Recognition of Nonrandom Patterns on Supply Performance by Employing Statistical Monitoring

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Abstract:

This paper introduces a practical methodology of assignable signals and Run chart tests for identification of nonrandom patterns of supplier performance by statistical monitoring. The assumption of normal distribution is one of the important factors to implement a control chart in industry and service. It is supposed that natural data shows lack of any nonrandom pattern signals or out of control points on control chart. The data of supplier's on-time delivery for automotive industry has been gathered and illustrated on control chart by employing appropriate transformation and assignable signals and run chart were tested on the control chart accordingly. The results show that tests were able to identify nonrandom patterns of supplier performance data. Out of control signals were removed from the control chart and show that on-time delivery performance was increased accordingly. The control chart with natural pattern can be used as pilot for monitoring supplier delivery over time and improve supplier delivery performance. [Journal of American Science 2010;6(4):114-122]. (ISSN: 1545-1003).

Key words: Run Chart Pattern Recognition (RCPR); Johnson Transformation; Supply Performance; Statistical Process Control (SPC); Anderson-Darling test (AD); On-Time Delivery (OTD)

1. Introduction:

In the 70's supply chain concentrated mainly on integration of warehousing and transportation within the company. In the 80's the focus of supply chain management moved to re-engineering of cost structured. At the end of 80's the focus again shifted from cost reduction to enhancing customer service. Today, successful SCM needs the recognition that the firm is simply one of the players in the long chain that begins with suppliers and includes transportation, manufacturers and customers (Rahul & Altekar, 2005). Firms cannot effectively compete in isolation of their suppliers and other parties in the supply chain. Interest in the approach of supply chain management has steadily increased since the 1980s when companies faced the benefits of cooperative relationships within and beyond their own company (Lummus & Vokurka, 1999).

Araz and Ozkarahan (2007) asserted that collaborating with the appropriate suppliers and managing them is taking more important now with the strategic cooperation being implemented with suppliers to obtain a competitive advantage and the involvement of suppliers in product development phases. Therefore, effective methods that have the capability of evaluating and continually monitoring suppliers' performance are still needed. Modern markets are competitive business environments where customers need their suppliers to be dependable in delivering on-time lots. One of the important goals of supply chain management is to improve delivery performance. In this context, the investment is needed to reduce delivery variance to a targeted goal as a part of an overall continuous improvement plan to improve supply chain performance (Guiffrida and Jaber, 2008). Moreover, delivery capabilities are highly important followed by production abilities, while value-adding capabilities such as process, managerial, financial, as well as communication/networking capabilities are also concerned as important when selecting a supplier (Pressey et al., 2009).

Ittner et al. (1999) examined whether supplier selection and monitoring practices affect the integration between supplier strategies and organizational performance. Automakers make significantly greater employ of suppliers for new product and process ideas and for accelerating the development process, and attend sessions at the supplier's firm more frequently. It is concluded that higher use of advanced selection and monitoring practices tends to increase profitability, product quality, and supplier performance in companies following supplier collaborative strategies, but has little effect on the performance of firms utilizing arms-length transactions. According to the conducted researches and cited by authors (Shin et al., 2000; Toni and Tonchia, 2001; Paulraj et al., 2006; Robb et al., 2008), it has been concluded that delivery performance, quality and cost are as most important indicators of supplier performances and monitoring tools are needed to control and improve supply performance indicators accordingly.

On the other hand, Statistical Process Control (SPC) is an effective tool for monitoring and evaluation of indicators over time. SPC is one of the techniques employed in quality assurance programs, for evaluating, monitoring and managing a process either manufacturing or service through the use of statistical methods (Anthony et al., 2000). The aim of any type of data analysis is to obtain understanding from data. When process performance data are monitored, it represents that it varies. The information in this variation is important to the understanding of how the process is performing and SPC is primarily the tool for understanding variation (Stapenhurst, 2005). It is because that the importance of quality has been long concerned as vital for both competition and survival in the business world. As such, more firms have adopted the use of SPC as a tool for achieving higher product quality (Duffuaa and Ben-Daya, 1995). This paper is aimed to represent the employing of control chart to monitor supply performance and how it can help companies to track their supplier performance by identification of caused signals on control charts. Moreover, using run chart test will be discussed accordingly. In this context, authors review on literature of assignable signals and common signals and patterns recognition. Montgomery (1997) cited that most processes do not perform in a state of statistical control. Consequently, the routine and attentive use of control charts will recognize assignable causes. If these causes can be removed from the process, variability will be reduced and the process will be improved. Figure 1 shows the process improvement tasks using the control chart. However, the process is out of control if any one or more of special caused rules for Shewhart's control chart is happened. A control chart may represent out-of-control signals either when one or more points fall beyond the control limits or the plotted points show some nonrandom pattern of behavior. The problem is pattern recognition, which is a systematic or nonrandom pattern on the control chart and identifying the reason for this behavior. Levine et al. (2001) asserted that a stable process is in a state of statistical control and has just chance or common signals of variability performing it.

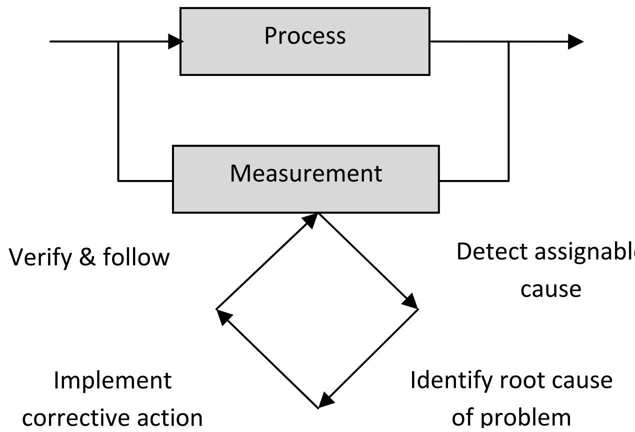

Figure 1. Process improvement using control chart (Montgomery, 1997)

Likewise, special causes of variability have relatively large impacts on the process and are not inherent to it. The circumstances or factors that cause this kind of variability may be recognized. The simplest rule for detecting the presence of a special cause is one or more points that fall beyond $\pm 3\sigma$ limits of the control charts. Monitoring of a process with a control chart can also support in process improvement. Pyzdek (2003) mentioned that a phenomenon will be cited to be controlled when, through the use of past history, it can be forecasted at least between control limits, how the phenomenon may be expected to vary in the future. A process control system is essentially a feedback system that integrates process outcomes with process inputs as depicted in Figure 2.

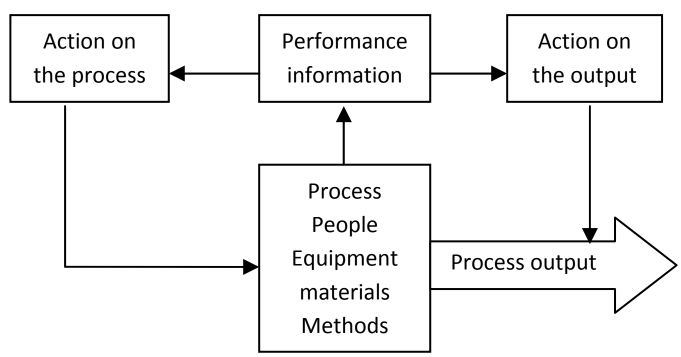

Figure 2. A process control system (Pyzdek, 2003)

Moreover, control chart interpretation is an art that can only be developed by looking at many control charts and probing patterns to identify the underlying system of cause at work. Eight sensitive run tests were indicated for analyzing the patterns variation in the various zones of control chart.

Besterfield (2009) asserted that when a process is in state of control, there occurs a normal pattern of variation, which is represented by control chart. Control limits (UCL and LCL) are usually structured at 3 standard deviations from the central line (CL). They are used as a basis to judge whether there is evidence of lack of control. When a process is out-of-control, the cause signals responsible for the condition must be identified. As such, Evan and Lindasay (2008) mentioned that when a process is in statistical control, the points on a control chart fluctuate randomly between the control limits with no recognizable pattern. Table 1 represents the recommended nonrandom patterns by several authors. It can be concluded that trend pattern, cyclic pattern, mixture and shift in mean are most highlighted patterns which should be recognized and corrective actions should be taken in account.

Table 1. Recommended nonrandom patter

Authors	Non random recommended patterns
Montgomery, (1997)	Cyclic pattern; Mixture pattern; Shift in process level pattern; Trend pattern; Stratification pattern
Levine et al., (2001)	The cyclic pattern; The mixture pattern; The trend pattern; The stratification pattern; Shift in process level pattern
Pyzdek, (2003)	Freaks; Drift; Cycles; Repeating patterns; Discrete data; Planned changed; Suspected differences; Mixture
Evan and Lindasay (2008)	On point out of control limits; Sudden shift in process average; Cycles; Trends; Hugging the centre line; Hugging the control limits pattern instability
Besterfield, (2009)	Change or jump in level; Trend or steady change in level; Recurring cycles; Two populations; Mistakes

Alwan (2000) discussed that how assignable patterns can be recognized by run chart tests and hypothesis testing evaluate them. In this context; a simple numerical check of randomness of a series is named a runs test. The run test classifies observations as being above (+) or below (-) some central line, usually the sample mean, which is the default value in Minitab software. To place the problem in a statistical hypothesis-testing framework, the following proposed hypothesis can be considered:

- *Null hypothesis* H_0:
  Process is random
- *Alternative hypothesis* H_1:
  Process is nonrandom

The number of runs observed from a process is one possible test statistic for deciding whether a process is random or not. A p *value* of hypothesis is defined as the probability of obtaining as observed sample value that deviate as far, or farther, from the expected value of the test statistic when the null hypothesis is true. In general, for a specified value of significant level α :

- If p *value* $\geq \alpha$, *accept* H_0
- If p *value* $< \alpha$, *reject* H_0

This paper aims to create connection between supply chain performance measurement by statistical monitoring and then test whether nonrandom of suppliers' delivery indicator can be recognized based on the run chart test or not. As nowadays, application of SPC has deployed to service and measuring performance indicator of systems. Although control charts were first developed and used in a manufacturing context, they are easily applied to service organizations such as hospital, bank, insurance company, post office, ambulance, police department, hotel transportation and auto service (Evans &Lindsay, 2008).

2. Methodology

Minitab identifies special cause signals as presented in Table 2. Out-of-control points appeared on the control charts labeled with rule 1 and caused signal patterns appeared and labeled from rule 2 until 8. Out of control signals are removed from variable and attribute control charts to make them "In control".

Many analyses require an assumption of normality. In SPC methodology, quantitative standard control charts are often based on the assumption that the observations are normally distributed. In practice, normality can fail and consequently the determination of assignable causes may result in error (Fournier et al., 2006). The Anderson-Darling statistic is a measure of how far the plot points fall from the fitted line in a probability plot. A smaller Anderson-Darling statistic indicates that the distribution fits the data better. If the $p-value$

(when available) for the Anderson-Darling test is lower than the chosen significance level (0.05 in this research), conclude that the data do not follow the specified distribution. Moreover, the Johnson transformation function is selected from three types of functions in the Johnson system. Consequently, the run chart shows if special causes are influencing your process. Run Chart performs two tests for randomness that provide information on the non-random variation due to trends, oscillation, mixtures, and clustering (Minitab, 2006).

Table 2 Assignable caused signals (Minitab, 2006)

Rules	Assignable caused signals
1	1 point > 3 standard deviation from centre line
2	9 points in a row on same side of centre line
3	6 points in a row, all increasing or all decreasing
4	14 points in a row, alternating up and down
5	2 out of 3 points > 2 standard deviation from centre line
6	4 out of 5 points > 1 standard deviation from centre line
7	15 points in a row within 1 standard deviation of centre line
8	8 points in a row > 1 standard deviation from centre line

Also, Castagliola and Castellanos (2008) investigated on process capability indices for bi-variate non normal distributions and cited that one possible solution for solving the problem of non normality is the use of Johnson system of distributions. According to reviewed literature, proposed methodology has been depicted in Figure 3.

The proposed methodology model is titled Run Chart Pattern Recognition algorithm (RCPR). To synchronization with process improvement in SPC as last authors have mentioned before, RCPR is homogenous built based on PDCA philosophy. It begins with identification of performance indicator of supply chain and goes through gathering data. Then gathering data, normality test and if required, doing transformation on data to meet data normality distributed. According to Minitab, eight special caused signals will be tested and moreover, run test is employed to identify nonrandom patterns on data. Root cause analysis is planned either to define corrective action or aiming with improvement plans.

To test the proposed methodology, data were gathered from automotive industry in Iran. The data are about on-time delivery of an OEM's vendor for 88 deliveries over time. The on-time delivery formulation was defined by the automaker as equation 1:

Equation 1:

$$OTD = \frac{\text{The number of on time delivered parts}}{\text{The number of ordered parts}} \times 100$$

3. Result and discussion

According to RCPR, on-time delivery (OTD) was selected as an important indicator of supply performance measurement. Data were depicted in Figure 4.

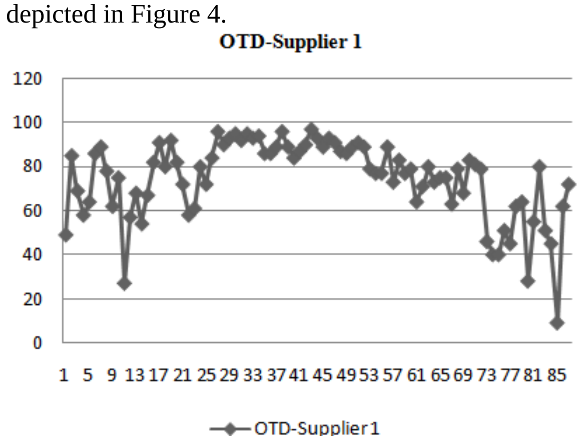

Figure 4 On-time delivery data of OEM's supplier for 88 deliveries to automaker

Data gathered of OEM's supplier was tested by Anderson-Darling (AD) normality test by significant level $\alpha = 0.05$ and results show that supplier OTD data are not normality distributed. Based on the proposed methodology, AD normality test shows that P-value is lower than 0.005 and the transformation should be employed. Johnson transformation was done on OTD-Supplier 1 data and results demonstrate that data are normally distributed in significant $\alpha = 0.05$. The optimal transformation function was recognized as equation 2:

Equation 2:

$$OTD\ Transformation\ function = -1.48174 + 0.946084 \times Ln\left(\frac{X+}{98.}\right.$$

$$Where\ X: on-time\ delivery\ \%$$

Figure 5 illustrates that outcome of transformation function on data before and after conversion.

As shown in Figure 5, $P-value$ for best fit after transformation is gained as 0.986781 which is higher than significant level $\alpha = 0.05$.

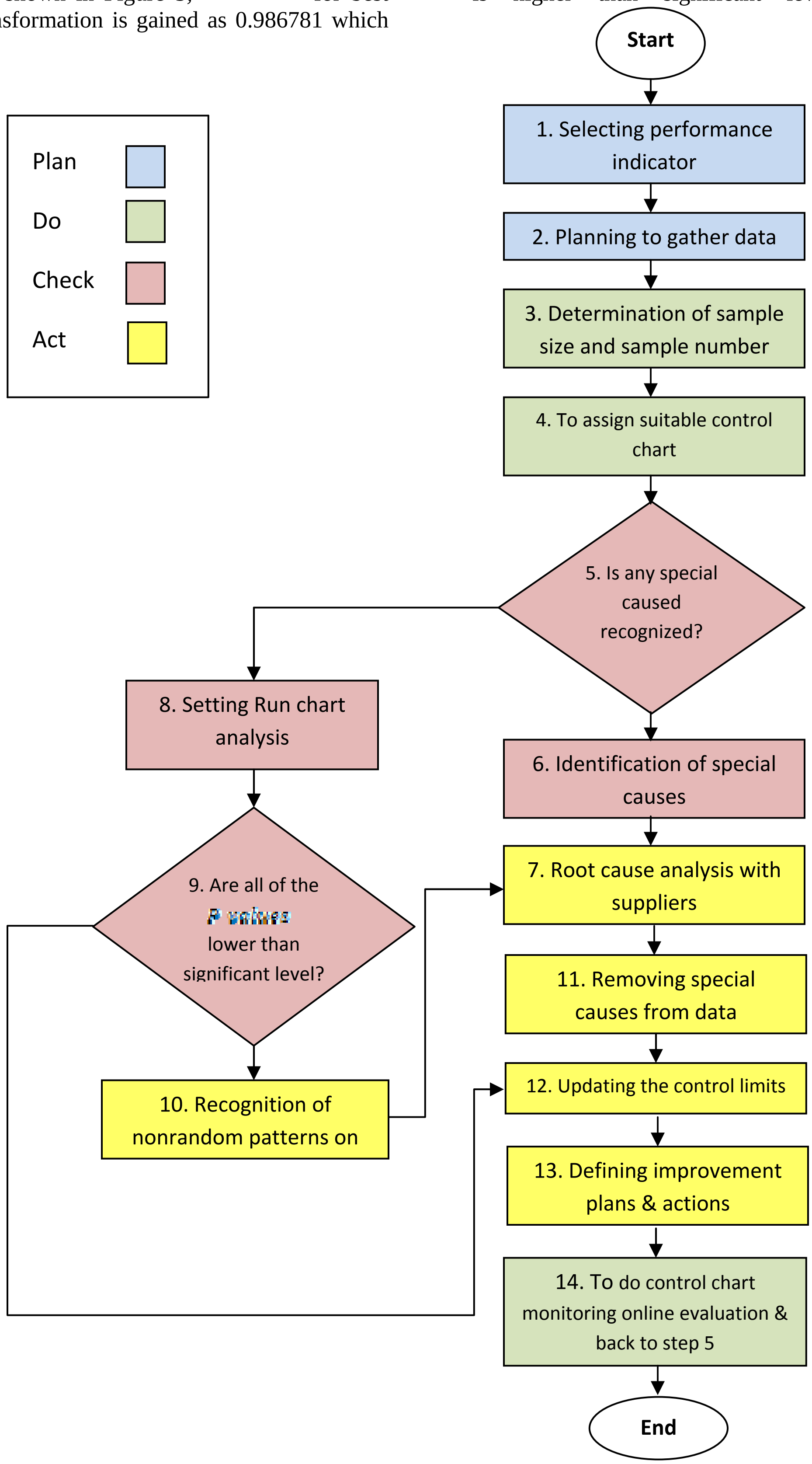

Figure 3. Process improvement by employing Run Chart Pattern Recognition algorithm (RCPR)

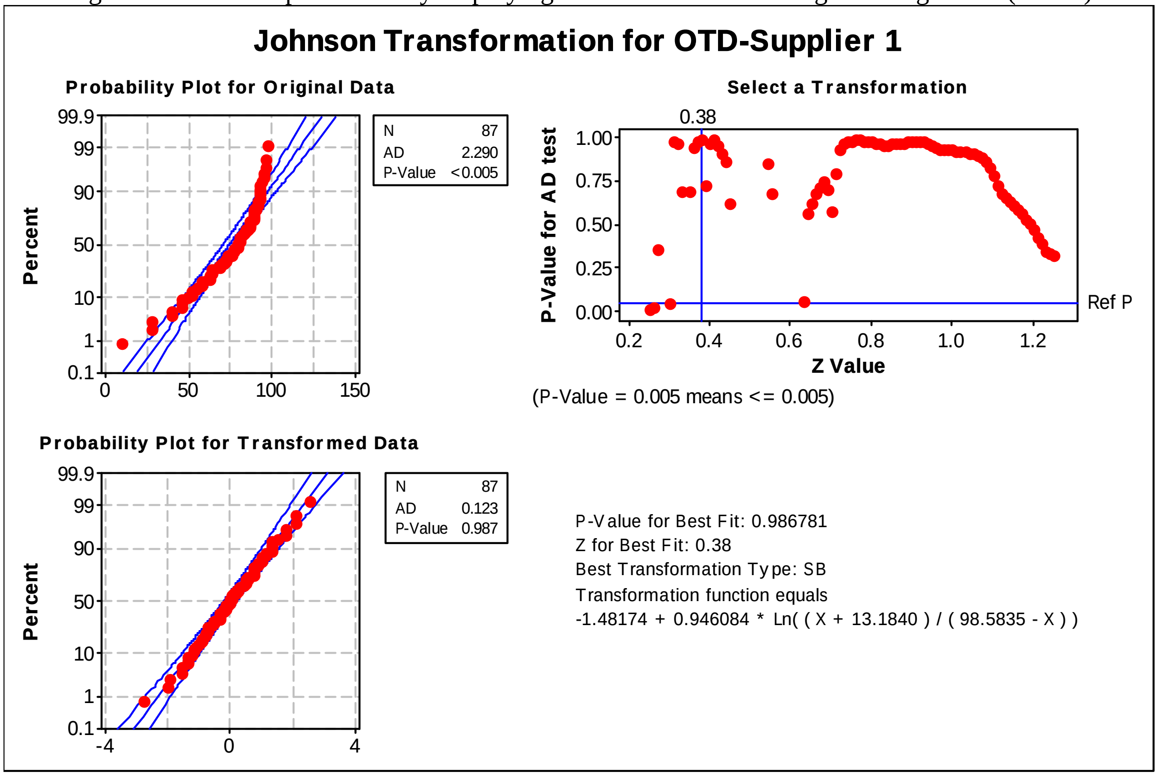

Figure 5. Johnson's transformation on "on-time delivery" data

Now the transformed data can be used for running control charts. An important point should not be forgotten that when data are not normally distributed, Central Limit Theorem (CLT) also may be employed. According to Hayter (2007), if $X_1, \dots, X_n$ is a sequence of independent identically distributed random variables with a mean μ and a variance σ^2, then the distribution of their average $\bar{X}$ can be approximated by a $N\left(\mu, \frac{\sigma^2}{n}\right)$ distribution. Similarly, the distribution of the sum $X_1 + \dots + X_n$ can be approximated by a $N(n\mu, n\sigma^2)$. When data are not normally distributed and we are interested to use $\bar{X}, R; \bar{X}, S$ control charts, it can be concluded that CLT can be employed. In this research, individual delivery monitoring was purposed and due to that the sample size or each delivery amount was targeted. In this context, individual X and moving range control chart (Figure 6) was illustrated and out-of-control signals were identified with red points accordingly. Moreover, Figure 6 represents that special cause signals as labeled by 1, 2, 5 and 6 were recognized on control charts according to mentioned rules in Table 2. Those signals should be analyzed and root causes to be identified by supplier cooperation.

Assignable caused signals are represented by red points on the control chart (Figure 6). It shows that delivery performance is affected with nonrandom condition and those should be identified and to be removed from control chart. It should be mentioned here that additive trend on delivery performance shows a desirable situation for both suppliers and their client even it is an out of control signals or assignable pattern. However, it should be investigated for further improvement in delivery process. In practice, when customers are monitoring their suppliers, while assignable cause signals alarmed (red points such as 11, 15, 74, 75, 80 and so on) root cause analysis should be taken in account to prevent delivery downturn.

Based on the RCPR algorithm, two consecutive steps were designed to identify out-of-control signals on data, out-of -control tests on control chart (Table 2's rules) and run chart tests (pattern recognition tests) included clustering, trends, mixtures and oscillation tests.

Figure 7 depicts the run chart test on OTD-Supplier 1 data and either the clustering test's $p-value$ is less than the significant level

($\alpha = 0.05$) or trend test and indicates a tendency for clustering and trend on on-time delivery data. The p value of mixtures and oscillation tests is higher than significant level. It can be concluded the data are included nonrandom patterns and according to RCPR algorithm, root cause analysis should be placed in account.

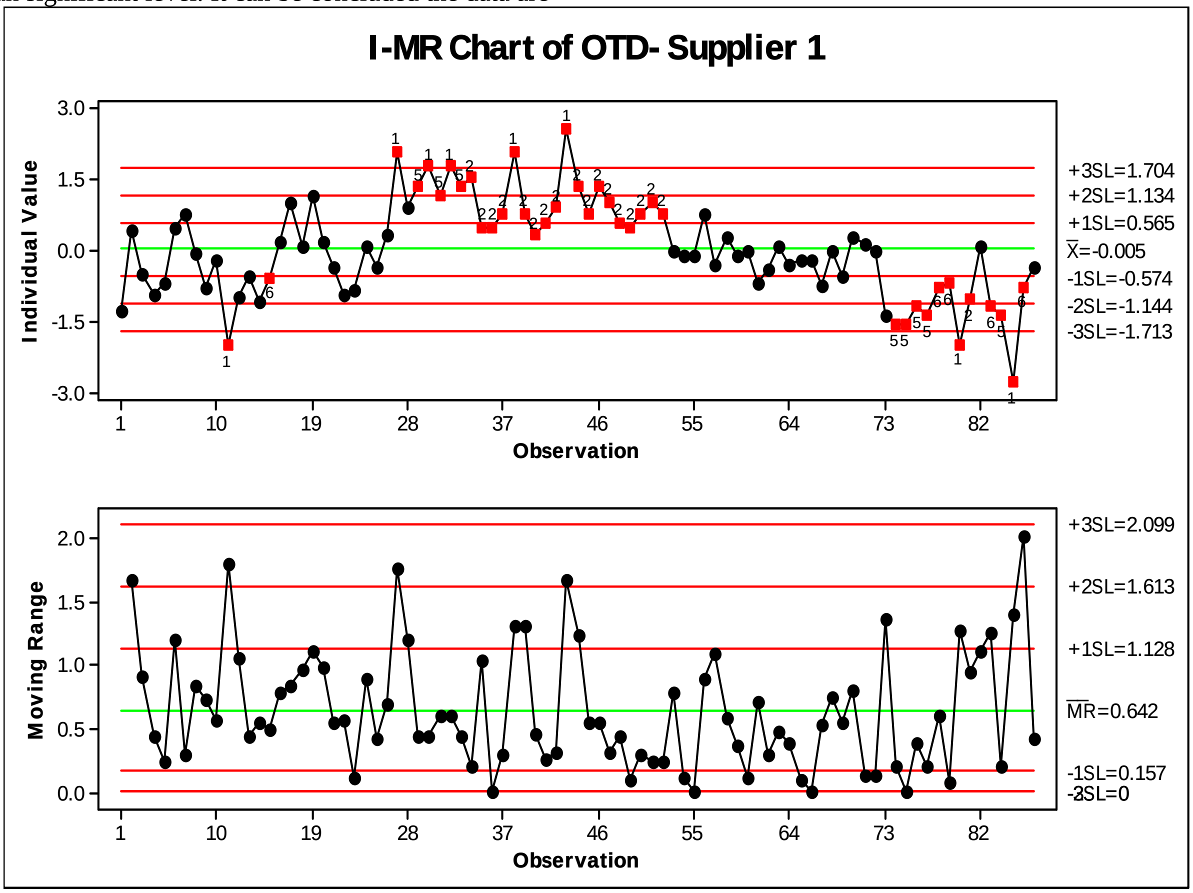

Figure 6. Individual X and moving range control chart for OTD transformed data

According to RCPR, the hypothesis in this section test whether OTD data has any nonrandom pattern signals. To test:

H_0: $OTD - Supplier\ 1\ data\ has\ a\ random\ sequence$

H_1: $OTD - supplier\ 1\ data\ has\ not\ a\ random\ sequence$

At Significant level $\alpha = 0.05$

$P - Value\ for\ clustering = 0.000$,

$P - Value\ for\ Mixtures = 1.000$

$P - Value\ for\ Trends = 0.043$,

$P - Value\ for\ Oscillation = 0.957$

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$p - Value\ for\ clustering = 0.000 < 0.05$, the null hypothesis is rejected and can be concluded that data has nonrandom sequence as recognized as clustering and likewise, as $p - Value\ for\ Trends = 0.043 < 0.05$, the null trend hypothesis test is rejected and can be concluded that data has nonrandom sequence as recognized by trend. According to RCPR, the next step is to identify the source of out of control signals and removing out of control points from primary control chart. In the first attempt to remove out of control signals from Individual X control chart (Figure 6), it was resulted that the mean of OTD was increased from -0.005 to 0.029. It can be interpreted that eliminating of out of control signals can lead to increase the delivery performance over time.

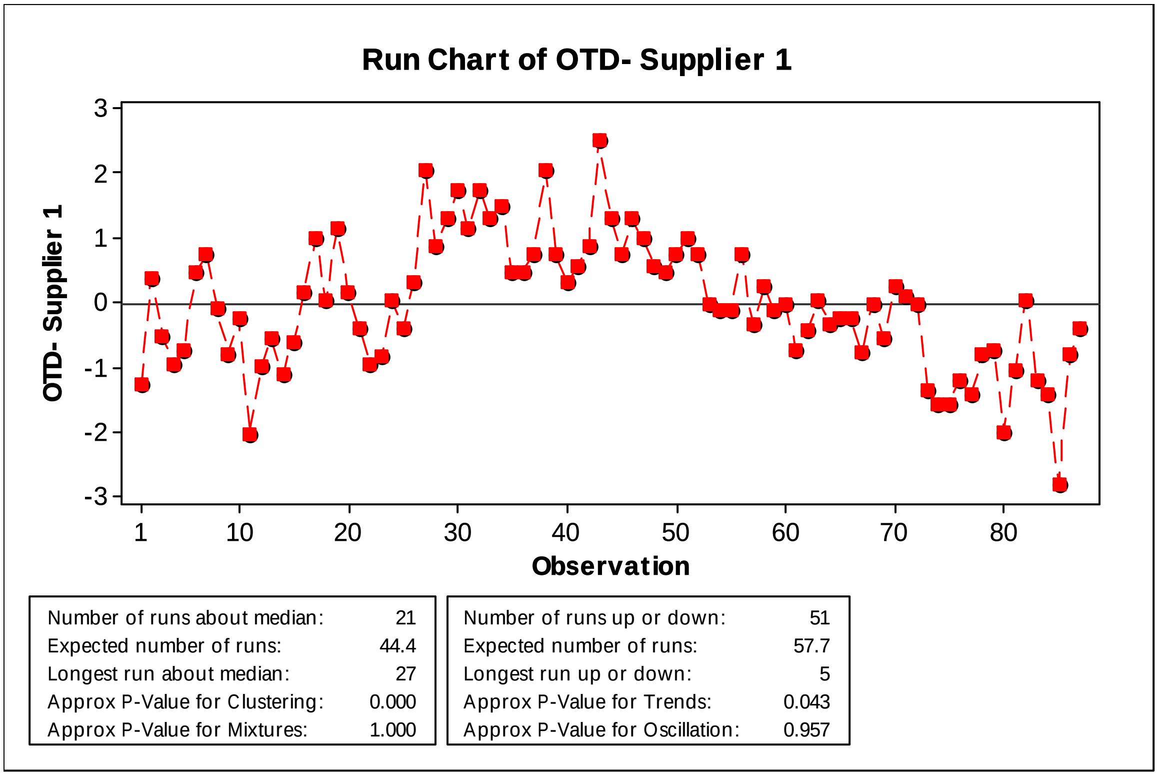

Figure 7 Run chart analysis on OTD-Supplier 1 data

4. Conclusion

Based on the mentioned methodology, run chart pattern recognition algorithm (RCPR) algorithm was proposed to identify the nonrandom supply performance patterns. The results show that caused signals can be identified by two consecutive steps. First, users can use Showhart's rules to identify the caused out of control signals and likewise run chart test which included trend, mixtures, oscillation and clustering tests. According to the gathered data from OEM for on-time delivery indicator, individual delivery and moving range chart was employed to monitor the supply trend and recognition of out of control signals. Afterwards, the run chart was provided with sample size $n = 1$ to recognition of caused signals. The results support that runs chart tests can recognize the nonrandom patterns on data in significant $\alpha = 0.05$. According to the results, it can be concluded the supplier delivery performance was affected by assignable trend and clustering pattern which does not let the process smoothly perform. Eliminating assignable signals (both run tests and Table 1's rules) assist to enhance delivery performance accordingly. In practice, central theorem limit (CLT) also can be used to establish the control chart. One of the advantages is that scale of data will not be changed and the essence of data will be kept accordingly. It was resulted that the mean value of transformed OTD was enhanced from -0.005 to 0.029. It can be interpreted that eliminating of out of control signals can lead to increase the delivery performance over time. In practice, when customers are monitoring their suppliers; while assignable cause signals root cause analysis should be taken in account to prevent delivery downturn. It make a feed back to supplier and let them go through their firm's processes and do problem solving activities to improve the performance and finally increasing OTD control chart central limit accordingly.

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