

Robustness to Non-Normality and Ar (2) Process of the Sampling Plans

Singh J.R.¹ and Singh D.P.^{2*}

^{1,2*} School of Studies in Statistics, Vikram University Ujjain, India 456010

Corresponding Author: chouhandharm@rediffmail.com

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Abstract: In this paper the effect of non-normality conjunction with AR (2) process has been examined on single sampling plan for known cv. The OC functions are calculated for typical non-normal population and for different roots values. The effect of AR (2) process on the OC function remains more or less of the same magnitude when we move from normal to non normal.

Key words: Single sampling plan, non-normality, OC function, auto-correlation, coefficient of variation

INTRODUCTION

Over the last decades quality issues have held the attention of both industry and research communities because of their impact on cost and, therefore, on profit. Quality costs include any cost that results from the fact that system, processes, products, and services are imperfect. More specifically, it consists of prevention costs, appraisal costs, internal and external failure costs, and it varies between 4 and 40% of the sales of a company (Montgomery, 2001). Consequently, the analysis and estimation of quality cost are of great importance. Usually, all quality cost categories can be expressed as functions of the actual quality of products (e.g., fraction non conforming of a lot); therefore, it is possible to derive the economically optimum quality of products, as well as the optimum quality control policy, i.e., the control policy that minimizes the expected quality related costs. Statistical quality control (SQC) aims at monitoring and improving the quality of products produced by a process and consists of three areas types. Design of experiment, statistical process control, and acceptance sampling Modern quality assurance systems usually place less emphasis on the latter while they attempt to focus their efforts on the other two types of SQC.

Significant reviews of papers concerning acceptance sampling are those of Wetherrill and Chiu (1975) and Wall the Elshennawy (1989). Both papers make extensive references of economically optimum sampling plans. Bia and Riew (1984) develop an economic acceptance sampling plan by attributes for cases where sampling is expensive or destructive. They present a linear cost model and they consider three decision criteria.

Even though lately acceptance sampling has given place to more advanced SQC techniques, the published research on this particular SQC area and especially on the economic design of sampling plans is still extensive. Ferrell and Chhoker (2002) have recently proposed an economic model for the design of acceptance sampling plans adopting the Taguchi approach. Gonzalez and Palomo (2003) use a Bayesian analysis in order to derive acceptance sampling plans regarding the number of defects per unit of product and apply their methodology to the paper pulp industry. The sampling plans are obtained following an economic criterion : the minimization of the expected total cost of quality. At the same time, Cassady and Nachlas (2003) define a generic framework for establishing three level acceptance sampling plans, using quality value functions. They not that there are many cases in which the quality of a product can be classified in three or more discrete levels : for example, a food product may be classified in three or more discrete levels : for example, a food product may be classified as good, marginal. Or bad, Chen, Choy et al. (2004) present and investigate a general model of acceptance sampling plan for the exponential distribution with exponentially distributed random censoring, based on Bayesian decision theory. In order to determine the optimal sampling pan they consider a loss function, which includes the sampling cost, the time consuming cost, and the decision loss to determine the optimal acceptance sampling plan. At the same time and in a similar study, Chen and Chou et al. (2004) develop a general Bayesian framework for designing a variable acceptance sampling plan with mixed censoring. A general loss function including the three partial cost of Chen and Choy et al. (2004) as well as the salvage value in introduced to determine the corresponding optimal sampling plan.

In this paper the effect of non-normality conjunction with AR (2) process has been examined on single sampling plan for known cv. The OC functions are calculated for typical non-normal population and for different roots values. The effect of AR (2) process on the OC function remains more or less of the same magnitude when we move from normal to non normal.

OC FUNCTION FOR NON NORMAL AND AR (2) PROCESS

Consider a manufacturing process where a quality characteristic is measured at equidistance time points 1, 2, 3, ... n. This situation may occur in a discrete manufacturing process which produces discrete time 1, 2, 3, ... n, with one quality characteristic of interest. It may also occur in a continuous manufacturing process where the quality characteristic of interest is measured at discrete equidistant time points. We denote the behavior of the quality characteristic as x_1, x_2, \dots, x_n . It will assumed that on EPC control action can be represented by some controllable variable or factor x_t , such that

$$x_t = \mu + \xi_t,$$

(1) where μ is a constant, and ξ_t is a stationary time series with zero mean and standard deviation σ . A Durbin and Watson (1950) “d” statistic can be used to detect the presence or absence of serial correlation. The problem, however, is that to do once the suspicion of dependence via the serial correlation test is confirmed. If serial correlation exist we use identification techniques to define the nature of ξ_t . When identification is complete, the likelihood function can provide maximum likelihood estimate of the parameters of the identified model.

Suppose that a correlation test revealed the presence of data dependence and identification technique suggested autoregressive model of order two AR(2) say, then we can express ξ_t of equation (1) as

$$\xi_t = \alpha_1 \xi_{t-1} + \alpha_2 \xi_{t-2} + \epsilon_k, \quad t = 1, 2, \dots, n \tag{2}$$

where

$$(i) \quad \epsilon_t \sim N(0, \sigma_\epsilon^2)$$

$$(ii) \quad \text{cov}(\epsilon_t, \epsilon_\gamma) = \begin{cases} \sigma_\epsilon^2 & t = \gamma \\ 0 & t \neq \gamma \end{cases} \tag{3}$$

The Class of stationary models that assume the process to remain in equilibrium about a constant mean level μ . The variance of AR (2) process is given by:

$$\sigma^2 = \left(\frac{1 - \alpha_2}{1 + \alpha_2} \right) \left[\frac{\sigma_\epsilon^2}{(1 - \alpha_2)^2 - \alpha_1^2} \right]. \tag{4} \quad \text{Following}$$

Kendall and Stuart (1976) it can be shown that for stationarity, the roots of the characteristic equation of the process in equation (2)

$$\phi(B) = 1 - \alpha_1 B - \alpha_2 B^2 \tag{5} \quad \text{must lies outside}$$

the unit circle, which implies that the parameters α_1 and α_2 must satisfy the following conditions :

$$\begin{aligned} \alpha_2 + \alpha_1 &< 1 \\ \alpha_2 - \alpha_1 &< 1 \\ -1 < \alpha_2 &< 1 \end{aligned} \tag{6}$$

Now If G_1^{-1} and G_2^{-1} are the roots of the characteristic equation of the process given by equation (5) then

$$G_1 = \frac{\alpha_1 + \sqrt{\alpha_1^2 + 4\alpha_2}}{2} \tag{7}$$

$$G_2 = \frac{\alpha_1 - \sqrt{\alpha_1^2 + 4\alpha_2}}{2} \tag{8}$$

For stationarity we require that $|G_i| < 1, i = 1, 2$. Thus, three situations can theoretically arise :

- (i) Roots G_1 and G_2 are real and distinct (i.e., $\alpha_1^2 + 4\alpha_2 > 0$)
- (ii) Roots G_1 and G_2 are real and equal (i.e., $\alpha_1^2 + 4\alpha_2 = 0$)
- (iii) Roots G_1 and G_2 are complex conjugate (i.e., $\alpha_1^2 + 4\alpha_2 < 0$).

When the serial correlation is present in the data, we have for the distribution of the sample mean \bar{x} , its mean and variance is given by,

$$E(\bar{x}) = \mu, \text{Var}(\bar{x}) = \frac{\sigma^2}{n} \lambda_{ap}(\alpha_1, \alpha_2, n), \tag{9}$$

where $\lambda_{ap}(\alpha_1, \alpha_2, n)$ depends on the nature of the roots G_1 and G_2 , and for different situations is given as follows :

(i) If G_1 and G_2 are real and distinct,

$$\lambda_{ap}(\alpha_1, \alpha_2, n) = \left[\frac{G_1(1-G_2^2)}{(G_1-G_2)(1+G_1G_2)} \lambda(G_1, n) - \frac{G_2(1-G_1^2)}{(G_1-G_2)(1+G_1G_2)} \lambda(G_2, n) \right] = \lambda_{rd}(\alpha_1, \alpha_2, n), \tag{10}$$

Where, $\lambda(G, n) = \left[\frac{1+G}{1-G} - \frac{2G}{n} \frac{(1-G^n)}{(1-G)^2} \right]$

(ii) If G_1 and G_2 are real and equal

$$\lambda_{ap}(\alpha_1, \alpha_2, n) = \left(\frac{1+G}{1-G} - \frac{2G(1-G^n)}{n(1-G)^2} \right) \left[1 + \frac{(1+G)^2(1-G^n) - n(1-G^2)(1+G^n)}{(1+G^2)(1-G^n)} \right] = \lambda_{re}(\alpha_1, \alpha_2, n) \tag{11}$$

(iii) If G_1 and G_2 are complex conjugate

$$\lambda_{ap}(\alpha_1, \alpha_2, n) = \left[\gamma(d, u) + \frac{2d}{n} (W(d, u, n) + Z(d, u, n)) \right] = \lambda_{cc}(\alpha_1, \alpha_2, n) \tag{12}$$

Where $\gamma(d, u) = \frac{1-d^4 + 2d(1-d^2) \cos u}{(1+d^2)(1+d^2 - 2d \cos u)}$,

$$W(d, u, n) = \frac{2d(1+d^2) \sin u - (1+d^4) \sin 2u - d^{n+4} \sin((n-2)u)}{(1+d^2)(1+d^2 - 2d \cos u)^2 \sin u},$$

$$Z(d, u, n) = \frac{2d^{n+3} \sin(n-1)u - 2d^{n+1} \sin(n+1)u + d^n \sin((n+2)u)}{(1+d^2)(1+d^2 - 2d \cos u)^2 \sin u},$$

$$d^2 = -\alpha_2,$$

and $u = \cos^{-1} \left(\frac{\alpha_1}{2d} \right).$

The x_t denote the change in the level of the compensating variable model at the time t, i.e., the adjustment made at the time point t. The ϵ_t is Gaussian white noise with variance σ_ϵ^2 . Throughout, we suppose that the noise variance is known. In practice, this is justified if reliable estimates of σ_ϵ^2 are available from the evaluation of a large number of previous values of the process, e.g., during the setup phase. The real-valued parameters α_1 and α_2 (the autoregressive parameters) determines the influence of the preceding time point (t - 1) and (t - 2) on the present time point t. We assume an in-control value $\alpha_1 = \alpha_2 = 0$ for the autoregression parameters. It is possible that the autoregression parameters may shift to an out-of-control value $(\alpha_1, \alpha_2) \neq 0$.

We consider the effect of autocorrelation equation (9). The AR(2) process will be used to model the data taken from auto correlated process of interest with known cv. Further, we assume that the non-normal population is represented by the first four terms of an Edgeworth series. To study the robustness of the control chart to non normality under AR(2) process, we examined the effect of non-normality and dependency on the OC and error of the first kind with known cv mean chart. We assume that the observations x_t ($t = 1, 2, \dots, n$) are address the problem of non-normality and dependency with known cv in

the control statistics \bar{x}^* . Following Srivastava and Banarasi (1982) $MSE(\bar{x}^*) = \frac{\sigma^2}{n} \left(1 - \frac{v^* \lambda_{ap}(\alpha_1, \alpha_2, n)}{n} \right)$ where

$$v = \frac{\sigma}{\mu}$$

In case of known cv the non-normal population is represented by the first four terms on Edgeworth series by Rao and Bhatt (1989) as, λ_3 and λ_4 are the measures of skewness and Kurtosis, We assume that the distribution of x_t is stationary and hence with loss of generality, we can denote the density function of x_t by $f(x)$ is

$$f(x) = \frac{1}{\sigma} \left[\phi\left(\frac{x-\mu}{\sigma}\right) - \frac{\lambda_3 \phi^{(3)}\left(\frac{x-\mu}{\sigma}\right)}{6} + \frac{\lambda_4 \phi^{(4)}\left(\frac{x-\mu}{\sigma}\right)}{24} + \frac{\lambda_3^2 \phi^{(6)}\left(\frac{x-\mu}{\sigma}\right)}{72} \right] \tag{12}$$

Where, $\phi(t) = \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{t^2}{2}\right]$ and $\phi^{(r)}(t) = \frac{d^r \phi(t)}{dt^r}$

Clearly a proportion p of the population (12) all be defective if

$$\mu + K_p \sigma = U \tag{13}$$

Where K_p is given by $\int_{K_p}^{\infty} \left[\phi(t) - \frac{\lambda_3 \phi^{(3)}(t)}{6} + \frac{\lambda_4 \phi^{(4)}(t)}{24} + \frac{\lambda_3^2 \phi^{(6)}(t)}{72} \right] dt = p,$ (14)

$$\int_{K_p}^{\infty} \phi(t) dt + \phi(K_p) \left[\frac{\lambda_3}{6} H_2(K_p) + \frac{\lambda_4}{24} H_3(K_p) + \frac{\lambda_3^2}{72} H_5(K_p) \right] = p, \tag{15}$$

Where $H_v(\mu)$ is well known Hermite polynomial of degree v in μ given by ,

$$\phi^{(v)}(\mu) = (-1)^v \phi(\mu) H_v(\mu) \tag{16}$$

The value of K_p corresponding to a given value of p can be approximately obtained by using the formula.

$$K_p = x_p + \frac{\lambda_3}{6} (x_p^2 - 1) + \frac{\lambda_4}{24} (x_p^2 - 3x_p) - \frac{\lambda_3^2}{72} (2x_p^3 - 5x_p), \tag{17}$$

$$\int_{-\infty}^{x_p} \phi(t) dt = 1 - p \tag{18}$$

The acceptance

criterion (with known CV) is set up as follows : Accept the lot if $\bar{X}^* + k MSE(\bar{X}^*) \leq U$ and reject it otherwise. The values of n, and k are determined for given set of p_1, p_2, α and β from the formulae

$$n = \left[(K_\alpha + K_\beta / K_{p1} - K_{p2})^2 \right] \tag{19}$$

$$k = \left[(K_\alpha K_{p2} + K_\beta K_{p1} / K_\alpha + K_\beta)^2 \right] \tag{20}$$

Where p_1, p_2, α and β are AQL, LTPD, producer's risk and consumer's risk respectively. For the AR(2) process the expression for $\lambda_{ap}(\alpha_1, \alpha_2, n)$ under three different situations are given in chapter-II vide equation (18), (19) and (20)

The probability L(p) of accepting a lot of quality p with known cv, i.e. the OC function of the plan under non-normal and AR (2) processes is

$$L(P) = \Phi(\xi_p) - \frac{\lambda_3 \phi^{(2)}(\xi_p)}{6\sqrt{n'}} + (\xi_p) + \frac{\lambda_4 \phi^{(3)}(\xi_p)}{24n'} + (\xi_p) + \frac{\lambda_3^2 \phi^{(5)}(\xi_p)}{72n'} \tag{21}$$

Where, $\xi_p = \frac{\sqrt{n'}}{M} (K_p - k)$ $n' = \frac{M^2}{n}$ and $M^2 = 1 - \frac{v^* \lambda_{ap}(\alpha_1, \alpha_2, n)}{n}$

TABULATION AND DISCUSSION OF RESULT

We give here an example for known cv, $p_1=0.5$, $\alpha=0.05$ and $p_2=0.3$, $\beta=0.10$. Now we consider a few non-normal population specified by the constant $(\lambda_3, \lambda_4)=(0,0), (-0.6,0), (0.6,0), (0,-1.0), (0,-1.0), (0,2.0)$, $v=0.04, 0.8$ and 1.2 along with three different roots for studying the effect of autocorrelation (and non-normality) on OC function with known CV.

Table-1: Values of OC Function under AR(2) Process with Known cv for (n=7, k=1.0232)

| v | Independent Observations ($\alpha_1=0.0, \alpha_2=0.0$) | | | | | | | | | |
|-----|---|--------|-------------------------------|--------|------------------------------|--------|-------------------------------|--------|------------------------------|--------|
| | $\lambda_3=0, \lambda_4=0$ | | $\lambda_3=-0.6, \lambda_4=0$ | | $\lambda_3=0.6, \lambda_4=0$ | | $\lambda_3=0, \lambda_4=-1.0$ | | $\lambda_3=0, \lambda_4=2.0$ | |
| | p | $L(p)$ | p | $L(p)$ | p | $L(p)$ | p | $L(p)$ | p | $L(p)$ |
| 0 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9500 | 0.0284 | 0.9572 | 0.0636 | 0.9439 | 0.0521 | 0.9497 | 0.0458 | 0.9506 |
| | 0.1000 | 0.7529 | 0.0902 | 0.7449 | 0.1127 | 0.7576 | 0.1127 | 0.7496 | 0.0746 | 0.7594 |
| | 0.1500 | 0.5140 | 0.1548 | 0.4988 | 0.1583 | 0.5289 | 0.1694 | 0.5137 | 0.1112 | 0.5145 |
| | 0.2000 | 0.3155 | 0.2181 | 0.3067 | 0.2018 | 0.3274 | 0.2225 | 0.3183 | 0.1550 | 0.3098 |
| | 0.2500 | 0.1781 | 0.2787 | 0.1779 | 0.2441 | 0.1808 | 0.2727 | 0.1812 | 0.2046 | 0.1720 |
| | 0.3000 | 0.0935 | 0.3364 | 0.0982 | 0.2860 | 0.0889 | 0.3207 | 0.0951 | 0.2586 | 0.0902 |
| | 0.3500 | 0.0457 | 0.3912 | 0.0518 | 0.3281 | 0.0384 | 0.3670 | 0.0459 | 0.3161 | 0.0454 |
| | 0.4000 | 0.0208 | 0.4432 | 0.0261 | 0.3709 | 0.0142 | 0.4120 | 0.0201 | 0.3761 | 0.0222 |
| 0.4 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9549 | 0.0284 | 0.9620 | 0.0636 | 0.9489 | 0.0521 | 0.9550 | 0.0458 | 0.9551 |
| | 0.1000 | 0.7593 | 0.0902 | 0.7520 | 0.1127 | 0.7635 | 0.1127 | 0.7623 | 0.0746 | 0.7654 |
| | 0.1500 | 0.5144 | 0.1548 | 0.4996 | 0.1583 | 0.5288 | 0.1694 | 0.5146 | 0.1112 | 0.5149 |
| | 0.2000 | 0.3104 | 0.2181 | 0.3021 | 0.2018 | 0.3217 | 0.2225 | 0.3077 | 0.1550 | 0.3050 |
| | 0.2500 | 0.1710 | 0.2787 | 0.1712 | 0.2441 | 0.1730 | 0.2727 | 0.1682 | 0.2046 | 0.1653 |
| | 0.3000 | 0.0871 | 0.3364 | 0.0920 | 0.2860 | 0.0821 | 0.3207 | 0.0857 | 0.2586 | 0.0843 |
| | 0.3500 | 0.0411 | 0.3912 | 0.0470 | 0.3281 | 0.0339 | 0.3670 | 0.0411 | 0.3161 | 0.0411 |
| | 0.4000 | 0.0180 | 0.4432 | 0.0229 | 0.3709 | 0.0119 | 0.4120 | 0.0187 | 0.3761 | 0.0194 |
| 0.8 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9597 | 0.0284 | 0.9667 | 0.0636 | 0.9540 | 0.0521 | 0.9598 | 0.0458 | 0.9596 |
| | 0.1000 | 0.7662 | 0.0902 | 0.7596 | 0.1127 | 0.7699 | 0.1127 | 0.7633 | 0.0746 | 0.7720 |
| | 0.1500 | 0.5148 | 0.1548 | 0.5005 | 0.1583 | 0.5289 | 0.1694 | 0.5146 | 0.1112 | 0.5153 |
| | 0.2000 | 0.3049 | 0.2181 | 0.2971 | 0.2018 | 0.3155 | 0.2225 | 0.3074 | 0.1550 | 0.2997 |
| | 0.2500 | 0.1635 | 0.2787 | 0.1641 | 0.2441 | 0.1648 | 0.2727 | 0.1661 | 0.2046 | 0.1583 |
| | 0.3000 | 0.0804 | 0.3364 | 0.0854 | 0.2860 | 0.0752 | 0.3207 | 0.0816 | 0.2586 | 0.0781 |
| | 0.3500 | 0.0365 | 0.3912 | 0.0421 | 0.3281 | 0.0296 | 0.3670 | 0.0363 | 0.3161 | 0.0368 |
| | 0.4000 | 0.0152 | 0.4432 | 0.0197 | 0.3709 | 0.0097 | 0.4120 | 0.0145 | 0.3761 | 0.0167 |
| 1.2 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9646 | 0.0284 | 0.9713 | 0.0636 | 0.9591 | 0.0521 | 0.9648 | 0.0458 | 0.9642 |
| | 0.1000 | 0.7737 | 0.0902 | 0.7678 | 0.1127 | 0.7769 | 0.1127 | 0.7709 | 0.0746 | 0.7791 |
| | 0.1500 | 0.5153 | 0.1548 | 0.5015 | 0.1583 | 0.5289 | 0.1694 | 0.5151 | 0.1112 | 0.5158 |
| | 0.2000 | 0.2988 | 0.2181 | 0.2915 | 0.2018 | 0.3088 | 0.2225 | 0.3013 | 0.1550 | 0.2939 |
| | 0.2500 | 0.1554 | 0.2787 | 0.1564 | 0.2441 | 0.1560 | 0.2727 | 0.1578 | 0.2046 | 0.1507 |
| | 0.3000 | 0.0736 | 0.3364 | 0.0787 | 0.2860 | 0.0681 | 0.3207 | 0.0745 | 0.2586 | 0.0718 |
| | 0.3500 | 0.0319 | 0.3912 | 0.0373 | 0.3281 | 0.0253 | 0.3670 | 0.0316 | 0.3161 | 0.0324 |
| | 0.4000 | 0.0126 | 0.4432 | 0.0167 | 0.3709 | 0.0077 | 0.4120 | 0.0119 | 0.3761 | 0.0141 |

Continued...

| V | Roots are Real and Distinct ($\alpha_1=0.3, \alpha_2=0.6$) | | | | | | | | | |
|-----|--|--------|-------------------------------|--------|------------------------------|--------|-------------------------------|--------|------------------------------|--------|
| | $\lambda_3=0, \lambda_4=0$ | | $\lambda_3=-0.6, \lambda_4=0$ | | $\lambda_3=0.6, \lambda_4=0$ | | $\lambda_3=0, \lambda_4=-1.0$ | | $\lambda_3=0, \lambda_4=2.0$ | |
| | p | $L(p)$ | p | $L(p)$ | p | $L(p)$ | p | $L(p)$ | p | $L(p)$ |
| 0 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9500 | 0.0284 | 0.9572 | 0.0636 | 0.9439 | 0.0521 | 0.9497 | 0.0458 | 0.9506 |
| | 0.1000 | 0.7529 | 0.0902 | 0.7449 | 0.1127 | 0.7576 | 0.1127 | 0.7496 | 0.0746 | 0.7594 |
| | 0.1500 | 0.5140 | 0.1548 | 0.4988 | 0.1583 | 0.5289 | 0.1694 | 0.5137 | 0.1112 | 0.5145 |
| | 0.2000 | 0.3155 | 0.2181 | 0.3067 | 0.2018 | 0.3274 | 0.2225 | 0.3183 | 0.1550 | 0.3098 |
| | 0.2500 | 0.1781 | 0.2787 | 0.1779 | 0.2441 | 0.1808 | 0.2727 | 0.1812 | 0.2046 | 0.1720 |
| | 0.3000 | 0.0935 | 0.3364 | 0.0982 | 0.2860 | 0.0889 | 0.3207 | 0.0951 | 0.2586 | 0.0902 |
| | 0.3500 | 0.0457 | 0.3912 | 0.0518 | 0.3281 | 0.0384 | 0.3670 | 0.0459 | 0.3161 | 0.0454 |
| | 0.4000 | 0.0208 | 0.4432 | 0.0261 | 0.3709 | 0.0142 | 0.4120 | 0.0201 | 0.3761 | 0.0222 |
| 0.4 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9760 | 0.0284 | 0.9817 | 0.0636 | 0.9714 | 0.0521 | 0.9765 | 0.0458 | 0.9752 |
| | 0.1000 | 0.7945 | 0.0902 | 0.7906 | 0.1127 | 0.7964 | 0.1127 | 0.7922 | 0.0746 | 0.7989 |
| | 0.1500 | 0.5168 | 0.1548 | 0.5042 | 0.1583 | 0.5292 | 0.1694 | 0.5166 | 0.1112 | 0.5172 |
| | 0.2000 | 0.2817 | 0.2181 | 0.2758 | 0.2018 | 0.2899 | 0.2225 | 0.2839 | 0.1550 | 0.2774 |
| | 0.2500 | 0.1336 | 0.2787 | 0.1357 | 0.2441 | 0.1325 | 0.2727 | 0.1353 | 0.2046 | 0.1301 |
| | 0.3000 | 0.0562 | 0.3364 | 0.0613 | 0.2860 | 0.0505 | 0.3207 | 0.0566 | 0.2586 | 0.0555 |
| | 0.3500 | 0.0212 | 0.3912 | 0.0257 | 0.3281 | 0.0157 | 0.3670 | 0.0207 | 0.3161 | 0.0222 |
| | 0.4000 | 0.0072 | 0.4432 | 0.0101 | 0.3709 | 0.0038 | 0.4120 | 0.0066 | 0.3761 | 0.0084 |
| 0.8 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9961 | 0.0390 | 0.9900 | 0.0636 | 0.9945 | 0.0521 | 0.9964 | 0.0458 | 0.9900 |
| | 0.1000 | 0.8653 | 0.0902 | 0.8680 | 0.1127 | 0.8639 | 0.1127 | 0.8644 | 0.0746 | 0.8673 |
| | 0.1500 | 0.5226 | 0.1548 | 0.5132 | 0.1583 | 0.5318 | 0.1694 | 0.5224 | 0.1112 | 0.5229 |
| | 0.2000 | 0.2188 | 0.2181 | 0.2166 | 0.2018 | 0.2221 | 0.2225 | 0.2200 | 0.1550 | 0.2163 |
| | 0.2500 | 0.0680 | 0.2787 | 0.0716 | 0.2441 | 0.0641 | 0.2727 | 0.0683 | 0.2046 | 0.0673 |
| | 0.3000 | 0.0165 | 0.3364 | 0.0196 | 0.2860 | 0.0128 | 0.3207 | 0.0162 | 0.2586 | 0.0171 |
| | 0.3500 | 0.0032 | 0.3912 | 0.0046 | 0.3281 | 0.0017 | 0.3670 | 0.0029 | 0.3161 | 0.0037 |
| | 0.4000 | 0.0005 | 0.4432 | 0.0009 | 0.3709 | 0.0001 | 0.4120 | 0.0004 | 0.3761 | 0.0007 |
| 1.2 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 1.0000 | 0.0290 | 1.0000 | 0.0636 | 1.0000 | 0.0521 | 1.0000 | 0.0458 | 1.0000 |
| | 0.1000 | 0.9939 | 0.0902 | 0.9670 | 0.1127 | 0.9930 | 0.1127 | 0.9940 | 0.0746 | 0.9780 |
| | 0.1500 | 0.5511 | 0.1548 | 0.5470 | 0.1583 | 0.5551 | 0.1694 | 0.5510 | 0.1112 | 0.5512 |
| | 0.2000 | 0.0391 | 0.2181 | 0.0408 | 0.2018 | 0.0372 | 0.2225 | 0.0390 | 0.1550 | 0.0391 |
| | 0.2500 | 0.0004 | 0.2787 | 0.0005 | 0.2441 | 0.0002 | 0.2727 | 0.0003 | 0.2046 | 0.0004 |
| | 0.3000 | 0.0000 | 0.3364 | 0.0000 | 0.2860 | 0.0000 | 0.3207 | 0.0000 | 0.2586 | 0.0000 |
| | 0.3500 | 0.0000 | 0.3912 | 0.0000 | 0.3281 | 0.0000 | 0.3670 | 0.0000 | 0.3161 | 0.0000 |
| | 0.4000 | 0.0000 | 0.4432 | 0.0000 | 0.3709 | 0.0000 | 0.4120 | 0.0000 | 0.3761 | 0.0000 |

Continued...

| V | Roots are Real and Equal ($\alpha_1=0.8, \alpha_2=-0.16$) | | | | | | | | | |
|-----|---|--------|-------------------------------|--------|------------------------------|--------|-------------------------------|--------|------------------------------|--------|
| | $\lambda_3=0, \lambda_4=0$ | | $\lambda_3=-0.6, \lambda_4=0$ | | $\lambda_3=0.6, \lambda_4=0$ | | $\lambda_3=0, \lambda_4=-1.0$ | | $\lambda_3=0, \lambda_4=2.0$ | |
| | p | L(p) | p | L(p) | p | L(p) | p | L(p) | p | L(p) |
| 0 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9500 | 0.0284 | 0.9572 | 0.0636 | 0.9439 | 0.0521 | 0.9497 | 0.0458 | 0.9506 |
| | 0.1000 | 0.7529 | 0.0902 | 0.7449 | 0.1127 | 0.7576 | 0.1127 | 0.7496 | 0.0746 | 0.7594 |
| | 0.1500 | 0.5140 | 0.1548 | 0.4988 | 0.1583 | 0.5289 | 0.1694 | 0.5137 | 0.1112 | 0.5145 |
| | 0.2000 | 0.3155 | 0.2181 | 0.3067 | 0.2018 | 0.3274 | 0.2225 | 0.3183 | 0.1550 | 0.3098 |
| | 0.2500 | 0.1781 | 0.2787 | 0.1779 | 0.2441 | 0.1808 | 0.2727 | 0.1812 | 0.2046 | 0.1720 |
| | 0.3000 | 0.0935 | 0.3364 | 0.0982 | 0.2860 | 0.0889 | 0.3207 | 0.0951 | 0.2586 | 0.0902 |
| | 0.3500 | 0.0457 | 0.3912 | 0.0518 | 0.3281 | 0.0384 | 0.3670 | 0.0459 | 0.3161 | 0.0454 |
| | 0.4000 | 0.0208 | 0.4432 | 0.0261 | 0.3709 | 0.0142 | 0.4120 | 0.0201 | 0.3761 | 0.0222 |
| 0.4 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9651 | 0.0284 | 0.9717 | 0.0636 | 0.9596 | 0.0521 | 0.9653 | 0.0458 | 0.9647 |
| | 0.1000 | 0.7744 | 0.0902 | 0.7686 | 0.1127 | 0.7775 | 0.1127 | 0.7717 | 0.0746 | 0.7798 |
| | 0.1500 | 0.5154 | 0.1548 | 0.5016 | 0.1583 | 0.5289 | 0.1694 | 0.5152 | 0.1112 | 0.5158 |
| | 0.2000 | 0.2982 | 0.2181 | 0.2910 | 0.2018 | 0.3081 | 0.2225 | 0.3007 | 0.1550 | 0.2933 |
| | 0.2500 | 0.1546 | 0.2787 | 0.1557 | 0.2441 | 0.1552 | 0.2727 | 0.1570 | 0.2046 | 0.1500 |
| | 0.3000 | 0.0729 | 0.3364 | 0.0780 | 0.2860 | 0.0674 | 0.3207 | 0.0738 | 0.2586 | 0.0712 |
| | 0.3500 | 0.0314 | 0.3912 | 0.0368 | 0.3281 | 0.0249 | 0.3670 | 0.0311 | 0.3161 | 0.0320 |
| | 0.4000 | 0.0124 | 0.4432 | 0.0164 | 0.3709 | 0.0075 | 0.4120 | 0.0117 | 0.3761 | 0.0138 |
| 0.8 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9796 | 0.0284 | 0.9848 | 0.0636 | 0.9753 | 0.0521 | 0.9801 | 0.0458 | 0.9787 |
| | 0.1000 | 0.8024 | 0.0902 | 0.7991 | 0.1127 | 0.8038 | 0.1127 | 0.8003 | 0.0746 | 0.8065 |
| | 0.1500 | 0.5174 | 0.1548 | 0.5052 | 0.1583 | 0.5293 | 0.1694 | 0.5172 | 0.1112 | 0.5178 |
| | 0.2000 | 0.2751 | 0.2181 | 0.2696 | 0.2018 | 0.2827 | 0.2225 | 0.2771 | 0.1550 | 0.2710 |
| | 0.2500 | 0.1256 | 0.2787 | 0.1280 | 0.2441 | 0.1240 | 0.2727 | 0.1271 | 0.2046 | 0.1225 |
| | 0.3000 | 0.0504 | 0.3364 | 0.0553 | 0.2860 | 0.0447 | 0.3207 | 0.0506 | 0.2586 | 0.0500 |
| | 0.3500 | 0.0179 | 0.3912 | 0.0221 | 0.3281 | 0.0129 | 0.3670 | 0.0174 | 0.3161 | 0.0189 |
| | 0.4000 | 0.0057 | 0.4432 | 0.0082 | 0.3709 | 0.0028 | 0.4120 | 0.0051 | 0.3761 | 0.0067 |
| 1.2 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9918 | 0.0420 | 0.9820 | 0.0636 | 0.9892 | 0.0521 | 0.9922 | 0.0458 | 0.9910 |
| | 0.1000 | 0.8407 | 0.0902 | 0.8401 | 0.1127 | 0.8402 | 0.1127 | 0.8393 | 0.0746 | 0.8434 |
| | 0.1500 | 0.5204 | 0.1548 | 0.5100 | 0.1583 | 0.5306 | 0.1694 | 0.5202 | 0.1112 | 0.5207 |
| | 0.2000 | 0.2417 | 0.2181 | 0.2383 | 0.2018 | 0.2466 | 0.2225 | 0.2432 | 0.1550 | 0.2386 |
| | 0.2500 | 0.0892 | 0.2787 | 0.0926 | 0.2441 | 0.0858 | 0.2727 | 0.0899 | 0.2046 | 0.0877 |
| | 0.3000 | 0.0271 | 0.3364 | 0.0311 | 0.2860 | 0.0224 | 0.3207 | 0.0269 | 0.2586 | 0.0276 |
| | 0.3500 | 0.0069 | 0.3912 | 0.0093 | 0.3281 | 0.0042 | 0.3670 | 0.0065 | 0.3161 | 0.0077 |
| | 0.4000 | 0.0015 | 0.4432 | 0.0025 | 0.3709 | 0.0005 | 0.4120 | 0.0012 | 0.3761 | 0.0019 |

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| V | Roots are Complex Conjugate ($\alpha_1=0.8, \alpha_2=-0.6$) | | | | | | | | | |
|-----|---|--------|-------------------------------|--------|------------------------------|--------|-------------------------------|--------|------------------------------|--------|
| | $\lambda_3=0, \lambda_4=0$ | | $\lambda_3=-0.6, \lambda_4=0$ | | $\lambda_3=0.6, \lambda_4=0$ | | $\lambda_3=0, \lambda_4=-1.0$ | | $\lambda_3=0, \lambda_4=2.0$ | |
| | p | $L(p)$ | p | $L(p)$ | p | $L(p)$ | p | $L(p)$ | p | $L(p)$ |
| 0 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9500 | 0.0284 | 0.9572 | 0.0636 | 0.9439 | 0.0521 | 0.9497 | 0.0458 | 0.9506 |
| | 0.1000 | 0.7529 | 0.0902 | 0.7449 | 0.1127 | 0.7576 | 0.1127 | 0.7496 | 0.0746 | 0.7594 |
| | 0.1500 | 0.5140 | 0.1548 | 0.4988 | 0.1583 | 0.5289 | 0.1694 | 0.5137 | 0.1112 | 0.5145 |
| | 0.2000 | 0.3155 | 0.2181 | 0.3067 | 0.2018 | 0.3274 | 0.2225 | 0.3183 | 0.1550 | 0.3098 |
| | 0.2500 | 0.1781 | 0.2787 | 0.1779 | 0.2441 | 0.1808 | 0.2727 | 0.1812 | 0.2046 | 0.1720 |
| | 0.3000 | 0.0935 | 0.3364 | 0.0982 | 0.2860 | 0.0889 | 0.3207 | 0.0951 | 0.2586 | 0.0902 |
| | 0.3500 | 0.0457 | 0.3912 | 0.0518 | 0.3281 | 0.0384 | 0.3670 | 0.0459 | 0.3161 | 0.0454 |
| | 0.4000 | 0.0208 | 0.4432 | 0.0261 | 0.3709 | 0.0142 | 0.4120 | 0.0201 | 0.3761 | 0.0222 |
| 0.4 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9556 | 0.0284 | 0.9627 | 0.0636 | 0.9497 | 0.0521 | 0.9555 | 0.0458 | 0.9558 |
| | 0.1000 | 0.7603 | 0.0902 | 0.7532 | 0.1127 | 0.7645 | 0.1127 | 0.7573 | 0.0746 | 0.7664 |
| | 0.1500 | 0.5145 | 0.1548 | 0.4998 | 0.1583 | 0.5288 | 0.1694 | 0.5142 | 0.1112 | 0.5149 |
| | 0.2000 | 0.3095 | 0.2181 | 0.3013 | 0.2018 | 0.3207 | 0.2225 | 0.3122 | 0.1550 | 0.3042 |
| | 0.2500 | 0.1698 | 0.2787 | 0.1701 | 0.2441 | 0.1717 | 0.2727 | 0.1726 | 0.2046 | 0.1642 |
| | 0.3000 | 0.0860 | 0.3364 | 0.0909 | 0.2860 | 0.0810 | 0.3207 | 0.0874 | 0.2586 | 0.0833 |
| | 0.3500 | 0.0404 | 0.3912 | 0.0462 | 0.3281 | 0.0332 | 0.3670 | 0.0403 | 0.3161 | 0.0404 |
| | 0.4000 | 0.0175 | 0.4432 | 0.0224 | 0.3709 | 0.0115 | 0.4120 | 0.0168 | 0.3761 | 0.0190 |
| 0.8 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9613 | 0.0284 | 0.9681 | 0.0636 | 0.9556 | 0.0521 | 0.9614 | 0.0458 | 0.9611 |
| | 0.1000 | 0.7685 | 0.0902 | 0.7622 | 0.1127 | 0.7721 | 0.1127 | 0.7657 | 0.0746 | 0.7742 |
| | 0.1500 | 0.5150 | 0.1548 | 0.5008 | 0.1583 | 0.5289 | 0.1694 | 0.5148 | 0.1112 | 0.5155 |
| | 0.2000 | 0.3030 | 0.2181 | 0.2954 | 0.2018 | 0.3134 | 0.2225 | 0.3055 | 0.1550 | 0.2979 |
| | 0.2500 | 0.1609 | 0.2787 | 0.1617 | 0.2441 | 0.1620 | 0.2727 | 0.1635 | 0.2046 | 0.1559 |
| | 0.3000 | 0.0782 | 0.3364 | 0.0833 | 0.2860 | 0.0729 | 0.3207 | 0.0793 | 0.2586 | 0.0761 |
| | 0.3500 | 0.0350 | 0.3912 | 0.0406 | 0.3281 | 0.0282 | 0.3670 | 0.0348 | 0.3161 | 0.0354 |
| | 0.4000 | 0.0144 | 0.4432 | 0.0187 | 0.3709 | 0.0090 | 0.4120 | 0.0136 | 0.3761 | 0.0158 |
| 1.2 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| | 0.0500 | 0.9669 | 0.0284 | 0.9734 | 0.0636 | 0.9616 | 0.0521 | 0.9672 | 0.0458 | 0.9665 |
| | 0.1000 | 0.7775 | 0.0902 | 0.7720 | 0.1127 | 0.7804 | 0.1127 | 0.7748 | 0.0746 | 0.7827 |
| | 0.1500 | 0.5156 | 0.1548 | 0.5020 | 0.1583 | 0.5289 | 0.1694 | 0.5154 | 0.1112 | 0.5160 |
| | 0.2000 | 0.2957 | 0.2181 | 0.2887 | 0.2018 | 0.3053 | 0.2225 | 0.2981 | 0.1550 | 0.2909 |
| | 0.2500 | 0.1513 | 0.2787 | 0.1526 | 0.2441 | 0.1516 | 0.2727 | 0.1536 | 0.2046 | 0.1469 |
| | 0.3000 | 0.0702 | 0.3364 | 0.0753 | 0.2860 | 0.0646 | 0.3207 | 0.0710 | 0.2586 | 0.0686 |
| | 0.3500 | 0.0297 | 0.3912 | 0.0349 | 0.3281 | 0.0233 | 0.3670 | 0.0293 | 0.3161 | 0.0304 |
| | 0.4000 | 0.0114 | 0.4432 | 0.0153 | 0.3709 | 0.0068 | 0.4120 | 0.0107 | 0.3761 | 0.0128 |

The values of the OC function computed by using equation (21) are presented on Table (1). From comparison on tables values it is observed that the OC curves for complex conjugate roots are closer to independent observations, while for other two roots marked difference has been seen by its OC curves. Producer's and consumer's risks are protected when the roots are

(i) real and distinct (ii) real and equal. The effect of skewness and kurtosis is substantial when the roots are real and distinct and real and equal. The plan is not robust to autocorrelation, while it is very robust against non-normality. The plans have shown to be sensitive to non normality as well as for autocorrelation.

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