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A Bayesian network analysis of workplace accidents caused by falls from a height

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ABSTRACT

This article analyses, using Bayesian networks, the circumstances surrounding workplace tasks performed using auxiliary equipment (ladders, scaffolding, etc.) that may result in falls. The information source was a survey of employees working at a height. We were able to determine the usefulness of this approach – innovative in the accident research field – in identifying the causes that have the greatest bearing on accidents involving auxiliary equipment: in these cases, the adoption of incorrect postures during work and a worker's inadequate knowledge of safety regulations. Likewise, the duration of tasks was also associated with both these variables, and therefore, with the accident rate. Bayesian networks also enable dependency relationships to be established between the different causes of accidents. This information – which is not usually furnished by conventional statistical methods applied in the field of labour risk prevention – allow a causality model to be defined for workplace accidents in a more realistic way. With this statistic tool, the expert is also provided with useful information that can be input to a management model for labour risk prevention.

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1. Introduction

Techniques used to manage accident prevention in companies include accident analyses, accident investigations, safety inspections and incident recall, etc. (Bird and Germain, 1990; Ley 31/1995), which provide management with information on the causes of accidents among particular groups of employees. Knowing the circumstances and causes of accidents enables corrective and preventative measures to be implemented that exercise greater control over factors that may cause accidents.

Different information sources are used in order to apply these analysis tools. *Fatality inspection records*, which are completed after the accident, have been used by some authors for their research (Janicak, 1998). These records reflect the circumstances of the accidents providing data, for example, on the job, type of activity, type of injury, direct cause of the injury, etc. In Spain, fatality records are the most widely used source of information for historical studies of workplace accidents (Orden TAS/2926/2002; Begueria, 1988). Other information sources – including risk reports (Bird and Germain, 1990) and worker surveys (Gillen et al., 2002; Kines, 2003; Paul and Maiti, 2007) – enrich the theories elaborated from the usual sources of information and provide additional, mostly sub-

jective, information (largely on the behaviour of the worker during the risk activity).

Irrespective of the information source, the data is usually analysed using conventional descriptive statistics (Kines, 2003), factorial analysis (Dedobbeleer and Beland, 1991), analysis of variance (Janicak, 1998), and multiple regression (Gillen et al., 2002). The conclusions obtained using these simple data processing techniques – which form the basis for many management models – enable the relationship between the accident and each causal variable to be analysed, but do not enable the interplay between causes to be determined. These techniques fail to reflect, therefore, the fact that an accident is usually the result of more than one factor – that is, the outcome may be greater than the sum of the parts (Bird and Germain, 1990).

More effective approaches to defining the interplay between variables have been developed by other 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 at a height that might result in personal injury or damage to property. BNs have been applied in several knowledge areas, such as medicine (Antal et al., 2007), ecology (Adriaenssens et al., 2004), environmental assessment impact (Baran and Jantunen, 2004; Marcot et al., 2001; Matías et al., 2006), business risk and product life-cycle analysis (Zhu and Deshmukh, 2003), and more recently, to handling data obtained as a result of prospection for minerals and

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rocks (Rivas et al., in press). In the workplace risk area, Galán et al. (2007) applied a canonical probabilistic test (based on Bayesian models) to the analysis of nuclear system safety and Papazoglou and Ale (in press) and Papazoglou et al. (2006) 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, concluding that BNs, in addition to their good predictive capacity, possess a satisfactory interpretative capacity in regard to workplace accidents, given that: (1) they enable different circumstances to be simulated and their effects on each of the variables in play to be probabilistically analysed; (2) they enable the use of discrete qualitative variables (such as the many parameters that have a bearing on accidents); and (3) they enable the causal dependency relationship between variables to be mapped.

Using BNs, we analysed workplace accidents caused by falls from a height in order to identify the most important causes of this kind of accidents and, most of all, to determine the relationships existing between these causes, which will allow the real circumstances of the unsafe work tasks performed at different heights to be defined.

We focused on falls, from a height of more than 2 m above floor level, of employees working in a standing position. In Spain, workplace falls from a height are a major cause of workplace fatalities, third only to accidents involving vehicles and heart attacks (Ministerio de Trabajo y Asuntos Sociales, 2006). These accidents, which occur most frequently in the construction and mining sectors, have been studied by several authors (Gillen et al., 2002; Janicak, 1998; Kines, 2003; Hale et al., 2007). A secondary aim of our analysis was to establish the need for reinforcing safety measures for this type of work.

As an information source for the analysis, we implemented a survey of workers who were interviewed as they performed a range of work tasks at more than 2 m above floor level (on ladders, structures, scaffolding or platforms). The use of information obtained during or immediately after the risk activity in prompt/no-delay interviews have enabled some authors to draw interesting conclusions on the causes of falls from a height (Kines, 2003). In our opinion, the use of information collected in the course of a task allows the circumstances of immediate relevance to an accident to be better analysed. In general terms (Bird and Germain, 1990), the causes of accidents at work can be classified on immediate causes (both substandard practices and substandard conditions) and basic causes (both personal and job factors). In the case of worker accidents caused by falls, the adoption of worker unsafe behaviours contributes directly or indirectly to around 90% of incidents (Holnagel, 1993). This unsafe behaviour can be directly related to substandard practices (using protective equipment incorrectly or removing safety devices), but also to substandard conditions (the existence of inadequate protection or incorrect task location). Worker inexperience, lack of motivation and fatigue are basic causes which often underlie immediate causes. In the present work, the questions posed are specifically related to worker behaviour (how the task is performed, the reasons for the application of alternative safety measures...) but also to substandard conditions (difficulties in applying legislations) which can condition the worker decisions.

Furthermore, issues in regard to immediate behaviour and decision-making – generally not recorded in accident reports – constitute non-measurable and non-quantifiable variables that are better modelled as categorical variables (or at least as ordinal variables). Although categorical variables are difficult to incorporate in conventional statistical techniques, they can be easily be analysed using BNs.

2. Materials and methods

2.1. Information sources

The data used to build the BNs was obtained from questionnaires administered to 393 workers employed in 103 small and medium enterprises in the construction, industrial and services sectors. The companies were all located in the Vigo region (north-western Spain), and the survey was conducted between 2003 and 2006. The following two kind of tasks were analysed:

2.1.1. Tasks performed using ladders

A total of 147 questionnaires were administered to workers on ladders, generally working at a height of around 3.5 m above floor level. These workers were questioned in regard to:

- The duration of the task.
- Experience in the job.
- Knowledge of the mandatory use of a safety harness and problems with safety harness use. (Spanish legislation requires safety harness to be used by workers on ladders performing tasks at heights of 3.5 m or more above floor level and by workers required to apply effort or adopt positions that might place them in danger [Real Decreto 1215/1997]).
- Specific training received on the risks associated with the use of ladders.
- Degree of hazard perception.
- Previous incidents or accidents using ladders.

2.1.2. Tasks performed on structures, scaffolds, platforms and/or auxiliary equipment

The 246 remaining questionnaires were administered to workers using other kinds of auxiliary equipment, such as structures, scaffolds or platforms. The height at which they were working at the time they were surveyed was about 2 m above floor level. Questions dealt with the following issues:

- The duration of the task.
- Experience in the job.
- Knowledge of the minimum height at which it is mandatory to apply specific protective measures. (For these types of structures, the Spanish law requires collective protective measures to be applied to workers performing tasks at heights above 2 m [Real Decreto 1627/1997; Real Decreto 486/1997]).
- Practical problems encountered in applying protective measures, according to the type of work being done and its duration.
- Specific training received on the risks associated with the use of auxiliary equipment.
- Reasons for incorrect posture (in the event of observing a worker adopting an incorrect posture while performing a task).
- Degree of hazard perception and perceived importance of adopting appropriate and safe postures.
- Previous incidents or accidents using this type of equipment.

2.2. Definition of the variables

The questions posed during the surveys enabled information to be extracted on the circumstances surrounding work tasks that could play a role in triggering an accident. Some circumstances are related to personal factors considered to be a basic cause of accidents (Bird and Germain, 1990), such as work experience or inadequate training. Other circumstances reflected in the questionnaires responded to behaviour patterns that could act as immediate causes of accidents (substandard practices) and whose measure

and definition are highly subjective, for example, the worker's perception of danger or the decision to adopt an inappropriate posture. All the circumstances reflected in the questionnaires constituted the variables used in the BN statistical analysis. These variables are listed and discussed below. Indicated for each variable are possible responses (reflecting different situations that might occur in reality), representing the different states that can be adopted in the BN.

2.2.1. Variables

- **Experience (E):** This variable was included so as to evaluate the relationship between experience and the other factors in the final outcome. Some authors (Hansen, 1989) have demonstrated a direct relationship between experience and accident rates, given that more experienced workers are usually given the most dangerous tasks. Although familiarity with a task can enhance the perception of risk, it can also have the opposite effect and lead to careless and unsafe behaviour (Bird and Germain, 1990; Paul and Maiti, 2007). In our BNs, this variable was defined in terms of one of three possible states: *State 1* (workers with >12 months' experience in the company); *State 2* (workers with >2 months' and <12 months' experience in the company); and *State 3* (workers with <2 months' experience in the company).
- **Task duration (TD):** This variable was included because task duration may affect the use and application of safety measures. In our BNs it was defined by one of three possible states: *State 1* (operations lasting >8 h, that is, a standard working day); *State 2* (operations lasting >2 h and <8 h); and *State 3* (operations lasting <2 h).
- **Training (T):** This parameter evaluates the kind of training given to a worker by a company. Three states representing different levels of training were defined for the BNs: *State 1* reflects task-specific training (applied and practical training of direct relevance to the post); *State 2* reflects generic training (theoretical training on general risk prevention); and *State 3* reflects the fact that a worker has received no training on workplace risks.
- **Knowledge of regulations (KR):** This variable reflects a worker's level of knowledge of regulations applicable to ladders, structures, scaffolding, platforms and auxiliary equipment in general. The worker's knowledge is assessed by means of specific questions posed in the survey. In the BNs this parameter was defined as one of three possible states: *State 1* (excellent knowledge of the regulations); *State 2* (some knowledge of the regulations); and *State 3* (poor knowledge of the regulations).
- **Hazard perception (HP):** This variable reflects the degree of risk perceived by the worker and associated with the task in hand. Although this perception will to an extent depend on the character or personality of the worker, training and knowledge of the corresponding regulations should theoretically have a bearing on a worker's capacity to perceive risk. In the BN, this variable takes one of two possible states: *State 1* – which reflects clear perception of a real risk and *State 2* – which reflects no perception of risk.
- **Safety harness use (SHU):** This variable reflects worker willingness to use a safety harness once informed that it is mandatory. The following two states were defined: *State 1* (the worker uses a safety harness) and *State 2* (the worker fails to use a safety harness).
- **Incorrect posture (IP):** This variable defines the posture of a worker performing a task at a height (just before the interview was conducted). An incorrect posture is defined as any deviation from normal work standards, including awkward postures, whether or not they are risky. Two states were defined: *State 1* (the worker complies with the regulations) and *State 2* (the

worker fails to comply with the regulations). These last two variables refer to behaviours and decisions that may not necessarily be dangerous (although they may reflect ignorance of regulations) and/or that may be voluntary (risk-taking behaviour, as defined in Paul and Maiti, 2007). In this last case, the worker's attitude may reflect the prioritisation of productivity or speed over safety (Kines, 2003).

- **Previous accidents or incidents (AI):** In addition to the above seven input variables, we also included an eighth variable as a prediction (output) variable, namely whether a worker has had *previous accidents or incidents* (AI). This was defined by one of two possible states: *YES* (the worker has previously had an accident/incident in similar conditions) and *NO* (the worker has never previously had an accident/incident in similar conditions).

2.3. Theoretical bayesian concepts

A Bayesian network is a random m -dimensional variable for which a structure of relationships that are frequently causal has been specified between its components (as also any missing relationships). Formally, therefore, a Bayesian network is a pair (X, G) composed of a random m -dimensional variable $X = (X_1, \dots, X_m)$ and a directed acyclic graph (DAG). This acyclic graph is composed in turn of a set of m vertices (associated with the random variables X_i , $i = 1, \dots, m$) and a set of arrows between these vertices that represents the relationships (generally causal) between these variables (Fig. 1).

If we denote as π_i the set of random variables that are the immediate predecessors of the variable X_i according to the DAG (the parents of X_i), the conditional independence relationships defined by G permit factorisation of the joint distribution via the following equation:

$$P(\mathbf{x}) = P(x_1, \dots, x_m) = \prod_{i=1}^m P(x_i | \pi_i) \quad (1)$$

where x_i is a realization of X . The expression of the joint distribution $P(x)$ in terms of conditional distributions requires factors whose

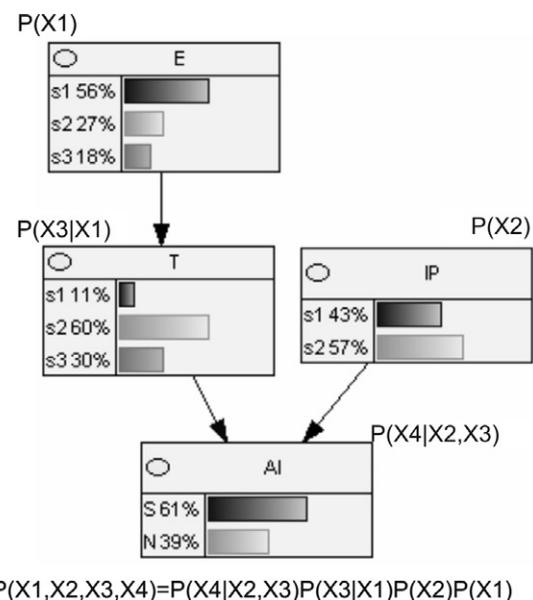


Fig. 1. Example of a directed acyclic graph composed of four nodes/variables, with arrows to symbolise the relationships between variables. T: training; IP: incorrect posture; E: experience; and AI: accidents/incidents.

number grows exponentially with the number of variables. The property of conditional independence between variables expressed in the DAG simplifies this calculation, reducing the number of factors to be included in the calculation.

For example, the relationships between variables established in Fig. 1 implies that the joint distribution is calculated through $P(X1, X2, X3, X4) = P(X4|X3, X2) \cdot P(X3|X1) \cdot P(X2) \cdot P(X1)$ instead of through $P(X1, X2, X3, X4) = P(X4|X3, X2, X1) \cdot P(X3|X2, X1) \cdot P(X2|X1) \cdot P(X1)$. The number of parameters to estimate is thus reduced from $(2 - 1) * 3 * 2 * 3 + (3 - 1) * 2 * 3 + (2 - 1) * 3 + (3 - 1) = 35$ to $(2 - 1) * 3 * 2 + (3 - 1) * 3 + (2 - 1) + (3 - 1) = 15$.

In order to construct a Bayesian network – in other words, in order to establish the joint distribution of the random vector – it is necessary to specify the conditional dependence (or independence) relationships between variables (that is to say, the structure) and the conditional probability distributions (i.e. the parameters of the conditional distribution).

The structure may be defined a priori (this was the procedure followed in this work) or by means of an estimate made from the data (structure learning). The structure may even be determined using a combined approach, by including some a priori information in the learning algorithm that will restrict the relationships permitted between the variables. The algorithms for learning the structure of a Bayesian network can be classified as either greedy search algorithms (e.g. Cooper and Herskovits's K2 algorithm in Cooper and Herskovits, 1992) which search all possible structures compatible with the prior knowledge and select the best according to a selection criterion, or algorithms which determine the conditioned independence relationships using statistical independence tests, e.g. the PC algorithm (see Spirtes et al., 2000).

Distribution parameters are trained by means of probability maximisation using multinomial frequencies for the sample. Once the structure and parameters have been determined from the data, the Bayesian network is ready to draw inferences. Inference is done by means of updates to the distribution of probabilities for the nodes in the form of new evidence incorporated in the network.

3. Results

As indicated above, the BNs presented in this work were constructed *a priori*. Two networks reflecting the two different work contexts were created, namely, a BN for work performed on ladders and a BN for work performed on scaffolding, platforms, structures, etc. (BN1 and BN2, respectively). The two networks are described below in terms of structure and capacity for interpreting the circumstances reflecting the work context and analysed through inference operations.

3.1. BN1: ladder-based tasks

Fig. 2 depicts BN1, composed of seven variables – six causal variables (TD = task duration, T = training; E = experience; SHU = safety harness use; KR = knowledge of regulations; and HP = hazard perception) plus the response variable (PA = previous accidents or incidents).

The structure of the network proposed for analysing ladder-based tasks follows the logical structure for variables defined in a loss causation model (Bird and Germain, 1990). For example, the training and experience variables (see Fig. 2) may be considered to be basic causes, which would explain unsafe behaviours or conditions that are the immediate cause of an accident, such as for example, incorrect posture or the decision not to use a safety harness. The basic causes are logically located at the start of the model, and links from these go to the immediate causes. Applying a similar criterion, it is quite possible that haste at work may lead to a failure to correctly attach safety mechanisms (which require time) and/or reduce a worker's concentration and consequently his/her capacity for recognising potential danger. For this reason a link is established between the task duration variable and the nodes for safety harness use and hazard perception.

Once the network has been structured and has learned the distribution parameters, it becomes a valuable tool for making estimates. The first information provided, on the basis of the probability distribution obtained for each variable, is data on the most typical circumstances arising among the sample of workers interviewed (Fig. 2).

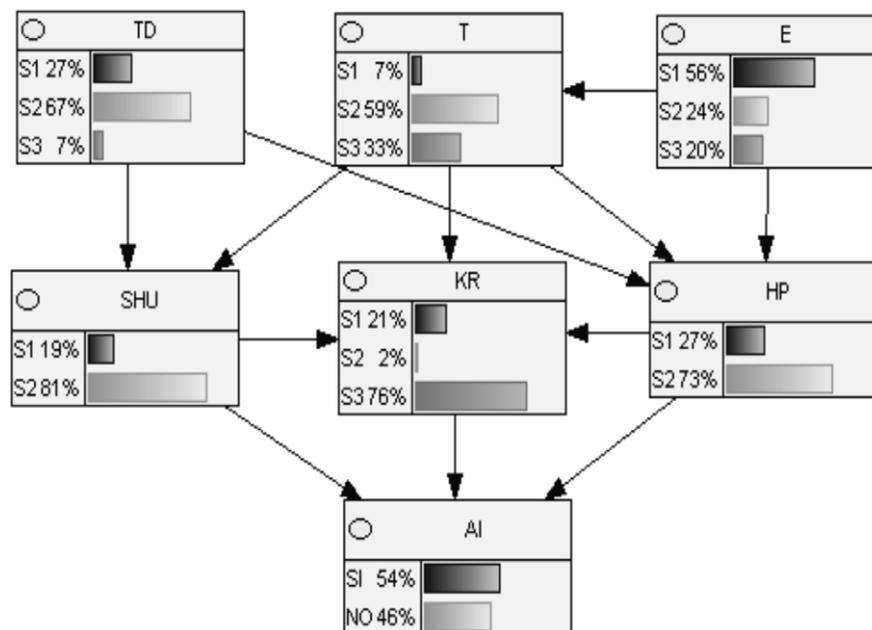


Fig. 2. Bayesian network structured to analyse ladder-based tasks. Abbreviations: TD = task duration; T = training; E = experience; SHU = safety harness use; KR = knowledge of regulations; and HP = hazard perception) plus the response variable (AI = previous accidents or incidents).

It can be deduced that the most typical task duration is >2 h but <8 h (State 2 = 67% in TD variable). The typical profile of the interviewed workers is an operator who has been with the company for more than 1 year (frequency of 56% for State 1 of the E variable), with generic training in risk prevention (frequency of 59% for State 2 of the T variable) and with inadequate knowledge of the regulations governing the use of ladders (frequency of 76% for State 3 of the NK variable). This typical worker, furthermore, does not consider him/herself to be in danger (frequency of 73% for State 2 of the HP variable), and almost never uses a safety harness on ladders (frequency of 81% for State 2 of the SHU variable). Of the respondents, 54% previously had a workplace accident.

The capacity for drawing inferences is the great advantage of this statistical tool. BNs are useful for estimating, in probabilistic terms, changes in one or more variables in response to the introduction of new evidence, i.e. when hypothetical situations are posed via other variables. This makes BNs very useful when interpreting the circumstances surrounding particular workplace tasks. Three illustrative examples follows:

- (1) If all tasks lasted less than 2 h (100% for State 3 of the TD variable, Fig. 3 top), it can be observed that 96% of the workers would not use a safety harness. If, on the other hand, a task lasted more than 8 h (100% for State 1, Fig. 3, bottom), the number of workers using a safety harness would increase. Shorter working days (or task duration) would appear to be associated with a lower perception of risk, possibly because haste leads to productivity taking priority over safety.
- (2) Analysing the relationship between the *training* node and the other variables, and comparing these relationships on the basis of training received (Fig. 4), it can be observed that the workers who received specific training (100% for State 1 of the T variable, top of the figure) are mostly workers (73%) with more than one year experience, who are aware of the regulations on the use of safety harness and who use a safety harness in 43% of cases. On the contrary, in the group of

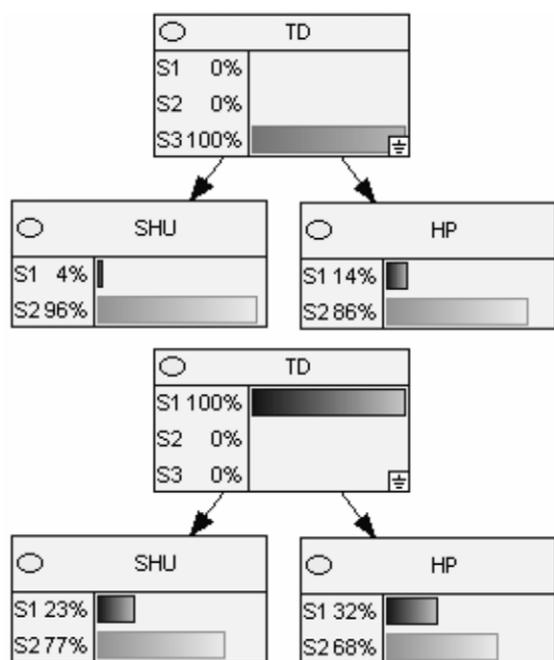


Fig. 3. Detail of Bayesian network for analysing ladder-based tasks, focusing on the variables TD (*task duration*), HP (*hazard perception*), and SHU (*safety harness use*). On the top, the established condition is that the task will last less than 2 h (State 3 = 100%). On the bottom, the established condition is that the task will last more than 8 h (State 1 = 100%).

workers who received no training (100% for State 3 of the variable T, Fig. 4, bottom), the long experience at work is reduced (from 73% to 53%) and also the use of safety harness (from 43% to 22%). With respect to the *hazard perception* variable, it can be observed that the non-perception of danger is higher among workers who have not received training (Fig. 4, bottom). The influence of the training node on the occurrence of an incident or accident (i.e. the *previous accidents or incidents* variable) is minimal.

- (3) The variable *knowledge of regulations* (KR) has a bearing on the degree to which a worker perceives danger (HP variable). If this knowledge is insufficient (State 3 of KR variable = 100%), the degree of danger perception is lower than if this knowledge is excellent (State 1 = 100%), at 18% and 25%, respectively. It also happens that no knowledge of the regulations coincides with a higher percentage of previous accidents among workers.

The variables *knowledge of regulations* (KR) and *safety harness use* (PPEPI) appear to be most associated with a worker having experienced an accident previously. Hence, it can be deduced that personal protective measures are associated with a reduction in the accident rate among all the workers sampled.

3.2. BN2: other tasks

This network, which analyses tasks performed on scaffolding, platforms, structures and other auxiliary equipment, is depicted in Fig. 5. It is formed of seven variables, that is, the same variables as for BN1, but including *incorrect posture* and excluding *safety harness use*. The dependency relationships between the variables are largely similar to those postulated for BN1. The *experience* and *training* nodes take precedence over nodes that define behaviours and which could reflect immediate causes (*hazard perception* and *incorrect posture*). The *task duration* node heads up the model together with the *experience* node, which is related directly with the *hazard perception* and *incorrect posture* nodes.

Bearing in mind the network probabilities distribution after parameter learning, it can be observed that, as far as the *knowledge of regulations* variable and *hazard perception* variable are concerned, the typical surveyed worker has a deficient knowledge of the regulations governing his/her work (Fig. 5) and has little perception of the potential dangers associated with a task. The level of training is, in general, also deficient (only 13% of the surveyed workers had received specific training). As for task duration, more than 50% of tasks lasted less than 8 h. The number of workers who had previously experienced an accident or incident was slightly higher than the number of those who had never had an accident.

The following observations are made in regard to information deduced by means of inference:

- (1) Comparing short-duration tasks and tasks lasting longer than a working day (Fig. 6, TD State 3 = 100% vs. TD State 1 = 100%, respectively):
 - For short-duration tasks (TD State 3 = 100%), the number of workers adopting incorrect postures is greater than for long-duration tasks (TD State 1 = 100%).
 - The number of previous accidents or incidents is slightly higher among workers who perform short-duration tasks.
 - The proportion workers who do not perceive potential danger is slightly higher (88%) for short-duration tasks.
- (2) As with BN1 (ladder-based task analysis), the *experience* variable demonstrates a dependency relationship with the *training* and *knowledge of regulations* variables. The percentage of workers who have received generic or no training is

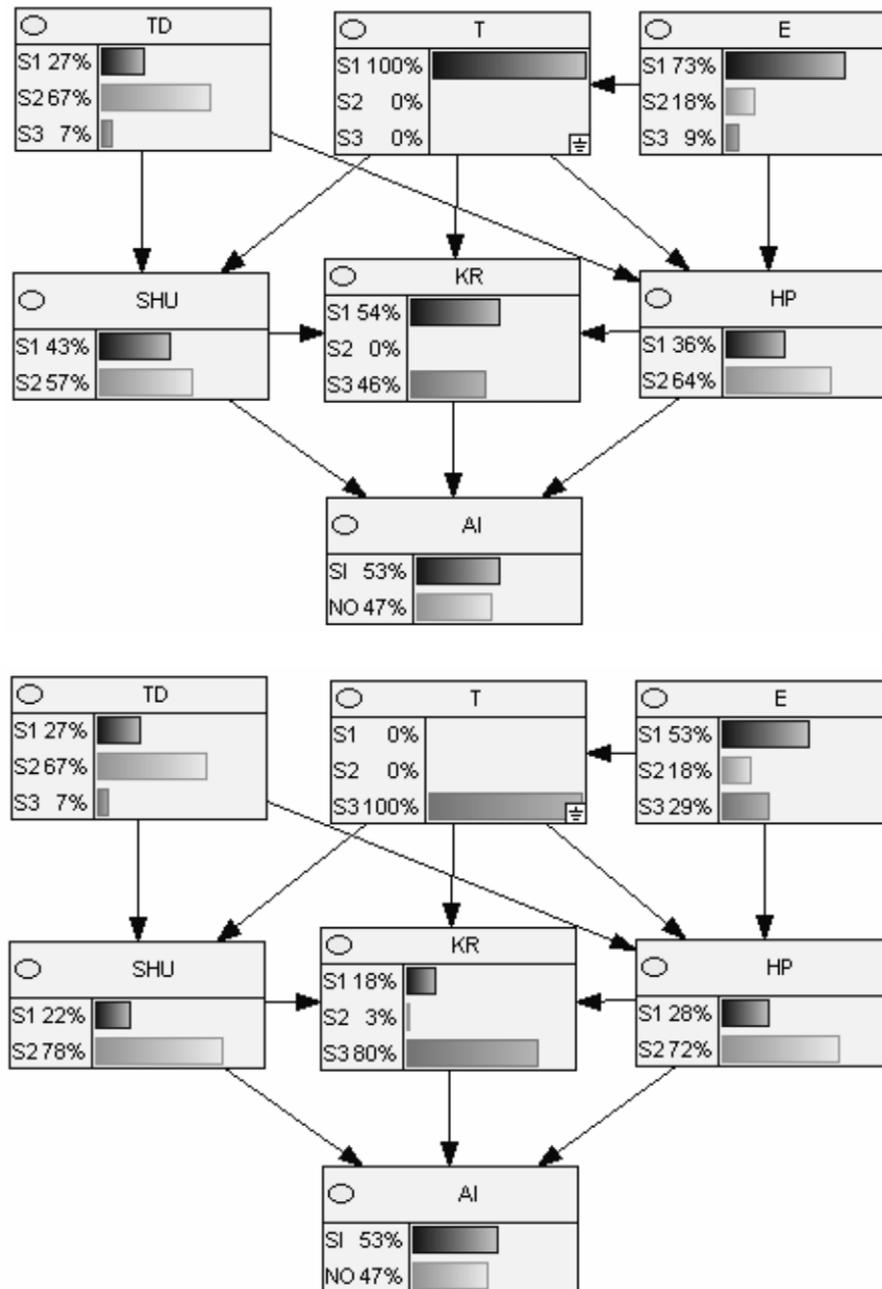


Fig. 4. Detail of Bayesian network for analysing ladder-based tasks, focusing on the variables T (training), TD (task duration), HP (hazard perception), SHU (safety harness use), KR (knowledge of regulations), E (experience) and AI (previous accidents or incidents). On the top, the established condition is that the worker has received specific training (State 1 = 100%). On the bottom, the worker has received no training (State 3 = 100%).

higher in the least experienced worker group. Comparing workers according to their experience (States 1 and 3), it can be observed that workers who have received specific training have a heightened perception of potential dangers and are more careful with posture than workers who have received general training.

- (3) In Fig. 7, it can be seen that workers who have a heightened sense of potential danger (State 1 = 100% of variable HP) also have a good knowledge of the regulations and typically adopt correct postures. The influence of the *hazard perception* variable on the *accident/incident* variable is, however, minimal.
- (4) Of all the variables, *incorrect posture* is the variable with the greatest bearing on the probability of a fall from an auxiliary item of equipment. Workers who adopt incorrect postures

on auxiliary equipment (State 2 = 100% of variable IP) have experienced an accident/incident in over 70% of the occasions that they work in these conditions. This percentage falls to 49% when they perform their task using a correct posture (State 1 = 100% of variable IP).

4. Conclusions

In this research we used Bayesian networks to analyse the factors affecting the performance of tasks that involve a high risk of falls from ladders or from other auxiliary equipment. This enabled us to identify the circumstances that have the greatest bearing on workplace accidents during both activities.

Task duration, as would be expected, seems to have a bearing on worker behaviour. In the case of ladder-based tasks, workers

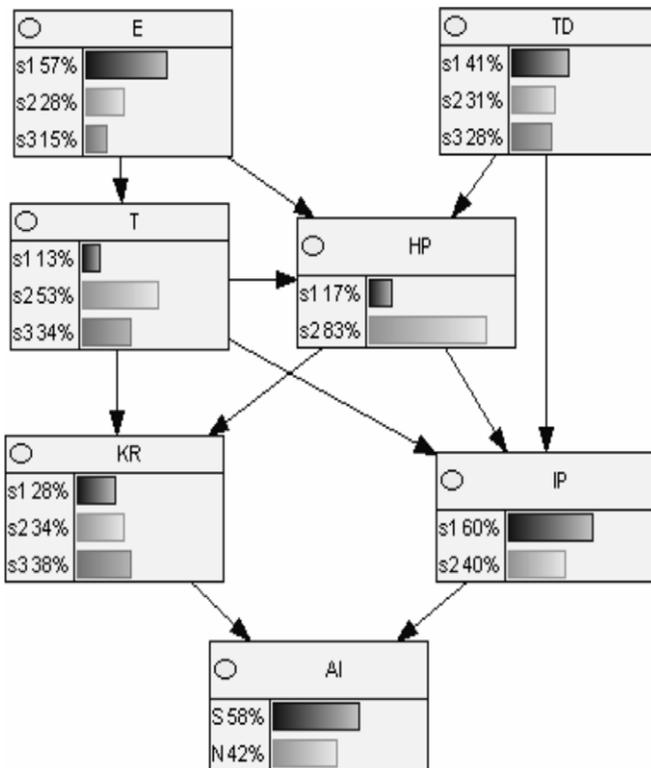


Fig. 5. Bayesian network analysing tasks performed on scaffolding, platforms, structures and other auxiliary equipment. Abbreviations: TD = task duration; T = training; E = experience; KR = knowledge of regulations; HP = hazard perception; IP = incorrect posture; and AI = previous accidents or incidents.

tend not to wear a harness if the task is of short-duration. In the case of scaffolding and similar equipment, haste is often the reason for adopting incorrect postures – a variable which, in this context, seems to be associated with a greater accident rate. In both situations, there appears to be a lower perception of potential danger in jobs of a short-duration.

The level of hazard perception seems to be connected with the training workers receive from their companies and with worker experience in the job. The higher the level of training and experience, the higher the level of hazard perception. It would seem, therefore, that experience has a bearing on accident rates in these tasks, although the relationship appears to be an indirect one (through its relationship with the level of training). This would indicate that – as found in other studies (Paul and Maiti, 2007) – although experience can help avoid risks, it is the immediate cause related to behaviour that ultimately causes an accident.

In the case of work performed on scaffolding and similar equipment, minimal or no training seems to lead to a higher frequency of incorrect postures – which are directly linked to higher accident rates. This fact is reflected in the majority of the companies within the group analysed; new or recently employed workers received inadequate or no training, despite the fact that Spanish legislation (Ley 31/1995) both requires workers to be trained before taking up their posts and indicates that this training must be theoretical and practical, as well as sufficient and suitable for the post.

In the groups analysed, immediate causes (following Bird and Germain, 1990) such as unsafe behaviour (like incorrect postures) and basic causes (e.g. lack of knowledge of regulations), respectively, have the greatest bearing on accident rates in the case of work carried out on scaffolding and similar equipment and in the case of work performed using ladders. In the case of ladders, cor-

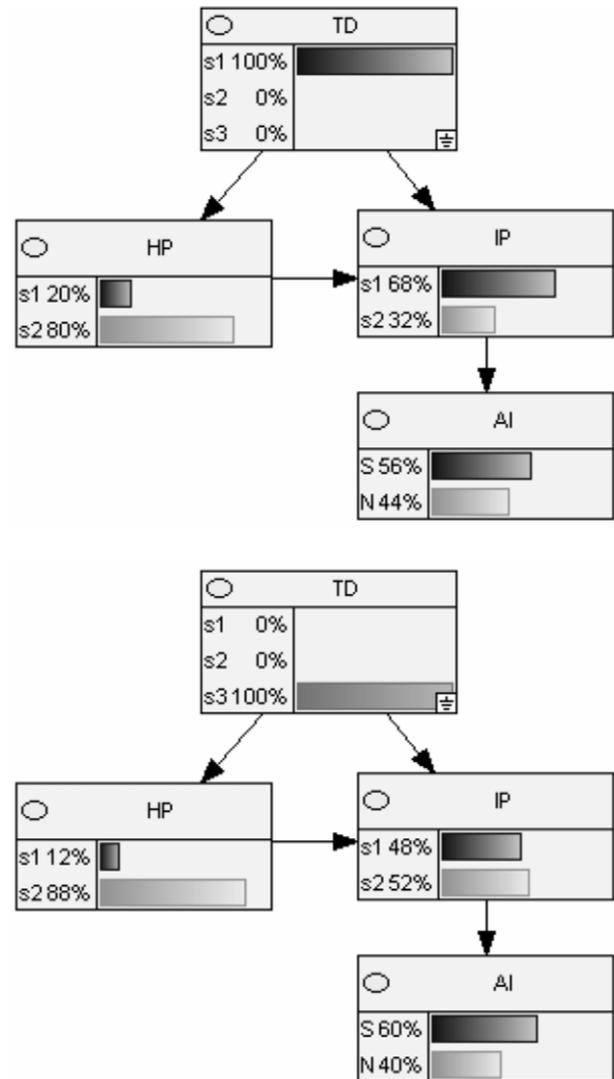


Fig. 6. Detail of Bayesian network for analysing tasks performed on auxiliary equipment, focusing on the variables TD (task duration), HP (hazard perception), IP (incorrect posture), and AI (previous accidents or incidents). On the top, the established condition is that task duration is more than 8 h (State 1 = 100%). On the bottom, the established condition is that task duration is less than 2 h (State 3 = 100%).

rective measures should be aimed at providing better training for workers; in the case of work carried out on scaffolding and similar equipment, unsafe behaviour could be avoided through task-specific training. The importance of training is undeniable, furthermore, in a sector in which employment is temporary and short-term and the physical location varies. Both the Bayesian networks presented in this work have shown that the level of training has an important bearing on accident rates. From the results of other works centred in the analysis of the causes of accidents by falls from ladders and scaffolds, it can be also deduced the importance of training in minimising the risks: in Papazoglou et al. (2006) and Papazoglou and Ale (in press), the variables introduced in the functional block diagrams are related to job factors and substandard conditions (like the type of ladder and its placement), contrary to the variables used in the present work, which are mainly related to the user behaviour. Nevertheless, it is undoubted that the correct choice of the material needed for developing the work and also its correct use are conditions which are only achieved following a task-specific training. Furthermore, Hale et al. (2007) obtain a high percentage of falls from ladders related to substandard practices (i.e. the use of a ladder in situations in which this is not the

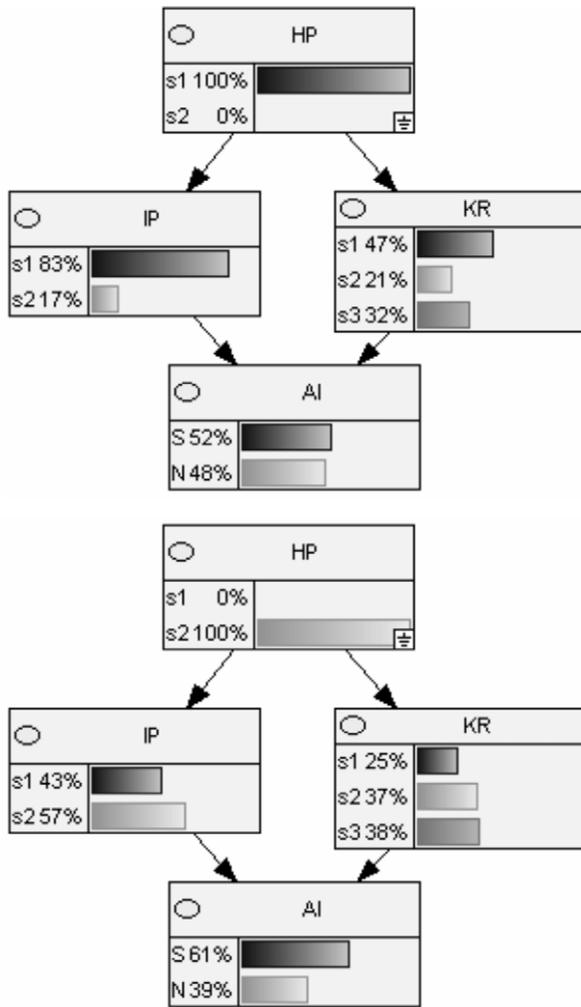


Fig. 7. Detail of Bayesian network for analysing tasks performed on auxiliary equipment, focusing on the variables HP (*hazard perception*), IP (*incorrect posture*), KR (*knowledge of regulations*), and AI (*previous accidents or incidents*). On the top, the established condition is that workers are aware of potential dangers (State 1 = 100%). On the bottom, the established condition is that workers are unaware of potential dangers (State 2 = 100%).

appropriate equipment, the incorrect placement and use of the ladder, etc.) and these practices can also be corrected through training.

Training is the most effective way to minimise the risks that arise from incorrect posture and other unsafe behaviours, but it is only effective if long-term and if given in circumstances of perseverance and control – above all in sectors such as construction and mining, which have high levels of temporary employment. Independently of whether long-term training is provided, our results lead us to believe that a short-term solution that could reduce accident rates would be to lower the working height at which it is mandatory to adopt protective measures (2 m in Spain). Other authors have found that accidents happen at lower heights and in situations perceived as non-hazardous (Kines, 2003). Although adopting measures to correct inappropriate behaviour is crucial to attaining greater integration of risk prevention in the management of these kinds of tasks, the adoption of collective protection measures would represent less effort and would ultimately be more effective.

The results of this research indicate that Bayesian networks are very useful in explaining the causes of falls. By identifying the dependency relationships between different variables (and

expressing these relationships in probabilistic terms), Bayesian networks offer a broad-based perspective on the circumstances surrounding work performed at a height that will enable us to define a preventative strategy that reflects a particular reality. Bayesian networks represent a statistical tool of huge potential in investigating the causes of accidents in the workplace. As an expert system, moreover, Bayesian networks allow us to build a knowledge base that progressively and incrementally grows with the inclusion of new data. In this research we have chosen to structure the networks a priori, but in earlier research – in this field of knowledge (Matías et al., 2008) as well as in others (Matías et al., 2006; Rivas et al., in press) – we established that fully or partially automated structuring (using algorithms that deduce the structure directly from the data) can throw up causal relationships that escape the attention of experts. In the case of data on the circumstances surrounding incidents in the workplace, automated models would reflect the effectiveness of a company's safety management and internal risk prevention procedures (this will be the subject of future research).

However, using BNs has its limitations, the most obvious being the use of discrete variables. If a large number of categories is selected for each variable – which is desirable so as not to lose information – then a large quantity of data that is representative of all possible combinations is required. As far as discretization is concerned, therefore, a compromise solution is required that does not endanger computational capacity.

As regards the sources of information used, surveys of workers have proved to be very useful in identifying causes other than those which can be quantitatively measured and evaluated. The inclusion of variables with high levels of subjectivity in problems like that analysed in this article – in which the protagonists are human beings whose behaviour is the cause of workplace accidents – offers a more realistic vision of a problem. In research into accidents or reports on workplace accident rates, the combined use of this source of information and Bayesian networks enables us to establish hypotheses more in keeping with reality compared to conventional techniques.

References

- Adriaenssens, V., Goethals, P.L.M., de Pauw, C.N., 2004. Application of Bayesian belief networks for the prediction of macroinvertebrate taxa in rivers. *Annales de Limnologie – International Journal of Limnology* 40 (3), 181–191.
- Antal, P., Fannes, G., Timmerman, D., Moreau, Y., De Moor, B., 2007. Bayesian applications of belief networks and multilayer perceptions for ovarian tumour classification with rejection. *Artificial Intelligence in Medicine* 29, 39–60.
- Baran, E., Jantunen, T., 2004. Stakeholder consultation for Bayesian decision support systems in environmental management. In: *Proceedings of the Regional Conference on Ecological and Environmental Modeling (ECOMOD 2004)*, 15–16 September 2004. Universiti Sains Malaysia, Penang, Malaysia.
- Beguiria, P.A., 1988. *Manual Para Estudios y Planes de Seguridad e Higiene, Construcción, 1a Edición*. Instituto Nacional de Seguridad e Higiene en el Trabajo, Ministerio de Trabajo y Asuntos Sociales, Gobierno de España.
- Bird, F.E., Germain, G.L., 1990. *Practical Loss Control Leadership*. International Loss Control Institute (Publ.), Revised Edition, 446pp.
- Cooper, G.F., Herskovits, E., 1992. A Bayesian method for the induction of probabilistic networks from data. *Machine Learning* 9, 309–347.
- Dedobbeleer, N., Beland, F., 1991. A safety climate measure for construction sites. *Journal of Safety Research* 22, 97–103.
- Galán, S.F., Mosleh, A., Izquierdo, J.M., 2007. Incorporating organizational factors into probabilistic safety assessment of nuclear power plants through canonical probabilistic models. *Reliability Engineering and System Safety* 92, 1131–1138.
- Gillen, M., Baltz, D., Gassel, M., Kirsch, L., Vaccaro, D., 2002. Perceived safety climate, job demands and co-worker support among union and non-union injured construction workers. *Journal of Safety Research* 33, 33–51.
- Hale, A.R., Ale, B.J.M., Goossens, L.H.J., Heijer, T., Bellamy, L.J., Mud, M.L., Roelen, A., Baksteen, H., Post, J., Papazoglou, I.A., Bloemhoff, A., Oh, J.I.H., 2007. Modelling accidents for prioritizing prevention. *Reliability Engineering and System Safety* 92, 1701–1715.
- Hansen, C.P., 1989. A causal model of the relationships among accidents, biodata, personality and cognitive factors. *Journal of Applied Psychology* 74, 81–90.
- Holnagel, E., 1993. *Human reliability analysis. Context and Control*. Harcourt Brace, London.

- Janicak, C.A., 1998. Fall related deaths in the construction industry. *Journal of Safety Research* 29, 35–42.
- Kines, P., 2003. Case studies of occupational falls from heights. Cognition and behaviour in context. *Journal of Safety Research* 34, 263–271.
- Ley 31/1995, de 8 de noviembre (Ley de Prevención de Riesgos Laborales). BOE (Boletín Oficial del Estado) no. 269, de 10.11.1995. Transposición de la Council Directive 89/391/EEC of 12 June 1989 on the Introduction of measures to encourage improvements in the safety and health of workers at work. *Official Journal L183*, 29/06/1989, pp. 0001–0008.
- Marcot, B.C., Holthausen, R.S., Raphael, M.G., Rowland, M.M., Wisdom, M.J., 2001. Using Bayesian belief networks to evaluate fish and wildlife population viability under land management alternatives from an environmental impact statement. *Forest Ecology and Management* 153, 29–42.
- Matías, J.M., Rivas, T., Ordóñez, C., Taboada, J., 2006. Assessing the environmental impact of slate quarrying using bayesian networks and GIS. In: *Proceedings of the Fifth International Conference on Engineering Computational Technology*. Las Palmas de Gran Canaria, pp. 345–346.
- Matías, J.M., Rivas, T., Martín, J.E., Taboada, J., 2008. A machine learning methodology for the analysis of workplace accidents. *International Journal of Computer Mathematics* 85 (3), 559–578.
- Ministerio de Trabajo y Asuntos Sociales, 2006. Boletín de estadísticas laborales. Gobierno de España, 11/2006. <<http://www.mtas.es/estadisticas>>.
- ORDEN TAS/2926/2002, 2002, de 19 de noviembre, por la que se establecen nuevos modelos para la notificación de los accidentes de trabajo y se posibilita su transmisión por procedimiento electrónico. BOE no. 279 de 21.11.2002. Gobierno de España.
- Papazoglou, I.A., Ale, B.J.M. A logical model for quantification of occupational risk. In *Reliability Engineering and System Safety*. <www.sciencedirect.com>.
- Papazoglou, I.A., Aneziris, O., Post, J., Baksteen, H., Ale, B.J.M., Oh, J.I.H., Bellamy, L.J., Mud, M.L., Hale, A., Goossens, L., Bloemhoff, A., 2006. Logical models for quantification of occupational risk: falling from mobile ladders. In: *International Conference on Probabilistic Safety Assessment and Management*, New Orleans, May 13–19, 2006, 2006.
- Paul, P.S., Maiti, J., 2007. The role of behaviour factors on safety management in underground mines. *Safety Science* 45, 449–471.
- Real Decreto 1215/1997, 1997, de 18 de Julio, por el que se establecen las disposiciones mínimas de seguridad y salud para la utilización por los trabajadores de los equipos de trabajo, en materia de trabajos temporales en altura. BOE (Boletín Oficial del Estado) no. 188 del 7.8.1997. Gobierno de España.
- Real Decreto 1627/1997, 1997. Sobre disposiciones mínimas de seguridad y salud en las obras de construcción. BOE (Boletín Oficial del Estado) no. 1256 del 25.12.1997. Gobierno de España.
- Real Decreto 486/1997. Sobre disposiciones mínimas de seguridad y salud en los lugares de trabajo. BOE (Boletín Oficial del Estado) no. 97 del 23.04.1997. Gobierno de España.
- Rivas, T., Matías, J.M., Taboada, J., Argüelles, A., in press. Application of Bayesian networks to the evaluation of roofing slate quality. *Engineering Geology*. doi:10.1016/j.enggeo.2007.06.002.
- Spirtes, P., Glymour, C., Scheines, R., 2000. *Causation, Prediction and Search*, second ed. The MIT Press.
- Zhu, J.Y., Deshmukh, A., 2003. Application of Bayesian decision networks to life cycle engineering in Green design and manufacturing. *Engineering Applications of Artificial Intelligence* 16, 91–103.