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Application of Bayesian networks for the prediction of gas accidents in semi-mechanized underground operations on the southern coast of Peru

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Abstract– Occupational health and safety are key factors in the development of underground operations and works. Reducing the risks associated with accidents caused by gases is essential to prevent risk situations and protect the integrity of workers. The present investigation evaluated the use of Bayesian networks as a different tool in accident investigation. The general objective is to propose an accident investigation model as a predictive tool for the control and subsequent reduction of gassing accidents. To establish this model, Bayesian networks and structural models were used that complemented the operation of the first iterations. Bayesian networks were used to identify related risk factors, assess their impact, and understand the interaction between them. The study was based on a comprehensive analysis of gas accidents over a 15-year period. The main finding of the investigation focuses on the identification of 3 critical zones within the Cinco Cruces operation with associated probabilities of 0.712, 0.446 and 0.652. The value of the Bayesian inference obtained is 0.36, which through the analysis of the ROC curve establishes it as a non-false positive of regular prediction. This makes it possible to identify which are the future conditions in which the events can be repeated and to which key safety factors they are linked. Based on them, an action plan was proposed to create a PETS (Written Safe Work Procedure), which includes recommendations, methodologies, equipment, and tools to prevent future gassing accidents. The incorporation of Bayesian networks makes it possible to adhere to predictive approaches to mining accident investigation processes.

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I. INTRODUCTION

Mining is a key industry for the development of the country because it is considered the engine of economic growth. The mining industry represents 62% of traditional exports and approximately 9.8% of gross domestic product [1]. In Peru, mitigating accidents caused by gases associated with underground mining is essential both for the country's economy and for the reputation of mining companies. Underground mines play a key role in Peru's economy, as they are an important source of income and employment. However, the presence of toxic and explosive gases in these environments presents significant risks to worker safety and mining production in general. Specifically, [2] they define that the occurrence of fatal and incapacitating accidents in the mining sector can be quantifiable at $140 million in net loss per year. Therefore, responding to the challenge is a key objective to ensure the life and well-being of workers, as well as to maintain the continuity of operations of mining companies and maintain their reputation both nationally and internationally. Mitigating gas accidents in Peru's underground mines promotes a safe working environment and builds trust in the mining industry, contributing directly to the country's sustainable development and economic prosperity. This study focuses on accidents caused by gases. According to mining inspection entities, only in the year 2022 the figure of 15 fatal accidents registered in underground mining was reached. All these fatalities were attributed to gas poisoning [3]. One of the main reasons associated with the aforementioned probability is the inadequate management of accident investigation processes. Mainly, because the techniques do not contemplate future scenarios; that is, they do not allow modeling future events or establishing action plans based on past events [4].

It is these situations that drive the direction of the investigation. The incorporation of preventive approaches to accident investigation methodologies allows establishing a better monitoring of the activities carried out in underground mining works. Therefore, the research proposal focuses on the application of Bayesian networks to determine the basic causes that produce accidents, as well as the determination of the critical path of occurrence. Bayesian networks can process the statistical information of all accidents caused by gases in similar operations and conditions so that they can intervene in improvement plans.

However, for this to work correctly, the joint probabilities of a base scenario must be determined to perform the first iteration or execution of the Bayesian network. It is in this scenario that the incorporation of structural models becomes relevant. Since it allows to mathematically model percentage values of occurrence between variables that apparently have no relationship. This particular behavior allows the result of the Bayesian network known as Bayesian inference to be categorized and measured on a representative scale [5]. Once

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the model and event-related forecasts are developed, multiple iterations are performed through Bayesian networks to determine the root causes and critical path of events. With this approach, prevention models and occupational safety work plans are created with the aim of reducing the rate of occurrence of incapacitating or fatal accidents caused by gases. The final deliverable of the investigation is an action plan adapted to the reality of the evaluated mine and based on its conditions and response capabilities. This study is accompanied by several studies on Bayesian networks, which provide a more precise approximation of the application of the technique in investigation processes, accident prevention. The application of Bayesian networks to accident investigation processes is a particularly optimal scenario because it allows you to analyze events, evaluate probabilities, and deliver inferences [6]. Classical accident investigation models do not consider the interactions between the basic causes that produced such accidents. Likewise, they do not incorporate historical data of similar events or the conditions under which they occurred. Bayesian networks are more efficient in this sense because they analyze the probabilities of future events based on parameters that have already triggered accidents. Therefore, the first iteration of the network is the most relevant in the process of obtaining an inference. Accidents caused by gases are not necessarily related to the geological conditions of the rock, but also to the lack of safe work procedures that allow the identification of risk areas. The scenario proposed for the development of the investigation corresponds to that of the Cinco Cruces mine.

II. STATE OF THE ART

Multiple investigations carried out for accident investigation processes in mining environments stipulate that the identification of risk factors is not done in an optimal way because it lacks some component that allows adequate processing of the information. Regarding this, [7] and [8] developed proposals to incorporate predictive attributes through the application of artificial intelligence. In the first case, text mining was applied in combination with Bayesian networks to identify risk factors in mine operational processes. In the second case, dynamic Bayesian networks were used to determine the basic causes of the accidents. Both proposed methodologies coincide in the processing of historical accident information in an accelerated and systematic manner, in order to identify what type of accidents are common. By defining these common parameters, the variables of the nodes of the Bayesian network are defined, which when executed will allow the identification of the basic causes and occurrence events according to their probability. Next, Fig. 1 shows the basic architecture of a Bayesian network, showing the parent nodes categorized with the prefix x and the child nodes categorized with the prefix y.

In the same way, [9] and [10] in consecutive years proposed a more efficient risk assessment model based on the application of Bayesian networks. Since through these you can define relationships of interaction or dependency between the basic causes. Fuzzy probabilistic systems acquire greater mathematical relevance because it considers scalers that adjust the obtaining of results in the evaluation of occupational risks in underground operations. The authors agree that Bayesian networks provide mathematical rigor to accident investigation processes. The results obtained show that events with a probability of occurrence of 50% or more in the posterior part of the diffuse network start from failures in the investigation processes. Fig. 2 shows the critical path of occurrence that can trigger accidents. Values that exceed 30% or 0.30 are considered as events that can significantly influence the future.

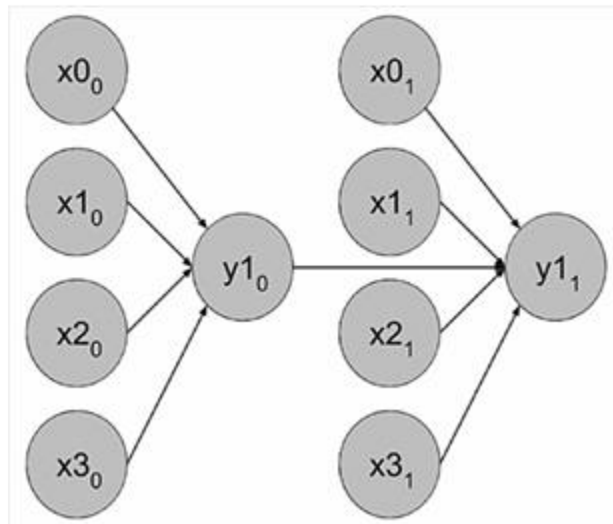

Fig. 1 Elementary architecture of a Bayesian network

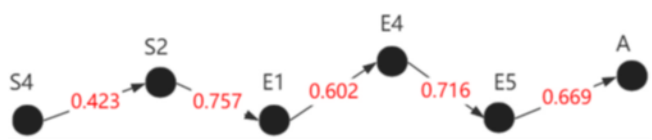

Fig. 2 Critical path of probabilistic event occurrence

Finally, [11] also agrees with the contribution of the previously mentioned authors, the integration of probabilistic analysis into networks makes it possible to define unsafe behaviors in terms of gas accidents. However, the authors define that greater mathematical rigor should be added to the probabilities associated with the network since they also start from a subjective component. With respect to the ideal tool that can be coupled to Bayesian networks [12], [13], [14] and [15] agree that the establishment of statistical components that make it possible to predict future accidents in mining operations must be linked to artificial intelligence. To do this, they established different models that identify which are the missing points in accident investigation. The authors partially agree on two aspects. The first of them, in the post-accident approach present in all the methodologies, generates slight mitigations of incidence in the future. While the second point is that it is only possible to generate predictive patterns by incorporating data mining, Bayesian networks or neural networks. Fig. 3 shows the results of a survey carried out on workers in the mining sector regarding the main problem within the Safety Management Systems, the relevant result is that the proposed changes do not mitigate the occurrence of events in the future; that is, control is raised, but it does not protect them.

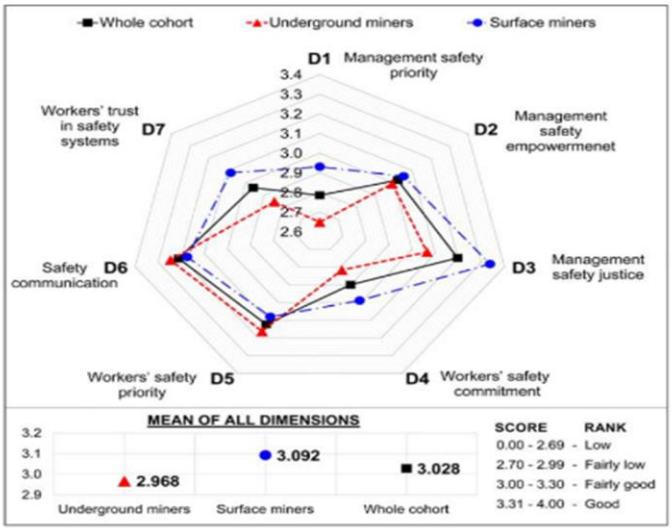

Fig. 3 Critical path of probabilistic event occurrence

Contrary to what has been shown, [16] differs in the application of Bayesian networks as such for accident investigation, since many of the components used to define the probability of initial occurrence of the accident are based on subjective experiences or called organizational human factors, which cannot be accurately emulated within artificial intelligence tools. The author suggests that the incorporation of structural models in combination with the Bayesian network allows to fill the lack of invariance of subjective events and therefore provides added value to the Bayesian network and its final product.

Regarding the establishment of action plans, [17], [18] and [19] jointly maintain that whatever the control that is applied after the identification of an improvement opportunity, an assimilation time is required within staff, which can vary from weeks to months. By proposing medium-term action plans such as the incorporation of safety standards, the aim is to strengthen the perception of safety among staff. However, the scope cannot be effectively dimensioned. The accident investigation and risk assessment processes of the operations in which it is applied are constantly carried out within the mine. For this reason, the authors defined that, if improvements are to be incorporated into accident investigation processes in a short period of time, this must meet rapid needs. The proposal of a risk assessment matrix based on the inclusion of analysis of past events can be considered as a viable alternative. Based on this, improvements can be implemented in the security management system. Company resources are used to define hierarchical controls. Next, in Fig. 4, the response flow is shown when faced with a change or opportunity for improvement within the Safety department of mining organizations. The FTHSR logo represents that it is transmitted to all middle and lower management personnel, while the DMR MHSI represents the high positions. Everything is related and recirculates to improve processes within an operation.

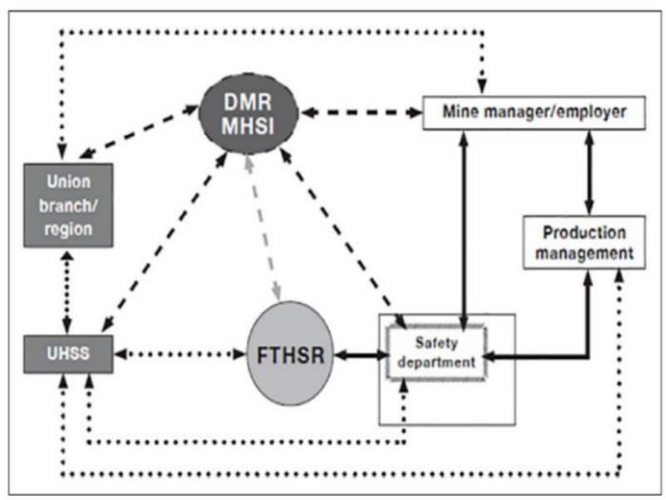

Fig. 4 Flow of a security improvement opportunity

III. Contribution

In the present investigation, the application of a predictive model of accidents produced by gases through Bayesian networks in the Cinco Cruces mining unit is proposed. Next, shown in Fig. 5, each step is detailed to achieve the completion of the research project.

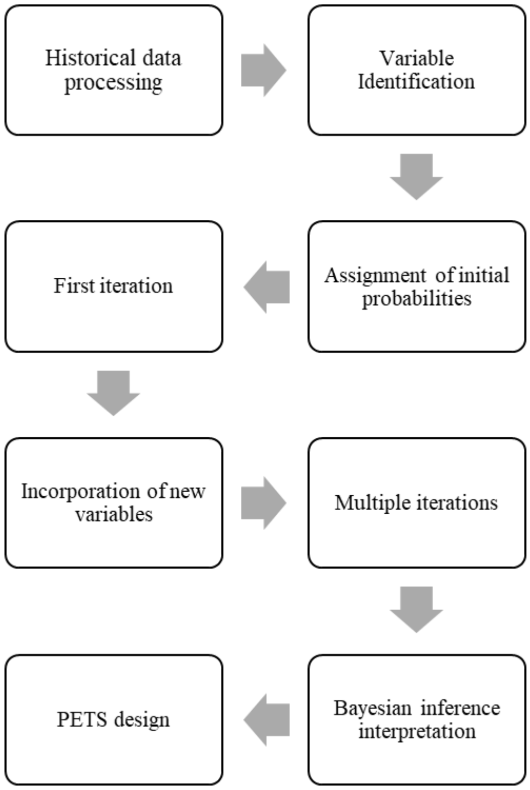

Fig. 5 Flowchart of the proposed methodology

A Bayesian network is a probabilistic reasoning representation that models a set of variables and their interdependent relationship. According to the model presented below, Bayesian predictive inference has been performed on a cause-effect relationship. Initially, these Bayesian models were built manually. However, this probabilistic model was designed on the basis of the Elvira software which allows for more defined structural parameters. One of the main advantages of Bayesian networks combined with structural models is their ability to model complex relationships between variables and estimate uncertainty in a systematic way. In these models, expert knowledge is combined with empirical data, which allows the interaction of different factors that interact in the occurrence of accidents. By combining quantitative and qualitative information, Bayesian networks allow a more accurate assessment of the probability of risks and accidents. In addition, they enable sensitivity and scenario analysis, which provide a complete picture of possible outcomes and help identify critical points in the system. This is particularly important in mine safety management, where early detection and risk mitigation are essential to prevent tragedies. Another important advantage is the ability to constantly update and improve the model as new information is collected. This means that Bayesian networks can adapt and evolve as new information is acquired, making them a dynamic and adaptable tool in the underground gas accident investigation process. The main essence of current accident investigation methods does not contemplate the possibility of predicting the occurrence of catastrophic events. For this reason, the paper focuses on the use of Bayesian network as a probabilistic and accident prediction method as it allows for more structure at all levels of inference. However, a possible limitation would be the limited number of variables which can make accident management difficult. Research is done reactively; that is, once the event occurs, the respective improvement or adequate control of the cause that generated it is carried out. The Bayesian network approach allows research processes to be carried out with a predictive-preventive approach. The certainty and precision of the Bayesian inference will depend on the variables defined in the nodes, while they present a lower degree of uncertainty, the greater the precision of the accident and therefore the control that can be applied to it. The Bayesian modelling process in this research will be developed through 9 set steps.

Step 1: Processing of historical data of gassing accidents.

Through the analysis of statistics and records, we proceed to collect information from the historical data of incapacitating accidents, fatalities and incidents within a period of 15 years. From this, the critical areas with the highest occurrence of accidents, the workplaces of the injured, the security controls and the activities that were carried out at the time the accident occurred will be identified.

Step 2: Identification of variables (Bayesian nodes)

The selection of variables or nodes of the Bayesian network starts from the activities that registered the highest rate of occurrence.

Step 3: Assignment of initial probabilities

Through structural modeling, 3 initial probabilities of occurrence are defined for the critical zones identified in step 1, this is of vital relevance for the network since if the structural models are not applied, the Bayesian inference will yield false positives.

Step 4: First iteration of the Bayesian network

With the variables of the nodes well defined and the conditional probabilities generated by the structural model, we will proceed to build the Bayesian network using the fuzzy technique; that is, multiple iterations will be carried out to identify a Bayesian inference (gassing accident). Likewise, the critical path of occurrence is identified and which of the nodes interacted with each other to produce said event.

Step 5: Extending the Bayesian network landscape and new iterations.

Once the inference or event has been identified, which represents the accident produced by gassing. We will proceed to incorporate more nodes which are generated from historical accidents at the national level. In this way, the Bayesian network is fed, and the iteration and occurrence estimation processes reflect a behavior analogous to reality.

Step 6: Multiple Iterations

4 more iterations are executed that allow to refine the initial Bayesian inference. Since the network is nourished by larger nodes and therefore by more scenarios and probabilistic conditions

Step 7: Interpretation of the Bayesian inference

Once the value of the Bayesian inference is obtained, its mathematical sensitivity and its degree of precision must be corroborated by means of the ROC curve.

Step 8: Design of the PETS

Based on the conditions identified, the job position, the controls established and the type of accident. An action plan is defined, embodied in a Written Safe Work Procedure. Which must be communicated to the Security area. Then we will proceed to raise the observations or establish an improvement plan.

IV. VALIDATION

The validation scenario will be carried out in the Cinco Cruces project, which is located within an IOCG (Iron Oxide Copper Gold) type deposit on the southern coastal strip of Peru.

The critical areas within the described methodology are relevant since they are added as auxiliary nodes in the Bayesian network. These auxiliary nodes in the investigation were defined as the areas in which the highest accident rate has occurred and are described in Table 1. It is important to mention that all these work zones correspond to blind tasks; that is, they only have one entrance and one exit. The concentration of harmful gases in these places is relevant and harmful to health.

TABLE I
CRITICAL INCIDENCE AREAS WITHIN THE MINE

Critical area	Percentage (%)
Fireplaces	33
Cruise	18
Galleries	20
Ramps	20
Sublevels	10

Likewise, the occupations of the personnel who suffered the greatest accidents over 15 years were identified. This provides relevant information to the investigation since the level of professional training and idiosyncrasies are considered as human factors, which can only be processed by incorporating structural models due to the mathematical uncertainty that involves emulating probabilities associated with fortuitous events. Table 2 shows the results obtained.

TABLE II
OCCUPATIONAL DISTRIBUTION PER ACCIDENT

Occupation	*Percentage (%)*
Driller	*20*
Scoop operator	*20*
Foreman	*12*
*E*lectrician	*10*
Helpers	*6*
biker	*4*
Overseer	*2*

The activities that the injured parties were carrying out are also an important factor to consider since it makes it possible to identify the nodes of the variables of the Bayesian network. The iteration process of each network depends on two factors. The first of them, in the definition of nodes and the second of the probabilities associated with said nodes. Table 3 shows the activities that triggered accidents and therefore the initial nodes that will be coupled with the probabilities.

TABLE III
ACTIVITY CARRIED OUT BY INJURED PARTY

Activity	Percentage *(%)*
Exploitation of labor	*31*
labor inspection	*24*
Service placement	*18*
Drilling and Blasting	*10*
Rock Unleashed	*8*
Material placement	*6*
Usage Verification	*2*
Object manipulation	*2*

Based on the definition of basic conditions or initial variables, the structural modeling of probabilities that will be coupled to the Bayesian network was executed. For this, the degree of training of the injured, the place of occurrence and the critical area were evaluated. Likewise, we will proceed to compare the probabilistic results generated with the structural model against the probabilities generated from a simple calculation of occurrence as shown below in Table 4 and Table 5 respectively.

TABLE IV
SIMPLE INITIAL PROBABILITIES

Critical area	Simple probability
Sublevels	0.672
Chimneys	0.475
Galleries	0.422

TABLE V
INITIAL STRUCTURAL PROBABILITIES

Critical area	Structural probability
Sublevels	0.742
Chimneys	0.544
Galleries	0.509

Once the initial probabilities and the nodes of the Bayesian network have been identified, the first iteration of the Bayesian network is executed. In this case the process is performed twice. A network generated with simple probabilities and another network generated using structural probabilities. After that, the network will be nourished by incorporating multiple nodes in an iterative process of 4 repetitions to obtain the Bayesian inference.

In this way, with a sensitivity value of 50% and by applying the ROC formula, the specificity value must be obtained to classify the inference. [20] He established that this probabilistic parameter makes it possible to identify whether a prediction is correct (standard positive) or not correct (false positive).

$$ROC = Sensitivity * times\ Specificity \qquad (1)$$

For the first case, a Bayesian inference value of 0.273 was obtained, which implies that its specificity value is 0.546 and since it falls in a bad prediction zone, the inference is a false positive. For the second case, a Bayesian inference value of 0.175 was obtained, which implies that its specificity value is 0.35 and since it falls in a regular zone, the inference is classified as a low standard positive. In Fig. 6 the interpretation of the networks obtained is identified.

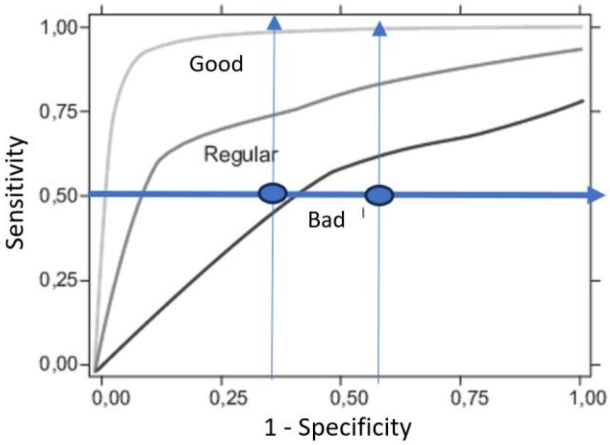

Fig. 6 Bayesian inference interpretation

Based on the calculation of the Bayesian inference coupled with structural models, the hazards associated with said events and the controls that were executed and that could not mitigate the accidents are identified. Using the IPERC matrix, these hazards were identified, and control proposals were generated, which were summarized in Table 7 and incorporated into the PETS as an improvement proposal (annex).

TABLE VI
ADDITIONAL CONTROLS TO INCORPORATE

Control measures to implement
PETS regarding inspections in blind work
Installation of the third line (valve)
AQI measurement
Built-in helmet oximeter
Bifurcated ventilation sleeves
Delimitation of the work area

V. DISCUSSION

On the one hand, [21] applied Bayesian networks to their accident investigation processes by analyzing 120 cases. Based on this, they defined 51 risk factors for and the definition of 17 strong association rules (critical path). Compared to the present investigation, 80 cases were analyzed, and 36 risk factors were identified, and 8 strong association rules were defined. The variation lies in the number of cases that were analyzed, since the first associated probabilities are defined from the base nodes and the application of structural models. On the other hand, [22] executed 6 iterations to the network to obtain an inference with an accepted mathematical profile. In the case of our research, 6 iterations were generated in the same way, the first 5 to feed the network and the last one by applying the controls and the new inference. This with the idea of predicting probabilities without control and with controls. On the other hand, [14] analyzed accidents in 50-year operations in order to effectively determine the probabilistic critical paths in which accidents occurred. A concatenation of 8 basic causes that acted simultaneously for the accidents to occur was identified. In the investigation, data from 15 years was analyzed in order to establish the critical path with 6 basic causes that constantly interact in the generation of accidents. The variation is produced by the number of years of analysis and the inclusion of geological factors typical of the operations analyzed. In addition, [15] defined that the application of Bayesian networks as a predictive model in research is vital since it allows emulating future behaviors and acting preventively. They established that generating more than 3 iterations in the network can generate a successful Bayesian inference (ROC value of 0.235). In the investigation, the incorporation of 5 iterations was proposed with the idea of profiling our results (ROC value of 0.273). A precision of analogous to that stipulated by the author. Finally, [19] concluded that the perception of improvements in the research processes occurs gradually in an average time of 6 months if they involve complex structural changes in the Occupational Safety Management Systems; however, through the application of focused solutions such as the establishment of a PETS, this time can be significantly reduced to a few months, since training is quickly carried out on the hazards and conditions encountered, regardless of the level of instruction of the personnel. Likewise, they established the concept that accident investigation processes must include simplified decision criteria for risk control. The probabilities associated with the events range between 40% and 75% and must be attended to immediately. In the case of the investigation, occurrence values ranging between 50% and 70% are obtained, so the need to establish rapid controls can be extrapolated. In his research, [18] managed to rescue the notion that the application of safe work procedures is a transversal tool to train personnel who are exposed to the potential hazards of mining operations. He applied the structuring of a PET on the activation of ventilation in mineral exploitation shafts. However, the application of PETS has certain limitations as well. Secondly, it is possible that, due to company policies, the application of PETS may not be viable in the short term because it implies a rapid response to avoid accidents but does not represent a structured solution to accident prevention. The Sharigh mining operation was the setting for the implementation of PETS following an accident analysis. This reduced the occurrence of gas accidents by 36%. The implementation of this safety control targeted substandard acts performed by workers. This meant a significant reduction in the occurrence of accidents; however, PETS alone did not reduce all accidents; this is due to other factors that interact to cause accidents to occur. These cannot be contemplated or combated from a simple analysis of the causes of accidents. Therefore, the integration of Bayesian networks provides better controls to be defined in the safety document and therefore in the direct prevention of accidents. It provides a short-term safety management approach to quickly reduce accidents that can be easily identified, but at the same time provides information that can allow iterations and thus plant simulations to future events.

Traditional accident investigation methodologies do not contemplate the idea of prevention through established controls. First of all, we have the cause tree, Ishikawa diagram, failure and error tree and the 5 whys. The stages of the accident investigation process are the collection of research, the documentary and information analysis, the determination of the causes and the definition of preventive measures, all this to be incorporated once the accident has occurred. Potentially, the implementation of Bayesian networks provides the predictive mathematical approach that none of the other methodologies possess. Table 7 shows how much time and money we can save up based on an estimate of the approximate cost when a person dies inside a mine proposed by the BCRP (2022), an amount of 125,000 USD and a maximum implementation time for improvement plans of up to 1 week was proposed. Compared to Bayesian networks, which can take about 4 days to implement if the correct information is available and a software cost of 6500 USD to emulate and report.

TABLE VII
COST EFFICIENCY TIME

Methodology	Time (days)	Cost (USD)
Ishikawa´s	7	125,000
Cause Tree	7	125,000
5 whys	7	125,000
Bayesian network	4	6,500

VI. CONCLUSIONS

The integration of Bayesian networks to the processes will allow to improve the interpretation of the information and establish precise controls that, when implemented, will seek to mitigate the occurrence of accidents/incidents due to gassing.

The percentage variation through the identification of practical and real scenarios is 33.16%, which gives greater precision to a practical scenario than to a theoretical one. Accordingly, it is correct to refer to an estimate greater than 30% leading to the occurrence of events.

Adding approximately 5 or 6 iterations to the Bayesian network will represent a higher degree of accuracy between the nodes and their relationship. This is recognized in the X:X+1 correlation where a probability Y and critical path N are obtained.

The operation of the Bayesian network depends on two factors, which are the basic probabilities calculated by means of structural models and the application of the basic structural model to define the first iterations.

RECOMMENDATIONS

A basic structural model base is recommended to be able to elaborate the Bayesian network, complementing it with approximately 5 iterations to ensure greater accuracy.

The database that supports the construction of the Bayesian network must have theoretical probabilities, so registration matrices or templates can be used that are adapted to the chosen implementation software,

To have greater precision, data from approximately 20 to 25 previous years should be analyzed, since this supports around 150 cases to be evaluated.

With the application of a Bayesian network, it would also be possible to monitor the working conditions exposed to the worker in real time for the activation of alarms and evacuation orders.

A significant challenge in emulating accidents using Bayesian networks is the acceptance of predictive iteration tools. Many in the industry are always somewhat suspicious of these methodologies, so having empirical evidence may help to make them a little more open-minded.

Applying PETS attacks the least intrinsically related accident problems, i.e., those that are most straightforward to solve. However, Bayesian networks require a little more time to apply, so their application horizon is long term. The action plans that are implemented by law must be applied as soon as possible, so a good interaction between the PETS and the information provided by Bayesian networks is fundamental to attack recent and historical gas accident problems.

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