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# A Likelihood Ratio Test Approach to Profile Monitoring in Tourism Industry

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## Abstract

A new statistical profile monitoring technique to monitor and detect changes in logistic profiles with an application in the tourism industry is presented in this paper. In the statistical process control literature, profile is usually referred to as a relationship between a response variable and one or more explanatory variables. In the tourism case study presented in this paper, time is considered as the explanatory variable and tourism satisfaction as the response variable. The Likelihood ratio test is used as a vehicle to detect any changes in the satisfaction profile in phase II of profile monitoring. The performance of the proposed method is evaluated using the average run length criterion. The numerical data indicate satisfactory results for the proposed approach.

**Keywords**: Statistical process control; Profile monitoring; Ordinal logistic; Regression; Likelihood ratio test; Customer satisfaction

**MSC 2010 No.:** 62J02, 62J05, 62J12, 62G10

## 1. Introduction

Tourism industry plays an important role in the economic performance of countries. According to researchers including [Hsieh and Lin (2010) and Keh et al. (2006)] the use of performance assessment methods in various sectors of the tourism industry can help to evaluate success of various development plans. Although many methods are available for performance evaluation, control charts could assess the tourists' satisfaction [Kenett and Salini (2012)]. This method provides useful information on changes over time and can effectively manage the satisfaction levels and complaint rate of tourists. Statistical Process Control (SPC) is a collection of proven tools used for process and product quality improvement (Montgomery, 2005). Control chart, as a featured tool of SPC, helps to improve manufacturing and service processes by distinguishing between the common and assignable causes of variation. Although the principles of SPC can be applied to service industry, a few researches have studied the application of SPC methods to the monitoring of customer activities so that appropriate marketing campaigns and service customizations can be developed [Samimi et al. (2010) and Jiang et al. (2007)].

Since its introduction by Walter A. Shewhart in 1924, researchers have developed and practically used many types of control charts. In the construction of control charts, two phases referred to as Phase I and Phase II are considered. In Phase I, one is usually concerned with process stability and parameter estimation. Retrospective analysis is used in this phase to construct control chart parameters. In Phase II, the constructed control chart is applied to the manufacturing or service process to detect assignable causes that may appear in the parameters of the underlying distribution. However, in certain applications, quality of a process or product can be effectively characterized by a statistical relationship between two or more variables. This functional relationship which could be linear or nonlinear in nature is referred to as "profile" (Kang and Albin, 2000). Profiles can be either linear or nonlinear in nature. Linear profile monitoring methods have been studied by many researchers including [Jensen et al. (2008), Noorossana et al. (2008), Noorossana et al. (2010), Jin and Shi (2001), Jensen and Birch (2009)] while others have studied nonlinear profile monitoring methods. Profile-monitoring techniques have been considered in various manufacturing. More discussions on profile monitoring could be found in Noorossana et al. (2011).

In this paper, we consider profiles with ordinal responses that have three levels or more. The Proportional Odds Model (POM) which is a well-known statistical technique for ordinal responses is regarded as the basis for modeling the relationship between the ordinal response and the independent variables. A Likelihood Ratio Test (LRT) method is developed to enhance monitoring performance of such profiles in phase II. Throughout the paper, we show that using this kind of profile could be suitable to control and improve the tourisms' satisfaction.

Section II discusses the Ordinal Logistic Regression (OLR) model and the estimation of the model parameters. Likelihood ratio test approach for monitoring OLR profiles is presented in Section III. Performance of the proposed approach is evaluated in Section IV using a real case study in tourism industry. Our concluding remarks are provided in Section V.

## 2. Ordinal Logistic Regression

In certain cases such as customer satisfaction, the relationship between response variable and explanatory variable could be modeled using multinomial or ordinal logistic regression. The major difference between them is that the multinomial variables do not have any natural order. On the other hand, ordinal variables are more practical both in the manufacturing industry where quality of a shipped product can be classified as “slightly damaged”, “moderately damaged”, or “severely damaged” and in the service industry where daily customer satisfaction could be classified as "very low", "low", "moderate", "high", or "very high" [Eboli and Mazzulla (2009) and Yeh et al. (2009)].

Consider an ordinal response variable $Y$ with categorical levels denoted by 1,2,…,k, and a $p$-dimensional vector of variables denoted by $\mathbf{x}=\left(x_{i1},x_{i2},...,x_{ip}\right)'$, $i=1,2,...,n$. McCullagh (1980) refers to the cumulative logistic model as proportional odds model which may be used to model the relationship between the ordinal response variable and a $p$-dimensional vector of variables. The cumulative logit model is defined as

$$\gamma_{ij}=\Pr(y\le j\mid\mathbf{x_i})=\frac{\exp(\alpha_j+\boldsymbol{\beta}'\mathbf{x_i})}{1+\exp(\alpha_j+\boldsymbol{\beta}'\mathbf{x_i})}, \tag{1}$$

where, $\alpha_j$ are the unknown intercept parameters satisfying the condition $\alpha_1\le\alpha_2\le...\le\alpha_{k-1}$ and $\boldsymbol{\beta}=(\beta_1,\beta_2,...,\beta_p)'$ is a vector of unknown regression coefficients. Equation (2) is provided with respect to the cumulative property of OLR:

$$\pi_j(\mathbf{x_i})=\Pr(y=j\mid\mathbf{x_i})=\Pr(y\le j\mid\mathbf{x_i})-\Pr(y\le j-1\mid\mathbf{x_i}). \tag{2}$$

Therefore, the likelihood function is defined as

$$\begin{aligned} L(\pi;y)&=\prod_{i=1}^{m}\prod_{j=1}^{k}\pi_j(\mathbf{x_i})^{y_{ij}}=\prod_{i=1}^{n}\prod_{j=1}^{k}\left(\Pr(y\le j\mid\mathbf{x_i})-\Pr(y\le j-1\mid\mathbf{x_i})\right)^{y_{ij}}\\ \Rightarrow l&=\log(L(\pi;y))=\sum_{i=1}^{n}\sum_{j=1}^{k}y_{ij}\log\left(\frac{\exp(\alpha_j+\boldsymbol{\beta}'\mathbf{x_i})}{1+\exp(\alpha_j+\boldsymbol{\beta}'\mathbf{x_i})}-\frac{\exp(\alpha_{j-1}+\boldsymbol{\beta}'\mathbf{x_i})}{1+\exp(\alpha_{j-1}+\boldsymbol{\beta}'\mathbf{x_i})}\right). \end{aligned} \tag{2}$$

The likelihood function is viewed as a nonlinear function of parameters $\left(\left\{\alpha_j\right\},\boldsymbol{\beta}\right)$. According to McCullagh (1980), the Fisher scoring algorithm may be applied to obtain approximate maximum likelihood estimates with the following iterative procedure:

**Step 1**: Initialize the values of $\xi^{(0)}=\left(\alpha_1^{(0)},\alpha_2^{(0)},...,\alpha_{k-1}^{(0)},\beta_1^{(0)},\beta_2^{(0)},...,\beta_p^{(0)}\right)$. It is better to obtain these values by using coefficient estimation methods in multivariate linear regression.

**Step 2:** **F**or $i$ =1,…, $n$ and $j$ = 1,…, $k$, determine

$$\gamma_{ij}^{(t)} = \frac{\exp(\alpha_j^{(t)} + \boldsymbol{\beta}'^{(t)} \mathbf{x_i})}{1+\exp(\alpha_j^{(t)} + \boldsymbol{\beta}'^{(t)} \mathbf{x_i})}, \tag{4}$$

and let

$$\Gamma^{(t)} = \left[\gamma_{ij}^{(t)}\right]_{\substack{i=1,\dots,n \\ j=1,\dots,k}}.$$

**Step3**: Determine

$$\pi_{ij}^{(t)} = \gamma_{ij}^{(t)} - \gamma_{i\,(j-1)}^{(t)}, \tag{5}$$

and set

$$\boldsymbol{\pi}^{(t)} = \left[\frac{1}{\pi_{ij}^{(t)}}\right]_{\substack{i=1,\dots,n \\ j=1,\dots,k}} \text{ and } \quad \boldsymbol{\pi}'^{(t)} = \left[\frac{1}{\pi_{i(j-1)}^{(t)}}\right]_{\substack{i=1,\dots,n \\ j=2,\dots,k+1}}.$$

**Step 4:** Determine

$$\begin{cases} Z_{ij}^{(t)} = \dfrac{y_{ij}^{(t)}}{\pi_{ij}^{(t)}} \\ Z_{i\,(j-1)}^{(t)} = \dfrac{y_{i\,(j-1)}^{(t)}}{\pi_{i\,(j-1)}^{(t)}} \end{cases}, \tag{6}$$

then,

$$\mathrm{Z}^{(t)} = \left[Z_{ij}^{(t)}\right]_{\substack{i=1,\dots,n \\ j=1,\dots,k}} \text{ and } \mathrm{Z}'^{(t)} = \left[Z_{i(j-1)}^{(t)}\right]_{\substack{i=1,\dots,n \\ j=2,\dots,k+1}}.$$

**Step 5**: The derivation with respect to $\xi_r$ is as follows:

$$\left(\frac{\partial l}{\partial \xi_r}\right)^{(t)} = X_r^T \Gamma^{(t)} \left(1-\Gamma^{(t)}\right)^T \left(Z^{(t)} - Z'^{(t)}\right)^T, \tag{7}$$

and

$$E\left[\frac{\partial^2 l}{\partial \xi_r \partial \xi_s^{'}}\right]^{(t)} = X_r^T \Gamma^{(t)2}\left(1-\Gamma^{(t)}\right)^2 M\left(-\pi^{(t)}+\pi^{'(t)}\right)^T X_s, \tag{8}$$

where, $M = diag(n_i)$.

**Step 6**: Update the new coefficient estimators using

$$\hat{\xi}^{(t+1)} = \hat{\xi}^{(t)} - \left(E\left[\frac{\partial^2 l}{\partial \xi_r \partial \xi_s^{'}}\right]^{(t)}\right)^{-1}\left(\frac{\partial l}{\partial \xi_r}\right)^{(t)}. \tag{9}$$

**Step 7:** **C**heck the stop criteria $\left(\left\|\hat{\xi}^{(t+1)}-\hat{\xi}^{(t)}\right\| \le \varepsilon\right)$. If this is satisfied, then set $t=t+1$ and return to step 2.

Moreover, by using the Monte Carlo simulation it could be shown that $\hat{\xi}$ has approximately multivariate normal distribution,

$$N_{m+k-1}\left(\xi, E\left[-\frac{\partial^2 l}{\partial \xi_r \partial \xi_s^{'}}\right]^{-1}\right),$$

as $n_i$ becomes large ($n_i$ is the sample size of $i^{th}$ setting of $\mathbf{x}$).

In the next section we use the above algorithm to propose the LRT approach.

## 3. The LRT Approach

Consider observations in the $l^{th}$ sample $\left(\mathbf{x}_i, y_{ijl}\right), i=1,2,...,n$ where subscript $i$ refers to the $i^{th}$ level of the explanatory variables, $j$ refers to the $j^{th}$ level of the response variable, and $l$ refers to the $l^{th}$ profile collected over the time. When the process is in statistical control, the profile can be modeled based on Equations (1) and (2)

$$y_{ijl} = n_i \times \left[\frac{\exp(\alpha_j + \boldsymbol{\beta}'\mathbf{x_i})}{1+\exp(\alpha_j + \boldsymbol{\beta}'\mathbf{x_i})} - \frac{\exp(\alpha_{(j-1)} + \boldsymbol{\beta}'\mathbf{x_i})}{1+\exp(\alpha_{(j-1)} + \boldsymbol{\beta}'\mathbf{x_i})}\right] + \varepsilon_i, \tag{10}$$
$$\mathbf{x}_l < \mathbf{x_i} < \mathbf{x}_h, \quad j=1,2,...,k-1,$$

where $\{\alpha_j\}$, $j=1,2,...,k-1$ and $\boldsymbol{\beta}'$ are known parameters and $\mathbf{x_i}$, $i=1,2,...,n$ are fixed values of the explanatory variables and $\varepsilon_i$ $(i=1,\dots,n)$ is the error term. Recall that, this paper studies the Phase II of ordinal profile monitoring. So, the coefficients of the base model (Equation (10)) are considered to be known which are determined in Phase I. Thus, for monitoring the base model over time, we need to re-estimate the coefficients of the base model (Equation (10)) over time. Estimates for the model parameters $\{\hat{\alpha}_j\}$ and $\hat{\boldsymbol{\beta}}$ sample $l$ can be obtained using the technique discussed in the previous section. These estimates may be used to develop the likelihood ratio test to evaluate process performance in phase II.

In the likelihood ratio test, the ratio of maximum likelihoods based on the reference and estimated models are compared. For the $l^{th}$ random sample collected over time, we have observations $(\mathbf{x}_i, \mathbf{y}_{il}), i = 1, 2, ..., n$. If $(\hat{\boldsymbol{\alpha}}_l, \hat{\boldsymbol{\beta}}_l)$ is the maximum likelihood estimates for the model parameters vector $(\alpha_{jl}, \boldsymbol{\beta}_l)$, then the two log-likelihood functions can be defined as

$$l(\boldsymbol{\alpha}_l, \boldsymbol{\beta}_l; \mathbf{y}) = \sum_{i=1}^{n}\sum_{j=1}^{k} y_{ijl} \log\left(\frac{1}{1+\exp(-\alpha_{jl} + \boldsymbol{\beta}_l' \mathbf{x_i})} - \frac{1}{1+\exp(-\alpha_{(j-1)l} + \boldsymbol{\beta}_l' \mathbf{x_i})}\right), \tag{11}$$

$$l(\hat{\boldsymbol{\alpha}}_l, \hat{\boldsymbol{\beta}}_l; \mathbf{y}) = \sum_{i=1}^{n}\sum_{j=1}^{k} y_{ijl} \log\left(\frac{1}{1+\exp(-\hat{\alpha}_{jl} + \hat{\boldsymbol{\beta}}_l' \mathbf{x_i})} - \frac{1}{1+\exp(-\hat{\alpha}_{(j-1)l} + \hat{\boldsymbol{\beta}}_l' \mathbf{x_i})}\right). \tag{12}$$

By considering Equations (11) and (12), one can construct a control chart using the following statistic:

$$\lambda_l = 2\left(l(\hat{\boldsymbol{\alpha}}_l, \hat{\boldsymbol{\beta}}_l; \mathbf{y}) - l(\boldsymbol{\alpha}_l, \boldsymbol{\beta}_l; \mathbf{y})\right). \tag{13}$$

This statistic which is usually referred to as the deviance follows an approximate chi-square distribution with $r$ degrees of freedom where $r$ is equal to the difference in the degrees of freedom of the reference model and the estimated model. Therefore, the recommended upper control limit for this chart would be

$$UCL = \chi^2_{\alpha,r}, \tag{14}$$

where large values of $\lambda_l$ indicate an out-of-control condition.

## 4. The Tourism Case Study

Quality is an important aspect of any service which requires constant attention in order to satisfy and even go beyond satisfaction to customer loyalty. So, there is a strong relationship between service quality and customer satisfaction. According to Eboli and Mazzulla (2009), customer satisfaction is a measure of company performance which requires improvement over time. Gursoy et al. (2003) and Gursoy et al. (2007) believe that in the field of hospitality such as tourism industry, customer satisfaction has a strong correlation with financial performance and survival of the company.

Here we consider a fixed planned tour of the tourism industry in Iran where the customer satisfaction index is being measured and monitored daily using a three scale questionnaire. Due to occasional tourists complains, the company has decided to measure and to monitor the customer satisfaction index for each tour over time. The satisfaction index is affected by various factors such as tour leader attitude, climate, facilities, scheduling, and transportation methods. Figure 1 shows the results of the customer satisfaction index for one of the tours. Since customer satisfaction index during this period forms a profile with ordinal response, then, the use of a statistical monitoring method with the purpose of identifying and eliminating barriers to customer satisfaction improvement in a reasonable time frame would be of concern.

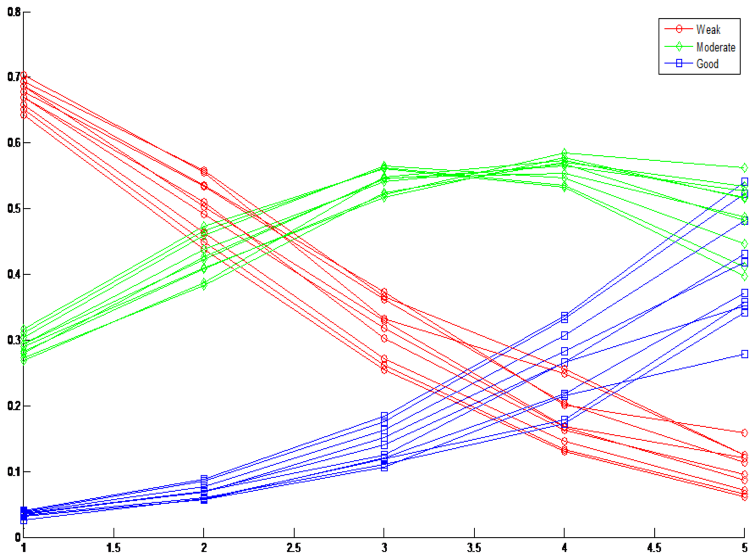


**Figure 1**. Customer Satisfaction Index for the Mentioned Tour

The dependent variable in this case study is customer satisfaction index which is tracked for each tourist at the end of each day with three possible values of "low", "medium", and "high". Time is considered as an explanatory variable. In this case study, the values of $\{\alpha_j\}$, $j=1,2$ and $\beta$ are obtained in Phase I (Recall that, in Phase I the coefficients of the base model are obtained and are validated). The equations of the base profile model are as follows:

$$\Pr(y \le 1 \mid \mathbf{x}_i) = \frac{\exp(3+0.2\mathbf{x}_i)}{1+\exp(3+0.2\mathbf{x}_i)} \qquad i=1,2,\ldots,5, \tag{15}$$

$$\Pr(y \le 2 \mid \mathbf{x}_i) = \frac{\exp(0.5+0.2\mathbf{x}_i)}{1+\exp(0.5+0.2\mathbf{x}_i)} \qquad i=1,2,\ldots,5, \tag{16}$$

where $x_i$ refers to a particular time for tourist $i$, $j$ refers to the level of satisfaction for this tourist.

Now changes in the satisfaction index may be monitored through changes in the parameters of the ordinal profile defined by Equations (15) and (16). In statistical process control, it is common to evaluate performance of a scheme by considering a shift in the parameter of interest being monitored as a multiple of the parameter standard deviation such as $\alpha_1 + \lambda\sigma_{\alpha_1}$ (Note that the estimators in Phase I are considered as parameters in Phase II). Hence, to evaluate the performance of the proposed scheme, we allow shifts in the profile parameters $\{\alpha_j\}$ and $\beta$ to appear as a multiple of their error standard deviations. To compute the variance of the coefficients of the above logistic regression, we use the inverse of the negative of the Hessian matrix obtained from the second derivative of the log-likelihood function. The covariance matrix is obtained from actual samples (without any shifts in the profile parameters) as:

$$\Sigma \cong \begin{bmatrix} 0.2023 & 0.1342 & -0.0401 \\ 0.1342 & 0.1391 & -0.0375 \\ -0.0401 & -0.0375 & 0.0125 \end{bmatrix}. \tag{17}$$

Based on the above equations, the upper control limits corresponding to an in-control average run length of 200 is calculated using 10,000 simulation runs for 100 tourists ($N$ = 100) and 30 tourists ($N$ = 30) in a planned tour. The upper control limits for the chi-square control charts are $UCL = 0.0048$ and $UCL = 0.0044$ for $N$ = 100 and $N$ = 30, respectively. Table 1 shows ARL values associated with shifts in the parameters of the LRT proposed approach for $N$ = 100. Table 2 shows the same results for $N$ = 30.

**Table 1.** ARL values with shifts in the parameters for $N$ = 100

| **Shifts (h)** | **0** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\alpha_1$ **to** $\alpha_1 + \lambda\sigma_{\alpha_1}$ | 200.6 | 122.99 | 42.51 | 14.57 | 5.47 | 2.75 | 1.62 | 1.21 | 1.06 | 1.01 | 1.00 |
| $\alpha_2$ **to** $\alpha_2 + \lambda\sigma_{\alpha_2}$ | 200.6 | 90.59 | 23.62 | 7.14 | 2.95 | 1.65 | 1.23 | 1.06 | 1.01 | 1.00 | 1.00 |
| $\beta$ **to** $\beta + \lambda\sigma_\beta$ | 200.12 | 89.80 | 23.08 | 6.90 | 2.90 | 1.62 | 1.18 | 1.05 | 1.01 | 1.00 | 1.00 |

**Table 2.** ARL values with shifts in the parameters for $N$ = 30

| **Shifts (h)** | **0** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\alpha_1$ **to** $\alpha_1 + \lambda\sigma_{\alpha_1}$ | 200.7 | 127.31 | 44.93 | 14.25 | 5.31 | 2.46 | 1.52 | 1.13 | 1.03 | 1.01 | 1.00 |
| $\alpha_2$ **to** $\alpha_2 + \lambda\sigma_{\alpha_2}$ | 200.7 | 97.95 | 26.38 | 8.09 | 3.46 | 1.88 | 1.30 | 1.10 | 1.03 | 1.00 | 1.00 |
| $\beta$ **to** $\beta + \lambda\sigma_\beta$ | 200.7 | 94.31 | 24.83 | 7.43 | 3.08 | 1.72 | 1.21 | 1.06 | 1.01 | 1.00 | 1.00 |

Based on the above numerical results, one can conclude that 1) likelihood ratio test has a sharp decline in the ARL value as the shift occurs in parameters, 2) for the results associated with $N$ =

100 in Table 1, it is obvious that likelihood ratio test has proper performance for large shifts in all of the parameters, and 3) for the case of $N$ = 30, based on the results in Table 2, the same conclusion is obtained but performance is relatively slower than the case of $N$ = 100. In other words, the ARL values for $N$ = 30 are larger than the ALR values for the case of $N$ = 100.

Performance of the proposed method in detecting shifts could be evaluated from another perspective of simultaneous shifts in the parameters. Yeh et al. (2009) use the following method to allow simultaneous shifts in the parameters:

$$\tilde{\xi} = \xi_0 + \Delta = \xi_0 + (\delta_1\sigma_1, \delta_2\sigma_2, \delta_3\sigma_3)', \tag{1}$$

where, $\delta_i\ \forall i = 1,2,3$ is a constant and $\sigma_i \forall i = 1,2,3$ is a diagonal value in the matrix defined in equation (17).

The ARL values for nine different $(\delta_1, \delta_2, \delta_3)$ vectors are demonstrated in Figure 2. These vectors are $(1,1,1)$, $(1,0,1)$, $(1,2,1)$, $(2,3,2)$, $(2,0,2)$, $(1,3,1)$, $(2.5,0,2.5)$, $(3,0.3,3)$ and $(3,0,3)$.

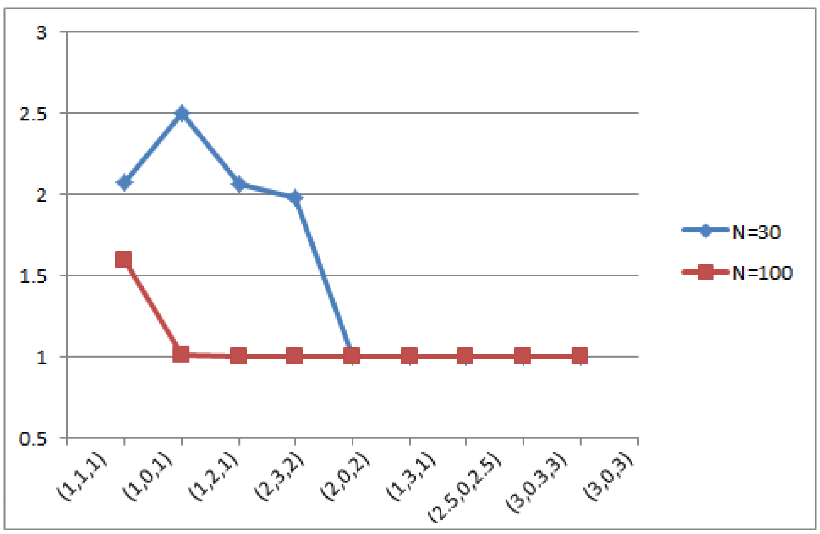


**Figure 2**. Simultaneous shifts in the parameters

## 5. Conclusions

Customer satisfaction is one of the most important issues in tourism industry. This index in the tourism industry depends on many factors such as tour leader attitude, climate, facilities, scheduling, and transportation method. In this study, we proposed a method based on the likelihood ratio test to monitor the customer satisfaction index in a planned tour. Results from a real case study indicate satisfactory performance for the proposed approach. In this research, we consider the logistic function as the link function. However, using other link functions could also be of potential interest.

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