.83	24.32	16.86	61.46	60.96	42.25	50.41	49.91	34.59	18.84	18.33	12.71	21.36	20.85	14.46	11.92	11.41	7.91	0.18	100.51	100.01	69.32	48.27	47.77	33.11	
	0.2	100.51	100.01	69.32	48.27	47.77	33.11	86.24	85.74	59.43	128.23	127.73	88.54	380.55	380.05	263.43	302.39	301.89	209.25	95.63	95.13	65.94	112.22	111.72	77.44	52	51.5	35.7	0.22	370.37	369.87	256.37	211.09	210.59	145.97	
	0.22	370.37	369.87	256.37	211.09	210.59	145.97	359.18	358.68	248.62	370.48	369.98	256.45	860.52	860.02	389.56	593.77	593.27	409.22	370.37	369.87	256.37	373.12	372.62	258.28	232.02	222.52	154.24	0.24	129.21	128.71	89.21	128.71	128.21	88.87	
	0.22	129.21	128.71	89.21	128.71	128.21	88.87	148.13	147.63	102.33	90	89.5	62.04	88.79	88.29	61.2	100.42	99.92	69.26	138.59	138.09	95.72	121.2	120.7	83.66	121.75	121.25	84.04	0.26	32.24	31.74	22	33.09	32.59	22.59	
	0.24	32.24	31.74	22	33.09	32.59	22.59	36.31	35.81	24.82	21.68	21.17	14.68	21.22	20.71	14.36	23.35	22.84	15.84	35.74	35.24	24.42	31.79	31.29	21.69	32.64	32.14	22.28	0.26	10.61	10.1	7	10.83	10.32	7.15	
	0.26	10.61	10.1	7	10.83	10.32	7.15	11.6	11.09	7.69	7.94	7.42	5.15	7.81	7.29	5.06	8.4	7.88	5.47	11.8	11.29	7.83	10.73	10.22	7.09	10.97	10.46	7.25	0.28	4.53	4	2.78	4.62	4.09	2.84	
	0.28	4.53	4	2.78	4.62	4.09	2.84	4.89	4.36	3.03	3.94	3.4	2.37	3.89	3.35	2.33	4.11	3.58	2.49	4.97	4.44	3.09	4.62	4.09	2.84	4.7	4.17	2.9	LCL	0.1132	0.1205	0.1147	0.1132	0.1132	0.1205	
	UCL	0.308	0.308	0.308	0.3095	0.3095	0.3095	0.3095	0.3095	0.3095	0.3095	0.3095	0.3095	0.308	0.308	0.308	0.308	0.308	0.308	0.308	0.308	0.308	0.308	0.308	0.308	0.308	0.308	0.308	UCL	0.308	0.3095	0.308	0.3095	0.308	0.3095	
Case 3: $\phi = 80$ $\sigma = 0.71$ $\tau = 51$	0.12	5.11	4.58	3.18	3.58	3.04	2.12	4.75	4.22	2.93	5.94	5.42	3.76	12.47	11.96	8.29	10.66	10.15	7.04	4.85	4.32	3	5.24	4.71	3.27	3.61	3.07	2.14	0.12	5.11	4.58	3.18	3.58	3.04	2.12	
	0.14	12.99	12.48	8.65	7.97	7.45	5.17	11.77	11.26	7.81	19.22	18.71	12.97	49.3	48.8	33.82	40.55	40.05	27.76	12.31	11.8	8.18	13.67	13.16	9.12	8.16	7.64	5.3	0.16	40.85	40.35	27.97	21.76	21.25	14.73	
	0.16	40.85	40.35	27.97	21.76	21.25	14.73	36.03	35.53	24.63	64.92	64.42	44.65	195.18	194.68	134.94	155.76	155.26	107.62	38.78	38.28	26.53	44.3	43.8	30.36	22.76	22.25	15.43	0.18	150.86	150.36	104.22	234.83	234.33	162.42	
	0.2	150.86	150.36	104.22	234.83	234.33	162.42	131.6	131.1	90.87	213.7	213.2	147.78	646.57	646.07	447.82	538.9	538.4	373.19	144.77	144.27	100	165.72	165.22	114.52	76.72	76.22	52.83	0.22	370.37	369.87	256.37	256.62	256.12	177.53	
	0.22	370.37	369.87	256.37	256.62	256.12	177.53	384.12	383.62	265.9	370.35	369.85	256.36	413.27	412.77	286.11	407.08	406.58	344.2	370.37	369.87	256.37	342.53	342.03	237.08	240.04	239.54	166.04	0.24	195.11	194.61	134.89	97.36	96.86	67.14	
	0.24	195.11	194.61	134.89	97.36	96.86	67.14	251.03	250.53	173.65	135.09	134.59	93.29	100.36	99.86	69.22	125.53	125.03	86.66	213.14	212.64	147.39	166.24	165.74	114.88	222.6	222.1	153.95	0.26	67.47	66.97	46.42	97.12	96.62	66.97	
	0.26	67.47	66.97	46.42	97.12	96.62	66.97	86.65	86.15	59.71	42.76	42.26	29.29	32.52	32.02	22.19	39.15	38.65	26.79	78.28	77.78	53.91	61.24	60.74	42.1	87.66	87.16	60.41	0.28	26.33	25.83	17.9	36.49	35.99	24.94	
	0.28	26.33	25.83	17.9	36.49	35.99	24.94	32.76	32.26	22.36	17.56	17.05	11.82	14.01	13.5	9.36	16.3	15.79	10.95	31.52	31.02	21.5	25.5	24.99	17.33	35	34.5	23.91	LCL	0.0884	0.0968	0.0884	0.0889	0.0884	0.0968	
	UCL	0.3506	0.3506	0.3506	0.3586	0.3586	0.3586	0.3586	0.3586	0.3586	0.3586	0.3586	0.3586	0.3506	0.3506	0.3506	0.3506	0.3506	0.3506	0.3506	0.3506	0.3506	0.3506	0.3506	0.3506	0.3506	0.3506	0.3506	UCL	0.3506	0.3586	0.3506	0.3586	0.3506	0.3586	
Case 4: $\phi = 31$ $\sigma = 1.2$ $\tau = 20$	0.12	15																																		

equivocally control limits of Simplex and Unit Gamma charts in Beta chart. The second block (columns 12–20) is related of employing equivocally control limits of Beta and Unit Gamma charts in Simplex charts (the true metrics are under the group of the columns named Simplex-true), and finally, the third block (columns 21–29) is related to employing equivocally control limits of Beta and Simplex charts in Unit Gamma charts (the true metrics are under the group of the columns named UGamma-true).

According to Table 2, the use of equivocal control limits produce a great variety of impacts: earlier/latter false alarms; in some cases, no false alarms (like cases 2 to 4, the Beta control limits wrongly used in Simplex chart yield $ARL_0 > 1000$). Small shifts may not be detected for case 4 of Table 2 ($ARL_1 > ARL_0 = 370$).

Tables 3 to 4 are built to describe the results related to the shifts of the average proportion in a single direction, respectively, considering only increases or decreases. The organization of the results follows the same pattern of Table 2.

Most of results show coherence. For example, the use of Beta control limits in Simplex chart provides earlier false and true alarms. Thus, it is expected that the true and false signals are postponed when Simplex control limits are used in Beta charts.

Bold values in Tables 2 to 4 are the values of the metrics obtained with equivocal control limits but indeed similar to those using correct control limits. Few scenarios with no impact in all metrics (in-control and out-of-control) are observed: Simplex control limits in Beta chart and vice versa (see Table 3—case 2) and Unit Gamma control limits in Beta chart and vice versa for moderate/large shifts (see Table 2—case 2). And also, scenario with better performance as using Beta control limits in Simplex chart as in-control metrics are similar and out-of-control metrics lower than the truly ones (see Table 2—case 1 for moderate/large increases).

Certainly, the variance size plays an important role as no impact in larger shifts for the lower variance cases (cases 1 and 2) is observed (the out-of-control metrics are similar).

About the control limits of the different charts, numerically, they are very similar. Less impact in true alarms is observed when the difference of the correct control limits and equivocal ones is approximately $< |0.002|$ like cases 1 and 2 in Tables 2 to 4. Even when the equivocal in-control metrics are similar to the “true” metrics, it does not assure equal performance for the whole set of shift (similar only for medium/larger shifts). The tail (left and right) densities of the three distributions are quite different; this explains the different performance observed in the four cases. Thus, it is essential to have knowledge which distribution follows the proportions and rates to design the control charts correctly. When this information is unknown (assuming

TABLE 3 Comparing the performance of the control charts: Increases in average proportion

μ	Case	Beta - True				Simplex				UGamma				Simplex - True				Beta				UGamma				UGamma - True				Beta				Simplex			
		ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL						
0.2	Case 1	0.2	370.37	369.87	256.37	493.34	492.84	341.61	1022.45	1021.95	708.36	370.26	369.76	256.3	284.73	284.23	197.01	720.38	719.88	498.98	370.37	369.87	256.37	162.91	162.41	112.57	205.54	205.04	142.12								
$\phi = 290$		0.22	40.87	40.37	27.98	50.99	50.49	35	90.08	89.58	62.09	33.82	23.09	33.82	23.09	28.12	27.62	19.14	54.26	53.76	37.26	51.73	35.51	26.88	26.38	18.28	32.3	31.8	22.04								
$\sigma = 0.5$		0.24	8.3	7.78	5.4	9.74	9.23	6.4	14.78	14.27	9.89	7.49	6.97	4.84	6.6	6.08	4.22	10.38	9.87	6.84	11.54	11.03	7.65	6.53	4.53	8.09	7.57	5.25									
$\tau = 155$		0.26	2.87	2.32	1.62	3.19	2.64	1.84	4.21	3.68	2.56	2.97	2.42	1.69	2.73	2.17	1.52	3.68	3.14	2.19	3.93	>3.39	2.36	2.8	2.24	1.57	3.07	2.52	1.76								
0.28		1.77	1.17	0.83	1.64	1.02	1.04	1.02	0.74	1.33	0.94	1.72	1.11	0.8	1.64	1.02	0.74	1.97	1.38	0.98	1.94	1.35	0.96	1.58	0.96	0.69	1.67	1.06	0.76								
CL		0.27			0.272				0.278			0.272			0.27			0.278			0.278			0.27			0.272			0.272							
Case 2		0.2	370.37	369.87	256.37	375.77	375.27	260.12	423.83	423.33	293.43	370.36	369.86	256.37	365.21	364.71	252.8	416.09	415.59	288.06	370.37	369.87	256.37	325.69	325.19	22.54	330.22	329.72	228.54								
$\phi = 148$		0.22	73.31	72.81	50.47	74.2	73.7	51.08	82.09	81.59	56.55	54.18	53.68	37.21	53.61	53.11	36.81	59.18	58.68	40.67	77.73	77.23	53.53	69.67	69.17	47.94	70.49	69.99	48.51								
$\sigma = 0.5$		0.24	19.98	19.47	13.5	20.18	19.67	13.64	21.9	21.39	14.83	14.54	14.03	9.73	14.42	13.91	9.64	15.54	15.03	10.32	21.74	21.23	17.86	19.35	13.42	20.05	19.54	13.55									
$\tau = 96$		0.26	7.27	6.75	4.68	7.32	6.8	4.72	7.81	7.29	5.06	5.87	5.35	3.71	5.84	5.32	3.69	6.18	5.66	3.93	7.91	7.39	5.13	7.36	6.84	4.75	7.41	6.89	4.78								
0.28		3.42	2.88	2	3.44	2.9	2.02	3.61	3.07	3.44	2.14	3.15	2.6	1.81	3.14	2.59	1.81	3.27	2.72	1.9	3.66	3.12	2.17	3.46	2.92	2.03	3.48	2.94	2.05								
CL		0.299			0.3				0.301			0.3			0.299			0.301			0.301			0.299			0.3			0.3							
Case 3		0.2	370.37	369.87	256.37	552.07	551.57	382.32	480.69	480.19	332.84	370.37	369.87	256.37	258.92	258.42	179.12	327.13	326.63	226.4	370.37	369.87	256.37	291.1	290.6	201.43	420.82	420.32	291.34								
$\phi = 80$		0.22	110.7	110.2	76.38	157.64	157.14	108.92	139.42	138.92	96.29	82.06	81.56	56.53	61.69	61.19	42.41	74.32	73.82	51.17	110.48	109.98	76.23	96.19	95.69	66.33	134.07	133.57	92.58								
$\sigma = 0.71$		0.24	39.49	38.99	27.02	53.78	53.28	36.93	48.3	47.8	33.13	27.46	26.96	18.69	21.82	21.31	14.78	25.95	25.45	17.64	44.76	44.26	30.68	36.91	36.41	25.24	49.59	49.09	34.03								
$\tau = 51$		0.26	16.57	16.06	11.14	21.6	21.09	14.62	19.69	19.18	13.3	12.2	11.69	8.1	10.13	9.62	6.67	11.44	10.93	7.58	19.27	18.71	12.97	16.24	15.73	10.91	21.03	20.52	14.23								
0.28		8.07	7.55	5.24	16.08	15.57	10.8	9.33	8.82	8.82	6.11	6.63	6.11	4.24	5.7	5.18	3.59	6.29	5.77	4	9.37	8.86	6.14	8.11	7.59	5.27	10.12	9.61	6.66								
CL		0.338			0.346				0.343			0.346			0.338			0.343			0.343			0.338			0.346			0.346							
Case 4		0.2	370.37	369.87	256.37	758.21	757.71	525.2	509.91	509.41	353.1	370.38	369.88	256.38	198.9	198.4	137.52	261.35	260.85	180.81	370.37	369.87	256.37	278.35	277.85	192.59	531.47	530.97	368.04								
$\phi = 31$		0.22	173.39	172.89	119.84	338.09	337.59	234	232.65	232.15	160.91	123.04	122.54	84.94	73.39	72.89	50.52	92.08	91.58	63.48	187.54	187.04	129.65	143.04	142.54	98.8	264.38	263.88	182.91								
$\sigma = 1.2$		0.24	87.26	86.76	60.14	162.14	161.64	112.04	114.58	114.08	79.07	53.15	52.65	36.49	34.36	33.86	23.47	41.62	41.12	28.5	100.5	100	69.31	77.81	77.31	53.59	139.13	138.63	96.09								
$\tau = 20$		0.26	46.94	46.44	32.19	83.17	82.67	57.3	60.34	59.84	41.48	27.6	27.1	18.78	19.01	18.5	12.83	22.39	21.88	15.17	56.66	56.16	38.93	44.54	44.04	30.52	77	76.5	53.03								
0.28		26.87	26.37	18.28	45.42	44.92	31.13	33.82	33.32	33.32	23.09	16.37	15.86	11	11.36	11.35	7.87	13.66	13.15	9.12	33.46	32.96	22.84	26.72	26.22	18.17	44.63	44.13	30.59								
CL		0.4313			0.4524				0.4408			0.4408			0.4313			0.4408			0.4408			0.4313			0.4524			0.4524							

TABLE 4 Performance of the control charts: Decreases in the average proportion

	Beta - True			Simplex			UGamma			Simplex - True			Beta			UGamma			UGamma - True			Beta			Simplex		
	μ	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL		
Case 1	0.2	370.37	369.87	256.37	267.92	267.42	185.36	809.99	58.09	561.1	370.37	369.87	256.37	537.4	536.9	372.15	1337.7	1337.2	926.88	370.37	369.87	256.37	187.05	186.55	129.31		
	$\phi = 290$	0.18	33.05	22.56	26.17	25.67	17.79	58.53	58.43	50.22	40.68	40.18	27.85	54.52	54.02	37.44	112.99	112.49	77.97	38.03	37.53	26.01	23.1	22.59	15.66		
	$\sigma = 0.37$	0.16	5.79	5.27	3.66	4.99	4.46	3.1	8.41	7.89	5.48	6.39	5.87	4.07	7.82	7.3	5.07	13.09	12.58	8.72	7.06	6.54	4.54	5.09	4.56		
	$\tau = 155$	0.14	1.96	1.37	0.97	1.82	1.22	0.87	2.4	1.83	1.29	1.78	1.18	0.84	1.96	1.37	0.97	2.58	2.02	1.41	2.33	1.76	1.24	1.94	1.35		
	CL	0.12	1.79	1.19	0.85	1.15	1.02	0.34	1.27	0.59	0.45	1.05	0.23	0.23	0.41	0.27	0.25	1.14	0.4	0.33	1.29	0.61	0.46	1.2	0.49		
Case 2	0.2	370.37	369.87	256.37	172.24	171.74	119.04	316.59	316.09	219.1	370.3	369.8	256.33	1026.21	1025.71	710.97	820.47	829.97	575.29	370.37	369.87	256.37	437.45	436.95	302.87		
	$\phi = 148$	0.18	58.89	58.39	40.47	32.67	22.3	52.02	51.52	35.71	71.56	71.56	40.25	171.05	170.55	118.22	142.57	142.07	98.48	56.43	55.93	38.77	64.3	63.8			
	$\sigma = 0.5$	0.16	13.28	12.77	8.85	8.52	8	5.55	12.11	11.6	8.04	15.47	14.96	10.37	31.17	30.67	21.26	26.98	26.48	18.35	12.56	12.05	8.35	13.83			
	$\tau = 96$	0.14	4.29	3.76	2.61	3.19	2.64	1.84	4.03	3.49	2.43	4.1	3.57	2.48	6.74	6.22	4.32	6.05	5.53	3.84	4.07	3.53	2.46	4.43			
	CL	0.12	1.99	1.4	0.99	1.67	1.06	0.76	1.91	1.32	0.93	1.57	0.95	0.68	2.04	1.46	1.03	1.92	1.33	0.94	1.9	1.31	0.93	1.97			
Case 3	0.2	370.37	369.87	256.37	177.81	177.31	122.9	322.4	321.9	223.12	370.37	369.87	256.37	1039.42	1039.42	720.47	852.11	851.61	590.29	370.37	369.87	256.37	429.49	428.99			
	$\phi = 80$	0.18	88.45	87.95	60.96	48.04	47.54	32.95	78.78	78.28	54.26	117.72	117.22	81.25	299.06	298.56	206.95	249.67	249.17	172.71	85.61	85.11	58.99				
	$\sigma = 0.71$	0.16	25.54	25.04	17.35	15.65	15.14	10.5	23.26	22.75	15.77	37.51	37.01	25.65	85.2	84.7	58.71	72.62	72.12	49.99	24.43	23.92	16.58				
	$\tau = 51$	0.14	9	8.49	5.88	6.19	5.67	3.93	8.38	7.86	5.45	12.15	11.64	8.07	24.1	23.59	16.36	21.13	20.62	14.3	8.6	8.08	5.61				
	CL	0.12	3.91	3.37	2.35	3	2.45	1.71	3.72	3.18	2.21	4.2	3.67	2.55	7.09	6.57	4.56	6.38	5.86	4.07	3.75	3.21	2.23				
Case 4	0.2	370.37	369.87	256.37	129.76	129.26	89.6	270.61	270.11	187.23	370.41	369.91	256.4	3142.94	3142.44	2178.17	1661.38	1660.88	1151.23	370.37	369.87	256.37	529.4	528.9			
	$\phi = 31$	0.18	136.69	136.19	94.4	51.27	50.77	35.19	103.79	103.29	71.59	189.71	189.21	131.15	418.63	418.13	982.97	777.81	777.31	538.79	132.04	131.54	91.18				
	$\sigma = 1.2$	0.16	54.28	53.78	32.38	21.87	15.16	42.82	42.32	29.33	95.1	94.6	65.57	625.15	625.32	355.86	355.36	246.32	51.59	51.09	35.41	67.54	67.04				
	$\tau = 20$	0.14	23.31	22.8	15.81	11.5	10.99	7.62	19.09	18.58	12.88	45.98	45.48	31.52	264.02	263.52	182.66	155.06	107.83	22.05	21.54	14.93					
	CL	0.12	10.88	10.37	7.19	6.13	5.61	3.89	9.25	8.74	6.06	21.07	20.56	14.26	103.75	103.25	71.57	64.01	63.51	44.02	10.3	9.79	6.79				

that the data are collected in-control state at Phase I), the following steps may help the practitioners when they are faced with such problem:

1. List the candidate distributions.
2. Obtain the maximum likelihood estimates of the parameters of the candidate distributions.
3. Calculate Akaike information criterion (AIC) and Bayesian information criterion (BIC) or alternatively get the p values of some well-known adherence tests—Kolmogorov-Smirnov, Anderson-Darling, Cramér von Mises, etc—for each candidate distribution.
4. Choose the distribution associated with the lowest value of AIC, BIC, or the largest p value.
5. Check the appropriateness of the choice by comparing the histogram of the data set and the probability density function of the best candidate distribution. If the choice is adequate, then find the control limits and apply the control chart, otherwise, go back to step 1.

5 | APPLICATION TO A REAL DATA SET

In this section, we illustrate our methodology by using a real data set. We consider a data set from SantAnna and ten Caten²⁴ consisting of a data set of the study of contaminated peanut by toxic substances in 34 batches of 120 pounds. The variable monitored is the proportion of non-contaminated peanuts. The data are 0.971, 0.979, 0.982, 0.971, 0.957, 0.961, 0.956, 0.972, 0.889, 0.961, 0.982, 0.975, 0.942, 0.932, 0.908, 0.970, 0.985, 0.933, 0.858, 0.987, 0.958, 0.909, 0.859, 0.863, 0.811, 0.877, 0.798, 0.855, 0.788, 0.821, 0.830, 0.718, 0.642, and 0.658. Obviously, due to the genesis of the Beta, Simplex and Unit gamma distributions, rates and proportions are by excellence ideally modelled by these distributions. Thus, the use of the Beta, Simplex, and Unit Gamma distributions for fitting this data set is well justified. In order to estimate the parameters of these models, we adopt the maximum likelihood method and all the computations were done using the R software. We will use the first 20 observations as the Phase I sample and the remaining 14 values as the Phase II observations, to demonstrate the application of the proposed control charts. The empirical mean and standard deviation for the first 20 observations are, respectively, 0.9536 and 0.0345.

The maximum likelihood estimates of the parameters (with corresponding standard errors in parentheses), AIC and BIC for the Beta, Simplex, and Unit Gamma models

for the first 20 observations are listed in Table 5. Since the values of the AIC and BIC are smaller for the Simplex distribution compared with those values of the other models, the Simplex distribution seems to be a very competitive model for these data.

Plots of the pdf of the Beta, Simplex and Unit Gamma fitted models to these data are displayed in Figure 2. They indicate that the Simplex distribution is superior to the other distributions in terms of model fitting. Additionally, it is evident that the Beta and Unit gamma distributions presents the same fit to the current data.

TABLE 5 Estimates of the parameters (standard errors in parentheses) and goodness-of-fit statistics for the proportion of noncontaminated peanut

Model		ML Estimates	AIC	BIC
Beta	$\hat{\mu}$	0.9533(0.0066)	-85.455	-83.464
	$\hat{\phi}$	40.442(15.948)		
Simplex	$\hat{\mu}$	0.9534(0.0072)	-88.653	-86.662
	$\hat{\sigma}^2$	3.5711(0.5653)		
Unit Gamma	$\hat{\mu}$	0.9534(0.0072)	-85.455	-83.463
	$\hat{\tau}$	2.2798(0.6715)		

Abbreviation: AIC, Akaike information criterion.

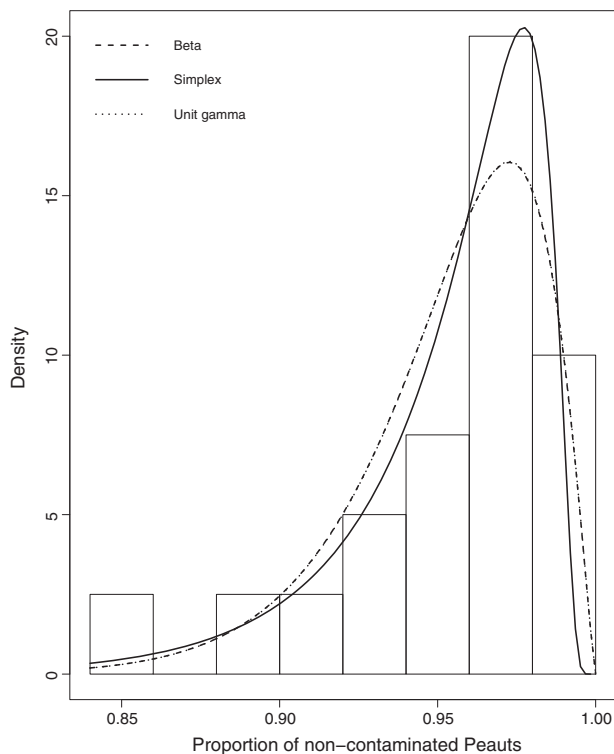


FIGURE 2 Estimated probability density function (pdf) for the Beta, Simplex, and Unit Gamma models for the proportion of noncontaminated peanut

In Figure 3, we present the control chart for the complete set of the available data (Phase I: 1-20; Phase II: 21-34) using error type I $\alpha = 0.0027$ to yield $ARL_0 = 370$. The control chart in Figure 3 does not trigger an alarm during Phase I, so we obtain no contradiction against the models. Note that the Beta and Unit gamma distributions present the same LCL and UCL to the current data.

Let us now proceed to Phase II analysis. Here, the Beta and Unit Gamma control chart triggers for the first time a signal at sample 25, whereas the Simplex control chart counterpart gives a signal at sample 32. Much earlier false alarms ($ARL_0 = 139$; $ARL_0 = 166.85$) is the consequence in case of the Beta or Unit Gamma control limits used equivocally in Simplex chart (see Table 6). Now, consider that the manager suspects that the quality of peanuts has deteriorated from $\mu_0 = 0.95$ to $\mu_1 = 0.8$. For such shift, no impact is observed in the performance metrics with all ARL_1 around three (see Table 6).

In a nutshell, our analysis clearly showed that the three models may be very useful in practice for describing proportion data.

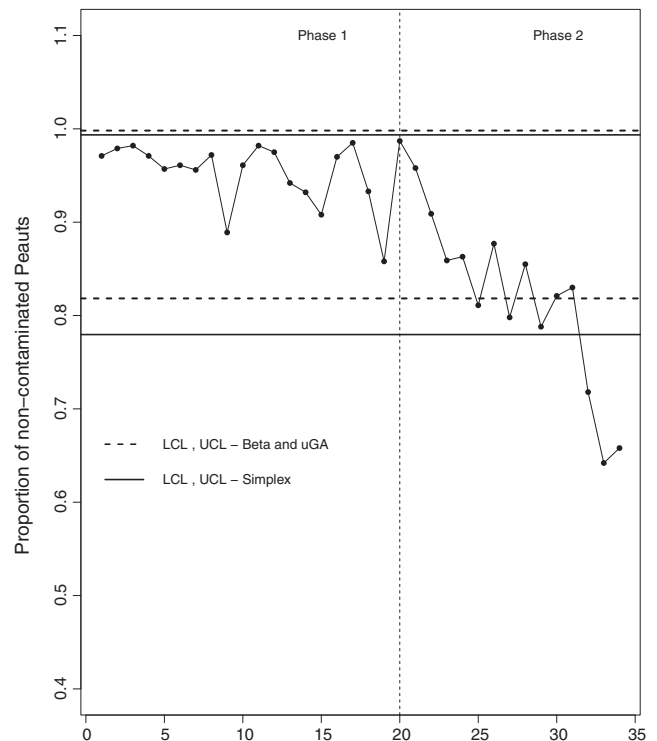


FIGURE 3 Control chart (in terms of ARL_1) for the proportion of noncontaminated peanut (Phase I: 1-20; Phase II: 21-34)

TABLE 6 Comparing the performance for the proportion of noncontaminated peanut

μ	Simplex - True			Beta			UGamma		
	ARL	SDRL	MRL	ARL	SDRL	MRL	ARL	SDRL	MRL
0.95	370.61	370.11	256.54	139.10	138.60	96.07	166.85	166.35	115.31
0.8	3.27	2.72	1.89	2.54	1.98	1.38	2.62	2.05	1.44
LCL	0.758			0.812			0.806		
UCL	0.993			0.997			0.998		

6 | CONCLUDING REMARKS

In this paper, we call attention for monitoring proportions and rates when they are not results of Bernoulli experiments. In practice, control charts based on Beta distributions are usually built as this distribution is a well-known one. However, there are other distributions to be considered as for example, Simplex and Unit Gamma distributions. The use of equivocal control limits provokes a great variety of impacts like anticipation/postponement of false alarms or even no false alarm and also no detection mainly in case of small shifts. The variance magnitude and shift sizes play an important role as lower impacts are observed for larger shifts and small variances.

Thus, to monitor proportions or rates (not from Bernoulli experiments and unknown baseline distribution), it is essential to identify which distribution better fits the data set among many candidate distributions and then design the control chart to avoid the use of equivocal control limits. Additionally, some guidelines are suggested for the practitioners when they are faced with this problem.

ACKNOWLEDGEMENT

The authors would like to acknowledge CNPq-Brazil for the partial financial support.

ORCID

Linda Lee Ho  <http://orcid.org/0000-0001-9984-8711>

REFERENCES

- Montgomery DC. *Introduction to Statistical Quality Control*. New York: John Wiley; 2009.
- Szarka III JL, Woodall WH. A review and perspective on surveillance of bernoulli processes. *Qual Reliab Eng Int*. 2011;27(6):735-752.
- Woodall WH. Control charts based on attribute data: bibliography and review. *J Qual Technol*. 1997;29(2):172-183.
- Chong ZL, Khoo MBC, Teoh WL, Yeong WC, Teh SY. Group runs double sampling np control chart for attributes. *J Test Eval*. 2017;45(6):2267-2282.
- Lee MH, Khoo MB. Optimal design of synthetic np control chart based on median run length. *Commun Stat Theory Methods*. 2017;46(17):8544-8556.
- Lee MH, Khoo MBC. Combined double sampling and variable sampling interval np chart. *Commun Stat Theory Methods*. 2017;46(23):11892-11917.
- Ho LL, da Costa Quinino R, Suyama E, Lourenço RP. Monitoring the conforming fraction of high-quality processes using a control chart p under a small sample size and an alternative estimator. *Stat Pap*. 2012;53(3):507-519.
- Quinino RC, Bessegato LF, Cruz FR. An attribute inspection control chart for process mean monitoring. *Int J Adv Manuf Technol*. 2017;90(9-12):2991-2999.
- Ho LL, Aparisi F. ATTRIVAR: optimized control charts to monitor process mean with lower operational cost. *Int J Prod Econ*. 2016;182:472-483.
- da Costa Quinino R, Ho LL, Trindade ALG. Monitoring the process mean based on attribute inspection when a small sample is available. *J Oper Res Soc*. 2015;66(11):1860-1867.
- Ho LL, Costa AFB. Monitoring a wandering mean with an np chart. *Production*. 2011;21(2):254-258.
- Wu Z, Khoo MBC, Shu L, Jiang W. An np control chart for monitoring the mean of a variable based on an attribute inspection. *Int J Prod Econ*. 2009;121(1):141-147.
- Bezerra EL, Ho LL, da Costa Quinino R. Gs2: An optimized attribute control chart to monitor process variability. *Int J Prod Econ*. 2018;195:287-295.
- Ho LL, Quinino RC. An attribute control chart for monitoring the variability of a process. *Int J Prod Econ*. 2013;145(1):263-267.
- Melo MS, Ho LL, Medeiros PG. Max D: An attribute control chart to monitor a bivariate process mean. *Int J Adv Manuf Technol*. 2017;90(1-4):489-498.
- Machado MAG, Ho LL, Costa AFB. Attribute control charts for monitoring the covariance matrix of bivariate processes. *Qual Reliab Eng Int*. 2018;34(2):257-264.
- Aparisi F, Lee Ho L. M-ATTRIVAR: an attribute-variable chart to monitor multivariate process means. *Qual Reliab Eng Int*. 2018;34(2):214-228.
- Melo MS, Ho LL, Medeiros PG. A 2-stage attribute-variable control chart to monitor a vector of process means. *Qual Reliab Eng Int*. 2017;33(7):1589-1599.
- Ho LL, da Costa Quinino R. Combining attribute and variable data to monitor process variability: MIX S 2 control chart. *Int J Adv Manuf Technol*. 2016;87(9-12):3389-3396.

20. Sampaio ES, Ho LL, de Medeiros PG. A combined control chart to monitor the process mean in a two-stage sampling. *Qual Reliab Eng Int.* 2014;30(7):1003-1013.
21. Aslam M, Arif OH, Jun CH. An attribute control chart for a Weibull distribution under accelerated hybrid censoring. *PLoS One.* 2017;12(3):e0173406.
22. Azam M, Ahmad L, Aslam M, Jun CH. An attribute control chart using discriminant limits for monitoring process under the Weibull distribution. *Prod Eng.* 2018;1-7.
23. Shafqat A, Hussain J, Al-Nasser AD, Aslam M. Attribute control chart for some popular distributions. *Commun Stat Theory Methods.* 2018;47(8):1978-1988.
24. SantAnna AMO, ten Caten CS. Beta control charts for monitoring fraction data. *Expert Syst Appl.* 2012;39(11):10236-10243.
25. Bayer FM, Tondolo CM, Müller FM. Beta regression control chart for monitoring fractions and proportions. *Comput Ind Eng.* 2018;119:416-426.
26. Jørgensen B. *The Theory of Dispersion Models.* London: Chapman and Hall; 1997.
27. Grassia A. On a family of distributions with argument between 0 and 1 obtained by transformation of the gamma and derived compound distributions. *Aust J Stat.* 1977;19:108-114.
28. Mousa A, El-Sheikh A, Abdel-Fattah M. A gamma regression for bounded continuous variables. *Adv Appl Stat.* 2016;49:305-326.
29. Eisenhart C, Hastay MW, Wallis WA. *Techniques of Statistical Analysis.* New York: McGraw-Hill; 1947.
30. Anscombe FJ. The transformation of poisson, binomial and negative binomial data. *Biometrika.* 1948;35:358-382.
31. Freeman MF, Tukey JW. Transformations related to the angular and the square root. *Ann Math Stat.* 1950;21:607-611.
32. Quesenberry CP. *SPC Methods for Quality Improvement.* New York: Wiley; 1997.
33. Ryan TP. *Statistical Methods for Quality Improvement.* New Jersey: John Wiley; 1989.
34. Ryan TP, Schwertman NC. Optimal limits for attributes control charts. *J Qual Technol.* 1997;29:86-96.
35. Acosta-Mejia CA. Improved p charts to monitor process quality. *IIE Trans.* 1999;31:509-516.
36. Shore H. General control chart for attributes. *IIE Trans.* 2000;32:1149-1160.

Linda Lee Ho is a full professor at University of São Paulo. Her main subjects are related to statistical process monitoring, design of experiments, and statistical models applied in industrial engineering.

Fidel Henrique Fernandes holds a degree in Statistics and a master's degree also in Statistics (Federal University of Rio Grande do Norte). Since 2018, he is a PhD student at Federal University of Pernambuco.

Marcelo Bourguignon is an assistant professor at the Federal University of Rio Grande do Norte, located in Natal (Brazil). He carried out his doctoral studies (2011–2014) at the Federal University of Pernambuco, Recife, Brazil. His studies were related to fatigue life models and count time series. He has recently won the “2017 ISI Jan Tinbergen Award”, a biennial award, named after the famous Dutch econometrician, recognize best papers from young statisticians from 138 developing countries. He was the first prize winner for his paper “Modelling time series of counts with deflation or inflation of zeros”.

How to cite this article: Lee Ho L, Fernandes FH, Bourguignon M. Control charts to monitor rates and proportions. *Qual Reliab Eng Int.* 2018;1–10. <https://doi.org/10.1002/qre.2381>