Effect of Cascade Property on the Performance of Simple Linear Profiles

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Abstract

Many products such as chemical items are produced through multistage processes. In these processes, the stages are usually dependent and the quality of the items in a specific stage not only depends on the operation condition of its current stage but also on the condition of the previous stage(s). This is so called the cascade property of multistage processes that makes the interpretation of signals obtained by control charts used to monitor the process difficult. As a result, some monitoring techniques have been developed in the literature to first either reduce or eliminate the cascade property of multistage processes, and then to use a proper scheme to interpret signals easily. In addition, sometimes the quality of the product is characterized by a relationship between a response variable and one or more explanatory variables known as profile. While fewer research works focus on profile monitoring of multistage processes, in this research, the effect of the cascade property on the performance of simple linear profile in terms of average run length is examined through simulation experiments, where the regression coefficients in the profile are estimated for a two-stage process.

Keywords
Cascade Property; Profile Monitoring; Multistage Processes; Phase II Monitoring; Average Run Length (ARL)

1. Introduction and Literature Review

Today many products are being produced in several serial stages of manufacturing plants, while their qualities are monitored using control charts. In these environments, due to the presence of the cascade effect, the quality of the products at the end of a given stage depends on both upstream stages and the current stage. Control chart application without giving an attention to the dependency among the steps leads to misleading results. In order to deal with the cascade effect, Zhang(1980) proposed a cause-selecting control chart(CSC), where its different extensions were proposed later in Zhang (1982, 1984, 1985a, 1985b, 1989a, 1989b, and 1992). Wade and woodall (1993) reviewed Zhang's studies and gave some remarks. Hawkins (1993) proposed a model-based regression adjustment called model-fixed. Shu et al. (2004), and Asadzadeh et al. (2008) introduced a new type multiple cause-selecting control chart (MCSC), and robust cause-selecting control chart, respectively. Hauk et al.(1999) extended the work of Hawkins (1993) to be applicable in multivariate multistage process. Furthermore, Niaki and Davoodi (2009) presented another multivariate-multistage quality control system. Other research works in this area include economic design of multistage control charts(Yang 1997,1998,2006), multistage process monitoring with autocorrelated observations(Leordo et al.2002, Shu and Tsung 2003,Yang and Yang2006), and adaptive cause selecting control charts(Yang and Shu2006, 2007a and 2007b). While all these researches assumed normal observations,Jearkpaporn et al.(2005 and 2007) investigated situationsin which the normality assumption of the quality characteristics is violated.

In recent decade, another topic that has received many attentions is an area so called profile monitoring. Profile is a relationship or a function representing the quality of a product or process in terms of one or more explanatory (independent) variables. Some authors such as Stover and Brill (1998), Kang and Albine (2000), Mahmodand Woodall (2004), Wang and Tsung (2005), and Woodall (2007) have discussed practical examples of profile monitoring. While some authors including Gupta et al. (2006), Zou et al. (2006) and Saghaaei et al. (2009) considered phase-II monitoring of simple linear profiles, Stover and Brill(1998), Mahmoud and Woodall (2004) and Mahmoud et al. (2007) investigated phase-Imonitoring applications of the profiles. Further, Kang

and Albine (2000) and Kim et al. (2003) investigated both phase-I and phase-II profile monitoring. Moreover, Kazemzadeh et al. (2008a) and (2008b) proposed methods to monitor processes using some more complicated forms of profiles such as polynomial profile. While all the aforementioned research works focus on univariate profile, Noorossana et al. (2009, 2010) introduced techniques to monitor multivariate multiple linear profile in phase I and multivariate simple linear profile in phase II.In addition, nonlinear profile monitoring was discussed by, Ding et al. (2006), Wiliams et al. (2007), Miguerza et al. (2007), Vaghefi et al. (2009), Qui and Zou (2010), and Qui et al. (2010).One of the key assumptions in the above research works is the normality and independency of the observations taken from the processes. However, in some practical cases it is quite possible to have correlated nonnormal error terms. Noorossana et al. (2010) investigated the case of violating normality assumption and Jensen et al. (2008), Noorossana et al. (2008), and Soleimani et al. (2009) considered independency violation conditions in simple linear profile monitoring.

All of the research works performed in profile monitoring involve either univariate or multivariate quality characteristics of a single stage. Nonetheless, the quality of a product that is produced in multistage processes is characterized by a profile in many situations. In these environments, if the stages are independent, then one can use common profile monitoring methods. However, the stages are generally correlated in real-world applications and the use of profile monitoring without paying attention to the relation between the stages causes error in both monitoring and signal interpretation. In this paper, the effect of the cascade property of a two-stage process on both the performance and the regression coefficient estimates of two common simple linear profile-monitoring methods is investigated. The structure of the remainder of the paper is as follows. Problem definition, assumptions, and modeling are presented in Section 2. The effects of the cascade property on the performance of simple linear profiles are investigated in Section 3 using simulation studies. Evaluation of the cascade effect on the regression parameter estimates of simple linear profiles is performed in Section 4. The final Section is assigned to conclusions.

2. Problem Definition, Assumptions, and Modeling

According to Zhang (1984), quality in multistage processes can be defined as overall quality and specific quality. Overall quality is the quality due to current stage and all previous stages. However, specific quality is only the quality of the current stage. Most of multistage monitoring techniques have been proposed to denote these qualities. Hence, specific quality and overall quality for a multistage process monitored by a simple linear profile can be represented by the state of regression parameters just in current stage and their state in current and previous stages, respectively.

For the jth sample collected over time, let observations (x_i, y_{ij1}) and (x_i, y_{ij2}) be the outputs of stage 1 and 2, respectively. The subscript i shows i^{th} observations within each profile and x_is are explanatory variables that are fixed and unique for all stages. We assume the relationships between stages are of a linear form. As we consider phase-II analysis, the in-control values of the parameters are assumed known. When the process is in statistical control, the model for all stages is as follows

Stage 1

$$y_{ij1} = A_0 + A_1 x_i + \varepsilon_{ij1} \qquad i = 1,2,\dots,n \qquad (1)$$

Stage 2

$$y_{ij2} = (\phi A_0 + \alpha_1) + (\phi A_1 + \alpha_2)x_i + \phi\varepsilon_{ij1} + \varepsilon_{ij2} \qquad (2)$$

Where A_0 and A_1 are intercept and slope of the first stage profile. α_1 and α_2 are the parameters in which show the special effect of operation in stage 2 on intercept and slope parameters, respectively and independent random variable of each stage are represented by $\varepsilon_{ij1} \sim N(0, \sigma_1^2)$ and $\varepsilon_{ij2} \sim N(0, \sigma_2^2)$. For simplification, σ_1^2 and σ_2^2 are assumedσ^2 . It should be noted that ϕ is the autocorrelation parameter of stages. Equation(2) shows the cascade effect of the first stage on the second stage, where a shift in all parameters of stage 1 affect the corresponding parameters in stage 2.

In the next Section, the effect of the cascade property on both the performance and the parameter estimates of simple linear profiles are investigated.

3. Evaluation of Cascade Effect on the Performance of Simple Linear Profiles

In order to investigate the effect of correlation between stages,let $y_{ij1} = 3 + 2x_i + \varepsilon_{ij1}$ and $y_{ij2} = (3\phi + \alpha_1) + (2\phi + \alpha_2)x_i + \phi\varepsilon_{ij1} + \varepsilon_{ij2}$ the profiles of the first and the second stages, where $x_i = [2,4,6,8], (3\phi + \alpha_1) = 2, (2\phi + \alpha_2) = 1,$ and ε_{ij1} and ε_{ij2} follow a standardized normal distribution.

The performance of the T^2(Kang &Albine 2000) and the MEWMA methods (Lowry et al. 1992) in terms of ARL criteria are compared. For this purpose, a simulation study involving 10,000 replicates is conducted. In the T^2 method, to achieve an overall in-control ARL of approximately 200 and in-control ARL of 400 for each stage, the upper control limit is equal to $\chi^2_{0.0025,2}$. For the MEWMA method, the upper control limit obtained by simulation is $h = 11.185$, where the smoothing constant θ is 0.2. Both negative and positive values for the autocorrelation parameter ϕ is considered as $\phi = [-0.9, -0.7, -0.5, -0.3, -0.1, 0, 0.1, 0.3, 0.5, 0.7, 0.9]$.

The results obtained for shifts in intercept, slope and standard deviation of stage 1 are summarized in Tables 1-3. ARL values of stage 2 for shifts in the first stage parameters (not shown here) are roughly the same as those values that are reported in Tables 1 through 3. According to the first column of these tables, it can be seen that by increasing the autocorrelation parameter, the overall in-control ARL of both methods decreases, where theT^2chart is affected more than the MEWMA method. Further, the results in Table 1 show that the out-of-control ARLs of the MEWMA method for very small shifts ($\lambda_1 \leq 0.4$) aredifferent from those obtained in independent condition ($\phi = 0$). However, for small to moderate shifts, the results are closer to the $\phi = 0$case.For moderate to large shifts $(1.2 \leq \lambda_1 \leq 2)$, the results are approximately the same as for $\phi = 0$. For the T^2scheme, it seems that out-of-control ARLs are significantly different from the ones obtained in the $\phi = 0$ case. This difference decreases in range of small through moderate shifts. However, for large shifts the results is similar to the independent condition.

Table 1: Effect of cascade property on overall ARL under different shifts in the intercept of stage 1 from A_0 to $A_0 + \lambda_1\sigma$

	λ_1										
	0	0.2	0.4	0.6	0.8	1	1.2	1.4	1.6	1.8	2
$\phi = 0.9$											
T^2	26.7	23.1	16.9	11.1	7.2	4.7	3.2	2.2	1.7	1.4	1.2
MEWMA	41.2	25.1	11.9	7	4.8	3.7	3	2.6	2.2	2	1.9
$\phi = 0.7$											
T^2	50.6	43.4	31.1	18.8	11.1	6.5	4	2.7	1.9	1.5	2
MEWMA	70.3	36.6	14.5	7.9	5.2	3.9	3.2	2.7	2.3	2.1	2
$\phi = 0.5$											
T^2	93.2	81.3	51.4	29.3	15.4	8.3	4.7	3	2	1.5	1.3
MEWMA	113.2	49	17	8.4	5.5	4.1	3.2	2.7	2.4	2.1	2
$\phi = 0.3$											
T^2	155.5	126.1	73.4	37	17.8	9.4	5.2	3.1	2.1	1.6	1.3
MEWMA	161.8	61.2	17.9	8.6	5.6	4.1	3.3	2.7	2.4	2.1	2
$\phi = 0.1$											
T^2	195.6	153.7	86.1	40.9	18.9	9.5	5.2	3.1	2.1	1.6	1.3
MEWMA	199.4	66.6	18.4	8.6	5.6	4.1	3.3	2.7	2.4	2.1	2
$\phi = 0$											
T^2	**200**	**160.8**	**87.5**	**41.6**	**19.2**	**9.6**	**5.2**	**3.2**	**2.1**	**1.6**	**1.3**
MEWMA	**200**	**67.5**	**18.3**	**8.6**	**5.5**	**4.1**	**3.3**	**2.7**	**2.4**	**2.1**	**2**
$\phi = -0.1$											
T^2	194.4	154.5	86.9	40.7	18.9	9.6	5.2	3.2	2.1	1.6	1.3
MEWMA	198.7	67	18.4	8.7	5.6	4.1	3.3	2.7	2.4	2.1	2
$\phi = -0.3$											
T^2	151.5	126.1	74.6	37.2	18	9.1	5.1	3.1	2.1	1.6	1.3

MEWMA	163.3	61	17.8	8.6	5.5	4.1	3.3	2.7	2.4	2.1	2
$\phi = -0.5$											
T^2	95.4	82.5	52.7	28.6	15.5	8.2	4.7	3	2.1	1.5	1.3
MEWMA	111.9	49.9	16.8	8.4	5.5	4.1	3.3	2.7	2.4	2.1	2
$\phi = -0.7$											
T^2	50.1	44.1	31	18.5	11	6.4	4	2.7	1.9	1.5	1.2
MEWMA	69.2	36.8	14.6	7.8	5.2	3.9	3.2	2.7	2.3	2.1	1.9
$\phi = -0.9$											
T^2	26.5	23	17	11	7.3	4.7	3.1	2.2	1.7	1.4	1.2
MEWMA	41.5	25.7	11.9	7	4.8	3.7	3	2.6	2.3	2	1.9

Based on the results shown in Table 2, for very small shifts of the slope($\beta_1 \leq 0.05$)ARLs in MEWMA method is sensitive to increase in autocorrelation parameter(ϕ), where by increasing the shift size, the impact of the cascade property reduces so that for moderate to large shifts ($0.15 \leq \beta_1 \leq 0.25$)MEWMA control chartis not sensitive to increase in ϕ. Further, for moderate to large shifts the T^2 method performs similar to the MEWMA. Nonetheless, T^2scheme is very sensitive to increase in autocorrelation parameter of the stages.

Table 2: Effect of cascade property on overall ARL under different shifts in the slope of stage 1 from A_1 to $A_1 + \beta_1\sigma$

	β_1										
	0	0.025	0.05	0.075	0.1	0.125	0.15	0.175	0.2	0.225	0.25
$\phi = 0.9$											
T^2	26.8	24.6	21.1	16.7	12.4	9.3	7	5.1	3.9	3	2.4
MEWMA	42.1	32	18.9	11.6	7.8	5.8	4.6	3.9	3.3	2.9	2.6
$\phi = 0.7$											
T^2	50.5	48	39.1	29.7	21.8	15.1	10.5	7.2	5.2	3.8	2.8
MEWMA	69	49.3	25.5	13.9	8.9	6.5	5	4.1	3.5	3.1	2.8
$\phi = 0.5$											
T^2	95.8	87.9	69.7	50.6	34.1	22.3	14.3	9.3	6.2	4.7	3.3
MEWMA	113.3	73.2	32.2	15.8	9.7	6.8	5.2	4.3	3.6	3.2	2.8
$\phi = 0.3$											
T^2	154.1	140.4	105.3	70.5	44.4	27.5	16.5	10.4	6.7	4.7	3.3
MEWMA	160.3	97.3	36.5	17	10	7	5.3	4.3	3.6	3.2	2.8
$\phi = 0.1$											
T^2	194.3	173.9	130.3	83.2	50.4	29.7	17.6	11.1	7.1	4.8	3.4
MEWMA	198.2	106.3	38.5	17.2	10.2	7.1	5.4	4.4	3.7	3.2	2.8
$\phi = 0$											
T^2	**200**	**181.5**	**132.5**	**84.6**	**51**	**30.1**	**17.8**	**11.1**	**7**	**4.9**	**3.5**
MEWMA	**200**	**111**	**38.6**	**17.4**	**10.1**	**7.1**	**5.3**	**4.3**	**3.7**	**3.2**	**2.8**

For standard deviation shifts, the results in Table 3 show that the MEWMA control chart acts similar to the situations in which the slope shifts. Moreover, T^2 control chart is robust to moderate through large shifts($1.4 \leq \gamma_1 \leq 2$).

Table 3: Effect of cascade property on overall ARL under different shifts in the error standard deviation of stage 1 from σ_1 to $\gamma_1\sigma_1$

	γ_1										
	1	1.2	1.4	1.6	1.8	2	2.2	2.4	2.6	2.8	3
$\phi = 0.9$											
T^2	26.6	14.2	8.5	5.5	4	3.2	2.6	2.2	2	1.8	1.7
MEWMA	42.7	25.5	16.3	11.6	8.5	6.8	5.6	4.7	4.1	3.6	3.2
$\phi = 0.7$											
T^2	50.5	24.5	12.6	7.5	5	3.7	3	2.5	2.2	2	1.8
MEWMA	69.1	37.9	21.8	14.6	10.4	8	6.5	5.2	4.6	3.9	3.5
$\phi = 0.5$											
T^2	94.9	37.4	16.4	9	5.7	4.2	3.3	2.7	2.3	2	1.9
MEWMA	111.9	52.2	28.2	16.9	12	8.8	7	5.7	4.7	4.1	3.6
$\phi = 0.3$											
T^2	154.1	49.5	18.8	9.9	6.2	4.3	3.3	2.7	2.4	2.1	1.9
MEWMA	162.6	66.1	31.2	18.6	12.4	9.2	7.1	5.8	4.8	4.2	3.7
$\phi = 0.1$											
T^2	191.9	54.5	20.3	10	6.1	4.4	3.4	2.8	2.4	2.1	1.9
MEWMA	199.4	71.3	33.1	18.8	12.4	9.2	7.2	5.8	4.8	4.1	3.6
$\phi = 0$											
T^2	**200**	**55.7**	**19.9**	**10.1**	**6.2**	**4.4**	**3.4**	**2.8**	**2.4**	**2.1**	**1.9**
MEWMA	**200**	**73**	**33.3**	**18.9**	**12.7**	**9.2**	**7.1**	**5.9**	**4.9**	**4.2**	**3.7**

Table 4 presents the results of investigating the performances of the scheme in the second stage. The in-control ARL is adjusted, so it is roughly 400 for each stage. As it can be seen when the stages are independent, shifts in the intercept of the first stage profile do not affect the corresponding parameter of the second stage profile. By increasing the autocorrelation parameter between the stages, the performance of the MEWMA control chart is affected. For example, refer to the situation in which $\phi = 0.1$ for large shifts of the first stage profile intercept ($\lambda_1 \geq 1.8$) and $\phi > 0.1$ for all shift sizes of this parameter, where the MEWMA control chart of the second stage gives false signals. In addition, while T^2 performs similar to the MEWMA scheme, the impact of increasing ϕ on the performance of T^2 control chart is less than that in the MEWMA chart.

Table 4: Effect of cascade property on ARL of stage 2 under different shifts in the intercept of stage 1 from A_0 to $A_0 + \lambda_1\sigma$

	λ_1									
	0.2	0.4	0.6	0.8	1	1.2	1.4	1.6	1.8	2
$\phi = 0.9$										
T^2	330	201.1	112	61.4	33.9	20	12.1	7.7	5.1	3.7
MEWMA	153.8	44	18.6	10.7	7.3	5.6	4.5	3.8	3.3	2.9
$\phi = 0.7$										
T^2	343.4	234.3	146.2	87	51.7	31.2	19.8	12.9	8.8	6.1
MEWMA	185.5	60.3	25.7	14.4	9.5	7	5.6	4.6	3.9	3.5
$\phi = 0.5$										
T^2	364.6	280.7	204.2	135.6	90.2	61.4	40.9	28.1	19.8	14.1
MEWMA	235.2	97.2	43.5	23.9	15.1	10.7	8.2	6.6	5.5	4.8
$\phi = 0.3$										
T^2	385.2	337.4	291.6	236.5	184.6	142.1	109.3	84.6	65.3	51.2

MEWMA	314.4	185.8	102.8	58.9	37.2	25.9	18.4	14.1	11.4	9.4
$\phi = 0.1$										
T^2	401.4	391.6	380.6	371.4	355.8	337.9	318.3	305.4	281.9	268
MEWMA	389.5	354.2	304.3	255.4	216.4	177.5	145.1	116.4	95.3	80.4
$\phi = 0$										
T^2	**400.1**	**403.3**	**397.8**	**400.8**	**401.2**	**394.1**	**403.8**	**396.7**	**399.1**	**396.6**
MEWMA	**399.5**	**396.1**	**399.1**	**407.6**	**394.4**	**404.2**	**401.3**	**398.7**	**401.5**	**405.7**

We note that the ARL values corresponding to negative autocorrelation parameters are not reported in Tables 2-4, because the results are the same as the positive ϕs.

4. Evaluation of the Cascade Effect on the Regression Parameter Estimates

In this Section, the effect of the cascade property on the estimates of the regression coefficients in the stage 2 is investigated. Suppose the profiles given in Section 3 with both positive and negative values of ϕ. We use 10,000 replications to estimate the regression parameters $B_0 = \phi A_0 + \alpha_1$, $B_1 = \phi A_1 + \alpha_2$, and their standard deviations denoted by $S(B_0)$ and $S(B_1)$.

Table 5 provides estimates for various autocorrelation parameters between the two stages. Results in this table show that while the parameter estimates remain unbiased for all value of ϕ, the obtained estimates for standard deviations are different from the ones obtained using the least square estimators (LSE), where the stages are independent. According to the LSE method when there is no autocorrelation, the standard deviations of the parameter estimates are:

$$STDEV(A_0) = \sqrt{\sigma^2\left(\frac{1}{n} + \frac{\bar{x}^2}{S_{xx}}\right)} \qquad (3)$$

$$STDEV(A_1) = \sqrt{\sigma^2 / S_{xx}} \qquad (4)$$

In this example, $STDEV(A_0)$ and $STDEV(A_1)$ are 1.2247 and 0.2236, respectively. The simulation results confirm these figures as well. However, when there is an autocorrelation, the standard deviations of the regression parameters are obtained greater than the values corresponding to the $\phi = 0$ condition. Therefore, it can be concluded the standard deviation of estimated regression parameters do not have the minimum variance property in autocorrelation conditions. Further, it can be shown that the variance of the profile coefficients in stage 2 are obtained by Equations(5) and(6).

$$Var(B_0) = \sigma^2(1 + \phi^2)\left(\frac{1}{n} + \frac{\bar{x}^2}{S_{xx}}\right) \qquad (5)$$

$$Var(B_1) = \sigma^2(1 + \phi^2) / S_{xx} \qquad (6)$$

Note that when stages are independent($\phi = 0$), the above equations reduce to (3) and (4). Also note that in Table 5, the exact and the simulated values of the standard deviations of the regression parameters are denoted by S_E and S_S, respectively.

Table 5: Effect of cascade property on the regression parameters of stage 2

$y_{ij2} = 2 + x_i + \phi\varepsilon_{ij1} + \varepsilon_{ij2}$						
ϕ	B_0	B_1	$S_S(B_0)$	$S_E(B_0)$	$S_S(B_1)$	$S_E(B_1)$
0.9	1.9645	1.0064	1.64	1.6477	0.297	0.3008
0.7	2.0209	0.9975	1.4926	1.495	0.272	0.2729
0.5	1.9935	1.0022	1.3708	1.3693	0.25	0.25
0.3	2.0204	0.9969	1.2852	1.2787	0.2343	0.2335
0.1	2.0175	0.9968	1.235	1.2309	0.226	0.2247
0	**1.9982**	**1**	**1.2165**	**1.2247**	**0.2219**	**0.2236**
-0.1	2.006	1.0005	1.2337	1.2309	0.2251	0.2247
-0.3	2.0002	1.0005	1.2626	1.2787	0.2319	0.2335
-0.5	1.9961	1.002	1.3685	1.3693	0.2511	0.25
-0.7	2.0047	0.9996	1.4918	1.495	0.2731	0.2729
-0.9	1.9797	1.003	1.6502	1.6477	0.3031	0.3008

5. Conclusions

In this paper, the effect of the cascade property of two-stage processes on the performance of simple linear profiles was investigated. Two well-known monitoring methods of profile monitoring, namely T^2 and MEWMA, were considered for this investigation. In addition, the effect of this property on the estimates of the regression parameters was studied through simulation. Simulation results showed the cascade property has considerable effect on the overall in-control ARLs of both methods and reduces these values significantly; leading to increased number of false alarms. Furthermore, shifts in the profile parameters of the first stage when the second stage is in-control make misleading results, where signal interpretation of the statistical state of the stage 2 becomes difficult. Simulation study also showed that the MEWMA method performs better than the T^2scheme where the effect of the cascade property on the overall in-control ARL was examined. However, in situation in which a shift occurs in the parameters of the first profile, the performance of theT^2 method is better in comparison with the MEWMA method. Simulation results showed the standard deviation of the regression parameter estimates also are affected by increasing values of autocorrelation parameter. All these results lead into the recommendation of considering the cascade property of multistage processes to obtain more useful and reliable profiles to monitor multistage processes in practice and reduce the errors of process state interpretation.

References

1. Asadzadeh Sh., Aghaie A., Shahriari H., Multistage process monitoring using robust cause selecting control chart; *Proceedings of the 38th International Conference on Computers and IndustrialEngineering*; 1666-1674, 2008.
2. Ding Y., Zeng L., Zhou, S., Phase I analysis for monitoring nonlinear profiles in manufacturing processes,*Journal of Quality Technology*, vol.38, pp.199–216, 2006.
3. Gupta S., Montgomery D. C., Woodall W. H., Performance evaluation of two methods for online monitoring of linear calibration profiles,*International Journal of Production Research*, vol.44, pp.1927–1942, 2006.
4. Hauck, D.J., Runger, G.C. and Montgomery, D.C., Multivariate Statistical Process Monitoring and Diagnosis with Grouped Regression-Adjusted Variables, *Communications in Statistics, Simulation and Computation*, vol.28, pp. 309-328,1999.
5. Hawkins, D.M., Regression Adjustment for Variables in Multivariate Quality Control, *Journal of QualityTechnology*, vol. 25, pp. 170-182, 1993.
6. Jearkpaporn D., Montgomery D.C., Runger G.C., Borror C.M., Model-based process monitoring using robust generalized linear models, *International Journal of Production Research*, vol.43, pp. 1337-1354, 2005.
7. Jearkpaporn, D., Borror, C.M., Runger, G.C. and Montgomery, D.C., Process Monitoring for Mean Shifts for Multiple Stage Processes, *International Journal of Production Research*, vol.45, pp. 5547-5570, 2007.
8. Jensen W. A., Birch J. B., Woodall, W. H., Monitoring correlation withinlinear profiles using mixed models,*Journal of Quality Technology*, vol.40, pp.167–183, 2008.
9. Kang, L., Albin, S.L., On-Line Monitoring When the Process Yields a Linear Profile, *Journal of Quality Technology*, vol.32, pp. 418-426, 2000.

10. Kazemzadeh R.B., Noorossana R., Amiri A., Phase I Monitoring of Polynomial Profiles, *Communications in Statistics-Theory and Methods*, vol.37, pp. 1671-1686, 2008a.
11. Kazemzadeh R.B., Noorossana R., Amiri A., Monitoring Polynomial Profiles in Quality Control Applications, *The International Journal of Advanced Manufacturing Technology*, vol.42, pp. 703-712, 2008b.
12. Kim, K. & Mahmoud, M.A. and Woodall, W.H., On the Monitoring of Linear Profiles, *Journal of Quality Technology*, vol.35, pp. 317-328, 2003.
13. Loredo E.N, Jearkpaporn D., Borror C.M. (2002), Model-based control chart for autoregressive and correlated data, *Quality and Reliability Engineering International* , vol.18, pp. 489-496, 2002.
14. Lowry C. A., Woodall W. H., Champ C. H., &Rigdon S. E., A Multivariate exponentially weighted moving average control chart, *Technometrics*, vol.34, pp. 45–53, 1992.
15. Mahmoud A.M. and Woodall W.H., Phase I Analysis of Linear Profiles with Calibration Applications, *Technometrics*, vol.46, pp. 380-391, 2004.
16. Mahmoud M. A., Parker P. A., Woodall W. H., & Hawkins D. M., A change point method for linear profile data. *Quality and Reliability Engineering International*,vol. 23, 247–268, 2007.
17. Moguerza J. M., Muõoz A., Psarakis S., Monitoring nonlinear profilesusing support vector machines.*Lecture Notes in Computer Science*, 4789, pp.574–583, 2007.
18. Niaki, S.T.A., Abbasi B. and Arkat J., A Generalized Linear Statistical Model Approach to Monitor Profiles, *International Journal of Engineering, Transactions A: Basics, Islamic Republic of Iran*, vol.20, pp. 233-242, 2007.
19. Niaki S.T.A., Davoodi M., Designing a multivariate-multistage quality control system using artificial neural networks, *International Journal of Production Research*, vol.47, no.1, pp.251-271, 2009.
20. Noorossana R., Amiri A., and Soleimani P., On the Monitoring of Autocorrelated Linear Profiles., *Communications in Statistics, Theory and Methods*, vol.37, pp. 425-442, 2008.
21. Noorossana R., Eyvazian M., Amiri A., and Mahmoud A.M., Statistical Monitoring of Multivariate Multiple Linear Regression Profiles in Phase I with Calibration Application, *Quality and Reliability Engineering International, Wiley Interscience*, vol.26, pp. 291-303, 2009.
22. Noorossana R., Eyvazian M., Vaghefi A., Phase II monitoring of multivariate simple linear profiles, *Computers and Industrial Engineering*, vol.57:, pp.425-436, 2010.
23. Noorossana R., Vaghefi A. and Dorri M., Effect of Non-Normality on the Monitoring of Simple Linear Profiles, *Quality and Reliability Engineering International, Wiley Interscience*, vol.27, pp. 1015-1021, 2010.
24. Qiu P., Zou C. , Control Chart for Monitoring Nonparametric Profiles With Arbitrary Design, *StatisticaSinica*, vol.20, pp.1655–1682, 2010.
25. Qiu P., Zou C., Wang Z., Nonparametric Profile Monitoring by Mixed Effects Modeling, *Technometrics*, vol.52, pp.265–277, 2010.
26. Saghaei A., Mehrjoo M. and Amiri A., A CUSUM-based Method for Monitoring Simple Linear Profiles, *The International Journal of Advanced Manufacturing Technology*,DOI: 10.1007/s00170-009-2063-2, 2009.
27. Shu L., Tsung F., On multistage statistical process control,*Journal of the Chinese Institute ofIndustrial Engineers*,vol.20, pp.1-8, 2003.
28. Soleimani P. , Noorossana R, and Amiri A., Simple Linear Profile Monitoring in the Presence of Within Profile Autocorrelation, *Computers and Industrial Engineering*, vol.57, pp.1015-1021, 2009.
29. Stover F. S., Brill, R. V., Statistical quality control applied to ion chromatography calibrations,*Journal of Chromatography A*, vol.804, pp.37-43, 1998
30. Vaghefi A., Tajbakhsh S.D. and Noorossana R., Phase II Monitoring of Nonlinear Profiles, *Communications in Statistics- Theory and Methods*, vol.38, pp. 1834-1851, 2009.
31. Wade M.R. , Woodall W.H., A Review and Analysis of Cause-Selecting Control Charts, *Journal of Quality Technology*, vol.25, pp. 161-169, 1993.
32. Wang K., Tsung, F., Using profile monitoring techniques for a data-rich environment with huge sample size. *Quality and Reliability Engineering International*,vol. 21, pp.677–688, 2005.
33. Williams J. D., Woodall W. H., and Birch J. B., Statistical Monitoring of Nonlinear Product and Process Quality Profiles,*Quality and Reliability Engineering International* ,vol.23, pp. 925-941, 2007.
34. Woodall, W. H., Current research on profile monitoring,*Revista Produco*,vol.17, pp.420–425, 2007.
35. Yang S.F., The Economic Design of Control Chart When There Are Dependent Process Steps, *International Journal of Quality and Reliability Management*, vol.14, pp. 606-615, 1997.
36. Yang S.F., Optimal process control for multiple dependent subprocesses; *Quality andReliability Engineering International*, vol.14, pp. 347-355, 1998.

37. Yang C.M., Yang S.F., Optimal control policy for dependent processes steps with over-adjusted means and variances, *International Journal of Advanced Manufacturing Technology* ,vol.29, pp. 758-765, 2006.
38. Yang S.F, Yang C.M., Effects of Imprecise Measurement on the Two Dependent Processes Control for the Autocorrelated Observations, *International Journal of Advanced Manufacturing Technology*, vol.26, pp. 623-630, 2005.
39. Yang S.F., Su H.C., Controlling-Dependent Process Steps Using Variable Sample Size Control Charts, *Applied Stochastic Models in Business and Industry*, vol.22, pp. 503-517, 2006.
40. Yang S.F., YangC.M., An Approach to Controlling Two Dependent Process Steps with Autocorrelated Observations, *International Journal of Advanced Manufacturing Technology*, vol.29, pp.170-177, 2006.
41. Yang S.F., Su H.C., Adaptive Sampling Interval Cause-Selecting Control Charts, *International Journal of Advanced Manufacturing Technology*, vol.31, pp. 1169-1180, 2007a.
42. Yang S.F., Su H.C., Adaptive control schemes for two dependent process steps, *Journal of Loss Prevention in the Process Industries* 20(1); 15-25, 2007b.
43. Zhang,G.X., A New Type of Quality Control Chart Allowing the Presence of Assignable Causes-the Cause-Selecting Control Chart, *ACTA ELECTRONICA SANICA*, vol.2. pp.1-10, 1980.
44. Zhang G.X., Multiple Cause-Selecting Control Charts, *ACTA ELECTRONICA SANICA*, vol.3, pp. 31-36, 1982.
45. Zhang, G.X., A New Type of Control Charts and Theory of Diagnosis with Control Charts , *World Quality Congress Transactions, American Society for Quality Control*, pp. 175-185, 1984.
46. Zhang G.X., Cause-Selecting Control Charts - A New Type of Quality Control Charts, *The QR Journal*, vol.12, pp. 221-225, 1985a.
47. Zhang G.X., Cumulative Control Charts and Cumulative Cause-Selecting Control Charts,*Journal of China Institute of Communications*, vol.6, pp.31-38, 1985b.
48. Zhang G.X., Brief Introduction to the Cause-Selecting Theory, *Economic Quality Control, Newsletter of Wursberg Research Group on Quality Control*, vol.4, pp. 58-70, 1989a.
49. Zhang G.X., A New Diagnosis Theory with Two Kinds of Quality, *World Quality Congress Transactions, American Society for Quality Control*, pp.594-599, 1989b.
50. Zhang G.X., Cause-Selecting Control Chart and Diagnosis, Theory and Practice, *Aarhus School of Business, Department of Total Quality Management, Aarhus, Denmark*, 1992.
51. Zou C., Zhang Y., Wang, Z., Control chart based on change-point model for monitoring linear profiles,*IIE Transactions*, vol.38, pp.1093–1103, 2006.