International Journal for Quality Research 18(2) 417–432
ISSN 1800-6450

Vladimir Shper [1]
Svetlana Sheremetyeva
Vladimir Smelov
Elena Khunuzidi

Article info:
Received 17.05.2023.
Accepted 12.12.2023.

UDC – 519.22
DOI – 10.24874/IJQR18.02-06

SHEWHART CONTROL CHARTS – AN IRREPLACEABLE TOOL OF EXPLANATORY DATA ANALYSIS WITH UNDERESTIMATED POTENTIAL

Abstract: *In this paper some issues relative to the gap between the traditional theory of control charts and real problems practitioners encounter are discussed. We consider both the general reasons for this discrepancy and different examples of misunderstandings. The trend to develop statistics as mathematical branch of science in the area of statistical process control has led to (i) ignoring many real complexities; (ii) creating many new types of charts that rarely help practitioners to improve their processes. We offer some practical advices, such as the introduction of two types of the assignable causes of variations (internal and external); the refusal from a traditional assumption that repetitive measurements are always normally distributed; the simple and practically convenient technique to calculate control chart limits for highly non-normal data. As the main direction for future efforts, we offer to start discussion about the implementation of Shewhart control charts into the program of school education.*

Keywords: *Shewhart control chart, assignable causes of variation, nonhomogeneity, nonrandomness, process stability, capability indices.*

1. Introduction

Very soon the World will be celebrating the one hundred year anniversary of Shewhart Control Chart – the indispensable tool of process stability analysis used successfully in practically all areas of human activity: in different industries (e.g., energy generation (Ozdemir, 2020), automobile production (Godina et al., 2018), semiconductor manufacturing (Spanos, 1992), aviation (Theroux et al., 2014), glass manufacturing (Awaj et al., 2013), etc., to name a few; in agriculture (Mertens et al., 2011), in government organizations (Prevette, 2006), in healthcare (Suman & Prajapati,, 2018), in education (Hanna et al., 2012), everywhere where the lean production is being implemented (Klochkov et al., 2019), and so on. Control charts are described in many old and new books (some of them will be referred to below), and there are international standards devoted to control charting as well as numerous sites on the Internet. On the other hand, most managers and engineers, and even not a small amount of statisticians are not familiar with this tool of data analysis (see, e.g., (Sheremetyeva & Shper, 2022). Moreover, very often control charts are being constructed in the wrong way and, as a result, do not allow a practitioner to get the benefit they could

[1] Corresponding author: Vladimir Shper
Email: vlad.shper@gmail.com

potentially deliver to her/him. Should we be concerned about this discrepancy? Without any doubts! Why? Because Shewhart control chart is the only tool that allows a practitioner to make an evidence-based decision if a process is stable or not. Without this knowledge, it is impossible to manage any system. "The leadership of people (manager, leader, supervisor, teacher) is entirely different in the two states, stable and unstable. Confusion between the two states leads to calamity… There are two mistakes in attempts to improve a process, both costly:
Mistake 1. To treat as a special cause any outcome, any fault, complaint, mistake, breakdown, accident, shortage, when actually it came from common causes. (Tampering.)
Mistake 2. To attribute to common causes any outcome, any fault, complaint, mistake, breakdown, accident, shortage, when actually it came from a special cause." (Deming, 2013).

All practitioners should know how to minimize the losses from these two mistakes. In order to reach this goal control charts must be constructed rightly. This is a big problem, because most practitioners create charts for their processes without careful analysis of the crux of the matter: if all assumptions which the theory of control charts is based on are applicable or not to their data. Unfortunately, many statistical handbooks, guides, and even standards do not help practitioners overcome this obstacle. They, certainly, mention all necessary assumptions somewhere at the very beginning of the introductory pages, but almost never outline how rare these assumptions are carried out in reality, and what to do when they are unfeasible. Moreover, there are many practical questions that are not being discussed in the current literature at all, and have not been ever discussed in the past. The goal of this paper – to attract the attention of statistical process control (SPC) experts to these unanswered questions and initiate at least the accompanying discussion. That is why we will present a brief survey of the opinions supporting our worries in section 1. Then section 2 is devoted to some specific issues which seem to us highly important. In section 3 we consider some ambiguity in one of the basic ideas of SPC – assignable causes of variation. Our proposals for further research and discussions are given in conclusion.

2. The important problems of Shewhart control chart application

We wrote in our recent paper (Sheremetyeva & Shper, 2022): "The implementation of Shewhart-Deming ideas into the minds of CEOs has not been realized either in the world or in our country. There is no friendship between business and the theory of variation – incomprehension is continuing". This is not just our viewpoint. Almost 30 years ago, in paper by Hoyer and Ellis (1996) said the following: "… our experience indicated that a sizable majority of *quality professionals* are not knowledgeable about basic issues of statistics and SPC. Our instructional activities in a broad range of academic, industrial, and service delivery environments have convinced us that there are many individuals who are "doing SPC" without understanding what it is about. It is not surprising to encounter, not just a few, but many individuals who have been entrusted with continuous improvement responsibilities *who cannot define an in-control process*, who cannot accurately distinguish between process control and process capability, who cannot distinguish between process capability and product capability, *who do not understand the basic structure of a control chart*, who do not have practical knowledge of the fundamental theorem of SPC, and *who do not understand the significance and relative importance of various signals of special causes of variation*. And why should they? Our review of a very large number of SPC textbooks reveals page after page of “cookbook” discussions of practically everything under the sun – with very little discussion on the foundation of SPC" (italic is ours, SSSH). We presented such a big piece from Spanos (1992) because our experience shows that if we substitute "quality professionals" with "engineers, or managers, or even, sometimes, statisticians" then at least the italic parts of this citation will stay quite reasonable.

A well-known expert in SPC W. Woodall in 2000 published a survey “Controversies and Contradictions in Statistical Process Control”. One of the main problems discussed there was the relationship between hypothesis testing and control charting. The main Woodall’s conclusion on this issue was that “At best the view that control charting is equivalent to hypothesis testing is oversimplification. At worst the view can prevent the application of control charts in the initial part of Phase I because of the failure of independence and distributional assumptions to hold”. We agree with this conclusion. Moreover, this widely spread view can prevent the right application of control charts both in Phase I and in Phase II. And what is more important, very few practitioners know about this problem and have ever pondered on it.

Steinberg (2016) wrote a survey of the state-of-the-art in industrial statistics, where he mentioned the following problems in SPC: multivariate data, profile data, and data from phasor measurement units. It is worth noting that at the very beginning of his article Steinberg outlined: “My focus is on statistical research, not on application of statistical methods and thinking in industry”. In spite of that, discussing the major challenges of time he made an important (to us) statement: “The call for modeling “real data” reflects a concern that too many research papers continue to rely on assumptions that just do not characterize the data encountered in industry”.

In 2017, Woodall wrote a follow-up to his survey of 2000 titled “Bridging the gap between theory and practice in basic statistical process monitoring”. This time he partly returns to the same problems as were discussed earlier, partly considers some new ones. Among the old problems, there was again the relation between statistical theory and practice. At the end of this paper, Woodall made a number of useful suggestions, which could have improved the quality of statistical papers in the area of SPC and the quality of concomitant researches. Simultaneously, he made a proposal that we consider completely unacceptable. Woodall thinks that practitioners should totally eliminate the use of the moving range chart. We beg to differ this suggestion and will explain our viewpoint below.

In 2023, Woodall published a new paper on SPC issues titled “Recent Critiques of Statistical Process Monitoring Approaches”. He wrote in the introductory paragraph: “Hundreds of flawed papers on statistical process monitoring (SPM) methods have appeared in the literature over the past five to ten years. The presence of so many flawed methods, and so much incorrect theory, reflects badly on the SPM research field. Critiques of the various misguided approaches have been published in the last two years in an effort to stem this tide. These critiques are briefly reviewed here”. Let us look at the flawed methods enlisted by Woodall: Use of Inadvisable Weighted Averages, Use of Auxiliary Information, Rules Equivalent to Runs Rules, Neutrosophic Methods, Mixing Various Charts, The Generally Weighted Moving Average Chart, Misuses of the EWMA Statistic, Repetitive Sampling Methods, using the coefficient of variation, the multivariate coefficient of variation, and various capability indices, etc.

We are sure that there are at least two root causes of such a sad situation. One was described in paper Hoyer and Ellis (1996) plus another one is more fundamental. In the report written in 1996, by G. Box noted: “An important issue in the 1930’s was whether statistics was to be treated as a branch of Science or Mathematics. To my mind unfortunately, the latter view has been adopted in the United States and in many other countries. Statistics has for some time been categorized as one of Mathematical Sciences and this view has dominated university teaching, research, the awarding of advanced degrees, promotion, tenure of faculty, the distribution of grants by funding agencies and the characteristics of statistical journals”. Judging by above-mentioned papers nothing has changed since 1930’s. All flawed techniques enlisted by Woodall in (2023) are math’s exercises or, as caustically noted by Quesenberry (1998) about one such work “Statistical Gymnastics”. Shewhart’s close friend and associate W. Edwards Deming ending the foreword to the 1939 Shewhart’s book wrote: “Another half-century may pass before the full spectrum of Dr. Shewhart’s contributions has been revealed in liberal education, science, and industry” (Shewhart, 1939/1986). It seems that one more half-century may pass before the main ideas of Shewhart and Deming has been comprehended by all who are trying to use control charts efficiently.

In 2016, Steinberg in his paper cites well-known statistician B. Gunter who wrote in 2008 panel discussion in *Technometrics* on the future of industrial statistics: “I fear that *Technometrics* has evolved from primarily making connections to the real, hard, and complex questions of scientific practice to primarily producing artificial formulations of those questions suitable for compact “solution” by mathematical characterization. … To understand what is useful and not merely wrong in industrial statistical practice, we need to pay much more attention to the messy details that make up reality”. Then Steinberg adds: “I don’t share Gunter’s opinion that most of our published research (whether in *Technometrics* or other journals) has become completely cut off from real problems. But I do share the concern that many of the most challenging and exciting problems arising today are not getting space in our journals and that we need better theory to guide us in attacking such problems”.

Let us sum up the main idea of all cited above papers: too many statistical works went far away from real practice and do not help practitioners in solving their real problems. This a direct contradiction to Shewhart-Deming approach and to the basic idea of Shewhart control chart, which “stands out as the only one that actually examines the data for the internal consistency which is a prerequisite for any extrapolation into the future. Thus, unlike all “tests” and “interval estimates” of statistical inference Shewhart’s process behavior charts are tools for Analytic Studies. Rather than mathematical modelling, or estimation, Shewhart’s charts are concerned with taking appropriate actions in the future, based upon an analysis of the data from the past. Out of all the statistical procedures available today, they alone were designed for the inductive inferences of the real world” (Sheremetyeva & Shper, 2022; Quesenberry, 1998). We see this tendency to leave reality for the world of math models in ignoring the problems of simple control charts in favor of more and more complex designs. Many (not all) books and standards that are being widely used by practitioners all over the world deliver the theory of control charts based on very unrealistic assumptions about real processes and their behavior (see, to name a few (Schindowski et al., 1974; Murdoch, 1979; Grant & Leavenworth, 1980; Kume, 1985; Duncan, 1986; Wheeler & Chambers, 1992; Rinne & Mittag 1993; Alwan, 2000; Montgomery, 2009; Davis, 2015; ISO 7870-2:2013). Below we will discuss more carefully some of the special issues: different types of assignable causes of variations, the examples of unanswered questions in the theory of control charts, etc.

3. The specific issues that need to be analyzed carefully

3.1. Different types of process instability require different types of assignable causes

In fig.1 one can see Shewhart control chart for the process of wholesale of ground buckwheat. The process is obviously nonhomogeneous and has different means and different variability in its dissimilar pieces.

The problem we'd like to discuss here is as follows. One can see two red circles which reveal the moments when the assignable causes of variation present in the process – two points are falling beyond the chart limits. And there is a green oval, which shows the moment when the process mean has changed. How the cause of this change should be called: common or assignable? Because common causes are considered as something "constant" (this term was used by W. Shewhart in his books 1939/1986; 1931/1980) and inherent to the process itself, we think that such causes should be named "assignable".

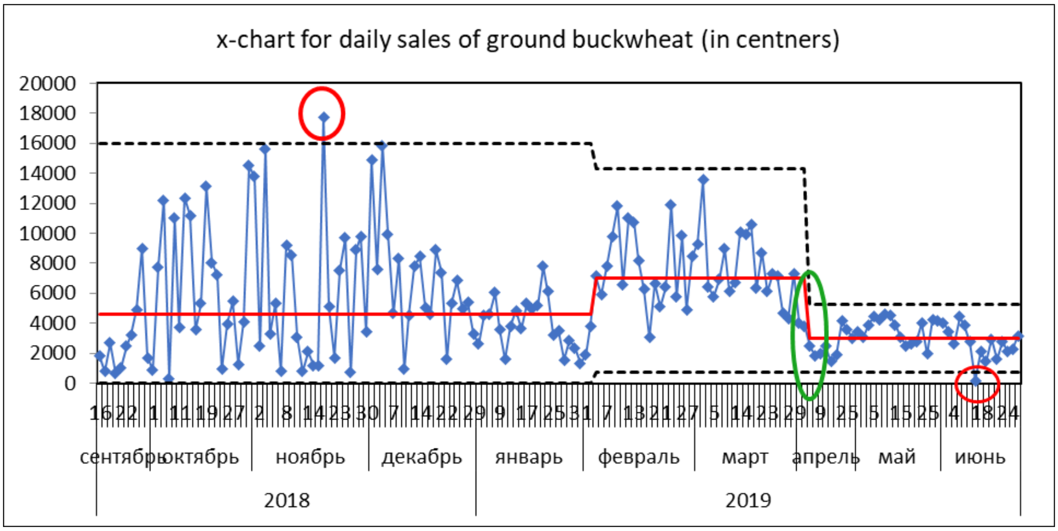

Figure 1. Daily sales of a distribution network. Here 1 centner = 100 kilograms

But is there any difference between these two cases: one when the assignable cause was evanescent and the system has not changed, and second when the assignable cause has changed the system? As far as we know, such a question has not been ever discussed in the SPC literature. Does it deserve of being discussed? We are sure it does because in the first case the search for the root cause of interference into the process have to be made by the process team (engineers, operators, linear managers, etc.); and in the second case this search is an act of top management – only CEOs are responsible for the system as a whole. We have already analyzed various definitions of assignable causes of variations in the paper "Assignable causes of variation and statistical models: another approach to an old topic" (Adler, Shper & Maksimova, 2011). Dr. Deming wrote in the Foreword to Shewhart's book (1939/1986): "The great contribution of control charts is to separate variation by rational methods into two sources: (1) the system itself ("chance causes," Dr. Shewhart called them, responsibility of management); and (2) assignable causes, called by Deming “special causes”, specific to some ephemeral event that can usually be discovered to the satisfaction of the expert on the job, and removed. A process is in statistical control when it is no longer afflicted with special causes. The performance of a process that is in statistical control is predictable”. The process change cannot be called “ephemeral” because something new came and remained within the process. That is Deming considered assignable causes as evanescent. Woodall (2000) provides the following definition: “’Common cause’ variation is considered to be due to the inherent nature of the process and cannot be altered without changing the process itself. ‘Assignable (or special) causes’ of variation are unusual shocks or other disruptions to the process, the causes of which can and should be removed”. Wheeler & Chambers in their book (1992) with a reference to Shewhart write that assignable cause “is characterized by a pattern of variation that changes over time”. Montgomery (2009) defines the assignable causes as those “that are not part of chance pattern”. Quality glossary by ASQ gives the following definition: “A name for the source of variation in a process that is not due to chance and therefore can be identified and eliminated” (*Quality Glossary of Terms, Acronyms & Definitions*). All these definitions do not make the answer to the question stated above more clear. That’s why we return to the proposal made in (Adler, Shper & Maksimova, 2011) to introduce two different types of assignable causes of variation. Slightly generalizing the definitions we here suggest the following versions:

Definition 1: An assignable cause of variation of type I (Intrinsic) does not change the system within which a process works (e.g., does not change the type of the underlying DF). As a consequence, it is quite natural to think that this type of assignable causes may belong to the system (though this is not a necessary condition).

Definition 2: An assignable cause of variation of type X (eXtrinsic) changes the system within which a process works (e.g., changes the type of the underlying distribution function (DF)). As a consequence it is quite natural to think that this type of assignable cause most probably does not belong to the system (though this is also not necessary).

If statistical community agrees with our suggestions, then the difference between dissimilar types of assignable causes of variation will help practitioners to grasp who, first of all, has to interfere into the process. This is a very important knowledge as it was explained above. The instability due to assignable causes of type I requires searching for a root cause inside the system. The instability due to assignable causes of type X requires searching for a root cause outside the system.

3.2. Examples of some underestimated problems

Below the three examples are given. They show the lack of new research trying to expand Shewhart control chart basics beyond the limits of traditional assumptions.

The first one was presented in (Adler, Shper & Maksimova, 2011) where the authors suggested that a point beyond a chart limit can appear from a distribution function differing from that one to which past data were belonging. Or, they proposed to refuse from traditional suggestion that the assignable cause of variation changes parameters of distribution function but does not change its type. It was shown that if the assignable cause of variations stemmed from another type of distribution function, then the resulting power functions might differ significantly from traditional ones. The authors of mentioned paper investigated the case when the assignable cause belonged to uniform and lognormal distributions. There are obviously numerous opportunities for further researches in this direction.

Later, Shper and Adler (2017) in paper on the problem of data succession was published. It raised a very important question about the data: in fact, there are almost no processes with really random data, but all the theory of Shewhart control charts is based on the assumption of data randomness. We guess that this tradition may be at least partly connected with the fact that Shewhart (and many of his followers) often repeated the phrase “system of chance causes” (Shewhart, 1931/1980, p.12). But the words “chance causes of variation” in no way mean random process data. Practically all processes have one or another type of patterns (they may be more or less obvious or hidden) and any pattern means nonrandomness. In his second book Shewhart devoted many pages to discussion about data randomness (Quesenberry, 1998; Steinberg, 2016; Woodall, 2017; 2023). And the theory of control charts for nonrandom processes has not been created yet.

Our third example concerns by paper Shper and Gracheva (2021) about the impact of transient process shift on control chart behavior. It was found out that under conditions of transient shift the chart for averages in some cases may lose its advantage before the chart for individuals (contrary to all SPC handbooks). This paper continued to widen the list of conditions that were ignored in traditional approach and that can impact significantly on Shewhart chart interpretation. But again, authors investigated the impact of transient shift on the operational characteristics of charts based on normality assumption. How the charts with non-normal data behave will remained an open question.

4. The problems of the lack of data normality

This section consists of two parts. Firstly, we will discuss if the results of measurements are always normally distributed. Secondly, we will present how the Shewhart chart limits are being changed when the distribution function is not normal, and give the most convenient for practitioners method of taking this change into consideration.

4.1. Are the measurement results normally distributed

One of the most stable mistakes about the universality of the normal law is an opinion that measurement results are always distributed according to the Gauss curve, and especially it is true when measurements are simply repeated. In order to check this assumption in practice we took three details and asked a skilled operator to measure each one 150 times (with the same tool, of course). The results are shown in fig.2. All three details were taken from one process but relate to different points of tolerance interval. Control charts for parts showed that we had a stable process for parts 1 and 2, but for part 3 the number of distinctive categories turned out to be only 3. All histograms are obviously non-normal, and testing the hypothesis on normality by using the procedure of (Ryan & Joiner, 1976) supported this conclusion. So, we may state that repeated measurements of an object may be as non-normal as measurements of any objects.

4.2. How the non-normality of distribution functions impacts the coefficients of Shewhart control charts?

The lack of normality is ignored by many practitioners because this is a widely spread opinion of many authors, books and even standards. For example, the standard ISO 7870-2:2013 in section 6 states: “For all variables control chart applications considered in this International Standard, it is assumed that the distribution of the quality characteristic is normal (Gaussian) and departures from this assumption will affect the performance of the charts. The factors used for computing control limits were derived using the assumption of normality. Since most control limits are used as empirical guides in making decisions, *reasonably small departures from normality* should not cause concern. In any case, because of the central limit theorem, averages tend to be normally distributed even when individual observations are not; this makes it reasonable for evaluating control to assume normality for X charts, even for sample sizes as small as 4 or 5. When dealing with individual observations for capability study purposes, the true form of the distribution is important… Although normality is necessarily assumed in the determination of the constants for the calculation of control limits for the range or standard deviation chart, *moderate deviations from normality* of the process data should not be of major concern in the use of these charts as an empirical decision procedure." (Italic by us, SSSH). But what are "*reasonably small departures from normality*" or "*moderate deviations from normality*". All these phrases are absolutely non-operational in the sense of "operational definitions" (Deming, 1987, ch.9). Obtained results (Shper & Sheremetyeva, 2022) let us define these words operationally and suggest an algorithm for construction of control charts under conditions of evident non-normality. Below we briefly present the main results of this.

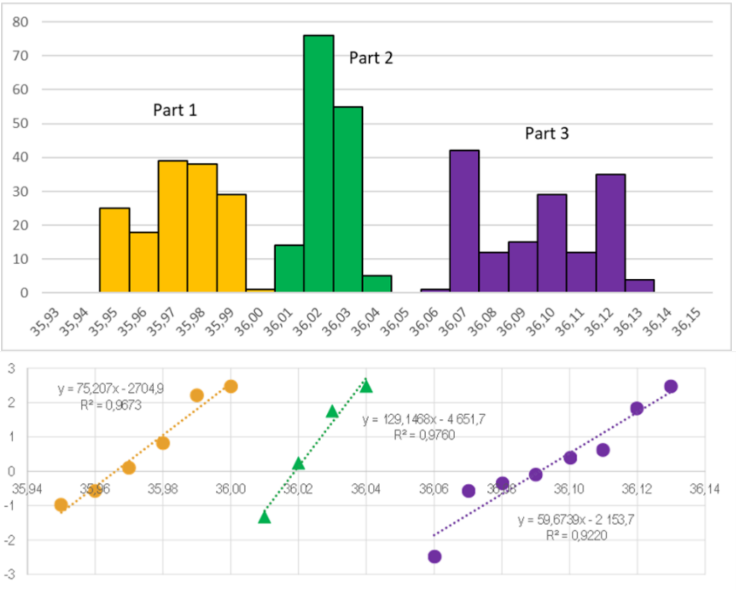

Figure 2. Histograms and empirical DFs for many repeated measurements

We constructed the chart for individuals and moving ranges (x-mR) for simulated exponentially distributed data using standard values for chart coefficients (Wheeler & Chambers, 1992). $E_2 = 2.66$; $D_4 = 3.27$. The x-mR chart for these data is shown in fig.3. Control limits for this chart are shown in fig.3 by short dashes. The process seems to be unstable as 7 points on the x-chart (1.8 % from the total number of points) and 9 points on the mR-chart (2.2 %) lie above the Upper Control Limits (UCL_x and UCL_{mR}).

But according to the results of (Shper & Sheremetyeva, 2022) for the exponential distribution function the coefficient d_2 should be equal to 2.99 instead of 2.66. This modified limit is shown by long dashes in fig.3. One can see that now only 6 points lie above the corrected limit. Similar considerations for the mR-chart give the following results: instead of 9 points beyond the chart limits, one gets only 4 such points – more than a two-fold decrease in signals. So in this case one can see that the number of false signals really decreased by 14 % for *x*-chart and by 44 % for *mR*-chart.

In table 1 the real data about the monthly number of technology violations at a big ore-dressing plant are presented. The question is: if the September value is a special cause of variation or not? Or, in other words, if the process is stable or not? In order to answer, one needs to construct an x-mR chart. The traditional approach leads to the following values: central line (CL) = 20.7, average moving range (AMR) = 13.2, UCL = 55.7; i.e. the value in September lies above the UCL. The process is unstable, the process team needs to look for a special cause. However, this result was obtained by using the traditional approach. Was this right or not?

In this case the sample size is too small so a histogram - necessary to understand if the data are normal or not - cannot be constructed. Therefore, one should look at a box-and whisker plot – fig.4. This plot shows that the data are obviously skewed. Is this departure from normality significant or not? One way to answer is to calculate data skewness and kurtosis. Excel gives the values of 2.0 for skewness and 4.7 for kurtosis. However, Excel calculates an excessive kurtosis. So non-excessive kurtosis is equal to 7.7. It was suggested in (Shper & Sheremetyeva, 2022) that for kurtosis values more than 7 it is recommended to use the corrected values of chart constants and if one does not know what distribution corresponds to her/his data it is necessary to take coefficients of the nearest point on Pearson curve plane (fig.4).

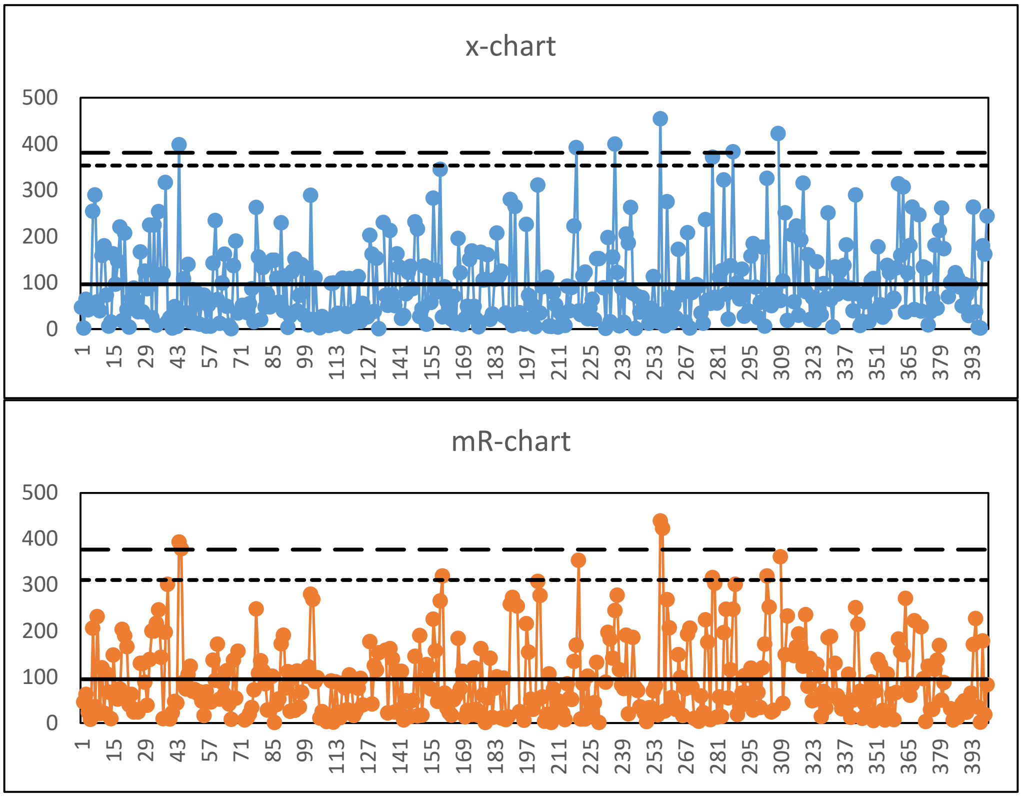

Figure 3. x-mR chart for simulated data

Table 1. Violations of technological discipline at the plant

Dynamics of technology violations during a year											
Jan	Febr	March	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec
13	14	8	11	14	8	33	24	60	15	22	26

For data in table 1, the nearest point is B_5 (Burr's distribution function – DF). The value of E_2 for this DF = 2.81, and corrected UCL = 57.7 (see table 2 in Shewhart, (1939/1986)). Ergo, the September point stayed above the UCL, and our conclusion has not changed. If, for example, our data were from exponential DF (if kurtosis turned out to be near 9), then the corrected coefficient would have been 2.99, corrected UCL = 60.1, and the process would have been stable.

These examples demonstrate an important feature of control charts which is frequently ignored by many authors and is rarely understood by practitioners: Shewhart control chart is principally a tool that requires a close interconnection between an investigator and the process. The construction of a good chart cannot be wholly algorithmized (Adler, (2018). The right application of Shewhart charts requires deep understanding of process specifics and simultaneously knowledge of the theory of variability. We are sure that this is maybe the main reason for many unsuccessful applications of this power tool in practice.

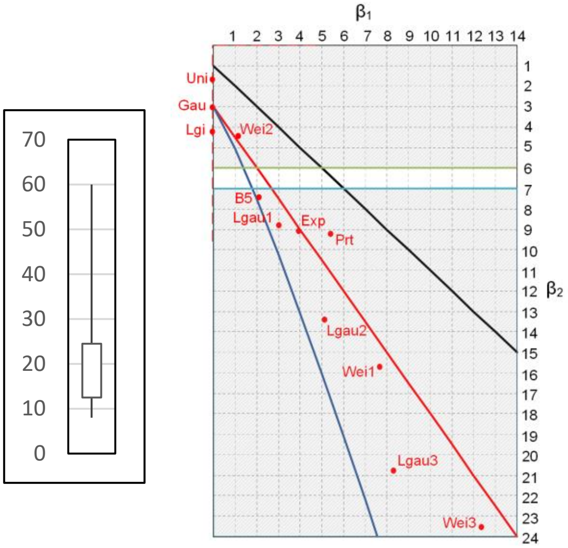

Figure 4. Box-and-whisker plot for table 1 data and Pearson curve plane from (Shper & Sheremetyeva, 2022)

5. Discussion

First of all, we'd like to come back to the problem of using moving range chart for process analysis. Woodall considers it excessive because, as Nelson (1982) pointed out: "the chart of the individual observations actually contains all the information available". However, neither Nelson, nor Woodall have not taken into account that moving range is sensitive to patterns, i.e. it "feels" the nonrandomness of data and may indicate its presence (Shper & Adler, 2017).

That's why we consider this Woodall's suggestion to be wrong.

As it was mentioned above, Shewhart control chart is the only tool to define if the process is stable or not. However, there may exist different types of instability. Naturally, different types of instability require different types of human reaction. Let us consider the process shown in fig.5. This is real process data taken from the metallurgical plant in Russia. The technology of this detail manufacturing was not changing during all time of observation as well as no system changes were being made. The process produced details within the Upper and Lower Specification Limits (USL and LSL) so the customer was satisfied. But what can be said about the process stability? We will discuss the answer from the viewpoint of an engineer not familiar with SPC (we'll call him a novice) and an engineer with experience in SPC (an expert).

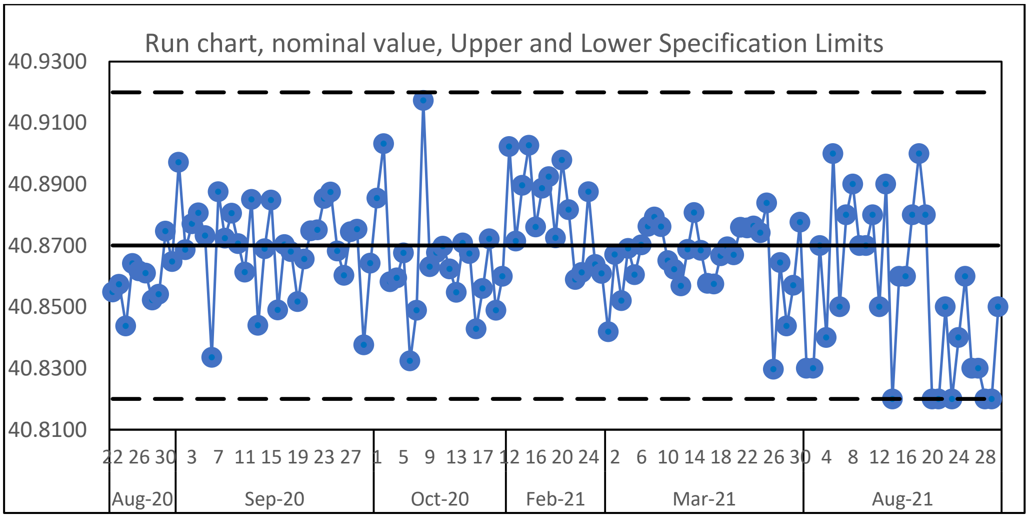

Figure 5. Run chart for the hole Ø40,87±0,05

A novice will take all data without any doubts and will get the x-mR chart presented in fig.6. Central Line (CL) will be equal to 40.865, UCL = 40.913, LCL = 40,817. This chart shows an unstable process (one point above UCL on x-chart and four points above UCLmR on mR-chart). Or, the process was stable in August and September of 2021, and in March of 2022; and it was unstable in October 2021 and in August 2022. It is clear that a novice will have no problems with process capability indices (PCI) calculation: C_p will be equal to 1.04 (0.1 divided by 6 sigma, where sigma = (Average Moving Range – AMR)/d_2. C_p equal to 1.04 corresponds to potential nonconformity level (NL) equal to 0.18% or process yield (PY) = 99.82%.

An expert will say that the process is obviously nonhomogeneous and should be stratified into homogeneous segments. Such stratification is shown in fig.7. One can see four segments with different values of CLs and different control limits:

Segment 1:
August-September-October 2020
CL = 40.8665   CLmR = 0.0173
UCL = 40.9124   LCL = 40.8206
UCLmR = 0.0564

Segment 2:
February 2021
CL = 40.8830   CLmR = 0.0189
UCL = 40.9331   LCL = 40.8329
UCLmR = 0.0616

Segment 3:
March 2021
CL = 40.8662 CLmR = 0.0123
UCL = 40.8990 LCL = 40.8334
UCLmR = 0.0403

Segment 4:
the end of March and August 2021
CL = 40.8537 CLmR = 0.0256
UCL = 40.9218 LCL = 40.7856
UCLmR = 0.0837

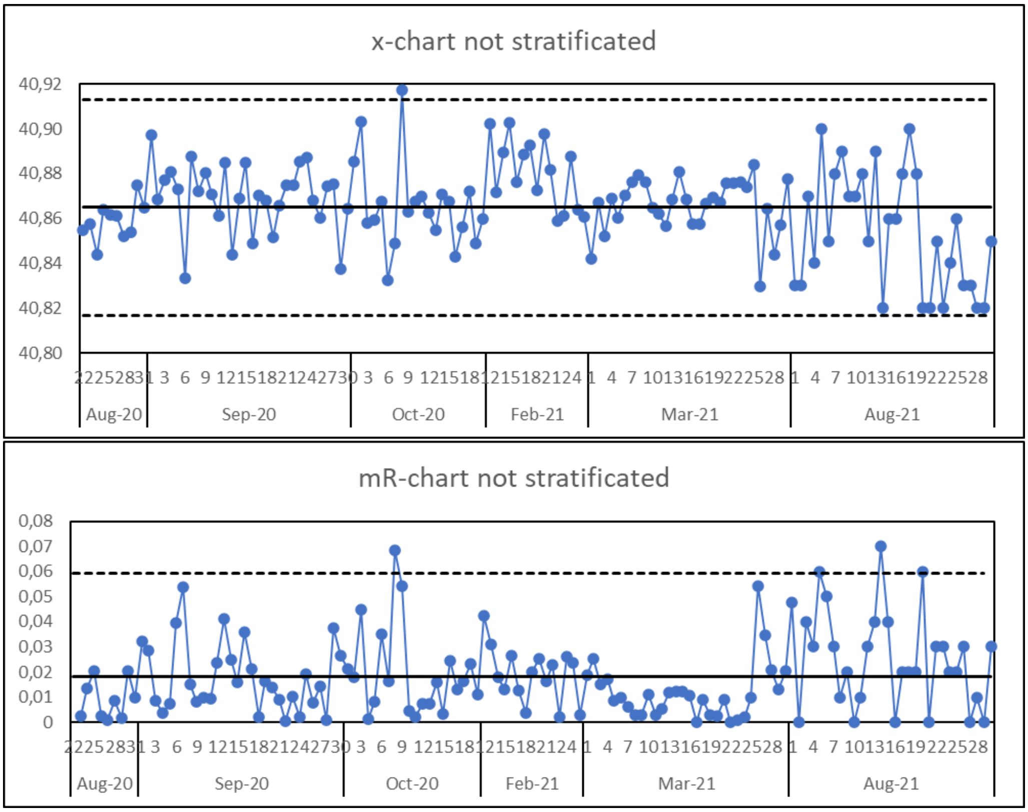

Figure 6. x-mR chart constructed by a novice

The values of PCIs for each segment will be as follows: Segment 1: Cp = 1.09; Segment 2: Cp = 1.00; Segment 3: Cp = 1.53; Segment 4: Cp = 0.73. If one calculates the NL for each segment, she/he will get the values differing from 4.7 ppm to 27525 ppm. The jaw-dropping difference! So, the problem is: which way of analysis is more appropriate for process improvement and how one can interpret process stability for such a process? We'll start with the second question because in fact we have already answered it in section 2.1.

This process is clearly nonhomogenous, therefore it should be divided into homogenous pieces. Its stability should be analyzed in accordance with these pieces. But what is the answer to the first question? It is not as simple as it may seem. The answer is "It depends". It depends on the goal and state-of-the art. Both ways may be right for one situation and wrong for another. This conclusion returns us to the beginning of this paper. In fact, Shewhart control charts are very simple technically and in no way they are simple for real application. The formulas they are based on may be easily used by pupils in primary school. However, the right application of Shewhart charts requires the deep understanding of the process under consideration and good knowledge of the many assumptions and limitations used in practice. Besides, it is necessary to possess the skill of combining knowledge from different areas of human activity into common practical work. That is why maybe the best approach to right using of this tool is teamwork.

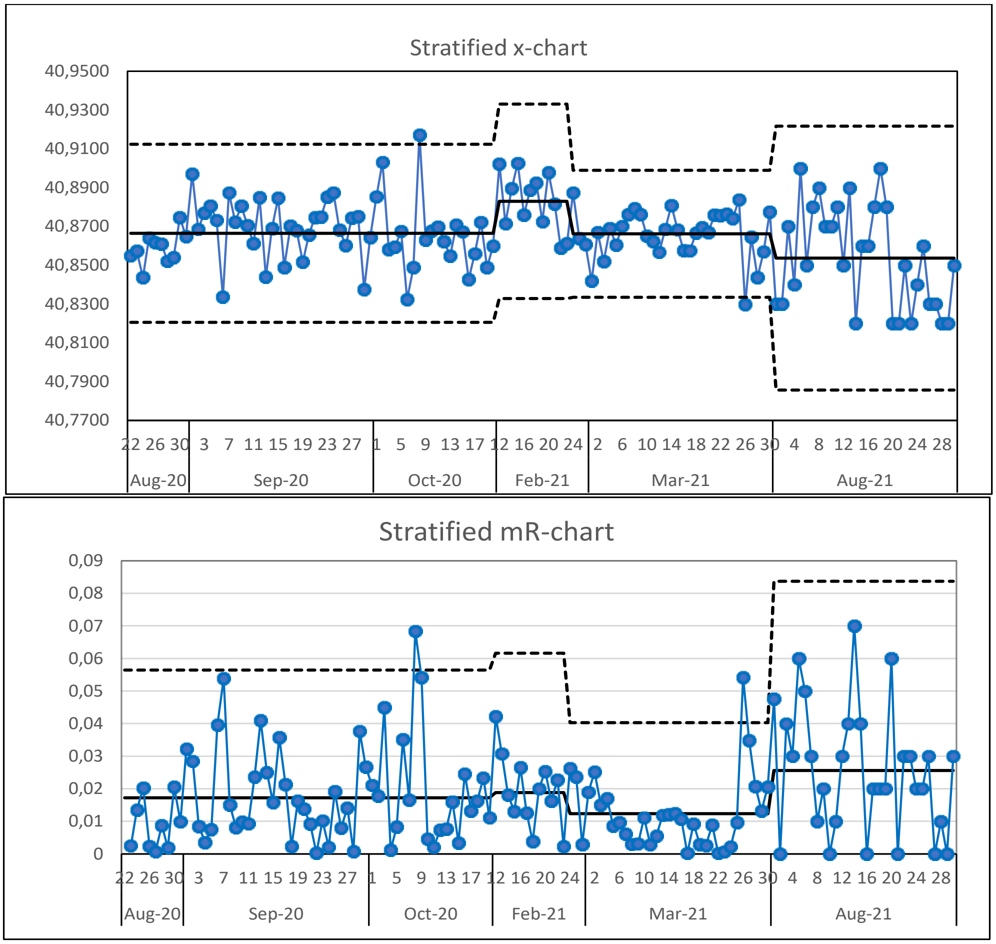

Figure 7. x-mR chart constructed by an expert

Finally, we can repeat the conclusion of Sheremetyeva & Shper (2022): “In order to start moving to the realization of H. Wells dream – “Statistical thinking will one day be as necessary for efficient citizenship as the ability to read and to write” – we need to begin the implementation of statistical thinking ideas into the primary school system”. This means that the construction of Shewhart control charts should be included into school programs and we offer to start a discussion on this in the community of SPC professionals.

6. Conclusions

We reviewed some problems in the area of Shewhart control chart applications and found that despite their all-round-the-world use, there were many gaps hindering more effective adoption of this powerful tool in practice. To decrease some of the deficiencies, we suggest

- to refuse from the normality assumption while analyzing the measurement systems;
- to use more accurate constants to calculate chart limits when process data are obviously non-normal;
- to introduce different types of the assignable causes of variations.

All these ideas will have a deep impact on the application of Shewhart charts by practitioners. They will allow them to decrease significantly the number of erroneous decisions based on misinterpreted data from real processes, that is, to improve the quality of their management system.

Maybe the most far-going idea stemming from our research is the following. The right application of control charts cannot be totally algorithmized. Such operations as the choice of chart type, the choice of phase I duration, the choice of right coefficients for control limits calculation, the choice of homogeneous segments, require deep knowledge of process features and additional analysis, for example, of DFs or the data sequence, etc. This knowledge cannot be installed into statistical programs beforehand – it emerges during the interaction between a man who manages a process and this process itself.

The authors hope that this article will promote the clear thought: Shewhart Control Charts seem to be a very simple tool of SPC, but this impression is deceptive because they cannot be used effectively without the profound knowledge of process itself and SPC basics.

The data that support the findings of this study are available on request from the corresponding author, (SV). The data are not publicly available due to privacy restrictions.

"All models are wrong,
But some are useful".
George Box

References:

Adler, Y., Shper, V., & Maksimova, O. V. (2011). Assignable causes of variation and statistical models: another approach to an old topic. *Quality and Reliability Engineering International, 27*(5), 623–628. https://doi.org/10.1002/qre.1207

Adler, Y. (2018). Algorithm unsolvable problems and artificial intelligence. *Economics and Management: problems and decisions*, *7/77*(5), 17–24 (in Russian).

Alwan, L. C. (2000). *Statistical Process Analysis*. ISBN 0071162275.

Awaj, Y. M., Singh, A. P., & Amedie, W. Y. (2013). Quality Improvement Using Statistical Process Control Tools in Glass Bottle Manufacturing Company. *International Journal for Quality Research*, 7(1), 107–126.

Davis, B. (2015). Data sanity: A Quantum Leap to Unprecedented Results. Medical Group Management Association/Center for Research in Ambulatory Health Care Administration. ISBN 1568294387.

Box, G. (1996). Scientific Statistics, Teaching, Learning, and the Computer. CQPI Report, No.146.

Deming, W. E. (2000). *Out of the crisis.* MIT Press. ISBN 0262541157.

Deming, W. (2013). *The Essential Deming. Leadership Principles from the Father of Quality*/Edited by J. Orsini. McGrow-Hill, NY. ISBN 0071790225.

Duncan, A. J. (1986). *Quality Control and Industrial Statistics*. 5th Edn. Irwin, Homewood, IL. ISBN 0256015589.

Godina, R., Pimentel, C., Silva, F., & Matias, J. C. O. (2018). Improvement of the statistical process control certainty in an automotive manufacturing unit. *Procedia Manufacturing, 17,* 729–736. https://doi.org/10.1016/j.promfg.2018.10.123

Grant, E. L., & Leavenworth, R. S. (1980). *Statistical quality control.* McGraw-Hill Companies. ISBN 0070241147.

Hanna, M. D., Raichura, N., & Bernardws, E. (2012). Using Statistical Process Control to Enhance Student Progression. *Journal of Learning in Higher Education, 8*(1), 71–82.

Hoyer, R.W., & Ellis, W.C. (1996). A Graphical Exploration of SPC. Quality Progress, №5, Part 1, 65–73; №6, Part 2, 57–63.

ISO 7870-2:2023. Control Charts – part 2: Shewhart Control Charts.

Klochkov, Y., Gazizulina, A., & Muralidharan, K. (2019). Lean Six Sigma For Sustainable Business Practices: A Case Study And Standardisation. *International Journal for Quality Research, 13*(1), 47–74. https://doi.org/10.24874/ijqr13.01-04

Kume, H. (1985). *Statistical Methods for Quality Improvement.* The Association for Overseas Technical Scholarship (AOTS).

Mertens, K., Decuypere, E., De Baerdemaeker, J., & De Ketelaere, B. (2010). Statistical control charts as a support tool for the management of livestock production. *The Journal of Agricultural Science, 149*(3), 369–384. https://doi.org/10.1017/s0021859610001164

Montgomery D. C. (2009). *Introduction to Statistical Quality Control*. 6th Edn. John Wiley & Sons.

Murdoch J. (1979). *Control Charts*. The Macmillan Press, Ltd. ISBN 0333264118.

Nelson, L. S. (1982). Control Charts for Individual Measurements. *Journal of Quality Technology, 14*(3), 172–173.

Ozdemir, A.C. (2020). Usability of control charts to monitor variation of quality parameters in coal-fired thermal power plants. *Mining, 59*(4), 247–253.

Prevette, S.S. (2006). Dashboards and Control Charts Experiences in Improving Safety at Hanford Washington. In Hanford Site (HNF), Richland, WA (United States)https://www.osti.gov/servlets/purl/876699 Accessed on 24.04.2023.

Quality Glossary of Terms, Acronyms & Definitions | ASQ | ASQ. (n.d.). https://asq.org/quality-resources/quality-glossary - Accessed February 23, 2023.

Quesenberry, C. (1998). Statistical Gymnastics. *Quality Progress*, Sept., 77–79.

Mittag, H., & Rinne, H. (2018). *Statistical methods of quality assurance.* In Chapman and Hall/CRC eBooks. https://doi.org/10.1201/9780203738542

Ryan, T. A. Jr., & Joiner, B. L. (1976). Normal Probability Plots and Tests for Normality – https://docplayer.net/21494161-Normal-probability-plots-and-tests-for-normality.html

Schindowski E., & Schürz O. (1974). *Statistische Qualitätskontrolle*. Veb Verlag Technik: Berlin.

Sheremetyeva, S., & Shper, V. (2022). Business and Variation: Friendship or Misunderstanding. *Standards and Quality, 2,* 92–97. doi: 10.35400/0038-9692-2022-2-72-21 (in Russian).

Shewhart, W. (1931/1980). *Economic Control of Quality of Manufactured Product*. ASQ Quality Press: Milwaukee.

Shewhart, W. (1939/1986). *Statistical Methods from the Viewpoint of Quality Control*. Dover Publications, Inc.: N.Y.

Shper, V., & Adler, Y. (2017). The importance of time order with Shewhart control charts. *Quality and Reliability Engineering International, 33*(6), 1169–1177. https://doi.org/10.1002/qre.2185

Shper, V., & Gracheva, A. (2021). Simple Shewhart Control charts: Are they really so simple? *International Journal of Industrial and Operations Research, 4*(1). https://doi.org/10.35840/2633-8947/6510

Shper, V., & Sheremetyeva, S. (2022). The Impact of Non-Normality on the Control Limits of Shewhart's Charts. *Russian journal of heavy machinery*, 1-2, pp. 16-29. ISSN 1024–7106

Spanos, C. J. (1992). Statistical process control in semiconductor manufacturing. *Proceedings of the IEEE, 80*(6), 819–830. https://doi.org/10.1109/5.149445.

Steinberg, D. M. (2016). Industrial statistics: The challenges and the research. *Quality Engineering, 28*(1), 45–59. https://doi.org/10.1080/08982112.2015.1100453

Suman, G., & Prajapati. (2018). Control chart applications in healthcare: a literature review. *International Journal of Metrology and Quality Engineering, 9*, 5. https://doi.org/10.1051/ijmqe/2018003

Theroux, E., Galarneau, Y., & Chen, M. (2013). Control charts for short production runs in aerospace manufacturing. *SAE International Journal of Materials and Manufacturing, 7*(1), 65–72. https://doi.org/10.4271/2013-01-2248

Wheeler D.J., & Chambers D.S. (1992). *Understanding Statistical Process Control.* 2nd Edn. SPC Press, Inc.: Knoxville.

Wheeler, D. (2004). *Advanced Topics in Statistical Process Control*. 2nd Edn. SPC Press: Knoxville.

Woodall, W. H. (2000). Controversies and contradictions in statistical process control. *Journal of Quality Technology, 32*(4), 341–350. https://doi.org/10.1080/00224065.2000.11980013

Woodall, W. H. (2016). Bridging the Gap between Theory and Practice in Basic Statistical Process Monitoring. *Quality Engineering*. https://doi.org/10.1080/08982112.2016.1210449

Woodall, W. H. (2023). Recent critiques of statistical process monitoring approaches. ResearchGate. Retrived from https://www.researchgate.net/publication/366090712_Recent_Critiques_of_Statistical_Process_Monitoring_Approaches_12722

Vladimir Shper
The National University of Science and Technology MISIS
Moscow,
Russia
vlad.shper@gmail.com
ORCID 0000-0002-0508-3330

Svetlana Sheremetyeva
The National University of Science and Technology MISIS
Moscow,
Russia
prosto_sveta92@mail.ru
ORCID 0009-0007-5276-1986

Vladimir Smelov
The National University of Science and Technology MISIS
Moscow,
Russia
b.c.21@mail.ru
ORCID 0000-0002-9438-4054

Elena Khunuzidi
The National University of Science and Technology MISIS
Moscow,
Russia
el_hun@mail.ru
ORCID 0000-0003-0637-4962