# Operational Risks Evaluation in Cement Industry using Bayesian Network with Uncertainty

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## Abstract

In order to ensure a successful cement manufacturing process and avoid negative consequences, it is crucial to identify and analyze potential risks. The aim of this research paper is to use two models, the Fault Tree analysis and Bayesian Networks, to identify and mitigate risks associated with the process. While both models are useful, the Bayesian Network model is the dominant one used in the research, and it has been combined with the Fault Tree model to address its limitations. Together, the two models work to produce the best possible outcome in terms of risk identification and mitigation. The paper intends to offer a solution to evaluate risk profiles in the cement industry using Bayesian models. The goal is to improve the methodologies of identifying risk events and categories by examining them under uncertainty. The results obtained from this research will help managers make better decisions by considering the significance of confidence intervals within the uncertainty region. This approach will ensure that the process is well-planned and that risks are identified and mitigated to avoid negative consequences, such as worker injuries and harm to third-party personnel.

**Keywords:** Operational Risk; Bayesian Network; Cement Industry; Monte Carlo Simulation; Uncertainty.

## 1. Introduction

The process of cement production is a critical, as cement is a versatile commodity with a wide range of applications, which makes it an essential material in many industries. Due to its high demand globally, many manufacturers have entered the market to meet the growing demand for cement. As a result, numerous employees are involved in the cement production process. For any cement manufacturer, successfully completing each stage of the production process with minimal risk is a significant achievement. To achieve this, companies have developed models aimed at minimizing operating costs while ensuring the production of high-quality cement. These models focus on risk management, which is a crucial aspect of the production process (Radosavljević, S., & Radosavljević, M, 2009).

The development of infrastructure is a crucial component in a country's progress, and cement is one of the critical elements in the construction sector. Cement production is a complex process that involves various components, including clay silica, gypsum, and limestone. Each component plays a vital role in the production process, and any risk associated with any of these components should be appropriately managed to avoid hindering productivity and revenue. One of the significant risks associated with cement production is pollution, particularly dust. The process of producing cement results in massive amounts of dust, which poses a severe health risk to both workers and the environment (Abuhasel 2019). Dust particles are harmful to human health and can lead to respiratory problems.

Additionally, dust accumulation in the atmosphere can make it challenging for meteorologists to create accurate weather predictions since the atmosphere is contaminated.

Moreover, the cement manufacturing process poses several hazards to workers, and it is essential to have the appropriate personal protective equipment (PPE) to mitigate these hazards. According to Pradosh and Bose (2002), workers in the cement industry are exposed to several health risks due to the hazardous materials produced during the various stages of the manufacturing process. Therefore, it is crucial to have the appropriate PPE to protect the workers' health and safety. Furthermore, risks are present at each stage of the cement manufacturing process, and it is crucial to identify and mitigate these risks to ensure a safe and efficient production process (Cox & Cheyne 2000). Any delay in production due to these risks can increase production costs, which can result in a reduction in revenue. It is crucial to identify and manage these risks appropriately to ensure a safe and efficient production process. The diagram below (Figure 1) illustrates a typical process used in cement manufacturing, highlighting the essential transformations required to produce cement.

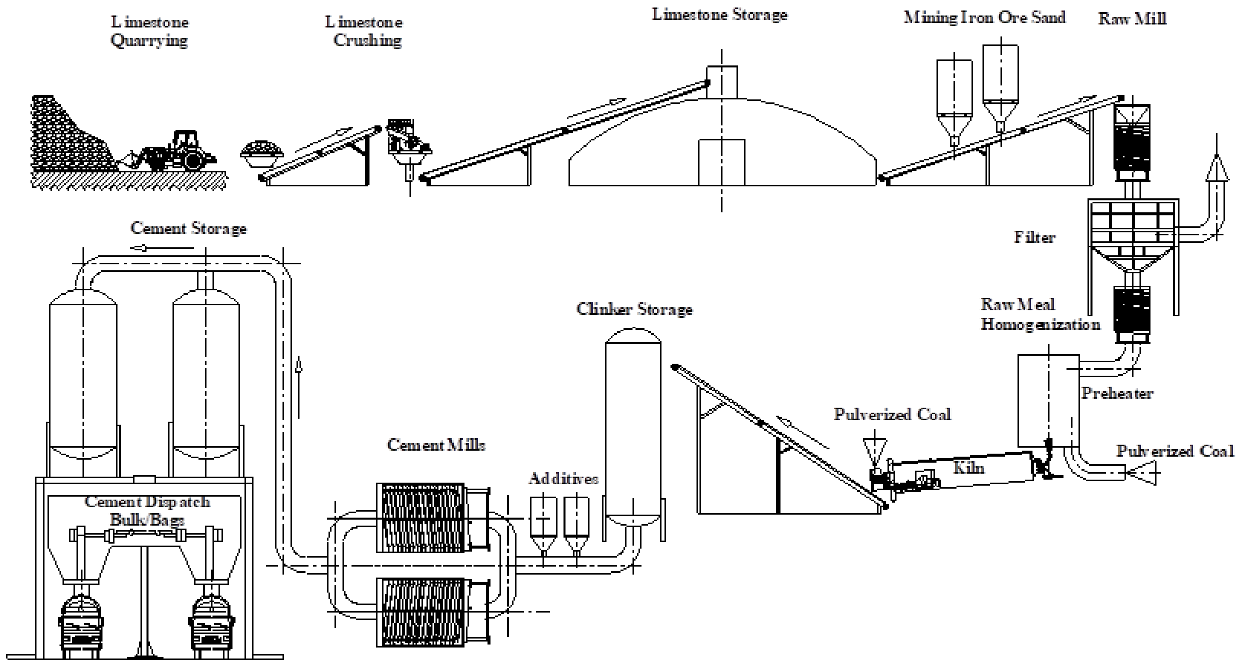


Figure 1 . Production line in cement industry.

The assessment of safety in operations is often based on the associated risks, which refers to the likelihood and potential magnitude of losses resulting from potential hazards (Khakzad et al. 2013). Several methods have been developed by researchers to analyze these risks accurately, including Fault Tree (FT), Event Tree (ET), Bow-Tie (BT), and Bayesian Network (BN) methods (Abimbola et al. 2015). Of these methods, the FT method has been successfully integrated with the BN method by scholars such as Khakzad et al. (2013). while Grayson and Gans (2012) have also combined FT with BN to produce reliable results. Although other methods have been used by various researchers, their accuracies have not been satisfactory, possibly because they are not robust enough on their own and require input from other methods.

In addition, these models often lack flexibility in updating their results when new information becomes available, which is not ideal for risk analysis since risks can occur at any stage of the process and are not always predictable (Grayson & Gans 2012) To overcome this limitation, conventional over-balanced drilling techniques can be used as an alternative to conventional drilling since they have similar applications (Pitblado et al. 2010). On the other hand, the BN model has been extended to handle more complex and risky situations, demonstrating its flexibility in providing solutions even in the most challenging scenarios. This makes it easier to interpret and manage risks in normal situations (Khan 2001). The use of artificial intelligence in BN modeling makes it a valuable tool in providing solutions for models with uncertainties, as it can make reliable inferences based on past data under similar conditions (Wu et al. 2023).

The BN model is known for its ability to produce complex results, but these results can sometimes be difficult to interpret. To address this, it is recommended that problems solved using this model be broken down into simpler, more understandable components (Khakzad et al. 2011). Therefore, this model is best suited for individuals with the skills to interpret the solutions provided and who understand the problem well enough to break it down into simpler components (Nadkarni & Shenoy, 2001). However, one disadvantage of the Bayesian model is that it requires the recall of past variables as it progresses to create reliable inferences (Abad-Grau& Arias-Aranda 2006). The need for past information can make the model slower and more complex, and is often criticized for relying on a large amount of redundant past information that may be difficult to obtain in risk management (Kassem et al. 2022). In addition, any modifications made to the model can have a significant impact on the entire process.

The BN model can be utilized as an approach to evaluate sourcing risks in supplier selection (Lockamy & McCormack, 2010). Researchers like Nepal and Yadav (2015) have employed the BN model to determine the risk posed by each supplier, and the associated costs for each risk type. To enhance supply chain risk management, BN can be combined with another method to predict the complex behavior of risk propagation. In the supplier selection process, Ferreira and Denis (2012) have integrated BN with fuzzy logic to improve the multi-criteria. Additionally, Min et al. (2019) have used the combination of BN and fuzzy logic to control the experiment and mitigate any potential risks associated with this process.

In this paper, a new approach for risk analysis in the cement industry is introduced. The approach involves calculating probabilities and identifying risk events and categories, and then examining the risk profiles of industry networks under uncertainty (Rawson & Brito 2022). The impact of uncertainty on production will be determined using Monte Carlo simulation, which involves generating repeated random numbers to obtain numerical results. The combination of risk factors and Monte Carlo simulation will be used to obtain a final probabilistic impact factor for a product that corresponds to its risk profile (Mahmood at el. 2023). The aim of this approach is to assist managers in decision-making by taking into account the importance of confidence intervals within the uncertainty region.

## 2. Methods

*2.1. Risk Assessment Methodology:*
A common method applied in different areas is the Fault Tree Analysis (FTA) due to its reliability. This method is applied in the stages of BN since the Bayer Network is not robust (Gharahasanlou et al. 2014). It requires the incorporation of other methods that are reliable at some stages of the process. This method provides quantitative and qualitative data that can be used to assess the risks (Deopale et al. 2023). A greater advantage of this method is its ability to scrutinize risks from the initial stages to the final stages of the system and, therefore, making it easy to mitigate the basic risks to avoid the occurrence of the high-end risks. All the assessments are done using this method are easily connected and the risk manager can able to mitigate the source risk which seems to create a high probability for the occurrence of the other risk (Ramesh & Saravannan 2011). Using this method, the probability of the risk can be derived from the equation below.

$$P = \prod_{i=1}^{n} P_i \tag{1}$$

OR gate denotes the occurrence of any input events. Its probability is as follows:

$$P = 1 - \prod_{i=1}^{n} (1 - P_i) \tag{2}$$

In cases of uncertainties, BN are considered. These networks have been tested and proven to be very effective where uncertainties prevail. The critical aspect of making this possible is the use of probabilistic methods applied in the model. There are two types of nodes in this network, the parent and the child nodes (Weber & Jouffe, 2006) as shown in Figure 2. The arcs connect the two nodes, where it originates former node and end at the latter node. These nodes, consequently, represent the chances of risks where conditional probability is used as the main determinants. BNs, in this system, are represented by the equation below and p($Y_i$) represents parent probability at node i:

$$P(y) = \prod_{i=1}^{n} P(Y_i/p(Y_i)) \tag{3}$$

$n$ denotes the basic events and it is independent on the chance that i$^{th}$ event of $P_i$ fails. BNs are dynamic and change of information is fed in the system. When information is updated, the past chances are also altered. In the formula below, M denotes the altered information which results in to change in probability.

$$P(Y/N) = \frac{P(Y,M)}{P(M)} = \frac{P(Y,M)}{\sum_X (Y,M)} \tag{4}$$

In a study by Bobbio et al.(2001), the Fault Tree and the Bayer Networks work in pairs. This correlation is as shown in Figure 3. Whereas the Bayer Network represents the whole process, the Fault Tree represents the stages of the Bayer Network. The initial stages of the Fault Tree signify the beginning of the larger network, and the network progresses as the stages advance. All the stages of the Fault Tree have their conditional probability.

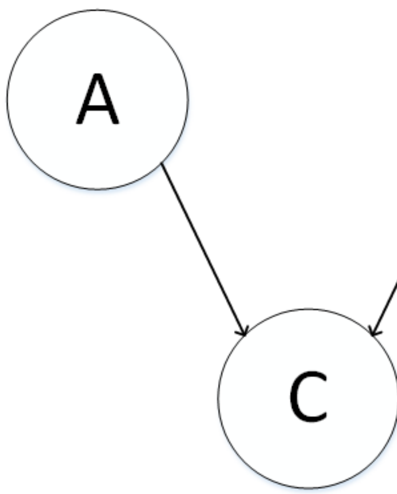


**Figure 2.** Example of the BN model.

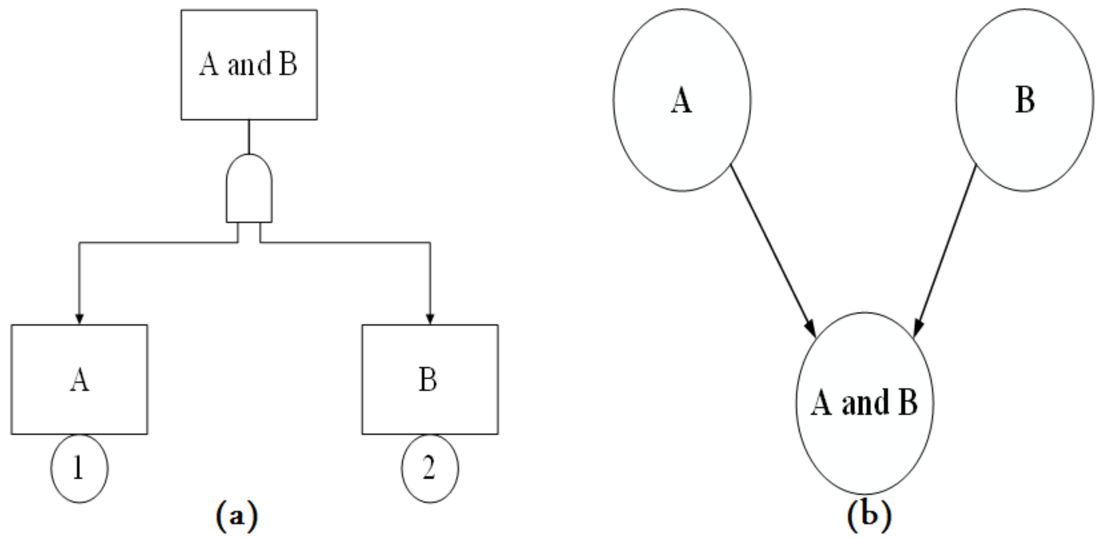


**Figure 3** (a). FT: AND gate, (b): BN: AND node.

*2.2. The Proposed Model for Risk Assessment Methodology:*

A survey was made in cement industry on about 45 persons to show the risks that impact productions. Based on the survey results, we found out that chilling and quality problems leading the risks that impact productions.

The BN were developed to provide data on the effects of production on the overall revenue gotten by the company. This analysis includes the operation of the process and the external risks which provide the basis for risk identification. The application of BNs in this process is as shown below Figure 4. The Nodes in this diagram define the variables and they contain states for each of the variables. The parent node is created by joining two child nodes by an edge. Child nodes partly depend on their parent's nodes. The probabilities of production process risks depend on: mining, crushing, pre blending, pounding in the vertical roller mill, heating beforehand, blazing and chilling. The operational risks are directly influenced by these probabilities. On the other hand, the external risks dependent on divestitures and disasters.

The calculated chances which form a joint probability distribution are then used to analyze any adverse effects that the production process will have on the running of the company.

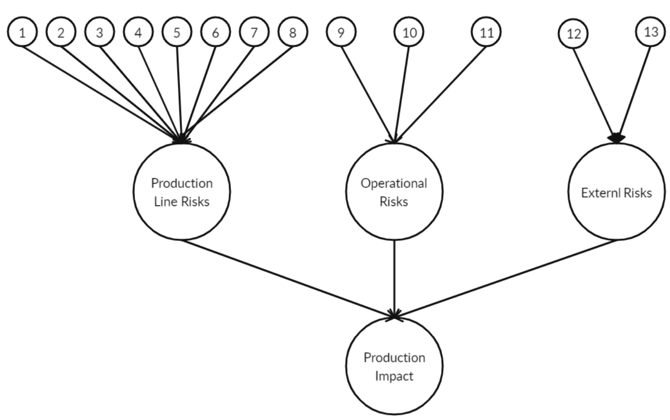


**Figure 4.** BN for production impact.

## 3. Data Collection

By using the standard law of Bayes' theorem as stated in equation 4, Where P(X|M) is the conditional chance of X, given M, also known as posterior chance, as shown in Figure 4, the BN built contains three variables that connect to production impact event, and each variable is represented by nodes. The nodes contain potential values for each variable. The probability of production depends on the prior probabilities. The prior probabilities associated with each node have no parents; the prior probabilities each node in Table 1 is the influence of the production line, operational, and external risks for the production impact of the company and to determine the effects of risk events.

Table 1. A priori probabilities for risk event variables.

| Number | Risk variables | Priori probabilities |
|---|---|---|
| 1 | Mining | 0.22 |
| 2 | Crushing | 0.15 |
| 3 | Pre blending | 0.11 |
| 4 | Pounding in Vertical Roller Mill | 0.20 |
| 5 | Heating beforehand | 0.12 |
| 6 | Blazing | 0.18 |
| 7 | Chilling | 0.30 |
| 8 | Crushing the Clinker | 0.10 |
| 9 | Quality problems | 0.30 |
| 10 | Delivery problems | 0.25 |
| 11 | Service | 0.09 |
| 12 | Merger/divestitures | 0.14 |
| 13 | Disasters | 0.16 |

The a priori probabilities for the 13 risks corresponding to cement industry which influence the operation of the production line and the associated risks are as shown Table I. This data is for each event. The random values are generated to provide data for a profile that is created using the BN. When the risk profile has been developed, it takes care of all the processes which affect the productivity of the system to the company. For a better visibility, the risk profile is displayed in a Table 2 as shown below. Such a table reserves a probability column for the effects of the production process on the output of the company. Given the risk event relationships exhibited in the production impact as showing Figure 4 along with the a priori probabilities for risk event variables contained in Table 1, the following probability computations regarding Production line risks, operational risks, external risks, and Production impact for productivity of the system to the company are provided:

$$P_{(\text{Production line risks })} = \frac{\sum(probability\ of\ production\ line\ risks\ \times probability\ of\ event\ occur)}{\sum(\text{probability}\ of\ event\ occur)}$$
$$= \frac{[(0.22\ \times 1) + (0.15 \times 1) + (0.11 \times 1) + (0.2 \times 1) + (0.12 \times 1) + (0.18 \times 1) + (0.30 \times 1) + (0.10 \times 1)}{1+1+1+1+1+1+1+1}$$
$$= \frac{1.38}{8} = 0.17$$

$$P_{(\text{operational risks })} = \frac{\sum(\text{probability of operational risks }\ \times \text{probability of event occur})}{\sum(\text{probability}\ of\ event\ occur)}$$
$$= \frac{[(0.3\ \times 1) + (0.25 \times 1) + (0.0.9 \times 1)}{1+1+1} = \frac{0.64}{3} = 0.21$$

$$P_{(\text{external risks})} = \frac{\sum(\text{probability } of \text{ external risks } \times \text{probability } of \ event\ occur)}{\sum(\text{probability } of\ event\ occur)}$$
$$= \frac{[(0.14 \ \times 1) + (0.16 \times 1)}{1+1} = \frac{0.3}{2} = 0.15$$

$$P_{(\text{Production impact})} = \frac{\sum(probability\ of\ production\ impact\ \ \times probability\ of\ event\ occur)}{\sum(\text{probability } of\ event\ occur)}$$
$$= \frac{[(0.17 \ \times 1) + (0.21 \times 1) + (0.15 \times 1)}{1+1+1} = \frac{0.53}{3} = 0.18$$

**Table 2. Probabilities for risk effect on the production rate.**

| Production line risks (Pr) | Operational risk (Pr) | External risk (Pr) | Production impact |
|---|---|---|---|
| 0.17 | 0.21 | 0.15 | 0.18 |

After the display of the risks in a table, the company weighs the impact of these risks and concentrates on mitigation the most substantial risks. These are the risks that significantly affect the production process and hence the revenue collected by the company.

## 4. Results and Discussion

If a company is not certain about the weight of risk from the table, it can conduct risk sensitivity analysis which involves a reduction of all the risks each at a time and after that using a probability and rank scale to rank the risks from the most effective to the least effective as far as production is concerned. When doing this analysis, the company is aware that risk reduction for a particular variable cannot be reduced to zero, which enables the risk manager to work with favorable parameters. The indicator of risk effect is revenue. At optimum revenue, risks have been successfully mitigated. A set up for risk analysis can be tabled as below Table3. We assume the monthly revenue based on the production of the Cement Company is 2.5 million. We can see that as the increasing of the production impact the value of risk will increase, which yield when A comparison of risk event based upon a priori risk event probabilities and worst-case for another one network by excluding the scenario where two risks have a 100% probability of occurrence at the same time, and show the effect of only one event has 0 or 100% probability of happening.

Table 3. Risk profile reduction analysis.

| process risk (Pr) | Operational risk (Pr) | External risk (Pr) | Production impact | Monthly revenue(million) | Value at Risk(probability of Production impact X monthly revenue impact |
|---|---|---|---|---|---|
| 0.17 | 0.21 | 0.15 | 0.18 | 2.5 | 450000 |
| 1 | 0.21 | 0.15 | 0.45 | 2.5 | 1125000 |
| 0 | 0.21 | 0.15 | 0.12 | 2.5 | 300000 |
| 0.17 | 0 | 0.15 | 0.11 | 2.5 | 275000 |
| 0.17 | 1 | 0.15 | 0.44 | 2.5 | 1100000 |
| 0.17 | 0.21 | 0 | 0.13 | 2.5 | 325000 |
| 0.17 | 0.21 | 1 | 0.71 | 2.5 | 1775000 |

Our approach of risk analysis for the production rate includes an unknown probabilistic entity. MCS was used for this purpose to determine the impact of each event under uncertainty. This method relies on random sampling to obtain results. A total of 1000 simulations were used to obtain the distribution for every risk type, i.e., production line risks, Operational risk and external risk under the causation of an unknown probabilistic variation shown in Figure 5. For this paper, the value of the standard deviation was assumed to be 0.1 for all purposes. The estimated risk probability for production impact can be used as the mean value for the simulation, for the estimated with uncertainty. All the mentioned risk factors were then traditionally fed into the BN to obtain the final probabilistic impact factor for production corresponding to the risk, as shown in Figure 6.

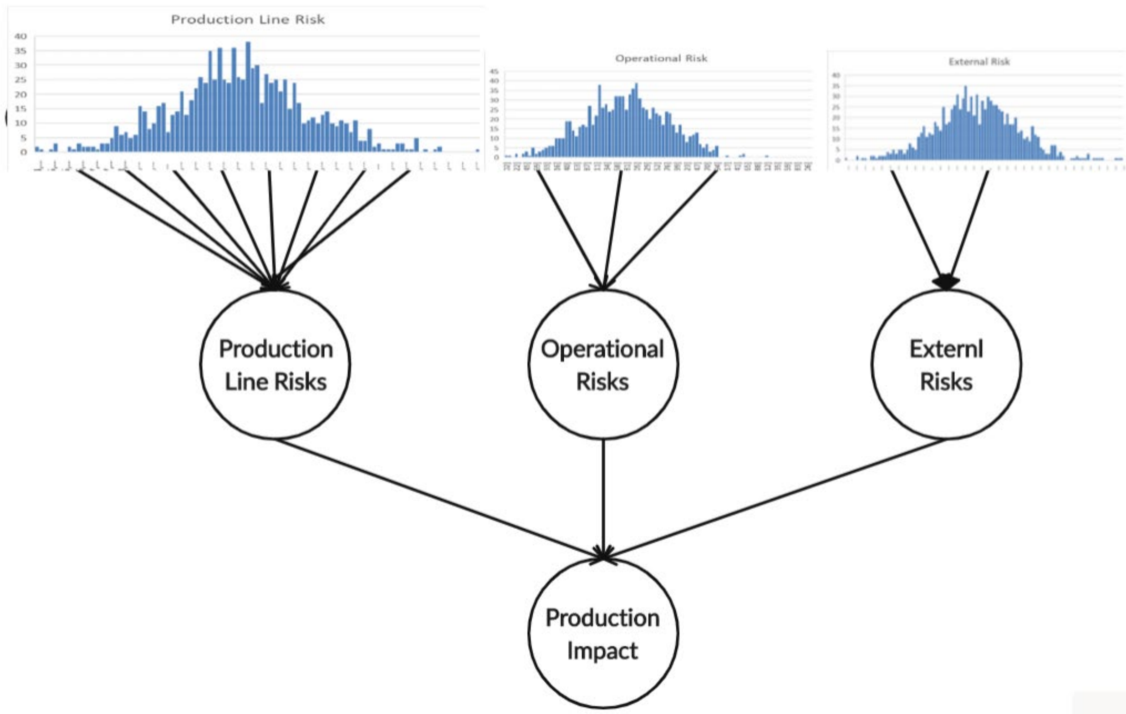


Figure **5.** Output of the BN for the values obtained from the MCS.

The main objective of this approach was to help the managers make an informed decision by considering the significance of confidence intervals within the uncertainty regions. A factor of uncertainty can be considered, which can be the average standard deviation from the estimates to the actual values in the past production rate quarters for the gross revenue. The output of the BN was achieved as a linear combination of the input probabilistic risk factors. The final impact factor achieved is as shown in Figure 6. Considering the factor of uncertainty, the same result is obtained corresponding to the mean of the given Figure 6. By this approach, we can have an idea of the probability of having a risk of losing more than 20% of the production or have an interval in which the loss is most likely to occur. This can be achieved by creating confidence intervals.

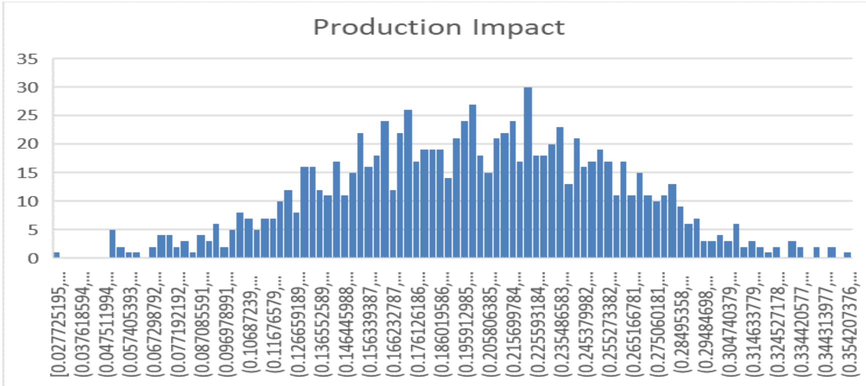


Figure 6 . Production Impact with uncertainty.

BN are used in developing the production risks' profile in order to determine how the revenue structure of their company is exposed. The profiles are, after that, used to rank the risks and know the methods to approach them. The revenue estimate is set, and the organization focuses on the most significant risks according to their ranking.

## 5. Conclusion

The cement manufacturing process involves multiple stages, each associated with specific risks that can collectively reduce a company's revenue. The present paper proposes a methodology using Bayesian networks (BN) to efficiently identify and mitigate these risks. The methodology is important and applicable to project managers in charge of production risk management. Organizations can use this methodology to approach risks and determine the best way to mitigate them while considering production status under uncertainty. One limitation of the paper is the ambiguity of the collected data, making it challenging to determine whether the company was being truthful or overrating risks. BNs are useful tools in monitoring risks in the industrial sector. Companies should regularly identify risks and create a BN risk profile to aid the risk management department in creating new strategies to curb risks and minimize their effects. The BN profile can then be updated as new information becomes available, making it a dynamic platform for risk management. The risks examined in this paper provide a general solution for the cement manufacturing process that can be applied at the industry level, rather than the company level. However, the success of the model is dependent on the honesty and accuracy of the parameters used in risk identification. Risk managers should regularly provide updated information to ensure the model remains relevant. The paper primarily focuses on the impact of the production process on a company's revenue, but other factors, such as the mode of manufacture, can also affect productivity. Thus, in application, all these factors should be factored in as they are mutually exclusive. Overall, this methodology can help companies in the cement industry, and other industries, identify and mitigate risks to minimize revenue loss and improve production efficiency.

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## Biography

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