Implementing EWMA Yield Index for Product Acceptance Determination in Autocorrelation Between Linear Profiles

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Abstract In this manuscript, a new sampling plan based on the exponentially weighted moving average (EWMA) yield index for lot sentencing for autocorrelation between linear profiles is proposed. The advantage of the EWMA statistic is the accumulation of quality history from previous lots. In addition, the number of profiles required for lot sentencing is more economical than the traditional single sampling plan. As the value of the smoothing parameter is equal to one, the sampling plan based on the EWMA statistic becomes a traditional single sampling plan. Considering the acceptable quality level at the producer's risk and the lot tolerance percent defective at the consumer's risk, the plan parameters are determined. The plan parameters are tabulated for various combinations of the smoothing constant of the EWMA statistic and the acceptable quality level and lot tolerance proportion defective at the producer's risk and the consumer's risk respectively.

Keywords Yield index · Acceptance sampling plans · Exponentially weighted moving average · Autocorrelation between linear profiles

Introduction

The existence of an intensely competitive business environment obliges manufacturers to protect the quality of their products in the most efficient and economical way possible. Judicious use of acceptance control can supplement and support applications of statistical process control (Schilling and Neubauer 2009). The use of acceptance sampling on its own provides a proven resource for the evaluation of products. When inspection is for the purpose of acceptance or rejection of a product, based on adherence to a standard, the type of inspection procedure employed is usually called acceptance sampling (Montgomery 2013). An acceptance sampling

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plan consists of the sample size to be used and the associated acceptance or rejection criteria.

A profile occurs when a critical-to-quality characteristic is functionally dependent on one or more independent variables. Thus, instead of observing a single measurement on each unit or product we observe a set of values over a range that, when plotted, takes the shape of a curve (Montgomery 2013). The curve explains the possible effect on the dependent variable that might be caused by different levels of the independent variable. A review of research topics on the monitoring of linear profiles is provided by Woodall (2007). Noorossana et al. (2011a, b) provided an inclusive review of profile monitoring. With the assumption that the process data are uncorrelated, many studies have been done by researchers on the monitoring of simple linear/nonlinear profiles (see Li and Wang 2010; Noorossana et al. 2010; Noorossana et al. 2011a, b; Chuang et al. 2013; Ghahyazi et al. 2014). For simple nonlinear profiles and linear profiles, a process-yield index S_{pkA} with a lower confidence bound is proposed by Wang and Guo (2014) and Wang (2014), respectively. However, process data in continuous manufacturing processes are often autocorrelated. In the presence of autocorrelation between profiles, Wang and Tamirat (2014) proposed a process-yield index $S_{pkA;AR(1)}$ and its approximate lower confidence bound (LCB).

In a highly competitive environment, acceptance sampling plans must be appropriately applied. For example, when the required fraction defective is very low, the sample size taken must be very large in order to adequately reflect the actual lot quality, to tackle this problem variable sampling plans based on capability indices have been developed by various authors including Pearn and Wu (2006, 2007), Wu and Pearn (2008), and Wu and Liu (2014). However, the sample size required by process capability based plans would be very large. For example, for auto correlated profiles with a given $\rho = 0.5$, and $n = 4$ it requires 1046 profiles at a consumer and producer risk of 0.05 and 0.10 respectively.

To improve the inspection efficiency, the accumulated quality history from previous lots should be included. The exponentially weighted moving average (EWMA) statistic has been widely used in quality control charts, which consider the present and past information. The weights decline geometrically with the time of the observations. This EWMA statistic is known to be efficient at detecting a small shift in the process ((Hunter 1986; Lucas and Saccucci 1990; Čisar and Čisar 2011; Montgomery 2013). The EWMA statistic based on yield index was first introduced in an acceptance sampling by Aslam et al. (2013). Yen et al. (2014) developed a variable sampling plan based on the EWMA yield index S_{pk} and Aslam et al. (2015) applied the EWMA statistic to the quality characteristic itself based on the mean and standard deviation to develop an acceptance sampling plan. However, the proposed methods consider only a single quality characteristic and cannot be applied to profile data. Furthermore, process autocorrelations may affect the performance of the process yield index. Based on our knowledge, there is no work on the sampling plans based on the yield index for autocorrelation between linear profiles. The main purpose of this paper is to develop a variable sampling plan based on yield index $S_{pkA;AR(1)}$ to deal with lot sentencing of auto correlated profiles.

In this study we propose a new method for economic appraisal of materials. In the presence of autocorrelation between linear profiles, we present a variable acceptance sampling plan using the EWMA statistic with yield index. Taking into account the acceptable quality level at the producer's risk and the lot tolerance percent defective at the consumer's risk, a non-linear optimization method is proposed to determine the number of profiles required for inspection and the corresponding acceptance or rejection criteria. The rest of this paper is organized as follows. In the next section, a yield index $S_{pkA;AR(1)}$ is summarized. Section "Proposed Sampling Plan" describes the proposed sampling plan based on the EWMA statistic. Finally, we offer a conclusion and suggestions for future studies.

Yield Index for Linear Profiles

In this section, we review the yield index for autocorrelation between linear profiles. The first order autocorrelation between linear profiles is modeled by

$$\begin{cases} y_{ij} = \alpha + \beta x_i + \varepsilon_{ij} \\ \varepsilon_{ij} = \rho \varepsilon_{i(j-1)} + a_{ij} \end{cases} \quad i = 1, 2, \ldots, n \text{ and } j = 1, 2, \ldots, k \tag{1}$$

where y_{ij} is the response value at the ith level of the independent variable from the jth profile, x_i is the ith level of the independent variable, n is the number of levels for the independent variable, k is the number of profiles, ε_{ij} denotes correlated random error, α is the intercept of linear profiles, β is the slope of linear profiles, ρ denotes the autocorrelation coefficient, and $a_{ij} \sim N(0, \sigma^2)$.

The process yield at the ith level of the independent variable can be derived by the process yield index proposed by Boyles (1994). This index is useful to describe the relationship between manufacturing specifications and actual process performance and is defined as follows:

$$\begin{aligned} S_{pki} &= \frac{1}{3}\Phi^{-1}\left[\frac{1}{2}\Phi\left(\frac{USL_i - \mu_i}{\sigma_i}\right) + \frac{1}{2}\Phi\left(\frac{\mu_i - LSL_i}{\sigma_i}\right)\right] \\ &= \frac{1}{3}\Phi^{-1}\left[\frac{1}{2}\Phi\left(\frac{1 - C_{dr_i}}{C_{dp_i}}\right) + \frac{1}{2}\Phi\left(\frac{1 + C_{dr_i}}{C_{dp_i}}\right)\right] \end{aligned} \tag{2}$$

where USL_i and LSL_i are the upper and lower specification limits of the response variable at the ith level of the independent variable, μ_i and σ_i are the process mean and the standard deviation at the ith level of the independent variable, $C_{dr_i} = (\mu_i - m_i/d_i)$, $C_{dp_i} = \sigma_i/d_i$, $m_i = USL_i + LSL_i/2$, $d_i = USL_i - LSL_i/2$, Φ is the cumulative distribution function of a standard normal distribution, and Φ^{-1} is the inverse function of Φ.

Wang and Tamirat (2014) derived the following estimator of the yield index for autocorrelation between linear profiles.

$$\hat{S}_{pkA;AR(1)} = \frac{1}{3}\Phi^{-1}\left[\frac{1}{2}\left\{1 + \sum_{i=1}^{n}\frac{1}{n}\left[2\Phi\left(3\hat{S}_{pki}\right) - 1\right]\right\}\right] \tag{3}$$

where

$$\hat{S}_{pki} = \tfrac{1}{3}\Phi^{-1}\left[\tfrac{1}{2}\Phi\left(\tfrac{USL_i - \bar{y}_i}{S_i}\right) + \tfrac{1}{2}\Phi\left(\tfrac{\bar{y}_i - LSL_i}{S_i}\right)\right] = \tfrac{1}{3}\Phi^{-1}\left[\tfrac{1}{2}\Phi\left(\tfrac{1-\hat{C}_{dr_i}}{\hat{C}_{dp_i}}\right) + \tfrac{1}{2}\Phi\left(\tfrac{1+\hat{C}_{dr_i}}{\hat{C}_{dp_i}}\right)\right],$$

$\hat{C}_{dr_i} = (\bar{y}_i - m_i/d_i)$, $\hat{C}_{dpi} = S_i/d_i$, $\bar{y}_i$ and S_i are the sample mean and the sample standard deviation at the ith level of the independent variable, which may be obtained from a stable process, and $\hat{S}_{pkA;AR(1)}$ is the estimator of the process-yield index $S_{pkA;AR(1)}$.

The asymptotic normal distribution of index $\hat{S}_{pkA;AR(1)}$ was derived by Wang and Tamirat (2014) and is given as follows:

$$\hat{S}_{pkA;AR(1)} \sim N\left(S_{pkA;AR(1)} + \sum_{i=1}^{n}\frac{[a_i(1-f)]}{12n\phi(3S_{pkA;AR(1)})}, \frac{\sum_{i=1}^{n}\left[\frac{ka_i^2F}{(k-1)^2} + b_i^2 g\right]}{36n^2k\phi(3S_{pkA;AR(1)})^2}\right) \tag{4}$$

where

$$a_i = \frac{d_i}{\sqrt{2}\sigma_i}\left\{(1 - C_{dr_i})\phi\left(\frac{1 - C_{dr_i}}{C_{dp_i}}\right) + (1 + C_{dr_i})\phi\left(\frac{1 + C_{dr_i}}{C_{dp_i}}\right)\right\},$$

$$b_i = \phi\left(\frac{1 - C_{dr_i}}{C_{dp_i}}\right) - \phi\left(\frac{1 + C_{dr_i}}{C_{dp_i}}\right),$$

$$f = 1 - \frac{2}{k(k-1)}\sum_{i=1}^{k-1}(k-i)\rho_i$$

$$g = 1 + \frac{2}{k}\sum_{i=1}^{k-1}(k-i)\rho_i$$

$$F = k + 2\sum_{i=1}^{k-1}(k-i)\rho^{2i} + \frac{1}{k^2}\left[k + 2\sum_{i=1}^{k-1}(k-i)\rho^i\right]^2 - \frac{2}{k}\sum_{i=0}^{k-1}\sum_{j=0}^{k-i}(k-i-j)\rho^i\rho^j$$

ρ_i is the ith lag autocorrelation, and ϕ is the probability density function of a standard normal distribution.

Proposed Sampling Plan

An acceptance sampling plan must consider two levels of quality such as the acceptable quality level (AQL) and the lot tolerance proportion defective (LTPD). The AQL is also called the quality level desired by the consumer. The producer's risk (α) is the risk that the sampling plan will fail to verify an acceptable lot's quality. The LTPD is also called the worst level of quality that the consumer can tolerate. The probability of accepting a lot with LTPD quality is the consumer's risk (β). An operating characteristic (OC) curve depicts the discriminatory power of an acceptance sampling plan. Thus, its designed plan parameters are determined by the OC curve, which must pass through the two designated points (AQL, 1 − α) and (LTPD, β).

In some situations, the accumulation of quality history from previous lots is available. We proposed the variable sampling plan using the EWMA statistic. The sampling procedure is described as follows:

Step 1: Choose the producer's risk (α) and the consumer's risk (β). Select the process capability requirements (C_{AQL}, C_{LTPD}) at two risks respectively.

Step 2: Select a random number of profiles k at the current time t and collect the preceding acceptance lots with their yield index values. Then, we compute the following EWMA sequence, say Z_t for t = 1, 2, 3, …,T.

$$Z_t = \lambda \hat{S}_{pkA;AR(1)t} + (1-\lambda) Z_{t-1} \tag{5}$$

where λ is a smoothing constant and ranges from 0 and 1. The choice of its optimal value is based on minimizing the sum of the square errors, $SSE = \sum_{t=2}^{T} \left(Z_t - \hat{S}_{pkA;AR(1);t}\right)^2$, where $Z_2 = \hat{S}_{pkA;AR(1);1}$ (Hunter 1986). To find the optimal λ value, a simple R program using the DEoptim algorithm is developed (Ardia et al. 2011).

Step 3: Accept the lot from the supplier if $Z_t \geq c$, where c is the critical value; otherwise reject it.

The OC function of our proposed plan is derived as follows:

$$P(Z_t \geq c) = P\left(\frac{Z_t - E(Z_t)}{\sqrt{\left(\frac{\lambda}{2-\lambda}\right) \frac{\sum_{i=1}^{n} \left[\frac{k a_i^2 F}{(k-1)^2} + b_i^2 g\right]}{36 n^2 k \phi(3S_{pkA;AR(1)})^2}}} \geq \frac{c - \left(S_{pkA;AR(1)} + \sum_{i=1}^{n} \frac{[a_i(1-f)]}{12 n \phi(3S_{pkA;AR(1)})}\right)}{\sqrt{\left(\frac{\lambda}{2-\lambda}\right) \frac{\sum_{i=1}^{n} \left[\frac{k a_i^2 F}{(k-1)^2} + b_i^2 g\right]}{36 n^2 k \phi(3S_{pkA;AR(1)})^2}}} \right) \tag{6}$$

In Eq. (5), the mean and variance of Z_t can be obtained as

$$E(Z_t) = S_{pkA;AR(1)} + \sum_{i=1}^{n} \frac{[a_i(1-f)]}{12n\phi(3S_{pkA;AR(1)})}$$

and

$$Var(Z_t) = \left(\frac{\lambda}{2-\lambda}\right) \frac{\sum_{i=1}^{n}\left[\frac{ka_i^2F}{(k-1)^2} + b_i^2 g\right]}{36n^2k\phi(3S_{pkA;AR(1)})^2}.$$

Therefore, Eq. (6) can be rewritten as follows:

$$P(Z_t \geq c) = 1 - P\left(Z < \frac{c - \left(S_{pkA;AR(1)} + \sum_{i=1}^{n}\frac{[a_i(1-f)]}{12n\phi(3S_{pkA;AR(1)})}\right)}{\sqrt{\left(\frac{\lambda}{2-\lambda}\right)\frac{\sum_{i=1}^{n}\left[\frac{ka_i^2F}{(k-1)^2}+b_i^2g\right]}{36n^2k\phi(3S_{pkA;AR(1)})^2}}}\right) \tag{7}$$

where Z is a standard normal random variable.

Finally, the lot acceptance probability, say $\pi_A(Z_t)$, is derived by

$$\pi_A(Z_t) = 1 - \Phi\left(\frac{c - \left(S_{pkA;AR(1)} + \sum_{i=1}^{n}\frac{[a_i(1-f)]}{12n\phi(3S_{pkA;AR(1)})}\right)}{\sqrt{\left(\frac{\lambda}{2-\lambda}\right)\frac{\sum_{i=1}^{n}\left[\frac{ka_i^2F}{(k-1)^2}+b_i^2g\right]}{36n^2k\phi(3S_{pkA;AR(1)})^2}}}\right) \tag{8}$$

The parameters of our proposed plan can be determined through the non-linear optimization problem given in Eq. (9), where the number of profiles (k) and critical value (c) are decision variables. For a particular sampling plan, the producer is interested in finding the probability that a type I error can be committed. Using Eq. (9), the producer is able to find a sampling plan which guarantees that the lot acceptance probability is larger than the desired confidence level, $1-\alpha$, at the lot acceptable quality level (C_{AQL}). Concurrently the consumer desires that, based on sample information, the probability that a bad (quality) population will be accepted is smaller than the risk at the lot tolerance proportion defective(C_{LTPD}). That is, $S_{pkA;AR(1)} = C_{AQL}$ for the producer and $S_{pkA;AR(1)} = C_{LTPD}$ for the consumer.

$$\begin{aligned}&\text{Minimize k}\\&\text{Subject to}\end{aligned} \tag{9a}$$

$$1 - \Phi\left(\frac{c - \left(C_{AQL} + \sum_{i=1}^{n}\frac{[a_i(1-f)]}{12n\phi(3C_{AQL})}\right)}{\sqrt{\left(\frac{\lambda}{2-\lambda}\right)\frac{\sum_{i=1}^{n}\left[\frac{ka_i^2F}{(k-1)^2}+b_i^2g\right]}{36n^2k\phi(3C_{AQL})^2}}}\right) \geq 1-\alpha \tag{9b}$$

$$1 - \Phi\left(\frac{c - \left(C_{LTPD} + \sum_{i=1}^{n} \frac{[a_i(1-f)]}{12n\phi(3C_{LTPD})}\right)}{\sqrt{\left(\frac{\lambda}{2-\lambda}\right)\frac{\sum_{i=1}^{n}\left[\frac{ka_i^2F}{(k-1)^2} + b_i^2 g\right]}{36n^2k\phi(3C_{LTPD})^2}}}\right) \leq \beta \tag{9c}$$

Given $\rho, \lambda, C_{AQL}, C_{LTPD}, \alpha$, and β as inputs, we evaluate the constraints (9b) and (9c), where the objective function is to minimize the number of profiles. A search procedure is considered to determine the plan parameters. First, 10,000 combinations of k and c are randomly generated, where k ranges from 2 to 3000 and c follows a uniform distribution from C_{AQL} to C_{LTPD}. The above procedure is repeated 1,000 times to determine the optimal parameters.

To investigate the performance of the proposed method, a computer program written in R language is used. In Tables 1 and 2, we tabulate sampling plan parameters for various combinations of two quality levels (C_{AQL}, C_{LTPD}) at $\alpha = 0.05$ and $\beta = 0.10$. The sampling parameters are found under a given $\lambda = 0.10, 0.20, 0.50$, and

Table 1 Plan parameters using the single sampling plan on EWMA yield index under various $(\lambda, C_{AQL}, C_{LTPD})$ at $\alpha = 0.05, \beta = 0.10, \rho = 0.5$ and $n = 4$

	$\lambda = 0.1$		$\lambda = 0.2$		$\lambda = 0.5$		$\lambda = 1.0$	
	$C_{AQL} = 1.33$		$C_{AQL} = 1.33$		$C_{AQL} = 1.33$		$C_{AQL} = 1.33$	
C_{LTPD}	k	c	k	c	k	c	k	c
1.15	36	1.2534	149	1.2348	1313	1.2295	2560	1.2347
1.10	15	1.2550	57	1.2159	499	1.2025	2105	1.2061
1.05	8	1.2691	28	1.2027	228	1.1771	1720	1.1749
1.00	5	1.2771	16	1.1948	118	1.1521	1046	1.1452
	$\lambda = 0.1$		$\lambda = 0.2$		$\lambda = 0.5$		$\lambda = 1.0$	
	$C_{AQL} = 1.5$		$C_{AQL} = 1.5$		$C_{AQL} = 1.5$		$C_{AQL} = 1.5$	
C_{LTPD}	k	c	k	c	k	c	k	c
1.25	11	1.4317	42	1.3803	353	1.3620	2120	1.3581
1.20	7	1.4314	22	1.3708	172	1.3366	1518	1.3320
1.15	4	1.4607	13	1.3687	94	1.3128	821	1.3044
1.10	3	1.4643	8	1.3703	58	1.2901	487	1.2771
1.05	3	1.4451	6	1.3708	36	1.2710	306	1.2507
	$\lambda = 0.1$		$\lambda = 0.2$		$\lambda = 0.5$		$\lambda = 1.0$	
	$C_{AQL} = 2.0$		$C_{AQL} = 2.0$		$C_{AQL} = 2.0$		$C_{AQL} = 2.0$	
C_{LTPD}	k	c	k	c	k	c	k	c
1.60	4	1.9094	9	1.8580	58	1.7907	493	1.7768
1.55	3	1.9262	6	1.8646	36	1.7712	304	1.7503
1.50	2	1.9317	5	1.8610	25	1.7523	201	1.7231
1.45	2	1.9488	4	1.8494	18	1.7345	140	1.6964
1.40	2	1.8900	3	1.8368	13	1.7249	98	1.6717

Table 2 Plan parameters using the single sampling plan on EWMA yield index under various $(\lambda, C_{AQL}, C_{LTPD})$ at $\alpha = 0.05, \beta = 0.10, \rho = 0.75$ and $n = 4$

	$\lambda = 0.1$		$\lambda = 0.2$		$\lambda = 0.5$		$\lambda = 1.0$	
	$C_{AQL} = 1.33$		$C_{AQL} = 1.33$		$C_{AQL} = 1.33$		$C_{AQL} = 1.33$	
C_{LTPD}	k	c	k	c	k	c	k	c
1.15	162	1.2447	696	1.2325	2680	1.2279	2761	1.2268
1.10	64	1.2404	268	1.2109	2176	1.2013	2314	1.2102
1.05	31	1.2498	124	1.1937	1074	1.1752	1920	1.1565
1.00	18	1.2674	67	1.1823	558	1.1491	1243	1.1379
	$\lambda = 0.1$		$\lambda = 0.2$		$\lambda = 0.5$		$\lambda = 1.0$	
	$C_{AQL} = 1.5$		$C_{AQL} = 1.5$		$C_{AQL} = 1.5$		$C_{AQL} = 1.5$	
C_{LTPD}	k	c	k	c	k	c	k	c
1.25	48	1.4113	196	1.3726	1679	1.3611	2612	1.3578
1.20	25	1.4248	97	1.3575	816	1.3350	2481	1.3290
1.15	14	1.4499	54	1.3500	444	1.3096	2123	1.2856
1.10	9	1.4710	33	1.3483	263	1.2851	1753	1.2642
1.05	6	1.4851	22	1.3514	165	1.2629	1483	1.2493
	$\lambda = 0.1$		$\lambda = 0.2$		$\lambda = 0.5$		$\lambda = 1.0$	
	$C_{AQL} = 2.0$		$C_{AQL} = 2.0$		$C_{AQL} = 2.0$		$C_{AQL} = 2.0$	
C_{LTPD}	k	c	k	c	k	c	k	c
1.60	9	1.9716	34	1.8482	263	1.7856	2210	1.7876
1.55	6	1.9895	22	1.8514	166	1.7632	1430	1.7489
1.50	4	1.9991	15	1.8593	110	1.7425	951	1.7214
1.45	3	1.9793	11	1.8680	77	1.7245	655	1.6959
1.40	2	1.9974	8	1.8658	56	1.7070	459	1.6682

1.0, considering two different autocorrelation coefficients $\rho = 0.5$ and 0.75 and n = 4 levels of the independent variable. The number of profiles required for lot sentencing with a smoothing parameter $\lambda < 1$ is more economical than the traditional single sampling plan $(\lambda = 1)$. The smaller the value of λ, the lower the number of profiles required. In practice, relatively small values of λ generally work best when the EWMA is the most appropriate model.

For instance, when C_{AQL} = 1.5, C_{LTPD} = 1.2, and n = 4, at given values of $\alpha = 0.05$, $\beta = 0.10$, and $\rho = 0.5$, the plan parameters (k and c) obtained with $\lambda = 0.10, 0.20$, and 0.50 are (7 and 1.4314), (22 and 1.3708), and (172 and 1.3366), respectively. In addition, with a given $\rho = 0.75$, we found that the plan parameters (k and c) obtained are (25 and 1.4248), (97 and 1.3575), and (816 and 1.3350), respectively. Increasing the autocorrelation coefficient significantly increases the number of profiles required to achieve the desired levels of protection for both producers and consumers.

Conclusion

In this paper, we developed an acceptance sampling plan based on the process yield index $S_{pkA;AR(1)}$ to deal with lot sentencing for autocorrelation between profiles. Our proposed method considers the quality history of the previous lot's information and the current lot; as a result the sample size required is smaller than the traditional single sampling plan. With a given $\lambda = 1$, the sampling plan based on the EWMA statistic is reduced to a traditional single sampling plan. In addition, we tabulated the required number of profiles k and the critical acceptance value c for various combinations of two quality levels (C_{AQL}, C_{LTPD}) at $\alpha = 0.05$ and $\beta = 0.10$ and with $\lambda = 0.10, 0.20, 0.50$, and 1.0 and $\rho = 0.5$ and 0.75 under n = 4. The proposed sampling plan provides the alternative for implementing the acceptance sampling plan.

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