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Phase II Monitoring of Logistic Regression Profile in Two-stage processes

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***Abstract*- In most of advanced processes, quality of a final product depends on the several quality characteristic in the previous stages. This is called a cascade property in multi-stage processes. On the other hand, sometimes the quality of a process or product is characterized by a relationship between a response variable and one or more explanatory variable(s).This relation is called profile. In some applications, the quality of a product is following binomial distribution. In these cases the logistic regression is used to model the relation between response variable and explanatory variables. In this paper, the monitoring logistic regression profile in a two stage process is investigated. The effect of cascade property on the performance of common control charts is studied. Finally two methods including T^2 based control chart and Skinner's residual based control chart are proposed for monitoring logistic regression profiles in a two stage processes in Phase II. The performance of the proposed methods is compared through simulation studies in terms of average run length criterion. The results show the suitable performance of tow proposed methods.**

Keywords-Two-stage process; Logistic regression profile; Skinner's residual

I. INTRODUCTION

Nowadays many manufacturing processes consist of several successive stages so that quality characteristics in subsequent stages are affected by the quality characteristic of preceding stages. In other words, quality of an item in a specific stage not only depends on the operation condition of its current stage but also is affected by the condition of its previous stage. This is called the cascade property of multistage processes, for which proper remedial measures have to be adopted in order to reduce or eliminate it and make control chart interpretations easy.

Model-based monitoring procedures are useful for the cascade effects in multistage processes. Similar to the regression control chart proposed by Mandle [1], Zhang's control chart that is called the cause-selecting control chart (CSC) is another method of monitoring multistage processes. Various extensions of CSC were also proposed by Zhang [2-6]. Wade and Woodall [7] reviewed Zhang's studies and proposed cause-selecting control chart with prediction limits as a modification of the common CSC. Moreover, Shu et al. [8] introduced a multiple cause-selecting chart (MCSC) and Asadzadeh et al. [9] proposed a robust cause-selecting control scheme.

In some applications, the quality characteristics in a stage of multistage processes are correlated. Hauk et al. [10] extended the work of Hawkins to handle the problem of multivariate-multistage process monitoring. Furthermore, Niaki and Davoodi [11] presented another multivariate-multistage quality control system by designing a single neural network. Skinner et al. [12] and Jearkpaporn et al. [13] investigated situations in which quality characteristic in multistage processes do not follow normal distribution. In addition to monitoring the mean of multistage processes in all the above works, Zeng and Zhou [14] studied the properties of a regression-adjustment-based method for monitoring the variation propagation in multistage processes.

The concentration of most of the studies in multistage process monitoring is mainly to use linear regression models to describe multistage processes. Some earliest research works focused on the attribute output data in multistage processes. Shang et al. [15] investigated the problem of multistage process monitoring of binary outputs. Yang and Yeh [16] used CSC charts to monitor dependent process stages with attribute data. They compared the performance of their proposed CSC chart with the ones of Shewhart attribute charts as well as a binomial bivariate control region.

In some practical situations, quality of a product or process can be characterized by a linear or nonlinear function between the response and one or more explanatory variables which is referred to as profile. Profile monitoring has received many attentions in the literature and the number of studies in this area is increasing. Practical applications of profile monitoring were discussed by some authors such as Stover and Brill [17], Kang and Albin [18], Mahmoud and Woodall [19], Wang and Tsung [20] and Woodall [21]. Phase II monitoring of simple

linear profiles considered by authors including Gupta et al. [22], Zou et al. [23], Saghaei et al. [24], Mestak et al. [25], Mahmoud and Woodall [26] and Mahmoud et al. [27]. Zou et al. [28] proposed a multivariate exponentially weighted moving average (MEWMA) control chart for monitoring general linear profiles. Kazemzadeh et al. [29] proposed some methods to monitor processes using some more complicated forms of profiles such as polynomial profile. Amiri et al. [30] introduced a new dimension reduction method for monitoring multiple linear profiles in Phase II. Noorosana et al. [31] reviewed the methods and applications of profile monitoring.

In most of the researches in the area of monitoring profiles, it is assumed that response variable follows normal distribution but in some cases this assumption is violated and response variable follows other distributions like Bernoulli distribution. In this situation the relation between the response variable and independent variable is modeled by another kind of regression named logistic regression. Yeh et al. [32] did a research on Phase I monitoring of logistic profile. They used logistic regression to model the relationship between a binary response and one or more continuous explanatory variables. They introduced five methods based on T^2 control chart to monitor the logistic regression profile in Phase I. Shang et al. developed three control charts for monitoring binary response variable profiles with considering a random explanatory variable. They presented a method based on EWMA-GLM chart. Noorosana and Izadbakhsh [33] presented a method to describe the profiles with multi-level response variable by using multi–nominal regression modeling Phase II. Also, Izadbakhsh et al. [34] did some researches for monitoring logistic regression profile with nominal response in both Phases I and II. Sharafi et al. [35] introduced a method to estimate the change point in the Binomial profile based on maximum likelihood estimator (MLE). Saghaei et al. [36] presented methods for monitoring Logistic profile in Phase II. Their work was based two EWMA control charts simultaneously and they presented two methods to calculate the statistics of these control charts. Their first method was based on Pearson's residual statistic and the other method was based on Anscombe's residual statistic. Khedmati et al. [37] proposed four methods including T^2 control chart, MEWMA, likelihood ratio test (LRT) and LRT/EWMA to monitor binary response profiles in Phase II. Based on their simulation's results, MEWMA and LRT/EWMA methods perform better than the other two methods under all shifts considered.

Somewhere, the quality of a product that is produced in multistage processes is represented by a kind of profile such as logistic regression profile. Niaki et al. [38] discussed about the profile monitoring in multistage process. They presented U statistic to monitor profile quality characteristics in multistage processes. In these situations, if the stages are independent, then one can use common profile monitoring methods. However, the stages are generally correlated and the use of profile monitoring without considering a relation between the stages causes error in both monitoring and signal interpretation. This effect called cascade property.

In this paper, the problem of logistic regression profile monitoring in a two stage processes is investigated. For this purpose, we considered a logistic profile as a quality characteristic in the second stage. Then, the effect of the cascade property is shown on the performance of logistic regression profile monitoring methods. Finally, two methods are proposed to eliminate this effect and make logistic profile monitoring schemes applicable for multistage processes.

The remainder of the paper is organized as follows: The Problem and model definition are discussed in Section 2. Section 3 is assigned to the proposed methods. Simulation studies are presented in Section 4. Concluding remarks are given in the final section.

II. PROBLEM DEFINATION AND MODEL ASSUMPTIONS

In this paper, we assumed a two stage process with logistic regression profile in the second stage and a univariate quality characteristic with normal distribution in the first stage. The cascade property is shown by added effect of first stage to the logistic regression model as defined in section A.

A. *Multistage process with logistic regression model definition*

Figure.1 shows the two stage process with univariate quality characteristic in the first stage and logistic regression profile in the second stage. According Fig1. We considered x_1 as first stage quality characteristic which follows normal distribution with parameters (μ, σ^2).

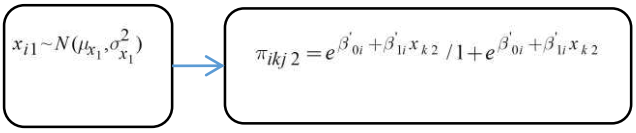

Figure1. The two stage process

Because of cascade property, the logistic regression model in the second stage is affected by the first stage quality characteristic. There are three types for modeling the cascade property in this problem discussed as follows:

a. The effect of cascade property on the intercept of logistic profile

In this scenario the effect of cascade property is considered on logistic regression model's intercept which is modeled as follows:

$$\begin{cases} x_{i1} \sim N(\mu_{x_1}, \sigma_{x_1}^2), \\ \pi_{ikj2} = e^{\beta_0+\gamma_1 x_{i1}+\beta_1 x_{k2}} / 1+e^{\beta_0+\gamma_1 x_{i1}+\beta_1 x_{k2}}, \end{cases} \quad (1)$$
$$i=1,\dots,n_1, k=1,\dots,n_2,$$

where β_0 and β_1 are logistic model's parameters and γ_1 is the effect parameter of the first stage quality characteristic on the intercept of logistic profile. Equation (1) is summarized as follows:

$$\begin{cases} x_{i1} \sim N(\mu_{x_1}, \sigma_{x_1}^2) \\ \pi_{ikj2} = e^{\beta'_{0i}+\beta_1 x_{k2}} / 1+e^{\beta'_{0i}+\beta_1 x_{k2}} \end{cases} \quad (2)$$
$$\beta'_{0i} = \beta_0 + \gamma_1 x_{i1}$$

b. The effect of cascade property on the slope of logistic profile

In this scenario the effect of cascade property is considered on logistic regression model's slope which is modeled as follows:

$$\begin{cases} x_{i1} \sim N(\mu_{x_1}, \sigma_{x_1}^2) \\ \pi_{ikj2} = e^{\beta_0+(\beta_1+\gamma_2 x_{i1})x_{k2}} / 1+e^{\beta_0+(\beta_1+\gamma_2 x_{i1})x_{k2}} \end{cases} \quad (3)$$
$$i=1,\dots,n_1, k=1,\dots,n_2,$$

where β_0 and β_1 are logistic model's parameters and γ_2 is the effect parameter of the first stage quality characteristic on the slope of logistic profile. Equation (3) is summarized as follows:

$$\begin{cases} x_{i1} \sim N(\mu_{x_1}, \sigma_{x_1}^2) \\ \pi_{ikj2} = e^{\beta_0+\beta'_{1i} x_{k2}} / 1+e^{\beta_0+\beta'_{1i} x_{k2}} \end{cases} \quad (4)$$
$$\beta'_{1i} = \beta_1 + \gamma_2 x_{i1}$$

c. The effect of cascade property on the intercept and slope of logistic profile

In this scenario the effect of cascade property is considered on logistic regression model's slope and intercept. The problem is modeled as follows:

$$\begin{cases} x_{i1} \sim N(\mu_{x_1}, \sigma_{x_1}^2), \\ \pi_{ikj2} = e^{\beta_0+\gamma_3 x_{i1}+(\beta_1+\gamma_3 x_{i1})x_{k2}} / 1+e^{\beta_0+\gamma_3 x_{i1}+(\beta_1+\gamma_3 x_{i1})x_{k2}}, \end{cases} \quad (5)$$
$$i=1,\dots,n_1, k=1,\dots,n_2,$$

where β_0 and β_1 are the intercept and slope of the second stage logistic profile respectively and γ_3 is the effect parameter of first stage quality characteristic on the slope and intercept of logistic profile. Equation (5) is summarized as follows:

$$\begin{cases} x_{i1} \sim N(\mu_{x_1}, \sigma_{x_1}^2), \\ \pi_{ikj2} = e^{\beta'_{0i}+\beta'_{1i} x_{k2}} / 1+e^{\beta'_{0i}+\beta'_{1i} x_{k2}}, \end{cases} \quad (6)$$
$$\beta'_{0i} = \beta_0 + \gamma_3 x_{i1},$$
$$\beta'_{1i} = \beta_1 + \gamma_3 x_{i1}.$$

Note that x_{i1} is the ith sample of the quality characteristic of the first stage and x_{ik2} is the kth level of the ith sample taken from the second stage.

Since the results of these three types are similar, in this paper only the results of type 'a' are reported.

III. Proposed Methods

In this section, we proposed two methods including T^2 and Skinner's residual based methods. Assume that there are p levels for the independent variable and n observation in each level of the variable. The proposed methods are as follows:

A. T^2 method

Yeh et al. [32] presented five different T^2 Hoteling control charts for logistic profile monitoring in Phase I. They compared performance of their methods under several out-of-control scenarios, including the presence of outliers, step shifts and drifts. The best method among those five methods is T_I^2 which performs well in detecting step shifts and drifts. The statistic of this method is computed by (7).

$$T_{I,j}^2 = \left(\hat{\boldsymbol{\beta}}_j - \boldsymbol{\beta}\right)^T \sum_I^{-1} \left(\hat{\boldsymbol{\beta}}_j - \boldsymbol{\beta}\right), \qquad j=1,2,\dots \quad (7)$$

where $\boldsymbol{\beta}_j$ is vector of parameters for j^{th} profile, $\boldsymbol{\beta}$ is the vector of the logistic profile parameters and $\sum_I$ is the variance covariance matrix of the $\boldsymbol{\beta}$ vector and computed by (8) as follows:

$$\sum_I = \frac{1}{m}\sum_{j=1}^{m} (\mathbf{X}^{\mathbf{T}}\mathbf{W}_{\mathbf{j}}\mathbf{X})^{-1}. \tag{8}$$

Note that in (8), m is number of profile. Hence, in this paper we developed this method for monitoring Logistic regression profiles. The T_I^2 method is based on the sample average and intra-profile pooling.

B. *Skinner's deviance residual statistic based method*

Skinner et al. [12] calculated the deviance residual for Possion distribution in a multistage process by using generalized likelihood ratio test. Asgari [34] calculated the deviance residual statistic for the binomial distribution similarly. The likelihood function for the binomial distribution is as follows:

$$L(y) = \prod_{i=1}^{n}\binom{n}{y_i}\pi_i^{\,y_i}(1-\pi_i)^{n-y_i}. \tag{9}$$

The generalized likelihood ratio statistic for hypothesis test of H_0: $\pi=\pi_0$ versus H_1: H_0 is not true, is given in (10).

$$\ln\left[L(y,n,\pi_1)\right]-\ln[L(y,n,\pi_0)]=\ln\left[\binom{n}{y}\pi_1^{\,y}(1-\pi_1)^{n-y}\right]-\ln\left[\binom{n}{y}\pi_0^{\,y}(1-\pi_0)^{n-y}\right]=$$
$$y\ln(\pi_1)+(n-y)\ln(1-\pi_1)-y\ln(\pi_0)-(n-y)\ln(1-\pi_0)=$$
$$y\ln\left(\frac{\pi_1}{\pi_0}\right)+(n-y)\ln\left(\frac{1-\pi_1}{1-\pi_0}\right). \tag{10}$$

By replacing $\boldsymbol{\pi_0}$ by $\mathbf{W}^{-1}(\mathbf{X}^{\mathrm{T}}\boldsymbol{\beta})$ and $\boldsymbol{\pi_1}$ by y/n and multiplying to 2 and then taking square root from that and multiple to sign[$\mathbf{y}$-$\boldsymbol{\mu}_0$], where $\mathbf{X}=(x_1,x_2,...,x_p)^T$, $\mathbf{W}=diag\left[n\pi_1(1-\pi_1),n\pi_2(1-\pi_2),...,n\pi_p(1-\pi_p)\right]$, and $\boldsymbol{\mu}_0=(n\pi_1,n\pi_2,...,n\pi_p)^T$. The deviance residual statistic (DR) for binomial distribution is computed as follows:

$$DR = sign\left[y-\mu\right]\left\{2\left[y\ln\left(\frac{\left(\frac{y}{n}\right)}{w^{-1}\left(X^T\beta\right)}\right)+(n-y)\ln\left(\frac{1-\frac{y}{n}}{1-w^{-1}\left(X^T\beta\right)}\right)\right]\right\}^{1/2}. \tag{11}$$

In this paper, the method presented by Asgari [38] is generalized for logistic regression profile, in which each level of independent variable (x) and response variable (y) is considered as a two stage process with y as a quality characteristic of the second stage and $\mathbf{X}$ as a quality characteristic of the first stage. Therefore, the statistic DR in (11) is calculated for each level of independent variable and finally the mean of DR values is computed. Hence, the proposed statistic is the mean of deviance residual statistic (DR) in each level of $\mathbf{X}$; computed for j^{th} sample as follows:

$$\overline{DR}_j = \sum_{k=1}^{p} DR_{kj} / p, \tag{12}$$

where DR_{ij} is the deviance residual statistic for k^{th} level of explanatory variable in j^{th} profile. To monitor $\overline{DR}_j$, we propose EWMA/R control chart which is presented by Kang and Albin[18]. The EWMA chart is used for monitoring the mean of $\overline{DR}_j$ and the corresponding statistic is computed by (13).

$$EWMA_j = \theta\overline{DR}_j + (1-\theta)EWMA_{j-1}, \tag{13}$$

where $0<\theta<1$ is the smoothing constant parameter and $EWMA_0 = 0$. The control limits of the EWMA chart are:

$$UCL = L_1\sigma_{DR}\sqrt{\frac{\theta}{(2-\theta)n}}$$
$$and \tag{14}$$
$$LCL = -L_1\sigma_{DR}\sqrt{\frac{\theta}{(2-\theta)n}},$$

where L_1 is the coefficient of control limits which is determined such that a specified in-control ARL is obtained, σ_{DR} is the standard deviation of DR statistic and is computed by using simulation runs.

The R chart is used along with the EWMA control chart to monitor the variance of the deviance residuals. In the R control chart, the statistic is $R_j = \max_j \overline{DR}_j - \min_j \overline{DR}_j$ and the control limits are:

$$UCL = \sigma_{DR}(d_2 + L_2 d_3)$$
$$and \tag{15}$$
$$UCL = \sigma_{DR}(d_2 - L_2 d_3),$$

where L_2 is the coefficient of control limits which is determined such that a specified in-control ARL is obtained and d_2 and d_3 are constants depends on the sample size.

IV. SIMULATION STUDY

In this section, we first investigated the effect of cascade property on the performance of the proposed methods when modeling this effect is ignored. Then, we model this property and evaluate the performance of the proposed methods, again.

A. *The Effect of cascade property on the Performance of the proposed methods when this property is neglected*

For the purpose of investigating the effect of the cascade property, a two stage process considered, in which z_{ij1} and $\pi_{ij2} = \frac{\exp(\mathbf{x}_i^T \boldsymbol{\beta}')}{1+\exp(\mathbf{x}_i^T \boldsymbol{\beta}')} = \frac{\exp(\eta_i)}{1+\exp(\eta_i)}$ are the normal quality characteristic of the first and logistic profile of the second stages, respectively, where $\mathbf{x_i} = [\log(0.1), \log(0.2), ..., \log(0.9)]$.

A simulation study involving 10,000 replicates is conducted to show the effect of cascade property under different shifts in the mean of first stage characteristic. To examine the effect of the cascade property on the performance of the proposed control chart, the in-control ARL is adjusted to 400 for control chart in each stage and the different shifts in the mean of first stage are investigated. Note that, we use common X-R control chart to monitor the mean of first stage. The results are summarized in Table 1. Based on results, when the first stage is out-of-control, because of cascade property, the second stage control chart gives out-off control signals although it is in-control. Next, we investigate elimination of the first stage effect on the proposed methods performance. The results are shown in Table 2. The results show that the proposed model eliminates the cascade property.

Table 1: Effect of the cascade property on the ARL of control charts in stage 2 under different shifts in the mean of the first stage quality characteristic

	Shift									
Methods	0.2	0.4	0.6	0.8	1.0	1.2	1.4	1.6	1.8	2.0
T^2	343.4	234.3	146.2	87.0	51.7	31.2	19.8	12.9	8.8	6.1
Skinner	330.0	201.1	112.0	61.4	33.9	20.0	12.1	7.7	5.1	3.7

Table 2: The effect of elimination of cascade property on the ARL of control charts in stage 2, under different shifts in the mean of the first stage quality characteristic

	Shifts									
	0.2	0.4	0.6	0.8	1.0	1.2	1.4	1.6	1.8	2.0
ARL_{stage1}	264.9	112.2	45.7	20.3	9.7	5.2	3.2	2.1	1.6	1.3
T^2_{Stage2}	402.5	402.4	397.6	399.2	399.7	403.4	398.6	401.7	398.3	396.3
ARL_{stage1}	264.9	112.2	45.7	20.3	9.7	5.2	3.2	2.1	1.6	1.3
$Skinner_{Stage2}$	398.2	402.8	398.8	402.9	391.2	397.3	398.1	408.8	392.9	402.1

B. *Performance evaluation*

In this section, we use the presented logistic regression model to compare the performance of the proposed methods. The model is defined in (16).

$$\pi_i = e^{\beta'_0+\beta'_1 x_{i2}} / 1+e^{\beta'_0+\beta'_1 x_{i2}} = e^{3+1.5x_1+2x_{i2}} / 1+e^{3+1.5x_1+2x_{i2}}. \quad (16)$$

Evaluating the performance of the proposed methods and comparison between them is done based on the ARL criterion. So, the in control ARL for each control charts in the second stage is set equal to 200. The aim of this research is only monitoring logistic regression in the second stage, then the out-off control ARL is calculated under different shifts in the regression parameters. The values of response variable for each level of independent variable in the second stage, including $\mathbf{X} = [\log(0.1), \log(0.2), ..., \log(0.9)]$ are calculated. We investigate first stage quality characteristic as standardized normal distribution,[N(0,1)].

It is assumed that n products are investigated in each level of explanatory variable. We investigate the performance of the proposed methods for n=60. To generate the values of y, the binomial distribution with parameters (n, π) is used

and the ARL values are obtained by 10000 simulation runs.

The UCL of these methods are set such that ARL_0 equal to 200 is obtained for both proposed methods. The UCL of the T^2 control chart is also set by simulation study. The smoothing constant θ for EWMA control chart is taken equal to 0.2. The in-control ARL of each EWMA and R control chart is set approximately equal to 400 and the combination of the EWMA an R control chart has an overall in-control ARL of approximately 200.The control limits of this method is also set by simulation study to obtain ARL_0 equal to 200 too.

The performance of the both methods under different step shifts is summarized in Tables 3 and 4 and the performance of the both methods under drift shifts is summarized in Tables 5 and 6.

Table 3. Performance of the both methods under different step shifts in β_0

Shift in β_0	ARL	
	T^2_I	Skinner
0.2	98.79	40.1
0.4	34.31	11.62
0.6	13.01	6.06
0.8	5.42	4.15
1	2.88	3.17
1.2	1.82	2.61
1.4	1.35	2.28
1.6	1.15	2.02
1.8	1.05	1.86
2	1.01	1.71

Table 4. Performance of the both methods under different step shifts in β_1

Shift in β_1	ARL	
	T^2_I	Skinner
0.2	93.12	30.86
0.4	30.41	10.9
0.6	10.59	5.51
0.8	4.58	3.96
1	2.5	2.11
1.2	1.61	1.65
1.4	1.24	1.6
1.6	1.09	1.16
1.8	1.03	1.03
2	1.01	1.01

Table 5. Performance of the both methods under drift shifts in β_0

Shift in β_0	ARL	
	T^2_I	Skinner
0.2	89.87	32.01
0.4	29.12	10.3
0.6	10.29	4.25
0.8	4.57	3.05
1	2.45	2.45
1.2	1.61	2.09
1.4	1.25	1.86
1.6	1.1	1.67
1.8	1.03	1.45
2	1.01	1.27

Table 6. Performance of the both methods under drift shifts in β_1

Shift in β_1	ARL	
	T^2_I	Skinner
0.2	88.24	21.92
0.4	27.89	7.3
0.6	9.83	4.35
0.8	4.2	3.12
1	2.33	2.49
1.2	1.52	2.12
1.4	1.21	1.91
1.6	1.07	1.72
1.8	1.02	1.52
2	1	1.33

It can be seen that Skinner residual based method has better performance in detecting both step and drift shifts among the proposed methods.

3. Conclusion

In this paper monitoring logistic regression profile in a two stage processes is investigated. Two methods proposed for monitoring this case. The simulation study showed the cascade property is eliminated by the proposed model. The results showed the desirable performance of both proposed methods. Based on results, the Skinner's residual based method has better performance rather than the T^2_I method.

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