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Application of Special Cause Control Charts to Green Sand Process

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Abstract

Statistical Process Control (SPC) based on the well known Shewhart control charts, is widely used in contemporary manufacturing industry, including many foundries. However, the classic SPC methods require that the measured quantities, e.g. process or product parameters, are not auto-correlated, i.e. their current values do not depend on the preceding ones. For the processes which do not obey this assumption the Special Cause Control (SCC) charts were proposed, utilizing the residual data obtained from the time-series analysis. In the present paper the results of application of SCC charts to a green sand processing system are presented. The tests, made on real industrial data collected in a big iron foundry, were aimed at the comparison of occurrences of out-of-control signals detected in the original data with those appeared in the residual data. It was found that application of the SCC charts reduces numbers of the signals in almost all cases It is concluded that it can be helpful in avoiding false signals, i.e. resulting from predictable factors.

Keywords: Quality management, Application of information technology to the foundry industry, Statistical process control, Time series analysis, Special cause control charts

1. Introduction

In contemporary manufacturing industry the Statistical Process Control (SPC) based on the well known Shewhart control charts is widely used. The classic SPC methods assume that the process output can be described by statistically independent observations fluctuating around a constant mean and is intended to detect signals which represent the special (assignable) causes of external disturbances increasing the process variation. The main steps include process monitoring, detection the out-of-control signals, finding and eventual elimination of their causes.

An application of traditional SPC charts requires that the observations are statistically independent and normally distributed and the standard deviation and mean of the observations should be stationary, i.e. independent of time. In real processes the measured quantities, such as process or product parameters, may be auto-correlated, i.e. their current values may depend on the preceding ones. For such processes these assumptions are violated which can cause appearing false out-of-control warning signals. To avoid such misleading situations, the so called Special Cause Control (SCC) charts have been proposed [1]. The idea was to use the time-series analysis to find the non-random components in the data and to apply the standard control chart procedures to the residuals. Several researches investigated performance of charts based on the residual data, in various aspects and in [2-7].

The classic SPC methods become commonly used also in foundry industry. The foundry technology covers a wide range of highly diversified processes, among which the green sand processing is one of the key issues deciding about quality of castings. Appropriate control methodologies and techniques are therefore particularly desirable for these processes. However, as remarked in [8], the green sand system variables are highly auto-correlated due to the continuous reuse of the sand, both in plants using batch and continuous mullers. Therefore, the application of the SCC charts seems to be a advisable decision.

In the above cited work [8], the statistical assumptions necessary for the traditional SPC control charts were evaluated using the original and residual data obtained from the green sand system operating in a medium-sized iron foundry (Neenah Foundry, USA). The properties subjected to the analysis were the sand permeability (conductivity) and the used sand temperature. The time-series analysis ARIMA type models were used to obtain the residual data. It was found that the residuals meet the assumptions necessary for SPC better than the original data.

This paper presents a comparative analysis of the occurrences of the typical out-of-control signals appearing on the Shewhart control charts with those which appear on the SCC charts, plotted for selected important green sand properties.

2. Methodology

The data used for the analysis included single measurements of the following properties of the green molding sand obtained after mulling process: moisture content, permeability, compression strength, compactibility as well as the temperature of the used sand. The data were collected in a large iron foundry, with average frequency of 30 minutes, during a year period of normal production. From the whole data set, two representative subsets of 100 measurements of each property were selected for the analysis, making altogether 10 sets of the original data.

The sequences of points, indicating the out-of-control signals, included the 8 standard patterns. Some of them are defined using the notion of the three zones above and below the chart centerline, typically denoted as: Zone A – the area between 2σ and 3σ above and below the center line; Zone B – the area between σ and 2σ, and Zone C – the area between the center line and σ, where σ is the standard deviation of the points from the centerline in a stationary process. In Table 1 definitions of the patterns are given.

Table 1.
Standard patterns (sequences) of points, indicating the out-of-control signals

Pattern type No.	Definition
1	1 point beyond Zone A
2	9 consecutive points on one side of central line
3	6 points in a row steadily increasing or decreasing
4	14 points in a row alternating up and down
5	2 out of 3 points in a row in Zone A or beyond
6	4 out of 5 points in a row in Zone B or beyond
7	15 points in a row in Zone C (above and below the center line)
8	8 consecutive points on both sides of the centerline with no points falling in zone C

In the present work the standard deviation of the points from the centerline (σ) was calculated on the basis of the first 30 points for each of the 100-points series.

MS Excel spreadsheet was programmed and used for automatic detection of the standard out-of-control patterns in the data. A screen copy of the spreadsheet's fragment is shown in Fig. 1. The values equal 1 in the 'Signal start' column indicate starting points of all sequences defined in the header. For example, if there are 10 consecutive points fulfilling the requirement for the Type 2 pattern, the value 1 appears two times in a row. The 'First signal start' column indicates only the first appearance of the pattern in the row. For the purpose of the present analysis the values calculated in 'Signal start' column were used for calculations of the numbers of the out-of-control pattern occurrences.

The time-series analysis can be made by many different methods. The most popular are probably the Autoregressive Integrated with Moving Average models (ARIMA). An alternative approach was suggested in [9] and applied in the present authors' earlier works [10-12]. The residual data are obtained from the original data by subtraction of three components of the time-series: the general trend (i.e. the mean's trend), the variability amplitude trend and the centered periodical component. The details are described in [10].

	Sigma	Upper limit of Zone C	Upper limit of Zone B	Upper limit of Zone A	Lower limit of Zone C	Lower limit of Zone B	Lower limit of Zone A		
	0,01288	0,01288	0,02576	0,03864	-0,0129	-0,0258	-0,0386		
		Type 2 (9 points in Zone C or beyond, on one side of central line)							
							Number of occurences:	**11**	**3**
Point No.	Deviation from mean	*Intermediate results of arythmetic and logic operations*						**Signal start**	**First signal start**
1	-0,01149	0	3	0	1	6	0	0	0
2	-0,00739	0	4	0	1	5	0	0	0
3	-0,00155	0	5	0	1	4	0	0	0
4	-0,00745	0	6	0	1	3	0	0	0
5	-0,0066	0	7	0	1	2	0	0	0
6	0,007497	1	8	0	0	1	0	0	0
7	0,006834	1	8	0	0	1	0	0	0
8	-0,00734	0	8	0	1	1	0	0	0
9	0,001771	1	9	1	0	0	0	1	1
10	0,022651	1	9	1	0	0	0	1	0
11	0,011731	1	8	0	0	1	0	0	0
12	0,007571	1	8	0	0	1	0	0	0
13	0,021694	1	7	0	0	2	0	0	0

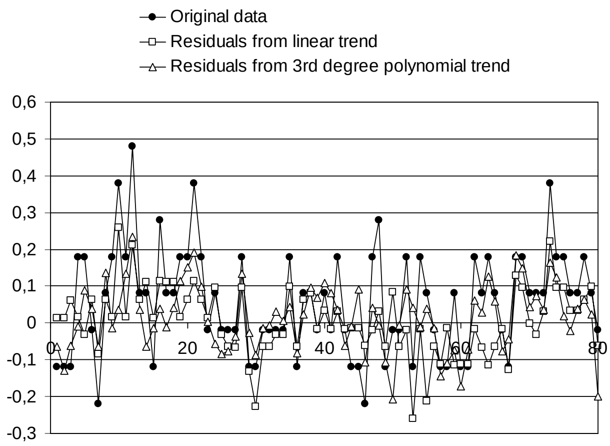
Fig. 1. A fragment of the spreadsheet programmed for automatic finding the standard out-of-control patterns in data

In the present work two different types of the mean's trend function were utilized: linear and curvilinear in the form of the 3rd order polynomial. From all periodical components detected in the time-series, only the most significant was subtracted, in spite of its statistical significance.

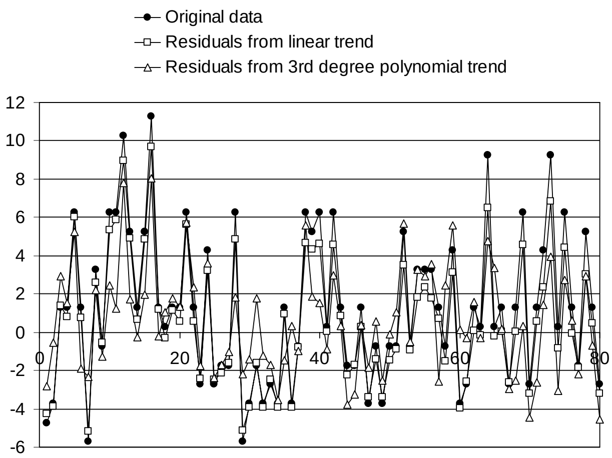
3. Results

In Fig. 2 two examples of the results obtained by application of the above described procedure of calculation the residuals from the original data are presented. It can be seen, that the differences between the original data and the residuals may vary significantly.

In Fig. 3 the variability of the data expressed by their standard deviation is shown for the three types of data sets, i.e. the original data and the residuals obtained by application of the two types of the mean's trend. The values plotted on this graph include all the points expressing the standard deviations calculated for the ten data sets of each type (see Chapter 2). It can be seen, that the variability of the residual data is significantly reduced compared to the original data, however, the type of the mean's trend used for calculations of the residuals has no noticeable effect.



(a)



(b)

Fig. 2. Transformation examples of the original data (used for Shewhart control charts) and residuals obtained from time-series analysis (used for Special Cause Control charts) for green sand properties: (a) moisture, (b) compactibility

As remarked in Chapter 1, the data used for finding the out-of-control signals (points' patterns) appearing on the control charts should be normally distributed. Removing the autocorrelations from the data, i.e. replacing the original data by the residuals, should lead to increase of the normality. The results obtained in [8] confirmed this expectation for the two investigated green sand variables. In the present work, from among several available types of tests for normality in data, the following two widely applied tests were chosen: Kolmogorov-Smirnov (K-S) and Shapiro-Wilk (S-W). In the K-S test the statistic D is computed, which higher values indicate higher likelihood that the random variable underlying the data set is normally distributed. In the S-W test the statistic W is computed, which higher values denote lower likelihood of the normality. In Fig. 4 the differences of normality between the original and the residual data, obtained in the present study, are presented. Like in Fig. 3, the values plotted on this graph include all the points expressing the standard deviations calculated for the ten data sets of each type described in Chapter 2. It can be seen that the residual data reveal significantly higher normality compared to the original data.

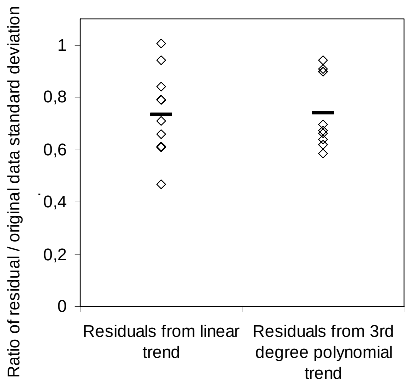


Fig. 3. Changes of the data variability resulting from the application of time-series models for all data sets; the horizontal bars denote average values for each data displayed on the X- axis

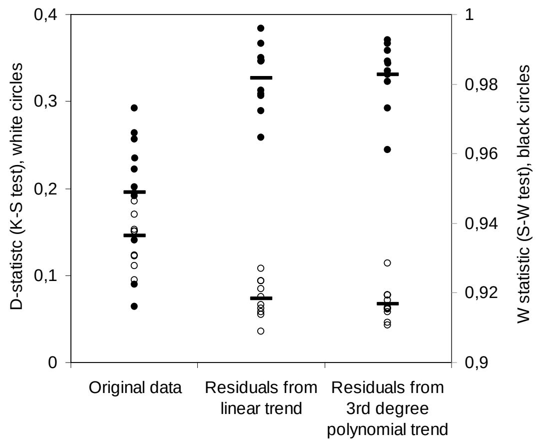


Fig. 4. Changes of normality of all data distributions resulting from the application of time-series models; the horizontal bars denote average values for each data displayed on the X- axis

The numbers of the out-of-control signals detected in all the original and residual data sets are plotted in Fig. 5 for all types of the standard patterns of points defined in Table 1. Pattern 3 (6 points in a row steadily increasing or decreasing) has not appeared in either of the sets and is skipped in this illustration. Each graph includes several curves, each representing one of the ten trios of the corresponding data (original and 2 residuals), as described in Chapter 2 (2 subsets for each of the five sand properties). It can be seen that in most of the cases the number of the out-of-control signals appearing on the both SCC charts is smaller than those observed on the corresponding Shewhart chart. The SCC charts for residuals obtained assuming the curvilinear mean's trend usually exhibit less out-of-control signals compared to those assuming linear trend.

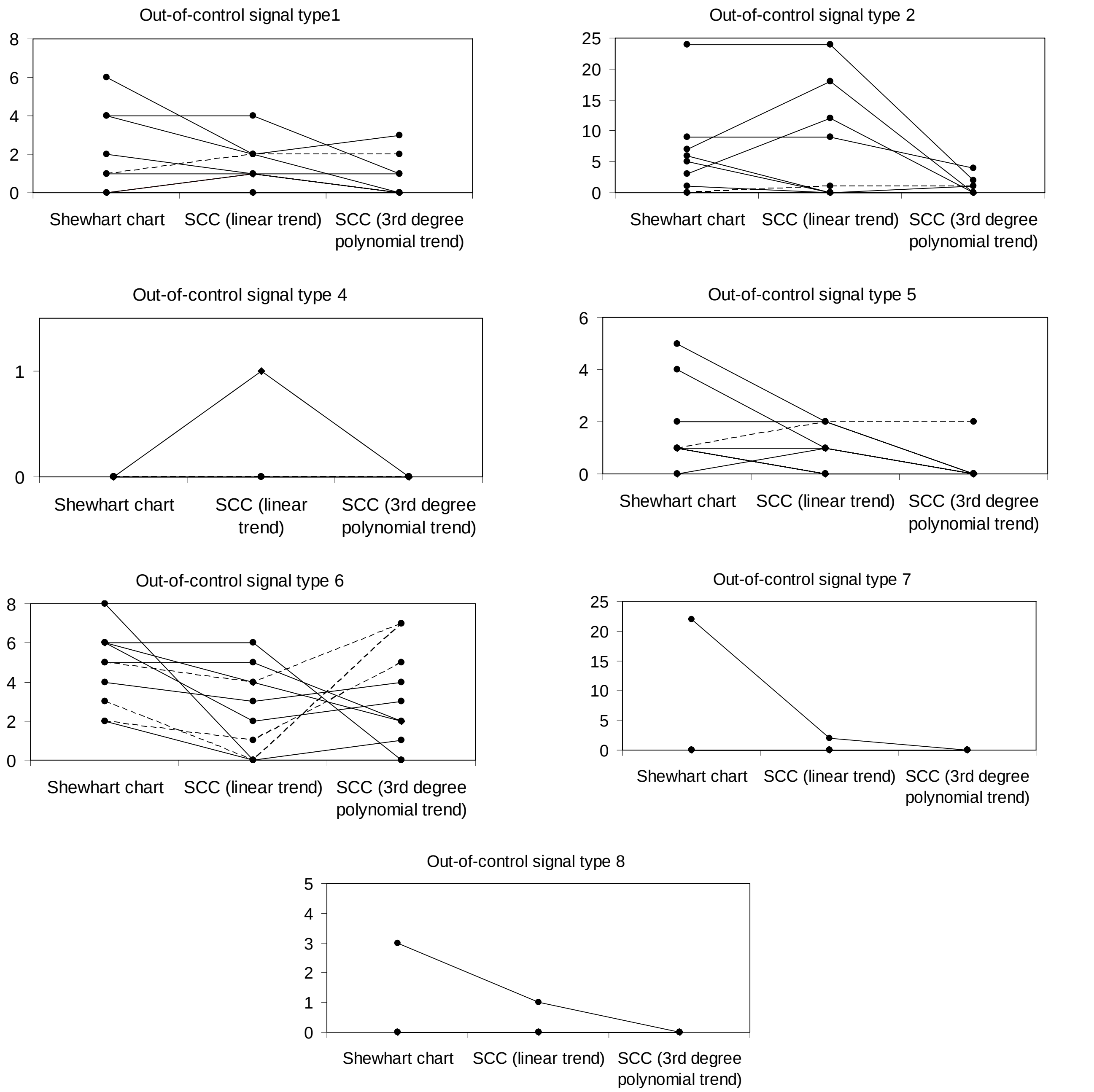


Fig. 5. Numbers of the out-of-control signals detected on traditional Shewhart charts and SCC charts obtained from the time-series models using two types of the mean's trend. The dotted lines indicate the cases in which one or both residuals exhibit larger number of the out-of-control signals than the corresponding original data

In principle, the above results are not surprising and may indicate that the original data exhibit some false out-of-control signals due to the autocorrelations which have been removed in the residual data.

In some cases, the SCC charts showed more patterns indicating the out-of-control signals than the Shewhart charts. This was observed mostly for the Type 6 out-of-control signals, i.e. 4 out of 5 points in a row in Zone B or beyond. In Fig. 6 a typical situation of this kind is presented.

The interpretation of such situations seems to be quite simple. The residual data may be characterized by a smaller variability, i.e. smaller standard deviation compared to the original data (cf. Fig. 3). Hence, the limits of the three zones, including inner limits of Zone B are narrower and exceeding them may be easier for a local series of several points. This suggestion concerns also the Type 5 out-of-control signals for which similar situation was also observed.

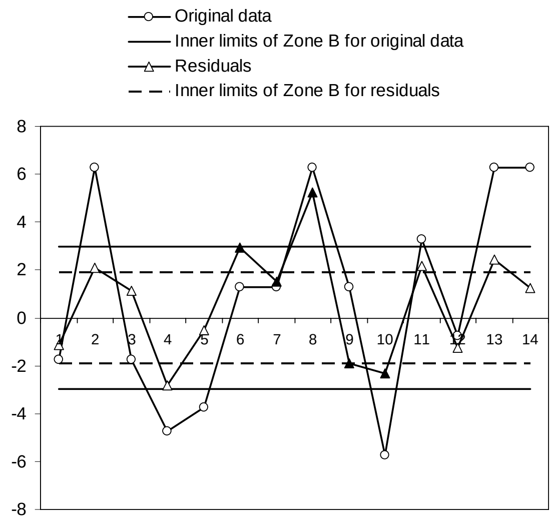


Fig. 6. Illustration of the appearance of the Type 6 out-of-control signal 6 (4 out of 5 points in a row in Zone B or beyond) on the SCC charts absent on the traditional Shewhart chart; the black triangles mark these five points

4. Summary of results, conclusions and further work

The numerical analysis of the foundry production data carried out in the present work was focused on the comparison of the behavior of two types of control charts: classic Shewhart charts, widely used in contemporary industry and the relatively new ones, called Special Cause Control charts. The latter are dedicated to detecting the out-of-control signals appearing in processes in which the measured variable values are not statistically independent, i.e. their current values depend on the preceding ones. These dependencies, called autocorrelations, can be expressed as the means's trend, the trend of the amplitude of the variable fluctuations and regularities of the fluctuations, usually identified as periodicity or seasonality. These components of the variable values are calculated using the methods of the time-series analysis and subtracted from the original values. The residuals are plotted on the control chart and checked for appearance of the characteristic patterns of points.

The original data used in the present study was raw, i.e. they were taken directly from the foundry records, without any information about possible autocorrelations or other regularities existing in them. The results of preliminary investigations, shown in Figs. 2, 3, and 4 suggested that some noticeable trends and especially periodic components were present in the original data. The remarkable reduction of the numbers of the out-of-control signals which appear on the SCC charts, i.e. utilizing the residual data, essentially confirms the applicability and usefulness of the new control charts in the SPC procedures implemented in the green sand processing.

However, in the opinion of the present authors, successful applications of the above approach require some comments and possible refinements. One is the choice of the mean's trend curve type, sometimes also called the general trend. The results presented in Fig. 5 show that the curvilinear trend often leads to larger reduction of the number of out-of-control signals compared to the linear trend. This observation is certainly not surprising, but the recommendation on utilization of the trend line of that kind is not obvious. A too flexible trend curve can reproduce some of the out-of-control patterns of points and this may lead to undesired removal of them from the data.

Another issue related to a proper application of the SCC charts is the problem of statistical significance of the periodical (seasonal) component in the original data. This can be tested, using for example the Bartlett's formula [10], however, several questions may arise. What significance level should be assumed in the tests? If several periodical components are significant should all of them be subtracted? How to handle the situations where all the periodical components are statistically insignificant? The present authors' experience with the time-series analysis indicates [12] that consideration of statistically insignificant periodical components can improve the predictive capabilities of the time-series. Nevertheless, all these issues certainly require further investigations.

The methodology used for constructing the SCC charts assumes subtraction of the autocorrelation components without analyzing their values, nature and causes. This seems to be a weakness of this approach since the autocorrelations appearing in data can be also considered as a kind of the process fault. As noticed in [13], a fault or problem in the process might be defined as a non-optimal operation, having a variety of the root causes such as hardware failures, a poor choice of operating targets, poor feedstock quality, poor controller tuning, sensor calibration errors, human errors etc. In the classic SPC the engineering staff make the decisions about the steps to take after getting results from the charts, including what needs to be improved and possible methods to improve it, based on their knowledge and experience. In our opinion, the procedures utilizing the SCC charts should include taking such actions twice, i.e. not only on the basis of the results from the charts but also from an analysis of the autocorrelation components detected in the original data.

The comments presented in this chapter imply that although applications of the SCC charts can bring reasonable improvements in practical statistical control of manufacturing processes, some important issues require a future research. This particularly concerns utilization of the information obtained from transformation of the data from original to residual as well as a justified concluding from the SCC charts.

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