ESTABLISHING A NEW ROCKBURST CLASSIFICATION SYSTEM USING BAYESIAN NETWORK

by

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ORIGINALITY STATEMENT

I, Kuandyk Maxutov, hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, or substantial proportions of material which have been accepted for the award of any other degree or diploma at Nazarbayev University or any other educational institution, except where due acknowledgement is made in the thesis.

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ABSTRACT

Rockburst is a phenomenon commonly described as a sudden and violent event in underground mines that result in significant damages to underground excavations, equipment. It also threatens the safety of the mine workers and the profitability of the operations. This clearly demonstrates the importance of understanding the rockburst mechanisms. The literature reveals that despite the advance in predicting rockburst, a reliable prediction of the phenomenon is till posing problems. Therefore, this study aims to establish a new rockburst classification system that can be used as a reliable tool for rockburst intensity evaluation. The research methodology relies on the Bayesian Network (BN) approach and actual rockburst records from various mines and tunneling projects across the world. Two main databases were considered: first contains rock mass parameters and seismic magnitudes while the third contains only rock mass parameters. In addition, a second database generated using Monte Carlo simulation technique, was used in order to increase the data size of the first database. The input parameters of the first and second databases included the stress conditions (E1), ground support capacity (E2), span (E3), geology (E4), peak particle velocity (PPV) and the output is defined as Rockburst Damage Scale (RDS). For the third database, the input parameters included the tangential stress (δ_θ), compressive stress (δ_c), tensile stress (δ_t), strain energy (W_{et}), ratio of normal stress to compressive stress (δ_θ/δ_c) and ratio of compressive stress to tangential stress (δ_c/δ_t). Three BN structures were constructed through Netica Software and consequently were evaluated with independent dataset. The results indicate that the classification accuracies vary between 70% and 82% depending on the database. Based on the obtained results, thresholds for rockburst intensity are proposed. The final results suggest that the newly proposed rockburst classification could contribute to a better rockburst management in mining and tunneling projects.

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CHAPTER 1: INTRODUCTION

1.1 Background

Rockburst is a phenomenon that can be described as a spontaneous ejection of strain energy accumulated in the surrounding rock mass in areas often associated with seismic activity (Kaiser and Cai 2012). Mining-induced seismicity is a widely used terminology in underground mining engineering that can describe an occurrence of seismic waves caused by deformation and failure of the rock mass within a complex mechanism (Li, Cai, and Cai 2007). Because of that high complexity, rockburst can be considered as a source of high potential hazard for underground mine in case of productivity and safety of workers. One of first rockburst incident was reported in the early 1900s in the Kolar gold mine, India (Deng 2021). Another early rockburst event was recorded in gold mines in the Witwatersrand, South Africa according to Blake and Hedley (2003). From that time going to the beginning of the 21st century, incidents associated with rockbursts have been periodically recorded around the world. For instance, in the period of time from 2001 to 2010 a total of 33 cases of rockburst incidents have taken place in hard coal mines in Poland (Patyñska 2013). As a result, many casualties were recorded which have a significant negative impact on the mentioned hard coal mines. Therefore, investigating rockburst intensity classification is of prime importance in mining industry.

1.2 Problem definition

Over the past few decades, the phenomenon of rockburst prediction has been extensively investigated using various approaches and a wide range of achievements have been made. Generally, methodologies used for rockburst prediction can be classified into five main groups: numerical (Wang et al. 2020), experimental (Gong et al. 2012; Hua and You 2001; Huang, Wang, and Chan 2001), empirical (Afraei, Shahriar, and Madani 2019; Zhou, Li, and Mitri 2018), analytical and data-based (Pu, Apel, and Hall 2020). Despite the extensive accomplishments, there is no widely accepted prediction tool, which might be capable to predict rockburst intensity with high level of accuracy. For instance, models built using machine learning algorithms were trained using relatively limited number of data points which also negatively influence the performance (Dong, Li, and Peng 2013b; Feng and Wang 1994). Additionally, some databases constructed in a result of mine site observations might possibly be incomplete, i.e. could have some missing data. Mostly used machine learning algorithms are not able to handle such kind of data sets (Ge and Feng 2008; Shirani Faradonbeh and Taheri 2019b).

Therefore, Bayesian Network (BN) is suggested to establish the model using comparatively larger database. It can be assumed that increasing number of data points is one way to improve an ability of the model to predict. Moreover, the BN can manage missing data using meaningful decisions for handling them.

1.3 Aim, objectives and research methods

Aim and objectives

This project aims to establish new classification tool using Bayesian Network as a prediction tool for rockburst occurrence and rockburst intensity. To reach this aim, the main objectives to be delivered are as follows:

1. Database preparation and Monte Carlo simulation of data.
2. Development of Bayesian Network for the selected databases
3. Validation of the models using independent data
4. Identification of rockburst intensity thresholds and proposing new rockburst intensity classifications

Methodology

The research methodology relies on the use of NETICA software which implements BNs. It allows the creations of nodes and the determination of relationship between them. The model is trained using prepared cases with purpose to provide prior probabilities for each node. Then the model is tested with certain cases in order to calculate posterior probability of occurrence for each state of output node i.e. rockburst intensity. The flowchart of the research is illustrated in Figure 1.

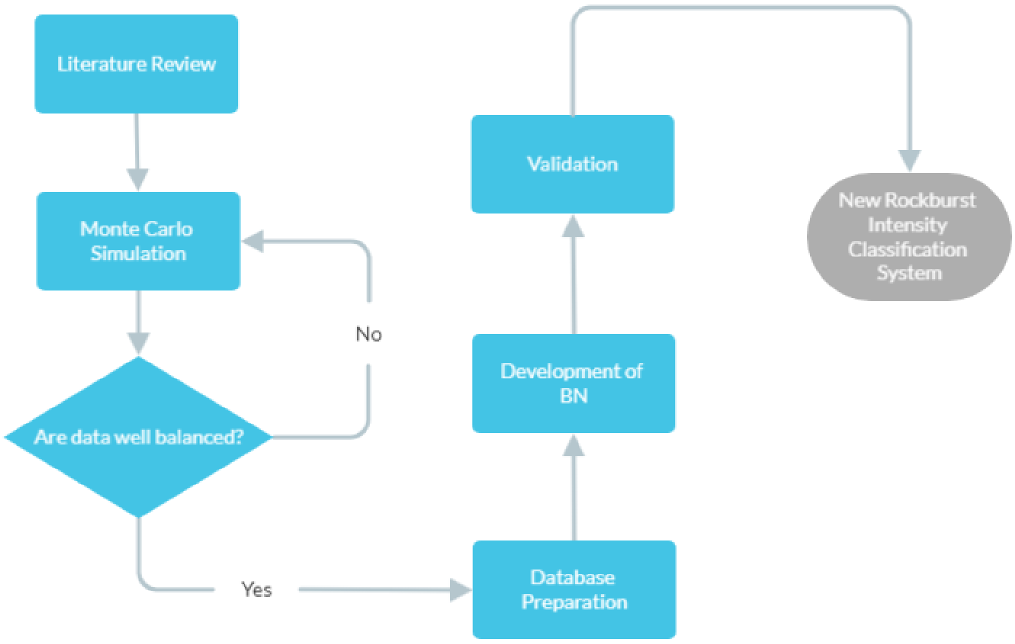


Figure 1. Overall research path

1.4 Project significance to the industry

It is expected that the results of this study contribute to solving a long standing issue related to mine safety. Rockburst poses a serious threat underground mining operation. Yet existing tools cannot always provide a very reasonable solution. The newly proposed classification can help to predict the intensity of the rockburst if used parameters are known or if there is a case where some parameters are missed. The reason is that BN is capable to handle an issue of missing data in comparison with other ML methods. There are two ways of applying the results of the study. The first is to use newly proposed classification system (table) and to determine possible intensity of the rockburst by selecting to which range the given value of each parameter is referring to. The second approach is using NETICA software and conducting belief-updating procedure in the BN model itself. This process gives probabilities in percentage for each intensity. Both approaches can provide valuable and reliable information regarding the rockburst intensity, which can help to avoid some unexpected and undesired consequences.

CHAPTER 2: LITERATURE REVIEW

2.1 Overview of rockburst

2.1.1 Historical background

Earliest cases of well documented rockburst occurrence have taken place in the beginning of 1900s in gold mines located in South Africa and India. Important contributions have been made by Blake and Hedley (2003), which provided quantitively reliable data on rockburst incidents around the world by making focus on the incidents, which were detected in Northern America. According to (Blake and Hedley 2003), earlier rockburst cases are related to the Springhill coal mine in Canada that was taken place in 1958 and resulted in 75 fatalities. One limitation of the study is that it briefly describes the rockburst incidents instead of providing detailed information. On the other hand study by Iannacchione and Zelanko (1995) provides a detailed analysis of 172 coal bump incidents collected by U.S. Bureau of Mines (USBM) and results were arranged into a database. The study includes appropriate tables, which contain information on the number of detected coal bumps, its characteristics as thicknesses of coalbeds associated with coal bumps, geographical locations, and geological maps of the mining region with indicated places where rockbursts occur. Based on the statistical data in the study it can be found that rockburst incidents between 1936 and 1993 resulted in 87 fatalities and 163 injuries in the USA. The study presents and examines past experiences of rockburst cases and finds out that these coal bumps appeared due to complexity of the mined areas that include factors such as stress, mining conditions and geology. Both presented papers have one common limitation that is related to time relevancy. Two papers provide statistics on rockburst incidents occurred in 20th century which can be considered as old data that are not actual today. Last five years of 20th century world underground mine industry has faced a significant number of rockburst incident, especially 1108 cases of rockburst occurrence were reported (Bennett and Marshall 2001).

A series of recent research on rockburst incidents have shown that such hazardous cases have been continuing to occur in a periodic manner from 2000 till present day. For example, in November 2011 Qianqiu Mine in Henan suffered from a severe rockburst that led to very serious consequences as 64 injuries and 10 lethal cases (Pu, Apel, and Xu 2019). According to Lu et al. (2015), three years later Qianqiu Mine experienced a serious rockburst incident which killed 6 miners. More recently, specifically, on 22 February 2020 Xinjulong coal mine suffered from the rockburst incident, which led to four lethal cases (Jiao et al. 2021). One year before in 2019 the same situation was recorded in the Longjiabao coal mine where nine lethal cases were detected (Jiao et al. 2021). Provided statistical data on the number and serious consequences of rockburst incidents demonstrate that rockburst prediction has not been solved yet from the first recorded cases till the present day. In order to solve that problem, it is necessary to examine and identify factors that positively influence rockburst by forcing it to occur as well as there are extensive number of papers on rockburst classification and types that provide valuable information with a good reliability and relevancy.

2.1.2 Factors influencing rockburst

Rockburst occurs as a result of spontaneous release of the energy that accumulated in the near rock mass (Wojtecki et al. 2021). According to Farhadian (2021) the rockburst phenomenon can be defined as undesired situation which possibly can take place under excavation process in regions with high geostress. As it was noticed tremendous attempts were made in order to solve the problem which poses number of threats to mine safety. Also, many scientists have put forward different views and opinions regarding the factors which potentially can cause the rockburst incident. For example, Gogolewska and Strzeszynska (2019) determined and examined factors that potentially can cause rockburst incidents based on the data obtained from three mines including Lubin Mine, Rudna Mine and Polkowice-Sieroszowice mine located in Lower Silesia, in SW Poland in the time period from 1987 till 2016. They found that number of tremors has no significant influence on the rockburst that is influenced most by the depth of the exploitation and chosen exploitation system, hence these factors can be considered as major factors influencing rockburst. From basic knowledge about mining induced seismicity it can be stated that seismicity and geology of the regions are differed from each other. Therefore, in that regard, one limitation of the paper is that it is difficult to conclude about rockburst caused factors in general because the data were taken from one mine site specifically.

In contradiction for the findings of the above mentioned study, Afraei, Shahriar, and Madani (2019) stated that the depth of the excavation cannot be considered as a major factor for rockburst occurrence. According to the paper, rockburst incidents have been recorded during the depth of the excavation was below than 300 meters. On the other hand, there were cases with excavation depth greater than 1500 meters and no rockbursts were detected. That information demonstrates an importance of identifying a systematic classification of parameters or factors that can lead to rockbursts. One of research works in that particular direction was conducted by Huang and Wang (1999). They consider the factors lead to rockburst by dividing them into two main groups including internal which is consisted of stress conditions and rock properties and external that includes dynamic disturbances. The paper stresses on the effect dynamic disturbances on the rockburst occurrence by using the method of numerical simulation with input data taken from a hydropower station located in China. Overall, the paper provided detailed analysis of received results and based on this it demonstrated a significance of consideration of dynamic disturbances as an external factor for the rockburst incidents. In order to make a conclusion stronger it can be suggested to take one of the internal factors as rock properties and perform a comparison analysis between methods. Moreover, Zhu et al. (2010) have identified a resultative contribution of dynamic disturbances as an external factor on the rockburst occurrence by implementing numerical simulation method. In contrast, Singh (1987) examined an impact of rock properties (internal factors) on the rockburst in terms of change in strain energy and has found that Burst Proneness Index (BPI) is significantly affected by geologic parameters and mining conditions including speed of compressional wave, compressive and point load strengths, rigidity modulus and brittleness. It can be suggested for further research to use additional data from other mine sites i.e. include more case studies in order to compare results from various geological regions. This limitation was successfully overcame in the paper written by Maleki and Lawson (2017). Authors have used the field data obtained from 25 cases occurred in U.S. mines and initially identified twenty-five geomechanical, geological and geometric factors which can have a potential impact on occurrence of the rockbursts. In a result of bivariate correlation and data reduction eight significant variables were determined. Finally, after two staged multiple regression analysis five variables were selected as most important. Moreover, one of the recent research has examined documented case studies of the rockburst and constructed a tabled list of them by indicating geological/geotechnical conditions, mining method geometry, contributing factors, rockburst type and hazard control (Keneti and Sainsbury 2018). The paper analyzed 26 cases of rockburst incident have taken place in various countries and as a result divided frequently appeared factors into two categories as loading associated factors including stress directions and magnitude, excavation geometry and excavation rate as well as its direction and property associated factors such as mineralogical properties, contrasting geomechanical properties, geological intensifiers.

2.2 SUMMARY OF EXISTED ROCKBURST PREDICTION METHODS

From the time when the first rockburst case was recorded the problem of its prediction was started to be considered as a severe issue and have been investigating through all the time till the present day. In a result of conducted research works all existed rockburst prediction methods were classified into common five groups: empirical, numerical, experimental, artificial intelligent and analytical. These five methods are grouped into two main groups including long-term and short-term rockburst prediction methods based on the time (stage) it is implemented during the mining project.

2.2.1 Empirical method

Vast amount of studies attempted to evaluate the possibility of rockburst occurrence by empirical methods. Zhou, Li, and Mitri (2018) found that these methods are generally implemented in the first steps of the mine planning process in order to identify the rockburst proneness of the underground opening and identified that existing empirical methods can be classified into two main categories as empirical criterion with single indicator and with multiple indicators. Based on the analysis of the existed literature authors determined that stress/strength, brittleness, energy and depth of the excavation can be considered as main parameters for the empirical method with single indicators. While empirical equations with multiple indicators include from three to five parameters as input variables. Overall, the paper provided list of existing studies implementing empirical methods with a good overview for each of them. It helps to easily navigate in the given topic and to find necessary papers. As a result of analysis of that paper and based on the background information on the rockburst topic it was investigated that there is an enormous number of criteria used in empirical equations. For example, Russenes (1974) classified the rockburst intensity around a tunnel based on the $\sigma_\theta\ /\sigma_C$. In the same way, Brown and Hoek (1980) provided σ_θ/σ_c as a criteria for rockburst occurrence. The difference of two empirical methods lies on the ranges in which rockburst intensity varies. The same empirical equation based on the Hoek-Brown criterion was provided by Martin, Kaiser, and McCreath (1999) where damage index D_i which can be defined as the ratio of the maximum tangential stress to uniaxial compressive strength was introduced. They determined that in case damage index exceeds 0.4 there is a high chance for the rockburst to be occurred. Also, there are number of studies which derived equations with empirical energy-based criteria. The earliest paper on the relation between energy release velocity and rockburst occurrence was investigated and established by Cook et al. (1966). In addition, Kaiser, Tannant, and McCreath and Salamon (1984) contributed by providing an equation for calculating the energy release rate which can be defined as the ratio of the change in strain energy (ΔU_m) to the change in the area of the excavated region (ΔA). Also, Chen et al. (2009) examined an effect of energy as the rockburst criterion and defined the energy discriminant index as an indicator of rockburst occurrence which is the ratio of energy storage to limited energy storage (U/U_o). In general, the papers demonstrated the influence of stress and strength on rockburst occurrence by providing appropriate empirical equations. Due to the fact that single indicator was obtained in a result of empirical equations, one limitation that is related to all of the papers mentioned above is that they provide one-sided, limited results. It is also, in general, can be considered as the limitation of the whole methodology that implements empirical equations with single indicator. There is a suggestion for further research to receive two or more indexes based on empirical equations with various parameters, then make a comparison based analysis which index can better predict the rockburst proneness. This limitation was addressed successfully in the empirical methods with multiple-index indicators. Number of comprehensive criterion with three (Lee et al. 1998; Lee, Park, and Lee 2004), four (Yi-an, Guang-zhong, and Zhi 1991) and five factors (Zhang and Fu 2008) was provided. For example, Lee, Park, and Lee (2004) have demonstrated a good correlation between three indexes including strain energy density (SED), brittleness (B_i) and uniaxial compressive strength (UCS) based on the test data. These well interrelated indexes give an opportunity to establish and suggest new scale system for rockburst intensity classification. A summary of the most commonly used rockburst classification is provided below in Table 1.

Table 1. Summary of the most commonly used rockburst hazard classification based on SED, Bi and UCS (Lee, Park, and Lee 2004)

SED	B_i	UCS (MPa)	Rockburst hazard
<50	< 5.75	< 78.40	Very low
~ 100	~ 7.85	~ 112.39	Low
~ 150	~ 9.87	~ 138.77	Moderate

~ 200	~ 12.18	~ 161.16	High

2.2.2 Experimental studies of rockburst

This study involved two stages in which two new test machines were provided and utilized in laboratory: modified true-triaxial apparatus (MTTA) for study of strainburst and dynamic true-triaxial apparatus (DTTA) for investigation of impact-induced rockburst. Manually created rockbursts triggered by above mentioned test machines gave a chance to make necessary observations on stress states and energy release rate. In a result, of the observations rockburst criteria including stress state, accumulated energy and dynamic disturbance were found as most significant. Moreover, the study proposed the new constant-resistance and large-deformation (CRLD) bolt/cable for the rockburst control and has demonstrated its ability to enhance the stability of the rock mass under loading/unloading conditions and under affect of seismic events which are triggered by dynamic disturbances. However, this paper is subject to several limitations. One of them is related to the lack of the prior research studies on the given topic. It can be suggested to provide more analysis of previous study on the experimental methods of the rockburst prediction. The second limitation includes the lack of separate experiments and discussions for each type of strainburst (instantaneous, delayed, pillar bursts) and impact-induced rockburst (affected by blasting, roof collapse, fault slip). In general, the paper has showed a valuable contribution to the study of the rockburst prediction and its control. In that regard, He et al. (2012) conducted the same laboratory experiments to evaluate an impact of similar factors, however, this provided more detailed analysis of previous studies on the topic in comparison with (He, Ren, and Liu 2018). Another study implementing experimental method (triaxial unloading test) to predict and reduce rockburst intensity was carried out by (Huang, Wang, and Chan 2001). As a result of the experiment, it was detected that (Em) under loading\unloading conditions have different influences on elastic moduli. Em value is greater under loading conditions rather than under unloading. Moreover, growth of unloading rate leads to reduce of the value of the rock strength. The paper has found that decreasing the amount of excavation speed can lead to reducing the level of rockburst intensity in regions with high in-situ stress. Another approach to predict rockburst was established by using the acoustic emission (AE) technique under true-triaxial conditions in the laboratory (He, Miao, and Feng 2010). Authors have identified low stress on rock samples results in low amplitude and high frequency of AE signals, and vice versa. It can be concluded that high stress leads to increase in amplitude of AE which cause fast emission of stored energy that can be considered as one of main reasons of the rockburst occurrence. Despite the fact that in each of the above mentioned papers real rockburst incident was tried to be designed in laboratory conditions using various test equipment, difference between artificially created and real rockburst occurred in the field can be potentially significant which can reduce an appropriateness of the results received in an experimental way. However, conducting in-situ experiments is expensive and demonstrated great difficulty in performance. It can be considered as one common limitations for the experimental methods.

2.2.3 Artificial Intelligence method and Mathematical modeling

One of the latest methods that have been developed for rockburst prediction is an implementation of various types of machine learning and mathematical modeling. There is significantly an enormous number of machine learning, artificial intelligence, mathematical modelling techniques that were utilized with purpose of rockburst prediction and control (Pu et al. 2019). However, due to the huge number of such methods a big challenge is to determine the most appropriate one. Different machine learning and mathematical algorithms demonstrated different behavior because of the complexity if the rockburst nature and its mechanism. One of the widely implemented machine learning techniques support vector machines (SVMs) have been demonstrating reasonably acceptable and reliable outcomes that allow to make predictions on potential rockburst occurrences with a good accuracy using both complete and incomplete data (He, Miao, and Feng 2010; Zhou, Li, and Shi 2012; Hong-Bo 2005; Feng and Zhao 2002; Pu et al. 2018; Ji et al. 2020a). Despite the fact that these studies used the same approach (machine learning methods), some of them implemented various techniques and algorithms. For example, Zhou, Li, and Shi (2012) have optimized and enhanced predictive accuracy of SVMs by using particle swarm optimization (PSO) and heuristic algorithms of genetic algorithm (GA) which increases an ability of the method to forecast the rockburst occurrence more precisely. One limitation of the paper is related to the lack of previous study on the particular topic. For further, research it can be suggested to add a deep analysis that identifies weak and strong sides of the earlier works. Also, another limitation concerns the absence of the information on the real life implementation of the method and results from field. Such kind of information might particularly prove the effectiveness and appropriateness of the SVMs in rockburst prediction. Overall, based on the methodologies and respective obtained results of the above mentioned papers, it can be stated that implementation of SVMs have made a significant contribution to establish a useful tool that can be potentially used in rockburst prediction activity. In addition, Jia, Lu, and Shang (2013) have implemented general regression neural network (GRNN) to construct regression model by getting tangential stress, UCS, tensile strength, elastic energy index as input parameters and PSO was utilized in order to optimize these parameters. After stages of building and optimization, developed model was used in real field, specifically, in Cangling tunnel and Dongguashan mine, and consequently demonstrated good rockburst predictive ability. Another group of machine learning method used for rockburst prediction include tree based methods such as Random Forest (RF) and decision tree. For instance, Pu, Apel, and Lingga (2018) have implemented decision tree model based on the 132 training samples from real rockburst cases by taking the ratio of maximum shear stress (σ_θ) to uniaxial compressive strength (σ_C), the ratio of σ_C to uniaxial tensile stress (σ_t) and linear elastic energy (W_{ET}) as partition attributes and in a result obtained the model with good predictive accuracy and performance that can be potentially used in mine projects for long-term rockburst prediction. However, as a machine learning method mostly depends on the database for training and testing, number of used training samples (132) can be considered as limited for such ML technique. Therefore, it is recommended to increase the amount of supportive database with purpose of enhancing reliability and applicability of given model. Recently, another study has approached the given problem by using decision tree model to take information about seismic event from the data which were provided in a result of MS monitoring and has found that obtained model might be considered as a useful tool for rockburst prediction and intensity classification (Zhao, Chen, and Zhu 2021). One limitation of the given paper concerns the lack of the analysis of the study on the previous implementation of decision tree model for rockburst evaluation. Also, it can be recommended to check the applicability and appropriability of the model in real life mine project. Earlier the same approach was introduced by Ghasemi, Gholizadeh, and Adoko (2020). One difference is that the second paper built two models: one for rockburst prediction and another for evaluation of rockburst intensity where both of them provided reasonably feasible results. Moreover, there is one common limitation for mentioned papers that should be addressed in further research. By implementing other machine leaning techniques or by taking available results from other studies it can be suggested to compare results in order to determine effective one. Another group of studies implemented RF method to classify and predict rockburst. For example, Dong, Li, and Peng (2013a) have trained 36 rockburst samples and received results have demonstrated good practicability of RF method in comparison with results from SVM and ANN. On the other hand, for further research number of rockburst samples are recommended to be increased with purpose of enhancing an accuracy and reliability of the obtained model.

Significant contribution to the area of rockburst prediction was done via using ML methods with mathematical and probabilistic approaches including Gaussian process (GP), adaptive neuro-fuzzy inference systems (ANFIS), quadratic discriminant analysis (QDA) and Bayesian Network (BN). For example, Su, Yan, and Chen (2010) have provided rockburst prediction method based on GP for binary classification model. Developed long-term prediction method is implemented for determining rockburst occurrence and its intensity level for Jinping II hydropower station. One weak point of the method is that it took relatively limited number of samples for training and testing. Mostly, in ML methods it is suggested to take extensive number of learning samples in order to reach reliable results with good accuracy. Overall, it can be stated that this method is not widely used in comparison with others. For example, significant number of papers have found that the model based on the knowledge of fuzzy mathematics in combination with neural networks such as fuzzy inference system (FIS) and adaptive neuro-fuzzy inference system (ANFIS) can be considered as a useful predictive mechanism (Adoko et al. 2013; Guo and Chen 2006; Jian-lin 2008). Model proposed by Jian-lin (2008) successfully introduced to real 23 underground mine projects as rockburst predictive tool. More recently, Adoko et al. (2013) have compared FIS and ANFIS and based on the several performance and error indices have stated that ANFIS model is significantly accurate therefore potentially can provide more reasonable results for rockburst prediction than knowledge based FIS model. It can be assumably stated that implementation of fuzzy probability with neural networks is relatively more accurate and reliable. That also can be supported by Jian et al. (2009) who have built a model based on fuzzy mathematics with use of enhanced back-propagation (BP) algorithm which was validated by practical utilization in Sanhejian Coal Mines. By contrast, Yıldırım et al. (2011) have identified that ANFIS has demonstrated lowest performance rate in comparison with feedforward neural networks (FFNNs) and probabilistic neural networks (PNNs) regarding the evaluation mine seismicity level of the geological region. It shows that the given method is need to be enhanced and developed in further research.

Due to rapid development of the ML techniques, especially supervised learning it is almost impossible to stop on each method and provide detailed explanation for wide variety and an enormous number of proposed models. Therefore, for more brief information constructing table (Table 2) with important key points of the proposed model was decided to be an effective solution. Basics of the table was obtained from (Zhou, Li, and Mitri 2018) with some modifications and changes. To be specific, models with accuracy below than 80% were removed from the table, moreover, new models as well as brief comments on the limitations of each paper/study were added.

Table 2. Papers that presented the supervised learning based rockburst models as rockburst predictive tools

Reference	**Algorithm**	**Accuracy**	**Number of data sets**	**Limitations**
Feng and Wang (1994)	ANN	100 %	10	Limited number of case histories. Time consuming, need a more time to fully iterate over all data. It might be difficult to receive good accuracy with large number of data sets.
Zhou et al. (2020)	ABC-ANN (hybrid method)	96.56 %	246 (data from (Zhou, Li, and Mitri 2016))	It can be suggested to select new database
Liang et al. (2020)	GBDT	91.67 %	246 Data taken from Jinping-II hydropower station	No comparison analysis with other short-term prediction methods
Ji et al. (2020b)	SVM-GA	85 %	156	More real data from mine site could enhance reliability and feasibility of the proposed model. Moreover, It can be suggested to implement PSO, because it enhances speed better than GA (Shi and Eberhart 1999).
Ge and Feng (2008)	AdaBoost-ANN	87.8-89.9%	36	Limited number of case histories

Adoko et al. (2013)	ANFIS	95.6 %	174	Different validation techniques were implemented. RMSE value was equal to 13.3.
Zheng et al. (2019)	BP neural network with entropy weight grey	90 %	20	Limited number of training data. According to Park and Sandberg (1991) from the training velocity perspective RBF network performs faster than BP within the similar applications.
Xue et al. (2020)	PSO-ELM	97.97 %	344	It can be suggested for further research to increase number of reliable sets in order to enhance stability of the proposed model.
Shirani Faradonbeh and Taheri (2019a)	Decision tree	81.48 %	134	Not able to deal with incomplete data. Limited number of training data.
Dong, Li, and Peng (2013a)	RF	100 %	46	Limited number of training data.

*Note (abbreviations): ANN – artificial neural network; ABC – artificial bee colony; GBDT – Gradient Boosted Decision Tree; RBF - radial basis function; BP – backpropagation; ANFIS - Adaptive neuro fuzzy inference system; SVM – support vector machine; GA – genetic algorithm; PSO – particle swarm optimization; ELM – extreme learning machine; RF – random forest.

In order to provide visual representations of differences between proposed ML based models Figure 2 was constructed. As previous research have shown most models used a very limited number of data which is not appropriate and not enough to get reliable results using ML techniques also it influences an accuracy of the model in a reasonable way. Therefore, to define which model is the most suitable and which is not, accuracy and number of datasets were chosen for scale graph.

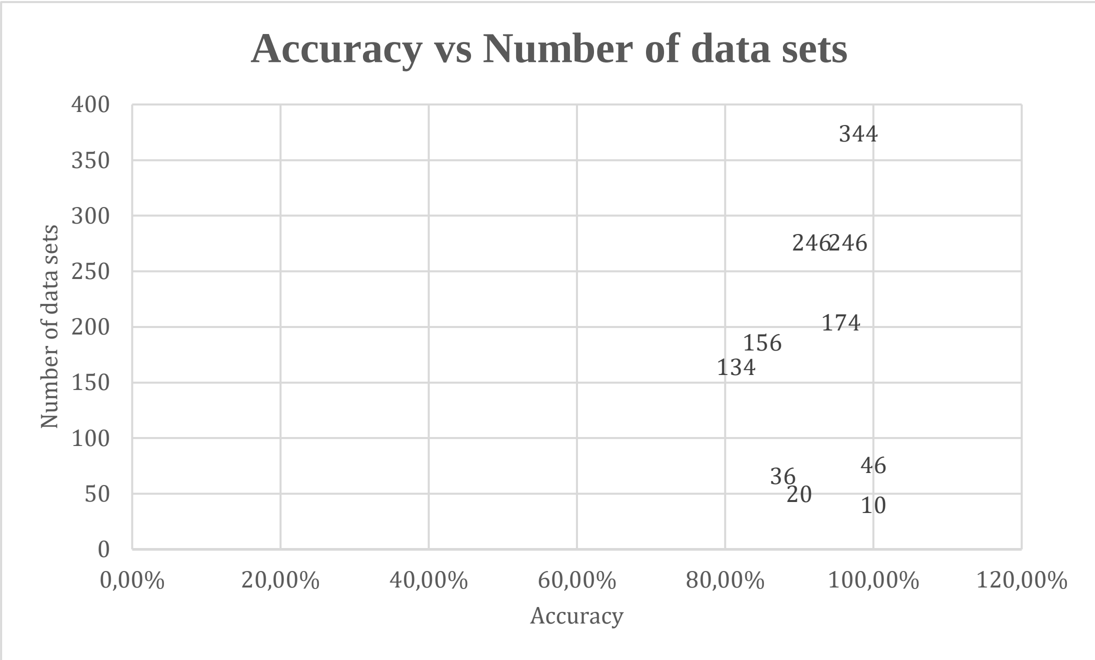


Figure 2. Appropriateness of proposed ML based models in the table

As it can be seen in the Figure 2, models in upper right corner of the graph can be potentially considered as most effective and appropriate in comparison with other models. As it can be seen from the graph PSO-ELM based model is located on the upper right corner which means that it has demonstrated comparatively appropriate results among other proposed models. In contrast, models that are located near to the lower left side can be probably considered as models that demonstrated relatively low appropriateness. According to the graph, ANN, RF, AdaBoost and BP based models might be an example of such tools.

More detailed analysis on the supervised machine learning techniques from the perspective of their accuracy, implementation difficulty and computational cost can be found in the paper by (Zhou, Li, and Mitri 2016).

CHAPTER 3: METHODOLOGY

3.1 Introduction

This chapter describes the different methods implemented in this research and it is organized as follows. Firstly, concise overview of the Monte Carlo Simulation technique used to generate additional data to increase the size of the database is provided. Next, the overview of the Bayesian Network methodology (BN) is presented. Finally, the rockburst database description is provided which includes a basic statistical analysis.

3.2 Monte Carlo simulation

As it was previously mentioned in above section two original databases need to be expanded in order to get more data. The reason for that like other ML methods for achieving more reliable data in Bayesian Network to train more precise model it is better to use more data. This subtask can be defined as significant part of data preparation procedure and can be performed by applying Monte Carlo Simulation. Monte Carlo simulation is a technique that is able to generate or simulate possible outcomes based on an estimated range of values by implementing a probability distribution including normal or uniform distribution (Gentle 2010).

3.3 Bayesian Network

Bayesian network can be defined as a directed acyclic graph where every vertex relates to a random variable, and the directed lines between nodes represent conditional independence relations between variables (Heckerman 2008). Vertices can represent variables of any type. Number of efficient techniques can be used to compute and train Bayesian networks. If the variables are discrete random variables, then such a network is called a discrete Bayesian network. Bayesian networks constructed with continuous variables are called dynamic Bayesian networks. If both discrete and continuous variables are implemented, these types of Bayesian networks are called hybrid. Bayesian networks, in which arcs, in addition to conditional independence relations, also encode causality relations, are called causal Bayesian networks.

The fundamental concept of BN mostly is probabilistic reasoning. After setting arbitrary variables for each node new probability distributions can be received for all nodes.

There are three main formulas used to set conditional relationship between variables. Firstly, the formula of BN is the formula for calculating conditional probability in statistics (Eq. 1):

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)} \tag{1}$$

Eq.2 is chain rule which is implemented to calculate $P(X_i)$ for i = 1, 2, 3, 4.

$$P(X_1, \dots, X_n) = P(X_1)P(X_2|X_1)P(X_n|X_1, \dots, X_{n-1}) \tag{2}$$

Thirdly, conditional rule in Eq. 3 can be applied to calculate joint probability distribution for X depending on the number of parent nodes of x_i:

$$P(x_1, \dots, x_n) = \prod_{i=1}^{n} P(x_i|\theta(x_i)) \tag{3}$$

In the equations (1), (2) and (3) $P(X)$ is a prior probability. $P(Y|X)$ is the probability of occurring event Y upon the condition event X is occurred. It is called posterior probability. $P(Y|X)$ is, vice versa, the likelihood of occurring event X, while event Y is true. $\theta(x_i)$ is a set of parent nodes of x_i.

In BN, each time when new observation data come already observed data are placed into historical data and consequently previous prior probability will be renewed.

Due to rapid development of machine learning, especially supervised ML techniques, Naïve Bayes, Augmented Naïve Bayes, Tree Augmented Naïve Bayes (TAN), Grow Shrink algorithm (Scutari 2010), Hill Climbing (Gámez, Mateo, and Puerta 2007), Tabu Search (Pan et al. 2019), PC (Spirtes et al. 2000) can be considered as most commonly used BN structure learning algorithms. In this paper it was decided to implement TAN to learn from data using the software Netica. de Campos et al. (2016) has proposed the study which examines the extended version of TAN and has demonstrated that this type of BN classifier outperformed the Naïve Bayes classifier in several experiments conducted by (Corani and De Campos 2010; Friedman, Geiger, and Goldszmidt 1997; Madden 2008). Friedman, Geiger, and Goldszmidt (1997) have analyzed performance level of TAN in a more detailed way. In this paper

Expectation Maximization (EM) algorithm is used as a tool for evaluating conditional probability tables (CPTs) for each nature node in BN. EM is an algorithm that can be applied in mathematical statistics to find maximum likelihood of parameters of probabilistic models in case when the model depends on some hidden variables (Moon 1996). The algorithm has two stages: estimation step (E-step) which is responsible for evaluation of missing variables and M-step which is used for improving the model to better explain the data by maximizing the model's parameters.

Bayesian Network Belief updating process can be considered as a series of complex computational steps which are NP-hard in the worst case. Junction Tree (JT) algorithm is used for BN belief updating in this paper. The algorithm is one of the integrated features of the Netica and is implemented automatically within the testing process. JT algorithm consists of basic 4 steps (Kahle et al. 2008):

1. Moralization – directed graph is transformed into undirected graph.
2. Triangulation – undirected graph can be considered as triangulated if and only is each cycle with capacity $n \geq 4$ has a chord.
3. Identification of cliques – in this step maximum number of cliques is determined.
4. Junction Tree formation – finally, junction tree is constructed.

This process has taken place once the CPTs are successfully received. It is required to evaluate the posterior probability of the given new rockburst influencing parameters. It must be assumed that there is a possibility that the data can be incomplete.

3.4 Rockburst database description

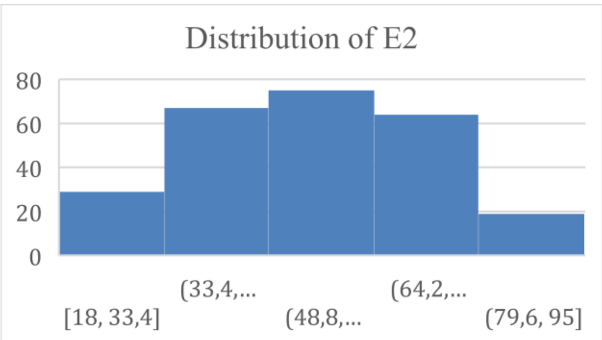
3.4.1 First database

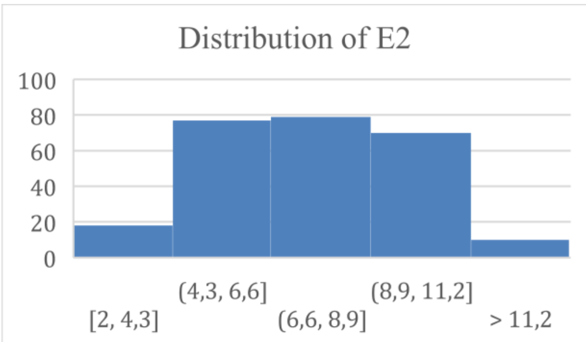
This database was initially compiled by Heal (2010). It consists of 254 cases of well detailed rockburst records from Australian and Canadian mines subjected to mining seismicity, including Kundana mines, Big Bell mines, Black Swan mines, Brunswick mines, Flaconbridge mines, Darlot mines, Junction mines, Kanowna Belle mines, MT Charlotte mines, Broken Hill mines and LNO mines.

The selected input parameters for the study include those that are more influential to rockburst damage: stress conditions (E1), ground support capacity (E2), excavation span (E3), effect of geological structure (E4), peak particle velocity (E5) and the output is defined as the rockburst damage scale (RDS) . The RDSs definitions are provided in Table 1. The database contains no cases of R1. There are four scales classifications of rockburst intensity where 116 of them correspond to R2, 48 rockburst cases were reported as R3, 63 rockburst cases have demonstrated R4 and remaining 27 cases are related to the events with R5. In order to describe the database in a more detailed way, histograms are provided in Fig. 2. As it can be seen in Fig. 2, the data are almost normally distributed. Also, basic statistical indices including mean and standard deviation, variance, minimum and maximum values which can be probably used to define the range within the prediction of rockburst occurrence and intensity can be relevant are represented in Table 3.

Table 3. Description of the damage scale (Heal 2010)

Damage scale	Rock mass damage	Support damage	Rockburst intensity
R1	No damage, minor loose	No damage	None
R2	Minor damage (<1 ton displaced)	Loaded support system, loose mesh, deformed plates	Light
R3	1-10 tons displaced	Some broken bolts	Moderate
R4	10-100 tons displaced	Major damage to support system	Major
R5	100+ tons displaced	Complete failure of support system	Severe





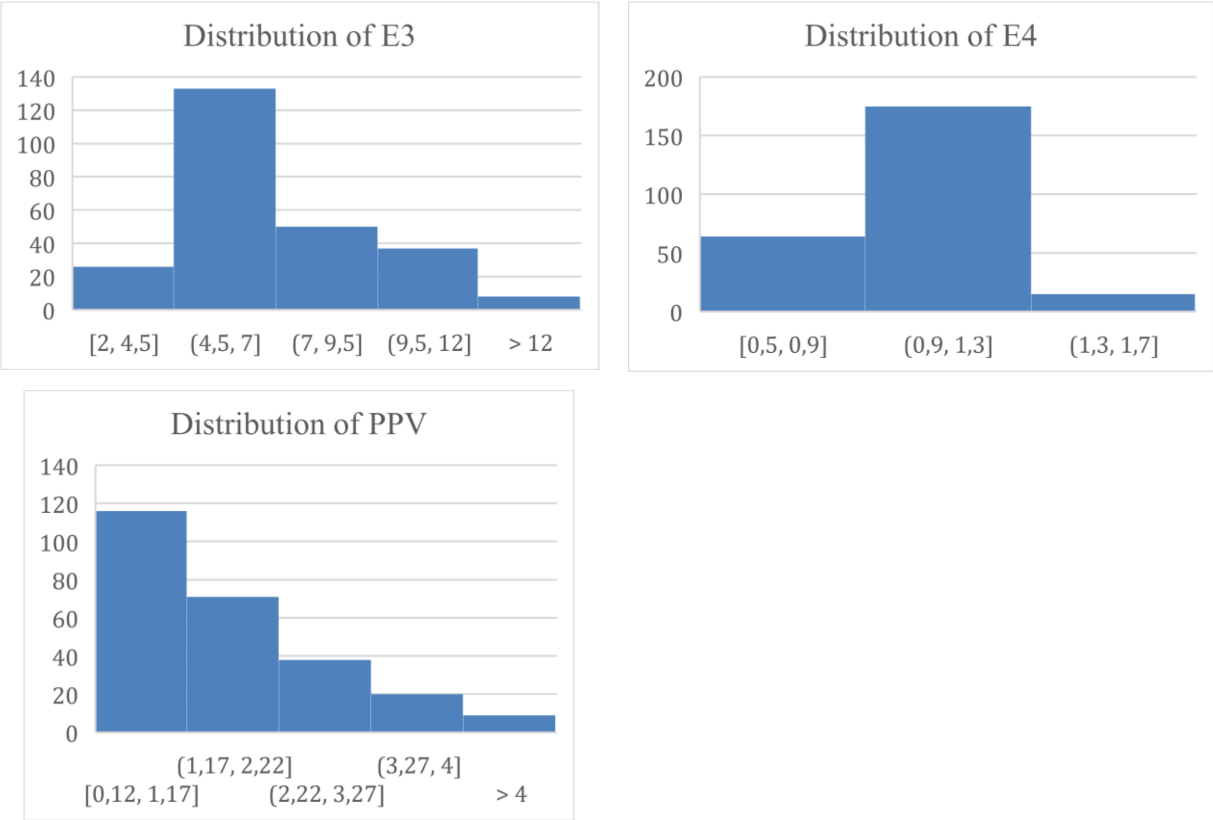


Figure 3. Distribution of five input parameters of the first database

Table 4. Statistical description of the dataset

Statistic	E1	E2	E3	E4	PPV
Minimum	18.00	2.00	2.00	0.50	0.12
Maximum	95.00	25.00	30.00	1.50	7.87
Range	77.00	23.00	28.00	1.00	7.75
Median	57.00	8.00	6.35	1.00	1.40
Mean	54.51	7.89	7.24	0.90	1.66
Variance (n-1)	317.35	17.82	9.07	0.07	1.71
Standard deviation (n-1)	17.81	4.22	3.01	0.26	1.31

Table 5. Correlation coefficients between the input parameters

	E1	*E2*	*E3*	*E4*	*PPV*
E1	1.00	**0.32**	-0.22	0.12	-0.09

E2	**0.32**	1.00	-0.22	-0.09	-0.03
E3	-0.22	0.05	1.00	-0.07	0.14
E4	0.12	-0.09	-0.07	1.00	-0.19
PPV	-0.09	-0.03	0.14	-0.19	1.00

3.4.3 An example of historical rockburst case: Kundana#6 case

This section reported on the characteristics of the rockburst and the excavation damage that occurred in Kundana mine (Heal 2010). In July 2003, rockburst event with medium (R4) intensity has taken place in the certain area of the mine which was supported by weld mesh with 5.6mm thickness and had square shape of 100x100 mm as well as 2.4 m and 3 m long cone bolts were utilized at 1.05-1.035 spacing. Despite the support and reinforcement system the observed area was absolutely failed, consequently, mostly in-tact rocks were ejected. Photo taken during an observation can be found in Figure 4.

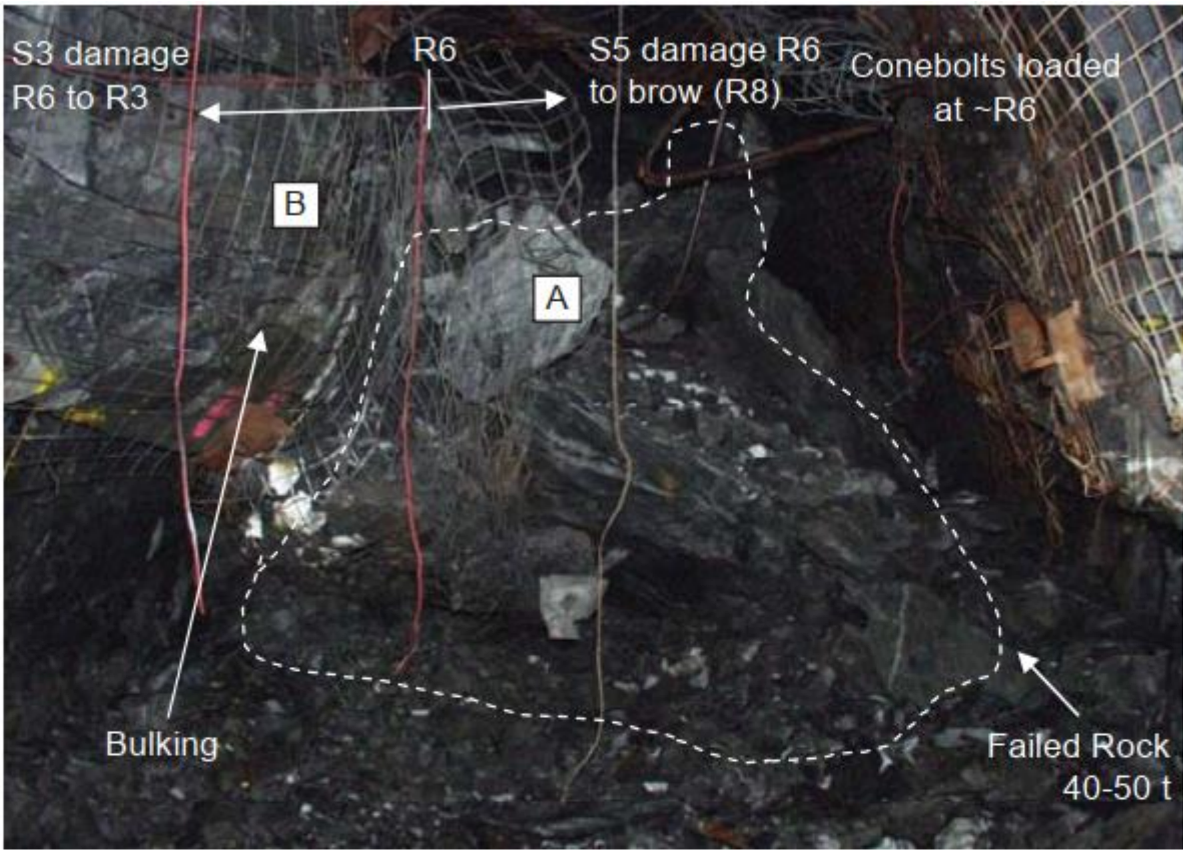


Figure 4. Photo of rockburst incident occurred in Kundana mine on July 2003 (Heal 2010)

3.4.3 Input parameter description

Stress conditions (E1)

Rockburst incident could possibly occur as a result of stress change due to dynamic load even in regions with low seismicity (Kaiser, McCreath, and Tannant 1996). This parameter can be defined as the ratio of the total maximum principal stress (σ_{1T}) to the uniaxial compressive strength of the rock (UCS) multiplied by 100 percent:

$$E_1 = \frac{\sigma_{1T}}{UCS} * 100\% \tag{4}$$

Ground Support Capacity (E2)

Previous literature demonstrated that ground support system plays a crucial role and has a significant influence on the intensity of rockburst incident. There are various types of ground support systems implemented in the underground mine. Heal and Potvin (2007) provided commonly used ground support systems. Heal (2010) classified and quantified the influence of the ground support systems on rockburst occurrence using five different numbers that can be seen from the following Table 6.

Table 6. Evaluating the Ground Support Factor (E2) based on the energy absorption of the ground support system Heal (2010)

Classification	Surface Support	Reinforcement	E2 rating
Low	None	Spot bolting	2
Moderate	Mesh or Fibrecrete	Pattern bolting	5
Extra bolting	Mesh or Fibrecrete	Pattern bolting with a second pass of Pattern bolting	8
High static strength	Mesh or Fibrecrete	Pattern bolting and Pattern Cable bolts	10
Very high dynamic capacity	Dynamic Surface Support	Pattern Dynamic Support	25

Span (E3)

Level of damage of rockburst can be directly proportional to the span of excavation that can be defined as the diameter of the largest circle which can be placed into the excavation (Heal 2010). It is measured in meters and has a range from 0 to 30 meters. This range is divided into 6 equal sub intervals each has five meters.

Geology (E4)

As geology of the region has a significant impact on the presense of the rockburst and its severity this factor should be taken into consideration during the calculating index of rockburst intensity. Desciption of each value for E4 can be found in Table 7. It is worth to mention that there rockmass is assumed to be homogenous.

Table 7.. Classification of input parameter E4 (Heal 2010)

Value	Description	Reason
0.5	High possibility of rockmass failure	Faults, shears or discrete contacts
1	Rock failure	Discontinuities, no major structural features
1.5	Rock mass is massive, stable	No major structural features

Peak Particle Velocity (PPV)

Peak Particle Velocity is a measure of effect of ground vibration caused by operations such as blasting (Holub and Rušajová 2011). This factor has a strong impact on the rockburst occurrence. For instance, Zhang et al. (2021) has stated that probably rockburst incident could take place when PPV value can lead to achieving its corresponding stress increment to relatively high value. Hence, they believed that this factor should be considered as one of the important indicators such as energy index etc.

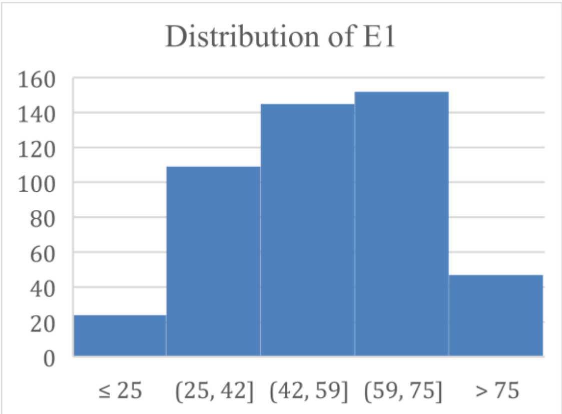
3.4.4 Second database

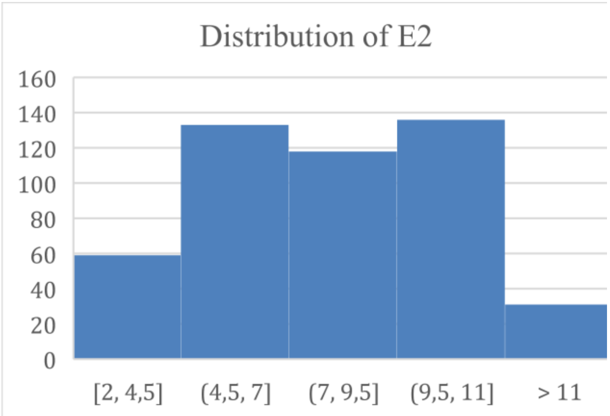
Simulated version of original 254 datasets was received as a result of implementation of Monte Carlo Simulation technique in Excel using NORM.INV function. In a result of generating data it was determined that there are negative data points. Since negative values for the given parameters are meaningless and not logical, absolute values of them were obtained by using ABSOLUTE function in Excel. Moreover, it can be detected that input parameters including E2, E4 and output parameter RDS are discrete variables, however results of simulation provided continuous variables. Using nested IF functions in Excel all simulated continuous variables were discretized.

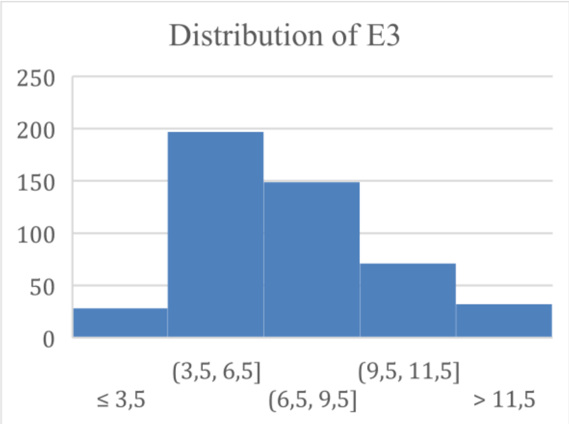
As this database was compiled from the previously described 254 datasets, it has exactly the same input parameters. However, since it is expanded version of the original database, it has 478 data points, and consequently basic statistics and corresponding histograms differ from the original version. Statistical description of the input parameters is represented in table 7.

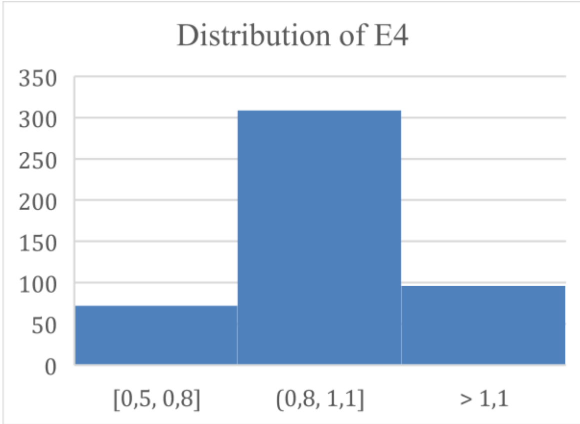
Table 8. Statistical description of the input parameters

	E1	E2_new	E3	E4_new	PPV
Unit	-	-	-	-	m/s
Min	1.00	2.00	0.01	0.50	0.00
Max	107.00	25.00	17.39	1.50	6.55
Mean	54.00	8.00	7.24	1.00	1.79
Stdev	18.49	3.45	2.89	0.29	1.13









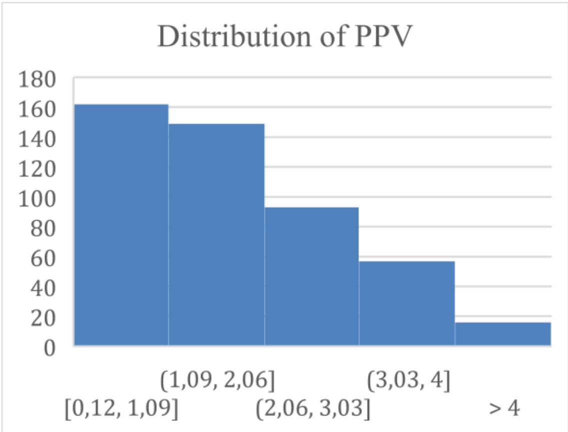


Figure 5. Histograms of five input parameters

3.4.5 Third database

The database contains 344 cases where rockburst did not occur (50 none rockburst cases) and took place with three different intensities including light (98 cases), moderate (123 cases) and strong (73 cases). Full database can be found in Appendix C. Each case is characterized by six mechanical properties such as tangential stress (δ_θ), compressive stress (δ_c), tensile stress (δ_t), strain energy (W_{et}), ratio of normal stress to compressive stress (δ_θ/δ_c) and ratio of compressive stress to tangential stress (δ_c/δ_t). These properties are used as input parameters for BN and column called Rockburst Intensity can be selected as output node. From statistical view data can be described as presented in table 8. Additionally, visual representation of distribution of each parameter is provided as histograms in figure 6.

Table 9. Statistical description of the input parameters

	δ_θ / *Mpa*	δ_c/ *Mpa*	δ_t / *MPa*	W_{et}	δ_θ/δ_c	δ_c/δ_t
Unit	Mpa	Mpa	Mpa	Joule	-	-

Min	2.60	20.00	0.40	0.81	0.05	2.52
Max	297.80	304.20	22.60	30.00	4.87	602.50
Mean	57.73	119.34	6.99	5.12	0.54	23.88
Stdev	48.07	46.91	4.20	3.66	0.58	34.26

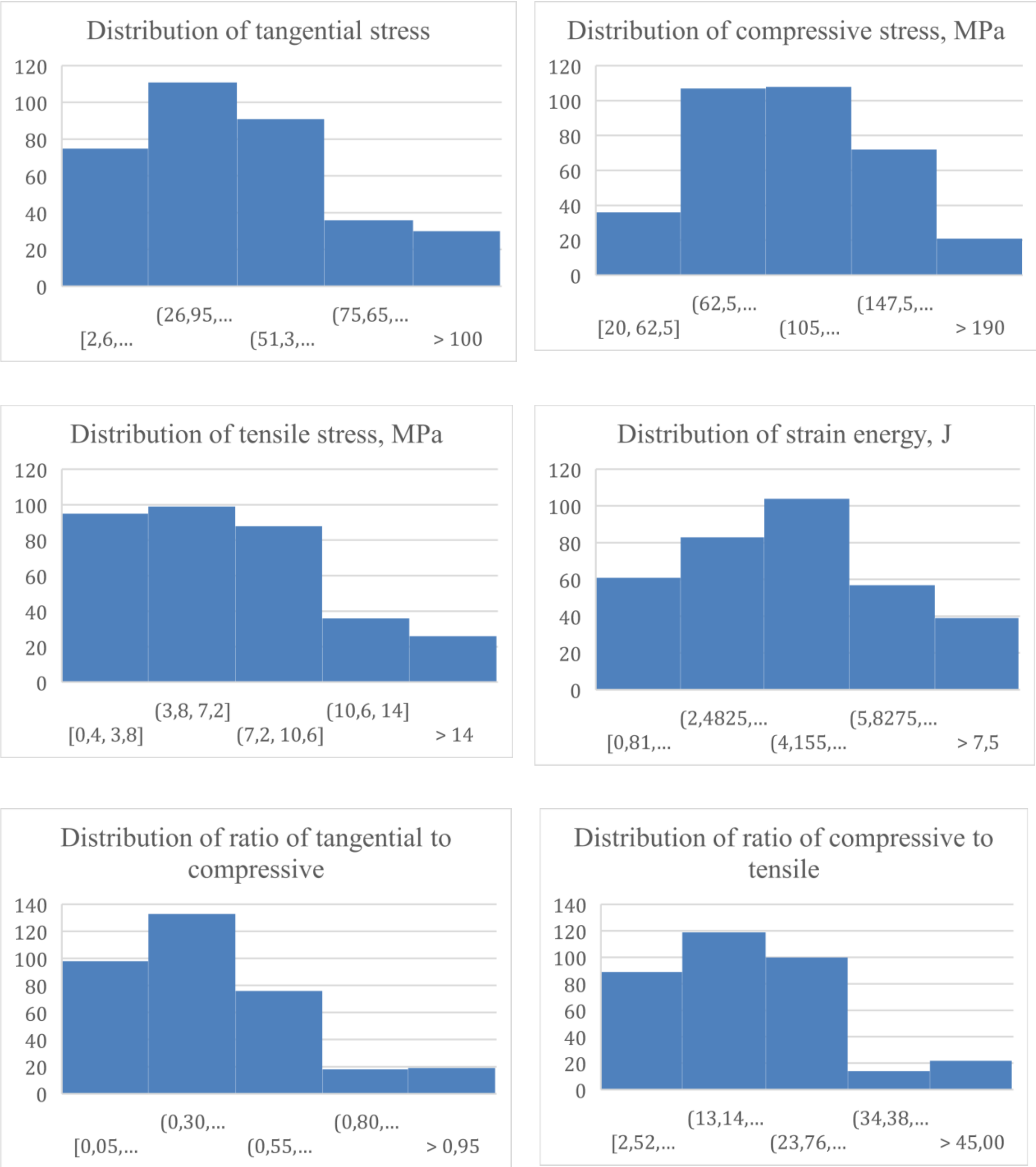


Figure 6. Distribution of six input parameters of the third database

3.5 Correlation between parameters

In order to determine cause dependencies between nodes, correlation between parameters should be calculated. Medium or strong correlations mean that there is a conditional relation between parameters. Correlation coefficients were determined in Excel. Results are provided in tables 9-12 for four databases.

Table 10. Correlation coefficients between parameters for the first database

	E1	*E2*	*E3*	*E4*	*PPV*
E1	1				
E2	**0.32**	1			
E3	-0.22	0.05	1		
E4	0.12	-0.09	-0.07	1	
PPV	-0.09	-0.03	0.14	-0.19	1

As it can be seen from the Table 10, E1 and E2 have stronger correlation in comparison with other parameters.

Table 11. Correlation coefficients between parameters for the second database

	E1	*E2*	*E3*	*E4*	*PPV*
E1	1				
E2	-0.04	1			
E3	-0.02	**0.87**	1		
E4	-0.06	-0.02	-0.02	1	
PPV	-0.06	-0.08	-0.08	0.02	1

According to the correlation results presented in the table 10, it can be noticed that E2 and E3 have strong correlation. Also, correlation coefficient of these two parameters is significantly higher comparing with other possible pairs of parameters. Since it can be stated that there should be established dependency between these two parameters.

Table 12. Correlation coefficients between parameters for the third database

	δ_θ / *Mpa*	δ_c/	δ_t /	W_{et}	δ_θ/δ_c	δ_c/δ_t

		Mpa	*MPa*			
δ_θ / *Mpa*	1					
δ_c/ *Mpa*	0.11	1				
δ_t / *MPa*	0.34	**0.45**	1			
W_{et}	**0.45**	0.24	0.34	1		
δ_θ/δ_c	**0.89**	-0.25	0.14	0.31	1	
δ_c/δ_t	-0.13	0.14	-0.33	-0.04	-0.14	1

Correlation between parameters δ_θ and σ_θ/σ_c was equal to 0.89 which means strong correlation. Also, two pairs of parameters have medium correlation as indicated in the table 11. In a result it was decided to put three dependency rows between these parameters.

CHAPTER 4: RESULTS

4.1 Data discretization

Once all data points were prepared and preprocessed, the next task was to construct the BN model. The process of the model construction had several steps which should be conducted in the following order. First step is data discretization. The model is consisted of nodes which have certain number of states. User can establish any amount of nodes and states depending on the result that should be achieved at the end. Each state can accept both discrete and continuous data. However, one issue is that continuous data should be divided into boxes with defined ranges, i.e. discretized. Accordingly, in order to obtain proper the BN model, it is crucial to confirm that all continuous data are well discretized and all values are within the ranges which are determined in a result of discretization process. There are three databases. Two of them, first database and its expanded version with 477 data points have three continuous variables, while in third database all variables are continuous. Then, each of them was grouped into three states: low, medium and high. Results of discretization of are presented in tables 13-16.

Table 13. Discretization results of continuous variables of the first database (254 data)

	E1	E3	PPV
Low	18.00-37.25	2.00-7.10	0.12-1.17
Medium	37.25-56.50	7.10-10.50	1.17-2.48
High	56.5-75.75	10.50-17.00	2.48-4.97
Very High	75.75-95.00	17.00-30.00	4.97-7.87

Table 14. Discretization results of continuous variables of the second database (simulated data)

	E1	E3	PPV
Low	1.00-42.33	0.00-5.79	0.00-1.75
Medium	42.33-60.66	5.79-8.85	1.75-3.14
High	60.66-114.00	8.58-30.00	3.14-17.00

Table 15. Discretization results of continuous variables of the third database (344 data)

	δ_θ / *Mpa*	δ_c/ *Mpa*	δ_t / *MPa*	W_{et}	δ_θ/δ_c	δ_c/δ_t
Low	2.60-40.40	20.00-91.05	0.40-5.95	0.81-5.12	0.05-0.66	2.52-20.52
Medium	40.40-120.20	91.05-162.10	5.95-11.50	5.12-10.41	0.66-1.46	20.52-150.51
High	120.20-297.80	162.10-304.20	11.50-22.60	10.41-30.00	1.46-4.87	150.51-602.50

4.2 Development of BN

The constructed models are shown in Figures 7-9. The nodes and dependencies were created and established using the results of discretization and correlation processes. The networks were constructed implementing TAN classifier integrated into the software. All four databases were transformed into Case File Format which is acceptable by the NETICA.

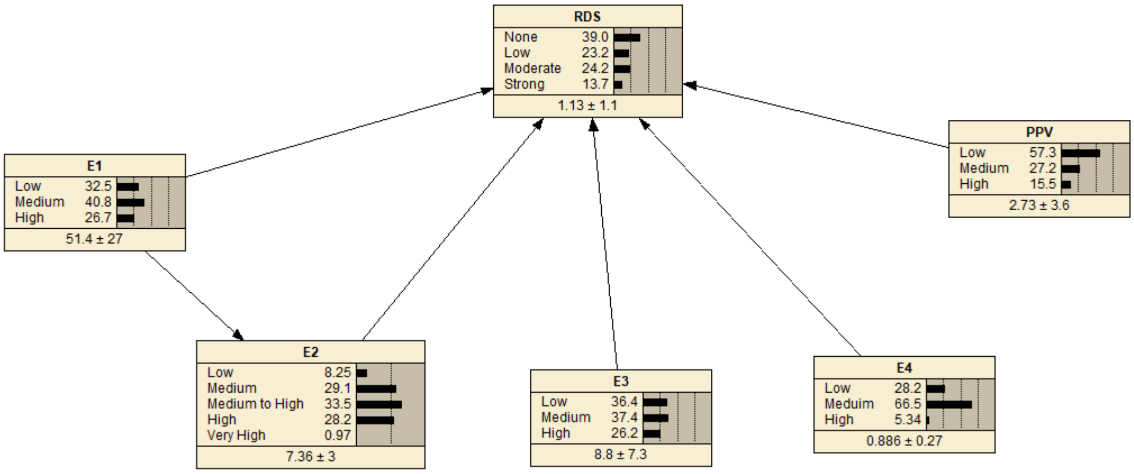


Figure 7. BN structure using the first database

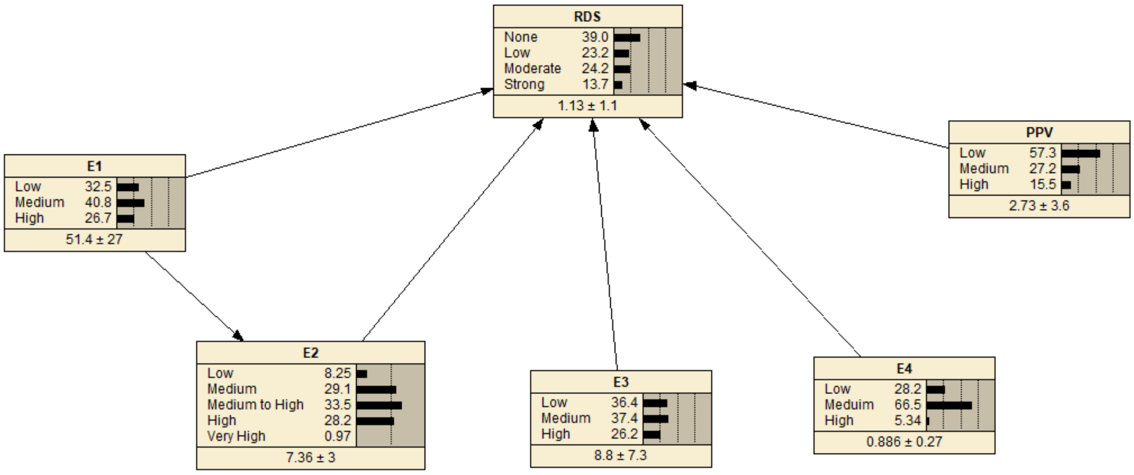


Figure 8. BN structure using the second database

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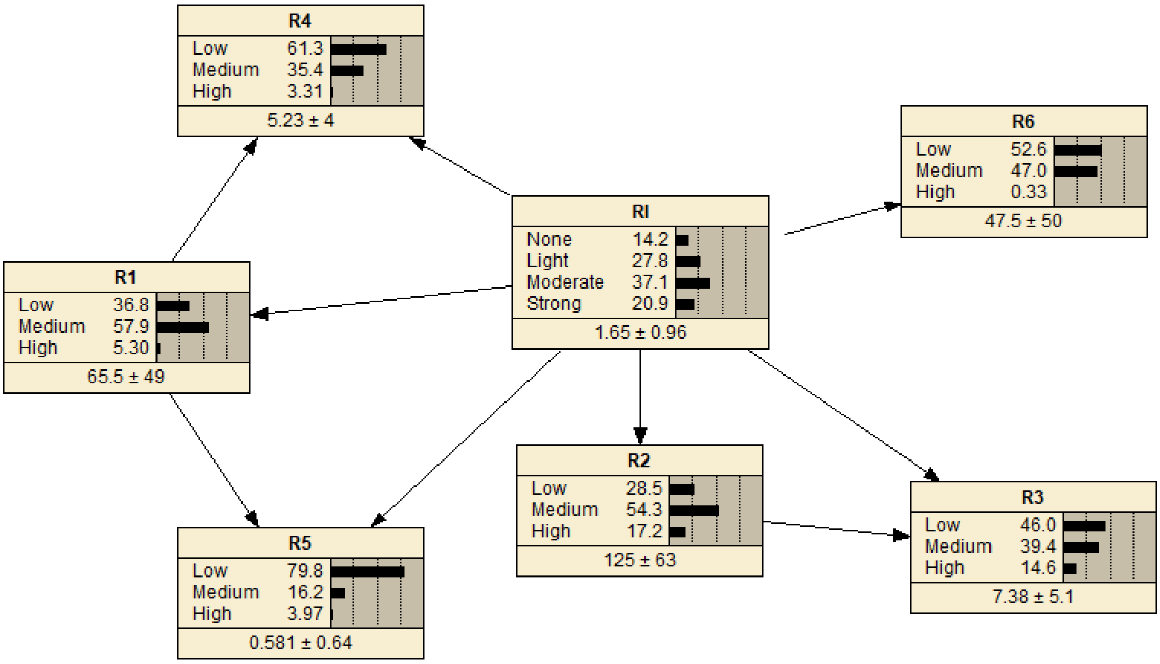

Figure 9. BN structure using the third database

4.3 Conditional Probability Tables

Once BNs were built, the next step is to divide each database into two groups: training and testing data. For first scenario, 214 data (80%) out of 254 were grouped into one file as training data and remaining 40 data (16%) were used for model testing. For the second database, 400 data points (84%) were used for training the model, and other data (77 data points, 16%) were implemented as testing data. For the third database, 342 data were divided as following: 302 data were used (88,3%) for training and 40 data (11,7%) were utilized for testing. For each scenario, the BN structure was learnt from the corresponding file which containing training data. As a result of learning using Expectation Maximization algorithm CPTs were obtained for each model. These tables displayed likelihood of output node (RDS for the first two databases and RI for last database) affecting by input nodes. The CPTs are presented in tables 16-34 which can be found in Appendices.

4.3.1 CPTs for the first database

Table 16 (sample of the results) shows a sample of the conditional probability of four intensities of output node. These probabilities are readily available in the report of the computations implemented in NETICA. As it can be seen, the highest likelihood is greater than 25%.. It is worth mentioning that the original version of the table is larger than presented, because it considers all 405 combinations (3 states of E1 * 5 states of E2 * 3 states of E3 * 3 states of E4 * 3 states of E5) for all states of five input parameters. Further table 16 will be used for building classification system in Discussions section.

Table 16. CPT for P(RDS|E1, E2, E3, E4, PPV) % > 25%

E1	E2	E3	E4	PPV	None	Low	Moderate	Strong
Low	Low	Low	Low	Low	0.00	100.00	0.00	0.00
Low	Low	Low	Medium	Low	0.00	66.67	33.33	0.00
Low	Low	Low	Medium	High	0.00	0.00	50.00	50.00
Low	Low	Low	High	Medium	0.00	100.00	0.00	0.00
Low	Low	Medium	Medium	Low	0.00	0.00	100.00	0.00
Low	Low	Medium	Medium	High	0.00	0.00	100.00	0.00
Low	Low	High	Medium	Medium	0.00	0.00	0.00	100.00
Low	Low	High	Medium	High	0.00	0.00	0.00	100.00
Low	Low	High	High	Medium	0.00	0.00	100.00	0.00
Low	Medium	Low	Low	High	0.00	0.00	100.00	0.00
Low	Medium	Low	Medium	Low	33.33	50.00	16.67	0.00
Low	Medium	Medium	Low	Low	0.00	50.00	50.00	0.00

4.3.2 CPTs for the second database

Table 22 (sample of the results) demonstrates conditional probability of four intensities of output node where the highest likelihood is greater than 25%. The table was retrieved from the report provided in the NETICA. The original version of the table is larger than presented, because it considers all 405 combinations (3 states of E1 * 5 states of E2 * 3 states of E3 * 3 states of E4 * 3 states of E5) for all states of five input parameters. Further information provided in the Table 22 will be used for building classification system in Discussions section.

Table 17. CPT for P(RDS|E1, E2, E3, E4, PPV) > 25%

E1	E2	E3	E4	PPV	None	Low	Moderate	Strong
Low	Low	Low	Low	Low	0.00	100.00	0.00	0.00
Low	Low	Low	Medium	Low	0.00	66.67	33.33	0.00

Low	Low	Low	Medium	High	0.00	0.00	50.00	50.00
Low	Low	Low	High	Medium	0.00	100.00	0.00	0.00
Low	Low	Medium	Medium	Low	0.00	0.00	100.00	0.00
Low	Low	Medium	Medium	High	0.00	0.00	100.00	0.00
Low	Low	High	Medium	Medium	0.00	0.00	0.00	100.00
Low	Low	High	Medium	High	0.00	0.00	0.00	100.00
Low	Low	High	High	Medium	0.00	0.00	100.00	0.00
Low	Medium	Low	Low	High	0.00	0.00	100.00	0.00
Low	Medium	Low	Medium	Low	33.33	50.00	16.67	0.00
Low	Medium	Medium	Low	Low	0.00	50.00	50.00	0.00

4.3.3 CPTs for the third database

Table 28 (sample of the results) demonstrates conditional probability of four intensities of output node where the highest likelihood is greater than 25%. The table was retrieved from the report provided in the NETICA. The original version of the table is larger than presented, because in total there are 6 input nodes with 3 states in each, it gives 729 different combinations. Further the table 28 will be used for building classification system in Discussions section.

Table 18. CPT for P(RI|R1, R2, R3, R4, R5, R6)

R4	R1	R5	R2	R3	R6	None	Light	Moderate	Strong
Low	Low	Low	Low	Low	Low	45.45	9.09	36.36	9.09
Low	Low	Low	Low	Low	Medium	20.83	25.00	41.67	12.50
Low	Low	Low	Low	Medium	Low	50.00	25.00	25.00	0.00
Low	Low	Low	Low	High	Low	0.00	100.00	0.00	0.00
Low	Low	Low	Medium	Low	Medium	39.13	43.48	8.70	8.70
Low	Low	Low	Medium	Medium	Low	7.69	46.15	38.46	7.69
Low	Low	Low	Medium	Medium	Medium	0.00	100.00	0.00	0.00
Low	Low	Low	Medium	High	Low	60.00	10.00	10.00	20.00

Low	Low	Low	High	High	Low	0.00	0.00	0.00	100.00
Low	Low	Medium	Low	Low	Low	50.00	0.00	0.00	0.00
Low	Medium	Low	Low	Low	Low	0.00	100.00	0.00	0.00
Low	Medium	Low	Low	Low	Medium	0.00	40.00	60.00	0.00
Low	Medium	Low	Low	Medium	Low	0.00	100.00	0.00	0.00

4.4 Testing the models

Once the model was trained and CPTs were obtained, the next step is to test and validate the model performance. The process of model testing can be performed in the NETICA. The testing results are provided as confusion matrix by the software. For the first database, case file containing randomly chosen 40 data points (16% of full database) was used as testing dataset. As it can be seen from Table 35 and according to the resutls , overall accuracy of the model was equal to 76.09%. Also, it can be noticed that R2 cases were more correctly predicted in comparison with other cases. It can be explained by the fact that number of R2 cases are greater than number of other cases as well as R2 cases are almost half (46%) of the whole database. For the second database, randomly selected 16% of the all data points was used for testing. As a result, confusion matrix was received with overall accuracy equal to 79.10% as it is presented in table 36. As it was mentioned before, this database was obtained in a result of extention of the first database by applying Monte Carlo Simulation technique. Main difference between original and extended databases is that the second was enlarged that R2, R3, R4 and R5 have almost the same number of cases. As a consequence this difference influenced main diagonal of the confusion matrix positively. Number of corrrectly predicted cases for R3, R4 and R5 is significantly higher than it was for the confusion matrix of the first database. It demonstrates that for BN to predict more precisely the dataset should be well balanced and it is better to implement more data points. For the third database, 40 data points were used for testing. As a result 70% of all tested cases were correctly predicted as it is demostrated in table 37. From the confusion matrix it is noticeable that in comparison with other cases light rockburst cases were more accurately predicted. For all three models it can be stated that accuracies are in acceptable level. The reason for lower accuracy of the third database is that it is not well balanced in comparison with previous two data sets.

Table 19. Confusion matrix of RDS node for the first database

Actual	Predicted				
	R2	R3	R4	R5	Percent Correct
R2	26	3	2	0	84%
R3	0	2	0	0	100%
R4	3	1	6	0	60%
R5	1	0	1	3	60%
Overall Percentage	87%	33%	67%	100%	76%

Table 20. Confusion matrix of RDS node for the second database

Actual	Predicted				
	R2	R3	R4	R5	Percent Correct
R2	28	4	2	2	78%
R3	3	7	0	0	70%
R4	1	1	9	0	82%
R5	0	1	0	9	90%
Overall Percentage	88%	54%	82%	82%	79.10%

Table 21. Confusion matrix of RI node for the third database

Actual	Predicted				
	None	Light	Moderate	Strong	Percent Correct
None	2	2	1	0	40%
Light	2	12	3	0	71%
Moderate	0	2	9	0	82%
Strong	0	1	0	1	50%
Overall Percentage	50%	71%	69%	100%	60.75%

4.5 Handling missing data

Once models are tested, next belief updating can be performed. One of the main advantages of the BNs over other predictive tools is an ability to deal with incomplete or missing data. The NETICA also has an appropriate feature which gives an opportunity to handle such kind of data if there are any. For instance, we can take following sets of data as input for the first model: E1 = 21.5 (Low), E2 – missing (* or ?), E3 = 12.25 (High), E4 = 0.5

(Low) and PPV = 2.42 (Medium) in which as it can be seen that E2 is missing. For the given condition beliefs were updated resulting in following inference: P (RDS = Moderate | E1 = Low, E3 = High, E4 = Low, PPV = Medium) = 44.4%. For the same conditions P (RDS = None | E1 = Low, E3 = High, E4 = Low, PPV = Medium) = 12.9%, P (RDS = Low | E1 = Low, E3 = High, E4 = Low, PPV = Medium) = 11.4% and P (RDS = Strong | E1 = Low, E3 = High, E4 = Low, PPV = Medium) = 31.3%. As it is presented above likelihood of occurring moderate rockburst is significantly higher than probabilities of other states of the output node. Also, it can be noticed that the results are calculated properly, i.e. without any errors. It means that BN is able to deal with incomplete data.

4.6 Sensitivity analysis

NETICA is capable to produce report on sensitivity analysis. Impact of input parameters on output node was assessed.

4.6.1 First database

As it can be seen from the table 38 PPV has the strongest effect comparing with other parameters while E1 has the least impact on the RDS.

Table 22. Sensitivity analysis of five input parameters of first database

Node	Variance Reduction	Percent	Mutual Info	Percent	Variance of Beliefs
RDS	1.16	100.00	1.91	100.00	0.52
PPV	0.06	4.86	0.04	2.24	0.00
E2	0.04	3.01	0.04	2.14	0.00
E1	0.03	2.91	0.03	1.42	0.00
E4	0.03	2.90	0.02	1.14	0.00
E3	0.01	0.53	0.01	0.67	0.00

4.6.2 Second database

It can be noticed that sensitivity analysis determined that two independent variables including PPV and E2 have more influence on the output.

Table 23. Sensitivity analysis of five input parameters of second database

Node	Variance	Percent	Mutual Info	Percent	Variance of

	Reduction				Beliefs
RDS	1.23	100.00	1.99	100.00	0.56
E2	0.02	1.71	0.03	1.33	0.00
PPV	0.01	1.20	0.01	0.60	0.00
E3	0.01	0.87	0.01	0.55	0.00
E1	0.01	0.84	0.01	0.36	0.00
E4	0.01	0.42	0.01	0.36	0.00

4.6.3 Third database

In the given probabilistic model it can be detected that output node RI is mostly influenced by two input parameters R1 and R4.

Table 24. Sensitivity analysis of input parameters of third database

Node	Variance Reduction	Percent	Mutual Info	Percent	Variance of Beliefs
RI	1.01	100	1.95	100	0.54
R1 (δ_θ)	0.05	4.55	0.05	2.49	0.00
R4 (δ_c)	0.04	4.36	0.05	2.43	0.00
R5 (δ_t)	0.01	0.64	0.02	0.79	0.00
R6 (W_{et})	0.00	0.30	0.02	0.75	0.00
R2 (δ_θ/δ_c)	0.00	0.14	0.01	0.46	0.00
R3 (δ_c/δ_t)	0.00	0.11	0.02	1.05	0.00

CHAPTER 5: DISCUSSIONS

5.1 Discussion of the results

In order to achieve last objective of the research new classification tables were provided. Taking CPTs as a basis and using COUNTIFS function in Excel frequencies of states of input nodes for each intensity of output node where the likelihood is equal or more than 50% were calculated. Results of calculation were included into tables 41-42 and 44. Based on these results new rockburst intensity classification systems which can be used for short-term (databases #1-2) represented in Table 43 and long-term prediction (database #3) presented in Table 45 were proposed.

A rockburst classification system for short-term prediction was constructed using CPTs of two models since both of them have the same input parameters and common output node RDS.

Table 25. Frequency of each state of input nodes for each intensity of output node with probability higher than 50% for the first database

E1	None	Low	Moderate	Strong
0	14	9	10	6
1	17	6	9	3
2	2	3	8	5
3	0	0	0	0
4	0	0	0	0

E2	None	Low	Moderate	Strong
0	0	4	4	4
1	8	5	10	2
2	10	3	4	8
3	14	5	9	0
4	1	1	0	0

E3	None	Low	Moderate	Strong
0	11	8	7	3
1	13	5	13	3
2	9	5	7	8
3	0	0	0	0
4	0	0	0	0

E4	None	Low	Moderate	Strong
0	23	9	12	6
1	4	3	2	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

PPV	None	Low	Moderate	Strong
0	10	3	10	5
1	4	1	8	8
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

Table 26. Frequency of each state of input nodes for each intensity of output node with probability higher than 50% for the second database

E1	None	Low	Moderate	Strong
Low	14	8	9	4
Medium	19	5	8	2
Medium to High	0	0	0	0
High	3	3	8	5
Very High	0	0	0	0

E2	None	Low	Moderate	Strong
Low	0	4	4	3
Medium	9	4	9	1
Medium to High	15	4	8	0
High	11	3	4	7
Very High	1	1	0	0

E3	None	Low	Moderate	Strong
Low	13	8	7	2

E4	None	Low	Moderate	Strong
Low	25	8	11	4

Medium	14	4	12	2
Medium to High	0	0	0	0
High	9	4	6	7
Very High	0	0	0	0
PPV	None	Low	Moderate	Strong
Low	10	3	10	4
Medium	0	0	0	0
Medium to High	4	1	8	6
High	0	0	0	0
Very High	0	0	0	0

Medium	0	0	0	0
Medium to High	4	3	2	0
High	0	0	0	0
Very High	0	0	0	0

Table 27. Proposed rockburst intensity classification (short-term)

	E1	E2	E3	E4	PPV
R2	42.33 – 60.66	8 or 10	5.79 – 8.58	0.5	0 – 1.75
R3	1 – 42.33	5	0 – 5.79	0.5	0 – 1.75
R4	1 – 42.33	5	5.79 – 8.58	0.5	0 – 1.75
R5	60.66 – 114	8 or 10	8.58 – 30	0.5	1.75 – 3.14

As it is demonstrated in the table 43, in order to obtain at least 50% of correct classification for R2, the results of the BN suggested that $42.33 < E1 < 60.66$; $E2 = 8$ or $E2 = 10$; $5.79 < E3 < 8.58$; $E4 = 0.5$; $0 < PPV < 1.75$. Low rockburst (R3) could possibly occurs if the following conditions are met: $1 < E1 < 42.33$; $E2 = 5$; $0 < E3 < 5.79$; $E4 = 0.5$; $0 < PPV < 1.75$. In case if $1 < E1 < 42.33$; $E2 = 5$; $5.79 < E3 < 8.58$; $E4 = 0.5$; $0 < PPV < 1.75$, medium rockburst might probably occur. In order to receive correct classification for R5 with probability above 50%, the outcomes of the model suggested that $60.66 < E1 < 114$; $E2 = 8$ or $E2 = 10$; $8.58 < E3 < 30$; $E4 = 0.5$; $1.75 < PPV < 3.14$.

Table 28. Frequency of each state of input nodes for each intensity of output node with probability higher than 50% for the third database

R4	None	Light	Moderate	Strong
Low	3	5	7	3
Medium	3	3	7	11
High	0	0	1	5

R1	None	Light	Moderate	Strong
Low	5	3	1	2
Medium	1	4	14	11
High	0	1	0	6

R5	None	Light	Moderate	Strong
Low	5	6	10	8
Medium	1	2	5	7
High	0	0	0	4
R3	None	Light	Moderate	Strong
Low	2	1	7	4
Medium	2	5	4	6
High	2	2	4	9

R2	None	Light	Moderate	Strong
Low	2	4	4	5
Medium	1	3	8	8
High	3	1	3	6
R6	None	Light	Moderate	Strong
Low	4	6	6	18
Medium	1	2	9	1
High	1	0	0	0

New rockburst intensity classification system for long-term prediction was built implementing CPTs of the BN constructed using third database.

Table 29. Proposed rockburst intensity classification (long-term)

	R1	R2	R3	R4	R5	R6
None	2.60 - 40.40	162.10 - 304.20	0.40 – 5.95	0.81 – 10.41	0.05 – 0.66	2.52 - 20.52
Light	40.40 – 120.20	20.00 - 91.05	5.95-11.50	0.81 – 5.12	0.05 – 0.66	2.52 - 20.52
Moderate	40.40 – 120.20	91.05 - 162.10	0.40 – 5.95	0.81 – 5.12	0.05 – 0.66	20.52 - 150.51
Strong	40.40 – 120.20	91.05 - 162.10	11.50 – 22.60	5.12 - 10.41	0.05 – 0.66	2.52 - 20.52

As it can be seen from the Table 45, in order to obtain at least 50% of correct classification for no rockburst occurrence, the results of the BN suggested that 2.60 < R1 < 40.40; 162.10 < R2 < 304.20; 0.40 < R3 < 5.95; 0.81 < R4 < 10.41; 0.05 < R5 < 0.66; 2.52 < R6 < 20.52. For light rockburst to be taken place, the results of the BN stated that 40.40 < R1 < 120.20; 20.00 < R2 < 91.05; 5.95 < R3 < 11.50; 0.81 < R4 < 5.11; 0.05 < R5 < 0.66; 2.52 < R6 < 20.52. Moderate rockburst could possibly occur if six input parameters are in the following ranges: 40.40 < R1 < 120.20; 91.05 < R2 < 162.10; 0.40 < R3 < 5.95; 0.81 < R4 < 5.11; 0.05 < R5 < 0.66; 20.52 < R6 < 150.51. For strong rockburst to be occurred, the results of the BN suggested that 40.40 < R1 < 120.20; 91.05 < R2 < 162.10; 11.50 < R3 < 22.60; 5.11 < R4 < 10.41; 0.05 < R5 < 0.66; 2.52 < R6 < 20.52.

5.2 Comparison with existing studies

a) *Database #1 and #2*

Number of studies have used the first database for short term rockburst prediction. As it can be seen from table 46 (Heal 2010) implemented Binomial Logistic Regression technique to evaluate the rockburst intensity and received the model with accuracy which varies from 28% to 71%. While Rock Engineering System proposed by (Li, Zaré, and Jimenez 2019) and the model based on stochastic gradient boosting methods provided by (Zhou et al. 2016) are capable to predict rockburst intensity with accuracy of 71%. Moreover, (Sansyzbekov and Adoko 2021) suggested the model which applies Multinomial Logistic Regression. The proposed model has a capability to correctly evaluate 55-75% of tested data. Comparatively, performance of the BN is slightly higher than other models' accuracies and it gives an opportunity to carefully conclude that Bayesian Network approach is applicable in solving an issue of rockburst intensity for short-term prediction.

Table 30. Summary of comparison with existing results for short-term rockburst prediction

Reference	Methods applied	Accuracy of the model (%)
(Heal 2010)	Binomial Logistic Regression	28 – 71
(Li, Zaré, and Jimenez 2019)	Rock Engineering System	71
(Sansyzbekov and Adoko 2021)	Multinomial Logistic Regression	55 – 75
(Zhou et al. 2016)	Stochastic gradient boosting methods	71
This study	Bayesian Network	76 – 79

b) *Database #3*

Table 47 is assembled to compare performance of the BN model with already established models, which implement SVM, PSO-Extreme Learning, PSO-SVM. As it can be noticed the difference between accuracies of models is not significant. However, according to the table 31 it is observable that performance ability of the newly obtained BN model is about 15-28% lower than other models' accuracies. This can be explained by the fact that the third database is not well balanced.

Table 31. Summary of comparison with existing results for long-term rockburst prediction

Reference	Methods implemented	Accuracy of the model (%)

(Pu et al. 2019)	Support Vector Machine (SVM)	85
(Xue et al. 2020)	Particle swarm optimization (PSO) – Extreme Learning Machine	97.97
(Zhou, Li, and Shi 2012)	PSO – SVM	90 <
This study	Bayesian Network	69

In addition, comparison of performances of three newly obtained models indicates that accuracy of the BN model constructed using third database (long-term) is lower than previous two models built implementing two databases for short-term rockburst prediction. From this it can be carefully stated that Bayesian Network is more appropriate for short-term rockburst prediction rather than for long-term.

CHAPTER 6: CONCLUSIONS

6.1 Summary of the results and limitations

In this study, BN models were implemented for rockburst intensity prediction on the basis of 3 databases with different structures. The results indicated that:

1. First model has demonstrated 76.09% accuracy that can be assumed as acceptable. The model obtained in a result of training the second database correctly predicted 79.10% of all tested data points. The third model has comparatively lower performance ability which was equal to 70%.
2. As it was presented in section 5.2, performances of first two models for short-term rockburst prediction are significantly higher than performance of existing models which used other types of ML algorithms. On the other hand, it can be noticed that accuracy of the third model for long-term rockburst prediction is lower comparing with other proposed models by the existing studies. It can be concluded that BN is more appropriate for short-term rockburst prediction. In general, these results have shown that the received models and classification tables can be considered as a valuable contribution for solving the rockburst prediction issue.
3. Moreover, BN has demonstrated an ability to handle missing data. Since other ML methods experience problems when these types of data are taken place, it can be suggested to apply models based on BN algorithm.

6.2 Study limitations

Nevertheless, it is worth mentioning some of the limitations associated with this research. First, as it was noticed in above sections for ML methods to obtain more reliable models it is more effective to use larger data points. This research implemented Monte-Carlo simulation technique in order to increase the size of the original database. First database was increased from 254 to 477 data points as a result of simulation. However, for ML methods the size of newly obtained database is also not so large. Second limitation is that obtained models were tested only using testing data in NETICA. Further research should address mentioned limitations. Number of data points need to be increased and model evaluation techniques such as k-fold cross validation can be used to test the models more deeply.

6.2 Final conclusions

On the basis of these results, it is concluded that BN can be considered as effective approach and BN based models can be utilized as predictive tools for evaluating rockburst intensity. The results of this research can be readily applied to a mine site. . Using the newly proposed classification system (table), the rockburst intensity can be determined by selecting to which range the given value of each parameter is referring to.

APPENDICES

Table 32. CPT for P(RDS|E1, E2, E3, E4, PPV) % > 25%

E1	E2	E3	E4	PPV	None	Low	Moderate	Strong
Low	Low	Low	Low	Low	0.00	100.00	0.00	0.00
Low	Low	Low	Medium	Low	0.00	66.67	33.33	0.00
Low	Low	Low	Medium	High	0.00	0.00	50.00	50.00
Low	Low	Low	High	Medium	0.00	100.00	0.00	0.00
Low	Low	Medium	Medium	Low	0.00	0.00	100.00	0.00
Low	Low	Medium	Medium	High	0.00	0.00	100.00	0.00
Low	Low	High	Medium	Medium	0.00	0.00	0.00	100.00
Low	Low	High	Medium	High	0.00	0.00	0.00	100.00
Low	Low	High	High	Medium	0.00	0.00	100.00	0.00
Low	Medium	Low	Low	High	0.00	0.00	100.00	0.00
Low	Medium	Low	Medium	Low	33.33	50.00	16.67	0.00
Low	Medium	Medium	Low	Low	0.00	50.00	50.00	0.00
Low	Medium	Medium	Medium	Low	100.00	0.00	0.00	0.00
Low	Medium	Medium	Medium	High	0.00	0.00	100.00	0.00
Low	Medium	Medium	High	Low	100.00	0.00	0.00	0.00
Low	Medium	Medium	High	Medium	0.00	0.00	100.00	0.00
Low	Medium	Medium	High	High	100.00	0.00	0.00	0.00
Low	Medium	High	Low	Low	0.00	25.00	50.00	25.00
Low	Medium	High	Low	Medium	0.00	100.00	0.00	0.00
Low	Medium	High	Medium	Low	66.67	33.33	0.00	0.00
Low	Medium	High	Medium	Medium	0.00	0.00	50.00	50.00
Low	Medium	High	High	Low	100.00	0.00	0.00	0.00
Low	Medium	High	High	Medium	100.00	0.00	0.00	0.00
Low	Medium to High	Low	Low	Low	100.00	0.00	0.00	0.00
Low	Medium to High	Low	Low	Medium	0.00	0.00	100.00	0.00
Low	Medium to High	Low	Low	High	100.00	0.00	0.00	0.00
Low	Medium to High	Low	Medium	Low	66.67	33.33	0.00	0.00
Low	Medium to High	Low	Medium	Medium	100.00	0.00	0.00	0.00

Low	Medium to High	Medium	Low	Low	50.00	50.00	0.00	0.00
Low	Medium to High	Medium	Low	High	33.33	0.00	66.67	0.00
Low	Medium to High	Medium	Medium	Low	100.00	0.00	0.00	0.00
Low	Medium to High	Medium	Medium	High	100.00	0.00	0.00	0.00
Low	Medium to High	High	Medium	Low	100.00	0.00	0.00	0.00
Low	High	Low	Low	Low	0.00	100.00	0.00	0.00
Low	High	Low	Medium	Low	33.33	66.67	0.00	0.00
Low	High	High	Low	Low	0.00	100.00	0.00	0.00
Low	High	High	Low	Medium	0.00	0.00	0.00	100.00
Low	High	High	Low	High	33.33	0.00	0.00	66.67
Low	High	High	Medium	Medium	100.00	0.00	0.00	0.00
Medium	Low	Low	Low	Medium	0.00	0.00	0.00	100.00
Medium	Low	Low	Medium	High	0.00	0.00	100.00	0.00
Medium	Low	Medium	High	Low	0.00	100.00	0.00	0.00
Medium	Medium	Low	Low	Low	0.00	33.33	66.67	0.00
Medium	Medium	Low	Medium	Medium	100.00	0.00	0.00	0.00
Medium	Medium	Medium	Low	Low	0.00	0.00	100.00	0.00
Medium	Medium	Medium	Medium	Low	0.00	100.00	0.00	0.00
Medium	Medium	Medium	Medium	Medium	75.00	0.00	0.00	25.00
Medium	Medium	Medium	Medium	High	0.00	0.00	100.00	0.00
Medium	Medium	High	Low	Medium	0.00	0.00	100.00	0.00
Medium	Medium	High	Medium	Low	50.00	50.00	0.00	0.00
Medium	Medium	High	High	Low	0.00	100.00	0.00	0.00
Medium	Medium to High	Low	Low	Low	100.00	0.00	0.00	0.00
Medium	Medium to High	Low	Medium	Low	50.00	50.00	0.00	0.00
Medium	Medium to High	Medium	Low	High	0.00	100.00	0.00	0.00
Medium	Medium to High	Medium	Medium	Low	50.00	37.50	12.50	0.00
Medium	Medium to High	Medium	Medium	Medium	100.00	0.00	0.00	0.00
Medium	Medium to High	Medium	Medium	High	0.00	0.00	50.00	50.00
Medium	Medium to High	Medium	High	Low	50.00	50.00	0.00	0.00

Medium	Medium to High	High	Medium	Low	0.00	0.00	100.00	0.00
Medium	Medium to High	High	Medium	Medium	100.00	0.00	0.00	0.00
Medium	High	Low	Low	Low	100.00	0.00	0.00	0.00
Medium	High	Low	Low	Medium	0.00	0.00	100.00	0.00
Medium	High	Low	Medium	Medium	100.00	0.00	0.00	0.00
Medium	High	Medium	Low	Low	100.00	0.00	0.00	0.00
Medium	High	Medium	Low	High	0.00	50.00	0.00	50.00
Medium	High	Medium	Medium	Low	100.00	0.00	0.00	0.00
Medium	High	Medium	Medium	Medium	100.00	0.00	0.00	0.00
Medium	High	Medium	Medium	High	100.00	0.00	0.00	0.00
Medium	High	High	Low	Low	100.00	0.00	0.00	0.00
Medium	High	High	Low	Medium	33.33	16.67	33.33	16.67
Medium	High	High	Low	High	0.00	0.00	0.00	100.00
Medium	High	High	Medium	Low	80.00	0.00	20.00	0.00
Medium	High	High	Medium	Medium	100.00	0.00	0.00	0.00
Medium	High	High	Medium	High	0.00	0.00	100.00	0.00
Medium	Very High	Low	Medium	Low	100.00	0.00	0.00	0.00
High	Medium	Low	Medium	Low	40.00	40.00	0.00	20.00
High	Medium	Low	Medium	Medium	33.33	33.33	0.00	33.33
High	Medium	Low	Medium	High	0.00	0.00	0.00	100.00
High	Medium	Medium	Medium	Low	0.00	0.00	100.00	0.00
High	Medium to High	Low	Low	Medium	0.00	0.00	100.00	0.00
High	Medium to High	Low	Medium	Low	60.00	20.00	20.00	0.00
High	Medium to High	Low	Medium	Medium	0.00	66.67	33.33	0.00
High	Medium to High	Medium	Low	Low	0.00	0.00	66.67	33.33
High	Medium to High	Medium	Low	Medium	0.00	0.00	100.00	0.00
High	Medium to High	Medium	Medium	Low	66.67	0.00	33.33	0.00
High	Medium to High	Medium	Medium	Medium	25.00	25.00	50.00	0.00
High	Medium to High	High	Medium	Low	0.00	100.00	0.00	0.00
High	Medium to High	High	Medium	High	0.00	0.00	100.00	0.00

High	High	Low	Low	Medium	0.00	0.00	100.00	0.00
High	High	Medium	Low	High	0.00	0.00	0.00	100.00
High	High	Medium	Medium	Medium	0.00	0.00	0.00	100.00
High	High	High	Low	Low	0.00	0.00	0.00	100.00
High	High	High	Low	High	0.00	0.00	0.00	100.00
High	High	High	Medium	Medium	0.00	0.00	100.00	0.00
High	Very High	Medium	Medium	Low	0.00	100.00	0.00	0.00

Table 33. CPT for P(E1)

Low	Medium	High
32.52	40.78	26.70

Table 34. CPT for P (E2|E1)

E1	Low	Medium	Medium to High	High	Very High
Low	20.40	38.81	23.88	16.42	0.00
Medium	3.57	27.38	27.38	40.48	1.19
High	0.00	20.00	54.55	23.64	1.82

Table 35. CPT for P (E3)

Low	Medium	High
36.41	37.38	26.21

Table 36. CPT for P (E4)

Low	Medium	High
28.16	66.51	5.34

Table 37. CPT for P(PPV)

Low	Medium	High
57.28	27.18	15.53

Table 38. CPT for P(RDS|E1, E2, E3, E4, PPV) > 25%

E1	E2	E3	E4	PPV	None	Low	Moderate	Strong

Low	Low	Low	Low	Low	0.00	100.00	0.00	0.00
Low	Low	Low	Medium	Low	0.00	66.67	33.33	0.00
Low	Low	Low	Medium	High	0.00	0.00	50.00	50.00
Low	Low	Low	High	Medium	0.00	100.00	0.00	0.00
Low	Low	Medium	Medium	Low	0.00	0.00	100.00	0.00
Low	Low	Medium	Medium	High	0.00	0.00	100.00	0.00
Low	Low	High	Medium	Medium	0.00	0.00	0.00	100.00
Low	Low	High	Medium	High	0.00	0.00	0.00	100.00
Low	Low	High	High	Medium	0.00	0.00	100.00	0.00
Low	Medium	Low	Low	High	0.00	0.00	100.00	0.00
Low	Medium	Low	Medium	Low	33.33	50.00	16.67	0.00
Low	Medium	Medium	Low	Low	0.00	50.00	50.00	0.00
Low	Medium	Medium	Medium	Low	100.00	0.00	0.00	0.00
Low	Medium	Medium	Medium	High	0.00	0.00	100.00	0.00
Low	Medium	Medium	High	Low	100.00	0.00	0.00	0.00
Low	Medium	Medium	High	Medium	0.00	0.00	100.00	0.00
Low	Medium	Medium	High	High	100.00	0.00	0.00	0.00
Low	Medium	Medium	Low	Low	0.00	25.00	50.00	25.00
Low	Medium	High	Low	Medium	0.00	100.00	0.00	0.00
Low	Medium	High	Medium	Low	66.67	33.33	0.00	0.00
Low	Medium	High	Medium	Medium	0.00	0.00	50.00	50.00
Low	Medium	High	High	Low	100.00	0.00	0.00	0.00
Low	Medium	High	High	Medium	100.00	0.00	0.00	0.00
Low	Medium to High	Low	Low	Low	100.00	0.00	0.00	0.00
Low	Medium to High	Low	Low	Medium	0.00	0.00	100.00	0.00
Low	Medium to High	Low	Low	High	100.00	0.00	0.00	0.00
Low	Medium to High	Low	Medium	Low	66.67	33.33	0.00	0.00
Low	Medium to High	Low	Medium	Medium	100.00	0.00	0.00	0.00
Low	Medium to High	Medium	Low	Low	50.00	50.00	0.00	0.00
Low	Medium to High	Medium	Low	High	33.33	0.00	66.67	0.00
Low	Medium to High	Medium	Medium	Low	100.00	0.00	0.00	0.00
Low	Medium to High	Medium	Medium	High	100.00	0.00	0.00	0.00

Low	Medium to High	High	Medium	Low	100.00	0.00	0.00	0.00
Low	High	Low	Low	Low	0.00	100.00	0.00	0.00
Low	High	Low	Medium	Low	33.33	66.67	0.00	0.00
Low	High	High	Low	Low	0.00	100.00	0.00	0.00
Low	High	High	Low	Medium	0.00	0.00	0.00	100.00
Low	High	High	Low	High	33.33	0.00	0.00	66.67
Low	High	High	Medium	Medium	100.00	0.00	0.00	0.00
Medium	Low	Low	Low	Medium	0.00	0.00	0.00	100.00
Medium	Low	Low	Medium	High	0.00	0.00	100.00	0.00
Medium	Low	Medium	High	Low	0.00	100.00	0.00	0.00
Medium	Medium	Low	Low	Low	0.00	33.33	66.67	0.00
Medium	Medium	Low	Medium	Low	60.00	20.00	20.00	0.00
Medium	Medium	Low	Medium	Medium	100.00	0.00	0.00	0.00
Medium	Medium	Medium	Low	Low	0.00	0.00	100.00	0.00
Medium	Medium	Medium	Medium	Low	0.00	100.00	0.00	0.00
Medium	Medium	Medium	Medium	Medium	75.00	0.00	0.00	25.00
Medium	Medium	Medium	Medium	High	0.00	0.00	100.00	0.00
Medium	Medium	High	Low	Medium	0.00	0.00	100.00	0.00
Medium	Medium	High	Medium	Low	50.00	50.00	0.00	0.00
Medium	Medium	High	High	Low	0.00	100.00	0.00	0.00
Medium	Medium to High	Low	Low	Low	100.00	0.00	0.00	0.00
Medium	Medium to High	Low	Low	Low	100.00	0.00	0.00	0.00
Medium	Medium to High	Low	Medium	Low	50.00	50.00	0.00	0.00
Medium	Medium to High	Medium	Low	High	0.00	100.00	0.00	0.00
Medium	Medium to High	Medium	Medium	Low	50.00	37.50	12.50	0.00
Medium	Medium to High	Medium	Medium	Medium	100.00	0.00	0.00	0.00

Medium	Medium to High	Medium	Medium	High	0.00	0.00	50.00	50.00
Medium	Medium to High	Medium	High	Low	50.00	50.00	0.00	0.00
Medium	Medium to High	High	Medium	Low	0.00	0.00	100.00	0.00
Medium	Medium to High	High	Medium	Medium	100.00	0.00	0.00	0.00
Medium	High	Low	Low	Low	100.00	0.00	0.00	0.00
Medium	High	Low	Low	Medium	0.00	0.00	100.00	0.00
Medium	High	Low	Medium	Medium	100.00	0.00	0.00	0.00
Medium	High	Medium	Low	Low	100.00	0.00	0.00	0.00
Medium	High	Medium	Low	High	0.00	50.00	0.00	50.00
Medium	High	Medium	Medium	Low	100.00	0.00	0.00	0.00
Medium	High	Medium	Medium	Medium	100.00	0.00	0.00	0.00
Medium	High	Medium	Medium	High	100.00	0.00	0.00	0.00
Medium	High	High	Low	Low	100.00	0.00	0.00	0.00
Medium	High	High	Low	Medium	33.33	16.67	33.33	16.67
Medium	High	High	Low	High	0.00	0.00	0.00	100.00
Medium	High	High	Medium	Low	80.00	0.00	20.00	0.00
Medium	High	High	Medium	Medium	100.00	0.00	0.00	0.00
Medium	High	High	Medium	High	0.00	0.00	100.00	0.00
Medium	Very High	Low	Medium	Low	100.00	0.00	0.00	0.00
High	Medium	Low	Medium	Low	40.00	40.00	0.00	20.00
High	Medium	Low	Medium	Medium	33.33	33.33	0.00	33.33
High	Medium	Low	Medium	High	0.00	0.00	0.00	100.00
High	Medium	Medium	Medium	Low	0.00	0.00	100.00	0.00
High	Medium to High	Low	Low	Medium	0.00	0.00	100.00	0.00
High	Medium to High	Low	Medium	Low	60.00	20.00	20.00	0.00
High	Medium to High	Low	Medium	Medium	0.00	66.67	33.33	0.00

High	Medium to High	Medium	Low	Low	0.00	0.00	66.67	33.33
High	Medium to High	Medium	Low	Medium	0.00	0.00	100.00	0.00
High	Medium to High	Medium	Medium	Low	66.67	0.00	33.33	0.00
High	Medium to High	Medium	Medium	Medium	25.00	25.00	50.00	0.00
High	Medium to High	High	Medium	Low	0.00	100.00	0.00	0.00
High	Medium to High	High	Medium	High	0.00	0.00	100.00	0.00
High	High	Low	Low	Medium	0.00	0.00	100.00	0.00
High	High	Low	Medium	Low	50.00	50.00	0.00	0.00
High	High	Medium	Low	High	0.00	0.00	0.00	100.00
High	High	Medium	Medium	Low	50.00	25.00	25.00	0.00
High	High	Medium	Medium	Medium	0.00	0.00	0.00	100.00
High	High	High	Low	Low	0.00	0.00	0.00	100.00
High	High	High	Low	High	0.00	0.00	0.00	100.00
High	High	High	Medium	Medium	0.00	0.00	100.00	0.00
High	Very High	Medium	Medium	Low	0.00	100.00	0.00	0.00

Table 39. CPT for P(E1)

Low	Medium	High
32.52	40.78	26.70

Table 40. CPT for P (E2| E1)

E1	Low	Medium	Medium to High	High	Very High
Low	20.90	38.81	23.88	16.42	0.00
Medium	3.57	27.38	27.38	40.48	1.19
High	0.00	20.00	54.55	23.64	1.82

Table 41. CPT for P (E3)

Low	Medium	High
36.41	37.38	26.21

Table 42. CPT for P (E4)

Low	Medium	High
28.16	66.51	5.34

Table 43. CPT for P(PPV)

Low	Medium	High
57.28	27.18	15.53

Table 44. CPT for P(RI|R1, R2, R3, R4, R5, R6)

R4	R1	R5	R2	R3	R6	None	Light	Moderate	Strong
Low	Low	Low	Low	Low	Low	45.45	9.09	36.36	9.09
Low	Low	Low	Low	Low	Medium	20.83	25.00	41.67	12.50
Low	Low	Low	Low	Medium	Low	50.00	25.00	25.00	0.00
Low	Low	Low	Low	High	Low	0.00	100.00	0.00	0.00
Low	Low	Low	Medium	Low	Medium	39.13	43.48	8.70	8.70
Low	Low	Low	Medium	Medium	Low	7.69	46.15	38.46	7.69
Low	Low	Low	Medium	Medium	Medium	0.00	100.00	0.00	0.00
Low	Low	Low	Medium	High	Low	60.00	10.00	10.00	20.00
Low	Low	Low	High	High	Low	0.00	0.00	0.00	100.00
Low	Low	Medium	Low	Low	Low	50.00	0.00	0.00	0.00
Low	Medium	Low	Low	Low	Low	0.00	100.00	0.00	0.00
Low	Medium	Low	Low	Low	Medium	0.00	40.00	60.00	0.00
Low	Medium	Low	Low	Medium	Low	0.00	100.00	0.00	0.00
Low	Medium	Low	Medium	Low	Low	0.00	33.33	50.00	16.67
Low	Medium	Low	Medium	Low	Medium	0.00	46.67	40.00	13.33
Low	Medium	Low	Medium	Medium	Low	0.00	46.15	46.15	0.00
Low	Medium	Low	Medium	Medium	Medium	16.67	33.33	33.33	16.67
Low	Medium	Low	Medium	High	Low	0.00	50.00	25.00	25.00
Low	Medium	Low	High	Medium	Low	0.00	50.00	50.00	0.00
Low	Medium	Low	High	Medium	Medium	0.00	0.00	57.14	42.86
Low	Medium	Low	High	High	Low	0.00	0.00	0.00	100.00

Low	Medium	Medium	Low	Low	Low	62.50	37.50	0.00	0.00
Low	Medium	Medium	Low	Low	Medium	0.00	0.00	100.00	0.00
Low	Medium	Medium	Low	Medium	Low	20.00	40.00	40.00	0.00
Low	Medium	Medium	Medium	Low	Medium	0.00	0.00	100.00	0.00
Low	Medium	Medium	Medium	Medium	Low	0.00	40.00	20.00	40.00
Low	Medium	Medium	Medium	Medium	Medium	0.00	0.00	100.00	0.00
Low	Medium	Medium	Medium	High	Low	0.00	0.00	0.00	100.00
Low	Medium	Medium	High	Low	Medium	0.00	0.00	100.00	0.00
Medium	Low	Low	Low	Low	Low	0.00	0.00	0.00	100.00
Medium	Low	Low	Low	Low	Medium	0.00	0.00	60.00	40.00
Medium	Low	Low	Medium	Low	Medium	28.57	28.57	42.86	0.00
Medium	Low	Low	Medium	Medium	Low	0.00	100.00	0.00	0.00
Medium	Low	Low	High	Low	Medium	50.00	50.00	0.00	0.00
Medium	Low	Low	High	Low	High	100.00	0.00	0.00	0.00
Medium	Low	Low	High	Medium	Medium	100.00	0.00	0.00	0.00
Medium	Low	Low	High	High	Low	100.00	0.00	0.00	0.00
Medium	Medium	Low	Low	Low	Low	0.00	0.00	0.00	100.00
Medium	Medium	Low	Low	High	Low	0.00	0.00	100.00	0.00
Medium	Medium	Low	Medium	Low	Medium	0.00	13.33	60.00	26.67
Medium	Medium	Low	Medium	Medium	Low	0.00	14.29	42.86	42.86
Medium	Medium	Low	Medium	Medium	Medium	0.00	0.00	100.00	0.00
Medium	Medium	Low	Medium	High	Low	0.00	0.00	50.00	50.00
Medium	Medium	Low	High	Medium	Medium	0.00	35.71	42.86	21.43
Medium	Medium	Low	High	Medium	Low	0.00	25.00	50.00	25.00
Medium	Medium	Low	High	High	Low	0.00	20.00	20.00	60.00
Medium	Medium	Medium	Low	Low	Low	0.00	0.00	50.00	50.00
Medium	Medium	Medium	Low	Low	Medium	0.00	0.00	33.33	66.67
Medium	Medium	Medium	Low	Medium	Low	0.00	100.00	0.00	0.00
Medium	Medium	Medium	Low	High	Low	0.00	0.00	50.00	50.00
Medium	Medium	Medium	Medium	Low	Medium	0.00	0.00	50.00	50.00
Medium	Medium	Medium	Medium	Medium	Low	0.00	28.57	14.29	57.14
Medium	Medium	Medium	Medium	High	Low	0.00	0.00	100.00	0.00
Medium	Medium	Medium	High	High	Low	0.00	0.00	0.00	100.00
Medium	High	Medium	Medium	High	Low	0.00	50.00	0.00	50.00
Medium	High	Medium	High	Medium	Low	0.00	0.00	0.00	100.00
Medium	High	Medium	High	Medium	Medium	0.00	100.00	0.00	0.00
Medium	High	High	Low	Low	Low	0.00	0.00	0.00	100.00
Medium	High	High	Low	High	Low	0.00	0.00	0.00	100.00
Medium	High	High	Medium	Medium	Low	0.00	0.00	0.00	100.00

High	Medium	Low	Medium	Medium	Low	0.00	0.00	0.00	100.00
High	Medium	Low	Medium	High	Low	0.00	0.00	100.00	0.00
High	Medium	Low	High	High	Low	0.00	0.00	0.00	100.00
High	Medium	Medium	Medium	Medium	Low	0.00	0.00	0.00	100.00
High	Medium	Medium	Medium	High	Low	0.00	0.00	50.00	50.00
High	High	Medium	Medium	Medium	Low	0.00	0.00	0.00	100.00
High	High	High	Medium	High	Low	0.00	0.00	0.00	100.00

Table 45. CPT for P(R1) in percentage

Low	Medium	High
36.16	58.31	5.54

Table 46. CPT for P(R2) in percentage

Low	Medium	High
28.66	54.40	16.94

Table 47. CPT for P(R3|R2) in percentage

R2 (δ_c)	Low	Medium	High
Low	76.14	14.77	9.09
Medium	41.32	41.92	16.77
High	7.69	71.154	21.15

Table 48. CPT for P(R4|R1) in percentage

R1 (δ_θ)	Low	Medium	High
Low	82.88	17.12	0.00
Medium	51.96	44.13	3.91
High	0.00	76.47	23.53

Table 49. CPT for P(R5|R1) in percentage

R1 (δ_θ)	Low	Medium	High
Low	98.20	1.80	0.00
Medium	73.74	26.26	0.00

High	0.00	29.41	70.59

Table 50. CPT for P(R6) in percentage

Low	Medium	High
52.77	46.91	0.33

CHAPTER 7: REFERENCES

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