Computers & Industrial Engineering 126 (2018) xxx–xxx

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

An overview on recent profile monitoring papers (2008–2018) based on conceptual classification scheme

Mohammad Reza Maleki[a], Amirhossein Amiri[a], Philippe Castagliola[b,*]

[a] Department of Industrial Engineering, Faculty of Engineering, Shahed University, Tehran, Iran
[b] Université de Nantes & LS2N UMR CNRS 6004, Nantes, France

ARTICLE INFO

Keywords:
Change point estimation
Control chart
Economic design
Parameter estimation
Statistical design
Survey
Phase I and Phase II

ABSTRACT

Sometimes the quality of a process is best expressed by a relationship between response variables and explanatory variables. Checking over the time the stability of such functional relationships using statistical methods is called "profile monitoring". Since 2007, when a detailed review paper in the field of profile monitoring was presented, an increasing number of papers have been published in this area. In this paper, we present a conceptual classification scheme and classify the papers in this area since 2008 up to 2018. The relevant papers are categorized and analyzed under different metrics and directions for future studies are recommended.

1. Introduction

Control charts, successfully used in many manufacturing and non-manufacturing situations, help quality practitioners to improve the quality of a process by reducing the sources of process variability. Controls charts trigger an out-of-control signal when the underlying chart statistic falls outside the control limits interval. If the signal is not a false alarm, the proper corrective action(s) must be implemented to remove the assignable cause(s). Depending on the type of the quality characteristic, control charts are usually splitted into two general categories: variable and attribute control charts. The variable control charts are used to monitor the quality characteristics such as length, temperature, and weight which are measured on a continuous scale. However, attribute control charts are constructed based on discrete or countable quality characteristics such as the number of non-conforming products. Moreover, depending on the number of quality characteristics of interest, many univariate and multivariate control charts have been proposed in order to distinguish between assignable and common causes of process variation. As the most common control charts for monitoring univariate control charts, we can refer to the traditional Shewhart-type charts, exponentially weighted moving average (EWMA) and cumulative sum (CUSUM) control charts. Also Hotelling's T^2, multivariate EWMA (MEWMA) and multivariate CUSUM (MCUSUM) are the most common multivariate control charts.

In some situations, however, the quality of a product is best characterized by a functional relationship between one response variable and one or more independent or explanatory variables. This functional relationship which is captured and monitored over the time is called a "profile". For each profile n measurements of the response variable are sampled along with the corresponding values of one or more explanatory variables (Noorossana, Saghaei, & Amiri, 2011a). As an example, the relationship between the amount of aspartame (an artificial sweetener) dissolved per liter of water as a response variable and the temperature level as an explanatory variable can be characterized by a profile. Profile monitoring deals with functional data or curves collected at regular time intervals. Generally, profile monitoring involves the use of various statistical techniques to monitor the process or the product profile. Control charts in the field of profile monitoring aim to quickly detect a possible deviation from a normal profile pattern. The importance of profile monitoring in manufacturing and non-manufacturing environments has led some researchers to focus on this area. One of the most extensive applications of profile monitoring is the calibration of measurement instruments to ascertain their proper performance over time, determine the optimum calibration frequency, and avoid over-calibration.

Because profile monitoring is a relatively new area in statistical process monitoring (SPM), the review paper of Woodall (2007) is a very important contribution. But, since 2008, a large number of papers have been published in the field of profile monitoring and no new review paper, summarizing the recent researches in this domain, has been provided. The goal of this paper is to fill this gap and to provide an up-to-date state of the art survey in the field of profile monitoring

* Corresponding author.
E-mail address: philippe.castagliola@univ-nantes.fr (P. Castagliola).

https://doi.org/10.1016/j.cie.2018.10.008
Received 13 July 2018; Received in revised form 4 October 2018; Accepted 4 October 2018
Available online 06 October 2018
0360-8352/

concerning papers published during the period 2008–2018. The outline of this paper is the following: In Section 2, the survey methodology to search relevant publications and to classify them is described. The conceptual classification scheme to analyze the selected papers is introduced in Section 3. Section 4 classifies the selected papers by considering the four criteria presented in Section 2. In Section 5, the analytic results are discussed. Some recommendations for research directions and future perspectives in profile monitoring are given in Section 6. Finally, conclusion remarks are given in Section 7.

2. Survey methodology

As mentioned in Li and Cavusgil (1995), there are three approaches including "Delphi", "meta-analysis" and "content analysis" to provide an investigation of the state of knowledge in a scientific area. Based on Li and Cavusgil (1995), "*In Delphi method, the experts who are familiar with a subject are surveyed while in meta-analysis method, the empirical studies on the same subject are gathered and statistically analyzed*". In content analysis, a systematic, qualitative and quantitative description of the manifest content of literature is conducted. This method, which is used in this paper, provides unbiased evaluations of the literature and has a potential capability to analyze and categorize studies in a systematic way. In order to conduct a content analysis-based survey, two general steps have to be implemented. In the first step, the survey sources as well as a procedure for searching the relevant documents are determined. The second step is devoted to identify instrumental categories for classifying and analyzing the resulting papers in step 1. The guidelines to establish these steps are discussed in the following subsections.

2.1. Survey sources and literature search procedure

To find the content of our survey through a computerized search, the following keywords have been taken into account: profile monitoring, regression profile, profile analysis, regression coefficients, quality profile, linear profile, nonlinear profile, multivariate profile, multiple linear profile, polynomial profile, generalized liner model (GLM). To collect the sources of our survey, we only focused on journal papers, however, proceedings, books, PhD/MSc dissertations, unpublished researches, etc. have been ignored. For each selected journal paper, the search process is narrowed in a backward and forward way. In the backward way, the references of each selected paper, published during 2008–2018, are assessed and the relevant journal papers are added into the survey. In the forward way, the journal papers that have referred to each selected document are found to be assessed. The journal papers are collected from main platforms/publishers like ScientDirect, John Wiley, Taylor & Francis, Springer link, Emerald Insight, de Gruyter, Growing Science, JSTOR and so on. It is worth to mention that only English written papers are included in this survey.

2.2. Classification procedure of the selected papers

The mentioned guideline in Section 2.1 led us to accept a total of 40 journals containing 195 papers. Here, these papers are analyzed by considering the following four criteria:

1. The number of publications per year in the period of 2008–2018.
2. The number of publications per journal.
3. The name of the author/coauthor.
4. The conceptual classification scheme which will be discussed in Section 3.

3. Presented criteria for the conceptual classification scheme

Here, the conceptual classification scheme containing seven general criteria and the corresponding sub-criteria for each one are discussed and summarized in Table 1. First, each criterion is defined and the possible potential states for each one are detailed.

Table 1
Questions and possible responses.

1. To which area of SPM does the selected paper belong?
   - (1.1) Statistical design of control chart
   - (1.2) Economic design (ED)\economic-statistical design (ESD) of control chart
   - (1.3) Change point estimation
   - (1.4) Analysis of process capability indices
   - (1.5) Parameter estimation
   - (1.6) Diagnosis
   - (1.7) Others
     - (1.7.1) Optimization
     - (1.7.2) Acceptance sampling

2. What type of regression profile is used?
   - (2.1) Linear profile
     - (2.1.1) Simple linear profile
     - (2.1.2) Multiple linear profile
     - (2.1.3) Polynomial Profile
     - (2.1.4) Simple linear Berkson profile
     - (2.1.5) Mixture linear profile
   - (2.2) Nonlinear profile
   - (2.3) Generalized linear model (GLM)-based profile
     - (2.3.1) Logistic profile
     - (2.3.2) Ordinal logistic profile
     - (2.3.3) Nominal logistic profile
     - (2.3.4) Poisson regression profile
     - (2.3.5) Gamma regression profile
     - (2.3.6) Weibull regression profile
   - (2.4) Nonparametric profile
   - (2.5) Others
     - (2.5.1) Geometric profile
       - (2.5.1.1) Roundness profile
         - (2.5.1.1.1) Circular profile
         - (2.5.1.1.2) Cylindrical profile
     - (2.5.2) Unaligned profile
     - (2.5.3) Wave profile
     - (2.5.4) Semiparametric profile

3. What is the type of process?
   - (3.1) Ordinary process
   - (3.2) Autocorrelated process
     - (3.2.1) Within-profile autocorrelation
     - (3.2.2) Between-profile autocorrelation
   - (3.3) Multi-stage process

4. What is the type of response data?
   - (4.1) univariate data
   - (4.2) multivariate data
   - (4.3) fuzzy data

5. Phase I or Phase II?
   - (5.1) Phase I analysis
   - (5.2) Phase II analysis

6. What type of criteria is used to assess the performance of the proposed method?

   Statistical design: Signal probability, ARL, SDRL, SS-ARL, SS-SDRL
   Economic and/or economic-statistical design: ARL_0, ARL_1, Cost, Optimum variables
   Change point estimation: $\bar{\hat{\tau}}$, $SD(\hat{\tau})$ & precision
   Capability analysis: C_{pu}, C^T_{puA}, C^T_{plA}, $C^T_{puA;PC}$
   Parameter estimation: Regression metrics, MSE, R^2, R^2_{adj}
   Other areas: Lot acceptance probability
   Diagnosis: Diagnosis probability, accuracy percent

7. Practical application

   Calibration application, Agriculture field, Optical imaging system, Semiconductor manufacturing industry, Automotive industry, Aluminum electrolytic capacitor manufacturing process, Turning process, Vertical density of particleboard, …

Now, each criteria and the corresponding sub-criteria given in Table 1 is illustrated as follows.

3.1. SPM area

Based on the selected papers, published during the period 2008–2018, seven general profile monitoring categories can be proposed:

- **Statistical design:** The main goal of statistical process monitoring (SPM) is to check the consistency of a process over the time using statistical methods. Control charts are the most effective tools for this aim. Designing control charts by considering some statistical metrics such as the run length (RL)-based characteristics like the average run length (ARL) and the standard deviation of run length (SDRL) is referred to as statistical design of control charts. The purpose of statistical design of control charts for monitoring profiles might include (i) detecting any disturbance occurred in particular features of a profile; (ii) detecting any disturbance in the profile mean; (iii) detecting any disturbance in the variation of the residual profiles, not only changes in noise but also in functional variation; (iv) detecting both persistent disturbances and single outlying profile; and (v) detecting disturbances away from the 'normal' profile toward one of several pre-specified 'abnormal' profiles (Chipman, MacKay, & Steiner, 2010).
- **Economic and/or economic-statistical design:** Determining the optimal parameters of control chart used to analyze the consistency of a profile or a curve by minimizing a cost function is called as "economic design" of profile monitoring control charts. In economic-statistical design of profile monitoring control charts, the chart parameters are calculated such that a cost function is minimized under one or several statistical constraints such as the ARL and average time to signal (ATS).
- **Change point estimation:** The time when a control chart triggers a signal does not usually reflect the real time of the profile change. Identifying the time when a curve or a profile first deviates from its in-control state, referred to as the "change point", is one of the most important post-signal activities. Correct estimation of change point reduces the time and cost of removing the assignable cause(s) and of refining the profile to its normal shape. The proposed estimators in the context of profile monitoring may be classified based on the type of the process change including step change (single step and multiple steps), drift, monotonic (isotonic and antitonic), and sporadic changes. Most of the researches in the context of estimating the time of profile disturbances have been devoted to step changes which is also one of the most potential change types in real applications. This kind of disturbance may occur due to the changing of the shift work or tool breakage. For more information about the change point estimation methods please refer to review paper by Amiri and Allahyari (2012).
- **Capability analysis:** Measuring the capability of the process to meet certain specifications is referred to as "process capability analysis". A process capability index reflects how well a given process fulfills the customer expectations and conforms to prespecified tolerances. The first process capability index in SPM proposed by Kane (1986) is defined as:

$$C_p = \frac{USL-LSL}{6\sigma}, \tag{1}$$

where USL and LSL are the upper and lower specification limits while σ denotes the standard deviation of the process. In the other words, the denominator reflects the actual process capability while the numerator reflects the consumer's quality requirements. After Kane (1986), many indices have been introduced by the researchers to assess the process capability under different assumptions. Until 2007 when Woodall (2007) provided the review paper in the field of profile monitoring, there was no research to assess the process capability in linear or nonlinear profiles. Since that time, some studies have been carried out to introduce some process capability indices for profiles with both univariate and multivariate response data. These publications will be discussed in Sections 4 and 5.

- **Parameter estimation:** As pointed out, the main purpose of Phase I profile monitoring is to estimate the regression coefficients to be used in Phase II analysis. These estimations have to be obtained from a stable in-control process with no outlying profile. In addition, the accuracy of the estimated regression coefficients is highly affected by the properties of the estimators. This issue will be more crucial in some complicated profiles such as nonlinear and GLM profiles where the common methods such as least square estimator cannot be used any longer. On the other hand, Phase II analysis of profiles are based on the assumption of known regression coefficients. However, in practical situations, the regression coefficients are frequently unknown and replaced by Phase I estimates. Hence, it is important to evaluate the effect of regression parameters estimation on the performance of Phase II profile monitoring by quality practitioners both in academic and practical points of view. Recently few attempts have been carried out to assess such effects.
- **Diagnosis:** In profile monitoring applications in both Phases I and II, it is important to find out out-of-control samples or the model coefficient(s) responsible for the process variation after the detection of an out-of-control signal. This capability to diagnose a change in one or more of the model parameters enables a classification of the nature and severity of the change (Mahmoud 2008). We refer the statistical methods to find the contributing parameter(s) as "diagnostic procedures". Utilizing such post-signal procedures also helps the quality practitioners to identify the root causes. As a consequence, eliminating such assignable causes by implementing proper corrective action(s) leads to reduce the process costs.
- **Other: including optimization and acceptance sampling:** Most of the selected papers in this survey except three ones namely, Abdella, Yang, and Alaeddini (2012), Abdella, Yang, and Alaeddini (2014) and Tamirat and Wang (2016) can be classified into one of the afore-mentioned categories. These three papers focused on optimization and acceptance sampling concepts. We have decided to merge these two areas into a specific category named as "other areas".

3.2. Type of profile

Depending on the application, the regression profiles may have different forms.

- **Linear profile:** As the simplest profile model, in many practical applications, quality-related response of interest is linked by a linear function to some independent variables. The linear profiles used in the literature of profile monitoring are now discussed:
  - **Simple linear profile:** In a simple linear profile, the most common one in the literature, the response variable is related to only one independent variable through a linear model. For the jth;$j = 1, 2, \ldots$ sampled profile which is denoted by $\{(x_i, y_{ij}), i = 1, \ldots, n\}$, where n is the number of experimental settings, we have the following model:

$$y_{ij} = \beta_0 + \beta_1 x_i + \varepsilon_{ij}, \tag{2}$$

where β_0 and β_1 are the intercept and slope coefficients, respectively while $\varepsilon_{ij}'s$ are iid normal random variables with mean zero and variance σ^2.

  - **Multiple linear profile:** If a regression profile has a multiple form with p predictor variables, $(x_1, x_2, \ldots, x_p)$, then the following model is used for the quality profile:

$$y_{ij} = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_p x_{ip} + \varepsilon_{ij}, \tag{3}$$

Obviously if $p = 1$, then the model reduces to a simple linear profile. Note that, the above-mentioned assumptions for the random errors held here for this type of profiles.

- **Polynomial profile:** Considering $\beta_0, \beta_1, ..., \beta_k$ as the nominal values of the in-control parameters, the polynomial regression profile of order k is represented by following formulation:

$$y_{ij} = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + ... + \beta_k x_i^k + \varepsilon_{ij}, \tag{4}$$

Similar to simple linear profiles, it is assumed that the errors are independent and identically distributed with a normal distribution. Here, we can also refer to simple linear Berkson profile and mixture linear profile as the other types of linear profiles. See Wang and Huwang (2012) and Wang and Wang (2016) for more information concerning such profiles.

- **Nonlinear profile:** In real-world cases, there exists a particular class of profile data that cannot be adequately represented by any kind of linear function and it is more appropriate to express them by nonlinear models. Generally, a nonlinear profile model is represented as:

$$y_{ij} = f(x_i, \beta) + \varepsilon_{ij}, \tag{5}$$

where f is nonlinear in parameters.

- **GLM profiles:** In some applications of profile monitoring, the normality assumption of the response variable is clearly violated and it is likely to face with discrete response data. Examples include the cases when the product is classified as accepted or defective or when the number of defects is considered as the quality characteristic of interest. To overcome this problem, the generalized linear models have been used to express a profile when the distribution of the response variable belongs to the family of exponential distributions, including the Bernoulli, Binomial, Poisson, Exponential and Gamma distributions. Recently, monitoring GLM profiles has attracted much attention from quality engineering practitioners. The most common types of GLM profiles are discussed as below:
  - **Logistic regression profile:** For the ith; $i = 1, ..., n$ treatment, the logistic regression model considering p predictors is given as:

$$\ln\left(\frac{\pi_i}{1-\pi_i}\right) = \mathbf{X}_i^T \boldsymbol{\beta}, \tag{6}$$

where $\mathbf{X}_i = (x_{i1}, ..., x_{ip})^T$, $\pi_i = p(y_i = 1)$ and $\boldsymbol{\beta} = (\beta_1, ..., \beta_p)^T$.

- Ordinal logistic profile: Sometimes, the response variable in the logistic regression model has a natural order which cannot be represented by a nominal variable. As an example, in a manufacturing application, the quality of a product can be classified as "slightly damaged", "moderately damaged", or "severely damaged". As another example in a service system, the customer satisfaction could be classified as "very low", "low", "moderate", "high", or "very high". Consider an ordinal response variable with categorical levels of $1, ..., K$ and a p-dimensional vector of variables denoted by $\mathbf{x_i} = (x_{i1}, ..., x_{ip})'$. For the ith;$i = 1, ..., n$ treatment, we denote the response vector by $\mathbf{y_i} = (y_{i1}, ..., y_{ik}, ... y_{iK})'$, where $y_{ik} = 0$ or 1 such that $\sum_{k=1}^{K} y_{ik} = 1; i = 1, ..., n$. For the ith;$i = 1, ..., n$ treatment, $\mathbf{y_i}$ follows a multinomial distribution with probability values $\mathbf{y_i} = (\pi_1(\mathbf{x}_i), ..., \pi_k(\mathbf{x}_i), ..., \pi_K(\mathbf{x}_i))'$, where $\sum_{k=1}^{K} \pi_k(\mathbf{x}_i) = 1$. Let $P(\nu_i = j|\mathbf{x_i}) = P(y_{ik} = 1|\mathbf{x}_i) = \pi_k(\mathbf{x}_i)$ and let ν_i denotes the random variable representing the category for which the result of the ith treatment falls in. As in McCullagh (1980), the relationship between an ordinal response variable and the vector of explanatory variables is defined as:

$$\ln\frac{P(\nu_i \leqslant k|\mathbf{x}_i)}{1-P(\nu_i \leqslant k|\mathbf{x}_i)} = \alpha_k + \mathbf{x}_i'\boldsymbol{\beta}, \tag{7}$$

where $\alpha_k; k = 1, ..., K-1$ and $\boldsymbol{\beta} = (\beta_1, ..., \beta_p)'$ are the regression parameters with $\alpha_k = \infty$.

- **Poisson Regression profile:** Sometimes, the discrete response values of interest are count data. As an example, the number of agglomerates ejected from a volcano in successive days as a response variable is a function of the agglomerates diameters as an explanatory variable (Amiri, Koosha, Azhdari, & Wang, 2015). In a Poisson regression model, the intensity parameter is a function of $\mathbf{X}_i^T$ through the following log link function:

$$\ln(\lambda_i) = \mathbf{X}_i^T \boldsymbol{\beta}, \tag{8}$$

The readers are referred to Agresti (2007) for detailed information concerning different types of generalized linear models.

- Nonparametric profile: According to Noorossana et al. (2011a), the parametric regression models are developed based on the assumption that there are parameters relating the structure of the explanatory variable, x_i, to the observed responses y_i. The parametric linear regression models are expressed as:

$$y_i = f(x_i, \boldsymbol{\beta}) + \varepsilon_i, \tag{9}$$

where $\boldsymbol{\beta}$ denotes the vector of regression parameters. The model based on Eq. (9) is not useful under three general cases (1) when the data does not follow a particular assumed parametric form, (2) when the parametric model is incorrectly specified, and (3) when the determination of the correct parametric form is difficult. Due to the mentioned reasons a more general form of profile, called as nonparametric model, is used as:

$$y_i = f(x_i) + \varepsilon_i, \tag{10}$$

- **Others**: As seen in Table 1, the, geometric, unaligned, wave and semiparametric regression profiles are labeled as "others" because they have not been frequently investigated in the literature of profile monitoring. These models are briefly expressed as follows:
  - **Geometric profile:** A geometric profile including roundness, flatness, and cylindricity is related to a two or three-dimensional spaces. This kind of profile is obtained by measuring the quality characteristic of interest in several locations. For more information concerning geometric profile monitoring, please refer to Colosimo, Semeraro, and Pacella (2008), Pacella and Semeraro (2011), Noorossana and Nikoo (2015) as well as Pacella, Grieco, and Blaco (2017)
    - **Roundness profile:** A roundness profile which is also a type of geometric profile includes two general types of circular and cylindrical profiles. A circular feature, in a product such as a shaft or a hole, is one of the most frequently encountered features in manufacturing systems. According to the standard (ISO/TS, 12181) a circular profile is the line extracted on a cross section of a surface of revolution (Pacella and Semeraro, 2011). Concerning the cylindrical profile, Colosimo, Cicorella, Pacella, and Blaco (2014) presented an example of deviations of a real cylindrical surface from the nominal one. Then, they mentioned that a circular profile is obtained by an ideal cross section of cylindrical components.
  - **Unaligned profile:** An unaligned regression profile has the general form of:

$$y_{ij} = g(f(x_{ij})) + \varepsilon_{ij}; i = 1, ..., n_j, j = 1, 2, ... \tag{11}$$

where g is a general function while f is a warping function that maps the explanatory variables of an unaligned profile to another scale so that the profiles become aligned. For detailed information, the interested readers are referred to Zang, Wang, and Jin (2016).

- **Wave profile:** The profiles such as B-spline models which look like a wave are called as wave profiles. According to Chang, Tavakkol, Chou, and Tsai (2014), a wave profile has a general form of:

$$y_i = \exp(a_i x_i^{b_i}). \tag{12}$$

- **Semiparametric profile:** A semiparametric regression model generally combines the advantages of a nonparametric approach (robustness) with the advantages of a parametric approach (efficiency). As a semiparametric scheme, we can refer to the mixed model robust profile monitoring (MMRPM) approach proposed by Abdel-salam, Birch, and Jensen (2013) which is robust to the model misspecification.

3.3. Process type

Different process types in the context of profile monitoring are classified into the following categories.

- Autocorrelated process: Most of the researches in profile monitoring context have assumed that the measurements within a profile or between consecutive profiles are independent. However, due to technology advances and product complexities, this assumption associated with the measurements is satisfied under very restricted laboratory conditions and there is no guarantee to be held in practical applications. Independency assumption may be violated due to the within or between profile autocorrelation. Here, both the mentioned autocorrelation structures are discussed:
  - **Within-profile autocorrelation:** In many industries, the response values are sometimes measured in intervals that are too close to each other which leads to a within-profile autocorrelation structure. As an example for this type of autocorrelation structure, we refer to the within-profile data in the apple trees example noted by Soleimani, Noorossana, and Amiri (2009) or the engine data provided by Amiri, Jensen, and Kazemzadeh (2010) both exhibit obvious serial correlation over time.
  - **Between-profile autocorrelation:** In some cases, between-profile data are autocorrelated due to the fact that the time of sampling between consecutive profiles is short. For example, the error values between successive profiles in an optical imaging system where the relationship between the line width and the measurement position is described by a regression model are autocorrelated.
- **Multi-stage process:** In some production systems, the final units are the output of several consecutive stages which are correlated. In such processes, referred to as “multi-stage” processes, the quality of the products not only depends on the operation condition of its current stage but it is also affected by the outcome of the previous stage(s). This property is referred to as the cascade property of multistage processes.
- **Ordinary process:** Other processes which are not classified as autocorrelated and multi-stage processes are considered in this survey as ordinary processes.

3.4. Type of response data

- **Univariate response:** The most efforts concerning the statistical analysis of different profiles in the literature have been devoted to the case of univariate response data. In this case, which is also the simplest one, only a single response variable is associated to an explanatory variable or to the vector of explanatory variables.
- **Multivariate response:** In some applications, the stability of more than one correlated profiles should be verified during the time. Monitoring this kind of “multivariate profiles” by some separate control charts leads to misleading results due to ignorance of the correlation structure between the response variables. A multivariate multiple linear profile (as a general multivariate regression model) with p response variables and q explanatory variables is defined as:

$$\mathbf{Y}_j = \mathbf{X}\mathbf{B}_j + \mathbf{E}_j, \tag{13}$$

where $\mathbf{Y}_j$ denotes the $n \times p$ matrix of response variables, $\mathbf{B}_j$ is a $(q + 1) \times p$ matrix of regression coefficients and $\mathbf{E}_j$ is the $n \times p$ matrix of error terms which are correlated. Obviously, if $q = 1$, this model reduces to a multivariate simple linear profile, while if $p = 1$, the model will be a multiple linear profile. Also, if $p = q = 1$, this model reduces to a simple linear profile.

- **Fuzzy response**: The traditional control charts to monitor different profiles have assumed that the response data has a crisp nature. In some manufacturing or non-manufacturing systems, however, the response data has a kind of uncertainty, fluctuations, impreciseness and vagueness or they may be “linguistic” type of quality characteristics. In these situations, a fuzzy regression model can be used to adequately represent the profile model.

3.5. Analysis stage

Similar to the other control charts, the profile monitoring approaches in the literature can be designed for Phase I or Phase II stages. The main purpose of the Phase I analysis is to check the statistical stability of the process using a historical data set. Once all assignable causes are accounted for, the regression coefficients are estimated using a set of “clean” profiles. Based on the information in Phase I, the main goal of the Phase II analysis is to detect the process disturbances as quickly as possible before producing lots of defective units.

3.6. Evaluation criterion

As noted, the statistical design of control charts for monitoring different profiles are categorized to Phase I and Phase II methods. For Phase I analysis, the signal probability criterion is used to evaluate the chart performance. This criterion is defined as the probability that, at least, one charted statistic falls outside the control limits interval. To assess the performance of Phase II methods, it is common to use some metrics based on the run-length characteristics of control charts such as the average run length (ARL), the standard deviation of the run length (SDRL), the average number of items observed (ANI), the average time to signal (ATS) and the adjusted average time to signal (AATS). Note that the run length metric is defined as the number of samples taken from the process until an out-of-control signal is detected.

3.7. Practical application

Different profile monitoring approaches have been applied in many applications either manufacturing or service systems. Many authors up to 2007 for example Stover and Brill (1998), Kang and Albin (2000), Mahmoud and Woodall (2004), Woodall, Spitzner, Montgomery, and Gupta (2004), Wang and Tsung (2005), and Woodall (2007) have discussed practical applications of profiles. The application of profile monitoring under different assumptions has been also well documented during the period 2008–2018 as well. Different applications of profile monitoring approaches in the literature during 2008–2018 are reported in the last column of Table 4.

4. Results

Here, the selected papers are analyzed by considering the four criteria mentioned in Section 2. Based on the proposed conceptual classification scheme in this Section, the differences between the selected papers as well as the research gaps will be highlighted in the following sections.

4.1. Number of publications per year

Profile monitoring appears to be more common both in practical and academic points of view since the review paper carried out by Woodall (2007) has been published. As seen in Fig. 1, there has been an increasing trend for papers published in different areas of profile

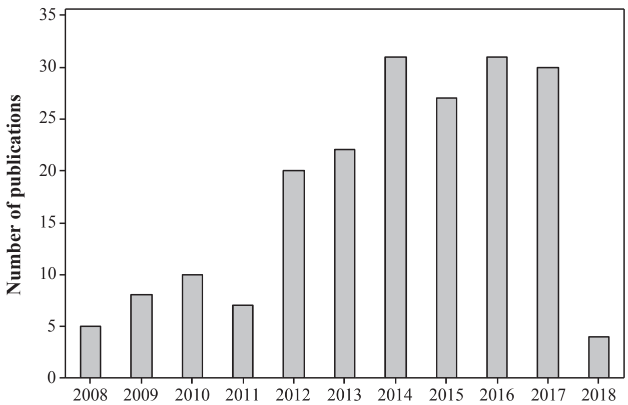

Fig. 1. Distribution of publications from 2008 to 2018.

monitoring during 2008–2018. Fig. 1 indicates that the number of publications has increased from only 5 papers in 2008 to 31 in 2017. This increasing trend is also more noticeable during 2012–2017 as there has been at least 20 publications per year in different areas of the profile monitoring field while during 2008–2011, the maximum number of publications is 10 in 2010.

4.2. Number of publications per journal

The journals containing the selected papers are summarized and sorted in Table 2. It is seen in Table 2 that all 195 selected papers are distributed in 40 different journals. Table 2 shows that in terms of the number of publications per journal, "Quality and Reliability Engineering International" is the journal that published the most papers during 2008–2018. This journal is followed by "Communications in Statistics-Simulation and Computation", "The International Journal of Advanced Manufacturing Technology", "Computers & Industrial Engineering", "Journal of Quality Technology" and Communications in Statistics—Theory and Methods. These five journals cover about 54% of all publications in the area of profile monitoring. Additionally, Table 2 shows how much the editors of some of the major journals in the engineering and statistical fields have been interested in publishing papers in the context of profile monitoring, and it significantly helps the researchers to properly select specific journals for their future works.

4.3. Name of the author/coauthor

The most active researchers in the area of profile monitoring, with at least three journal papers, are listed in Table 3. As seen in terms of number of publications, Amiri, A. has been the most active researcher in the profile monitoring area. He is followed by Noorossana, R., Zou, C., Niaki, S. T. A., and Kazemzadeh, R. B. each of them having published at least 10 articles in this domain. The other researchers have had less than 10 publications. Furthermore, the results in Table 3 can motivate the interested researchers to select proper authors to collaborate with.

Fig. 2 depicts the countries based on the affiliation of the contributing authors for all 195 reviewed papers. As it can be seen, the most active researchers in the field of profile monitoring are from Iran. After that, researchers from USA, China, Taiwan and Italy also have a considerable contribution in this field. Note that the item labeled as "Other" are those countries with less than 3 contributions including France, Greece, Pakistan, Spain with 2 and Costa Rica, Gambia, Malaysia, Oman, Singapore, Tunisia, United Arab Emirates with 1 contribution.

Table 2
Title of journals containing the relevant papers.

Journal title	Frequency
Quality and Reliability Engineering International	44
Communications in Statistics—Simulation and Computation	19
The International Journal of Advanced Manufacturing Technology	17
Computers & Industrial Engineering	14
Communications in Statistics—Theory and Methods	10
Journal of Quality Technology	10
Scientia Iranica	9
IIE Transactions	6
International Journal of Industrial Engineering & Production Research	6
International Journal of Production Research	6
Journal of Statistical Computation and Simulation	5
International Journal of Quality Engineering and Technology	5
International Journal of Engineering	5
Quality Technology & Quantitative Management	4
Journal of Applied Statistics	3
Technometrics	3
Journal of Process Control	2
International Journal of Quality & Reliability Management	2
Journal of Industrial Engineering International	2
Applied Stochastic Models in Business and Industry	2
Statistica Sinica	2
Quality Engineering	1
Economic Quality Control	1
Quality & Quantity	1
Computational Statistics & Data Analysis	1
Expert Systems with Applications	1
International Journal of Productivity and Quality Management	1
Applications & Applied Mathematics	1
Journal of Quality and Reliability Engineering	1
International Journal of Industrial Engineering Computations	1
International Journal of Manufacturing Technology and Management	1
International Journal of Data Analysis Techniques and Strategies	1
Journal of Optimization in Industrial Engineering,	1
Chinese Journal of Mechanical Engineering	1
Annals of Operations Research	1
Decision Science Letters	1
Journal of Chemometrics	1
Iranian Journal of Fuzzy Systems	1
Journal of Engineering Research	1
Journal of the Royal Statistical Society	1

4.4. Presented conceptual classification scheme

The classification of the selected papers with respect to the presented conceptual classification scheme is given in Table 4. For each content, a detailed analysis will be presented in Section 5 and, based on that, the research gaps and the research directions for future studies will be introduced in Section 6.

5. Analytic results

In this section, a comprehensive analysis with respect to each content, namely, SPM area, profile type, process type, type of response quality characteristic, analysis stage and the evaluation index is discussed.

5.1. Analysis of the SPM area

Fig. 3 illustrates the distribution of the selected papers with respect to the SPM area. Note that some of the selected papers have focused on more than one areas. As a consequence, for some papers, there are more than a single tick mark in the columns associated to the SPM area. For example, in Xu et al. (2012), both statistical monitoring and change point estimation have been studied. Hence, in our analysis in Fig. 3, this paper has been classified in both areas. As it can be seen in Fig. 3, with 156 papers, the most frequent area belongs to "statistical design" of

Table 3
Active researchers in the area of profile monitoring.

Author	Affiliation/country	Publications
Amiri, A.	Department of Industrial Engineering, Faculty of Engineering, Shahed University, Tehran, Iran	47
Noorossana, R.	Department of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran	36
Zou, C.	Institute of Statistics and LPMC, Nankai University, Tianjin, China	17
Niaki, S. T. A.	Department of Industrial Engineering, Sharif University of Technology, Tehran, Iran	16
Kazemzadeh, R. B.	Industrial Engineering Department, Faculty of Engineering, Tarbiat Modares University, Tehran, Iran	10
Soleimani, P.	Industrial Engineering Department, South Tehran Branch, Islamic Azad University, Tehran, Iran	9
Khedmati, M.	Department of Industrial Engineering, Sharif University of Technology, Tehran, Iran	8
Saghaei, A.	Industrial Engineering Department, Science and Research Branch, Islamic Azad University, Tehran, Iran	8
Wang, Z.	School of Mathematical Sciences, Nankai University, Tianjin, China	8
Woodall, W. H.	Virginia Polytechnic Institute and State University, Blacksburg, USA	8
Colosimo, B. M.	Dipartimento di Meccanica, Politecnico di Milano, Milan, Italy	7
Aminnayeri, M.	Department of Industrial Engineering, Amirkabir University, Tehran, Iran	6
Birch, J. B.	Virginia Polytechnic Institute and State University, Blacksburg, USA	6
He, Z.	College of Management and Economics, Tianjin University, Tianjin, China	6
Mahmoud, M. A.	Department of Statistics, Cairo University, Cairo, Egypt	6
Pacella, M.	Dipartimento di Ingegneria dell'Innovazione, Università del Salento, Lecce, Italy	6
Tsung, F.	Department of Industrial Engineering and Logistics Management, Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong	6
Wang, Y. H. T.	Department of Statistics, Tamkang University, New Taipei City, Taiwan	6
Yeh, A. B.	Department of Applied Statistics and Operations, Bowling Green State University, Bowling Green, USA	6
Zhang, Y.	School of Business, Tianjin University of Commerce, Tianjin, China	6
Ayoubi, M.	Industrial Engineering Department, Iran University of Science and Technology, Tehran, Iran	5
Huwang, L.	Institute of Statistics, National Tsing Hua University, Hsinchu, Taiwan	5
Sogandi, F.	Department of Industrial Engineering, Amirkabir University, Tehran, Iran	5
Wang, F. K.	Department of Industrial Management, National Taiwan University of Science and Technology, Taipei, Taiwan	5
Eyvazian, M.	Industrial Engineering Department, Iran University of Science and Technology, Tehran, Iran	4
Fan, S. K. S.	Department of Industrial Engineering and Management, National Taipei University of Technology, Taipei City, Taiwan	4
Ghashghaei, R.	Department of Industrial Engineering, Faculty of Engineering, Shahed University, Tehran, Iran	4
Grasso, M.	Dipartimento di Meccanica, Politecnico di Milano, Milan, Italy	4
Izadbakhsh, H.	Industrial Engineering Department, Kharazmi University, Karaj, Iran	4
Jensen, W. A.	W. L. Gore & Associates, Inc., Flagstaff, AZ 86003–2400, U.S.A.	4
Maleki, M. R.	Department of Industrial Engineering, Faculty of Engineering, Shahed University, Tehran, Iran	4
Paynabar, K.	H. Milton Stewart School of Industrial & Systems Engineering, Georgia Institute of Technology, USA	4
Qiu, P.	Department of Biostatistics, University of Florida, USA	4
Shang, Y	College of Management and Economics, Tianjin University, Nankai District, Tianjin, China	4
Sharafi, A.	Department of Industrial Engineering, Amirkabir University, Tehran, Iran	4
Tamirat, Y.	Department of Industrial Management, National Taiwan University of Science and Technology, Taipei, Taiwan	4
Zerehsaz, Y.	Department of Industrial and Operations Engineering, University of Michigan, Ann Arbor, USA	4
Alaeddini, A.	Department of Mechanical Engineering, university of Texas at San Antonio, USA	3
Chang, S. I.,	Department of Industrial and Manufacturing Systems Engineering, Kansas State University, Manhattan, Kansas, USA	3
Chen, Y.	Pfizer Inc., Andover, MA 01810, USA	3
Dorri, M.	Industrial Engineering Department, Islamic Azad University-South Tehran Branch, Tehran, Iran.	3
Abdella, G. M.	Department of Industrial and Systems Engineering, Wayne State University, Detroit- Michigan, USA	3
Hosseinifard, S. Z.	School of Mathematical and Geospatial Sciences, RMIT University, Melbourne, Australia	3
Jen, C. H.	Department of Information Management, Lunghwa University of Science and Technology, Taiwan	3
Jin, J.	Department of Industrial and Operations Engineering, University of Michigan, Ann Arbor, MI, USA	3
Koosha, M.	Industrial Engineering Department, Iran University of Science and Technology, Tehran, Iran	3
Li, Z.	Institute of Statistics and LPMC, Nankai University, Tianjin, China	3
Mahlooji, H.	Department of Industrial Engineering, Sharif University of Technology, Tehran, Iran	3
Nikoo, M.	Industrial Engineering Department, Science and Research Branch, Islamic Azad University, Tehran, Iran	3
Semeraro, Q.	Dipartimento di Meccanica, Politecnico di Milano, Milan, Italy	3
Shahriari, H.	Faculty of Industrial Engineering, K. N. Toosi University of Technology, Tehran, Iran	3
Soleymanian, M. E.	Sauder School of Business, University of British Columbia, Canada	3
Taheriyoun, A. R.	Department of Statistics, Faculty of Mathematical Sciences, Shahid Beheshti University, G.C. Tehran, Iran	3
Tsai, T. R.	Department of Statistics, Tamkang University, Tamsui District, New Taipei, Taiwan	3
Vaghefi, A.	Industrial and System Engineering Department, Rutgers, The State University of New Jersey, Piscataway, USA	3
Vargas, J. A.	Departamento de Estadística, Universidad Nacional de Colombia, Bogotá, Colombia	3
Wang, Q	School of Business, Tianjin University of Commerce, Tianjin, China	3
Yang, S. F.	Department of Statistics, National Chengchi University, Taipei, Taiwan	3
Zhang, M.	College of Management and Economics, Tianjin University, Tianjin, China	3

profile monitoring control charts which is followed by "change point estimation", "Diagnosis" and "process capability analysis" with 35, 22 and 15 papers, respectively. It is concluded that an increasing interest on diagnosis approaches has appeared by quality engineering researchers in recent years. As it can be seen, the number of papers in this subarea has increased from 6 in 2008–2013 to 16 papers in 2014–2018. Fig. 3 also indicates that only three papers have limited their focus on the economic or the economic-statistical design of control charts for profile monitoring. It seems that there have not been adequate efforts in this subarea of profile monitoring. Moreover, these three papers have focused on simple linear profile and the economic and economic-statistical design of other profile types has clearly been ignored in the literature of profile monitoring in the period 2008–2018.

5.2. Analysis of the type of profile

The classification of the selected papers with regard to the type of profile, is depicted in Fig. 4. Note that in Fig. 4, simple linear, multiple linear, polynomial, simple linear Berkson and mixture linear profiles are all classified as "linear profiles". As it can be seen, during 2008–2018, 111 publications over 195 selected ones (57.2% of all reviewed papers) are related to linear profiles. The GLM profiles and the

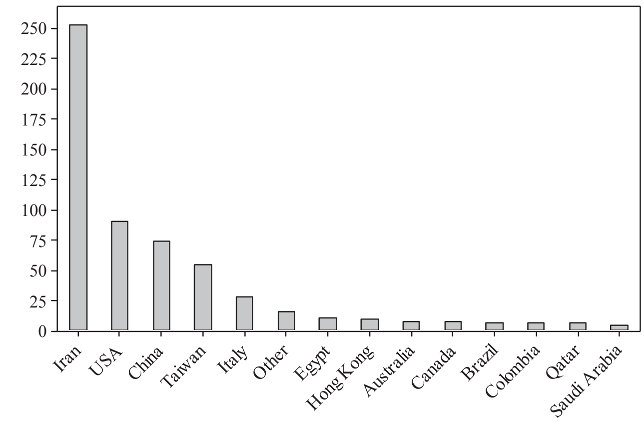

Fig. 2. Number of contributions of each country based on affiliation in 195 reviewed papers.

nonlinear profiles are the second and third frequent models with 33 (17%) and 32 (16.5%) papers, respectively. Recall that geometric, wave, semiparametric and unaligned profiles are all categorized as "others" type of profiles. In the context of GLM profiles, most of the selected researches i.e. 22 out of 33 publications (about 66.7%) are dedicated to different types of logistic regression profiles including ordinary logistic profile, nominal logistic profile as well as ordinal logistic profile. Hence, more efforts on other types of GLM profiles such as Poisson, Gamma and Weibull regression profiles have to be carried out.

5.3. Analysis of the type of the process

The classification of the reviewed papers considering the type of process is depicted in Fig. 5. As seen in Table 4, some researches have limited their efforts on two process types. For example, in Noorossana, Saghaei, and Dorri (2010c), both within-profile and between-profile autocorrelation structures have been discussed. So, we decided to assign this study to both types in our analysis. As seen in Fig. 5, most of the papers (totally 144 ones) have limited their focus on ordinary processes. Concerning monitoring autocorrelated regression profiles, most of the researches have focused on within-profile autocorrelation and it seems that more attentions should be carried out on monitoring profiles considering between-profile autocorrelation. Moreover, most of the researchers have assumed a first order autoregressive model, AR(1), to account for the autocorrelation structure within or between profiles. Other types of time series models such as the moving average (MA), the autoregressive-moving average (ARMA), the autoregressive integrated moving average (ARIMA), the autoregressive conditional heteroskedasticity (ARCH) and the generalized autoregressive conditional heteroscedasticity (GARCH) have been partially or completely ignored by the researchers. Moreover, most of the efforts to monitor autocorrelated profiles have been dedicated to linear profiles. Also, it is seen in Table 4 and Fig. 5 that there is no published paper analyzing profiles in a multi-stage process context in the period of 2008–2013. However, during the period 2014–2017, six papers did appear in this area.

5.4. Analysis of the type of response variable

Here, a classification analysis concerning the type of response variable is provided in Fig. 6. As seen, most of the publications in this regard, i.e. 165 out of 195 reviewed papers (84.6%), have been devoted to the univariate response variable case. This category is followed by the multivariate and fuzzy response data case each with 26 (13.3%) and 4 (2.1%) publications, respectively.

5.5. Analysis of the analysis stage

In this subsection, the analysis stage is analyzed and the results are depicted in Fig. 7. Note that the papers concerning estimating process capability as well as acceptance sampling (totally 15 papers) are classified neither as Phase I nor Phase II. As seen, most of the researches (122 papers) have been performed on Phase II analysis and Phase I analysis of profiles have been investigated in only 37 publications. Also, in 21 researches, both Phases I and II have been studied, simultaneously.

5.6. Analysis of the evaluation criterion

For each paper analyzed in our survey, the metric used to evaluate the performance of the proposed method are reported in the seventh column of Table 4. A seen in the area of statistical design of control charts, signal probability and ARL are the most common metrics for Phase I and Phase II analysis, respectively. For change point estimation, the average and the standard deviation of estimated change point parameter denoted by $\bar{\hat{\tau}}$ and $SD(\hat{\tau})$, respectively are the most common indices. Also in this regard the probability in which the estimated change point parameter lies in the specified tolerances, denoted by $p(|\hat{\tau}-\tau| \leqslant \mathrm{i});\mathrm{i} = 0, 1, 2, 3, 4, 5$ is used in many papers.

5.7. Analysis of the practical application

A seen in the last column of Table 4, different profile monitoring approaches have been applied in various practical applications both in manufacturing and nonmanufacturing cases. We can refer to calibration, agriculture, optical imaging system, semiconductor manufacturing industry, automotive industrial group, Aluminum electrolytic capacitors manufacturing process and vertical density of particleboard as the most frequent applications.

6. Discussion and directions for future studies

In this paper, a conceptual classification scheme for reviewing the papers in profile monitoring area during the period 2008–2018 was carried out. Based on some features, the selected papers were classified. Now, based on the presented content analysis, the main research gaps and potential research directions for future studies are detailed as follows:

1. Different Phase II profile monitoring schemes in the literature are proposed based on the assumption that the regression parameters and the distribution of data are known. However, the process parameters are rarely known and they have to be estimated based on the in-control reference data in Phase I. In this case, when the regression parameters are estimated, the performance of the profile monitoring schemes will differ compared to the known parameters. Before 2008, there is no research to evaluate the effect of parameter estimation on the performance of control charts for monitoring regression profiles. Fortunately, during the period 2008–2018, this effect has been investigated by some few papers namely Mahmoud (2012), Aly, Mahmoud, and Woodall (2015) and Chen, Birch, and Woodall (2016). All these three works have been carried out on univariate response variable. It seems that evaluating the impact of parameter estimation on the control charts designed for monitoring multivariate profiles can be viewed as a potential research area for quality engineering researchers. Moreover, all these works have assumed that the response values within and between profiles are independent. As a consequence, analyzing the performance of autocorrelated profiles when the process parameters are estimated may be fruitful as a future study.
2. In some profile monitoring applications, it is likely to face with linguistic or non-deterministic response variable. As discussed,

Table 4
Classifications of publications in the area of profile monitoring.

Research	Area							Profile type	Process type
	Statistical design	ED\ESD	Change point	Capability analysis	Parameter estimation	Other	Diagnosis		Ordinary
Jensen, Birch, and Woodall (2008)	✓							Linear profile	
Colosimo et al. (2008)	✓				✓			Roundness profile	
Kazemzadeh, Noorossana, and Amiri (2008)	✓		✓					Polynomial Profile	✓
Mahmoud (2008)	✓		✓				✓	Multiple linear profile	✓
Noorossana, Amiri, and Soleimani (2008)	✓							Simple linear profile	
Kazemzadeh, Noorossana, and Amiri (2009)	✓							Polynomial Profile	✓
Saghaei, Mehrjoo, and Amiri (2009)	✓							Simple linear profile	✓
Shiau, Huang, Lin, and Tsai (2009)	✓							Nonlinear profile	
Soleimani et al. (2009)	✓							Simple linear profile	
Vaghefi, Tajbakhsh, and Noorossana (2009)	✓							Nonlinear profile	✓
Yeh, Huwang, and Li (2009)	✓							Logistic profile	✓
Zhang, Li, and Wang (2009)	✓							Simple linear profile	✓
Zou, Qiu, and Hawkins (2009)	✓							Nonparametric profile	✓
Amiri et al. (2010)	✓							Polynomial profile	
Chang and Yadama (2010)	✓							Nonlinear profile	✓
Ho, El Said, and Kim (2010)	✓				✓		✓	Simple linear profile	✓
Li and Wang (2010)	✓							Simple linear profile	✓
Mahmoud, Morgan, and Woodall (2010)	✓		✓				✓	Simple linear profile	✓
Noorossana, Eyvazian, Amiri, and Mahmoud (2010a)	✓							Multiple linear profile	✓
Noorossana, Eyvazian, and Vaghefi (2010b)	✓							Simple linear profile	✓
Noorossana et al. (2010c)	✓							Simple linear profile	
Qiu and Zou (2010)	✓							Nonparametric profile	✓
Qiu, Zou, and Wang (2010)	✓							Nonparametric profile	
Eyvazian, Noorossana, Saghaei, and Amiri (2011)	✓							Multiple linear profile	✓
Fan, Yao, Chang, and Jen (2011)	✓		✓		✓			Nonlinear profile	✓
Hosseinifard, Abdollahian, and Zeephongsekul (2011)	✓							Linear profile	✓
Noorossana, Vaghefi, and Dorri (2011b)	✓							Simple linear profile	✓
Pacella and Semeraro (2011)	✓							Roundness profile	✓
Paynabar and Jin (2011)	✓		✓					Nonlinear profile	
Shang, Tsung, and Zou (2011)	✓							Logistic profile	✓
Abdella et al. (2012)						✓		Polynomial profile	✓
Amiri, Eyvazian, Zou, and Noorossana (2012)	✓							Multiple linear profile	✓
Ebadi and Amiri (2012)				✓				Simple linear profile	✓
Hosseinifard and Abbasi (2012a)				✓				Simple linear profile	✓

(continued on next page)

Table 4 (*continued*)

Research	Area							Profile type	Process type
	Statistical design	ED\ESD	Change point	Capability analysis	Parameter estimation	Other	Diagnosis		Ordinary
Hosseinifard and Abbasi (2012b)				✓				Simple linear profile	✓
Hung, Tsai, Yang, Chuang, and Tseng (2012)	✓							Nonparametric profile	
Mahmoud (2012)	✓							Simple linear profile	✓
Neto and De Magalhães (2012)	✓							Nonlinear profile	✓
Noghondarian and Ghobadi (2012)	✓							Simple linear profile	✓
Noorossana and Ayoubi (2012)	✓							Simple linear profile	✓
Paynabar, Jin, and Yeh (2012)	✓		✓					Logistic profile	✓
Saghaei, Rezazadeh-Saghaei, Noorossana, and Dorri (2012)	✓							Logistic profile	✓
Sharafi, Aminnayeri, and Amiri (2012)			✓					Logistic profile	✓
Soleimani and Noorossana (2012)	✓							Simple linear profile	
Wang and Huwang (2012)	✓		✓				✓	Simple linear Berkson profile	✓
Xu et al. (2012)	✓		✓					Multiple linear profile	✓
Yu, Zou, and Wang (2012)							✓	Nonlinear profile	✓
Zhang, He, Fang, and Zhang (2012)	✓							Nonlinear profile	✓
Zi, Zou, and Tsung (2012)	✓							Multiple linear profile	✓
Zou, Ning, and Tsung (2012)	✓							Multiple linear profile	✓
Abdel-Salam et al. (2013)	✓							Semiparametric profile	
Amiri, Mehrjoo, and Pasek (2013)	✓							Simple linear profile	✓
Amiri and Moein (2013)	✓							Simple/multiple linear profile	✓
Chuang, Hung, Tsai, and Yang (2013)	✓							Nonparametric profile	
Ebadi and Shahriari (2013)				✓				Simple linear profile	✓
Fan, Chang, and Aidara (2013)	✓				✓			Nonlinear profile	✓
Gani and Limam (2013)	✓							Simple linear profile	✓
Keramatpour, Niaki, Khedmati, and Soleymanian (2013)	✓		✓					Polynomial profile	
Koosha and Amiri (2013)	✓							Logistic profile	
Narvand, Soleimani, and Raissi (2013)	✓							Linear profile	
Nikoo and Noorossana (2013)	✓							Nonlinear profile	✓
Noorossana, Aminnayeri, and Izadbakhsh (2013a)	✓							Ordinal logistic profile	✓
Noorossana, Saghaei, Izadbakhsh, and Aghababaei (2013b)	✓							Nominal logistic profile	✓
Paynabar, Jin, and Pacella (2013)							✓	Nonlinear profile	
Sharafi, Aminnayeri, and Amiri (2013a)			✓					Poisson profile	✓
Sharafi, Aminnayeri, Amiri, and Rasouli (2013b)			✓					Logistic profile	✓
Sheu, Ouyoung, and Hsu (2013)	✓							Nonlinear profile	

(*continued on next page*)

Table 4 (*continued*)

Research	Area							Profile type	Process type
	Statistical design	ED\ESD	Change point	Capability analysis	Parameter estimation	Other	Diagnosis		Ordinary
Soleimani, Narvand, and Raissi (2013a)	✓							Linear profile	
Soleimani, Noorossana, and Niaki (2013b)	✓							Simple linear profile	
Soleymanian, Khedmati, and Mahlooji (2013)	✓							Logistic profile	✓
Yeh and Zerehsaz (2013)	✓							Simple linear profile	✓
Zand, Yazdanshenas, and Amiri (2013)			✓					Logistic profile	✓
Abdella et al. (2014)	✓					✓		Simple linear profile	✓
Adibi, Montgomery, and Borror (2014a)	✓							Multiple linear profile	✓
Adibi, Montgomery, and Borror (2014b)	✓							Simple linear profile	✓
Amiri and Mohebbi (2014)		✓						Simple linear profile	✓
Amiri, Saghaei, Mohseni, and Zerehsaz (2014a)							✓	Multiple linear profile	✓
Amiri, Zou, and Doroudyan (2014b)	✓							Simple linear profile	✓
Ayoubi, Kazemzadeh, and Noorossana (2014)			✓					Multiple linear profile	✓
Chang et al. (2014)	✓							Wave profile	✓
Chou, Chang, and Tsai (2014)	✓							Nonlinear profile	✓
Colosimo et al. (2014)	✓							Cylindrical profile	
Farahani, Noorossana, and Koosha (2014)	✓							Simple linear profile	✓
Ghahyazi et al. (2014)	✓							Simple linear profile	
Ghobadi, Noghondarian, Noorossana, and Mirhosseini (2014)	✓							Simple linear profile	✓
Grasso, Colosimo, and Pacella (2014)	✓						✓	Nonlinear profile	✓
Huwang, Wang, and Shen (2014a)	✓							Multiple linear profile	✓
Huwang, Wang, Xue, and Zou (2014b)	✓		✓				✓	Multiple linear profile	✓
Jen and Fan (2014)	✓				✓			Nonlinear profile	✓
Keramatpour, Niaki, and Amiri (2014)	✓							Polynomial profile	
Nemati Keshteli, Kazemzadeh, Amiri, and Noorossana (2014a)				✓				Simple linear profile	✓
Nemati Keshteli, Kazemzadeh, Amiri, and Noorossana (2014b)				✓				Circular profile	✓
Noorossana, Izadbakhsh, and Nayebpour (2014a)	✓							Ordinal logistic profile	✓
Noorossana, Niaki, and Ershadi (2014b)		✓						Simple linear profile	✓
Sharafi, Aminnayeri, and Amiri (2014)			✓					Logistic profile	✓
Sogandi and Amiri (2014a)			✓					Gamma profile	✓

(*continued on next page*)

Table 4 (*continued*)

Research	Area							Profile type	Process type
	Statistical design	ED\ESD	Change point	Capability analysis	Parameter estimation	Other	Diagnosis		Ordinary
Sogandi and Amiri (2014b)			✓					Gamma profile	✓
Soleimani and Noorossana (2014)	✓							Simple linear profile	
Viveros-Aguilera, Steiner, and MacKay (2014)	✓							Circular profile	✓
Wang and Tamirat (2014)				✓				Simple linear profile	
Zhang, He, Shan, and Zhang (2014a)	✓							Simple linear profile	✓
Zhang, He, Zhang, and Woodall (2014b)	✓							Simple linear profile	
Zou, Tseng, and Wang (2014)	✓							Nonlinear profile	✓
Aly et al. (2015)	✓							Simple Linear profile	✓
Amiri et al. (2015)	✓							Poisson profile	✓
Atashgar, Amiri, and Nejad (2015)	✓						✓	Nonlinear profile	✓
Cano, Moguerza, Psarakis, and Yannacopoulos (2015)	✓							Nonlinear profile	✓
Chen, Birch, and Woodall (2015a)	✓				✓			Nonparametric profile	✓
Chen, Birch, and Woodall (2015b)					✓			Polynomial profile	
Colosimo, Meneses, and Semeraro (2015)	✓				✓			Nonparametric profile	
Guevara and Vargas (2015)				✓				Nonlinear profile	✓
Hadidoust, Samimi, and Shahriari (2015)	✓		✓					Nonlinear profile	✓
Kazemzadeh, Noorossana, and Ayoubi (2015)			✓					Multiple linear profile	✓
Khedmati and Niaki (2015)			✓					Simple Linear profile	
Mahmoud, Saad, and El Shaer (2015)	✓							Multiple linear profile	✓
McGinnity, Chicken, and Pignatiello (2015)	✓							Nonlinear profile	✓
Moghadam, Raissi Ardali, and Amirzadeh (2015)	✓							Simple linear profile	✓
Niaki, Khedmati, and Soleymanian (2015)	✓							Simple linear profile	
Nikoo and Noorossana (2015)	✓							Nonlinear profile	✓
Noorossana, Fatemi, and Zerehsaz (2015a)	✓							Simple linear profile	✓
Noorossana, Niaki, and Izadbakhsh (2015b)	✓							Nominal logistic profile	✓
Noorossana and Nikoo (2015)	✓							Geometric profile	
Noorossana and Zerehsaz (2015)	✓							Simple linear profile	✓
Riaz and Touqeer (2015)	✓							Simple/multiple linear profile	✓
Shadman, Mahlooji, Yeh, and Zou (2015)	✓		✓					GLM profile	✓
Vakilian, Amiri, and Sogandi (2015)			✓					Simple linear profile	
Wang and Tamirat (2015)				✓				Simple linear profile	

(*continued on next page*)

Table 4 (*continued*)

Research	Area							Profile type	Process type
	Statistical design	ED\ESD	Change point	Capability analysis	Parameter estimation	Other	Diagnosis		Ordinary
Xu, Peng, and Reynolds (2015)	✓		✓					Multiple linear profile	✓
Zeng and Chen (2015)	✓				✓			Polynomial profile	✓
Zhang, Ren, Yao, Zou, and Wang (2015)	✓				✓			Nonlinear profile	✓
Abdella, Kim, Al-Khalifa, and Hamouda (2016)	✓							Polynomial profile	✓
Amiri, Khosravi, and Ghashghaei (2016)	✓							Simple linear profile	✓
Ayoubi, Kazemzadeh, and Noorossana (2016)			✓					Multiple linear profile	✓
Chen et al. (2016)	✓							Polynomial profile	✓
De Magalhães and Von Doellinger (2016)	✓							Simple linear profile	✓
Ershadi, Noorossana, and Niaki (2016)		✓						Simple linear profile	✓
Grasso, Menafoglio, Colosimo, and Secchi (2016)	✓							Nonlinear profile	✓
Guevara and Vargas (2016)				✓				Nonlinear profile	✓
Huwang, Wang, Yeh, and Huang (2016)	✓		✓				✓	Ordinal/nominal logistic profile	✓
Jensen, Grimshaw, and Espen (2016)	✓							Nonlinear profile	✓
Kamranrad and Amiri (2016)	✓							Simple linear profile	
Karimi Ghartemani, Noorossana, and Niaki (2016)				✓				Simple linear profile	✓
Kazemzadeh et al. (2016a)	✓							Simple linear profile	✓
Kazemzadeh, Amiri, and Mirbeik (2016b)			✓					Simple linear profile	
Khedmati and Niaki (2016a)	✓						✓	Simple linear profile	
Khedmati and Niaki (2016b)	✓						✓	Simple linear profile	
Khedmati and Niaki (2016c)	✓							Multiple linear profile	
Moghadam, Raissi Ardali, and Amirzadeh (2016)	✓							Simple linear profile	✓
Noorossana, Aminmadani, and Saghaei (2016)	✓							Simple linear profile	✓
Panza and Vargas (2016)	✓							Weibull profile	✓
Paynabar et al. (2016)	✓		✓				✓	Nonlinear profile	✓
Qi, Wang, Zi, and Li (2016)	✓							Poisson profile	✓
Abbasi Charkhi, M., Aminnayeri, M., and Amiri, A. (2016)				✓				Logistic profile	✓
Shahriari, Ahmadi, and Samimi (2016)					✓			Nonlinear profile	✓
Shang, Man, He, and Ren (2016)	✓		✓				✓	Logistic profile	✓
Tamirat and Wang (2016)						✓		Simple linear profile	
Wang (2016)				✓				Simple linear profile	✓
Wang and Tamirat (2016)				✓				Simple linear profile	✓
Wang and Wang (2016)	✓							Mixture simple linear profile	✓
Zang et al. (2016)	✓							Unaligned profile	✓

(continued on next page)

Table 4 (*continued*)

Research	Area							Profile type	Process type
	Statistical design	ED\ESD	Change point	Capability analysis	Parameter estimation	Other	Diagnosis		Ordinary
Zhang, He, Zhang, and Wang (2016)	✓							Simple linear profile	✓
Amiri, Sogandi, and Ayoubi (2017)	✓							Linear/GLM profile	✓
Awad (2017)	✓				✓			Polynomial profile	✓
Chiang, Lio, and Tsai (2017)	✓			✓				Simple linear profile	
Ding, Tsung, and Li (2017)	✓							Ordinal logistic profile	✓
Esmaeeli et al. (2017)	✓						✓	Simple linear profile	
Fan, Jen, and Lee (2017)	✓				✓			Nonlinear profile	✓
Ghashghaei and Amiri (2017a)	✓						✓	Multiple linear profile	✓
Ghashghaei and Amiri (2017b)	✓						✓	Multiple linear profile	✓
Ghashghaei, Amiri, and Khosravi (2018)	✓							Multiple linear profile	✓
Grasso, Colosimo, and Tsung (2017)	✓							Nonlinear profile	✓
Hakimi et al. (2017)	✓				✓			Logistic profile	✓
Kalaei et al. (2017)	✓							Simple linear profile	
Khedmati and Niaki (2017)	✓							Linear profile	
Maleki et al. (2017a)	✓							Logistic profile	
Maleki et al. (2017b)			✓					Logistic profile	
Maleki et al. (2017c)	✓		✓					Poisson Profile	
Motasemi, Alaeddini, and Zou (2017)	✓							Multiple linear profile	✓
Nie and Du (2017)	✓		✓					Polynomial profile	✓
Pacella et al. (2017)	✓						✓	Roundness profile	✓
Pini, Vantini, Colosimo, and Grasso (2017)	✓							Nonlinear profile	
Riaz, Mahmood, Abbasi, Abbas, and Ahmad (2017)	✓							Simple linear profile	✓
Sayyad, Niaki, and Afshar-Najafi (2017)	✓							Simple linear profile	✓
Shadman, Zou, Mahlooji, and Yeh (2017)	✓		✓				✓	GLM profile	✓
Sogandi and Amiri (2017)			✓					GLM profile	✓
Taghipour, Amiri, and Saghaei (2017)	✓							Simple linear profile	
Wang and Huang (2017)	✓		✓					Simple linear profile	
Xia and Tsung (2017)	✓						✓	Multiple linear profile	✓
Yang, Zou, and Wang (2017)	✓							Nonparametric profile	✓
Zhang, Shang, Gao, and Wang (2017a)	✓							Simple linear profile	✓
Zhang, Shang, He, and Wang (2017b)	✓							Simple linear profile	✓
Cheng and Yang (2018)	✓							Multiple linear profile	
Gomaa and Birch (2018)	✓						✓	Nonlinear profile	
Khosravi and Amiri (2018)	✓							Logistic profile	✓
Maleki, Castagliola, Amiri, and Khoo (2018)	✓							Poisson profile	✓

(*continued on next page*)

Table 4 (*continued*)

Research	Process type			Type of response data			Phase		Performance criterion	Practical application
	Correlated		Multi-stage							
	Within	Between		Univarite	Multivarite	Fuzzy	I	II		
Jensen, Birch, and Woodall (2008)	✓			✓			✓		Signal probability	Calibration application
Colosimo et al. (2008)		✓		✓				✓	ARL, estimated parameters	Turning process
Kazemzadeh, Noorossana, and Amiri (2008)				✓			✓		Signal probability, $\bar{\hat{\tau}}$, $SD(\hat{\tau})$ & precision	–
Mahmoud (2008)				✓			✓		Signal probability	Calibration application
Noorossana, Amiri, and Soleimani (2008)		✓		✓				✓	ARL	–
Kazemzadeh, Noorossana, and Amiri (2009)				✓				✓	ARL	–
Saghaei, Mehrjoo, and Amiri (2009)				✓				✓	ARL	–
Shiau, Huang, Lin, and Tsai (2009)	✓			✓			✓	✓	ARL	Vertical density profiles
Soleimani et al. (2009)	✓			✓				✓	ARL	Agriculture field
Vaghefi, Tajbakhsh, and Noorossana (2009)				✓				✓	ARL	Pharmaceutical industry
Yeh, Huwang, and Li (2009)				✓			✓		Signal probability	Aircraft construction
Zhang, Li, and Wang (2009)				✓				✓	ARL	Optical imaging system
Zou, Qiu, and Hawkins (2009)				✓				✓	ARL & SDRL	Semiconductor manufacturing industry
Amiri et al. (2010)	✓			✓			✓		Regression metric, R^2_{adj}	Automotive industrial group
Chang and Yadama (2010)				✓				✓	ARL	Forging tonnage profiles
Ho, El Said, and Kim (2010)				✓			✓		Regression metric	Market risk
Li and Wang (2010)				✓				✓	AATS	Optical imaging system
Mahmoud, Morgan, and Woodall (2010)				✓				✓	SS-ARL & SS-SDRL	–
Noorossana, Eyvazian, Amiri, and Mahmoud (2010a)					✓		✓		Signal probability	Calibration application
Noorossana, Eyvazian, and Vaghefi (2010b)					✓			✓	ARL	Calibration application
Noorossana et al. (2010c)	✓	✓		✓				✓	ARL	–
Qiu and Zou (2010)				✓				✓	ARL, SDRL	Semiconductor Application
Qiu, Zou, and Wang (2010)	✓			✓				✓	ARL & SDRL	Aluminum electrolytic capacitor manufacturing process
Eyvazian, Noorossana, Saghaei, and Amiri (2011)					✓			✓	ARL	Calibration application

(*continued on next page*)

Table 4 (*continued*)

Research	Process type			Type of response data			Phase		Performance criterion	Practical application
	Correlated		Multi-stage							
	Within	Between		Univarite	Multivarite	Fuzzy	I	II		
Fan, Yao, Chang, and Jen (2011)				✓			✓	✓	AIC, SIC, ARL	Fluorescence anisotropy of phospholipid in liver of a marine fish
Hosseinifard, Abdollahian, and Zeephongsekul (2011)				✓				✓	ARL	–
Noorossana, Vaghefi, and Dorri (2011b)				✓				✓	ARL	–
Pacella and Semeraro (2011)				✓				✓	ARL	Turning process
Paynabar and Jin (2011)	✓	✓		✓			✓		Signal probability & $\bar{\hat{\tau}}$, $SD(\hat{\tau})$	Engine head assembly process.
Shang, Tsung, and Zou (2011)				✓				✓	ARL & SDRL	Electronic industry
Abdella et al. (2012)				✓				✓	ARL	–
Amiri, Eyvazian, Zou, and Noorossana (2012)				✓				✓	ARL	–
Ebadi and Amiri (2012)					✓		–			
S_{pk}^{T}, $[\hat{C}_{PM}, PV, LI]$, $M\hat{C}_{pc}$										
Hosseinifard and Abbasi (2012a)				✓			–		C_{pu}	Food industry
Hosseinifard and Abbasi (2012b)				✓			–		C_{pu}	–
Hung, Tsai, Yang, Chuang, and Tseng (2012)	✓			✓			✓	✓	Type I and II errors	AIDS data
Mahmoud (2012)				✓				✓	ARL & SDRL	–
Neto and De Magalhães (2012)				✓			✓		Type I and II errors	Wood board production
Noghondarian and Ghobadi (2012)						✓	✓		Similarity index	Customer satisfaction
Noorossana and Ayoubi (2012)				✓				✓	ARL & SDRL	–
Paynabar, Jin, and Yeh (2012)				✓			✓		Signal probability & $\bar{\hat{\tau}}$, $SD(\hat{\tau})$	Cardiac surgery
Saghaei, Rezazadeh-Saghaei, Noorossana, and Dorri (2012)				✓				✓	ARL	Press machining
Sharafi, Aminnayeri, and Amiri (2012)				✓				✓	$\bar{\hat{\tau}}$, $SD(\hat{\tau})$ & precision	–
Soleimani and Noorossana (2012)	✓				✓			✓	ARL	–
Wang and Huwang (2012)				✓				✓	ARL, $\bar{\hat{\tau}}$, $SD(\hat{\tau})$ & precision, Diagnosis percentage	Semiconductor manufacturing industry
Xu et al. (2012)				✓				✓	ATS & $\hat{\tau}$	Optical imaging system
Yu, Zou, and Wang (2012)				✓				✓	Test power, accuracy measure	Aluminum electrolytic capacitor manufacturing process

(*continued on next page*)

Table 4 (*continued*)

Research	Process type: Correlated: Within	Process type: Correlated: Between	Process type: Multi-stage	Type of response data: Univarite	Type of response data: Multivarite	Type of response data: Fuzzy	Phase: I	Phase: II	Performance criterion	Practical application
Zhang, He, Fang, and Zhang (2012)				✓				✓	ARL	Blade manufacturing process
Zi, Zou, and Tsung (2012)				✓				✓	ARL & SDRL	Aluminum electrolytic capacitor manufacturing process
Zou, Ning, and Tsung (2012)					✓			✓	ARL & SDRL	Logistic company
Abdel-Salam et al. (2013)	✓			✓			✓		SIMSE & Signal probability	Automobile engine data
Amiri, Mehrjoo, and Pasek (2013)				✓				✓	ARL	–
Amiri and Moein (2013)				✓			✓		Accuracy percent	Calibration application
Chuang, Hung, Tsai, and Yang (2013)	✓			✓			✓	✓	ARL, SDRL & ATS	AIDS data
Ebadi and Shahriari (2013)				✓			–		$\hat{C}_{PKA}$ & $\hat{C}_{PM}$	–
Fan, Chang, and Aidara (2013)				✓			✓	✓	Regression metric & ARL	Reflow process data
Gani and Limam (2013)				✓				✓	ARL	–
Keramatpour, Niaki, Khedmati, and Soleymanian (2013)	✓			✓				✓	ARL, $\bar{\hat{\tau}}$, $SD(\hat{\tau})$ & precision	Automobile engine data
Koosha and Amiri (2013)	✓			✓			✓		Signal probability	–
Narvand, Soleimani, and Raissi (2013)	✓			✓				✓	ARL	Agricultural field
Nikoo and Noorossana (2013)				✓				✓	ARL	Vertical density of particleboard
Noorossana, Aminnayeri, and Izadbakhsh (2013a)				✓				✓	ARL	Customer satisfaction/ livestock farm building
Noorossana, Saghaei, Izadbakhsh, and Aghababaei (2013b)				✓				✓	ARL	Alloy fasteners manufacturing
Paynabar, Jin, and Pacella (2013)	✓				✓		✓		Eigen vectors & hierarchical bayes based classifiers	Forging process
Sharafi, Aminnayeri, and Amiri (2013a)				✓				✓	$\bar{\hat{\tau}}$, $SD(\hat{\tau})$ & precision	–
Sharafi, Aminnayeri, Amiri, and Rasouli (2013b)				✓				✓	$\bar{\hat{\tau}}$, $SD(\hat{\tau})$ & precision	–
Sheu, Ouyoung, and Hsu (2013)	✓			✓				✓	Signal probability	Vertical density of particleboard
Soleimani, Narvand, and Raissi (2013a)	✓			✓				✓	ARL	Agriculture field
Soleimani, Noorossana, and Niaki (2013b)	✓				✓			✓	ARL	Machining process
Soleymanian, Khedmati, and Mahlooji (2013)				✓				✓	ARL & SDRL	Soft drink manufacturing

(*continued on next page*)

Table 4 (*continued*)

Research	Process type			Type of response data			Phase		Performance criterion	Practical application
	Correlated		Multi-stage							
	Within	Between		Univarite	Multivarite	Fuzzy	I	II		
Yeh and Zerehsaz (2013)				✓			✓		Signal probability	Rocket motor manufacturing
Zand, Yazdanshenas, and Amiri (2013)				✓			✓		$\bar{\hat{\tau}}$, $SD(\hat{\tau})$ & precision	Aircraft construction
Abdella et al. (2014)				✓				✓	ATS	–
Adibi, Montgomery, and Borror (2014a)				✓				✓	ARL	–
Adibi, Montgomery, and Borror (2014b)				✓				✓	ARL	–
Amiri and Mohebbi (2014)				✓				✓	ARL_0, ARL_1, cost, optimum variables	–
Amiri, Saghaei, Mohseni, and Zerehsaz (2014a)					✓			✓	Accuracy percent	Automotive industrial group
Amiri, Zou, and Doroudyan (2014b)				✓				✓	ARL	Aluminum electrolytic capacitor manufacturing process
Ayoubi, Kazemzadeh, and Noorossana (2014)					✓			✓	$\bar{\hat{\tau}}$ & precision	Automotive industrial group
Chang et al. (2014)				✓			✓	✓	Type I Type and II errors, sensitivity, specificity, accuracy, detecting time	Curing process
Chou, Chang, and Tsai (2014)					✓		✓	✓	ARL	Curing process
Colosimo et al. (2014)	✓			✓				✓	ARL, SDRL	Lathe turning
Farahani, Noorossana, and Koosha (2014)				✓				✓	ARL	–
Ghahyazi et al. (2014)			✓	✓				✓	ARL	–
Ghobadi, Noghondarian, Noorossana, and Mirhosseini (2014)						✓	✓		Signal probability	Tourism industry
Grasso, Colosimo, and Pacella (2014)					✓		✓	✓	ARL, confidence intervals, cumulative explained variance, fault detection percentages	Industrial sensor fusion application
Huwang, Wang, and Shen (2014a)				✓				✓	ARL	Aluminum electrolytic capacitor manufacturing process
Huwang, Wang, Xue, and Zou (2014b)				✓				✓	ARL, SDRL, $\bar{\hat{\tau}}$, $SD(\hat{\tau})$, precision & accuracy percent	Semiconductor manufacturing industry
Jen and Fan (2014)				✓			✓	✓	Regression metric & ARL	Reflow process
Keramatpour, Niaki, and Amiri (2014)	✓			✓				✓	ARL	–

(continued on next page)

Table 4 (*continued*)

Research	Process type			Type of response data			Phase		Performance criterion	Practical application
	Correlated		Multi-stage							
	Within	Between		Univarite	Multivarite	Fuzzy	I	II		
Nemati Keshteli, Kazemzadeh, Amiri, and Noorossana (2014a)				✓			–		C_P, C_{PK}, C_{PL}	–
Nemati Keshteli, Kazemzadeh, Amiri, and Noorossana (2014b)				✓			–		C_P & C_{PK}	Automotive industrial group
Noorossana, Izadbakhsh, and Nayebpour (2014a)				✓				✓	ARL	Tourism industry
Noorossana, Niaki, and Ershadi (2014b)				✓				✓	ARL_0, ARL_1, cost, optimum variables	–
Sharafi, Aminnayeri, and Amiri (2014)				✓				✓	$\hat{\bar{\tau}}$, $SD(\hat{\tau})$ & precision	–
Sogandi and Amiri (2014a)				✓				✓	$\hat{\bar{\tau}}$, $SD(\hat{\tau})$ & precision	–
Sogandi and Amiri (2014b)				✓				✓	$\hat{\bar{\tau}}$, $SD(\hat{\tau})$ & precision	Injection process
Soleimani and Noorossana (2014)		✓			✓			✓	ARL	–
Viveros-Aguilera, Steiner, and MacKay (2014)					✓		✓	✓	ARL	–
Wang and Tamirat (2014)		✓		✓			–		$S_{pkA;AR(1)}$	Optical imaging system
Zhang, He, Shan, and Zhang (2014a)				✓				✓	ARL	–
Zhang, He, Zhang, and Woodall (2014b)	✓			✓				✓	ARL	–
Zou, Tseng, and Wang (2014)	✓			✓			✓		Type I and Type II errors	Semiconductor manufacturing industry
Aly et al. (2015)				✓				✓	SDARL	–
Amiri et al. (2015)				✓			✓		Signal probability	Volcano
Atashgar, Amiri, and Nejad (2015)				✓				✓	ARL, correct classification	–
Cano, Moguerza, Psarakis, and Yannacopoulos (2015)				✓			✓	✓	SDRL, ATS	Wood manufacturing, stamping, forging & aluminum electrolytic capacitator process
Chen, Birch, and Woodall (2015a)				✓			✓		Correct classification, signal probability	Automotive industrial group
Chen, Birch, and Woodall (2015b)	✓			✓			✓		FCC, sensitivity, specificity, FPR, FNR, POS	Automotive engine
Colosimo, Meneses, and Semeraro (2015)	✓			✓				✓	ARL, SDARL, Type II error	Vertical density of particleboard
Guevara and Vargas (2015)				✓			–		$C_{pu(prf)}$, $C_{pl(prf)}$, $C_{p(prf)}$, $C_{pk(prf)}$	Vertical density of particleboard
Hadidoust, Samimi, and Shahriari (2015)				✓				✓	ARL, SDRL, $\hat{\bar{\tau}}$, $SD(\hat{\tau})$	Vertical density of particleboard

(*continued on next page*)

Table 4 (*continued*)

Research	Process type			Type of response data			Phase		Performance criterion	Practical application
	Correlated		Multi-stage							
	Within	Between		Univarite	Multivarite	Fuzzy	I	II		
Kazemzadeh, Noorossana, and Ayoubi (2015)					✓			✓	$\bar{\hat{\tau}}$ & Precision	Calibration application
Khedmati and Niaki (2015)	✓			✓				✓	$\bar{\hat{\tau}}$, $SD(\hat{\tau})$ & precision	–
Mahmoud, Saad, and El Shaer (2015)				✓				✓	ARL	–
McGinnity, Chicken, and Pignatiello (2015)				✓				✓	ARL, SDRL	Vertical density of particleboard
Moghadam, Raissi Ardali, and Amirzadeh (2015)						✓		✓	ARL	Ceramic and tile industry
Niaki, Khedmati, and Soleymanian (2015)	✓			✓			✓		Signal probability	Agriculture field
Nikoo and Noorossana (2015)				✓				✓	ARL	Vertical density of particleboard
Noorossana, Fatemi, and Zerehsaz (2015a)				✓				✓	ARL	Adhesive manufacturing
Noorossana, Niaki, and Izadbakhsh (2015b)				✓				✓	ARL	Alloy fasteners
Noorossana and Nikoo (2015)	✓			✓				✓	ARL	–
Noorossana and Zerehsaz (2015)				✓				✓	ARL	–
Riaz and Touqeer (2015)				✓			✓		Signal probability	–
Shadman, Mahlooji, Yeh, and Zou (2015)				✓			✓		Signal probability, $\bar{\hat{\tau}}$, $SD(\hat{\tau})$	Carbon black filler
Vakilian, Amiri, and Sogandi (2015)	✓			✓				✓	$\bar{\hat{\tau}}$, $SD(\hat{\tau})$ & precision	Agriculture field
Wang and Tamirat (2015)	✓			✓			–		$S_{pkA;AR(1)}$	Agriculture field
Xu, Peng, and Reynolds (2015)				✓				✓	SSATS, $\hat{\tau}$	Optical imaging system
Zeng and Chen (2015)				✓			✓		Regression metric & chart statistic	Low-E glass manufacturing process
Zhang, Ren, Yao, Zou, and Wang (2015)					✓		✓		Type I error, empirical power, regression metric	Semiconductor manufacturing industry
Abdella, Kim, Al-Khalifa, and Hamouda (2016)				✓				✓	ARL	–
Amiri, Khosravi, and Ghashghaei (2016)				✓			✓	✓	ARL	Leather industry
Ayoubi, Kazemzadeh, and Noorossana (2016)					✓			✓	$\bar{\hat{\tau}}$ & Precision	Automotive industrial group
Chen et al. (2016)				✓				✓	ARL	–
De Magalhães and Von Doellinger (2016)				✓				✓	ARL	Semiconductor manufacturing industry
Ershadi, Noorossana, and Niaki (2016)				✓				✓	ATS_0, ATS_1, cost, optimum variables	–
Grasso, Menafoglio, Colosimo, and Secchi (2016)				✓				✓	ARL, confidence interval	Waterjet cutting process
Guevara and Vargas (2016)					✓		–		$MC_{pl(prf)}$	Sugar production

(*continued on next page*)

Table 4 (*continued*)

Research	Process type			Type of response data			Phase		Performance criterion	Practical application
	Correlated		Multi-stage							
	Within	Between		Univarite	Multivarite	Fuzzy	I	II		
Huwang, Wang, Yeh, and Huang (2016)				✓				✓	ARL, $\bar{\hat{\tau}}$, $SD(\hat{\tau})$, correct classification	White wine production process
Jensen, Grimshaw, and Espen (2016)				✓			✓	✓		Oven-temperature data
Kamranrad and Amiri (2016)	✓			✓				✓	ARL, MAD, IQR	–
Karimi Ghartemani, Noorossana, and Niaki (2016)				✓			–		MCpM	Leather industry
Kazemzadeh et al. (2016a)				✓				✓	ATS, ANI, ANS	Leather industry
Kazemzadeh, Amiri, and Mirbeik (2016b)	✓			✓				✓	$\bar{\hat{\tau}}$, $SD(\hat{\tau})$ & precision	Agriculture field
Khedmati and Niaki (2016a)			✓	✓				✓	ARL & correct classification	–
Khedmati and Niaki (2016b)			✓	✓				✓	ARL & correct classification	–
Khedmati and Niaki (2016c)		✓		✓				✓	ARL	Optical imaging system
Moghadam, Raissi Ardali, and Amirzadeh (2016)						✓		✓	Process state	–
Noorossana, Aminmadani, and Saghaei (2016)				✓				✓	ARL	Optical imaging system
Panza and Vargas (2016)				✓				✓	ARL, SDRL	Electrical application
Paynabar et al. (2016)					✓		✓		Type I error, Signal probability, Bias of $\hat{\tau}$, $SD(\hat{\tau})$, RSM, precision diagnosis accuracy	Forging process
Qi, Wang, Zi, and Li (2016)				✓				✓	RL distribution, ARL, SDRL, RMI, CED	–
Abbasi Charkhi, M., Aminnayeri, M., and Amiri, A. (2016)				✓			–		C_p	Forming press process
Shahriari, Ahmadi, and Samimi (2016)				✓			✓		MSE	–
Shang, Man, He, and Ren (2016)				✓			✓		Signal probability, Bias of $\hat{\tau}$, Precision, accuracy of identifying shift directions	Aluminum electrolytic capacitor manufacturing process
Tamirat and Wang (2016)	✓			✓			–		Lot acceptance probability	Agriculture field
Wang (2016)					✓		–		TS_{pKA}	–
Wang and Tamirat (2016)					✓		–		C^T_{puA}, C^T_{plA}, $C^T_{puA;PC}$ & $C^T_{plA;PC}$	Logistic service/ calibration application
Wang and Wang (2016)				✓				✓	ARL, SDRL	Semiconductor manufacturing industry
Zang et al. (2016)				✓				✓	ARL	Ingot growth process

(*continued on next page*)

Table 4 (*continued*)

Research	Process type			Type of response data			Phase		Performance criterion	Practical application
	Correlated		Multi-stage							
	Within	Between		Univarite	Multivarite	Fuzzy	I	II		
Zhang, He, Zhang, and Wang (2016)				✓				✓	ARL, SDRL	Shaft turning process
Amiri, Sogandi, and Ayoubi (2017)					✓			✓	ARL	Air conditioner production
Awad (2017)				✓			✓	✓	Estimated regression parameters, R^2_{adj}	Fuel systems
Chiang, Lio, and Tsai (2017)	✓			✓				✓	BC_p, BC_{pk}	–
Ding, Tsung, and Li (2017)				✓				✓	ARL, standard error	Plastic manufacturing process
Esmaeeli et al. (2017)			✓	✓				✓	ARL, correct diagnosis	–
Fan, Jen, and Lee (2017)				✓			✓	✓	R^2, R^2_{adj} & ARL	Aluminum alloy rim process
Ghashghaei and Amiri (2017a)					✓			✓	ARL, SDRL, accuracy percentage	Calibration application in automotive industrial group
Ghashghaei and Amiri (2017b)					✓			✓	ARL, accuracy percentage	Calibration application in automotive industrial group
Ghashghaei, Amiri, and Khosravi (2018)					✓			✓	ARL	Calibration application in automotive industrial group
Grasso, Colosimo, and Tsung (2017)				✓			✓		Misclassification error	End-milling
Hakimi et al. (2017)				✓			✓	✓	Estimated regression parameters, ARL	–
Kalaei et al. (2017)			✓	✓			✓		Signal probability	Piston manufacturing line
Khedmati and Niaki (2017)			✓	✓			✓		Signal probability	Piston machining process
Maleki et al. (2017a)	✓			✓				✓	ARL	–
Maleki et al. (2017b)	✓			✓				✓	$\bar{\hat{\tau}}$, $SD(\hat{\tau})$ & precision	–
Maleki et al. (2017c)	✓			✓			✓		Signal probability, $\bar{\hat{\tau}}$, $SD(\hat{\tau})$ & precision	Number of thefts
Motasemi, Alaeddini, and Zou (2017)				✓			✓	✓	ARL, signal probability	–
Nie and Du (2017)				✓			✓		Idac, nsp	Image data
Pacella et al. (2017)				✓			✓	✓	ARL, SDRL	Leather industry
Pini, Vantini, Colosimo, and Grasso (2017)	✓			✓				✓	ARL	Remote laser welding
Riaz, Mahmood, Abbasi, Abbas, and Ahmad (2017)				✓				✓	ARL, EQL, RARL & PCI	Electrical application

(*continued on next page*)

Table 4 (*continued*)

Research	Process type			Type of response data			Phase		Performance criterion	Practical application
	Correlated		Multi-stage							
	Within	Between		Univarite	Multivarite	Fuzzy	I	II		
Sayyad, Niaki, and Afshar-Najafi (2017)				✓			✓	✓	ARL, SDRL, RLE	Aluminum electrolytic capacitor manufacturing process
Shadman, Zou, Mahlooji, and Yeh (2017)				✓				✓	ARL, SDRL, $\bar{\hat{\tau}}$, $SD(\hat{\tau})$, diagnosis probability	Carbon black filler in a rubber mix
Sogandi and Amiri (2017)				✓				✓	$\bar{\hat{\tau}}$, $SD(\hat{\tau})$ & precision	Volcano
Taghipour, Amiri, and Saghaei (2017)	✓				✓		✓		Signal probability	–
Wang and Huang (2017)		✓		✓				✓	ARL	Aircraft industry
Xia and Tsung (2017)				✓			✓	✓	ARL, diagnosis percentage	Deep reactive ion etching process
Yang, Zou, and Wang (2017)				✓				✓	ARL, SDRL, Median, quartiles, False alarm rate	Industrial etching process
Zhang, Shang, Gao, and Wang (2017a)				✓				✓	ARL	Cylindrical part manufacturing processes
Zhang, Shang, He, and Wang (2017b)				✓				✓	ARL, SDRL	Cylindrical part manufacturing processes
Cheng and Yang (2018)	✓			✓				✓	ARL, accurate detection	Babyfinder
Gomaa and Birch (2018)	✓			✓			✓		Percent control	Bioassay experiments
Khosravi and Amiri (2018)				✓			✓	✓	ARL	Beverage industry
Maleki, Castagliola, Amiri, and Khoo (2018)				✓				✓	ARL, SDRL	–

The abbreviations used in Table 4 are described as follows:
SS-ARL: steady-state ARL, SS-SDRL: steady-state standard deviation run length.
AIC: Akaike's information criterion, SIC: Schwarz information criterion.
MAD: Median Absolute Deviance, IQR: Inter quantile Range (IQR).
ANS: average number of samples until a signal, MSE: Mean Squared Error.
For more information about RMI and CED metrics, please refer to Qi et al. (2016).
Idac: Identification accuracy of change point, Nsp: non-signal probability.
EQL: Extra quadratic loss.
RARL: relative average run length.
PCI: Performance comparison index.
RLE: relative lost in efficiency.

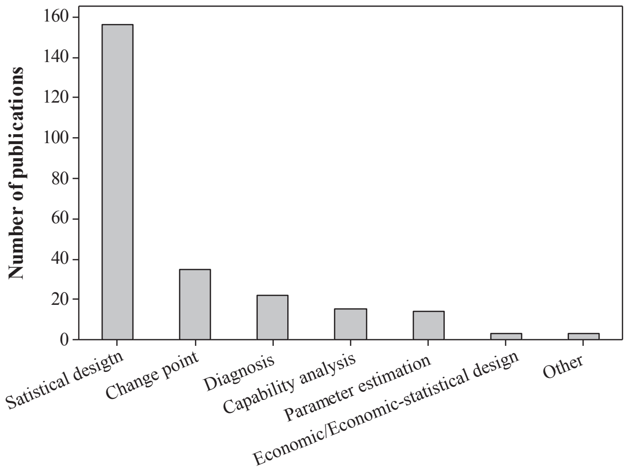

Fig. 3. Distribution of the selected papers with respect to SPM area.

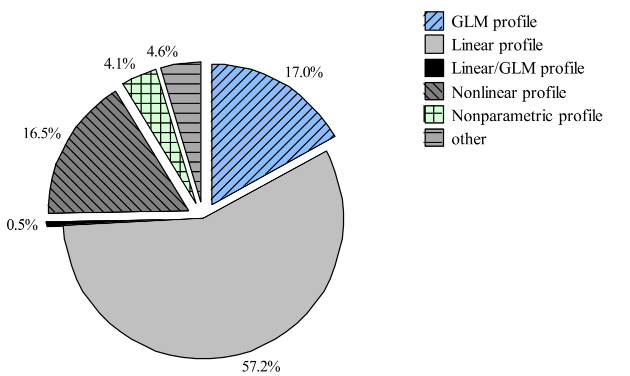

Fig. 4. Distribution of the selected papers with respect to profile type.

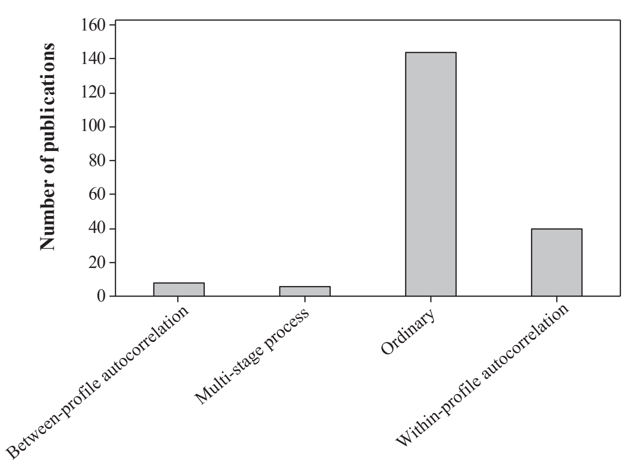

Fig. 5. Distribution of the selected papers with respect to process type.

there are only 4 publications during the period of 2008–2016 to monitor fuzzy quality profiles in which a linear regression model has been assumed to represent the profile model. As a research gap, analyzing the fuzzy profiles with the other regression models such as nonlinear regression models is recommended for future works. Also all these four publications have focused on statistical design of profile monitoring control charts. Here, there is a need to develop fuzzy approaches to other profile monitoring areas such as change point estimation, process capability analysis and so on.

3. In some manufacturing or non-manufacturing systems, it is

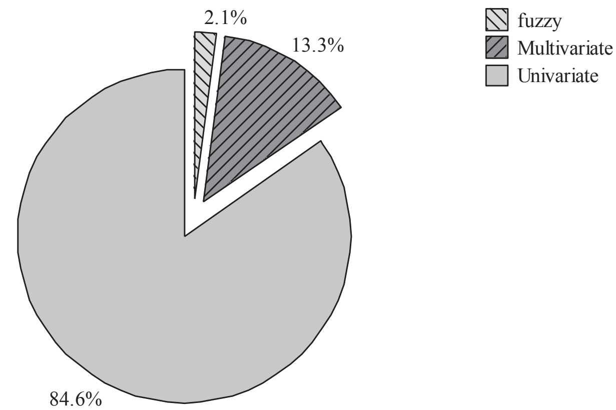

Fig. 6. Distribution of the selected papers with respect to the type of response data.

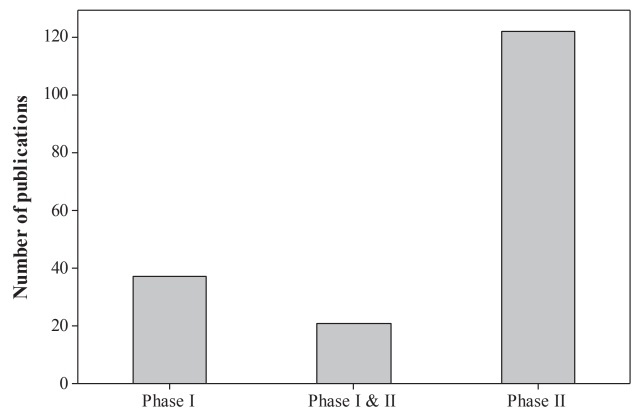

Fig. 7. Distribution of the selected papers with respect to the analysis stage.

important to monitor profiles in multi-stage processes. As noted, among all of the selected papers in the field of profile monitoring, only Ghahyazi, Niaki, and Soleimani (2014), Khedmati and Niaki (2016a), Khedmati and Niaki (2016b), Esmaeeli, Sadegheih, Amiri, and Doroudyan (2017), Kalaei, Atashgar, Niaki, and Soleimani (2017) and Khedmati and Niaki (2017) have investigated such processes. Additionally, all these papers have used a linear regression model to represent the relationship between the response and the explanatory variable(s). Consequently, analyzing other regression models such as GLM and nonlinear profiles may provide many opportunities for further researches in the field of profile monitoring. Also, all the mentioned researches have been proposed for statistical design of control chart. So, it is important to take into account the change point estimation as well as process capability analysis of such multi-stage processes with profile data.

4. Accurate measurement is a rare phenomenon in any manufacturing and service environment where human involvement is necessary (Maleki, Amiri, and Taheriyoun, 2017a, 2017b; Maleki, Amiri, Taheriyoun, & Castagliola, 2017c). However, all of the publications in the field of profile monitoring except one by Noorossana and Zerehsaz (2015) have assumed that the measurements are accurate. In the mentioned paper, Noorossana and Zerehsaz (2015) investigated the effect of measurement errors on phase II monitoring of simple linear profiles. Future researches to incorporate gauge measurement errors on analyzing different types of profiles could be useful.
5. In some practical environments, quality characteristics can be represented by correlated profiles where the response quality characteristics follow both continuous or discrete distributions. As

another recommendation, it is useful for quality engineering researchers to narrow their attempts to analyze this kind of multivariate profiles with mixed response quality characteristics.

6. In some production systems, it is not possible to achieve enough data to perform Phase I analysis and to estimate the process parameters. Self-starting control charts can be used when the adequate reference data in Phase I is not available, when the production process is slow or the cost of out-of-control production at the beginning of the process is high. Also there has been some efforts to establish self-starting control charts for monitoring univariate or multivariate processes, however, using such methods to monitor different types of profiles is recommended as a future perspective in profile monitoring.
7. Ghashghaei and Amiri (2017a) as well as Ghashghaei and Amiri (2017b) presented some methods for the simultaneous monitoring of profile mean and variability of a multivariate multiple linear profile. Some more researches are needed in this area for example for monitoring autocorrelated profiles.
8. The applications of profile monitoring can be investigated in the other areas of SPM for example in "healthcare", handling the "big data" or "high-dimensional data" (See the multichannel data modeled by Paynabar, Zou, & Qiu, 2016), monitoring "image data" (see Koosha, Noorossana, & Megahed, 2017), "social network monitoring" (see Azarnoush, Paynabar, Bekki, & Runger, 2016, Woodall, Zhao, Paynabar, Sparks, & Wilson, 2017 as well as Fotuhi, Amiri, & Maleki, 2017).
9. Bayesian statistics and methods can also be applied and evaluated in the area of profile monitoring. As far as we know, nothing has been proposed in this area.
10. Adaptive control charts have been applied in linear profiles by some authors such as Abdella et al. (2014), De Magalhães and Von Doellinger (2016) and Kazemzadeh, Amiri, and Kouhestani (2016a). However, it seems that more researches are needed in this area. Typically, developing adaptive control charts for monitoring autocorrelated profiles as well as multi-stage processes with profile data can be fruitful areas for future researches.
11. As seen in Table 4, most of the proposed indices for testing the capability of processes with profile data have been provided for linear regression profiles. Here, developing process capability indices for more complicated profiles rather than linear profile can be considered as the future researches. Also taking into account the fuzzy response data to propose novel process capability indices must be considered by researchers.
12. Robust estimators also can be developed in the area of profile monitoring for some complicated regression models. As an example, in the regard of GLM profiles, Hakimi, Amiri, and Kamranrad (2017) developed some robust approaches to estimate the logistic regression profile parameters in order to decrease the effects of outliers on the performance of T^2 control chart. Developing robust approaches to the other types of GLM profiles such as Poisson, Ordinal logistic and Gamma regression profiles is recommended as the other future directions.
13. In recent years, applications of control chart for detecting process changes in high-dimensional image data have been adopted by quality practitioners. Using profile monitoring approaches for monitoring such processes in industry as well as for medical applications is clearly recommended for future studies. Interested readers are referred to Megahed, Woodall, and Camelio (2011) and Megahed, Wells, Camelio, and Woodall (2012).

7. Conclusion remarks

Motivated by the initial review paper of Woodall (2007), an up-to-date state of the art survey in the field of profile monitoring concerning papers published during the period 2008–2018 has been presented in this paper. For this aim, the survey methodology to search relevant publications and to classify them has been precisely described. A total of 195 documents published during 2008–2018 have been analyzed and classified and the analytic results have been summarized and discussed. The most important findings are the followings:

1. After the review paper of Woodall (2007), a considerable attention has been given to different areas of profile monitoring over the last decade and, in particular, during the period 2012–2017 in which the number of publications has increased a lot.
2. The review papers considered in this survey are all published in 40 different journals. Among them, nine journals (including Computers & Industrial Engineering) contain about 68 percent of all published papers.
3. Most of the publications in the context of profile monitoring come from authors only originated from five countries. As shown, the authors from Iran, USA, China, Taiwan and Italy had a great contribution in the literature of profile monitoring over the past decade.
4. Most of the researchers have limited their focus on the "statistical design" of profile monitoring control charts. After that, it can be seen that "change point estimation", "Diagnosis" and "process capability analysis" have been investigated by the researchers.
5. The assumption of linear model and, more particularly, simple linear model to express the profile data is the most common profile regression model.
6. Although monitoring of autocorrelated and multi-stage processes is rapidly under development in the literature of profile monitoring, however, most of the efforts have still been conducted on monitoring ordinary processes.
7. It is obvious that facing with multivariate response variables in different profile monitoring applications is avoidable. However, it seems that most studies in the past decade have been devoted to the univariate response variable case.

Even if significant developments have been proposed over the last decade in the profile monitoring literature, after providing analytical results in this paper, some issues have been identified and recommended for future investigations. Finally, some recommendations to fulfill the identified research gaps have been presented for future studies.

Acknowledgment

The authors appreciate professor Woodall and anonymous reviewers for their precious comments which led to a significant improvement in the survey.

References

Abdella, G. M., Kim, J., Al-Khalifa, K. N., & Hamouda, A. M. (2016). Double EWMA-based polynomial quality profiles monitoring. *Quality and Reliability Engineering International, 32*(8), 2639–2652.
Abdella, G. M., Yang, K., & Alaeddini, A. (2014). Multivariate adaptive approach for monitoring simple linear profiles. *International Journal of Data Analysis Techniques and Strategies, 6*(1), 2–14.
Abdella, G. M., Yang, K., & Alaeddini, A. (2012). Effect of location of explanatory variable on monitoring polynomial quality profiles. *International Journal of Engineering-Transactions A: Basics, 25*(2), 131–140.
Abdel-Salam, A. S. G., Birch, J. B., & Jensen, W. A. (2013). A semiparametric mixed model approach to Phase I profile monitoring. *Quality and Reliability Engineering International, 29*(4), 555–569.
Adibi, A., Montgomery, D. C., & Borror, C. M. (2014a). A p-value approach for Phase II monitoring of multivariate profiles. *International Journal of Quality Engineering and Technology, 4*(2), 133–143.
Adibi, A., Montgomery, D. C., & Borror, C. M. (2014b). Phase II monitoring of linear profiles using a p-value approach. *International Journal of Quality Engineering and Technology, 4*(2), 97–106.
Agresti, A. (2007). *An introduction to categorical data analysis.* John Wiley.
Aly, A. A., Mahmoud, M. A., & Woodall, W. H. (2015). A comparison of the performance of Phase II simple linear profile control charts when parameters are estimated. *Communications in Statistics-Simulation and Computation, 44*(6), 1432–1440.
Amiri, A., & Allahyari, S. (2012). Change point estimation methods for control chart

postsignal diagnostics: A literature review. *Quality and Reliability Engineering International, 28*(7), 673–685.

Amiri, A., Eyvazian, M., Zou, C., & Noorossana, R. (2012). A parameters reduction method for monitoring multiple linear regression profiles. *The International Journal of Advanced Manufacturing Technology, 58*(5–8), 621–629.

Amiri, A., Jensen, W. A., & Kazemzadeh, R. B. (2010). A case study on monitoring polynomial profiles in the automotive industry. *Quality and Reliability Engineering International, 26*(5), 509–520.

Amiri, A., Khosravi, P., & Ghashghaei, R. (2016). A self-starting control chart for simultaneous monitoring of mean and variance of simple linear profiles. *International Journal of Engineering-Transactions C: Aspects, 29*(9), 1263–1272.

Amiri, A., Koosha, M., Azhdari, A., & Wang, G. (2015). Phase I monitoring of generalized linear model-based regression profiles. *Journal of Statistical Computation and Simulation, 85*(14), 2839–2859.

Amiri, A., Mehrjoo, M., & Pasek, Z. J. (2013). Modifying simple linear profiles monitoring schemes in Phase II to detect decreasing step shifts and drifts. *The International Journal of Advanced Manufacturing Technology, 64*(9–12), 1323–1332.

Amiri, A., & Moein, E. (2013). Some notes on diagnostic procedures in simple and multiple linear regression profiles monitoring. *Communications in Statistics-Simulation and Computation, 42*(5), 981–1002.

Amiri, A., & Mohebbi, M. (2014). Economic-statistical design of EWMA-3 control chart for monitoring simple linear profiles. *International Journal of Quality Engineering and Technology, 4*(4), 290–314.

Amiri, A., Saghaei, A., Mohseni, M., & Zerehsaz, Y. (2014a). Diagnosis aids in multivariate multiple linear regression profiles monitoring. *Communications in Statistics-Theory and Methods, 43*(14), 3057–3079.

Amiri, A., Sogandi, F., & Ayoubi, M. (2017). Simultaneous monitoring of correlated multivariate linear and GLM regression profiles in Phase II. *Quality Technology & Quantitative Management*. https://doi.org/10.1080/16843703.2016.1226706 In press.

Amiri, A., Zou, C., & Doroudyan, M. H. (2014b). Monitoring correlated profile and multivariate quality characteristics. *Quality and Reliability Engineering International, 30*(1), 133–142.

Atashgar, K., Amiri, A., & Nejad, M. K. (2015). Monitoring allan variance nonlinear profile using artificial neural network approach. *International Journal of Quality Engineering and Technology, 5*(2), 162–177.

Awad, M. (2017). Fault detection of fuel systems using polynomial regression profile monitoring. *Quality and Reliability Engineering International, 33*(4), 905–920.

Ayoubi, M., Kazemzadeh, R. B., & Noorossana, R. (2014). Estimating multivariate linear profiles change point with a monotonic change in the mean of response variables. *The International Journal of Advanced Manufacturing Technology, 75*(9–12), 1537–1556.

Ayoubi, M., Kazemzadeh, R. B., & Noorossana, R. (2016). Change point estimation in the mean of multivariate linear profiles with no change type assumption via dynamic linear model. *Quality and Reliability Engineering International, 32*(2), 403–433.

Azarnoush, B., Paynabar, K., Bekki, J., & Runger, G. (2016). Monitoring temporal homogeneity in attributed network streams. *Journal of Quality Technology, 48*(1), 28–43.

Cano, J., Moguerza, J. M., Psarakis, S., & Yannacopoulos, A. N. (2015). Using statistical shape theory for the monitoring of nonlinear profiles. *Applied Stochastic Models in Business and Industry, 31*(2), 160–177.

Chang, S. I., Tavakkol, B., Chou, S. H., & Tsai, T. R. (2014). Real-time detection of wave profile changes. *Computers & Industrial Engineering, 75*, 187–199.

Chang, S. I., & Yadama, S. (2010). Statistical process control for monitoring non-linear profiles using wavelet filtering and b-spline approximation. *International Journal of Production Research, 48*(4), 1049–1068.

Chen, Y., Birch, J. B., & Woodall, W. H. (2015a). A phase I cluster-based method for analyzing nonparametric profiles. *Quality and Reliability Engineering International, 31*(8), 1675–1689.

Chen, Y., Birch, J. B., & Woodall, W. H. (2015b). Cluster-based profile analysis in phase I. *Journal of Quality Technology, 47*(1), 14–29.

Chen, Y., Birch, J. B., & Woodall, W. H. (2016). Effect of phase I estimation on phase II control chart performance with profile data. *Quality and Reliability Engineering International, 32*(1), 79–87.

Cheng, T. C., & Yang, S. F. (2018). Monitoring profile based on a linear regression model with correlated errors. *Quality Technology & Quantitative Management, 15*(3), 393–412.

Chiang, J. Y., Lio, Y. L., & Tsai, T. R. (2017). MEWMA control chart and process capability indices for simple linear profiles with within-profile autocorrelation. *Quality and Reliability Engineering International, 33*(5), 1083–1094.

Chipman, H. A., MacKay, R. J., & Steiner, S. H. (2010). Comment: nonparametric profile monitoring by mixed effects modeling. *Technometrics, 52*(3), 288–293.

Chou, S. H., Chang, S. I., & Tsai, T. R. (2014). On monitoring of multiple non-linear profiles. *International Journal of Production Research, 52*(11), 3209–3224.

Chuang, S. C., Hung, Y. C., Tsai, W. C., & Yang, S. F. (2013). A framework for nonparametric profile monitoring. *Computers & Industrial Engineering, 64*(1), 482–491.

Colosimo, B. M., Cicorella, P., Pacella, M., & Blaco, M. (2014). From profile to surface monitoring: SPC for cylindrical surfaces via Gaussian processes. *Journal of Quality Technology, 46*(2), 95–113.

Colosimo, B. M., Meneses, M., & Semeraro, Q. (2015). On the effectiveness of profile monitoring to enhance functional performance of particleboards. *Quality and Reliability Engineering International, 31*(8), 1665–1674.

Colosimo, B. M., Semeraro, Q., & Pacella, M. (2008). Statistical process control for geometric specifications: On the monitoring of roundness profiles. *Journal of Quality Technology, 40*(1), 1–18.

De Magalhães, M. S., & Von Doellinger, R. O. S. (2016). Monitoring linear profiles using an adaptive control chart. *The International Journal of Advanced Manufacturing Technology, 82*(5–8), 1433–1445.

Ding, D., Tsung, F., & Li, J. (2017). Ordinal profile monitoring with random explanatory variables. *International Journal of Production Research, 55*(3), 736–749.

Ebadi, M., & Amiri, A. (2012). Evaluation of process capability in multivariate simple linear profiles. *Scientia Iranica, 19*(6), 1960–1968.

Ebadi, M., & Shahriari, H. (2013). A process capability index for simple linear profile. *The International Journal of Advanced Manufacturing Technology, 64*(5–8), 857–865.

Ershadi, M. J., Noorossana, R., & Niaki, S. T. A. (2016). Economic-statistical design of simple linear profiles with variable sampling interval. *Journal of Applied Statistics, 43*(8), 1400–1418.

Esmaeeli, H., Sadegheih, A., Amiri, A., & Doroudyan, M. H. (2017). Monitoring two-stage processes with a profile at the second stage. *Communications in Statistics-Simulation and Computation, 46*(3), 2457–2473.

Eyvazian, M., Noorossana, R., Saghaei, A., & Amiri, A. (2011). Phase II monitoring of multivariate multiple linear regression profiles. *Quality and Reliability Engineering International, 27*(3), 281–296.

Fan, S. K. S., Chang, Y. J., & Aidara, N. (2013). Nonlinear profile monitoring of reflow process data based on the sum of sine functions. *Quality and Reliability Engineering International, 29*(5), 743–758.

Fan, S. K. S., Jen, C. H., & Lee, T. Y. (2017). Modeling and monitoring the nonlinear profile of heat treatment process data by using an approach based on a hyperbolic tangent function. *Quality Engineering, 29*(2), 226–243.

Fan, S. K. S., Yao, N. C., Chang, Y. J., & Jen, C. H. (2011). Statistical monitoring of nonlinear profiles by using piecewise linear approximation. *Journal of Process Control, 21*(8), 1217–1229.

Farahani, E., Noorossana, R., & Koosha, M. (2014). Profile monitoring in the presence of outliers. *The International Journal of Advanced Manufacturing Technology, 74*(1–4), 251–256.

Fotuhi, H., Amiri, A., & Maleki, M. R. (2017). Phase I monitoring of social networks based on poisson regression profiles. *Quality and Reliability Engineering International* In press.

Gani, W., & Limam, M. (2013). On the use of the K-chart for phase II monitoring of simple linear profiles. *Journal of Quality and Reliability Engineering*.

Ghahyazi, M. E., Niaki, S. T. A., & Soleimani, P. (2014). On the monitoring of linear profiles in multistage processes. *Quality and Reliability Engineering International, 30*(7), 1035–1047.

Ghashghaei, R., & Amiri, A. (2017a). Maximum multivariate exponentially weighted moving average and maximum multivariate cumulative sum control charts for simultaneous monitoring of mean and variability of multivariate multiple linear regression profiles. *Scientia Iranica* In press.

Ghashghaei, R., & Amiri, A. (2017b). Sum of squares control charts for monitoring of multivariate multiple linear regression profiles in phase II. *Quality and Reliability Engineering International, 33*(4), 767–784.

Ghashghaei, R., Amiri, A., & Khosravi, P. (2018). New control charts for simultaneous monitoring of mean vector and covariance matrix of multivariate multiple linear profiles. *Communications in Statistics-Simulation and Computation* In press.

Ghobadi, S., Noghondarian, K., Noorossana, R., & Mirhosseini, S. M. S. (2014). Developing a multivariate approach to monitor fuzzy quality profiles. *Quality & Quantity, 48*(2), 817–836.

Gomaa, A. S., & Birch, J. B. (2014). A semiparametric nonlinear mixed model approach to phase I profile monitoring. *Communications in Statistics-Simulation* In press.

Grasso, M., Colosimo, B. M., & Pacella, M. (2014). Profile monitoring via sensor fusion: the use of PCA methods for multi-channel data. *International Journal of Production Research, 52*(20), 6110–6135.

Grasso, M., Colosimo, B. M., & Tsung, F. (2017). A phase I multi-modelling approach for profile monitoring of signal data. *International Journal of Production Research, 55*(15), 4354–4377.

Grasso, M., Menafoglio, A., Colosimo, B. M., & Secchi, P. (2016). Using curve-registration information for profile monitoring. *Journal of Quality Technology, 48*(2), 99–127.

Guevara, R. D., & Vargas, J. A. (2015). Process capability analysis for nonlinear profiles using depth functions. *Quality and Reliability Engineering International, 31*(3), 465–487.

Guevara, R. D., & Vargas, J. A. (2016). Evaluation of process capability in multivariate nonlinear profiles. *Journal of Statistical Computation and Simulation, 86*(12), 2411–2428.

Hadidoust, Z., Samimi, Y., & Shahriari, H. (2015). Monitoring and change-point estimation for spline-modeled non-linear profiles in phase II. *Journal of Applied Statistics, 42*(12), 2520–2530.

Hakimi, A., Amiri, A., & Kamranrad, R. (2017). Robust approaches for monitoring logistic regression profiles under outliers. *International Journal of Quality & Reliability Management, 34*(4), 494–507.

Ho, L. L., El Said, M., & Kim, R. W. (2010). Monitoring the parameters of the market model by linear profile procedures. *Economic Quality Control, 25*(1), 81–96.

Hosseinifard, S. Z., & Abbasi, B. (2012a). Evaluation of process capability indices of linear profiles. *International Journal of Quality & Reliability Management, 29*(2), 162–176.

Hosseinifard, S. Z., & Abbasi, B. (2012b). Process capability analysis in non normal linear regression profiles. *Communications in Statistics-Simulation and Computation, 41*(10), 1761–1784.

Hosseinifard, S. Z., Abdollahian, M., & Zeephongsekul, P. (2011). Application of artificial neural networks in linear profile monitoring. *Expert Systems with Applications, 38*(5), 4920–4928.

Hung, Y. C., Tsai, W. C., Yang, S. F., Chuang, S. C., & Tseng, Y. K. (2012). Nonparametric profile monitoring in multi-dimensional data spaces. *Journal of Process Control, 22*(2), 397–403.

Huwang, L., Wang, Y. H. T., & Shen, C. C. (2014a). Monitoring general linear profiles when random errors have contaminated normal distributions. *Quality and Reliability Engineering International, 30*(8), 1131–1144.

Huwang, L., Wang, Y. H. T., Xue, S., & Zou, C. (2014b). Monitoring general linear profiles using simultaneous confidence sets schemes. *Computers & Industrial Engineering, 68*, 1–12.
Huwang, L., Wang, Y. H. T., Yeh, A. B., & Huang, Y. H. (2016). Phase II profile monitoring based on proportional odds models. *Computers & Industrial Engineering, 98*, 543–553.
Jen, C. H., & Fan, S. K. S. (2014). Profile monitoring of reflow process using approximations of mixture second-order polynomials. *Journal of Chemometrics, 28*(12), 815–833.
Jensen, W. A., Birch, J. B., & Woodall, W. H. (2008). Monitoring correlation within linear profiles using mixed models. *Journal of Quality Technology, 40*(2), 167–183.
Jensen, W. A., Grimshaw, S. D., & Espen, B. (2016). Nonlinear profile monitoring for oven-temperature data. *Journal of Quality Technology, 48*(1), 84–97.
Kalaei, M., Atashgar, K., Niaki, S. T. A., & Soleimani, P. (2017). Phase I monitoring of simple linear profiles in multistage processes with cascade property. *The International Journal of Advanced Manufacturing Technology*. https://doi.org/10.1007/s00170-016-9691-0 In press.
Kamranrad, R., & Amiri, A. (2016). Robust holt-winter based control chart for monitoring autocorrelated simple linear profiles with contaminated data. *Scientia Iranica. Transaction E, Industrial Engineering, 23*(3), 1345–1354.
Kane, Victor E. (1986). Process capability indices. *Journal of Quality Technology, 18*(1), 41–52.
Kang, L., & Albin, S. L. (2000). On-line monitoring when the process yields a linear profile. *Journal of Quality Technology, 32*(4), 418–426.
Karimi Ghartemani, M., Noorossana, R., & Niaki, S. T. A. (2016). A new approach in capability analysis of processes monitored by a simple linear regression profile. *Quality and Reliability Engineering International, 32*(2), 209–221.
Kazemzadeh, R. B., Amiri, A., & Kouhestani, B. (2016a). Monitoring simple linear profiles using variable sample size schemes. *Journal of Statistical Computation and Simulation, 86*(15), 2923–2945.
Kazemzadeh, R. B., Amiri, A., & Mirbeik, H. (2016b). Step change point estimation of the first-order autoregressive autocorrelated simple linear profiles. *Scientia Iranica. Transaction E, Industrial Engineering, 23*(6), 2995–3008.
Kazemzadeh, R. B., Noorossana, R., & Amiri, A. (2008). Phase I monitoring of polynomial profiles. *Communications in Statistics—Theory and Methods, 37*(10), 1671–1686.
Kazemzadeh, R. B., Noorossana, R., & Amiri, A. (2009). Monitoring polynomial profiles in quality control applications. *The International Journal of Advanced Manufacturing Technology, 42*(7–8), 703–712.
Kazemzadeh, R. B., Noorossana, R., & Ayoubi, M. (2015). Change point estimation of multivariate linear profiles under linear drift. *Communications in Statistics-Simulation and Computation, 44*(6), 1570–1599.
Keramatpour, M., Niaki, S. T. A., & Amiri, A. (2014). Phase-II monitoring of AR (1) autocorrelated polynomial profiles. *Journal of Optimization in Industrial Engineering, 7*(14), 53–59.
Keramatpour, M., Niaki, S. T. A., Khedmati, M., & Soleymanian, M. E. (2013). Monitoring and change point estimation of AR(1) autocorrelated polynomial profiles. *International Journal of Engineering-Transactions C: Aspects, 26*(9), 933–942.
Khedmati, M., & Niaki, S. T. A. (2015). Identifying the time of a step change in AR(1) auto-correlated simple linear profiles. *Journal of Industrial Engineering International, 11*(4), 473–484.
Khedmati, M., & Niaki, S. T. A. (2016a). A new control scheme for Phase-II monitoring of simple linear profiles in multistage processes. *Quality and Reliability Engineering International, 32*(7), 2559–2571.
Khedmati, M., & Niaki, S. T. A. (2016b). Monitoring simple linear profiles in multistage processes by a MaxEWMA control chart. *Computers & Industrial Engineering, 98*, 125–143.
Khedmati, M., & Niaki, S. T. A. (2016c). Phase II monitoring of general linear profiles in the presence of between-profile autocorrelation. *Quality and Reliability Engineering International, 32*(2), 443–452.
Khedmati, M., & Niaki, S. T. A. (2017). Phase-I monitoring of general linear profiles in multistage processes. *Communications in Statistics-Simulation and Computation, 46*(6), 4465–4489.
Koosha, M., & Amiri, A. (2013). Generalized linear mixed model for monitoring autocorrelated logistic regression profiles. *The International Journal of Advanced Manufacturing Technology, 64*(1–4), 487–495.
Koosha, M., Noorossana, R., & Megahed, F. (2017). Statistical process monitoring via image data using wavelets. *Quality and Reliability Engineering International*. https://doi.org/10.1002/qre.2167 In press.
Khosravi, P., & Amiri, A. (2018). Self-starting control charts for monitoring logistic regression profiles. *Communications in Statistics - Simulation and Computation* In press.
Li, T., & Cavusgil, S. T. (1995). A classification and assessment of research streams in international marketing. *International Business Review, 4*(3), 251–277.
Li, Z., & Wang, Z. (2010). An exponentially weighted moving average scheme with variable sampling intervals for monitoring linear profiles. *Computers & Industrial Engineering, 59*(4), 630–637.
Mahmoud, M. A. (2008). Phase I analysis of multiple linear regression profiles. *Communications in Statistics—Simulation and Computation, 37*(10), 2106–2130.
Mahmoud, M. A. (2012). The performance of phase II simple linear profile approaches when parameters are estimated. *Communications in Statistics-Simulation and Computation, 41*(10), 1816–1833.
Mahmoud, M. A., Morgan, J. P., & Woodall, W. H. (2010). The monitoring of simple linear regression profiles with two observations per sample. *Journal of Applied Statistics, 37*(8), 1249–1263.
Mahmoud, M. A., Saad, A. E. N., & El Shaer, R. (2015). Phase II multiple linear regression profile with small sample sizes. *Quality and Reliability Engineering International, 31*(5), 851–861.
Mahmoud, M. A., & Woodall, W. H. (2004). Phase I analysis of linear profiles with calibration applications. *Technometrics, 46*(4), 380–391.
Maleki, M. R., Amiri, A., & Taheriyoun, A. R. (2017a). Phase II monitoring of binary profiles in the presence of within-profile autocorrelation based on markov model. *Communications in Statistics-Simulation and Computation*. https://doi.org/10.1080/03610918.2016.1249880 In press.
Maleki, M. R., Amiri, A., & Taheriyoun, A. R. (2017b). Identifying the time of step change and drift in phase II monitoring of autocorrelated logistic regression profiles. *Scientia Iranica* In press.
Maleki, M. R., Amiri, A., Taheriyoun, A. R., & Castagliola, P. (2017c). Phase I monitoring and change point estimation of autocorrelated poisson regression profiles. *Communications in Statistics-Theory and Methods* In press.
Maleki, M. R., Castagliola, P., Amiri, A., & Khoo, M. B. C. (2018). The effect of parameter estimation on phase II monitoring of poisson regression profiles. *Communications in Statistics-Simulation and Computation* In press.
Mccullagh, P. (1980). Regression models for ordinal data. *Journal of the royal statistical society Series B (Methodological),* 109–142.
McGinnity, K., Chicken, E., & Pignatiello, J. J. (2015). Nonparametric change point estimation for sequential nonlinear profile monitoring. *Quality and Reliability Engineering International, 31*(1), 57–73.
Megahed, F. M., Wells, L. J., Camelio, J. A., & Woodall, W. H. (2012). A spatiotemporal method for the monitoring of image data. *Quality and Reliability Engineering International, 28*(8), 967–980.
Megahed, F. M., Woodall, W. H., & Camelio, J. A. (2011). A review and perspective on control charting with image data. *Journal of Quality Technology, 43*(2), 83–98.
Moghadam, G., Raissi Ardali, G. A., & Amirzadeh, V. (2015). Developing new methods to monitor phase II fuzzy linear profiles. *Iranian Journal of Fuzzy Systems, 12*(4), 59–77.
Moghadam, G., Raissi Ardali, G. A., & Amirzadeh, V. (2016). New fuzzy EWMA control charts for monitoring phase II fuzzy profiles. *Decision Science Letters, 5*(1), 119–128.
Motasemi, A., Alaeddini, A., & Zou, C. (2017). An area-based methodology for the monitoring of general linear profiles. *Quality and Reliability Engineering International, 33*(1), 159–181.
Narvand, A., Soleimani, P., & Raissi, S. (2013). Phase II monitoring of auto-correlated linear profiles using linear mixed model. *Journal of Industrial Engineering International, 9*(1), 12.
Nemati Keshteli, R., Kazemzadeh, R. B., Amiri, A., & Noorossana, R. (2014a). Developing functional process capability indices for simple linear profile. *Scientia Iranica. Transaction E, Industrial Engineering, 21*(3), 1044–1050.
Nemati Keshteli, R., Kazemzadeh, R. B., Amiri, A., & Noorossana, R. (2014b). Functional process capability indices for circular profile. *Quality and Reliability Engineering International, 30*(5), 633–644.
Neto, F. M., & De Magalhães, M. S. (2012). A Laplacian spectral method in phase I analysis of profiles. *Applied Stochastic Models in Business and Industry, 28*(3), 251–263.
Niaki, S. T. A., Khedmati, M., & Soleymanian, M. E. (2015). Statistical monitoring of autocorrelated simple linear profiles based on principal components analysis. *Communications in Statistics-Theory and Methods, 44*(21), 4454–4475.
Nie, B., & Du, M. (2017). Identifying change-point in polynomial profiles based on data-segmentation. *Communications in Statistics-Simulation and Computation, 46*(4), 2513–2528.
Nikoo, M., & Noorossana, R. (2013). Phase II monitoring of nonlinear profile variance using wavelet. *Quality and Reliability Engineering International, 29*(7), 1081–1089.
Nikoo, M., & Noorossana, R. (2015). Monitoring nonlinear profiles using wavelets. *International Journal of Industrial Engineering & Production Research, 26*(2), 95–104.
Noghondarian, K., & Ghobadi, S. (2012). Developing a univariate approach to Phase-I monitoring of fuzzy quality profiles. *International Journal of Industrial Engineering Computations, 3*(5), 829–842.
Noorossana, R., Aminnayeri, M., & Izadbakhsh, H. (2013a). Statistical monitoring of polytomous logistic profiles in Phase II. *Scientia Iranica, 20*(3), 958–966.
Noorossana, R., Aminmadani, M., & Saghaei, A. (2016). Effect of phase I estimation error on the monitoring of simple linear profiles in phase II. *The International Journal of Advanced Manufacturing Technology, 84*(5–8), 873–884.
Noorossana, R., Amiri, A., & Soleimani, P. (2008). On the monitoring of autocorrelated linear profiles. *Communications in Statistics—Theory and Methods, 37*(3), 425–442.
Noorossana, R., & Ayoubi, M. (2012). Profile monitoring using nonparametric bootstrap T^2 control chart. *Communications in Statistics-Simulation and Computation, 41*(3), 302–315.
Noorossana, R., Eyvazian, M., Amiri, A., & Mahmoud, M. A. (2010a). Statistical monitoring of multivariate multiple linear regression profiles in Phase I with calibration application. *Quality and Reliability Engineering International, 26*(3), 291–303.
Noorossana, R., Eyvazian, M., & Vaghefi, A. (2010b). Phase II monitoring of multivariate simple linear profiles. *Computers & Industrial Engineering, 58*(4), 563–570.
Noorossana, R., Fatemi, S. A., & Zerehsaz, Y. (2015a). Phase II monitoring of simple linear profiles with random explanatory variables. *The International Journal of Advanced Manufacturing Technology, 76*(5–8), 779–787.
Noorossana, R., Izadbakhsh, H., & Nayebpour, M. R. (2014a). A likelihood ratio test approach to profile monitoring in tourism industry. *Applications & Applied Mathematics, 9*(2), 518–527.
Noorossana, R., Niaki, S. T. A., & Ershadi, M. J. (2014b). Economic and economic-statistical designs of phase II profile monitoring. *Quality and Reliability Engineering International, 30*(5), 645–655.
Noorossana, R., Niaki, S. T. A., & Izadbakhsh, H. (2015b). Statistical monitoring of nominal logistic profiles in phase II. *Communications in Statistics-Theory and Methods, 44*(13), 2689–2704.
Noorossana, R., & Nikoo, M. (2015). Phase II monitoring of geometric profiles. *Communications in Statistics-Simulation and Computation, 44*(4), 1036–1049.
Noorossana, R., Saghaei, A., & Amiri, A. (2011a). *Statistical analysis of profile monitoring.* John Wiley & Sons.

Noorossana, R., Saghaei, A., & Dorri, M. (2010c). Linear profile monitoring in the presence of non-normality and autocorrelation. *International Journal of Industrial Engineering & Production Optimization, 21*(4), 221–230.

Noorossana, R., Saghaei, A., Izadbakhsh, H., & Aghababaei, O. (2013b). Monitoring multinomial logit profiles via log-linear models. *International Journal of Industrial Engineering & Production Research, 24*(2), 137–142.

Noorossana, R., Vaghefi, A., & Dorri, M. (2011b). Effect of non-normality on the monitoring of simple linear profiles. *Quality and Reliability Engineering International, 27*(4), 425–436.

Noorossana, R., & Zerehsaz, Y. (2015). Effect of measurement error on phase II monitoring of simple linear profiles. *The International Journal of Advanced Manufacturing Technology, 79*(9–12), 2031–2040.

Pacella, M., Grieco, A., & Blaco, M. (2017). Machine vision based quality control of free-form profiles in automatic cutting processes. *Computers & Industrial Engineering, 109*, 221–232.

Pacella, M., & Semeraro, Q. (2011). Monitoring roundness profiles based on an unsupervised neural network algorithm. *Computers & Industrial Engineering, 60*(4), 677–689.

Panza, C. A., & Vargas, J. A. (2016). Monitoring the shape parameter of a weibull regression model in phase II processes. *Quality and Reliability Engineering International, 32*(1), 195–207.

Paynabar, K., & Jin, J. (2011). Characterization of non-linear profiles variations using mixed-effect models and wavelets. *IIE Transactions, 43*(4), 275–290.

Paynabar, K., Jin, J., & Pacella, M. (2013). Monitoring and diagnosis of multichannel nonlinear profile variations using uncorrelated multilinear principal component analysis. *IIE Transactions, 45*(11), 1235–1247.

Paynabar, K., Jin, J., & Yeh, A. B. (2012). Phase I risk-adjusted control charts for monitoring surgical performance by considering categorical covariates. *Journal of Quality Technology, 44*(1), 39–53.

Paynabar, K., Zou, C., & Qiu, P. (2016). A change-point approach for phase-I analysis in multivariate profile monitoring and diagnosis. *Technometrics, 58*(2), 191–204.

Pini, A., Vantini, S., Colosimo, B. M., & Grasso, M. (2017). Domain-selective functional analysis of variance for supervised statistical profile monitoring of signal data. *Journal of the Royal Statistical Society: Series C (Applied Statistics), 67*(1), 55–81.

Qi, D., Wang, Z., Zi, X., & Li, Z. (2016). Phase II monitoring of generalized linear profiles using weighted likelihood ratio charts. *Computers & Industrial Engineering, 94*, 178–187.

Qiu, P., & Zou, C. (2010). Control chart for monitoring nonparametric profiles with arbitrary design. *Statistica Sinica, 20*(4), 1655–1682.

Qiu, P., Zou, C., & Wang, Z. (2010). Nonparametric profile monitoring by mixed effects modeling. *Technometrics, 52*(3), 265–277.

Rezaye Abbasi Charkhi, M., Aminnayeri, M., & Amiri, A. (2016). Process capability indices for logistic regression profile. *Quality and Reliability Engineering International, 32*(5), 1655–1661.

Riaz, M., Mahmood, T., Abbasi, S. A., Abbas, N., & Ahmad, S. (2017). Linear profile monitoring using EWMA structure under ranked set schemes. *The International Journal of Advanced Manufacturing Technology, 91*(5–8), 2751–2775.

Riaz, M., & Touqeer, F. (2015). On the performance of linear profile methodologies under runs rules schemes. *Quality and Reliability Engineering International, 31*(8), 1473–1482.

Saghaei, A., Mehrjoo, M., & Amiri, A. (2009). A CUSUM-based method for monitoring simple linear profiles. *The International Journal of Advanced Manufacturing Technology, 45*(11–12), 1252–1260.

Saghaei, A., Rezazadeh-Saghaei, M., Noorossana, R., & Dorri, M. (2012). Phase II logistic profile monitoring. *International Journal of Industrial Engineering & Production Research, 23*(4), 291–299.

Sayyad, A., Niaki, S. T. A., & Afshar-Najafi, B. (2017). A non parametric approach to monitor simple linear profiles in phases I and II. *Communications in Statistics-Theory and Methods, 46*(11), 5203–5222.

Shadman, A., Mahlooji, H., Yeh, A. B., & Zou, C. (2015). A change point method for monitoring generalized linear profiles in phase I. *Quality and Reliability Engineering International, 31*(8), 1367–1381.

Shadman, A., Zou, C., Mahlooji, H., & Yeh, A. B. (2017). A change point method for phase II monitoring of generalized linear profiles. *Communications in Statistics-Simulation and Computation, 46*(1), 559–578.

Shahriari, H., Ahmadi, O., & Samimi, Y. (2016). Estimation of complicated profiles in phase I, clustering and S-estimation approaches. *Quality and Reliability Engineering International, 32*(7), 2455–2469.

Shang, Y., Man, J., He, Z., & Ren, H. (2016). Change-point detection in phase I for profiles with binary data and random predictors. *Quality and Reliability Engineering International, 32*(7), 2549–2558.

Shang, Y., Tsung, F., & Zou, C. (2011). Profile monitoring with binary data and random predictors. *Journal of Quality Technology, 43*(3), 196.

Sharafi, A., Aminnayeri, M., & Amiri, A. (2012). Identifying the time of step change in binary profiles. *The International Journal of Advanced Manufacturing Technology, 63*(1–4), 209–214.

Sharafi, A., Aminnayeri, M., & Amiri, A. (2013a). An MLE approach for estimating the time of step changes in poisson regression profiles. *Scientia Iranica, 20*(3), 855–860.

Sharafi, A., Aminnayeri, M., Amiri, A., & Rasouli, M. (2013b). Estimating the change point of binary profiles with a linear trend disturbance. *International Journal of Industrial Engineering & Production Research, 24*(2), 123–129.

Sharafi, A., Aminnayeri, M., & Amiri, A. (2014). Estimating the change point of binary profiles in phase II. *International Journal of Productivity and Quality Management, 14*(3), 336–351.

Sheu, S. H., Ouyoung, C. W., & Hsu, T. S. (2013). Phase II statistical process control for functional data. *Journal of Statistical Computation and Simulation, 83*(11), 2144–2159.

Shiau, J. J. H., Huang, H. L., Lin, S. H., & Tsai, M. Y. (2009). Monitoring nonlinear profiles with random effects by nonparametric regression. *Communications in Statistics—Theory and Methods, 38, 10*, 1664–1679.

Sogandi, F., & Amiri, A. (2014a). Change point estimation of gamma regression profiles with a linear trend disturbance. *International Journal of Quality Engineering and Technology, 4*(4), 352–368.

Sogandi, F., & Amiri, A. (2014b). Estimating the time of a step change in gamma regression profiles using MLE approach. *International Journal of Engineering-Transactions B: Applications, 28*(2), 224–231.

Sogandi, F., & Amiri, A. (2017). Monotonic change point estimation of generalized linear model-based regression profiles. *Communications in Statistics-Simulation and Computation, 46*(3), 2207–2227.

Soleimani, P., Narvand, A., & Raissi, S. (2013a). Online monitoring of auto correlated linear profiles via mixed model. *International Journal of Manufacturing Technology and Management, 27*(4–6), 238–250.

Soleimani, P., & Noorossana, R. (2012). Investigating effect of autocorrelation on monitoring multivariate linear profiles. *International Journal of Industrial Engineering & Production Research, 23*(3), 187–193.

Soleimani, P., & Noorossana, R. (2014). Monitoring multivariate simple linear profiles in the presence of between profile autocorrelation. *Communications in Statistics-Theory and Methods, 43*(3), 530–546.

Soleimani, P., Noorossana, R., & Amiri, A. (2009). Simple linear profiles monitoring in the presence of within profile autocorrelation. *Computers & Industrial Engineering, 57*(3), 1015–1021.

Soleimani, P., Noorossana, R., & Niaki, S. T. A. (2013b). Monitoring autocorrelated multivariate simple linear profiles. *The International Journal of Advanced Manufacturing Technology, 67*(5–8), 1857–1865.

Soleymanian, M. E., Khedmati, M., & Mahlooji, H. (2013). Phase II monitoring of binary response profiles. *Scientia Iranica. Transaction E. Industrial Engineering, 20*(6), 2238–2246.

Stover, F. S., & Brill, R. V. (1998). Statistical quality control applied to ion chromatography calibrations. *Journal of Chromatography A, 804*(1), 37–43.

Taghipour, M., Amiri, A., & Saghaei, A. (2017). Phase I monitoring of within-profile autocorrelated multivariate linear profiles. *Journal of Engineering Research* In press.

Tamirat, Y., & Wang, F. K. (2016). Sampling plan based on the exponentially weighted moving average yield index for autocorrelation within linear profiles. *Quality and Reliability Engineering International, 32*(5), 1757–1768.

Vaghefi, A., Tajbakhsh, S. D., & Noorossana, R. (2009). Phase II monitoring of nonlinear profiles. *Communications in Statistics—Theory and Methods, 38* 11, 1834–1851.

Vakilian, F., Amiri, A., & Sogandi, F. (2015). Isotonic change point estimation in the AR (1) autocorrelated simple linear profiles. *International Journal of Engineering-Transactions A: Basics, 28*(7), 1059–1067.

Viveros-Aguilera, R., Steiner, S. H., & MacKay, R. J. (2014). Monitoring product size and edging from bivariate profile data. *Journal of Quality Technology, 46*(3), 199.

Wang, F. K. (2016). Process yield analysis for multivariate linear profiles. *Quality Technology & Quantitative Management, 13*(2), 124–138.

Wang, Y. H. T., & Huwang, L. (2012). On the monitoring of simple linear Berkson profiles. *Quality and Reliability Engineering International, 28*(8), 949–965.

Wang, F. K., & Tamirat, Y. (2014). Process yield analysis for autocorrelation between linear profiles. *Computers & Industrial Engineering, 71*, 50–56.

Wang, F. K., & Tamirat, Y. (2015). Process yield analysis for linear within-profile autocorrelation. *Quality and Reliability Engineering International, 31*(6), 1053–1061.

Wang, F. K., & Tamirat, Y. (2016). Process yield for multivariate linear profiles with one-sided specification limits. *Quality and Reliability Engineering International, 32*(4), 1281–1293.

Wang, K., & Tsung, F. (2005). Using profile monitoring techniques for a data-rich environment with huge sample size. *Quality and Reliability Engineering International, 21*(7), 677–688.

Wang, Y. H. T., & Huang, W. H. (2017). Phase II monitoring and diagnosis of autocorrelated simple linear profiles. *Computers & Industrial Engineering, 112*, 57–70.

Wang, Y. H. T., & Wang, H. (2016). On the monitoring of mixture simple linear profiles. *Journal of Statistical Computation and Simulation, 86*(15), 3009–3024.

Woodall, W. H. (2007). Current research on profile monitoring. *Production, 17*(3), 420–425.

Woodall, W. H., Spitzner, D. J., Montgomery, D. C., & Gupta, S. (2004). Using control charts to monitor process and product quality profiles. *Journal of Quality Technology, 36*(3), 309–320.

Woodall, W. H., Zhao, M. J., Paynabar, K., Sparks, R., & Wilson, J. D. (2017). An overview and perspective on social network monitoring. *IISE Transactions, 49*(3), 354–365.

Xia, Z., & Tsung, F. (2017). A computationally efficient self-starting scheme to monitor general linear profiles with abrupt changes. *Quality Technology & Quantitative Management* In press.

Xu, L., Peng, Y., & Reynolds, M. R., Jr (2015). An individuals generalized likelihood ratio control chart for monitoring linear profiles. *Quality and Reliability Engineering International, 31*(4), 589–599.

Xu, L., Wang, S., Peng, Y., Morgan, J. P., Reynolds, M. R., Jr, & Woodall, W. H. (2012). The monitoring of linear profiles with a GLR control chart. *Journal of Quality Technology, 44*(4), 348–362.

Yang, W., Zou, C., & Wang, Z. (2017). Nonparametric profile monitoring using dynamic probability control limits. *Quality and Reliability Engineering International, 33*(5), 1131–1142.

Yeh, A. B., Huwang, L., & Li, Y. M. (2009). Profile monitoring for a binary response. *IIE Transactions, 41*(11), 931–941.

Yeh, A. B., & Zerehsaz, Y. (2013). Phase I control of simple linear profiles with individual observations. *Quality and Reliability Engineering International, 29*(6), 829–840.

Yu, G., Zou, C., & Wang, Z. (2012). Outlier detection in functional observations with applications to profile monitoring. *Technometrics, 54*(3), 308–318.

Zand, A., Yazdanshenas, N., & Amiri, A. (2013). Change point estimation in phase I monitoring of logistic regression profile. *The International Journal of Advanced Manufacturing Technology, 67*(9–12), 2301–2311.
Zeng, L., & Chen, N. (2015). Bayesian hierarchical modeling for monitoring optical profiles in low-E glass manufacturing processes. *IIE Transactions, 47*(2), 109–124.
Zang, Y., Wang, K., & Jin, R. (2016). Unaligned profile monitoring using penalized methods. *Quality and Reliability Engineering International, 32*(8), 2761–2776.
Zhang, Y., He, Z., Fang, J., & Zhang, M. (2012). Nonparametric control scheme for monitoring phase II nonlinear profiles with varied argument values. *Chinese Journal of Mechanical Engineering, 25*(3), 587–597.
Zhang, Y., He, Z., Shan, L., & Zhang, M. (2014a). Directed control charts for detecting the shape changes from linear profiles to quadratic profiles. *International Journal of Production Research, 52*(11), 3417–3430.
Zhang, Y., He, Z., Zhang, C., & Woodall, W. H. (2014b). Control charts for monitoring linear profiles with within-profile correlation using Gaussian process models. *Quality and Reliability Engineering International, 30*(4), 487–501.
Zhang, Y., He, Z., Zhang, M., & Wang, Q. (2016). A score-test-based EWMA control chart for detecting prespecified quadratic changes in linear profiles. *Quality and Reliability Engineering International, 32*(3), 921–931.
Zhang, J., Li, Z., & Wang, Z. (2009). Control chart based on likelihood ratio for monitoring linear profiles. *Computational Statistics & Data Analysis, 53*(4), 1440–1448.
Zhang, J., Ren, H., Yao, R., Zou, C., & Wang, Z. (2015). Phase I analysis of multivariate profiles based on regression adjustment. *Computers & Industrial Engineering, 85*, 132–144.
Zhang, Y., Shang, Y., Gao, N., & Wang, Q. (2017a). Monitoring prespecified changes in linear profiles using control charts with supplementary runs rules. *Communications in Statistics-Simulation and Computation,* 1–15.
Zhang, Y., Shang, Y., He, Z., & Wang, Q. (2017b). CUSUM schemes for monitoring prespecified changes in linear profiles. *Quality and Reliability Engineering International, 33*(3), 579–594.
Zi, X., Zou, C., & Tsung, F. (2012). A distribution-free robust method for monitoring linear profiles using rank-based regression. *IIE Transactions, 44*(11), 949–963.
Zou, C., Ning, X., & Tsung, F. (2012). LASSO-based multivariate linear profile monitoring. *Annals of Operations Research, 192*(1), 3–19.
Zou, C., Qiu, P., & Hawkins, D. (2009). Nonparametric control chart for monitoring profiles using change point formulation and adaptive smoothing. *Statistica Sinica,* 1337–1357.
Zou, C., Tseng, S. T., & Wang, Z. (2014). Outlier detection in general profiles using penalized regression method. *IIE Transactions, 46*(2), 106–117.