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Original Research Article

UNDERUTILISATION OF SPC WITHIN THE MINING INDUSTRY: INSIGHTS, CROSS-INDUSTRY COMPARISONS, AND OPPORTUNITIES

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Abstract

Statistical Process Control (SPC) is a quality control methodology that has been adopted extensively across numerous industries. It serves as an effective instrument for identifying and resolving process inconsistencies and variability, ensuring optimal efficiency and consistent product quality. By leveraging statistical methods, SPC aims to minimise waste and ensure that a product meets quality standards. Despite the extensive implementation of SPC in various manufacturing sectors, including the automotive, electronics, healthcare and hi-fi technologies sectors, its application in the mining industry remains underdeveloped and lacks comprehensive documentation in academic literature. This article aims to address this gap by exploring existing applications and explaining the potential reasons why the mining industry is an outlier. Furthermore, it endeavours to propose innovative applications of SPC. It has been determined that the mining industry is sufficiently specific in nature to potentially render the known applications of SPC ineffective, due to the limited human control that can be exercised over the quality and characteristics of the mined ore or material. Consequently, alternative and unconventional methodologies employing SPC are proposed as a potential solution, including techniques for predicting the depletion of a source (or a vein). The article also offers guidelines for practitioners that can allow them to implement SPC methods more rigorously, while avoiding the issues identified herein. A discussion on where to look for potential areas of SPC implementation in mining is also offered.

Keywords: statistical process control, control charts, QC&A, mining

1. INTRODUCTION

Quality control and assurance (henceforth abbreviated as QC&A) is undoubtedly present in the mining industry and has been identified as a subject to various standards. state regulations and surveillance [1, 2, 3]. Micon International, a renowned consultancy agency specialising in the mining industry, has QC&A as a priority for the sector [4]. However, in practice, QC&A programmes are seldom implemented in the real operational context of the mining industry [4], and are often perceived as an

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onerous obligation rather than as a potential avenue for innovation and process improvement [2, 4]. This attitude may be one of the factors contributing to a dilatoriness in adopting more sophisticated QC&A frameworks and reluctance to experiment with modern tools and methods.

1.1. Literature on QC practices in mining industry

It is not readily apparent whether the paucity of scholarly research is a consequence of the restricted practical innovation, or whether the latter is a consequence of the former. Nevertheless, it is evident that there is a significant gap in the existing academic literature with regard to rigorous studies concerning QC&A in the mining industry. Examples of such scarce literature include a review by Smee et al. [3], which recommends practices for meeting international QC&A standards established for publicly listed companies in the mineral exploration, analysis and mining industries. Additionally, Smee played a role in the Oyu Tolgoi (Turquoise Hill in English) mining project in the South Gobi region of Mongolia, a venture which may have provided him with inspiration for later work. During the entire duration of the Oyu Tolgoi project, C. Foster, the project manager, implemented a series of quality control (QC) techniques, which included some innovative applications of existing techniques, making this one of the few isolated examples. In a report by Sketchley et al. [5], which focuses on meeting QC requirements during the Oyu Tolgoi project, such practices are described, along with recommendations for future projects. The report concludes that the implementation of well-designed QC&A programmes at an early stage is necessary for the success of a resource delineation project. Potential benefits mentioned in the report included increased accuracy and reliability of samples' data, time savings and compliance with regulators' requirements [5]. Previous works by Sketchley in topics of QC include research into sampling protocols of gold deposits [6].

Later implementations of QC&A practices, which were also described in a scholarly venue, include a case study of Havelock Mine in Eswatini, which largely duplicates the methods used during Oyu Tolgoi project and it also ends with similar conclusions [7]. Other reviews of QC&A methods include an article by Scogings and Coombes [8] and a monograph chapter by Méndez [9].

1.2. SPC

SPC is a data-driven technique that plays a crucial role in ensuring the quality of products and services across a range of industries. It employs statistical methods to monitor and control processes, enabling organisations to guarantee that their products and services meet defined quality standards. By utilising statistical measures such as the mean, median, variance, and standard deviation, SPC provides a comprehensive understanding of process performance and variation, facilitating the identification and rectification of any discrepancies from the desired outcomes [10, 11]. It has its origins in the broader field of statistics, where it employs a range of tools and techniques to analyse and interpret data. These methods facilitate the detection of patterns, prediction of outcomes and informed decision-making regarding process adjustments.

The technique has deep connections to the Six Sigma (6σ) methodology, which is rooted in the reduction of defects and variability in processes [11]. Furthermore, SPC is closely aligned with the principles of Lean, which are concerned with the minimisation of waste and the optimisation of efficiency in processes [11]. The combination of Lean and Six Sigma, often referred to as Lean Six Sigma, integrates the strengths of both approaches to create a powerful framework for process improvement. The utilisation of Lean tools facilitates the streamlining of workflows and the elimination of superfluous steps, whereas Six Sigma provides the analytical rigour necessary to control process variation. Collectively, they enhance the effectiveness of SPC by enabling continuous monitoring and adjustment of processes in a way that reduces defects and increases efficiency.

1.3. Control and run charts

One of the principal instruments employed within the SPC paradigm are control charts, which serve as graphic representations of data over time. Control charts are employed for the purpose of monitoring and evaluating the performance of a given process. This is achieved by plotting data points in chronological order and then comparing them against the established control limits [12], which can be established arbitrary, but usually are assumed to be around three standard deviations away from the mean. The aforementioned limits, assist in determining whether a process is operating within an acceptable range of variation or if it is exhibiting signs of deviation. Control charts facilitate the differentiation between normal process variation, which is intrinsic to any process, and special cause variation, which signals an unusual event that necessitates investigation [12]. By monitoring these variations, control charts enable organisations to maintain consistent quality and detect potential issues in a timely manner, thus preventing the occurrence of significant defects or inefficiencies.

There are numerous types of control charts, each designed for specific types of data and processes [13]. For instance, an X-bar (also called $\bar{X}$ chart or XS-X or XR-X chart, depending on the calculation of control lines) is frequently employed to monitor the average of a process, whereas an R (XR-R) chart tracks the range of variation within subgroups. There is also s (XS-S) chart that tracks the standard deviation. In fig. 1. four different types of control charts are presented, modelled on example data. In the case of attributes data, where items are classified as defective or not, p-charts and c-charts are typically utilised. The adaptability of control charts makes them indispensable for implementing SPC across a diverse range of contexts, including manufacturing and service industries.

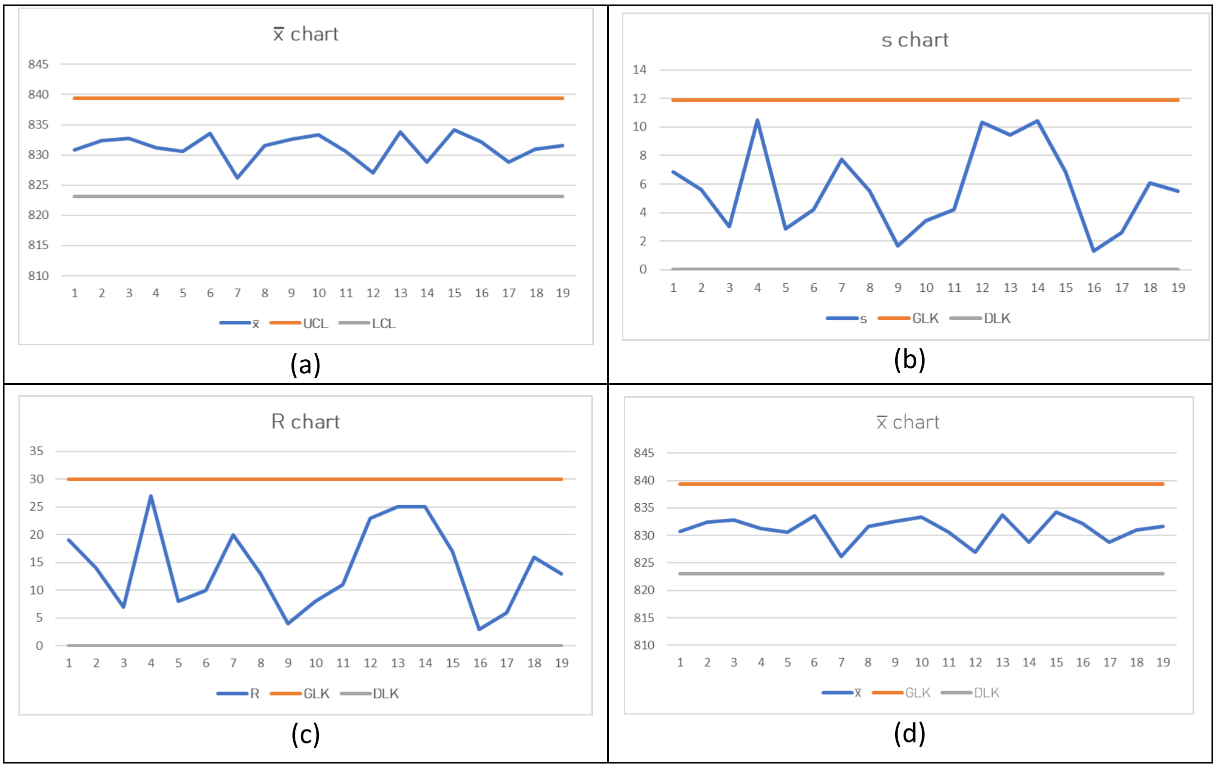


Fig. 1. Four types of most commonly used control charts: (a) XS-X chart (b) XS-S chart (c) XR-R chart (d) XR-X chart. Source: own calculations in Excel on generated data

In addition to control charts, another valuable tool employed in SPC is the run chart. Although similar in appearance to a control chart, a run chart is a more straightforward tool, designed primarily for tracking data over time without control limits [14, 15]. The run chart enables organisations to identify trends, shifts or cycles in process performance, thus facilitating the detection of patterns or gradual changes that may not immediately indicate a process is out of control but nevertheless suggest the need for attention [14, 15]. Run charts are particularly beneficial during the initial stages of process analysis, when the available data may be insufficient to establish control limits [16]. They assist in the identification of trends or non-random patterns, which may indicate underlying process issues, such as a systematic drift or a recurring problem [14, 15, 16]. To illustrate, a run chart can demonstrate whether a process consistently performs below or above a desired target, indicating the necessity for adjustments even before the process reaches the point of being classified as out of control.

Although run charts lack the statistical rigour of control charts with their established control limits, they are straightforward to use and effective for rapid visual analysis of ongoing performance. Collectively, run charts and control charts provide a complementary approach to process performance monitoring, offering both a simple and more advanced method for ensuring consistency and detecting issues promptly.

1.4. Capability Analysis

Capability analysis is a tool used to quantitatively assess process performance in accordance with predefined specifications and requirements. The capability indices are calculated as shown in equations 1.1-1.4 [17]:

$$C_p = \frac{U-L}{6\sigma}, \tag{1.1}$$

$$C_{pk} = \min\left(\frac{\mu-L}{3\sigma}, \frac{U-\mu}{3\sigma}\right), \tag{1.2}$$

$$C_c = \max\left(\frac{\tau-\mu}{\tau-L}, \frac{\mu-\tau}{U-\tau}\right), \tag{1.3}$$

$$C_{pm} = \frac{U-L}{6\sqrt{\sigma^2+(\mu-\tau)^2}}, \tag{1.4}$$

where:

- U - upper limit of size,
- L - lower limit of size,
- σ - standard deviation of the process,
- μ - mean of the process,
- τ – target dimension.

In the event that the product undergoing examination comprises a multitude of components that are in need of capability testing, it is possible to index all of the parameters in addition to this.

The capability indices are then compared to p, k, c and m, which represent the limits of allowable capabilities (see eq. 1.5 – 1.8) [17].

$$C_p \geq p, \tag{1.5}$$

$$C_{pk} \geq k, \tag{1.6}$$

$$C_c \leq c, \tag{1.7}$$

$$C_{pm} \geq m, \tag{1.8}$$

If all of the above inequalities are satisfied, then the process can be considered to be within statistical tolerance [17]. Further inequalities can be introduced to test, whether the process in question is in statistical control, as shown in eq. 1.9-1.12.

$$\sigma \leq \frac{U-L}{6p}, \tag{1.9}$$

$$L + 3k\sigma \leq \mu \leq U - 3k\sigma \tag{1.10}$$

$$\tau(1-c) - Lc \leq \mu \leq \tau(1-c) + Uc \tag{1.11}$$

$$\sigma^2 + (\mu - \tau)^2 \leq \left(\frac{U-L}{6m}\right)^2 \tag{1.12}$$

If the inequalities above hold, the process can be considered to be statistically controllable [17].

While capability analysis can be a highly effective tool, it will not be discussed in depth in this article as it is a technique that is best suited to manufacturing environments. Therefore, it may prove challenging to apply this technique to the excavation processes. Additionally, capability analysis is more complex and time-consuming to set up and utilise compared to the use of control charts, the latter of which provide a graphical representation of process stability, which is more readily comprehended.

1.5. Problem statement

This article identifies two principal challenges that underscore the need for a more in-depth examination of SPC in the mining industry. Firstly, the underutilisation of SPC tools, such as control charts and run charts, reflects a critical gap in the adoption of advanced quality control methodologies. This gap is closely tied to the broader issue of limited innovation within QC&A practices in the mining sector, as highlighted in earlier sections. Despite the proven benefits of SPC tools in reducing variability and improving efficiency in other industries, their application in mining remains limited and inconsistent.

Secondly, there is a significant lack of scholarly literature that systematically explores SPC in the context of mining operations. While QC&A is more broadly addressed (although still scarcely), SPC, a subset of this paradigm, is rarely examined with the statistical rigor it demands. The extant literature is dominated by case studies, many of which fail to establish robust methodologies or explore novel applications of SPC tailored to the unique challenges of the mining industry.This observation aligns with broader critiques of the state of QC&A research in mining, emphasising the need for studies that bridge the gap between theoretical advancements and practical applications.

In order to address the identified gaps, this study performs a comprehensive review of existing SPC practices in the mining sector. The study contextualises these practices by examining successful implementations in other industries, including the automotive, food, and healthcare sectors. Through this cross-industry perspective, the study identifies transferable practices and methodologies that can inform the more effective application of SPC tools in mining. The study also performs a critical evaluation of existing mining-specific research, highlighting its limitations and areas where methodological improvements are necessary.

A significant contribution of this article lies in the formulation of pragmatic guidelines for practitioners. The guidelines are meticulously crafted to assist mining professionals in executing statistically robust SPC methodologies, circumventing prevalent inconsistencies and misinterpretations. Additionally, the guidelines facilitate the adaptation of SPC tools to the unique characteristics of their operations. By proffering actionable recommendations, this article serves as a crucial nexus between academic research and industry practice, paving a route towards enhanced process monitoring and control in mining.

In addition to identifying optimization opportunities, the article proposes two innovative applications of SPC in mining - the use of control charts for detecting resource depletion and their application in atmospheric monitoring, such as tracking CO2 levels in mining environments. These novel uses of SPC demonstrate its potential to address operational challenges unique to mining, expanding its applicability beyond traditional quality control functions.

Finally, the article examines the extent of controllability over natural variability at different stages of the mining process, from excavation to processing. By linking the degree of variability control to the applicability of SPC, the study provides a nuanced understanding of where SPC can deliver the most value. This analysis not only advances the theoretical understanding of SPC in mining but also equips practitioners with the tools and insights needed to implement these methods effectively in their operations.

2. SPC METHODS IN INDUSTRY

SPC, as part of the QC&A paradigm, is mainly used as a means of process control, while in reality, as a tool from the Lean 6σ family, it can also be used to improve and optimise processes, eliminate waste and reduce unwanted variation.

2.1. SPC in other industries

SPC is most commonly deployed in the manufacturing sector, where the majority of innovation in this field is currently occurring [18]. For instance, automotive manufacturers utilise SPC to oversee assembly line operations, thereby reducing defects and minimising waste through real-time data analysis [19]. Additionally, SPC is employed to minimise the variation of processes' outputs [20, 21, 22]. In her article, Golińska asserts that the implementation of SPC and the analysis of data from control cards can not only stabilise production processes but also have a beneficial effect on reducing production costs [19]. A significant outcome of her research is the demonstration of the capacity of SPC procedures to facilitate organisational compliance with safety standards [19].

Furthermore, SPC is utilised in the healthcare sector, where it fulfils a pivotal function across numerous domains. Suman and Prajapati collated and analysed forty scholarly descriptions of SPC's applications in different hospital departments, including emergency and surgical care, radiology, and pulmonology [23]. A similar review was conducted by Thor et al., in which 57 articles were analysed and 12 categories of benefits, 6 categories of limitations, 10 categories of barriers, and 23 factors that facilitate its application were identified [24]. The majority of applications of SPC were found to be in the field of anaesthesia [24].

Lim et al. describe the utilisation of SPC across the food industry [25]. Of note is their identification of resistance to the adaptation of SPC techniques as a significant challenge within the industry, which bears resemblance to the situation in the mining industry.

2.2. Current use of SPC in mining industry and critic thereof

The current applications of SPC within the mining industry are primarily limited to the control of the desired mineral or ore content within a sample, or alternatively, the contamination percentage. A review of the literature on the subject reveals that the most comprehensive work has been conducted in the context of gold mining. Notable contributions to this field include the aforementioned article by Sketchley [6], as well as a comprehensive account by Dominy. Along with other prominent researchers in the field, Dominy has made significant contributions to the scholarship of sampling procedures in gold mining, and has articulated some of the most effective practices [26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36]. It is noteworthy that SPC was not a primary focus in any of the aforementioned studies, despite the presence of control charts in several of them. Control charts have been employed to monitor mineral content in samples at Havelock Mine, Eswatini, as detailed in another previously referenced article [7]. Smee et al. provided an overview of the technical aspects of the then-current usage of SPC in mining, within the broader review of QC&A practices, as previously discussed [3]. However, there is little to none literature concerning specifically the SPC practices in the mining industry, especially with regard to innovative applications.

The application that will be of focus in this section is the one that was found to be the most present in the literature – controlling the mineral (ore) concentration in the mined material - specifically, as described by Sketchley [6]. The unit used in his article is grammes/tonne, and the control lines were set by using ± 2 standard deviations, which should guarantee that approximately 95% of the observations fall between UCL and LCL, assuming that the batches' averages were normally distributed. In fig. 2., a replication of one of the charts used by Sketchley is presented.

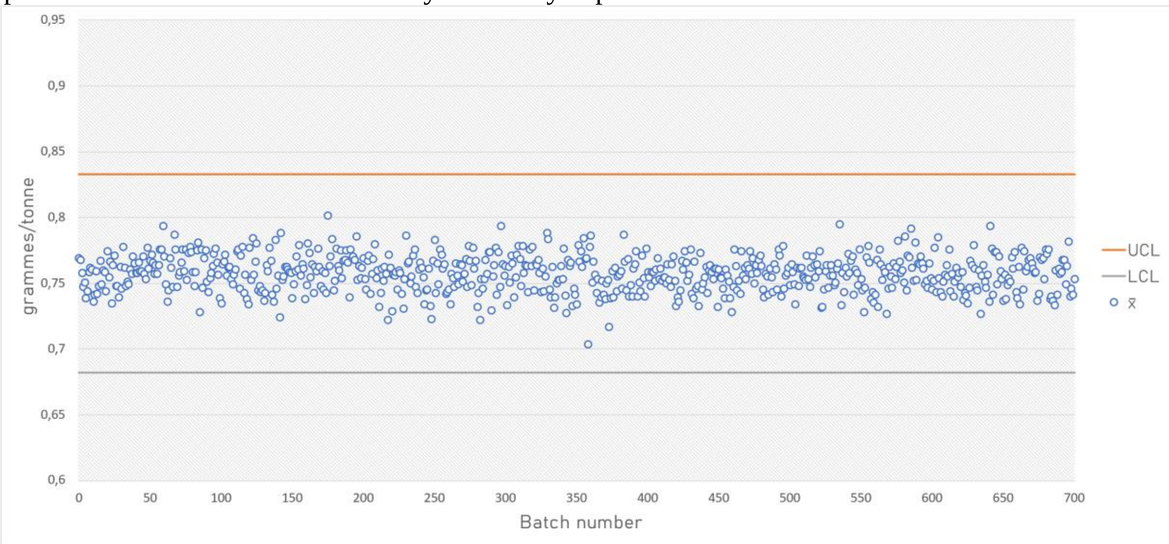


Fig. 2. A replication of the chart used by Sketchley [6]. Source: Own calculation on data generated from normal distribution, replicated from Sketchley's original article [6]; visualisation created in Excel using built-in functions and Analysis ToolPak add-in

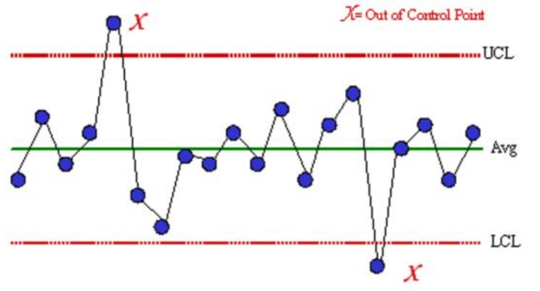
The data employed for the replication of the original chart were derived from a normal distribution with a mean of $\mu = 0.7583$ and a standard deviation of $\sigma = 0.04168$. The values were obtained by visually inspecting the original chart, and normal distribution was used. his was on the basis of Sketchley's indirect assumption of normality of the data, which was based on the reasoning that 95% of the data points should fall within the range of $\bar{X} \pm 2s$, where $\bar{X}$ is the sample average and s is the sample's standard deviation. This assumption was, however, erroneous insofar as normality cannot be assumed without prior testing. Even a visual test confirms that the data did not follow a Gaussian distribution. Nevertheless, the author elected to utilise the normal distribution in the interests of expediency, given that it would not unduly complicate further reasoning. Control lines were then set at $\bar{X} \pm 2s$ levels, respectively.

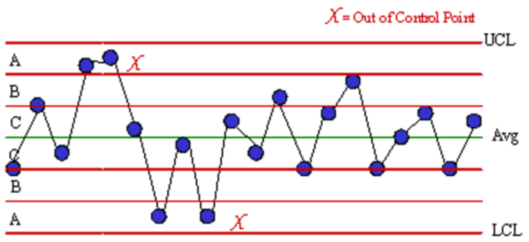
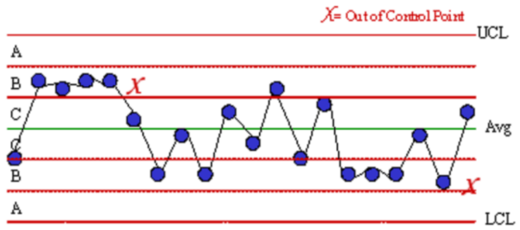
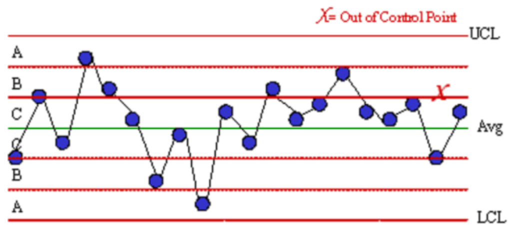
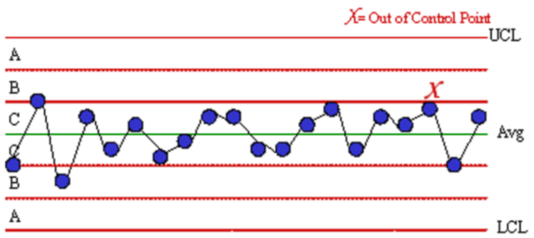
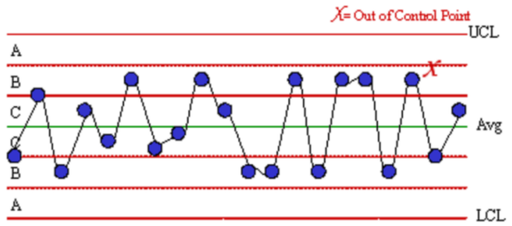
The initial observation to be made is that the presented chart is relatively straightforward in design, which is not inherently problematic. However, in the context of this particular case, this simplicity serves to limit the usefulness of the chart. It is not a run chart, as the points represent the mean values of batches, with control lines being present. However, the utility of such a chart is comparable to that of a run chart. It is conceivable that the researcher was not required to make it any more complicated, as he was merely attempting to illustrate that the gold concentration in the samples is predominantly concentrated around the mean. However, this further substantiates the underutilisation of control charts, as he subsequently employs other visualisations but does not utilise any other control chart. Had he correctly employed the control chart, it would have conveyed a more comprehensive understanding of the stability of the aforementioned metric to the readers.

The control lines were set at $\bar{X} \pm 2s$ levels, which in itself can be criticized. It is crucial to ascertain that the data in question is drawn from a Gaussian distribution, which is not a given, before assuming that 95% of observations fall inside an interval. While such a property can be empirically discovered in other settings, it is not a stable feature if the data follows any other distribution. Secondly, the control lines were set too broadly, which can be argued from two viewpoints – meritoriously and statistically. If the permitted deviation in gold concentration were to be 2s, as posited in the discussed paper, it would signify that one sample could contain ~ 0.61 grammes per tonne, while another could contain ~ 0.83 grammes per tonne, representing a 36% discrepancy. Notwithstanding this considerable divergence, the process would still be deemed to be within control. Based on the prices recorded on October 16, 2024, this would equate to a €17.37 difference in the value of gold within a given sample set. Secondly, the SPC should not merely provide assurance to a company that its process is stable, which could be achieved by setting control lines at an arbitrary wide margin. Rather, SPC should facilitate continuous improvement and reduction of variation. As put by The W. Edward Deming Institute – "You might not *like* what the data tells you about your stable process. […] Once your process is producing predictable results, you can start working to improve the process, usually by finding ways to reduce variation" [37]. Furthermore, the acceptability of a metric's stability is contingent upon the mineral or issue under examination. In the case of resources with greater economic value (e.g., gold, platinum, uranium), the control lines should be established in a manner that constrains the permissible range of variation. Conversely, in resources with comparatively lower economic value, the lines could be set to accommodate a broader spectrum of acceptable volatility. Methodologies have been developed by practitioners and researchers for the establishment of more sophisticated control lines, facilitating enhanced reliability in insights and signal interpretation. These methods integrate a set of constants, techniques, and formulas that can be employed in calculating the levels of control lines. In certain applications, there are also non-constant control lines that permit even more advanced analyses.

Signals that were developed in the theory of control charts offer a very vast range of indicators for an instable process (also called *process out of control*), which are not utilised by Sketchley. Again, it is probably a case of him just not needing anything more sophisticated, but oversimplification to some degree is found in all of the control charts, that were encountered by the author while studying the existing literature on the subject. Some of the instability signals are presented in the table 1.

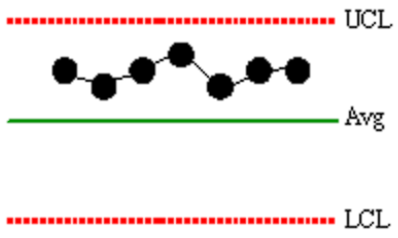
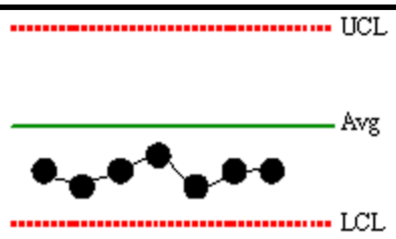
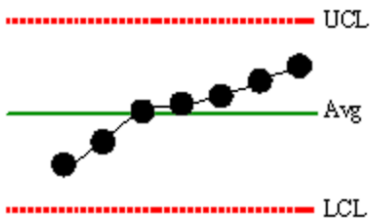
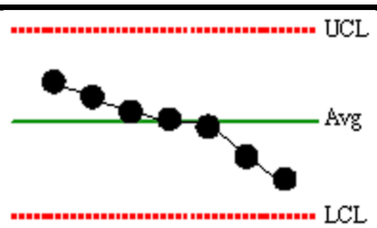
Table 1. Some of the instability signals addressed by a control chart. Source: Inspiration and graphics from *SPC for Excel* [38], with consent from the author

Signal	Possible meaning	An action to take	Illustration
Any point outside the UCL or LCL	There is a special, nonsystematic cause for variation interrupting the process, which may be a one-time shock.	The process should be inspected and the outlying cause of variation should be removed, if it pertains.	

Two out of three consecutive points are on the same side of the average in zone A or beyond	There exists a special cause for variation in the process, possibly a systematic one.	The process should be inspected and the special cause should be removed.	
Four out five consecutive points are on the same side of the average in zone B or beyond	There exists a special cause for variation in the process, possibly a systematic one.	The process should be inspected and the special cause should be removed.	
Seven consecutive points are in zone C, on either side of the average	There exists a special cause stagnating variation	The process should be inspected if there exists a special cause, it should be removed	
Fifteen or more consecutive points fall in zone C either above or below the average	There exists a consistent sampling stratification (such as averaging samples from different processes), causing misleading measurements	The reason for stratification should be identified and the sampling procedure corrected	
Eight or more consecutive points fall on one side of the average or the other (possibly alternating), with no points in zone C	There are two or more processes being tested on the same control chart (so called *mixture*)	Sampled processes should be separated, such that only one process is being tested on the chart	

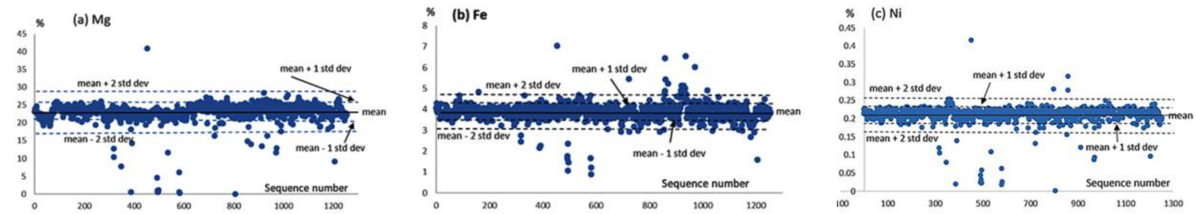
Other well-known control-chart-based methods for testing process stability are the "rule of seven" tests, which indicate when a process is out of control [38]. The four types of these tests are presented in tab. 2.

Table 2. “Rule of seven” instability signals.. Source: Inspiration and graphics from *SPC for Excel* [38], with consent from the author

Signal	Possible meaning	Illustration
Seven consecutive points lying above the average	**The process is out of control**	
Seven consecutive points lying below the average		
Seven consecutive points form a growing trend		
Seven consecutive points form a descending trend		

Nevertheless, in contrast to the wealth of developed signals, the sole signal employed across the majority of QC&A studies in the mining sector is the initial signal presented in tab. 1. - namely, a point falling outside of the upper and lower control limits. This approach has a detrimental impact on process control procedures and restricts the types of irregularities that would be identified through the use of a control chart.

One can notice, that in fig. 2. there are no distinct zones (A, B, C), as there are in illustrations in tab. 1, effectively precluding the detection of the majority of instability signals. This may signify a misleading assumption in the mining industry that a stable process is one which does not produce outliers. It may be logical to adhere to this conviction; nonetheless, as indicated in tab. 1., there may still be a specific underlying cause for variation, even despite the absence of any outlier. Furthermore, such a simplified chart may also prove inadequate for ensuring the correctness of sampling procedures, such as avoiding the mixture of processes and detecting sampling stratification. Despite this critique, a positive notion can be mentioned, as in the aforementioned QC study of Havelock mine in Eswatini, a more advanced control chart, with six distinctive zones, is present [7]. The charts excerpted from their work are presented in fig. 3.



(a) (b) (c)

Fig. 3. Control charts presenting a distribution of assay results for the tailings samples in a case study of Havelock Mine in Eswatini. Source: Excerpted from [7], with consent from the authors

While statistics are employed in numerous other mining industry applications, including sampling and remote sensing, this article does not intend to provide an exhaustive discussion of them. Furthermore, there is undoubtedly scope for a more critical analysis of SPC in the mining industry. However, the above considerations are intended to provide an overview of the situation.

It also must be noted that this section's intention was not, in and of itself, to engage in a critique of Sketchley's work. The example presented was merely an illustrative device, chosen because of its suitability as a case study for the wider industry context; given that Sketchley's paper was one of the few examples to employ control charts in the mining industry. Accordingly, it is imperative to recognise that any evaluative assertion herein is not intended to be a personal critique of a specific author or publication, but rather a critique of the entire industrial sector. It is also crucial to acknowledge that the works cited represent a valuable contribution to the field and are scarce in the context of the topics discussed, thus warranting recognition as a vital source of information.

2.3. Possible optimisations of current SPC applications

The diversity of control charts and stability testing techniques offers significant opportunities for advancing quality control in the mining industry. However, critical issues in current SPC implementations, particularly those observed in prior research, highlight the need for a more rigorous and methodical approach. Inconsistencies such as improperly calculated control limits, unreliable sampling methods, and misinterpretations of SPC signals are among the most pressing challenges that undermine the reliability and effectiveness of SPC tools in mining operations. This subsection provides guidelines for researchers and practitioners for the correct and statistically rigorous implementation of control charts in the mining industry.

A fundamental improvement lies in the accurate determination of control limits, with one of the recurring flaws observed in existing practices being the use of static or arbitrary control lines, which fail to account for the inherent variability of mining processes or the true distribution of the processes' metrics. Instead, control limits must be calculated using statistically robust methods such as moving range or exponentially weighted moving average (EWMA) approaches, or an extensive study must be conducted to determine the distribution of the tested metric, instead of unfoundedly assuming normality (if static control lines are to be used). These methods could ensure that control charts effectively distinguish between normal process variability and meaningful deviations.

Another critical aspect is the refinement of sampling methodologies. Existing sampling methodologies frequently fail to adequately capture the variability inherent in mining processes, resulting in skewed data and unreliable analyses. A more effective strategy involves the implementation of stratified sampling techniques, particularly in environments characterised by geological heterogeneity. By ensuring that samples represent the full spectrum of variability within the process, practitioners can significantly improve the accuracy and reliability of SPC analyses, thereby reducing the risk of misinterpretation.

Misinterpretation of SPC signals has also emerged as a significant issue. This is frequently attributable to a paucity of understanding regarding the distinctive characteristics of mining operations or insufficient training in SPC techniques. To address this, it is imperative to implement systematic and exhaustive training programmes for personnel, ensuring that they are adequately equipped to accurately interpret SPC outputs within the context of mining operations. Training should emphasise the importance of understanding process dynamics and external factors, such as equipment efficiency and environmental conditions, which can influence SPC signals and necessitate a more nuanced approach to interpretation.

Finally, the long-term effectiveness of SPC tools necessitates continuous evaluation and adaptation. As mining operations evolve and integrate advanced technologies, SPC frameworks must also be updated to reflect these changes. The integration of automated data collection systems and predictive analytics, for instance, has been demonstrated to enhance SPC tools' capacity to detect trends and anticipate deviations before they escalate. This adaptive approach enhances process stability and ensures the relevance and effectiveness of SPC in meeting the demands of modern mining operations.

By addressing these challenges, practitioners can overcome the inconsistencies and limitations previously identified in applications of SPC. The integration of advanced technologies, statistically rigorous methods, targeted training programmes, and improved sampling strategies is pivotal in leveraging the full potential of SPC as a critical tool for monitoring and optimising mining processes.

2.4. Possible reasons for paucity of SPC innovation and scholarship in the mining industry

It would be simply naive to assume that a draught of innovation and scholarship in mining industry concerning SPC (and broader – QC&A) is just a result of the industry's idleness or backwardness. This is simply not the case, as the mining companies are actively undertaking activities to upgrade used technology, modernise practices or otherwise – simply innovate. On the contrary, mining companies are actively innovating in areas that address both operational efficiency and environmental sustainability, as demonstrated by their efforts to embrace new technologies and modernize their processes [39, 40]. In fact, innovation in the mining sector has been driven by both necessity and opportunity. The industry's focus on sustainable practices, efficiency, and adaptation to environmental regulations has fostered a climate of continuous technological improvement [39, 41]. A research on Brazil's mining sector shows how firms are combining hands-on learning with advanced R&D to remain competitive and forward-thinking [41]. Therefore, while there is a noticeable gap in the adoption of SPC and QC&A, it is definitely not due to the industry's resistance to change, as mining companies have proven their capacity for innovation in other areas, demonstrating that the industry is evolving in ways that make the most immediate and significant impact. Instead, the author suspects that there must be underlying reason that either prevent development of such practices or make them relatively thriftless.

RTIMS

First reason, that should be discussed is that Real Time Information Management Systems (RTIMS) are still an emerging concept within the mining industry [42]. RTIMS are sophisticated digital platforms that are designed to continuously collect, process, and manage data from a multitude of sources in real time. The integration of data streams from sensors, equipment, and other monitoring instruments into a unified platform facilitates the generation of real-time insights pertaining to operational performance. This facilitates quick identification of changes or disruptions, enabling action to be taken. In contrast to conventional systems that rely on delayed data processing, such as these usually used in mining industry, RTIMS provide instantaneous feedback, facilitating more informed decision-making through the ability to make real-time adjustments to processes. It is readily apparent why the incorporation of RTIMSs is pivotal to the advancement and execution of SPC procedures. The utilization of real-time data permits the generation of real-time control charts, thereby enabling organizations to promptly address process variations, as opposed to doing so after a significant delay. If the instability of a process is identified with a significant time lag, the underlying special cause for variation may already be undetectable, resulting in a heightened risk of future process inconsistency and quality deterioration. In this context, the real-time feedback facilitated by RTIMS assumes critical importance, as it prevents defects from becoming compound problems. In the absence of continuous, real-time data, the development of SPC methods may prove futile for mining companies. Furthermore, the unreliability of delayed reporting could be used as a compelling argument against the integration of more sophisticated QC&A systems. The investment in RTISM systems, as a step towards more precise, more effective, and more productive QC&A, may not be immediately apparent, given that the literature on this topic, with a specific focus on the mining industry, is not yet well-described [42]. Lack of real-time data also make it more difficult to establish reliable control levels.

While RTISM has already been adopted in other, more modern and less conservative sectors for a considerable period of time, it would be reasonable to assume that it will take a while longer for it to be adopted in the mining industry (although in some cases, the process has already begun) [42]. This is due primarily to the conservative and heavy character of the majority of mines in the world [42]. However, it seems reasonable to hypothesize that as the sector undergoes a process of modernization, an increasing number of excavation companies will adopt RTISM. This will facilitate the advancement of SPC techniques, with mines in developed countries leading the way.

A comprehensive review of RTISM in the mining sector is presented in a recent article by Shimaponda-Nawa et al. [42]. The authors assess the current state of RTISM in the sector and develop a framework for measuring its maturity. Their findings can be used to adapt RTISMs in mines and incorporate systems to track their long-term performance, which is dependent on their maturity. The article is highly recommended as a complement for those wishing to gain further insight into this topic.

The nature of the mineral resources

Another reason, why the degree of innovation of SPC in the mining sector is lesser than in other industries, is the nature of mineral resources' excavation itself. The author suspects, that it even may be a primary reason for the issue in question.

In other industries, for example the automotive industry, the producer has near-complete control over the parameters of the final product. To illustrate, consider a producer of engine pistons testing the stability of the volume of metal of the piston blank (see [43]). The average is A (or A could be also an arbitrary nominative optimum), and UCL and LCL have been set at $\pm 2\%$ of A respectively [43]. Should the control chart signal the process to be unstable, the process can be inspected immediately and the source of the variability identified and removed. Should the problem be identified as a miscalibrated machine or an aperture that is too wide (or too narrow), the machine can be repaired and the process stabilised. In the event of the metric being controlled relating to a parameter of the steel cast (e.g., friability), it would be possible to conduct an inspection of the pig iron and subsequently implement a corrective measure to adjust the recipe or calibrate the casting environment in order to achieve a stable process.

It is often unfeasible to implement such adjustments in the mining industry, particularly when the inspected process is not solely dependent on machinery or human input. The majority of the most critical operating indicators are uncontrollable due to the fact that mining is not a process of creation, but one of utilising existing resources. The intrinsic quality, attributes and specifications of these resources are inherently fixed and unalterable. Consequently, attempts to control their stability are futile, as even if the process instability could be detected, there is little that can be done to significantly stabilise it or even to identify the underlying cause.

One might even posit that any metric associated mineral extraction is, in essence, a stochastic process, given the intrinsic uncertainty associated with the geological characteristics of the subsurface [44]. Notwithstanding the utilisation of sophisticated exploration techniques, including geological surveys, geophysical imaging and drilling, the precise distribution of mineral deposits, ore grades and structural formations remains probabilistically known prior to the commencement of actual excavation. As mining progresses, the true nature of the ore body is revealed, often diverging from initial models due to the natural heterogeneity. Furthermore, variability in mineral composition, vein orientation, and rock stability contribute to the randomness of the extraction process. Furthermore, individual parameters of the resource being mined, such as the iron content in a given sample or the grade of ore, may themselves constitute a stochastic process [44].

In light of the inability to rectify the process and its inherent unpredictability, it is understandable that practitioners may perceive the investment in innovating SPC (or QC&A as a whole) or testing more advanced techniques than those already in use to be futile and uneconomical, and this perspective is not unfounded. While some techniques may be applied to the monitoring of controlled processes, such as the fineness of aggregates or operational efficiency, the stagnation of SPC techniques is, to some extent, an understandable consequence of the constraints they face.

3. PROPOSED NEW APPLICATIONS OF SPC

It is unlikely that there will be significant advances in the area of SPC within the mining industry unless there are new, practical applications that encourage such innovation by demonstrating significant financial profitability and applicability to an increasing number of mining operations.

Furthermore, such novel applications must be designed with the alignment to the specific characteristics of mineral excavation activities, so that operators can have direct agency over the processes being controlled.

Therefore, it was decided that some potential applications, which are not yet described in existing literature, should be proposed. It is acknowledged that this may include some cases that have not yet been documented, and are therefore unknown to the author. It should be noted that the author considers the discovery of new applications of SPC in mining operations to be a topic warranting extensive further investigation. The identification of such applications is not the primary objective of the presented article; rather, the focus has been on describing the current problems of the subject and identifying the principal underlying causes.

Finally, the author will seek to address the natural variability of mining processes and associated quality metrics in a holistic manner, and the extent to which they are controllable.The objective is to provide guidelines on where to look for possible implementations of SPC – from the excavation, through transportation, ending with processing.

3.1. Ensuring safety by controlling the levels of carbon dioxide in mine air

Carbon dioxide is a constituent of mine air and is present in significantly higher concentrations than in the air on the surface [45, 46]. Exposure to this gas in excess of recommended levels may result in adverse health effects, including a reduction in systolic and diastolic blood pressure [47]. Nevertheless, it is impractical and uneconomical to attempt to achieve the same CO_2 levels in mines as in the atmosphere at surface level. It is therefore necessary to establish an acceptable level of carbon dioxide in mine air. Once appropriate ventilation systems and other safety measures have been established, the stability of the CO_2 condensation should be monitored continuously. In the event of instability, the reaction should be immediate and the underlying cause should be identified and rectified. The underlying cause may be a malfunction of the ventilation system or the inadvertent opening of a CO2 deposit. In some cases, it may be sufficient to control only the upwards instability, although this would depend on the specific circumstances. Additionally, it would be necessary to implement a real-time data-gathering device, which ideally would be part of a larger RTISM.

Control charts are the optimal tool for such applications. The central line should be established at the value of the safe CO_2 concentration level, while the UCL should be set at the level at which CO_2 could begin to present a health hazard. Furthermore, an LCL could be set, such as in the event the mine's air is treated by machinery that oxidises its content. Should this occur, the LCL would indicate that the oxidisers are operating at optimal efficiency, thereby averting the risk of oxygen poisoning. Alternatively, an LCL could still be established, albeit not as a health hazard indicator but rather as a marker of an effective ventilation system that can support the implementation of lower CO_2 standards.

It is not necessary to track all of the instability signals (for example, there is no requirement to test for the processes' mixture, as this is not a possibility in such a scenario). However, every test that detects a special variability cause could be beneficial, as detecting an observation outside of the control lines is a final warning and could typically have been prevented by eliminating special causes at an earlier stage [48].

It is important to note that the statistical analysis of CO2 variation in mine air has been previously discussed in scholarly literature by Hebda-Sobkowicz et al. [49]. However, this analysis did not utilise SPC tools and was not conducted within the context presented here.

3.2. Predicting source's (or vein's) depletion

Further applications could be found in the prediction, or rather the early detection, of imminent source (or vein) depletion. As previously stated, SPC is already employed on occasion to monitor the composition of a mineral in a given sample. Similarly, the aforementioned controlling procedure could be deployed to identify the likelihood of source depletion at an earlier stage. This would entail implementing additional procedures to regulate the process flow and detect indications of downward instability. In this context, control charts could prove invaluable as an objective tool capable of facilitating such control. Even basic run charts could offer assistance in this regard, given their potential to reveal a negative trend in the sample's averages.

In addition to mineral concentration, SPC can incorporate a range of other process-related factors, that are also a potential indicator of the source depleting, to provide a more holistic view of the resource.

The continuation of extraction often necessitates deeper drilling to achieve comparable quality or volume of minerals, an endeavour that increases operational costs and extraction difficulty. The tracking of drill depth over time within an SPC framework can facilitate the identification of trends that are correlated with a decline in mineral yield. For instance, if the average mineral concentration begins to decline while drill depth continues to increase, this may indicate that the accessible, high-quality mineral reserves are being depleted. SPC can flag these changes, allowing operators to assess the sustainability of the additional depth and to determine whether alternative areas should be explored.

Integrating sample location data into SPC, frequently employing geospatial mapping in conjunction with control charts, permits the geographical monitoring of mineral concentrations across diverse mine regions. A multivariate approach has the potential to track spatial variation over time, thus revealing specific zones that may approach depletion sooner than others. Patterns of spatially correlated depletion can guide mine planners' decisions regarding targeted adjustments to the extraction plan, the redistribution of resources, or the initiation of exploration in adjacent zones. Furthermore, this approach allows companies to focus on local areas with higher yields, thus optimising resource allocation and improving cost-effectiveness.

Monitoring extraction efficiency is crucial, as a decline in efficiency may signal that the accessible minerals are becoming more difficult to recover, possibly due to lower concentration or increasing geological resistance. In SPC, a decrease in extraction efficiency—particularly when coupled with falling mineral concentration or rising drill depths—can reinforce indicators of resource exhaustion. Tracking efficiency alongside mineral output allows for real-time adjustments in the extraction process, such as modifying the extraction technique, adding equipment, or planning a transition to new mining areas.

Multivariate control charts would track these parameters simultaneously, enabling a deeper analysis and helping pinpoint depletion-prone areas. As extraction challenges or drilling depths increase or concentration drops, a correlated analysis of these factors can provide a fuller depletion forecast, allowing teams to make timely decisions about shifting or adjusting operations.

3.3. Addressing the extent of control over natural variability of mining processes

Mining operations are characterised by significant variability, which is attributable to both natural and operational factors. The extent to which this variability can be controlled varies across the various stages of the mining process, from excavation to processing. As discussed in earlier sections, especially section 2.4, this disparity in controllability informs the strategic application of monitoring and control frameworks. In this subsection, the extent of control possible at different stages will be assessed, and it will be explained how such control aligns with SPC methodologies.

Variability in excavation and safety

The excavation stage is predominantly influenced by geological heterogeneity, which dictates the distribution and quality of ore deposits. As outlined in Subsection 2.4, this stage is marked by inherent unpredictability that limits direct control over variability. Even with advanced geological surveys, the erratic distribution of valuable minerals presents challenges in maintaining consistency. Selective mining techniques can mitigate some variability by targeting high-grade zones, but this approach relies on the precision of prior sampling and geological modelling

Safety parameters during excavation, such as air quality and equipment performance, are also subject to variability due to fluctuating environmental conditions, like weather or seismic activity [51]. Therefore, these parameters are only partially controllable, but some of the external risks can be mitigated by implementing early warning signals [48].

Two of the potential implementations of SPC within these domains were previously outlined in subsections 3.1 and 3.2. The author anticipates that, despite the limited scope for controlling natural variability at these stages, researchers and practitioners will identify numerous additional applications of QC&A in these areas.

Variability in transportation and stockpiling

The transportation and stockpiling stages introduce variability that is predominantly operationally driven, as noted in earlier discussions. Variability during transportation often arises from material segregation, caused by the uneven distribution of particles of different sizes and densities during loading, hauling, and unloading [52, 53]. This segregation can lead to inconsistencies in material composition, which, if left unchecked, propagate downstream and affect processing efficiency [52, 53]. Blending inconsistencies are another common issue, often resulting from improper mixing of materials sourced from different areas of the mine [54]. Additionally, external factors such as weather can exacerbate variability, with fluctuations in moisture content during transport and stockpiling being particularly impactful [51]. Wet or overly dry material can alter handling properties and complicate subsequent beneficiation processes [55].

While these factors can be managed through standardized procedures, such as controlled loading and unloading techniques, these measures are not always sufficient. Weather-induced moisture variability, for instance, often necessitates real-time monitoring and dynamic adjustments [51]. Maintaining homogeneity in stockpiles thus becomes a critical task, requiring continuous observation of material properties. Advanced sensors and monitoring systems can track key parameters such as particle size distribution and moisture content, enabling operators to detect deviations early. Corrective actions, such as re-blending or moisture adjustments, can then be implemented to ensure the material entering processing plants remains within acceptable specifications.

Systematic monitoring practices, particularly for moisture content and material composition, can also help reduce variability in stockpiles. These practices, while not eliminating variability entirely, can significantly mitigate its impact on downstream operations. For example, consistent monitoring and adjustments ensure that feed material entering crushers or mills meets operational standards, enhancing throughput and minimizing energy consumption.

While complete control over variability-inducing factors in transportation and stockpiling is rarely achievable due to external influences, the ability to respond dynamically to variability represents a significant step toward controllability of process quality. One could

Controllability in processing operations

The processing stage offers the highest degree of controllability in the mining value chain, as variability at this stage is primarily operational and occurs within a controlled environment. Variables such as grind size, reagent dosages, flotation times, and recovery rates can be closely monitored and adjusted to ensure operational stability and optimal product quality [56]. The controlled conditions of processing plants enable the implementation of precise monitoring systems, allowing operators to identify deviations in real time and make rapid adjustments. For example, fluctuations in particle size distribution can be addressed through adjustments to grinding processes, ensuring that input materials meet the specifications required for downstream separation techniques [57].

Additionally, the integration of automated control systems and advanced data analytics further supports variability management. These systems can predict potential deviations based on historical data and current trends, enabling proactive interventions that stabilize operations before significant disruptions occur [18]. For instance, maintaining reagent dosages within optimal ranges not only improves recovery rates but also minimizes chemical usage, contributing to both economic and environmental sustainability [56].

Linking controllability to SPC applicability

The applicability of SPC is contingent upon the varying levels of control over variability across mining stages. SPC is most effective in stages where variability is manageable, such as during processing and stockpiling, where tools such as control charts and process capability analysis can monitor trends and deviations, enabling real-time adjustments and optimizing output quality. In less controllable stages like excavation, SPC serves a diagnostic function, providing insights that support adaptive strategies rather than acting as a primary control mechanism.

This underscores the importance of aligning the implementation of SPC with the extent of controllable variability at each stage. Mining operations should therefore prioritise SPC implementation in areas where it can deliver the greatest impact, such as in the optimisation of processes in beneficiation plants, material handling during transportation, or in safety warning systems. By doing so, operators can maximise efficiency while acknowledging the limitations inherent to certain stages of the mining process.

4. CONCLUSIONS

This study has provided a comprehensive examination of Statistical Process Control (SPC) techniques and their potential in the mining industry, with a particular emphasis on advancing both theoretical understanding and practical applications. It began by introducing and reviewing key SPC methods, such as control charts and run charts, highlighting their value in monitoring process stability and improving operational efficiency. The article also serves a didactic purpose, offering practitioners and researchers a structured overview of these tools to encourage broader adoption and deeper understanding within the mining sector.

Through a cross-industry comparison, the study demonstrated the successful implementation of SPC in industries such as automotive, food, and healthcare. These industries leverage SPC to reduce variability, optimize processes, and ensure product quality. This analysis identified transferable practices that can be adapted to address the specific challenges of mining, particularly in the context of variability and process control.

An evaluation of the current use of SPC in the mining industry revealed significant gaps and limitations. Existing studies often lack statistical rigor and fail to account for the unique characteristics of mining processes. The critique of these studies informed the development of practical guidelines aimed at improving the application of SPC in mining. These guidelines emphasize the need for robust statistical methodologies, refined sampling strategies, and integration with predictive and real-time monitoring technologies.

The study also explored the reasons behind the paucity of innovation and scholarship surrounding SPC in mining. Factors such as the inherent unpredictability of geological conditions, logistical challenges in real-time data collection, and a general resistance to adopting manufacturing-derived techniques were identified as key barriers. These insights underscore the importance of tailoring SPC tools to align with the distinctive requirements of mining operations.

Building on this foundation, the study proposed novel applications of SPC in mining, including the use of control charts for monitoring safety-critical parameters, such as CO_2 levels in underground mines, and detecting resource depletion through mineral composition analysis. These applications demonstrate that, when adapted appropriately, SPC can go beyond traditional quality control roles to address critical challenges in resource management and safety.

A key contribution of this article is the detailed analysis of the extent of controllability over natural variability in mining processes. The study demonstrated that SPC is most applicable in stages where variability is manageable, such as processing and material handling. Conversely, in stages dominated by geological unpredictability, such as excavation, SPC serves a diagnostic role, providing insights to inform adaptive strategies. By linking variability controllability to SPC applicability, the article offers a nuanced framework for integrating SPC into mining operations.

In conclusion, this article advances the understanding and applicability of SPC in the mining industry by providing a structured overview of methods, identifying transferable practices, proposing innovative applications, and addressing key barriers to adoption. The development of practical guidelines for practitioners bridges the gap between academic research and industrial implementation, providing actionable strategies for improving process monitoring, safety, and efficiency.

4.1. Future research directions

A key avenue for future research should be the application of the SPC theories, as proposed, through detailed case studies conducted within various mining operations. The utilisation of SPC in practical settings enables researchers to offer pragmatic insights into its deployment, evaluating its efficacy in addressing particular mining challenges and discerning potential constraints in situ. Such case studies would not only validate the theoretical findings but would also enable researchers to identify the nuances and adjustments needed to adapt the SPC tools for use in different mining environments, such as underground and open-pit mines.

The application of advanced control charts, including R charts and those with moving control lines, presents a further opportunity for the practical implementation of SPC in the mining industry. In contrast to static charts, which are often inadequate in dynamic contexts, these advanced charts are capable of adapting to the inherent variability inherent to mining operations, thereby facilitating more sensitive and accurate monitoring of processes. R charts, for instance, are particularly efficacious in monitoring fluctuations within batch processes, and could facilitate a more refined approach to measuring ore quality consistency or equipment performance over time. Similarly, charts with moving control lines could better accommodate gradual shifts in mineral quality, which might occur as veins deplete or drilling reaches greater depths. Implementing these advanced SPC tools within live mining operations and evaluating their outcomes in case studies could provide invaluable insights, potentially encouraging wider adoption and adaptation across the industry. There are myriads of types of control charts, all of which could potentially be put to use in the mining industry.

In addition to the aforementioned potential application of control charts to monitor CO_2 levels, future research on SPCs could significantly benefit the monitoring of other safety parameters in underground mining environments, where variables such as air quality, gas levels, and temperature are crucial to worker health and safety. The capacity of SPCs to monitor these environmental parameters in real time could facilitate the early detection of instability or hazardous conditions, such as spikes in methane levels, thereby enabling prompt intervention. The application of control charts, in particular those with adaptable control limits, enables researchers to explore effective methods for monitoring safe ranges and to set automatic alarms when safety thresholds are exceeded. This is analogous to the approach described in the context of CO2 levels. Such research could focus on the utilisation of bespoke control charts, such as CUSUM or EWMA charts, which are attuned to minor fluctuations and trends over time. Furthermore, the implementation of SPC in underground settings through case studies would facilitate an assessment of its practical impact, potentially demonstrating the efficacy of SPC as a valuable tool for predictive safety management and proactive risk mitigation in mining operations.

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