PROBABILISTIC APPROACH AS A SUPPORT SYSTEM FOR SAFETY-CRITICAL ENVIRONMENTS BY KNOWLEDGE DRIVEN BAYESIAN NETWORKS

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ABSTRACT
Probability estimation is an integral part of risk analyses. This work intends to propose a probabilistic approach as a support system for risk assessment in order to establish a deeper understanding of accident causation pathways as a means for proposing improved preventive strategies, especially at the level of organizational and structural factors. This study addresses the problem of "damaging event" probability estimation with few statistics by the use of Knowledge Driven Bayesian Network (KDBN), that models the a priori knowledge of the risk context dynamics. Moreover the proposed approach aims at providing a quantitative methodological technique useful to monitor, prevent, and evaluate, and assess the risks at workplace.

Keywords: Knowledge Driven Bayesian Network, safety, probabilistic risk analysis, risk assessment.

1. INTRODUCTION

Safety-critical environments are those domains in which hardware failure or late decision-making by operators could result in loss of life, significant property damage (Naderpour et al., 2014, a; Del Rio *et al.*, 2013). Since the beginning of the industrial revolution, many serious accidents at large-scale technological systems that have had grave consequences (Falcone et al., 2007; Bruzzone *et al.*, 2014).

Promoting situation awareness is an important design objective for a wide variety of domains, especially for process systems where the information flow is quite high and poor decisions may lead to serious consequences (Naderpour et al., 2014, b). In the present work we use an approach based on Bayesian Network (BNs) to describe the circumstances and relationships between circumstances due to accidents at workplace.

In fact, in our opinion BNs are powerful conceptual, mathematical and software tools used to model complex problems with variables related by probabilistic links (Washington and Oh, 2006). Furthermore BNs are used for professional and academic applications in a great variety of domains: medical, financial, industry, security, space, artificial intelligence.

Definitely, BNs provide an attractive means for modeling and communicating complex structures and BN form the basis for efficient algorithms, both for propagating evidence and for learning about parameters.

This study wants to give three important contributions. First, it proposes a situational network modeling process which is used to model risks situations at workplace. Second, it presents a situation assessment model that exploits the specific capabilities of Bayesian networks and risk analysis. The proposed situation assessment model can be applied to different scenario. Third, it develops a model for managing risks situations in safety critical environments in which the degree of automation and complexity continues to increase and the number of operators decreases, and where each operator must be able to comprehend and respond to a growing amount of risky status and alert information. More in detail, the model exploits the knowledge of experienced operators for building the network structure, thus overcoming the lack of statistics usually needed for learning conventional Bayesian nets and compensating it with the use of a contextual risk model. Moreover, as better explained in Section 3, the proposed approach joins the low complexity of a the most widely used technique for risk evaluation, namely the risk matrix method, with the completeness and repeatability of the AISS approach, much less used due to its complexity.

According to our previous work (D'Elia *et al.*, 2013) in which we presented general features for the Knowledge Driven Bayesian Network (KDBN) model, in the present research our aim is to furnish a deeper analysis of the model from a practical point of view. Our preliminary work took into account the mathematical theory underlying the model. Now a complementary analysis is presented. To this purpose, it was decided to apply our model to a real case study which was specifically developed for use in the investigation and analysis of occupational accidents within industrial settings, in order to evaluate in practice the ability of KDBN models to catch real risky situations. Definitively, the model represents an *innovative decision support system* to manage risks situations in safety-critical environments in which the effect of situational complexity on human decision-makers is a concern.

The paper is organized as follows. Section 2 presents literature overview. In section 3 problem statement is analyzed; section 4 presents methodological approach and finally results and conclusions are presented.

2. LITERATURE OVERVIEW

As stated by Jacinto (Jacinto et al., 2009) the first aim of accident research is to understand accidents; this is generally done through the search of their causes, so that adequate prevention measures can be designed.

Analysis of accidents is not well supported by conventional and qualitative methods due to data scarcity (Khakzad et al., 2014) as for example by the *Risk Matrix method.* This method is a well-known qualitative method that is used during risk assessment to define the various levels of risk as the product of the harm probability categories and harm severity categories (Encyclopædia Britannica, 1911; Fabiano *et al.*, 2004). However, Risk Matrix Method is a very subjective method that sometimes could also be arbitrary because it depends on the experience of the expert (De Felice and Petrillo, 2012).

Thus, in the absence or shortage of adequate tools the evolution of investigative methods over time reveals various trends, showing a gradual shift from searching for a single/immediate cause, to the recognition of multiple causes, in which management and organization failures and their interactions with the working activities became an important issue for the understanding of accidents (Roed-Larsen, 2003). One of this method is the *AISS Method* proposed by Association Internationale de la Sècuritè Sociale that that takes into account different parameters such as the material, work equipment; the environment; the organization of work, etc. (ISSA, 2001). The AISS method presents several weaknesses because it is quite complicated to use it due to several parameters to be considered.

From this point of view considerable research have been conducted to develop safety performance assessment using the Bayesian technique (Yu, and Abdel-Aty, 2013). 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). BNs have been applied in several knowledge areas, such as medicine, environmental assessment, business risk and product life-cycle analysis, etc. In the workplace risk area some applications are from Galán et al. (2007) that applied a canonical probabilistic test (based on Bayesian models) to the analysis of nuclear system safety; Papazoglou et al. (2006) that applied functional block diagrams and event trees to quantify the risk of falls. More specifically for construction and mining accidents, Matías et al. (2008) compared the predictive capacity of BNs with other expert systems.

The Bayesian framework provides a complete and coherent way to balance the empirical data and prior expectations, which would be very promising to be applied in safety analyses (Jang et al., 2010). As stated Ahmed *et al.*, (2011) one key advantage of the Bayesian inference method compared to the conventional frequent inference approach is that extra knowledge and experience about the data can be used as prior information in the analyses.

This study fills the gap in formulating a Bayesian model in safety at workplace.

3. PROBLEM STATEMENT

The classical approach used for risk assessment is based on the Risk Matrix method, which provides a statistical evaluation for risk given by eq. 1, where P represents the frequency of occurrence of the damage D and D represents the damage value.

$$R = P \cdot D \tag{1}$$

The risk expressed by eq. 1 is associated to a given activity, and its value can be eventually reduced through the application of some safety regulations. In this context the risk can be indicated as *original* (R_o), if no regulations are applied, and as dynamic (R_t) otherwise. In this paper, a Bayesian model for dynamic risk assessment is proposed. More formally, the expression of the dynamic risk is given by eq. 2, where x is the activity under observation, $\underline{DB}$ is a vector of safety regulations applied and D is the damage occurred.

$$R_t(x) = P(D|x, \underline{DB}) \cdot D \tag{2}$$

As introduced in section 2, another method to the risk evaluation has been proposed by AISS (ISSA, 2001), but it is not much used due to its complexity. This method uses in fact a more complex approach in respect to the risk matrix method: it starts by the consideration that accidents on working sites depend on many different factors, such as bad design, bad conditions for equipment, insufficient cleaning, floor encumbrances, environment illumination, noise and so on. All of these factors can be grouped into three main categories: job material and equipment; environment; job human organization. The AISS method associates to each of these classes a risk evaluation, identifying four operational phases: (1) evaluation of the global risk related to the job place, given by eq. 3, where M_a represents the risk factor related to the material or the equipment used, and Env represents the effect of the environment; (2) estimation of the worker ability to dominate the risky situation; (3) evaluation of the risk of accidents, given by eq. 4, where P is the worker ability evaluated during phase 2, weighted through the factor k related to the influence of material/equipment;

(4) contextualization of risk evaluation in acceptable ranges.

$$R_g = M_a \cdot Env \quad (3)$$

$$R_{acc} = R_g \cdot kP \quad (4)$$

The approach proposed in this paper can be considered as placed in the middle of the two previously described methods, joining in some way the low complexity (hence the simple applicability) of the risk matrix approach with the greater completeness and repeatability of the AISS approach, which considers the risky different factors more in detail during the evaluation process. The proposed method is based on the use of Bayesian networks to calculate the joint probability given by eq. 2 by taking into account information related to the entire working context, namely organization, material, equipment, workers training, environment conditions, application of safety regulations, relationships among dangerous events and damages occurred.

4. METHODOLOGICAL APPROACH

4.1. Basic principles

As already stated, the probability P of eq. 2 is very complex to calculate, since it depends on many parameters. *Bayesian Networks* can be viewed as a valid tool to describe this probability, because they allows to structure a complex problem as a combination of less complex sub-problems, hence easier to solve, built by considering the cause-effect relationships between the entities involved in the problem itself.

More specifically, in the risk assessment model addressed by this paper the statistical-physical entities considered are:

- Damages D_i
- Dangerous Events E_m
- Causes C_n
- Duties and Bans DB_j

These domains conceptually corresponds to the variables of the AISS method. The choice of these kinds of entities responds to the necessity of respecting the indications of the reference Legislative Decree 81/08 and of exploiting the information provided by the operators experience on field, in order to compensate the lack of statistics needed by conventional BN learning algorithms. The structure of the net should be indeed derived and built up through a learning process; however, since the problem involves a huge number of variables, a significant number of statistics would be needed to properly learn the net. In order to overcome this difficulty, the proposed approach, called *Knowledge Driven Bayesian Network* (*KDBN*), exploits the knowledge of experienced operators for building the network structure, allowing them to transfer part of their know-how in the system.

After the problem variables have been identified, a phase of evaluation and review of the relationships among them can be performed, in order to understand in which way they co-operate to determine the risk. Finally, the results of the risk evaluation process are analyzed, deciding if they can be accepted as they are or if a new and improved evaluation should be carried out.

From the Bayesian network point of view, the elements of these four domains corresponds to the nodes of the DAG (Direct Acyclic Graph) defining the network structure: to each of them a random variable is associated, and the edges between these nodes represents the conditional probabilities (i.e. the cause-effect relationships) which relate them.

In Figure 1 is shown the conceptual scheme of the proposed KDBN approach.

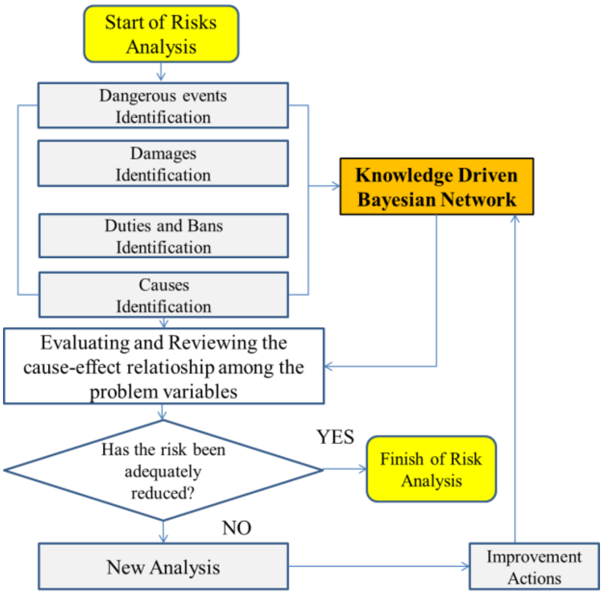

Figure 1: Conceptual scheme of the proposed KDBN approach

4.2. Knowledge Driven Bayesian Network

Figure 6 shows the general structure of the proposed Knowledge Driven Bayesian Network: damages are depicted in red, dangerous events in yellow, the causes are displayed in green, and finally the duties and bans are depicted in white/grey. The duties and bans can directly influence the damages and the cause, through which their effect reaches the dangerous events; finally dangerous events, produce an immediate consequence on damages. This approach significantly reduces the number of parameters defining the problem, making the KDBN method usable also in the case of having a small number of statistical data available for the risk evaluation.

The probability of occurrence of a certain damage D_i, related to a particular job activity x, given that a number of safety regulations $\underline{DB}$ is applied, namely $P(D_i|x, \underline{DB})$, is given by eq. 5 (x is omitted for shortness), where the sums are over all the possible dangerous events and over all the possible combinations of causes.

$$P\left(D_i|x, \underline{DB}\right) = \sum_m \sum_n P\left(D_i, E_m, \underline{C_n}|\underline{DB}\right) \qquad (5)$$

Each node of the KDBN net is influenced only by the nodes directly connected to it. This leads to the decomposition of the joint probability $P(D_i, E_m, \underline{C_n}|\underline{DB})$ in three terms, as expressed by eq. 6.

$$P(D_i, E_m, \underline{C_n}|\underline{DB}) = P(D_i|E_m, \underline{DB}) \cdot P(E_m|\underline{C_n}) \cdot P(\underline{C_n}|\underline{DB}) \qquad (6)$$

Given the network structure, to further reduce the complexity of the problem the three terms of eq. 6 can be structured in turn and calculated on the basis of the experts knowledge, available in terms of relative frequencies of incidence between the couples of entities, namely $P(E_m|C_n)$, $P(D_i|E_m)$, $P\left(D_i|DB_j\right)$, and $P(C_n|DB_j)$. More specifically, these terms represents the cause-effect relationships among the couples of variables involved in the KDBN.

The statistical surveys about the accidents occurred in the work sites provide an information which can be inserted in the KDBN system in the form of global parameters, namely $\alpha, \beta, \gamma, \delta', \phi$. These parameters can be possibly estimated during the learning phase, and are involved in the calculation of each element of eq. 6.
For a deeper description of these parameters see (D'Elia *et al.*, 2013).

- $\boldsymbol{P\left(D_i|E_m, \underline{DB}\right)}$

The term $P\left(D_i|E_m, \underline{DB}\right)$ represents the probability that a certain damage D_i occurs given that a dangerous event E_m happened and given that some safety regulations $\underline{DB}$ have been applied. The calculation of this probability takes into account two contributions: $P(D_i|E_m)$, which expresses how the dangerous event E_m can lead to a certain damage D_i; $P\left(D_i|DB_j\right)$, which conveys the influence of the safety regulation DB_j on the damage D_i. More specifically, the duty and bans $\underline{DB}$ have the effect of reducing the amount of the damage D_i through a "discount" mechanism: if a DB is applied, it introduces a probability mass which moves from the more serious damage (the considered one D_i) to the immediately less serious damage (namely D_{i+1}), hence reducing the probability of occurrence of D_i and contemporarily increasing the probability of occurrence of D_{i+1}. Contemporarily D_i receives the percent discount coming from the immediately more serious damage D_{i-1}. This leads to the formulation of eq. 7 and 8, where P_R indicates the residual probability remained after the application of the discount mechanism.

$$P\left(D_i|E_m, \underline{DB}\right) = \begin{cases} (1-\Phi)P' & \text{if } D_i \neq \text{NotDamage} \\ \Phi + (1-\Phi)P' & \text{if } D_i = \text{NotDamage} \end{cases} \qquad (7)$$

$$P' = P(D_i|\varepsilon_m)P_R(D_i|\underline{DB}) + P(D_{i+1}|\varepsilon_m)[1 - P_R(D_{i+1}|\underline{DB})] \quad (8)$$

- $\boldsymbol{P(E_m|\underline{C}_n)}$

The term $P(E_m|\underline{C}_n)$, given by eq. 9, represents the probability that a given combination of causes $\underline{C}_n$ brings to a dangerous event E_m. E_m has its own frequency of occurrence, namely $P_o(E_m)$, which is grown by the influence of the causes $\underline{C}_n$, in particular each cause of the combination moves a statistical weight, namely $P_L(E_m|C_j)$, from the situation in which no dangerous event E_{NotD} occurs in favor of the occurrence of E_m. This behavior is expressed by the sum of eq. 9, which is performed over all possible causes.

$$P(E_m|\underline{C}_n) = P_o(E_m) + \sum_j C_j \cdot P_o(E_{NotD})P_o(E_m)P_L(E_m|C_j)$$
(9)

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

The term $P(\underline{C}_n|\underline{DB})$ represents the probability of having a certain combination of causes $\underline{C}_n$ (determining the dangerous events) given that a number of safety regulations $\underline{DB}$ has been applied. The application of a each duty&ban affects the frequency of occurrence of a particular cause by introducing a statistical *discount* (as seen for the influence of DBs on the damages), represented by a probabilistic weight moving from the considered cause to the not contemplated cause. The expression of this probability is given by eq. 10, which refers to eq. 11, 12 and 13, where P_R indicates the residual probability of the cause after the application of the discount mechanism, and the product is done over all the L possible duties and bans.

$$P(\underline{C}_n|\underline{DB}) = (1 - \delta') \cdot P'' \quad (10)$$

$$P'' = \prod_{i=1}^{K} P_c \quad (11)$$

$$P_c = \begin{cases} P(C_i|\underline{DB}) & if\ C_i = 1 \\ 1 - P(C_i|\underline{DB}) & if\ C_i = 0 \end{cases} \quad (12)$$

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

For a more theoretical description of the proposed model see (D'Elia *et al.*, 2013).

5. CASE OF STUDY

As case of study for the risk evaluation, in this work the use of the **circular saw** has been considered. The values for damages, dangerous events, causes and duties and bans considered are described in the following.

- **Damages:** three levels of damages have been used, namely *serious*, *slight* and *very slight*.
- **Dangerous Events:** *instability*, *impact*, *slipping/tumble*, *pricks/cuttings*, *electrical danger*, *chemical agent*, *noise*.
- **Causes:** five causes have been considered, namely *not-adequate training*, *organization*, *not-adequate working area*, *behavior*, and *mechanical malfunctioning*.
- **Duties and Bans:** *safety gloves*, *safety glasses*, *safety visors*, *cleaning of the surrounding area*, *protection of the transmission organs*, *pieces-pushing devices*, *controls protection*, *masks for the protection of the breathing apparatus*, *dust extractors*, *ears protection*, *grounding of metal bodies*, *IP 54 electrical protection*.

The global parameters used for the risk evaluation are then described in Table 1.

Table 1: Parameters used for the risk evaluation in the case of the circular saw

Parameters	Value
α	0.1
β	0.3
γ	0.98
δ'	0
Φ	0.8

In order to show how not to apply some safety regulations can negatively influence the risky situation, thus increasing the risk value, three evaluation tests have been taken in consideration: (1) no safety regulation applied; (2) all safety regulations applied; (3) two meaningful safety regulation not applied among all. For all the tests the results will be shown in terms of graphs and tables reporting the evaluation statistics for risks and damages.

5.1. No safety regulations applied

As evidenced in the problem statement, in the case of no safety regulations applied the risk is called *original risk*. The first test has been performed considering all the duties&bans as turned off. Figure 2 shows the probability of the damages related to the considered activity (circular saw), while Figure 3 shows the risk values estimated for each type of damage. A quantitative description of the results achieved is reported in Table 2. It can be noticed that, if no duty&ban is applied, the original risk associated to the serious damage is more relevant than the other kind of risks.

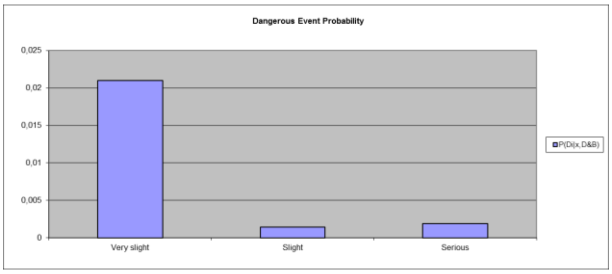

Figure 2: Probability of damages if no DB is applied in the case of circular saw

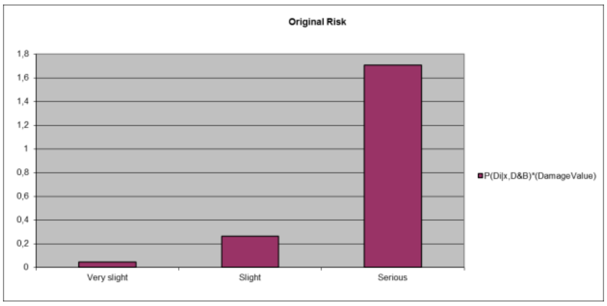

Figure 3: Original Risk in the case of circular saw

Table 2: Values of the probability of damages and associated risks in the case of no DB applied

Damages	**P(Di|x,DB)**	**Risk**
No Damage	0,97564652	0
Very slight	0,021004691	0,047260556
Slight	0,00145032	0,26432082
Serious	0,001898469	1,708621714

5.2. All safety regulations applied

When all the safety regulations provided for a specific job activity are applied, the risk should assume the minimum value. Figure 4 and Figure 5 respectively show the probability of the damages and the distribution of risk in the case of all duties and bans applied, while Tab. 3 reports the values associated to the graphs.

In respect of the original risk, it can be seen that the application of all possible safety indications reduces the probability associated to each kind of damage, with a consequent decrease of the amount of the associated risks. The percentage of reduction depends in general on how each DB influences each damage. For the case of study proposed in this paper, the influence of all DBs determined that the risk associated to the very slight damage decreases from 0.04 to 0.002, the risk associated to the slight damage decreases from 0.26 to 0.18, and the risk associated to the serious damage decreases from 1.70 to 0.52.

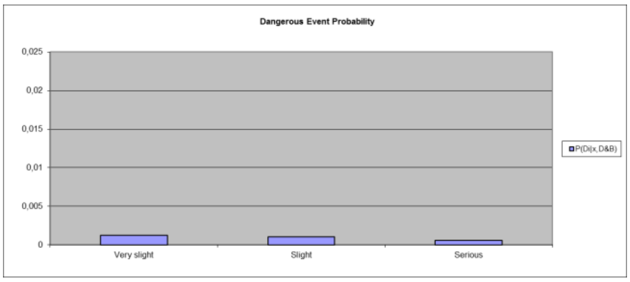

Figure 4: Probability of damages obtained for each damage when all DBs are applied, in the case of circular saw

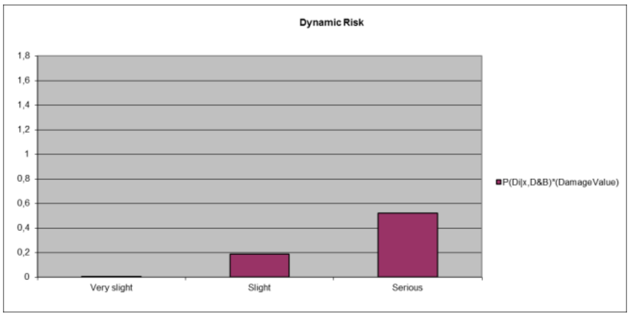

Figure 5: Risk evaluation when all DBs are applied, in the case of circular saw

Table 3: Values of the probability of damages and associated risks when all DBs are applied, in the case of circular saw

Damages	**P(Di|x,DB)**	**Risk**
No Damage	0,997139489	0
Very slight	0,001250616	0,002813886
Slight	0,001030433	0,187796446
Serious	0,000579462	0,521516094

5.3. Some safety regulations not applied

An intermediate situation occurs when some of the safety regulations provided are not applied. The choice about what DBs are preferable to be considered in the task of reducing risk can be done in reference of the influence that such DBs have on damages For this third kind of test two DBs which among all influence more significantly the serious damage have been chosen, namely *pieces-pushing devices* and *controls protection*. The results are shown in Table 4. As expected, it can be seen that the removal of these DBs mainly affects the risk associated to the serious damage, which increases from 0.52 to 0.82. The DBs *discount* mechanism applies percent reductions that propagate through each kind of damage; hence also the values achieved for the slight and very slight damage are influenced, even if this happens in a minor way. In particular, the value of the risk associated to the very slight damage remains almost unvaried, while the risk associated to the slight damage decreases, since the *discount* introduced by the considered DBs to the serious damage, and weighting on the slight damage, is missing. Moreover, the results achieved for this third experimental test show that the proposed model has a predictive ability, since it allows to determine which safety regulations are more decisive in the task of reducing risk, thus possibly assisting the expert operators in designing and managing the job context and activity.

Table 4: Values of damages and associated risks in the case of two DB not applied

Damages	**P(Di|x,DB)**	**Risk**
No Damage	0,997092465	0
Very slight	0,001285025	0,002891306
Slight	0,000710522	0,129492701
Serious	0,000911988	0,820789194

5.4. Comparison with statistical surveys

The results obtained by the risk evaluation process can be compared with the statistical surveys in order to understand the ability of the model to describe real situation of risk in the workplace. More specifically the national statistics data on the accidents occurred in the case of circular saw, in a period of one year, were available. These statistics considered the situation in which all the safety regulations are respected, hence the comparison with the results obtained for the second experimental test was possible (Table5). The statistics shows that, among all the registered accidents, the 45% led to a very slight damage, the 30% led to a slight damage and the 25% led to a serious damage; in the experimental test the obtained percentages have been 43.72% for the very slight damage, 36.02% for the slight damage and 20.26% for the serious damage. From the comparison it can be noticed that the risk evaluation results are quite adherent to a real situation such as the circular saw, showing the effectiveness of the proposed approach.

Table 5: Comparison of the risk evaluation with the statistical surveys

Damages	**Statistical Surveys**	**KDBN approach**
Very Slight	45%	43,72%
Slight	30%	36,02%
Serious	25%	20,26%

6. CONCLUSIONS

In this paper a new probabilistic approach based on Knowledge Driven Bayesian Network to support process operators in risks situations has been proposed. The methodology presented in the study comprised two main stages: (1) define an analytical framework for the analysis of systemic factors, and (2) identify the systemic/organizational contributing factors through an in-depth investigation and analysis of a number of accidents. A quantified detailed logical model based on a real case study was defined in order to assess the relevant contribution of the various risks factors. In this way a rational prioritization of the available risk reducing measures were identified. The results of this research indicate that Bayesian networks are very useful in explaining the causes of falls.

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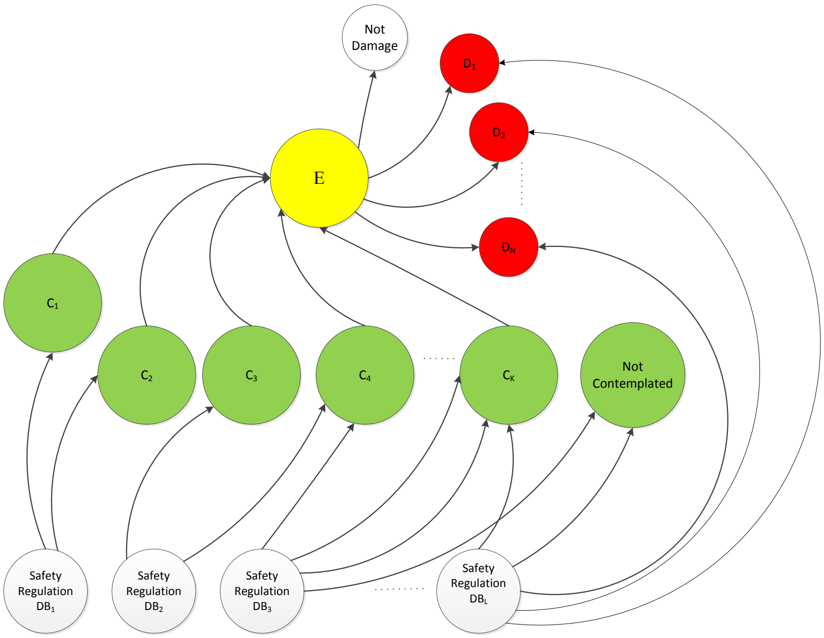

Figure 6: Generic model of the proposed Knowledge Driven Bayesian Network

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