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Process Capability Index for Logistic Regression Profile Based on S_{pmk} Index

M. Rezaye Abbasi Charkhi[a], M. Aminnayeri[*a], A. Amiri[b]

[a]*Industrial Engineering Department, Faculty of Engineering, Amirkabir University of Technology Tehran Polytechnic, Tehran, Iran*
[b]*Industrial Engineering Department, Faculty of Engineering, Shahed University, Tehran, Iran*

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ABSTRACT

A profile is a relationship between a response variable and one or more independent variables that can describe the quality of a process or product. On the other hand, for an in-control process, capability indices are criteria for process quality improvement that allows meeting customer expectations. Although a considerable number of applications and monitoring methods have been already proposed for profiles, a few researches have focused on the process capability index of profiles. In this paper, we propose a new S_{pmk} index to measure process capability when the quality of process is characterized by a logistic regression profile. In addition, we present an approximate (1-α)100% confidence interval based on percentile bootstrap method. The performance of the proposed index and corresponding confidence interval is evaluated through simulation studies. The result shows that when the number of observations in each level increases the index performs better. Furthermore, increasing number of levels leads to improving precision of the proposed index. Also, the coverage rates of the confidence intervals are greater than 93.6% lower limit of the stated nominal in most cases. Finally, the application of the proposed index is illustrated through a real case.

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1. INTRODUCTION

In statistical process control (SPC), control charts are recognized as powerful tools to monitor the quality of process or product with one or more quality characteristics. Sometimes, process quality is characterized better via the relationship between a response variable and one or more explanatory variables. This relation is known as profiles [1]. Since there are different types of profiles in the literature, selecting the appropriate model among them is very significant [2]. The model should not only be simple but also describe the profile data as well. Furthermore, for each model a monitoring method must be designed which could effectively detect changes and be proper for interpretation of out-of-control warning. A review of the existing literature reveals that profiles could be classified into categories such as simple linear, multiple linear, polynomial, multivariate, logistic, non-linear, spline, wave-shaped and non-parametric profiles. Several studies have been done for profile monitoring by many researchers (see Mestek et al. [3], Stover and Brill [4], Kang and Albin [1], Kim et al. [5], Mahmoud et al. [6], Zou et al. [7], Croakin and Varner [8], Wang and Tsung [9], Gupta et al. [10], Kermanpour et al. [11], Niaki et al. [12], Abdella et al. [13]). A comprehensive review on this topic could be found in Noorosana et al. [14].

One of the concepts which is considered alongside control charts is process capability. For an in-control process, the process capability index (PCI) quantifies the relationship between the actual process performance and the specification limits. This concept allows meeting customer expectations, hence it would be acceptable for both the customer and manufacturer. Despite several studies that have been carried out for profiles and the number of researches carried out for their monitoring, there are few attempts that have been focused on PCI in the profiles. As Wood et al. [15] has

*Corresponding Author's Email: mjnayeri@aut.ac.ir (M. Aminnayeri)

mentioned, there has been no research on evaluating the process capability in profiles up to the year 2007. The first attempt at presenting the PCI of simple linear profile was done by Shahriari and Sarafian [16]. Their method could distinguish efficient and inefficient response variables at different levels of the independent variable. Determining the capability of simple linear profiles was attempted by Razavi et al. [17]. Hosseinifard and Abbasi [18] proposed a method to estimate the PCI of linear profiles based on nonconforming items. These authors [19] also estimated the process capability index of linear profiles under non-normal conditions by using gamma distribution as well as Burr distribution. They proposed five methods of estimating PCI of non-normal linear profiles where the three proposed methods need an estimation of a cumulative distribution function of the process. A Burr XII distribution was used to estimate the cumulative distribution function. Since the PCIs calculated by estimating cumulative distribution functions are inconsistent with the true value, the artificial neural networks are applied for specifying PCI of non-normal linear profiles. Ebadi and Shahriari [20] introduced a method to estimate PCI of linear profiles. Three methods for measuring PCI of multivariate linear profiles were introduced by Ebadi and Amiri [21]. These three methods are based on three different approaches. The first method is based on the average percentage of nonconforming items. The second one is based on introducing a multivariate capability vector that separates the process dispersion and its centrality to measure process capability index, and the third is based on principal component analysis. Simulation results showed that the simultaneous application of these three methods could provide comprehensive information about the process capability index of multivariate linear profiles. Wang [22] proposed a method for circular profiles. In another attempt, Wang [23] proposed a method to measure the exact value of PCI for simple linear profiles. Subsequently, Wang [24] introduced two new methods to measure the PCI of simple linear profiles with a one-sided specification limit. Wang et al. [25] presented a method to estimate PCI of simple linear profiles with AR(1) auto correlated data. Wang et al. [26] suggested a method to measure the PCI of non-linear profiles. Guevara et al. [27] presented a method to evaluate PCI of non-linear profiles based on depth function. Nemati Keshteli et al. [28] explained a functional approach to measure PCI of circular profiles. Karimi Ghartemani et al. [29] introduced a new method to determine PCI of simple linear profiles.

In some situations in real world such as biology, environment and services, the response variable may follow binary or binomial distribution and the relationship between response and explanatory variables is well modeled by a logistic regression profile. Evaluating the capability of such processes has not been studied in the literature. Hence, in this paper, we introduced a method to measure PCI of logistic regression profiles based on S_{pmk} index. The new index takes into account process variability, departure of the profile mean from target value and proportion of nonconforming items.

The paper is organized as follows: section 2 gives a brief description of logistic regression profiles. In section 3, an index to estimate the process capability of logistic regression profiles is presented. In section 4, performance of the proposed method is evaluated through simulation studies. In the next section, the performance of the proposed index is presented by a real case, and finally conclusions and remarks for future research are provided.

2. LOGISTIC REGRESSION PROFILE

The logistic regression model is an important member of generalized linear model in which the response variable follows binomial distribution.

Consider the set of observation $\{\mathbf{x}_i, z_{ij}\}_{i=1}^{n}$ which in $\mathbf{x}_i = (x_{i1}, x_{i2}, x_{i3}, ..., x_{ip})^T$ and z_{ij}, are the jth binary response variables in the ith level of the explanatory variable. The probability of success in z_{ij} is equal to $\pi_i, i = 1, 2, ..., n,\ \ j = 1, 2, .., m$ where m is the number of bernoulli variable in each level and $\mathrm{E}(z_{ij}) = \mu_i = \pi_i$, $\mathrm{Var}(z_{ij}) = \pi_i(1-\pi_i)$. We denote $\pi_i = \pi(\mathbf{x}_i)$ as the probability of a bernoulli process as a function of $\mathbf{x}_i$. In the logistic regression model there are different kinds of link functions which represent the relationship between the response variable and independent variable(s). Usually the link function of logit $g(\pi_i)$ is used for logistic regression as follows:

$$g(\pi_i) = \log \frac{\pi_i}{1-\pi_i} = \beta_1 x_{i1} + \beta_2 x_{i2} + ... + \beta_p x_{ip}, \tag{1}$$

where $\boldsymbol{\beta} = (\beta_1, \beta_2, ..., \beta_p)^{\mathbf{T}}$ is the parameters vector of the model in which β_i 's are real. When the response variable is binary, empirical observations reveal that the response function is a non-linear, s-shaped form. This function is called logistic regression and is defined as follows:

$$\pi_i = \frac{\exp(\mathbf{x}_i^T \boldsymbol{\beta})}{1+\exp(\mathbf{x}_i^T \boldsymbol{\beta})}. \tag{2}$$

The most prevalent method for estimation of parameters in the logistic regression model is the maximum likelihood estimation parameters method. Several studies have been carried out on estimating logistic regression parameters. For more information about parameter estimation in the logistic regression model see (Myers et al. [30] McCullagh and Nelder [31], Yeh et al. [32]).

In the following section, a method is proposed to determine the process capability index of logistic regression profiles.

3. DETERMINING PROCESS CAPABILITY INDEX FOR LOGISTIC REGRESSION PROFILE

Chen et al. [33] proposed a new capability index under non-normal distribution. The proposed index is as follows:

$$S_{pmk}=\frac{\phi^{-1}\left(\frac{1+F(USL)-F(LSL)}{2}\right)}{3\sqrt{1+\left(\frac{\mu-T}{\sigma}\right)^2}}=\frac{\phi^{-1}\left(1-\frac{P}{2}\right)}{3\sqrt{1+\left(\frac{\mu-T}{\sigma}\right)^2}}, \tag{3}$$

where $F(x)$ denotes cumulative distribution of the process, μ and σ are the mean and standard deviation of the process respectively, and T is Target value. USL and LSL are upper and lower specification limits, respectively. Besides, ϕ^{-1} is inverse of cumulative distribution of standardized normal distribution and P the percentage of nonconforming items.

Accordingly, based on Equation (3), in this section a method to calculate PCI of logistic regression profile is introduced. Consider a process in which the relationship between response variable and explanatory variables are described by logistic regression profile. The percentage of nonconforming items in each level which is equal to the mean of the profile, is calculated by using Equation (2).Suppose that response values follow binomial distribution. As a result, we have:

$$\pi_i=P_{(y_{(i)})}, \tag{4}$$

$$\mathrm{E}(y_{(i)})=\mu_i=mP_{(y_{(i)})}, \tag{5}$$

$$\mathrm{Var}(y_{(i)})=mP(y_{(i)})(1-P(y_{(i)})), \tag{6}$$

where $P_{(y_{(i)})}$ denotes the percentage of nonconforming items in each level. A new process capability index S_{pmk} for each level is proposed as follows:

$$S_{pmk_{(y_{(i)})}}=\frac{\phi^{-1}\left(1-\frac{P_{(y_{(i)})}}{2}\right)}{3\sqrt{1+\frac{(mP_{(y_{(i)})}-T_{(y_{(i)})})^2}{mP_{(y_{(i)})}(1-P_{(y_{(i)})})}}}. \tag{7}$$

After computing PCI in each level, the total percentage of nonconforming items should be calculated. According to the literature (Wang [23] and Wang et al. [26]), the total percentage of nonconforming items is calculated by the following equation:

$$P_{\mathrm{Profile}}=\frac{\sum_{i=1}^{n}P_{(y_{(i)})}}{n}. \tag{8}$$

Now, overall PCI is determined by the following equation using the total percentage of nonconforming items:

$$S_{pmk_{(profile)}}=\frac{\phi^{-1}\left(1-\frac{P_{(profile)}}{2}\right)}{3\sqrt{1+\frac{(mP_{(profile)}-T_{(profile)})^2}{mP_{(profile)}(1-P_{(profile)})}}}, \tag{9}$$

where $P_{(profile)}$ is the total percentage of nonconforming items, $mP_{(profile)}, mP_{(profile)}(1-P_{(profile)})$ are the mean and variance of the profile respectively, and $T_{(profile)}$ is target value of the profile which is the average number of nonconforming items based on customer expectations.

On the other hand, in most situations engineers are interested in evaluating confidence interval of process yield. Note that in constructing a confidence interval for process capability, an initial assumption about the distribution of a given population is required. Since the distribution of S_{pmk} index is unknown, we have to use a method for computing confidence intervals which does not need any assumptions about the distribution of given population. For this purpose, nonparametric methods should be used. Afron [34] proposed a nonparametric computer based method known as bootstrap. The bootstrap is data based simulation method for statistical inference which is classified into parametric and nonparametric bootstrap methods. In nonparametric bootstrap method when the distribution of given population is unknown, resampling with replacement in main sample is done. Hence, in computing bootstrap confidence interval no initial assumption about given population is required. In this paper, we use percentile bootstrap confidence interval method to calculate a confidence interval of process capability index.

Suppose that θ is parameter of interest, $\hat{\theta}$ an estimate of θ based on observed data and $\hat{\theta}^*$ a bootstrap estimator which is calculated based on bootstrap sample. Resampling is replicated B times and B bootstrap estimators as $\hat{\theta}_1^*,\hat{\theta}_2^*,...,\hat{\theta}_B^*$ are generated. After sorting out bootstrap estimators $\hat{\theta}^*$, (1-α)100% confidence interval is calculated by the following equation:

$$[\hat{\theta}^*_{(\frac{\alpha}{2}\times B)}, \hat{\theta}^*_{((1-\frac{\alpha}{2})\times B)}]. \tag{10}$$

As a result, based on Equation (10), confidence interval of S_{pmk} index is calculated as

$$[\hat{S}^*_{pmk_{(\frac{\alpha}{2}\times B)}}, \hat{S}^*_{pmk_{((1-\frac{\alpha}{2})\times B)}}]. \tag{11}$$

In practice, a process is called capable to meet customer expectations if $S_{pmk} > 1$, marginally capable if $S_{pmk} = 1$ and incapable if $0 \le S_{pmk} < 1$.

4. PERFORMANCE OF THE PROPOSED INDEX

In this section, we evaluate the performance of the proposed method outlined in Section 3, using MATLAB software through simulation studies. For this purpose, we consider a logistic profile from Yeh et al. [32]. The underlying in-control logistic profile model, includes 9 levels of the explanatory variables, and the fixed values of explanatory variables are set as log(0.1), log(0.2), log(0.3),…, log(0.9) where the logistic regression profile is defines as:

$$\pi_i = \frac{e^{(3+2x_i)}}{1+e^{(3+2x_i)}}. \tag{12}$$

Number of observations in each level (m) is set equal to 25, 50, 100, and 1000 in the simulation runs. Furthermore, several number levels (l) and several number of profiles (k) have been considered. 1000 simulation runs are used to estimate PCI. The results of computed process capability are summarized in Table 1. The simulation algorithm is briefly explained as follows:

1. First, the percentage of nonconforming items in each level is calculated. Since the target value is not determined in the example, we suppose that the target value is calculated by multiplying of average percentage of nonconforming items obtained by Equation (12) and number of observations in each level. In fact, the target value is calculated as follows:

$$\text{Target Value} = \frac{m\sum_{i=1}^{9}\pi_i}{9}., \tag{13}$$

where π_i is calculated by Equation (12), m number of observation in each level and i the number of levels.

2. Next, the binomial random numbers are generated with the parameter obtained from the previous step (This step is repeated 1000 times.).
3. Further, a logistic regression is fitted on the dataset, including y's and x's which results would be 1000 profiles.
4. Then, in this step, the percentage of nonconforming items is calculated in each level for each profile.
5. Following that, the total percentage of nonconforming items of each profile is determined (based on Equation (8)).
6. At the end of simulation procedure, the overall PCI of each profile is calculated and the average is reported.

$\hat{S}_{pmk}$ is calculated on the basis of the six mentioned steps. However, S_{pmk} is calculated by using Equation (9).

7. In this step, 95% confidence interval and coverage rate are calculated. For a confidence level of 95%, lower limits of stated nominal value for coverage rate is equal to 93.6% which is computed as:

$$(0.95-1.96\sqrt{0.05\times(0.95/replication)})\times 100\%.$$

As the results in Table 1 show, the coverage rates in most cases are above 93.64%.

On the basis of results in Table 1, proposed method for computing process capability index can effectively estimate PCI of the logistic regression profile. When the number of observations in each level increases, the performance of the proposed index improves. Hence, we conclude that the number of observations in each level affects the estimation of PCI. In addition when the number of levels increases, the value of the proposed index decreases. Note that when the number of levels enhance, the total percentage of nonconforming items becomes larger, and as a result, the value of process capability index naturally decreases. Generally, increasing number of levels leads to improving precision of the proposed index. As the results show, since the values of process capability indices are less than 1 for the considered example, the process is incapable of meeting customer expectations.

5. A REAL CASE

In this section, we illustrate how the proposed method can be applied to real application. Hence, we consider a real case based on data set from Saghaei et al. [35]. The study was carried out on the press machine in which the relationship between the percentage of defective products and the speed of the press is modeled by a logistic regression profile. The observations of the example are presented in the Table 2 in which the probability of defective items is the mean long-term probability at each level based on 100 samples.

TABLE 1. Simulation results of estimated process capability index and corresponding confidence interval

k	l	m	S_{pmk}	$\hat{S}_{pmk}$	CI	CR (%)
100	5	25	0.1890	0.1935	[0.1873-0.2033]	93.7
		50		0.1899	[0.1875-0.1921]	93.7
		100		0.1894	[0.1873-0.1917]	94.8
		1000		0.1891	[0.1885-0.1899]	93.8
	9	25	0.1180	0.1214	[0.1177-0.1250]	93.6
		50		0.1198	[0.1178-0.1218]	94.3
		100		0.1195	[0.1178-0.1215]	94.5
		1000		0.1183	[0.1179-0.1199]	93.8
	12	25	0.0921	0.0933	[0.0905 -0.0941]	94.4
		50		0.0928	[0.0909-0.0947]	94.7
		100		0.0925	[0.0912-0.0929]	93.7
		1000		0.0922	[0.0918 -0.0923]	93.7
1000	5	25	0.1890	0.1900	[0.1881-0.1919]	93.7
		50		0.1898	[0.1884-0.1904]	93.4
		100		0.1894	[0.1885-0.1899]	94.3
		1000		0.1891	[0.1889-0.1892]	93.7
	9	25	0.1180	0.1214	[0.1178-0.1250]	93.6
		50		0.1203	[0.1178-0.1229]	94.7
		100		0.1193	[0.1179-0.1199]	93.7
		1000		0.1182	[0.1178-0.1184]	93.7
	12	25	0.0921	0.0926	[0.0916 -0.0932]	94.1
		50		0.0923	[0.0917-0.0926]	94.7
		100		0.0922	[0.0918-0.0926]	94.3
		1000		0.0921	[0.0919 -0.0925]	93.7

TABLE 2. The probability of defective products at different levels of the speed

Speed of machine press	Probability of defective products
0.25	0.005
0.50	0.006
0.75	0.008
1.00	0.010
1.30	0.015
1.50	0.019
1.80	0.026
2.00	0.035

The underlying logistic regression model in which the parameters are estimated using the data presented in the Table 2 and based on the Newton-Raphson method, is as follows.

$$\pi_i = \frac{e^{(5.702-1.174x_i)}}{1+e^{(5.702-1.174x_i)}}. \tag{14}$$

The results obtained for calculating the process capability index of the example are demonstrated in Table 3. The result shows the suitable performance of the proposed index in real application. We conclude that this process is incapable of meeting customer expectations.

TABLE 3. Results of the estimated process capability index and the corresponding confidence interval

m	S_{pmk}	CI
100	0.0065	[0.0040-0.0095]

6. CONCLUSION AND FURTHER RESEARCHES

There are many real cases in which the generalized linear regression models such as logistic regression are used to describe profiles. Considering intense competitiveness between industries, cost minimization and quality improvement are recognized as significant points which must be certainly considered. Hence, providing a process which meets customer expectations is extremely valuable.

In this paper, we proposed a method to estimate the process capability index of logistic regression profiles. In the proposed method, process capability index is computed by using the percentage of nonconforming items of the profile and departure of the process mean from the target value. Simulation studies was applied to evaluate performance of the proposed index. According to the results, as the number of observations increases, the performance of the index improves. In addition, when the number of levels increases, the value of the proposed index decreases. Since the logistic regression profile is a well-known generalized linear model with vast applications, developing process capability index for nominal and ordinal logistics regression profiles can be investigated as future researches. In addition, more accurate indices would be required to compute process capability of a logistic regression profile. Using transformation methods could be considered as a future study in this area as well. Furthermore, providing a relationship between percentage of nonconforming items and process capability index in each level and total process capability index can be considered as future research work. Finally, investigating the statistical properties of the proposed process capability index could be fruitful area for future study.

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M. Rezaye Abbasi Charkhi[a], M. Aminnayeri[a], A. Amiri[b]

[a]Industrial Engineering Department, Faculty of Engineering, Amirkabir University of Technology Tehran Polytechnic, Tehran, Iran
[b]Industrial Engineering Department, Faculty of Engineering, Shahed University, Tehran, Iran

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Processes Capability Index

چکیده

پروفایل رابطه‌ای میان یک متغیر پاسخ و یک یا چند متغیر مستقل است که بیانگر کیفیت محصول یا عملکرد فرآیند می-باشد. از طرف دیگر، شاخص‌های توانایی فرآیند معیاری برای بهبود کیفیت فرایند جهت نیل به انتظارات مشتری هستند. اگرچه تا کنون موارد کاربردی زیادی برای پروفایل‌ها مطرح و روش‌های مختلفی برای پروفایل‌ها ارائه شده است، اما تحقیقات چندانی در زمینه تعیین شاخص توانایی فرآیندهای پروفایلی انجام نشده است. در این مقاله یک شاخص S_{pmk} جدید برای پایش قابلیت فرآیند پروفایل لجستیک پیشنهاد شده است. به علاوه، فاصله اطمینان $100\%(1-\alpha)$ شاخص S_{pmk} براساس روش بوت استرپ صدکی محاسبه شده است.عملکرد این شاخص و فاصله اطمینان متناظر با آن به وسیله مطالعات شبیه‌سازی ارزیابی شده است. نتایج نشان می‌دهد که هر چه تعداد مشاهدات در هر سطح بیشتر باشد، شاخص تخمین بهتری را نشان می‌دهد. همچنین، افزایش تعداد سطوح منجر به افزایش دقت شاخص خواهد شد. به علاوه، نتایج نشان می‌دهد که نرخ پوشش دهی در بسیاری از موارد از حد اسمی ۹۳/۶٪تعیین شده بزرگتر است. نهایتاً، عملکرد شاخص با یک مثال واقعی نشان داده شده است.

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