A BAYESIAN NETWORK ANALYSIS FOR SAFETY MANAGEMENT

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ABSTRACT
This paper presents a methodology for safety analysis at workplace. The methodology incorporates Bayesian approach to assess the safety associated with safety requirements specifications. In this paper we propose a particular bayesian network, called Knowledge Driven Bayesian Network (KDBN), able to solve the problem of data availability thanks to the particular structure of the network itself. A case study based on marble industry is used to demonstrate the methodology.

Keywords: bayesian network, safety, prevention, decision support analysis

1. INTRODUCTION

The 19th century and first half of the 20th century is one of those periods in history of rapid economical, technical and social changes (Swuste et al., 2010). In this period occupational safety is developing into a professional field. Since then, the concept of safety culture has attracted a great deal of research attention from a range of academic disciplines (Parker et al., 2006; Falcone *et al.*, 2007 a).

Empirical research on safety climate and safety culture has developed considerably but, unfortunately, theory has not been through a similar progression (Guldenmund, 2000; Falcone *et al. 2007* b). Techniques used to manage accident prevention in companies include accident analyses, accident investigations, safety inspections and incident recall, etc. (Martín et al., 2009; Silvestri *et al*., 2012; De Felice and Petrillo, 2012).

Effective approaches to defining the interplay between variables have been developed by authors, for example, using structural equation models (Paul and Maiti, 2007). In the present work we use an approach based on Bayesian Networks (BNs) to describe the circumstances (and relationship between circumstances) associated with tasks performed.

In particular our aim is to provide a "system" for the automatic control of the safety of workers, that, from one side, may lower the cost of development of the security project, supporting the operator, and on the other side may ensure a higher quality of the final result.

Assuming that the effectiveness of a security project strongly depends on the *know-how* of the company that produces it, the existence of mechanisms for the exchange of know-how is of great importance for a company: the stratification of know-how can occur in various ways, such as through the experience of the staff or through the mere storage of past projects.

The proposed system regulates the stratification and the exchange of know-how; it is based on a database, called the knowledge-base, which contains aspects of know-how related to the activities, subject to the risk of dangerous events, which can generate different types of damage; in more detail the database contains the know-how organized as a catalog of predictors of risk associated with work activities.

The application part of the system, based on the written information in the database, automatically calculates the risk to which a worker is subjected when performing a certain activity.

The objective is therefore to allow, on one side, to stratify the experience of the operators, and on the other side to make "repeatable" and "less subjective" the risk assessment of an activity; moreover the use of computational methods for the risk assessment makes the effectiveness of the security project more measurable, both a priori, with the predictors, and a posteriori, with a matching between the statistical data and prediction models.

The paper is structured in section 2 in which literature review is presented; section 3 in which problem statement is analyzed; section 4 in which methodological approach is defined and finally conclusions and results are presented.

2 LITERATURE REVIEW

There has been a steady growth of interest in the application of Bayesian Network (BN) to risk analysis due to its capability to model complex system (Lu *et al*., 2011).

The BN is "a theory of reasoning from uncertain evidence to uncertain conclusions" because it can conduct the factorization of the joint distribution of variables according to the conditional dependencies (Dempster, 1990). BNs have been applied in several knowledge areas.

In Table 1 is shown a brief report on some papers present in literature.

Table 1: Major works on BNs

Authors	Year	Topic
Zhu and Deshmukh	2003	Business risk and product life-cycle analysis
Matías et al.	2008	construction and mining accidents
Adriaenssens et al.	2004	Ecology
Marcot et al. Baran and Jantunen Matías et al.	2001 2004 2006	Environmental assessment impact
Flage et al.	2012	Maintenance optimization model
Antal et al	2007	Medicine
Martín et al. Papazoglou et al.	2009 2006	Risk of falls
Huang and Abdel-At Miranda-Moreno et al.	2010 2013	Traffic and Road safety analysis
Galán et al. Zhang et al.	2007 2013	Workplace risk area

3. PROBLEM STATEMENT

According to the guidelines of the Legislative Decree 81/08, the risk to the health and safety of workers in the performance of their duties can be evaluated through the Equation (1):

$$R = PxD \tag{1}$$

where D is the magnitude of damage value and P is the probability of occurrence of a dangerous event.

The probability P depends on many factors: it depends on the activity the worker is doing, so it may depend from the equipment used, from the working environment, etc. Be x a generic activity that the worker is doing, the Equation 1 can be rewritten as follow:

$$R_o = P(D|x \epsilon X) * Damage\ Value \tag{2}$$

where X is the set of all the activities that a worker, depending on the role and the working field, is called upon to perform; R_o is the original risk, i.e. the risk to which a worker is subjected if requirements for safety will not be respected.

Furthermore, we can say that, fixed a certain working field and a certain role, a worker is potentially exposed to a set of dangerous events (a vector $\underline{\varepsilon}$), which can produce a damage to the worker.

When some requirements for safety are respected, the risk decreases, hence we introduce $R_t(x)$ as the risk at time t, which is a function of requirements for safety; but the risk also depends on other factors, such as wrong behavior or improper training of workers, or wrong organization of the working area.

We can consider these last three factors as some of causes that can potentially result in a dangerous condition to the worker. Consequently the probability of damage depends on the same factors, hence the whole problem is well described by the joint probability, see Equation 3:

$$R_t(x) = P\left(D|\underline{\varepsilon}, \underline{C}, \underline{DB}, x \in X\right) * Damage\ Value \tag{3}$$

where $\underline{C}$ is a the vectors of causes and $\underline{DB}$ is the vectors of duties and bans, i.e. requirements for safety.

In this context, the Bayesian networks are a useful tool for calculating the joint probability. However, the Bayes networks require a huge amount of statistical data to be reliable, which could be not available on the first use of the system.

The statistical data are usually accumulated in long time intervals, more over they are difficult to find in the literature; our proposal is a particular Bayes network, called Knowledge Driven Bayesian Network (KDBN), that solves the problem of availability of data, since, as said before, it allows operators experts in security to transfer part of their know-how in the model of risk assessment, due to the particular structure of the network itself.

The network KDBN exploits the a-priori knowledge of the experts on security and requires a much smaller amount of data to be operative. The result of our study is a model useful to identify the circumstances that have the greatest bearing on workplace accidents during working activities. A real case study will be analyzed.

4. METHODOLOGICAL APPROACH

This paper aims to address two related issues when applying hierarchical Bayesian models for marble industry. A simulation framework was developed to evaluate the performance of alternatives.

4.1 Mathematical model

Face a real problem, with a growing number of variables in relationships between them, requires tools that allow us to manage and assess uncertainty. A quantitative approach that allows the integration of uncertainty in the reasoning, comes from the Bayesian networks: powerful mathematical and conceptual tools that allow applications to manage complex problems with a large number of variables, bound together by probabilistic and deterministic relationships.

Bayesian networks (BNs), also known as belief networks (or Bayes nets for short), belong to the family of probabilistic graphical models (GMs). These graphical structures are used to represent knowledge about an uncertain domain. In particular, each node in the graph represents a random variable, while the edges between the nodes represent probabilistic dependencies among the corresponding random variables.

A Bayesian network specifies a joint distribution, which describes the problem, in a structured form, represented dependence/independence via a directed graph; in general, given the bayesian network, the full joint probability is defined as follows, see Equation 4:

$$p\ (X_1, X_2, \ldots X_N) = \prod_i p\ (X_i | parents(X_i)) \tag{4}$$

where parents (X_i) are all parents nodes influencing the child node X_i.

In this section we describe the proposed model by applying it to a problem of safety in the marble industry. Table 2 shows some statistical data. The proposed method adopts a Bayesian probabilistic model to efficiently manage various uncertainties that can occur in the sector of stone extraction and processing, subjected to dangerous events related to the use of explosives or to cutting tools etc.

As said before, BNs allow the understanding of a complex problem, thanks to the definition of the links between the involved random variables. BNs require two components:

1. The graph structure (conditional independence assumptions).
2. The numerical probabilities (for each variable given its parents).

Thanks to the a-priori knowledge of the problem we can define the structure of the network, depicted in Figure 3.

Set a particular kind of dangerous event (ε = Rising, Slip, Tumble, Crash), the diagram of Figure 3 correlates all the variables involved. The variables in green circles are predisposing the dangerous event, then they represent the causes of the dangerous event. When a dangerous event occurs, it can result in a damage, that can be very serious, serious, slight or very slight; in the white circles the cases that the occurrence of a dangerous event does not involve in damage (Near messes and No Damage) are represented, that are fortunately much more recurring. The variables in gray circles represent the requirements of safety and, if applied, decrease the probability of the variables (in green circles) predisposing the danger. In the proposed model safety requirements are called duties and bans (DB). In the gray circles there are also Personal Protective Equipments (PPE), like gloves, safety shoes and safety glasses, which decrease the probability of the cause, but they also decrease the entity of damage (this type of relationship is represented by arrows from DBs, in gray circles, to damages, in red circles).

The model just described is contextualized in a particular case. Our proposal is a generic model, shown in the Figure 4, which is valid for all cases concerning safety at work. We assume relationship between events and damages is always the same for different events and conditional probabilities can change in relation to the events. In the green circles the generic causes predisposing a dangerous event: for example "poor illumination" and "structural deficiencies" of Figure 4 are represented, in the generic model, with "working area not-adequate" and "organization".

Table 2: Marble industry – Italian statistical data for Accident (2011) - Number of cases 33,178

Events	Damages	Causes	Probability of Damage	Severity of the damage	Personal protective equipment (PPE)
Pick up Slip Falling Bump	Dislocation, distortion, distraction	Structural deficiencies Poor Illumination	Very serious damage	Serious	Safety Shoes Education / Information Safety Signs Ergonomics
Pick up Slip Falling Bump	Contusion	Structural deficiencies Poor Illumination	Very serious damage	Medium	Education / Information Ergonomics
Pick up Slip Falling Slice	Injuries	Equipment non complying	Serious damage	Serious	Education / Information Ergonomics
Pick up Slip Falling Bump	Fracture	Structural deficiencies Poor Illumination	Serious damage	Medium	Education / Information Ergonomics
Skin contact Slice	Foreign objects	Equipment non complying Presence of irritant or flammable substances	Slight damage	Slight	Education / Information Safety goggles Protective gloves
Pick up	Strain injury	Structural deficiencies	Slight damage	Medium	Education / Information Ergonomics
Skin contact Inhale	Injuries caused by other agents	Presence of irritant or flammable substances	Slight damage	Medium	Education / Information Safety goggles Protective gloves
Crush Inhale Ingest	Anatomical loss	Equipment non complying Presence of irritant or flammable substances	Very Slight damage	Medium	Education / Information Ergonomics

In the lower part of the figure, the DBs (i.e. the safety requirements) are represented in the gray circles, which, if respected, lower the probability of the causes and therefore the likelihood of dangerous event.

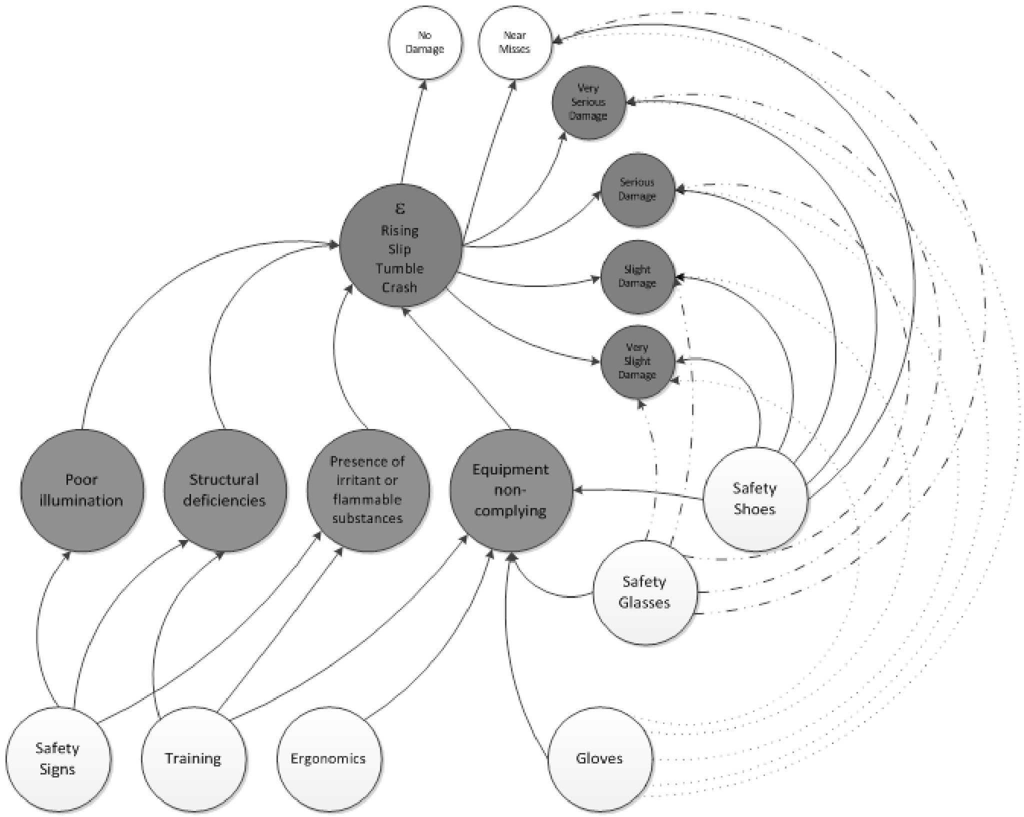

Figure 3: Specific Model

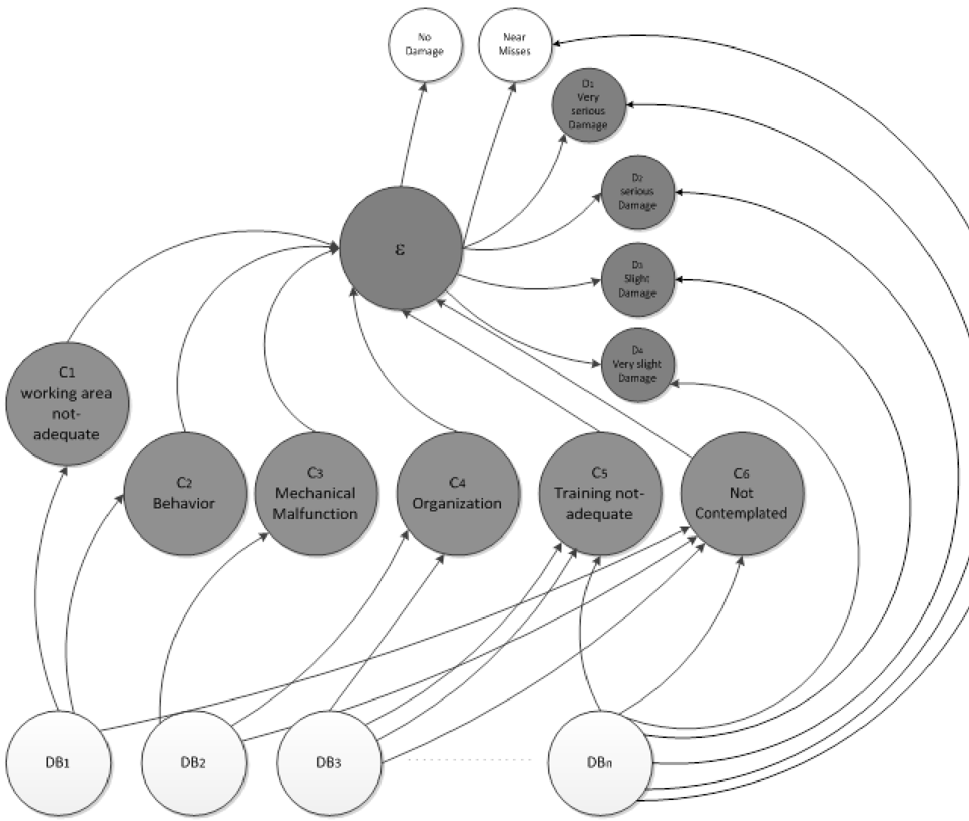

Figure 4: Generic Model

In this paper a risk assessment algorithm, which implements the Bayesian Network already illustrated, are proposed.

The network's learning is achieved by using a set of parameters conveniently chosen, in order to take into account some special or not contemplated cases: for example, no dangerous events can happen, or there is no cause although dangerous events and damages are present, or, even more, no damage occurs even if a dangerous event takes place.

Table 3 illustrates the model's parameters, their physical meaning and the way in which they have been defined and evaluated.

Table 3: Parameters used in the Dynamic risk assessment algorithm

PARAMETERS	PHYSICAL MEANING
$\alpha = P(NotC = 1)$	It represents the probability of the *not contemplated cause*, which corresponds to any cause not comprised into the set C_1, ..., C_6 previously defined. In other words, α indicates how the model is adherent to the reality: as lower the value of α is, as more corresponding to the real situation the model is.
$\beta = p$ where $p = P(C_i = 1) = \frac{\#causes}{\#observations}$	It represents the probability that a given causes, among the set C_1, ..., C_6, occurs. A possible evaluation of this parameter comes from the experience at working sites: it is defined as the ratio between the times in which the given cause C_i occurs and the number of total observations.
$\gamma = 1 - P(\varepsilon_R)$ where $\varepsilon_R = \bigcup_i \varepsilon_i$ represents the combination of all the dangerous events.	This parameter represents the probability that no dangerous events occur.
$\delta = 1 - \frac{\#not\ compliance}{\#observations}$	This parameter represents the company's reliability.
$\phi = \frac{\#days\ \ no\ damages\ occurred}{\#working\ days}$	The meaning of this parameter is expressed in terms of 1-ϕ, which is the accidents' rate, i.e. the frequency of accidents' occurrence, measured in days and number of injured workers.

4.2 Algorithm implementation

The aim of the risk assessment algorithm is to provide the probability of occurrence of one of the risk reported in Table 4:

Table 4: Types of risk

Ro	Original Risk	$R_o(x) = P(D \mid x \in X) * DamageValue$ It is defined by considering no DBs applied.
R_t	Risk at time t	$R_t(x) = P(D_i \mid x \in X, \underline{DB}) * DamageValue$ This kind of risk is computed at time t, by considering only the DBs satisfied (possibly not the DBs requested by the project safety plan.
R_P	Project risk	$R_P = P(D_i \mid x \in X, \underline{DB}) * DamageValue$ This kind of risk is evaluated by considering all DBs requested by the project safety plan.
R_{RES}	Residual Risk	This kind of risk represents the inferior limit of the risk's value, below which, even all the DBs are satisfied, the risk cannot assume any value.

x is the activity that workers are performing and that typically exposes them to a certain risk. The algorithm is conveniently adjusted on the model's parameters previously described in Table 3. The output of the algorithm is expected to be a dynamic risk R_t that, given the maximum permissible risk R_{MAX}, satisfying the following condition, see Equation 5:

$$R_{RES} < R_P < R_{MAX} < R_o \tag{5}$$

where the worst (most dangerous) situation occurs when: $R_{MAX} < R_t < R_o$.

In order to calculate the risk at the time t, $\mathbf{R_t}$, given a certain activity x, we are interested in the calculation of the following probability (Equation 6):

$$\boldsymbol{P(D_i \mid \underline{DB})} = \sum_{\mathbf{m}} \sum_{\mathbf{n}} \mathbf{P}(\mathbf{D_i}, \boldsymbol{\varepsilon_m}, \underline{\mathbf{C_n}} \mid \underline{\mathbf{DB}}) \tag{6}$$

which represents the probability of the damage D_i, when a vector of duty and buns are respected. The summation for m takes into consideration all possible dangerous events (ε_m), while the summation for n takes into consideration all possible combination of the causes predisposing the dangerous event ε_m. The probability in the second member of Equation 6, thanks to the relations set in the Bayesian network of Figure 4, can be written as follows (Equation 7):

$$P\left(D_i, \varepsilon_m, \underline{C_n} \middle| \underline{DB}\right) = P(D_i \mid \varepsilon_m, \underline{DB}) P\left(\varepsilon_m \middle| \underline{C_n}\right) P\left(\underline{C_n} \middle| \underline{DB}\right) \tag{7}$$

Defined the structure of the network, we need the numerical probabilities, i.e. a sufficient number of statistics that allow us to define the conditional probabilities of the formula. The available data on the sector of marble industry, are unfortunately insufficient, frequently not reliable, incomplete and lacking in degree of detail. The selection and retrieval of data, both historical statistics or deducted through the control and measurements made by experts, is a very important aspect that influence the reliability of the system. A Bayesian network is able to accumulate, in a rather long time, the statistical data defining the problem, that are difficult to find in the literature. However, the system, in order to be reliable at the first start, needs of a great deal of data; in this paper we propose a particular bayesian network, called Knowledge Driven Bayesian Network (KDBN), able to solve the problem of data availability thanks to the particular structure of the network itself, which allows experienced operators (in this case in road safety) to transfer part of their know-how in the system.

Nowadays the term "know-how" means all technical, industrial and commercial knowledge, often secret, of a company, it is a competitive asset of extraordinary importance for any business. Because of its importance, its management must be careful; indeed the know-how is the most fragile asset, its value can be subjected to leaks of information, perhaps caused by disloyal employees; but its fragility is also linked to the difficulty encountered in the transfer of Know-How from experienced to less experienced employees inside the same company.

The KDBN exploits the a-priori knowledge and requires a much smaller amount of data to be operational; it is based on a database of specific knowledge (that could be empty at the first), and allows the expert operator to insert probability data based on its experience and personal evaluations (hence to insert part of its know-how) so as to allow the system to stratify and to share with all in the company.

We discuss below the calculation of each factor in the right side of Equation 7:

- $\boldsymbol{P(D_i|\varepsilon_m, \underline{DB})}$

The computation of this probability is related to the parameter Φ, which represents, as described in Table 3, the probability of "No Damage" (see Figure , i.e. $\Phi = \mathrm{P(NotD)}$. The term $\mathrm{P}(\mathrm{D_i}|\varepsilon_\mathrm{m}, \underline{\mathrm{DB}})$ must be weighted with (1-Φ) as follows (Equation 8):

$$P(D_i|\varepsilon_m, \underline{DB}) = \begin{cases} (1-\Phi)\mathrm{P}' & \text{if } D_\mathrm{i} \neq \mathrm{NotDamage} \\ \Phi + (1-\Phi)\mathrm{P}' & \text{if } D_\mathrm{i} = \mathrm{NotDamage} \end{cases} \quad (8)$$

where P' is given as follows (Equation 9):

$$P' = P(D_i|\varepsilon_m)P_R(D_i|\underline{DB}) + P(D_{i+1}|\varepsilon_m)[1 - P_R(D_{i+1}|\underline{DB})] \quad (9)$$

The duty and bans (DB), which act directly on the damage (PPE), have the effect of reducing the extent of damage; in other words we can say that the PPEs reduce the probability of the damage D_{i+1}, of greater extent, and increase the damage D_i, of less extent. The equation 9 expresses this concept, where the term $P_R(D_i|\underline{DB})$ is the residual probability of the damage D_i, with the application of $\underline{DB}$ and having transfer his discount to the damage D_{i-1}.

- $\boldsymbol{P(\varepsilon_m|\underline{C_n})}$

In this case we have to consider the parameter γ, which is the probability of the Not-Dangerous event, in fact (Equation 10):

$$\gamma = P(\varepsilon_{NotD}) = 1 - P(\varepsilon_R) \quad (10)$$

A particular combination of the causes $\underline{\mathrm{C_n}}$ predisposes to a dangerous event ε_m, and, at the same time, reduces the $\mathrm{P}(\varepsilon_\mathrm{NotD})$, this implies that the probability $\mathrm{P}(\varepsilon_\mathrm{NotD})$ is reduced of a portion equal to the sum of all portions subtracted to it and transferred to the dangerous events.
Therefore, set a dangerous event $\varepsilon_\mathrm{m} \neq \varepsilon_\mathrm{NotD}$, the probability is as follows (Equation 11):

$$P(\varepsilon_m|\underline{C_n}) = P_o(\varepsilon_m) + \sum_j P_o(\varepsilon_{NotD})P_o(\varepsilon_m)P_L(\varepsilon_m|C_j) \quad (11)$$

where $\mathrm{P_o}(\varepsilon_\mathrm{m})$ is the original probability of the event (ε_m) and we assume it is given by the formula below (Equation 12):

$$P_o(\varepsilon_m) = \begin{cases} \gamma & \text{if } \varepsilon_m = \varepsilon_{NotD} \\ \frac{1}{K-1}(1-\gamma) & if\ \varepsilon_m \neq \varepsilon_{NotD} \end{cases} \quad (12)$$

where K is the number of dangerous events.

- $\boldsymbol{P(\underline{C_n}|\underline{DB})}$

It represents the probability of the causes combination $\underline{\mathrm{C_n}}$ to occur given the application of a combination of duty and bans $\underline{\mathrm{DB}}$. The D&Bs, if applied, reduce the possibility that a certain union of causes generates a dangerous event. Therefore, also in this case the discount mechanism can be used: the reduction introduced by the application of the DBs does affect directly the so called 'Not-Contemplated Cause', that is any cause which does not belong to the set $C_1, \ldots, C_k$ (where K is the number of causes define for the network model). We may indicate with $P_R(C_i|DB_j)$ the residual probability of the cause C_i given that the duty and ban DB_j – hence the discount - has been applied. If all the $\underline{\boldsymbol{DB}}$ are considered, the probability $P(C_i|\underline{DB})$ can be expressed as follows (Equation 13):

$$P(C_i|\underline{DB}) = p \cdot \prod_{j=1}^{L} P_R(C_i|DB_j) \quad (13)$$

where L is the number of duty and bans applied. p, that represents the marginal probability of the occurrence of the cause C_i, is defined in relation to the α and β parameters previously described:

$$p = \begin{cases} \alpha & if\ C_i\ is\ the\ Not\ contemplated\ Cause \\ \beta & otherwise \end{cases}$$

In order to define the overall probability $P(\underline{C_n}|\underline{DB})$ a further parameter should be introduced. The expression of this probability is (Equation 14):

$$P(\underline{C_n}|\underline{DB}) = (1-\delta') \cdot P'' \quad (14)$$

Let's define at first the parameter δ'. Supposing to model the situation in which some of the causes are *on* – i.e. some causes occurred – as a Bernoulli random process, we may define δ' as the probability of having an entire combination of null causes when the bernoullian process is off. The situation of having all causes equal to zero may happen either if the modeling process is off and if the modeling process is on but no cause occurs. This situation can be expressed with the following formulation (Equation 15):

$$\delta = \delta' + (1-\delta')\cdot\delta'' \quad \rightarrow \quad \delta' = \frac{\delta-\delta''}{1-\delta''} \tag{15}$$

where δ is the probability of having all null causes, while $(1-\delta')\cdot\delta''$ is the probability of having all causes equal to zero since the process is on but no causes occurs. δ'' is not a real parameter for the network model, since it depends by the probability $P(C_i|\underline{DB})$ as follows:

$$\delta'' = \prod_{i=1}^{K}(1 - P(C_i|\underline{DB}) \tag{16}$$

where K is the number of causes of the network model. Turning back to the equation defining $P\left(\underline{C_n}\middle|\underline{DB}\right)$, we have to define what P'' represents. It corresponds to the product of the probabilities $P(C_i|\underline{DB})$ considered as follows:

$$P_c = \begin{cases} P(C_i|\underline{DB}) & if\ C_i = 1 \\ 1 - P(C_i|\underline{DB}) & if\ C_i = 0 \end{cases}$$

$$P'' = \prod_{i=1}^{K} P_c$$

4.3 Data Collection

The risk assessment algorithm implements the computation of the risk's probability regarding a given network starting by the knowledge of the following conditional probabilities: 1) $P(\varepsilon|C_i)$; 2) $P(D_i|\varepsilon)$; 3) $P(D_i|\underline{DB})$; 4) $P(C_i|\underline{DB})$. These probabilities, whose values are archived in database, defined the KDBN – *Knowledge Driven Bayesian Network*.

They are provided as inputs to the KDBN network as a-priori knowledge coming from the expertise acquired by security-experienced operators.

Thanks to this a-priori knowledge, the KDBN network needs a reduced amount of data in order to be operative. In fact it takes as inputs the conditional probabilities indicated in the points from 1 to 4, transferred by experts in the network. In the tables (Tables 5, 6, 7 and 8) below are reported the conditional probabilities used for testing the KDBN on the specific problem presented in this paper.

Table 5: Damages/Duties and Bans. (In the table the $P_R(D_i|\underline{DB})$ inserted in the KDBN by the expert)

Damages / DutiesAndBans	1 Safety Shoes	2 Training	3 Safety Signs	4 Ergonomics	5 Safety Glasses	6 Gloves
Very Serious	10	0	0	0	10	10
Serious	10	0	0	0	10	10
Slight	20	0	0	0	20	20
Very Slight	30	0	0	0	30	30
Near Misses	30	0	0	0	30	30

Table 6: Events/Causes (In the table the $\boldsymbol{P_L(\varepsilon_m|C_j)}$ inserted in the KDBN by the expert)

Eventi \ Causes	Training Not-Adequate	Mechanical Malfunction	Behaviour	Organization	Working Area Not-Adequate
Rising	25	40	30	20	15
Slip	25	20	25	20	20
Tumble	25	30	20	30	20
Crash	20	10	20	30	40

Table 7: Causes/Duties and Bans (In the table the $\boldsymbol{P_R(C_i|DB_j)}$ inserted in the KDBN by the expert)

Causes / Duties And Bans	1 Safety Shoes	2 Training	3 Safety Signs	4 Ergonomics	5 Safety Glasses	6 Gloves
Training Not-Adequate	10	10	10	10	10	10
Mechanical Malfunction	40	30	20	20	20	30
Behaviour	20	30	40	35	40	40
Organization	30	30	30	35	30	20
Working Area Not-Adequate	0	0	0	0	0	0

Table 8: Causes/Duties and Bans (In the table the $\boldsymbol{P(D_i|\varepsilon_m)}$ inserted in the KDBN by the expert.)

Damages / Dangerous Events	Rising	Slip	Tumble	Crash
Very Serious	10	10	10	10
Serious	10	10	10	10
Slight	20	20	20	20
Very Slight	30	30	30	30
Near Misses	30	30	30	30

4.4 Results

The model's parameters are set as in Table 7; remember that α indicates how the model is adherent to the reality, as lower the value of α is, as more corresponding to the real situation the model is, so we have supposed a good adherence.

Since statistics show that the stone industry is characterized by a very high accident rate compared to other sectors, we have also supposed a significant presence of the causes predisposing the dangerous event (parameter β), in consequence we have reduced the probability of no-dangerous event (parameter γ and Φ); furthermore, since we supposed safety in the stone industry unreliable, we set parameter δ' near zero.

Table 9: Values of the models parameter use for testing

Parameters	Value
α	0,1
β	0,3
γ	0,8
δ'	0
ϕ	0,8

The following (see Figure 1 and Figure 2) are two types of tests: the first having assumed all DBs respected, in the second we simulated a bad behavior by workers, assuming the breach of some PPE.

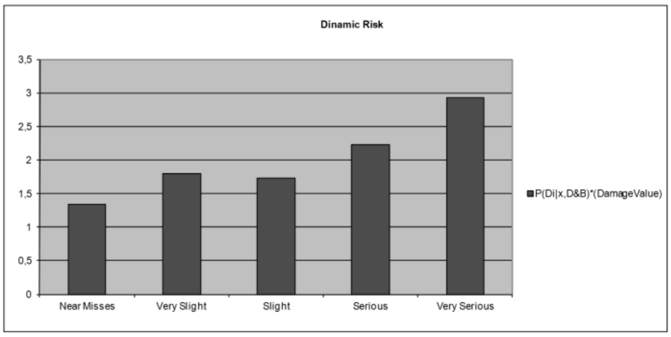

Figure 1: Risk obtained for each type of damage

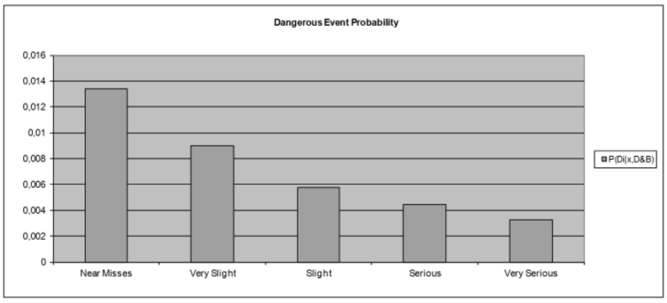

Figure 2: Probability of Damage having assumed all DB respected

In Table 10 is shown numerical results.

Table 10: Numerical results of the graphs in Figure 1-2

Damages	P(Di|x,DB)	Risk
No Damage	0,964120474	0
Near Misses	0,013406225	1,340622473
Very Slight	0,008959827	1,791965372
Slight	0,00578702	1,736106102
Serious	0,004468742	2,234370788
Very Serious	0,003257713	2,931941348

Having respected all the DB, in the first case we get a probability of damage, expressed in days, equal to the probability of having one very serious damage every year, and nearly two slight damage each year. Obviously, the situation gets worse if some DB are not respected, particularly if they are PPE. In the second test we have supposed that one PPE (safety shoes) is not respected, results are shown in Table 11.

Table 11: Numerical results of the second test, obtained supposing not respected the PPE "Safety shoes"

Damages	P(Di|x,DB)	Risk
No Damage	0,961685	0
Near Misses	0,013570838	1,357083815
Very Slight	0,009906712	1,981342369
Slight	0,006649711	1,994913208
Serious	0,004523613	2,261806358
Very Serious	0,003664126	3,29771367

In Table 12 the two cases (test 1 and test 2) are compared in terms of number of damage per year.

Table 12: Comparing results of Test1(all DB respected) and Test2(only one PPE not respected)

Damages	Test1: #damages per year	Test2: #damages per year
Very Slight	3,27	3,61
Slight	2,11	2,43
Serious	1,63	1,65
Very Serious	1,18	1,34

5. CONCLUSION

The model presented in this paper introduces a novel approach to assess safety at workplace. The BN model not only can perform risk assessment but also can help to simulate "critical" situation assessment during the work.

The model has taken into consideration a particular case study concerning safety in marble industry. The assessment results obtained by the BN model offered many useful suggestions to security work for the particular sector, and played a decisive role in reducing risk. In future work risk assessment algorithm could be improved in order to manipulate, with new parameters, the dependence with the structure of the network and the used statistics.

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