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STATISTICAL PROCESS CONTROL IMPLEMENTATION AS EARLY WARNING SIGNAL FOR SAFETY INTERVENTION IMPROVEMENT AT MINING OPERATION

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Abstract. *As the frequency, severity, and costs of safety risks continue to become a challenge for mining industry, the company understood that the existing safety analytic does not provide adequate information, as it has been relying predominantly on collecting and evaluating aggregated data of lagging indicators about past accidents. This method has been negatively driving the organization to carry out repetitive cycle of accident analysis and problem solving, and therefore, undertaking reactive responses. This paper investigated how statistical process control, in particular control charts, can be applied to hazards data, as the leading indicator of accidents, to detect statistically trends in safety process and safety behavior, aiming to control the safety process in real-time manner before the occurrence of accidents. The result showed that the latest iteration of control limits development in Phase 3 is suitable as the control chart for safety process in one of case study mine operation site. Furthermore, the implementation of control charts to hazards data not only it helps the organization to transition its safety analytic to leading indicator analysis, it enables the organization to control safety process in real-time practice and to carry out timely safety intervention long before the potential occurrence of severe accidents, in which within this case, the first early warning signal was triggered 49 days before the occurrence of the fatality accident.*

Keywords: *control chart, SPC, safety performance, safety process intervention, safety behavior*

1. Introduction

1.1. Background

As one of coal mining company in Indonesia, the company has been spending years implementing its own safety management system, emphasizing on safety behavior improvement through range of safety programs from workforce safety training and coaching, safety inspection and observation, safety communication and campaign, and top-management safety committee meeting. Despite this level of safety management implementation, the company has seen its safety performance remains unaltered and continue to experience serious safety accidents and fatalities. Non-injury accidents have also remained fluctuate throughout all mine operation sites. Furthermore, as depicted in Figure 1, direct loss cost due to accidents has gradually increased, showing the increasing remedy to each occurrence of accident.

As shown in Figure 2, despite the flatline in accident frequency during Y2018 and Y2019, the Loss Time Injury Severity Rate (LTISR), one of safety performance lagging indicator widely used in mining industries, has recurred in Y2019, which put the mining operation under greater risk to scale up its production level. One fatality accident in July 2019 has become a big wake up call to the company to re-evaluate and to take a closer look at its existing safety programs and safety interventions. Safety analytic within mining operation has then become one of the issues highlighted by the company to leverage large quantities of mine safety data that will allow the company to recognize the behavior or pattern in the safety process and to determine the effective safety intervention to reduce the safety risks for the organization.

This substandard safety performance has raised concerns in the management, because this has exposed the company to risks of decrease in productivity, risks of profitability and financial burden, negative effects on reputation in the eye of its customers, and risks of talent management. Ineffective safety management may also lead to severe repercussion, as part of compliance control, by either local or central government of Indonesia.

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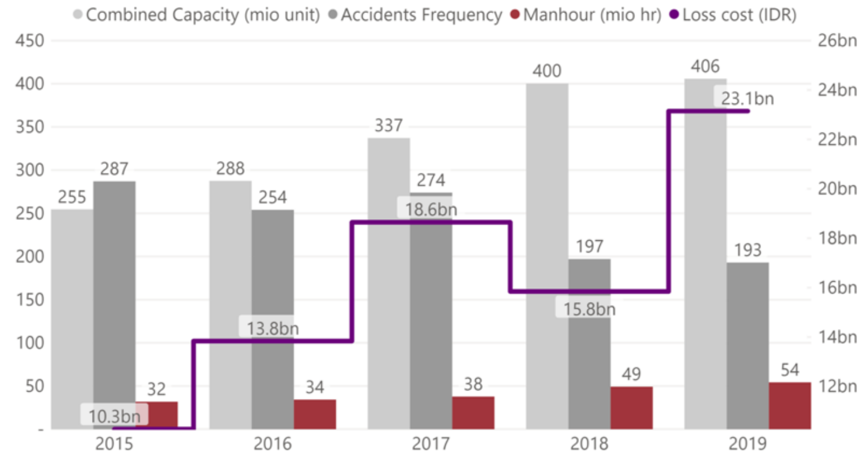

Figure 1. Direct loss cost due to accidents (in IDR billion) overlaid on top of combined production capacity of overburden and coal (in million unit), accidents frequency, and manhour

Production day loss and restricted work days due to accidents may directly impact on productivity and production output. Reviewing the latest fatality accident at one of the company's mine site in July 2019, the production loss due to three days full-fleet suspension for accident investigation and nearly eight weeks of partial-fleet suspension during post-investigation recovery to fully comply with all recommendations of mine inspectors from central government was about 2.4 million BCM of overburden and coal production loss of about 190K ton at 12.4 average strip ratio during those weeks. This can further be translated as indirect cost due to accident. The potential loss of revenue of 190K ton of coal due to fatality accident in July 2019 was about \$8.6 million. This indirect cost due to one fatality accident alone was already 5.3 times higher than total direct cost of all accidents for Y2019.

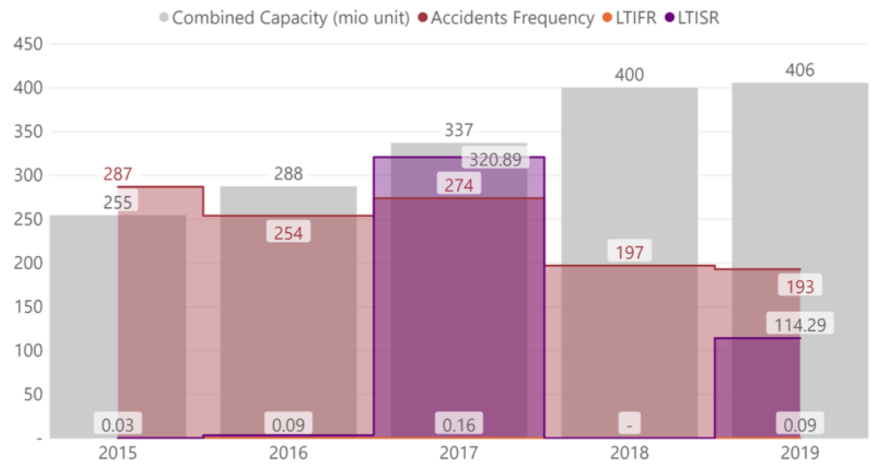

Figure 2. Production capacity against safety performance of Accidents Frequency, LTIFR, and LTISR

Frequent or severe accidents might also expose the company to severe repercussion by either local or central government, through Directorate of Energy and Mineral Resources, as part of compliance control enforcement to mining companies in Indonesia. Having evaluated an increase in Y2019 frequency and severity of fatality accidents in Indonesia, the central government issued a letter on 15 August 2019 regarding the obligations of mining companies with regard to mining fatality accident, including suspension of all mining operation until all recommendations of accident investigation have been fully executed and

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complied and reported back to Chief of Mine Inspector. To another extent, the central government utilize the safety performance as one indicator element for contract of work extension evaluation. This is by far the most critical risk as the government may evaluate and, to a certain length, may invoke the company's working permit.

1.2. Problem Definition

As the frequency, severity, and costs of safety risks continue to rise, it is necessary for the company to take a closer look at its existing safety programs and how it fits the existing and future challenges faced by the organization. Naturally, safety programs were developed based on the result of safety analysis, aiming to improve the safety performance by reducing the accidents frequency and mitigating the accidents severity. Thereafter, safety analytic has become an important element for safety programs development and safety performance control. It has become a key factor to understand the dynamic of mine safety accidents and the necessary intervention required to mitigate the impact of accidents or to prevent the occurrence of accidents. Traditionally, safety has been a difficult performance element to measure quantitatively. Predictive approaches are rarely applied, but the company understood that existing performance measurements has not been providing adequate information to immediately perform effective control to the identified hazards, neither to substandard action nor substandard condition. Therefore, the management was concerned that whether the existing safety analytic fits to the challenges and how it should be enhanced to adapt to current and future challenges.

Meanwhile, as part of digital transformation in safety management within its mining operational, the company has launched a mobile application called *Beats* in early Q2 of Y2019. The main objective of Beats was to improve safety behavior of the workforces through improving time efficiency of safety process to collect, process, and report hazards identification activities from all level of workforces. Beats was designed to lessen the complexity of safety process in order to improve workforce's safety behavior by making hazards reporting effortless. Initially, any hazard found should be reported through different kind of communication form and manually filed to Safety Department. The area supervisor will then be assigned to respond and improve the substandard act or remedy the substandard condition. Once completed, it has to be reported back manually to Safety Department, which then collected by the one who initiated the hazard report, confirmed that hazards have been remedied and filed the confirmation report back to Safety Department. To this end, the ones who filed hazards situation were the one being burdened by their action due to the requirement to be back and forth between filing the hazard report and confirming the remedied situation. Meanwhile, the area supervisors who need to remedy the situation were frustrated because they need to be back and forth between remedying the situation and ensuring the paperwork is completed. This cumbersome and inefficient process has been significantly improved through Beats by eliminating the back and forth process, cut any intermediary process of reporting to Safety Department, and discard all manual paperwork. Additionally, data related to those hazards were all integrated into Beats' system and effortlessly retrieved for the purpose of analysis or reporting. This changes has improved safety behavior of mine workforces. It positively encouraged workforces to proactively carry out safety inspection and observation during mine operational activities, as shown by the increasing number of hazards reported after *Beats* implementation. The daily average of hazards number reported by workforces was increase from average of 149 hazards reported per day before *Beats* implementation to average of 947 hazards reported per day between April to December 2019, after *Beats* implementation. Despite its widely implementation, the management was concerned on how the company can use these hazards data, which are deemed as the leading indicator of accidents, to improve its safety analytic methods.

Furthermore, a typical safety committee meeting in the company usually discuss previous period's accidents and actions that have been and being done to prevent their recurrence. The following period, a similar cycle arises again and the company creates new list of preventive programs and actions. The organization respond to the latest performance results and incorporate new and ever-changing fixes on each period . In these situations, instead of the actions driving the numbers, it is

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the numbers that are driving the actions. Wheeler depicts to this behavior as “numerical naivete” [1]. In his book, Wheeler explained the answer to numerical naivete involves the following three remedies, which include understanding variations, distinguishing common from special causes of variation, and using statistical process control (SPC) methods, in particular control charts.

Meanwhile, as outlined in the accident and loss causation model [2], the immediate causes of accidents are formed as hazards. As a result, hazards, which have been collected through Beats, can be considered as the leading indicator of accidents. It can be used as safety performance measurement instead of the traditional accidents’ ratios. Despite the potential it has, Beats’ data are not yet used for improving the safety performance nor for accident prevention.

Refer to all of above, the following questions have driven and guided the overall research process, which include:

1. How can the company use SPC, in particular the control charts, to monitor and control the safety process over time by analyzing hazards, as the leading indicator of accidents?
2. Furthermore, and during real time process monitoring, how can the organization act to the early warning signals detected by the control charts, to improve safety performance?

2. Research Objective

Many applications of control charts for safety improvement have always been focusing on the accident frequencies or accidents ratios, which are deemed as lagging indicator of safety performance. Unlike many safety analytic studies that discussing the implementation of control charts onto the accident frequency or accidents ratios, this research has been focusing on the implementation of control charts onto the leading indicator of accidents, aiming to control the safety process. This approach was established based on the premise that by combining the control charts application to control the process and the theoretical foundation of accident prevention, safety process and safety behavior can therefore be monitored in real-time manner through hazards, in which the company can act upon, to improve its safety performance. The objectives of the research are therefore to:

1. Demonstrate the value of statistical process control method over aggregate data evaluation using real historical hazards and accidents data;
2. Develop the control charts as method to control the safety process over time in one of the company’s mining operation site by using leading indicators data of accident;
3. Develop a framework flow for *Out of Control Action Plan* (OCAP) when safety intervention is required and develop and propose the new safety analytic framework incorporated the control chart and OCAP implementation;
4. Evaluate the opportunities and limitations of expanding the control charts implementation for future development throughout the company.

3. Theoretical Foundation

3.1. The Loss Causation Model of Accident

In 1931, H. W. Heinrich, one of the pioneers of industrial safety and accident prevention, published the results of a study he performed while working for Traveler’s Insurance. His original work was a theory of industrial accident prevention. He revealed a relationship between serious accidents, minor accidents, and near misses, in which that for every “major injury” resulting from a single accident, there were 29 “minor injuries” resulting from accidents and 300 no-injury accidents or near misses. The figure produced by this analysis was depicting these ratios, came to be known as Heinrich’s Triangle [3].

Furthermore, Heinrich also developed a loss causation model of accident, which then known as the Domino Theory. The model was developed based on the assumption that the occurrence of a preventable injury is the natural culmination of a series of events or circumstances, which invariably occur in a fixed or logical order. An accident is merely a link in the chain. (Heinrich, 1931, as cited in [4]). The model proposed that accident factors can be illustrated as linearly being lined up sequentially like dominos. Heinrich proposed five factors contributing to accident sequence, which, in sequences, were the social environment, the fault of person, the unsafe acts, mechanical and physical hazards, the accident, and the injury.

In 1969, F. E. Bird developed the theory further and produced an update to the triangle that showed a relationship of one serious injury accident to 10 minor injury accidents, to 30 damage causing accidents, and to 600 near misses [5]. Bird argued that the majority of accidents could be predicted and prevented by an appropriate intervention. His theory was later expanded upon by Bird and Germain in 1985's Practical Loss Control Leadership and the sequential domino representation was continued. However, they identified the requirement for the management of the organization to directly involve to prevent the accidents and shifting from focusing on the human factor, which was previously defined by Heinrich as Man Failure. They updated the domino model to reflect the involvement of the management with the causes and effects of accident loss and incorporated arrows to show the multi-linear interactions of the cause and effect sequence, as shown in Figure 3. The model became known as the Loss Causation Model, which adopted by many organizations to control and prevent accident.

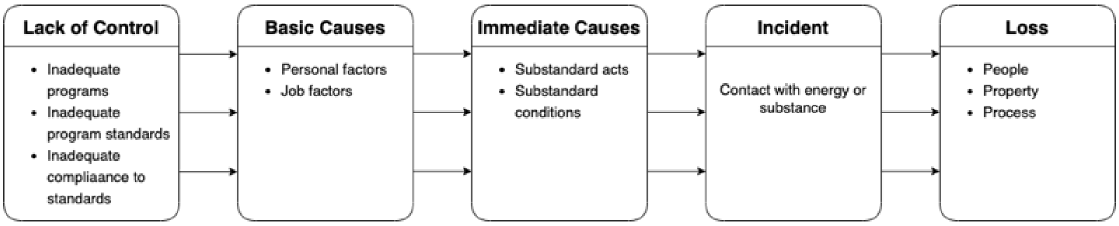

Figure 3. The International Loss Control Institute's Loss Causation Model [4]

One of the underlying principles of the Loss Causation Model is that the involvement of the management has become one of chain link in the domino effect under Lack of Control. The model incorporated hazards as the immediate causes of accidents, linking to the basic causes and then to Lack of Control. Bird and Germain also highly emphasized that the model does not intend to place the blame on individual for committing substandard acts or for allowing the existence of substandard conditions. The model intends to encourage the management of the organization to assess the safety management system that influences the human safety behavior and the implementation of safety intervention.

3.2. Statistical Process Control and Control Charts

The organization analyzes numbers usually to identify changes in a process and to identify special causes which require investigation. In short, the organization needs to know when a change has occurred in the process. Furthermore, the organization needs to know about the process changes in a timely manner in order to respond appropriately. However, even when the process does not change, the number can. Therefore, to analyze the numbers, the organization need to be able to distinguish and separate those changes in the numbers that represent changes in the process from any noises.

SPC and control chart was developed by Walter A. Shewhart of the Bell Telephone Laboratories in 1924. SPC is basically a time series graph of process data that separates signal of special cause from noise in process data. These charts provide advantages of visually uncomplicated to help the organization to understand, control, and improve the process by statistically separate the trends of special causes from random noises of common causes.

While there are several different types of control charts, the general format and interpretation of the most common type consists of a horizontal center line which represents the mean value of the characteristic of quality being assessed. The two other horizontal lines above and under the mean line are the upper control limit and the lower control limit. They define the central tendency and the range of natural variation of the process data. The control limits are statistically calculated based on the probability distribution of the sample's characteristics, such as normal distribution, Poisson distribution, or binomial distribution. For the bell-shaped normal distribution, data points that fall outside the upper or lower three standard deviation control limits exceed the 99.73% range in which almost of all data value are expected to be found if the process exhibits statistically control condition.

When the process is in control state, all

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sample points are randomly scattered around the mean and are within the control limit lines. However, in a process that is not in control, the data points could be either outside the upper or lower three standard deviation control limits, or show a systematic trend or non-random manner. This situation is interpreted as signs that investigations and interventions are required to identify and to eliminate the special cause or causes responsible for the occurrence of this behavior. Therefore, in addition to values outside of control limits, various between-limits rules have also been defined to aid in the objective interpretation of process data pattern.

Since most processes, from time to time, do not always operate in statistical control, the most important uses of control chart are to improve the process. It helps the organization in understanding and identifying special causes occurrences. When the special causes can be eliminated or reduced by the organization then the process will be improved.

3.3. Statistical Process Control for Safety Analytic

Despite how SPC, specifically control charts, can be utilized as an important management control tools for performance measurement of processes, the most pervasive misunderstanding regarding the implementation of SPC is that it only applies to production line manufacturing. This occurs due to its origination of development to solve manufacturing problems, which it did in an outstanding way. Therefore, the adaptation to manufacturing industry was very straightforward. However, Stapenhurst [6] argued that since SPC is about monitoring process performances, therefore if the organizations are able to measure performance, then the likelihood is that SPC is the tool for analyzing these process performances. The number of accidents per month may well refer to the number of rejected items on a production line, equally well it can refer to the number of hazards per month on each location as the leading indicator for accident. The key for the implementation is therefore how to apply the statistical thinking into the most real "big data" problem of safety analytic, which often are large, complex, and unstructured, which might not well-defined in textbooks or scientific researches, and often, the fundamental problem to be solved is unclear [7].

The applications of SPC and control chart in non-manufacturing industry are not uncommon. SPC and control chart have been extensively implemented in healthcare industries, including the application of control charts in emergency department, surgery department, epidemiology department, radiology department, pulmonary department, and cardiology department [8]. Control charts have also been applied for quality and performance improvement in services and hospitality industry including administration process improvement in hospital [8], services quality control at hotel [9], and sales process control in commercial company [10].

Out of the application of SPC and control charts outside manufacturing industry, several have been utilized as methodology and tools for safety monitoring and safety analysis. These include the application of SPC to analyze the highway-accident data [11], the application of SPC for safety management analysis in construction industry [12], and control chart implementation for accident frequency analysis [13].

Nevertheless, most of the adaptation of control charts for safety analytic focused on the accident frequencies or accident ratios as its data points of analysis. Instead of focusing on the lagging indicators, this research focused its analysis on the leading indicator of accidents, the hazards numbers, based on the adoption of accident and loss causation model. To this end, the implementation of control charts for safety analytic required the organization to change its view regarding the role of statistics in quality control. The organization needs to transition its focus onto statistical engineering rather than statistical tools. The statistical engineering integrates the idea of processes, variation, analysis, developing knowledge, taking action, and quality improvement. It brings together the statistical tools and other methodologies, constructed specifically to address the issue [7].

As there are variety of different types control chart, selecting the suitable control chart for datasets at hands is not straightforward. Sometimes the choice of chart to construct means little difference to the conclusion drawn, whilst in other situation it does. For charting purpose, data can be categorized into two types of variables and attributes data. Variables data usually acquired from process measurement. The characteristic of the data is its precision, in

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which the number of decimal places recorded. Meanwhile, attributes data, or also known as counts data, are defined because they are based on whether an item has an attribute or not. These data are always count and, therefore, its characteristics are whole numbers, and for this reason they are sometimes called discrete data.

In many situations it may not be apparent which chart type should be used to analyze a dataset. For instance, both the *c* and *u* control charts are used to identify variation in counting type data or attributes data. Using a case study, Stapenhurst [6] explained and described that whilst it is important to consider carefully what chart is appropriate in any situation, using the "incorrect" chart may still provide accurate information about process performance.

To this end, hazards data was considered as attribute data, composed of count of hazards finding during the progress of mining activities. Usually, the decent control chart for this type of data were either *c* or *u* control chart. Stapenhurst [6, p. 270] pointed out that the selection between *c* and *u* chart should consider the area of opportunity. In the case of hazards finding, the area of opportunity would be the working manhours within the mine site over time. If the area of opportunity does not vary by more than 25% from the average, then *c* chart is suitable as the control chart. However, with regards to the utilization of *c* chart, Stapenhurst [6, p. 264] also pointed out that if the average (mean) of data being plotted is large (greater than 5), then the *X/MR* charts can be used instead of *c* chart.

The *X/MR* variable charts are often used in place of the *c, u, np,* and *p* attribute charts. Meanwhile, Wheeler [14] as cited by Stapenhurst [6, p. 272] suggested to always use *X/MR* charts unless the specific statistical distribution that the attributes charts assume aligned with the data it plotted. The underlying reasoning of this last guideline was that the *X/MR* chart is more robust than the attributes charts to deviations from the initial assumed distributions. The main difference between the *c*, *u*, and the *X/MR* chart was that the limits for the *c* and *u* attributes charts were based on the theoretical distributions associated with counts data of Poisson distribution. The appropriate attribute chart with its limits should be used if the data followed these distributions. However, as cited by Stapenhurst [6, p. 272], Wheeler [14] argued that in this aforementioned case the *X/MR* chart will emulate these limits. Furthermore, the attribute chart limits will be inaccurate if the data do not follow the theoretical distribution. Nevertheless, the *X/*MR chart will be the better chart to use because the *X/MR* limits are empirical and do not rely on these distributions being followed.

4. Methodology

The methodology framework proposed in this research aimed to address the limitation of the existing safety analytic frameworks in the company, which will be further described in subsequent section. Refer to Bird's study on industrial safety and accident prevention, the propose framework recognizes that despite the accidents in mining operational are inevitable, it does not stop the company for believing that they are also preventable. One fundamental key is how the company controls hazards as the foundation of the occurrence probability of serious accidents. Moreover, hazards identification exercised by the company does not only act as a safety program, aiming to identify and remove hazards found in mining operational. It also acts as data representation of safety behavior and safety awareness level of the workforce, thus represents the quality of safety process. The numbers of hazards identification are therefore can be used as leading indicator for safety behavior and safety performance measurement instead of traditional lagging indicators of accidents frequencies or ratios. Furthermore, taking into account the Bird's work on hazards control, by carrying out the analytic works directly on the number of hazards, the company takes the advantages of controlling mining safety performance through the hazards numbers, which are the leading indicator to serious accidents on top of the pyramid.

Additionally, the implementation of control chart onto hazards numbers will enable the company to determine whether safety processes in mining exhibit common cause variation (in statistical control), or whether, and when, special or assignable cause variation is occurring (out-of-control process). It may not be possible to completely eliminate variability, but the control chart is an effective tool in reducing variability as much as possible, thus reducing the occurrence probability of serious accidents.

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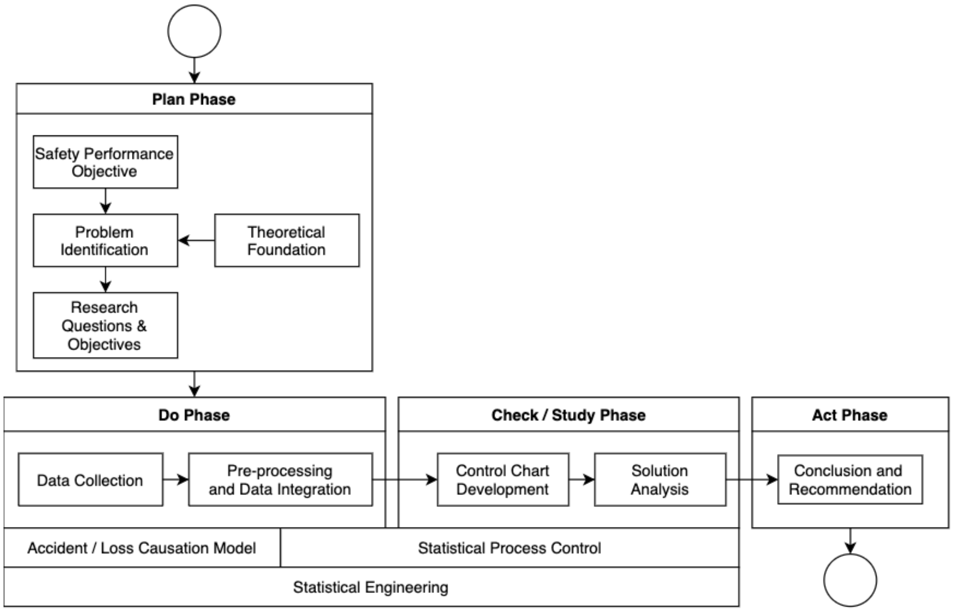

Figure 4. Research methodology frameworks for control charts implementation in mining operation

To this end, the research methodology incorporates a process flow of Plan, Do, Check or Study, and Act phase as its framework, as shown in Figure 4. The Plan phase consists of the problem identification and formulation of research questions based on the issue of the business in regard to safety performance objective.

The Do phase consists of data collection, data preparation and pre-processing. In order to test the suitability of control chart implementation for safety performance measurement, it was necessary to collect qualitative and quantitative data from different sources in the company. The research involves primary and secondary data of hazards identification report and accidents data and report from Y2018 and Y2019. It included data as results of group discussion among cross function division and department. Y2018 data up to first quarter of Y2019 were all secondary data, collected manually from HSE Division. Y2019 data were combination of primary and secondary data. Hazards data directly acquired from Beats database. Data validation and cleansing was required to maintain data consistency out of those different process and time of data acquisition. Meanwhile, the Study phase covers the main development of control chart and the analysis of the propose solution with regard to the initial research questions and objectives. It is then followed by the conclusion and recommendation within the Act phase.

The framework incorporates the Loss Causation Model and SPC along the Do and Study phase. The underlying reasoning of this was to incorporate the model as early as possible during the process, aiming to eliminate special causes variation in order to create a predictable process. In this context, predictability was assumed as the certainty that any controlled metric or measurement will vary in between the two control limits. A second premise for the implementation of SPC was to exercise control on process inputs rather than the outputs, therefore it was important for the organization to understand the relationship between accidents numbers and its leading indicators, as pointed out in Accident/Loss Causation Model. Furthermore, since in practice, business issues are usually large, unstructured, and complex, statistical engineering guided the utilization of statistical methods for safety performance management with business acumen.

5. Problem Analysis

5.1. Current Safety Analytic

One important feature of the safety analytic is to measure, monitor, and report the safety performance over time and respond correspondingly. However, based on the observation and group discussions, the company’s current safety analytic framework, as shown in Figure 5, incorporated flaws over time that negatively drives the organization to

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carry out repetitive cycle of accident analysis and problem solving. As outlined in Table 1, these discussed flaws were categorized into three parameters of Measurement, Performance Indicators, and Intervention Responses, which can be described as follow:

1. The company's current safety performance measurement relies predominantly on collecting and evaluating aggregated data about past accidents and comparing them to previous period or to a specific number;
2. Most of indicators for safety intervention analysis are reactive or "lagging" indicators. Although leading indicators, such as hazards numbers of substandard actions or conditions, have been used from time to time, however, the same aggregated past data analysis method is being used for these kinds of data;
3. This method is lagging behind the process, especially during mine sequencing operation, thereby delay occurs to making quantitative improvements or safety intervention to the ongoing process. The company, thereafter, undertakes reactive responses based on the result of this past data analysis, exercises the recommended safety interventions to the ongoing mining operations.

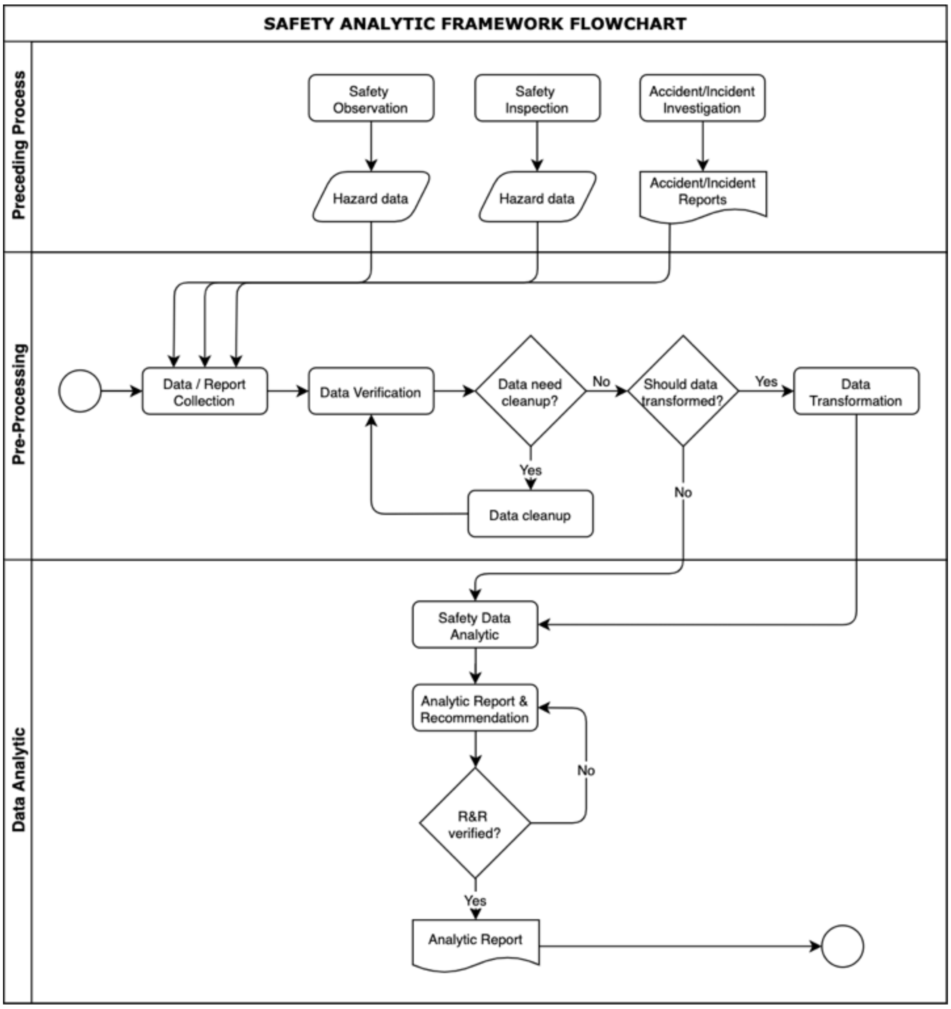

Figure 5. General framework of the existing safety analytic in the company

Table 1. Table Observed parameter for safety and accident data analytic

Parameter Observed	Parameter Attributes (Voices of Customers)
Measurement	• Aggregated accident data • Monthly to weekly periodic basis • Past accident/incident data analysis/evaluation

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Parameter Observed	Parameter Attributes (Voices of Customers)
Performance indicators	• Lagging indicator, i.e. accident and incident ratios, as performance indicator • Leading indicator, i.e. hazards, is also being used during performance review, nevertheless, is viewed as aggregated data
Intervention responses	• Reactive, based on the analytic result • Lagging behind the process of mine sequencing

5.2. Accident Investigation and Hazard Reporting

Incidents investigation and hazard reporting are both safety procedures that are part of the company's safety management system. The Incident Investigation and Reporting procedure provides guideline and framework for accident investigation [15]. It also details the reporting framework for accident reporting and intervention recommendation to reduce any potential of accident recurrence. Meanwhile, the Hazard Reporting procedure provides guidelines and framework for hazard reporting and intervention action [16]. One thing in common with the procedure for accident investigation is that hazard identification and report are registered and recapped as part of safety records, which afterward are utilized for safety performance evaluation and performance management report.

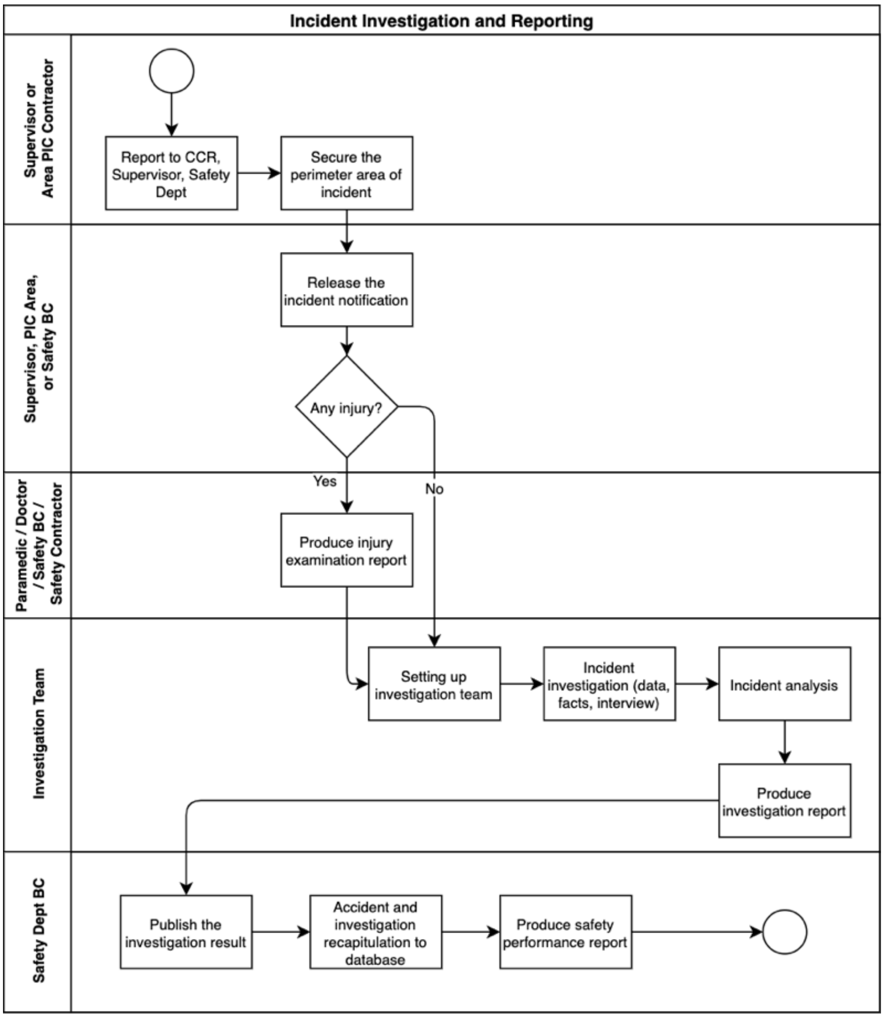

Figure 6. Accident investigation and reporting framework, simplified version

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Based on the observation, the existing framework of accident investigation and hazards reporting, as depicted in Figure 6, clearly incorporated the same flaws as discussed earlier, in which over time, negatively drive the organization to carry out repetitive cycle of accident analysis and problem solving. These flaws include:

1. The framework of both procedures clearly shows that the company predominantly depends on evaluating aggregate records of past accidents and hazards for safety performance evaluation and safety performance report;
2. Although the company combines this evaluation with leading indicator of hazards, however the analytical process is still based on aggregate data of past hazards;
3. The company depends on this aggregate data analytic to drive its safety performance, undertakes reactive intervention based on these evaluation result.

5.3. Improving Safety Behavior and Awareness through Hazards Identification

Aiming to improve its safety performance, the company emphasized hazard control, through hazards identification, performed by all workforces. Furthermore, the company believed hazards identification, which widely exercised by all workforces in the operational activities, can be used as indicator of safety awareness or behavior in the organization. Having understood this, the organization introduced *Beats*, a mobile application tool, to report substandard actions and substandard conditions found during inspection and observation of operational activities. Introduced in the beginning of 2019 and formally released on April 2019, Beats was widely accepted by workforces for its easiness to report any hazard found during operational activities. Looking into the increasing number of hazards finding that was reported by mine workforces per day after Beats implementation in Y2019, as shown in Figure 7, the management believed that *Beats* was a success story with regards to how a safety application can increase safety awareness and safety behavior of all workforces.

Meanwhile, the company looked into mine plan sequencing and its relation with hazards identification. A time scale of planning activities take place between the long-term life of mine as strategic mine planning on mine expansion, infrastructure development, and mine closure to short-term mine planning, focusing on operational or day-to-day positioning of equipment, drilling and blasting, mine road development, and control of coal product characteristic or quality delivered to the crusher. Under each horizon, mine sequencing becomes part of the mine scheduling for materials extraction. In short-term mine plan, blocks selection should consider the mining operational process. In general, this includes allocation area for land clearing, drilling and blasting, mine road positioning, overburden removal, coal mining, and shifting to each process. As part of the short-term mine planning procedure within the company, during cascading into daily operational plan, mine planner incorporates hazard mapping into the selected allocation blocks for the period. The objective is to provide preliminary information for operational supervisor during operational activity. Meanwhile, detail hazards identification will be performed during each operational activity. Considering the nature of the mine sequencing and its dynamic during operational implementation, hazards occurrence will become inherent factors in mine operational activities. Therefore, the pattern of hazards identification by workforce during operational activities can be utilized as an indicators of safety awareness of workforce in the organization.

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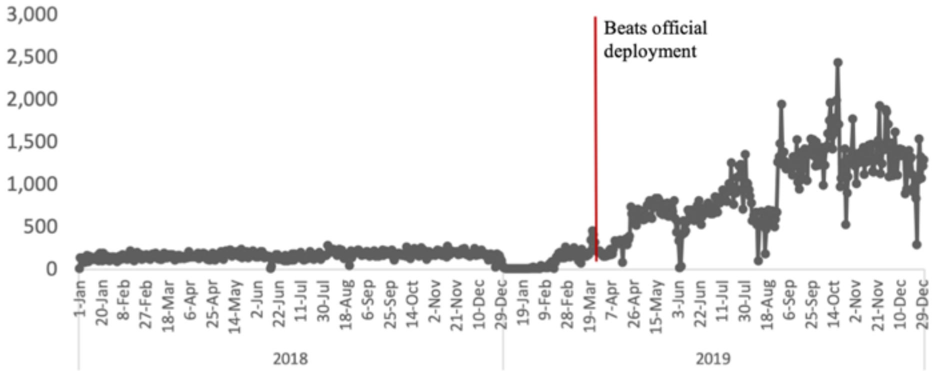

Figure 7. The increasing number of hazards finding per day reported by workforces after Beats implementation in all mine operation area

Despite this, the management was concerned that although this trend showed a good sign of increase in safety awareness, the safety performance showed plateau progress as repetitive accidents occurred in mining operation. During a focus group discussion, the company addressed how current safety analytic has been performed. Predictive approaches were rarely implemented, but the organization understood that current performance measurements did not provide adequate information to immediately perform effective hazards controls to eliminate or mitigate accidents occurrence potential. The existing safety analytic framework should be enhanced with new analytical methods to adapt to current and future challenges. A causal-effect analysis was discussed to identify causal factors to improve the existing safety analytic in mining operations.

5.4. Causes and Effects of the Existing Aggregate Safety Analytic

In analyzing the overall plateau of safety performance, group discussions between Technical Services Division, System and Compliance Division, and HSE Division were held to specifically discuss the limitation of the existing aggregate safety analytic. The objective of the discussions was aiming to improve the analytic process to support the organization improving its safety performance.

During group discussion, the organization recognized the need to transition from aggregate measurement to accident's leading indicator which can represent the ongoing quality of safety process yet can be acquired timely so that the most effective safety interventions can be implemented. The use of timely monitoring to this indicator will allow the organization to recognize the behavior or pattern in the process, to investigate the trends, and implement the most effective interventions, prevent the accidents, and lower the risks to the organization.

Major causal categories were identified on why the existing safety analytic was ineffective to promote better safety outcome and then laid out into cause-and-effect diagram, as shown in Figure 8. The categories included manpower, methods, measurements, and systems management or procedures, which were further cascaded into several leading sub-categories that prominently assigned as the causal factors. Through group discussions, the team agreed and decided that methods and measurements categories contained the most critical causal categories to address to as the starting point. These categories contained the underlying factors that causing the limitation of the existing safety analytic, in which focusing on lagging indicators, aggregate numbers comparison, and control charting has not yet utilized as process behavior control, which leads to over-control or tampering to all variations in the process.

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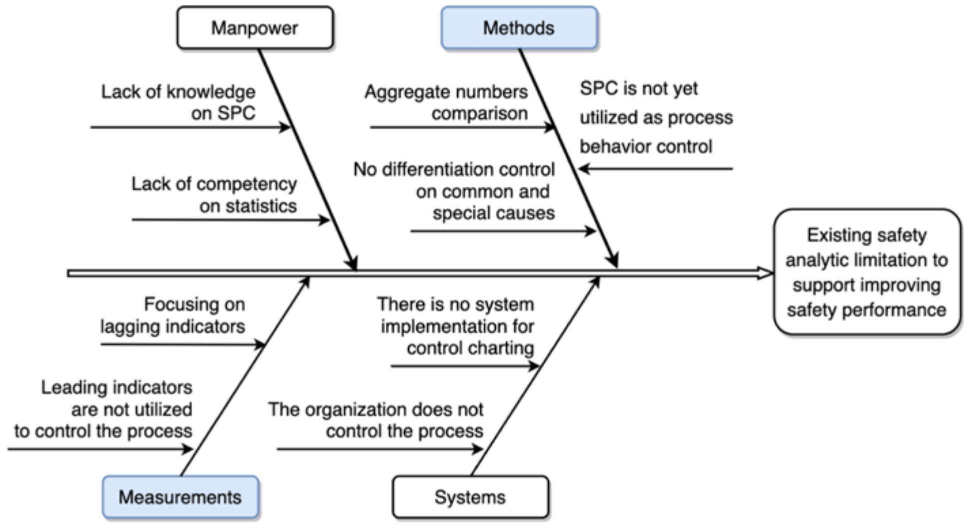

Figure 8. Cause-and-effect diagram for the existing safety analytic limitation to support improving safety performance

6. Business Solution

6.1. The Application of Control Chart to Hazards

Control chart usage involves Phase I and Phase II applications, with two distinct objectives. Control chart in Phase I is primarily utilized to assist the organization to bring the process into a state of statistical control or simply put as the control chart development. During Phase I, process data is gathered and analyzed all at once in retrospective analysis, constructing trial control limits to determine if the process has been in control over the period of time during which the data were collected, and to see if reliable control limits can be established to monitor future process. Meanwhile, Phase II begins after the "clean" set of process data gathered under stable conditions and representative of in-control process performance. In phase II, the control chart is utilized to monitor the process by comparing the sample statistic for each successive sample as it is drawn from the process to the control limits [17].

Phase I process involved several iterations of trial control limit calculation, identifying points that are outside the control limit, investigating the special causes, and once these special causes identified and confirmed, points outside the control limits were then excluded and a new set of revised control limits were calculated.

The research explored and evaluated control charts implementation onto hazards profile, which were derived from Beats data since its deployment, to reflect future application in the mine operation. To this end, the application of control chart would measure the quality of safety behavior or safety awareness in mining process through retrospective hazards number variability analysis. It is fairly typical in Phase I to assume that the process is initially out of control, therefore the objective of the analyst is to bring the process into a state of statistical control.

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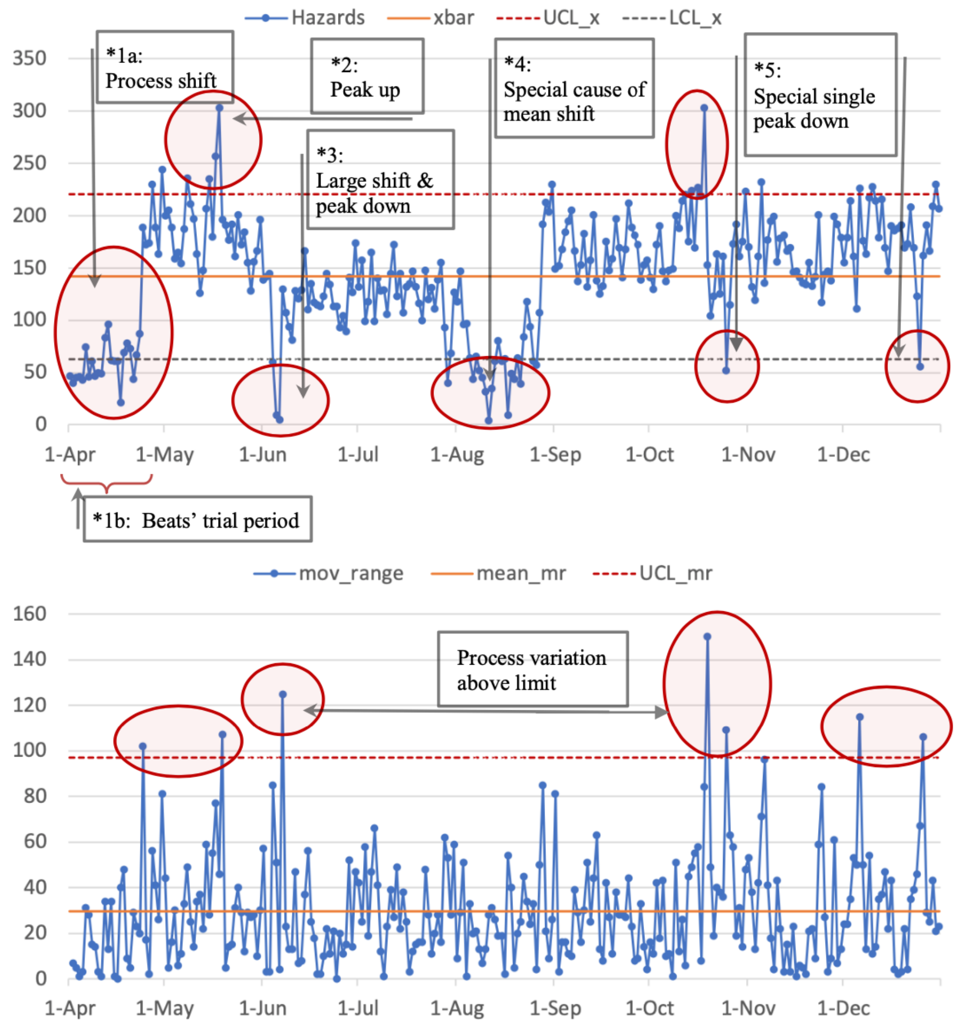

Figure 9. First iteration of special causes identification cycle on *X/MR* chart for hazards at one of mine operation areas, showing that safety process or behavior was out of statistical control

As part of retrospective analysis, daily hazards data of the case study mine site from April to December 2019, all at once, were plotted on the control charts. The control limits were calculated based on these hazards data point. The initial plot of hazards profile from April to December 2019, as depicted in Figure 9, indicated that safety process in mining activities was out of statistical control, as shown by sudden shift of hazards numbers and smaller sustained shift of hazards over the time on the *X* chart. The *MR* chart showed similar out of control signals out of plotted moving range of hazards, particularly during single peak up and single peak down values deviating from the mean in the *X* chart, which shows the variability of hazards data during these particular condition. The first pass analysis identified points which were outside the trial control limits. These points were then investigated, looking for potential assignable or special causes. Since this phase involved retrospective analysis, there were no out of control action plan implemented. Once these special causes identified and confirmed, points outside the control limits were then excluded and a new set of revised control limits were calculated. These hazards were then compared again to the revised control limits.

Meanwhile, a group discussion was held to examine non-random causal factors affecting the profile of hazards numbers based on field experience, especially within case study mine site. Based on the discussion, the non-random causal factors affecting hazards numbers trend might include management's and supervisors' pressure to control hazards or simply stated as safety pressure, production and productivity pressure, motivation and commitment on safety, individual safety competency, reactive

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compliance behavior, and confidence in safety intervention. Detail causal factors, typical safety behavior effect, and non-random pattern are described in the Table 2.

Table 2. Non-random pattern identification based on causal factors and its typical safety behavior

Causal Factor	Typical Safety Behavior	Typical Non-random pattern
Accidents' control pressure and safety pressure	As accident increases, the management and supervisors were under pressure to control the situation through stringent and repetitive hazards control. They often directed frontline workforces to conduct repetitive hazards identification or tampering the process.	Sudden and repetitive spikes of hazards or consecutive hazards number above the mean.
Production and productivity pressure	Production pressure occurred when there were gap between actual production and its target. As management put more emphasis on production relative to safety, this created an indifferent behavior to safety.	Sudden peak down or repetitive consecutive hazards number below the mean might occur in the control chart.
Motivation and commitment to safety	Most of the time this factor generated normal variation, however often motivation might degrade over the time or due to lack of incentives. Hazards number might gradually decrease over the time. The opposite could also occur due to increase in motivation or due to strong incentives.	Hazards number might gradually decreasing or increasing over the time.
Individual safety competency	Segregation level of competency between individual generated consequences, either positive or negative, to hazards identification and safety intervention to control the hazards. This occurred typically during changes of supervisor within an area.	Hazards number gradually shifted or suddenly shifted from the mean.
Reactive compliance behavior	The typical safety behavior of this factor would be the same as the above safety pressure factor. This factor also related to the safety motivation and commitment factor. However, this factor emphasized on the behavior of workforces. Workforces tend to wait for direction or performed hazards identification and control only to fulfill their obligation or only seeking compliance.	Mixed of sudden shift or consecutive hazards number within an area around the mean might occurred in the control charts.
Confidence in safety intervention	This behavior occurred mainly because workforces felt that no matter what safety intervention were, safety performance was going plateau. This behavior related to the effectiveness of safety interventions, which were based on the existing safety analytic method. This created mixed behavior of low confidence level to the applied safety intervention.	The condition drove hazards number to gradually decreasing or generated consecutive hazards number around one side of the mean.

Furthermore, non-random patterns have also been examined to recognized non-random casual factors affecting the hazards profile during mine operational activities. In addition to basic rule of "one or more points outside of the 3-sigma control limit", non-random rules were developed and applied to detect trend in safety process and safety behavior based on those non-random causal factors, as outline in Table 3. These non-random rules were treated as supplementary rules to increase the sensitivity of the control charts to be applied in the case study mine site.

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Table 3. Rules for control chart implementation at case study mine operation site

Rule #	Rule Test
Rule 1, basic rule	one or more points outside of the 3-sigma control limit
Rule 2, supplementary	two out of last three consecutive points on the same side of between 2 and 3 sigma from the mean
Rule 3, supplementary	four out of five consecutive points on the same side of between 1 and 3 sigma from the mean
Rule 4, supplementary	eight consecutive points on one side of the mean
Rule 5, supplementary	six consecutive points steadily increasing or decreasing

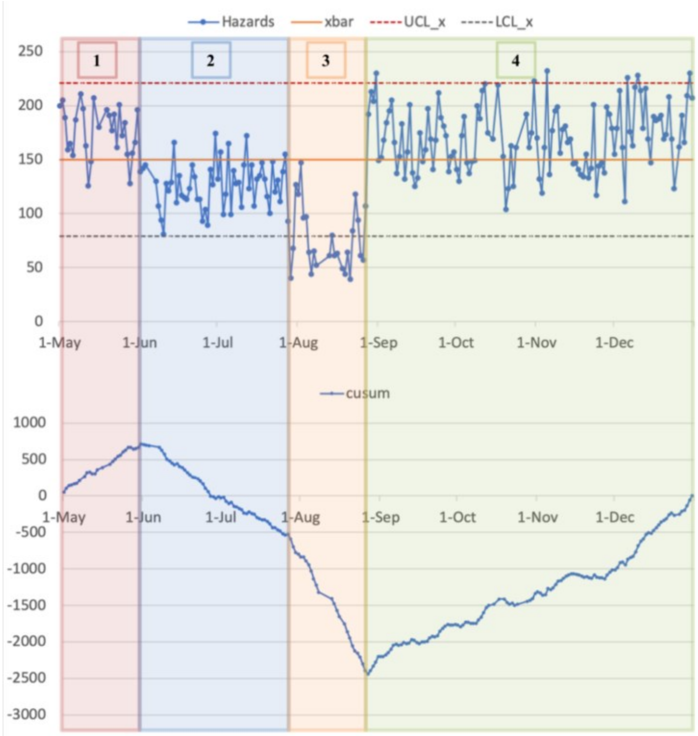

Figure 10. Phase's zone of process' shift for hazards number in case study mine site

Having recognized the mean shifts in the process, the trial control limit should be adjusted based on any changes in the safety process which drove the movement of hazards numbers during the period. To determine the process' shifts, Montgomery [17] pointed out that if the process remains in control at the target value μ_0, the cumulative sum of difference between the hazards number in each period and the. average number of hazards would be a random walk with mean zero. However, if the mean shifts upward to some value $\mu_1 > \mu_0$, then an upward or positive drift will develop in the cumulative sum (cusum) chart. Conversely, if the mean shifts downward to some $\mu_1 < \mu_0$, then a downward or negative drift in cusum chart will develop. Therefore, if a significant trend develops in the plotted points either upward or downward, we should consider this as evidence that the process mean has shifted [17, p. 416]. To determine the shift points in the process, the X chart was then divided into phase zones which might indicate the occurrence of the process shift in the safety behavior for further investigation, as depicted in above Figure 10.

The X control chart was divided into 4 phase zones with regards to the occurrence possibility of safety process changes during the period. Further data exploration to production report and safety investigation report and discussion with Mine Operation Senior Manager and HSE General Manager were conducted to determine the occurrence of process changes and its causal factors. Based on these, the following description explain whether

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or not process changes occurred within each phase zones:

1. Phase 1. The zone was between 1 May up to 1 June. It was considered as the initial phase of the changes in safety process since the implementation of Beats. Hazards numbers increased which indicated the increase of safety behavior of the workforces;
2. Phase 2. Safety behavior was decreasing, indicated by the decrease of the hazards numbers since 1 June to 28 July. However, based on the discussion with HSE General Manager, there were no evidence of changes in the implementation of safety process. Safety inspection, safety observation, and risks assessment among other safety process were performed in accordance to each guideline or procedure. Despite this, another causal factor occurred during the period which then were captured by non-random test. Along with Mine Operation Senior Manager, production data was explored to determine the driving factor. It appeared that the overburden and coal production were behind the production plan during this Phase 2, as shown in Figure 11. This indicated production or productivity pressure occurrence that affecting the safety behavior during this period. As described within non-random pattern, sudden peak down or repetitive consecutive hazards number below the mean might occur in the control chart;

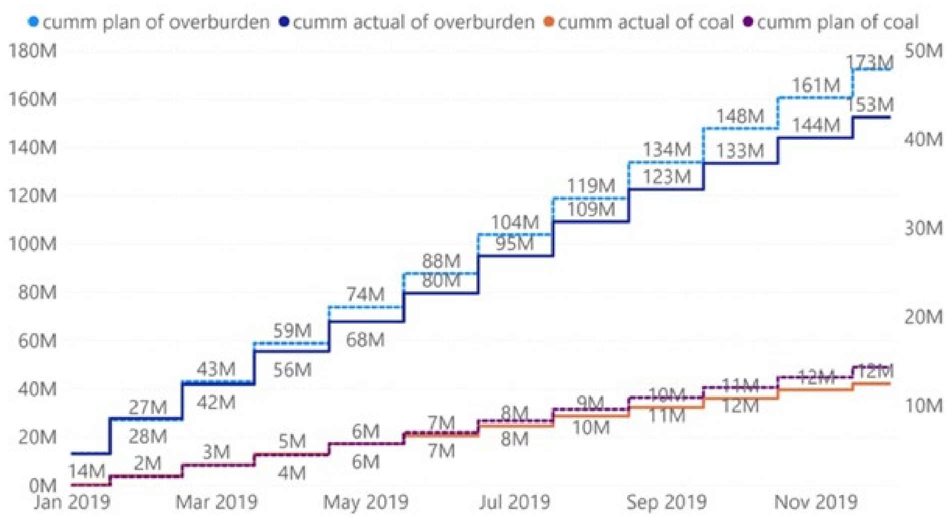

Figure 11. Y2019 production profile of overburden and coal in case study mine site

3. Phase 3. Phase 3 was separated from Phase 2 since the date of the fatality accident, 28 July 2019. During this period, safety process under mining operation was consolidated and tested, as part of follow-up recommendation after fatality. Accident, before being regulated;
4. Phase 4. This phase was started when all mining operational activities were recommenced. New mining processes, including improvement to daily operational plan and mine operational activities within soft material premises, were exercised. New safety processes, covering specific safety inspection and safety observation for high risk areas and critical tasks and Last-Minute Check program implementation for soft material operation, were also exercised throughout mine operation area.

To this end, trial control limits were adjusted in accordance to changes in safety process. Phase 2 was combined into Phase 1 since there was no change in safety process during this period, while Phase 3 and Phase 4 became Phase 2 and Phase 3 respectively. As the new trial control limits were computed, hazards numbers were plotted again into the *X/MR* control chart for the purpose of subsequent iteration analysis, which is depicted within Figure 12. The focus of the subsequent iterations was to determine whether safety process could be controlled using the new control limits. Therefore, the main concern was

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the application of basic criterion or Rule 1.

Having applied the new trial control limit and the new mean for Phase 3, the *MR* chart showed that the process variation was in control. Furthermore, the *X* control chart also showed that the process was in state of statistical control compare to previous baseline. Nevertheless, non-random patterns from supplementary rules were still detected in the process, specifically Rule 3 and Rule 4. As described earlier, Rule 1 was determined as the basic criterion while the other rules were supplementary criteria to increase the sensitivity of the control charts. When several of these sensitizing rules were applied simultaneously, the company could use the supplementary rules as early warning signals of the process' behavior for graduated scale responses before safety behavior or safety process going into out of control state beyond the control limit.

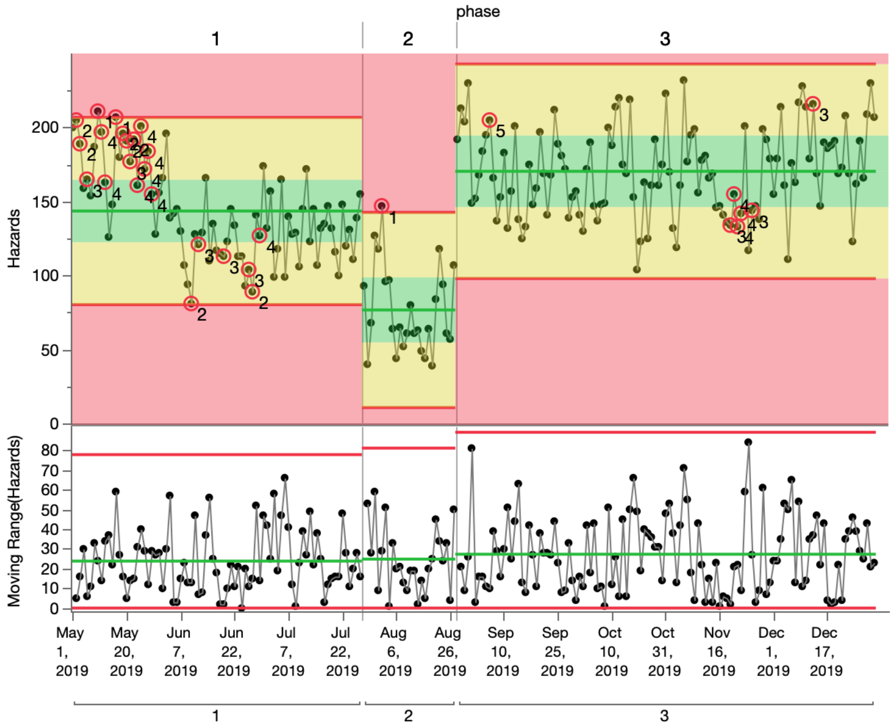

Figure 12. Hazards data under new trial control limit on each phase, showing that in Phase 3 safety behavior or process is in state of statistical control without Rule 1 being detected

To this end, the utilization of the above *X/MR* control chart with the latest control limit in Phase 3 was believed to be able to control the safety process and safety behavior in case study mine operation site. The additional application of sensitizing rules can further increase the sensitivity of the control chart. However, the rules can only be applied as early warning signals for small shifts in the safety process.

6.2. Out of Control Action Plan

By monitoring the hazards through control charts, the company will be able to control the safety process and safety behavior in (near) real time. Furthermore, the organization would then be able to exercise the required intervention to the process effectively once a signal detected by the control chart. The hazards plot on the *X* control chart along with its cusum chart can be used to explain this further.

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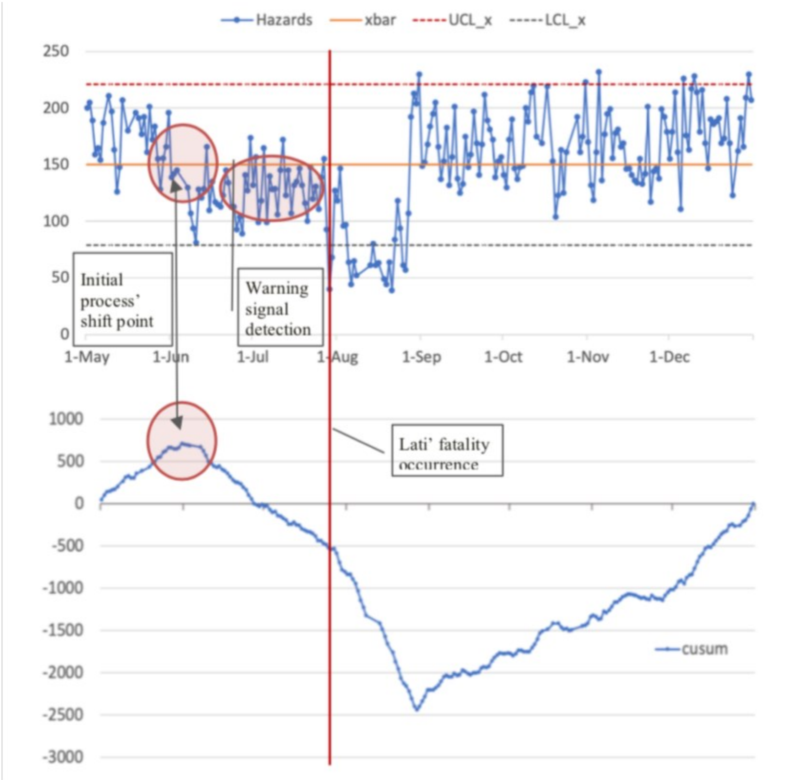

Figure 13. Warning signal detection and the occurrence of fatality accident at one of mine operation areas

Figure 13 shows the initial control chart for hazards at one of mine operation areas, combined with its respective cusum chart. As previously described, the safety process began to shift downward in the beginning of June. Although the hazards number movements were still within the control limit, it run below the initial mean during June and July. As explained earlier, safety process was likely under production or productivity pressure, causing the safety process to shift compare to previous state, as indicated by the downward movement of hazards in the control chart. Since the process was still within the control limit, Rule 1 signal was not triggered. Having looked back into Figure 12, the first warning signal was triggered in 10 June 2019 in the form of Rule 2 (2 out of 3 points in a row beyond two-sigma). The first signal was then followed up by series of signals of Rule 3, Rule 4, and Rule 2 during the period of June and July. Hazards numbers stay below the mean, as the cusum chart still showed declining trend in the period of July, until the occurrence of fatality accident in 28 July 2019.

Having evaluated this case, the organization could use these signals to initiate intervention to the safety process to mitigate the impact of the accident. During a real-time monitoring, these repetitive signals could be used as early warning signal to initiate investigations on what the special causes would be and to exercise any required intervention effectively to improve the process long before the occurrence of severe accident, or even to prevent the occurrence of severe accidents. The process of investigation and exercising the intervention associated with the trigger of warning signal was thereafter could be summarized as out of control action plan. Therefore, an important part of the corrective action process associated with the control charts usage is the *Out of Control Action Plan* (OCAP). An OCAP is usually a flowchart or text-based description of the sequence of activities that must be performed following the occurrence of out of control signals from the control charts [17].

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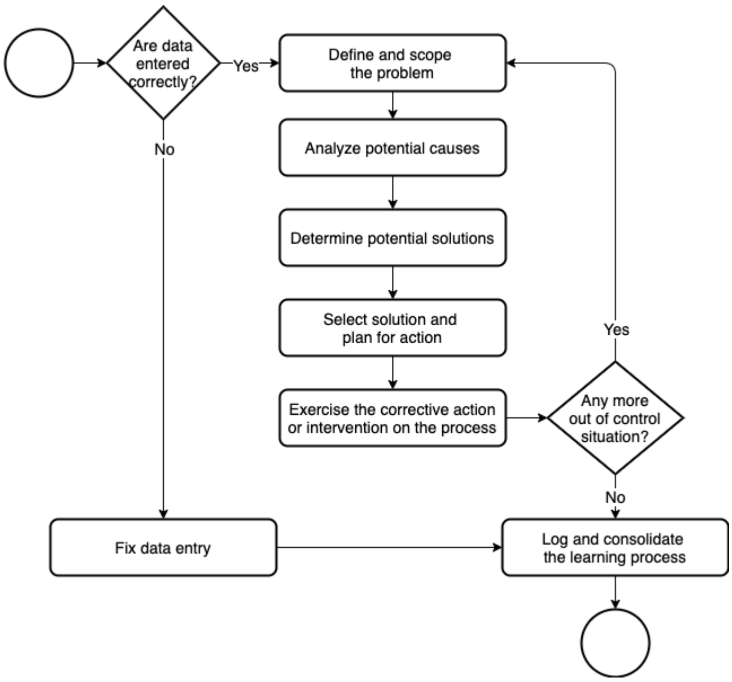

Figure 14. *Out of Control Actions Plan (OCAP)* framework for corrective action or intervention implementation due to warning signal occurrence in mine operation

With regards to the control charts implementation to safety process at case study mine site, an OCAP framework was developed, as shown in Figure 14. The main focus of this OCAP framework will be to regulate the organization to analyze the potential causes, to determine the potential solutions, and to carry out the corrective actions or interventions, if necessary, once warning signal detected by the control charts.

7. Business Solution Analysis

As illustrated within the above Business Solution section, several important distinctions exist between the existing traditional measurement practices and the measurement implementation using control charts to monitor and control the safety process in mining operation. With regards to the implementation of control charts as safety analytic method at case study mine site, three distinctions and benefits were identified as the improvement over the existing safety analytic method, which can be further explained as follows:

1. The most important distinction is that data should be collected and evaluated through the control charts in almost continues manner for the real time or near real time monitoring purpose, rather than retrospectively in large aggregate quantities. The typical current manner of reporting key performance data is to summarize several aggregate values in accordance to specific period time, such as annually, quarterly, monthly, or weekly Therefore, the control charts implementation fully aligns with how currently Beats collects hazards data, in which considered as almost in continues stream. Furthermore, it directly answers concerns of the management on how to utilize Beats’ vast data collection to help the organization improve its safety performance. By transitioning from aggregate safety analytic to real time safety analytic, the company will also benefit from a timely intervention once signal triggered, rather than waiting until the period of aggregate data reporting, thus reducing the lagging time of safety intervention;
2. As previously described, the company has been emphasizing more on lagging indicator, such as accidents ratios, to control the safety process in mining operation. Unlike the traditional measurement currently applied in the company, the control charts are applied directly onto hazards, as the leading indicator of accidents. The control charts implementation will help the organization to transition from lagging indicator to

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leading indicator in the safety analytic process. The control charts help the company to monitor and control the safety process over time by analyzing the leading indicator of accidents. As outlined within Figure 13 and 14, the control charts will help the organization to identify the occurrence of special variations in the safety process through hazards, instead of the accident numbers, as the control charts trigger the signal, thus helping the organization to exercise the safety intervention before any severe accident occurred. To this end, the application of control charts to the leading indicator of accidents will also benefit the organization since it can be used as a control tool for accident prevention.

3. Accompanied by the OCAP, the control charts implementation helps the company to actively bring the safety process into statistical control condition, which enhancing the continues improvement process in the organization.

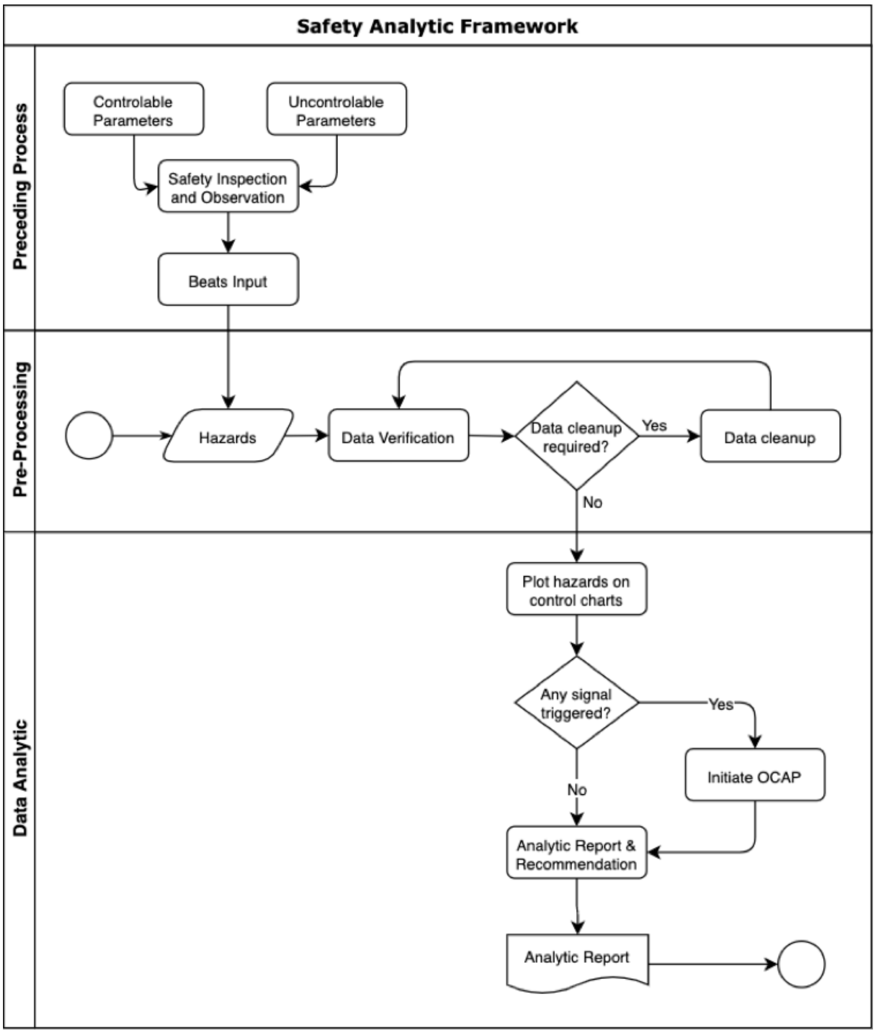

Figure 15. Safety analytic framework proposal, having incorporated the control charts application and OCAP in the process

Having studied its advantages over the existing safety analytic method, the control charts implementation will only be effective once it is embedded within the safety analytic framework. Control charts development was only the beginning step of safety analytic improvement. It should be followed by way of management's commitment to strengthen its position and adoption rate. Therefore, the subsequent step of the control charts

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implementation is to incorporate the application of control charts and the OCAP into the safety analytic framework as shown in Figure 15. This safety analytic framework incorporates the element of substandard actions and substandard conditions within loss causation model, which are defined as hazards, as the main data for the purpose safety analytic. The framework also align of how the company currently collect hazards data to the control chart implementation into more frequent (or real-time) data monitoring, to pose control strategies in order to mitigate the effects of variation in the safety process in timely manner.

8. Conclusion and Recommendation

8.1. Conclusion

Unlike many safety analytic studies that discussing the implementation of control charts onto the accident frequency or accidents ratios, this research explored and investigated the implementation of control charts onto the leading indicator of accidents, aiming to control the safety process in real-time manner through hazards. Not only hazard is a leading indicator of accidents, it also represents as an indicator of the safety process and safety behavior of the organization. This improvement enables the company to transition from aggregate lagging indicator to leading indicator analysis. Furthermore, having evaluated the result of Beats implementation, hazards data are available in daily periodic basis as its smallest increment data acquisition. It can realistically be considered as near real-time hazards monitoring by the company, which therefore promote a real-time safety process analysis.

Subsequently, the research explored and evaluated control charts implementation onto hazards profile, which were derived from Beats data, starting from the inception period of Beats to end of Y2019. Phase I control chart development was focused on trial control limit establishment. During Phase I, process data is gathered and analyzed all at once in retrospective analysis, constructing trial control limits to determine if the process has been in control over the period of time during which the data were collected, and to see if reliable control limits can be established to be used to monitor future process. The process involved several iterations of trial control limit calculation, identifying points that are outside the control limit, investigating the special causes, and once these special causes identified and confirmed, points outside the control limits were then excluded and a new set of revised control limits were calculated. Non-random patterns were also exercised in the control charts, based on the typical pattern that potentially occurred in hazards identification process. To this end, the application of control chart would measure the quality of safety behavior or safety awareness in mining process through retrospective hazards number variability analysis. Eventually the process was stabilized within the control limit, and a clean set of data that represents in-control process performance was obtained for use in Phase II.

It was shown that the latest iteration of control limits development in the period of August to December 2019 was suitable as the control charts for safety process in the case study mine site. The *X* chart's LCL, Mean, and UCL are 95.22, 170.55, and 245.87 respectively. Meanwhile the *MR* chart's LCL, Mean, and UCL are 0.00, 28.33, and 92.54.

During the process of control chart development, non-random patterns have also been examined to recognize non-random causal factors affecting the hazards profile in the case study site, which include management's and supervisors' pressure to control hazards or simply stated as safety pressure, production and productivity pressure, motivation and commitment on safety, individual safety competency, reactive compliance behavior, and confidence in safety intervention. In addition to basic rule of "one or more points outside of the 3-sigma control limit", non-random rules were developed and applied to detect trend in safety process and safety behavior based on those non-random causal factors. These non-random rules were treated as supplementary rules to increase the sensitivity of the control charts to be applied in mine operation area.

Based on the results of the research, the proposed framework of control charts implementation for safety analytic at the case study site offers advantages which can be summarized as follows:

1. As hazards being collected in almost continues manner, the combination of Beats and control charts give the organization opportunity to control safety process in real time practice, rather than retrospectively in large aggregate quantities. By transitioning from aggregate

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safety analytic to real time safety analytic, the company will gain benefit from a timely intervention once signal triggered, rather than waiting until the period of aggregate data reporting, thus reducing the lagging time of safety intervention;
2. The control charts implementation helps the company to transition its safety analytic method from lagging indicator to leading indicator analysis. Since the process' indicator has shifted to hazards, as the leading indicator of accidents, the interventions to the safety process are carried out before any potential occurrence of severe accidents, as qualitatively shown in Figure 13, in which within this case study, the first warning signal was triggered in 10 June 2019. This signal was then followed by series of warning signals until the occurrence of fatality accident in 28 July 2019. To this end, any triggered signal by the control charts serves as early warning signal and control tool for accident prevention in the organization;
3. Since the method is applied onto hazards identification profile, not only it gives the company the ability to quickly detect the occurrence of special causes variation in the safety process, it can also detect shifts in safety behavior of mine workforces to carry out the safety process itself in the mine. Therefore, the investigation and safety intervention actions can be undertaken by the organization to improve the safety behavior once signal is triggered;
4. Accompanied by the OCAP, the control charts implementation helps the company to actively bring the safety process into statistical control condition, which indirectly enhancing the continues improvement process within the organization.

8.2. Recommendation for Future Works

Based on the result within this paper, opportunities and risks of future works relating to the application of control charts in the company can be described as follows:

1. *Project expansion to other sites*. While the result clearly encourages the control charts implementation, this research focused its scope area only in one of mine operation sites. However, the approach of control charts implementation in the case study site can be extended to other mine sites to further strengthen the control chart application as the safety analytic method in the whole company;
2. *Data standardization*. As the control charts implementation is extended to all mine sites, data standardization shall become an important risk to manage by the organization. It is expected that there may be inherent data elements and patterns associated with the site location or the specific area within the large mine site location, which are not aligned with other mine sites. Data standardization will be beneficial during data preparation, as it will reduce time for data verification. Furthermore, data standardization will help the company to pinpoint special causes variation while doing data analysis, refer to the safety analytic framework;
3. *Control charts development for each site.* As described earlier, Phase I focuses on constructing the trial control limit through iteration process of trial control limit calculation, identifying points that are outside the control limit, investigating the special causes, and once these special causes identified and confirmed, points outside the control limits are then excluded and a new set of revised control limits are calculated. As data vary among sites, the control charts development is established independently within each site. This process highly depends on data availability of process data and support data during special causes investigation;
4. *Data aggregation*. Data availability is a major concern for real-time safety analytic. As discussed earlier, longer monitoring period leads to higher degree of aggregation, therefore creates subsequent loss of information in the process, which potentially reduces the ability to detect out-of-control condition earlier. The control charts implementation in the research posits that daily period aggregation is the smallest increment that realistically can be considered as real-time hazards control by the company at the moment. New data acquisition method by using combination of sensor and video camera surveillance analytic, integrated into Beats server, has a potential to significantly improve the method proposed in the final project to real

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time safety analytic and safety intervention. While this may involve investment in capital expenditure, time, and human resources allocation, the potential upside of the ability to timely monitor and detect special causes variation demonstrated in the research should motivate the company to pursue this matter, which will need to be investigated at length in future studies.

References

[1] D. Wheeler, Understanding Variation: The Key to Managing Chaos, Knoxville: SPC Press, 2000.

[2] F. E. Bird and G. L. Germain, "Practical Loss Control Leadership," International Loss Control Institute, Inc. , Loganville, Georgia, 1985.

[3] H. W. Heinrich, Industrial Accident Prevention, New York: McGraw-Hill, 1941.

[4] HaSPA, OHS Body of Knowledge. Models of Causation: Safety, Tullamarine, Victoria: Safety Institute of Australia, 2012.

[5] P. Hughes and E. Ferrett, Introduction to Health and Safety at Work, Elsevier Limited, 2007.

[6] T. Stapenhurst, Mastering Statistical Process Control, Burlington: Elsevier Butterworth-Heinemann, 2005.

[7] R. Hoerl and R. Snee, "Statistical Engineering: An Idea Whose Time Has Come?," *The American Statistician,* 2015.

[8] G. Suman and G. Prajapati, "Control chart applications in healthcare: a literature review," *International Journal of Metrology and Quality Engineering, Vol. 9,* 2018.

[9] W. S. Ferreira, M. H. G. Dompieri, A. Santos, S. L. Russo and A. E. Paixao, "Analysis through control charts of the number of guests of a hotel establishment in Aracaju, Sergipe, Brazil," *Revista Espacios, Vol 38,* p. 4, 2017.

[10] A. Scordaki and S. Psarakis, "Application of statistical process control in service industry: A case study of the restaurant sector," 2005.

[11] M. Norden, J. Orlansky and H. Jacobs, "Application of Statistical Quality-Control Techniques to Analysis of Highway-Accident Data," 1956.

[12] Z. Liu, "Safety Management Analysis for Construction Industry: Statistical Process Control (SPC) Approach," Morehead State University, 2016.

[13] A. Schuh-Renner, J. Camelio and W. Woodall, "Control Charts for Accident Frequency: A Motivation for Real-Time Occupational Safety Monitoring," *International Journal of Injury Control and Safety Promotion, Vol. 12,* 2013.

[14] D. Wheeler, Making Sense of Data, SPC Press, 2003.

[15] HSE Department, "Prosedur Pelaporan dan Investigasi Insiden dan Pelanggaran Golden Rules, P-OHS-10," Berau Coal, Tanjung Redeb, 2016.

[16] HSE Department, "Prosedur Hazard Report, P-OHS-14," Berau Coal, Tanjung Redeb, 2016.

[17] D. C. Montgomery, Introduction to Statistical Quality Control, Wiley, 2013.