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Risk of human fatality in building fires: A decision tool using Bayesian networks

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ABSTRACT

The Netherlands is the most densely populated country of the European Union, which makes space very expensive. This leads to increasing complexity of the cities' layout and other public spaces, together with a large number of people involved. Authorities would like to know whether new and innovative building designs ensure an appropriate level of safety of people in case of fire, before the accident happens, and to be prepared for the so-called "low probability–high consequences" accidents. Therefore, they need a tool to help them estimate the extent of a fire in a building, given any combination of possible conditions and any unexpected course of events during an emergency. This paper discusses the possibility of using Bayesian belief nets for this task. Using this approach, the people in charge can take decisions at different stages of the design process of a building regarding the location, the structure, the loading of the building, the types of fire protection systems inside the building, as well as the characteristics of the fire brigade that fights the possible fire. In the current study, usefulness of the approach is investigated using a small example. This will show the feasibility of the approach for the Netherlands situation and give authorities involved confidence that building a large comprehensive model would fulfil their needs for a support tool in the planning process. The effort to gather real data therefore was restricted as demonstration of fitness for purpose was the primary objective.

1. Introduction

The complexity of our society is continuously increasing. Advanced technology allows the accommodation of a large population with increasing demands on goods and mobility in the very small space that the Netherlands provide. Therefore, the available space is used at maximum. As an example, preparations are made to build a roof over several kilometres of a 10 lane highway – that carries dangerous goods – and to build offices and may be even houses on top of it. But this intense use of space does not go without a price. There is an increased potential for an accident to become a large-scale disaster. For example, an explosion of a track carrying dangerous goods on the highway mentioned above may end in a large number of causalities among the people living or working in the buildings on top of the highway. Although such an accident remains a rare event, its consequences can reach a large extent. Therefore, the authorities would like to know the consequences of such an accident and to prepare for intervention, before the accident happens.

The people in charge of taking decisions in the design phase of such a complex project need a tool that helps them to choose among the alternative designs that one which ensures with a certain probability the smallest damage. Given the fact that solutions for the large demand on space are innovative designs, the outcome of a possible accident and in particular a fire in such a building cannot be estimated based on past experience and statistical data. Moreover, prescriptive codes cannot be applied to these innovative designs. Therefore, new methods to test the level of safety of people inside buildings are needed. These methods should take into consideration all uncertain conditions in which a future possible fire could take place and, therefore, should be based on computer simulations.

There is a large range of models that simulate the evacuation of a building, from simple models that simulate only the movement of people within the building, to very complex models that attempt to incorporate human behaviour [1,2]. They are used in order to decide on the structure of the building, the position of the exits, the size of the doors, corridors, and staircases. They can estimate the time needed to evacuate the whole building or only some parts of the building. They help also to find bottlenecks of a building regarding evacuation (where people may be trapped, where queues can be formed, etc.). However, they cannot consider the conditions outside buildings, for example, how neighbourhood of buildings, weather conditions, or intervention of fire fighting services can influence evacuation, and, implicitly, the outcome of a fire in terms of number of deaths. As an example,

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one of the tunnels in the High Speed Railway Line is designed for quick evacuation of passengers from the tunnel but further investigations, with the tunnel already finished, show that there is not enough space at ground level to accommodate the fleeing crowd, let alone vehicles and equipment of emergency services. This example shows the need to include in models not only people evacuation, but also fire development and rescue services' actions, taking into account the characteristics of people and structure, location, and the external factors. For this particular case, if all these factors are included into the Bayesian belief net (BBN) model, one may set values for the available safe place and may obtain that the number of people at risk is high, or that the probability to have a high-consequence fire is high.

The goal of the model presented in this paper is to put together not only people and their behaviour during evacuation, but also fire fighters' actions, structure of the building, and characteristics of the building and the environment, in an overall model. Model results are more useful in a comparative sense rather than in an absolute sense. Using this tool, more alternatives can be compared with each other, with the actual level of safety, the desired level of safety, or with existing codes and procedures. The model could be used to analyze the "what-if" scenarios, as well as the low probability–high-consequence scenarios.

The model proposed in this paper is based on the Bayesian belief net approach, a probabilistic method that can accommodate the complexity of the system under analysis. In Section 2 of the paper, the approach chosen to reach the goal of the work is presented. This section is a short summary of general characteristics, advantages and disadvantages of this method, comparisons with methods used before, and a short presentation of attempts to use the BBN approach in the field of fire safety. The model for percentage of deaths in a fire is presented in Section 3. Three phases of building up the BBN model for fire safety are presented here. First, the process of building the graphical structure of the network and of quantifying it is succinctly described. The last part of the section presents some example of analysis and results that can be obtained using this method in order to give an idea about applicability of the BBN approach for the estimation of probability distribution of percentage of deaths in case of fire. The last section of the paper presents the conclusions and gives directions about the future work to be done.

2. Method

In recent years, fire regulations in the Netherlands have tended to change from prescriptive codes to performance-based regulations. This change of principles makes possible more flexible and innovative designs and cost-effective structures. However, it also increases the number of studies that involve risk analysis by demand of authorities, who want to be assured that the solutions chosen are acceptable. This section of the paper presents three methods that are used in risk analysis in general and fire safety in particular.

2.1. Basic principles of fault tree and event tree analysis

Event tree (ET) and fault tree (FT) methods are very popular and diffused techniques for analyzing large critical systems. While the FT method is used to analyze causes of failure of systems, the ET technique shows consequences of such an undesired event. The FT method is a top-down approach, starting with the unwanted event, also called top event, which is the failure of the system, and analyzes different ways in which it can occur. Each event is characterized by the probability of occurrence and non-occurrence, and the probability of the top event can be computed. On the other hand, the ET analysis begins with an initiating event and consequences of that event are followed through a series of potential paths. Each event is assigned a probability of occurrence and the probability of various possible outcomes can be computed. Thus, the ET method is a forward method with an intuitive character; but it does not explicitly represent the state of the system and its environment, which may influence the consequences of the events.

The ET method represents the process as a chronological sequence of events, hence using a linear time order. On the other hand, the FT analysis is not able to capture sequence dependencies in a system. A more complex version of FT, called dynamic FT analysis, can include the sequence dependencies, but it has the disadvantage of being difficult to be implemented [3].

Another major disadvantage of FT is the fact that it can incorporate only binary events (working/not working). This condition is more relaxed in the ET analysis, where discrete events with more than two states can be modelled. But, still, only events with a finite number of states can be modelled. This characteristic of the two methods makes their application in the field of fire safety to be based on many assumptions, which limits the subject of the analysis. For example, there are many events or factors influencing the outcome of a fire in a building that have not only more states, but a continuous set of states. Moreover, they cannot be discretised. An example of such a factor is the time until people start the evacuation in a building. If one wants to discretise this factor as "small", "medium", and "large", the question is what would be the interval of values for each of the categories. The best way to model this factor is to assume that it is a continuous random variable following a certain distribution.

Moreover, in the FT analysis, relations between events and causes are represented by means of logical AND/OR gates. In the process of a fire in a building, there are many uncertainties and, usually, the occurrence of a combination of certain events does not ensure the occurrence of another event, but rather does influence the probability of occurrence of that event. For example, poor training of occupants of a building and a late alarm time make a longer evacuation time more probable. It is not for sure that the evacuation time is longer, because there may be some other factors, such as a small distance to exits, which may reduce the evacuation time.

The big disadvantage of both FT and ET methods is that they are not able to capture the dependability between events. This is a main characteristic of a fire in a building, in which there are multiple dependencies between factors. For example, area of the building influences both the time until critical conditions are reached and the evacuation time. Hence, random variables associated with the time until critical conditions are reached and the variable associated with the evacuation time are not independent variables.

FT and ET analyses have been applied successfully in many fields, and also in the field of fire safety [4]. In [5,6], the ET approach was used in order to compute the risk to which occupants of a building may be subjected if a fire breaks out in that building. The branches of the ET used in these papers denote the functioning/failure of the protection systems (alarm, sprinklers, and emergency doors). Using the ET approach, scenarios were defined and for each of the scenarios, the probability of occurrence and the consequences were computed. In [7], the ET approach was used in order to quantify the risk in chemical process industries. However, in all these references, only parts of the complex system of a fire, for example fire suppression systems, are considered. None of these papers includes all the parts involved in a fire in a building (such as fire, building itself, people inside the building, fire brigade, and environmental conditions). Moreover, the variables included are characterized by two states, functional/non-functional.

Hence, while FTs and ETs have been demonstrated to be useful tools for analyzing complex technical systems where certain events must occur in order for other events to occur, following a linear time or causal order, they fail to adequately represent the uncertainty and multi-dependencies between factors in a complex system like an emergency situation. These major disadvantages of the ET and FT approaches are solved by the BBN approach.

2.2. Basic principles of Bayesian belief net method

Bayesian belief nets are "a theory of reasoning from uncertain evidence to uncertain conclusions" [8]. They provide a framework for graphical representation of the logical relationships between variables and capture the uncertainty in the dependencies between these variables using conditional probabilities [9].

By definition, BBNs are directed acyclic graphs representing high-dimensional uncertainty distributions [10,11]. They consist of nodes and arcs; the nodes represent random variables and the arcs represent causal relations between variables. The arcs are directed from the "parent" or cause node to the "child" or effect node. The variables associated with each node can be discrete or continuous. The causal relations between variables are expressed in terms of conditional probabilities. The model is probabilistic rather than deterministic and this makes it possible to include factors that influence the frequency of events, but do not determine their occurrence.

In Fig. 1a, an example of discrete belief net with three nodes is presented. The graphical structure shows that the variable B is influenced by variables A and C, and variables A and C are independent. Each node has two possible values, corresponding to the working (OK) and failure (Not OK) states of an electronic component of a system, for example. In Fig. 1b, the probability tables for nodes A and C and the conditional probability table for node B are given. The probabilities assigned in Fig. 1b are arbitrary, for the purpose of illustration only. In a real example, they can be obtained from recorded data or can be derived from experts using appropriate methods for probability elicitation [12,13]. It can be seen that for node B, the probability table lists the probabilities that this node takes one of its values, for all combinations of parents' values (A and C). For example, the probability that node B takes value OK, when node A takes value OK and node C takes value Not OK, is 0.75.

Basically, there are three main steps in building and using BBNs. The first stage, problem structuring, includes the determination of variables and their cause–effect relationships, while the second stage includes conditional probabilities for each variable's states, given the state of parent variables. The conditional probabilities may be derived from historical data or may be elicited by experts in the field, using tested elicitation procedures [12,13]. In fact, one of the advantages of BBN method is that it is able to combine the two sources of information about the variables included into the model. Moreover, being a graphical model, it allows the experts to concentrate in the first phase on building up the qualitative structure of the problem, before they address issues on quantitative specification. Such models encode the natural judgement of relevance and irrelevance, which can be formulated prior to any quantification. Vertices in the graph represent variables. Instead of saying what an edge between two nodes represents, it is rather easier to say what a missing edge means: irrelevance. In this sense, a direct edge can be interpreted as a probabilistic influence, a causal relation, or, more weakly, a direct relevance.

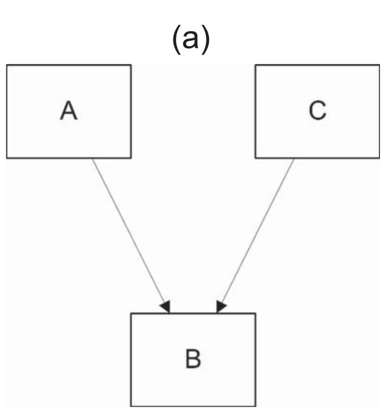
During the third stage, called inference, evidence, in the form of knowledge abut the state of one or more variables, is entered into the BBN and the probabilities of the other variables are updated. The evidence can be propagated through the network forward and backward, making possible two types of reasoning: predictive reasoning, when the probability of occurrence of some child nodes is computed based on evidence on some of the parent nodes, and diagnostic reasoning, when the posterior probability of any set of variables that may cause the evidence is computed.

For the network represented in Fig. 1a, given the information that variable A is working, in a predictive reasoning, one would be interested how the probability that variable B takes also the value OK. Before any evidence, using the probability laws and the probability values from Fig. 1b, $P(B=\text{OK})$ can be computed as follows:

$$\begin{aligned}P(B=\text{OK}) &= P(B=\text{OK}/A=\text{OK},\ C=\text{OK})P(A=\text{OK})P(C=\text{OK})\\ &\quad + P(B=\text{OK}/A=\text{OK},\ C=\text{Not OK})P(A=\text{OK})P(C=\text{Not OK})\\ &\quad + P(B=\text{OK}/A=\text{Not OK},\ C=\text{OK})P(A=\text{Not OK})P(C=\text{OK})\\ &\quad + P(B=\text{OK}/A=\text{Not OK},\ C=\text{Not OK})P(A=\text{Not OK})\\ &\quad \times P(C=\text{Not OK})\\ &= 0.8\times0.6+0.75\times0.4=0.48+0.3=0.78\end{aligned}$$

Given the evidence that $A=\text{OK}$, the new probability that B is working is

$$\begin{aligned}P(B=\text{OK}/A=\text{OK}) &= P(B=\text{OK}/A=\text{OK},\ C=\text{OK})P(C=\text{OK})\\ &\quad + P(B=\text{OK}/A=\text{OK}, C=\text{Not OK})\\ &\quad \times P(C=\text{Not OK})\\ &= 0.8\times0.7\times0.6+0.75\times0.7\times0.4\\ &\quad +0.6\times0.3\times0.6+0.1\times0.3\times0.4\\ &= 0.336+0.21+0.108+0.012=0.666\end{aligned}$$



(b)

A	
OK	**NotOK**
0.70	0.30

C	
OK	**Not OK**
0.60	0.40

		B	
A	**C**	**OK**	**Not OK**
OK	**OK**	0.80	0.20
OK	**Not OK**	0.75	0.25
Not OK	**OK**	0.60	0.40
Not OK	**Not OK**	0.10	0.90

Fig. 1. BBN example: (a) network with three nodes and (b) conditional probability tables (CPT).

For a diagnostic reasoning, suppose that information that B is not working is available. Then, one may be interested in the probability that A is not working too. In this case, according to the values from Fig. 1b, prior to any evidence, $P(A = \text{Not OK}) = 0.3$. After the information that B is not working, the probability that A is not working too can be computed using the Bayes' rule:

$$P(A = \text{Not OK}/B = \text{Not OK}) = \frac{P(B = \text{Not OK}/A = \text{Not OK})P(A = \text{Not OK})}{P(B = \text{Not OK})}$$

Applying the probability laws and using the values from Fig. 1b, it follows that

$$P(A = \text{Not OK}/B = \text{Not OK}) = 0.529$$

There is an increasing trend in the developing software tools that facilitates modelling with Bayesian networks. They can support a large number of nodes and can make many calculations in a very short interval of time. The application area of BBNs is therefore expending rapidly. BBNs have been applied on a large scale in medical fields, for diagnosis, treatment selection, planning, and prognosis [14]. Another field where BBNs are applied is software systems, where they are used for software quality [15] and software safety evaluation [16], as well as for software dependability [17]. BBNs have found successfully application in causal modelling of air safety as well [18]. There are also several works in the field of fire safety in which the BBN approach is used in order to compute the probability of flashover given that the fire started [19], to model causal links between essential requirements and cumulative requirements imposed on building performance [20]. In [21], the fire protection systems are analyzed; the network used contains chance nodes as fire start, detection, tampering, sprinklers, smoke detection, fire brigade, fire flashover, and structural collapse. However, people are not included and the fire brigade is represented only in a simplistic way, by specifying only if it is involved or not. The variables are discrete, having only two states, usually denoted by Yes/No or Acting/Not acting. A more complex BBN model for the estimation of the life risk in a building due to fire is used in [22], but, still, the variables used there are discrete and they have only two states. The author concludes that there is need to have an estimation of fatal accidents as average values with standard deviation instead of deterministic approximations. If the problem of assessing probabilities in a consistent way is added in cases where variables have more then two states, it becomes clear that the use of continuous variables is preferable. Of course, a mixed model that can accommodate both continuous and discrete variables is the best.

Discrete BBNs are used more often, mainly due to the numerous existing commercial tools with advanced graphical user interfaces.[1] The discrete version of BBNs is very efficient as long as a simple system, thus a simple structure of the network, is used. In this case, the user has to assign marginal distribution for each of the source nodes and conditional probability tables for the child nodes. This is a simple process as long as there is a complete database or the nodes can take two or three possible values and the child nodes do not have too many parents. But the numbers of probabilities that have to be assigned for a child node increases exponentially with the number of parents that influence that node and with the number of states that each parent can take. For example, if a child node with three possible states has six parents, each having three possible values, the conditional probability table for the child node contains $3 \times 3^6 = 2187$ probabilities that have to be assigned in a consistent way. This is the main disadvantage of discrete BBNs, which makes the application of this version to complex systems difficult.

The continuous version of BBNs solves the problem of assigning huge numbers of probabilities. Until recently, the continuous BBNs were restricted to joint normal distributions [23]. One can also use discrete–continuous models, in which continuous nodes can have discrete parents, but not discrete children [24]. However, the normal and discrete-normal BBNs are difficult to use when normality condition does not hold.

In [25], the authors propose a distribution-free BBN method that supports both discrete and continuous variables. In this version of BBNs, the nodes are associated with arbitrary continuous or discrete variables and the relations between variables are expressed in terms of (conditional) rank correlations. The quantification of such a network means the assignment of one-dimensional marginal distribution for each node and a (conditional) rank correlation for each arc in the model. The quantification of the network can be made using recorded data or experts in the field, for both marginal distributions [12,13] and rank correlations [26]. Moreover, the proposed method can also incorporate functional relations between variables, which is a very important issue in fire modelling because of the numerous differential equations describing fire development [27,28]. In the current project, the latest version of BBNs is used. A more detailed description of the method and the sampling algorithm, as well as a comparison of this method with others, can be found in [25]. The algorithm is then implemented in UniNet,[2] an uncertainty analysis software package used for dependence modelling of high-dimensional distributions.

In the next sections of the paper, the general steps of the building process of the network used for the BBN model are presented and a very simple example is used in order to show the type of results obtained with this method and the way in which they can be interpreted and used.

3. Model for the percentage of deaths in building fires

This section presents the three steps that have been followed through building the model for human damage produced by fire in a public building and the type of results that can be produced using the BBN method. Given the large structure of the resulting network and the goal of the paper to introduce the application of the BBN method in the field of fire safety, as well as to show the capabilities and usefulness of the method in this field, a more reduced structure of the network is used as an example. Therefore, the results of the experts' interviews for quantifying the network are not described in detail.

3.1. Graphical structure and quantification of the network

Many discussions can arise regarding the factors that influence the number of fatalities in a fire. If a database exists, then the factors can be selected after a careful analysis of this database. The level of details is chosen according to the task of the study or after discussions with people who are going to use the results of the analysis. If no pertinent historical or experimental data are available, the factors are chosen with the help of experts in the field.

Although the graph has a great importance for the BBN approach, in most of the applications of this method there is no information about how the graph is built. Often only the

[1] http://www.cs.ubc.ca/~murphyk/Bayes/bnsoft.html.

[2] UniNet is produced within the Department of Applied Mathematics at Delft University of Technology and can be downloaded from http://dutiosa.twi.tudelft.nl/~risk.

quantification phase of the BBN is described. The building process of the network itself however is not merely a simple mechanistic stage of the BBN approach. Especially when there are no data or the existing data do not contain enough details, the building of the network is an essential and important step of the modelling process. Moreover, in dealing with complex systems, the building process may be equally complicated due to the large number of variables involved.

The same difficulties are met in finding the structure of the BBN model for the percentage of fatalities in a building fire. The difficulties come from the fact that fire in a building is a very complex process that involves at least four factors: the fire itself, environment, rescue services, and people. In the literature there are known simulations models for fire and smoke development [2], for people behaviour during evacuation [1,29], but there is a lack of models that put together these four sub-systems and, especially, interactions between them [30].

Moreover, during a fire in a building, there are three main time lines: the fire time line (the process), people time line (people), and rescue service time line (organization). It is often but not always clear what the order of events is for each of the time lines separately, but when they are put together and influences between these time lines are studied, the order of events' occurrence is very uncertain [31]. Hence, there is uncertainty not only about the value that a variable can take, but also about the order of occurrence of events, which makes the use of ET and FT approaches almost impossible, if all three time lines are considered.

Literature from the fire engineering field mentions many factors as having an important role in deciding the outcome of a fire in a building. In most of the cases, only factors that influence parts of the fire process are enumerated. Usually, the studies are grouped around four main subjects: evacuation, fire and smoke development, and rescue actions. However, we do not know a model that gives a comprehensive view of a fire in a building [30,32], and it is difficult to put together all the factors in order to obtain a complete model and it is even more difficult to specify interactions between factors.

Therefore, interviews with experts on the important aspects of a fire in a building have been organized, in order to find the factors that have to be included into model. Until now, three groups of experts have been interrogated: fire fighters, facility managers, and people from insurance. The experts were asked to give a list of factors that influence the outcome of a fire, grouped into four classes: factors related to the building, factors related to people inside the building, factors related to location of the building, and some external factors. An interview was organized for each group of experts and it was conducted by open questions. The three interviews resulted in a list of 101 factors, out of which 77 were distinct. However, the influences between factors could not be recovered from the experts' statements. Moreover, the 77 factors were basic factors; the factors related to the processes taking place during a fire in a building were not mentioned by experts [33]. Therefore, the resulting list of factors was combined with a top-down approach in which the building process of the network starts with the top event, the percentage of people dying in a building fire, and goes back to the basic factors, through the factors representing the processes taking place during a fire. Although the quantification of the network is not yet taken into consideration, during the building up process of the network, the modeller has to have in mind what data are available or can be obtained from experts, what factors can be quantified, and which have to be replaced by proxy variables [34]. However, the model presented in this paper is only a reduced version of a more complex and detailed model.

The next step is to quantify the structure of the network, which means setting up the marginal distributions for each node and the (conditional) rank correlation for each arc existing in the network. Most of the marginal distributions were taken from literature in the field, but expert judgment exercises were also conducted in which the experts were asked to give the 5th, 50th, and 95th percentiles, according to their beliefs for the variables under study [12]. The (conditional) rank correlations were obtained from experts using the probability of exceedance and following the procedure described in [26]. The use of the algorithm presented in [25] and implemented in UniNet allows factors that are functional relations of their parent nodes. For example RSET, which is the sum of the four component times, or time when critical conditions are reached, is expressed in terms of differential equations. The percentage of deaths is computed outside of the UniNet software due to the mode complex procedure used for computations, which are neither analytical nor implicit. Basically, the sample of the joint distribution of the other nodes produced by UniNet is exported to Matlab and Monte Carlo simulations are used for deriving the distribution of the percentage of deaths. However, taking into account the introductory character of this paper, detailed formulas are not needed here. The important aspect is that functional relations can be introduced into the version of BBN used in this research.

Finally, the model has to be validated as a whole or only in part. The validation has to be done with data that have not been used for quantification. Since there is a lack of data for all the networks, only partial validation studies can be performed [33]. Currently, the process of evaluation of the network is under development. However, the purpose of this paper is not to present a complete model for the percentage of fatalities in a fire, with all factors and definitions set up, but a very simplified version, just to show how the model and its results can be used. Therefore, the model presented in Fig. 2 is a reduced one that serves the task of introducing the use of the BBN approach for developing an integrated model for fire risk in building fires.

3.2. *Inference*

This section presents several examples of analyses that can be performed with the model proposed in the previous sections. The authors would like to emphasise that the numerical results are not important in an absolute sense, but rather they show the feasibility of the model and increases the confidence that a complete model with data obtained from real databases will fulfil the need for a support tool in the planning process.

For example, authorities might be interested in increasing the safety of people in a building by either performing more frequent evacuation exercises or by increasing the number of people with special training, who can help others during evacuation. The current situation is that the exercises are performed once every 3 years (People Training $= 3 \times 365 = 1095$ days) and there are 3% people with special training (BHV $= 0.03$) to help in case of a fire. The people in charge of taking the decision have to choose between performing evacuation exercises more often (once every year, meaning People Training $= 365$), or training more people (BHV $= 0.07$). An ideal case would be to do both, but given the shortage of funds, this is not possible.

The actual situation (Base Case) and the three alternative scenarios are presented in Table 1.

The results of the simulations for the four cases are presented in Fig. 3. As has been expected, performing evacuation exercises more often increases the awareness of the people in the building and their reaction time and, consequently, the evacuation time will decrease, which makes the percentage of people dying to decrease. This can be seen by comparing the Base Case with Scenario 1. There is a probability of 91.4% that there is no victim in

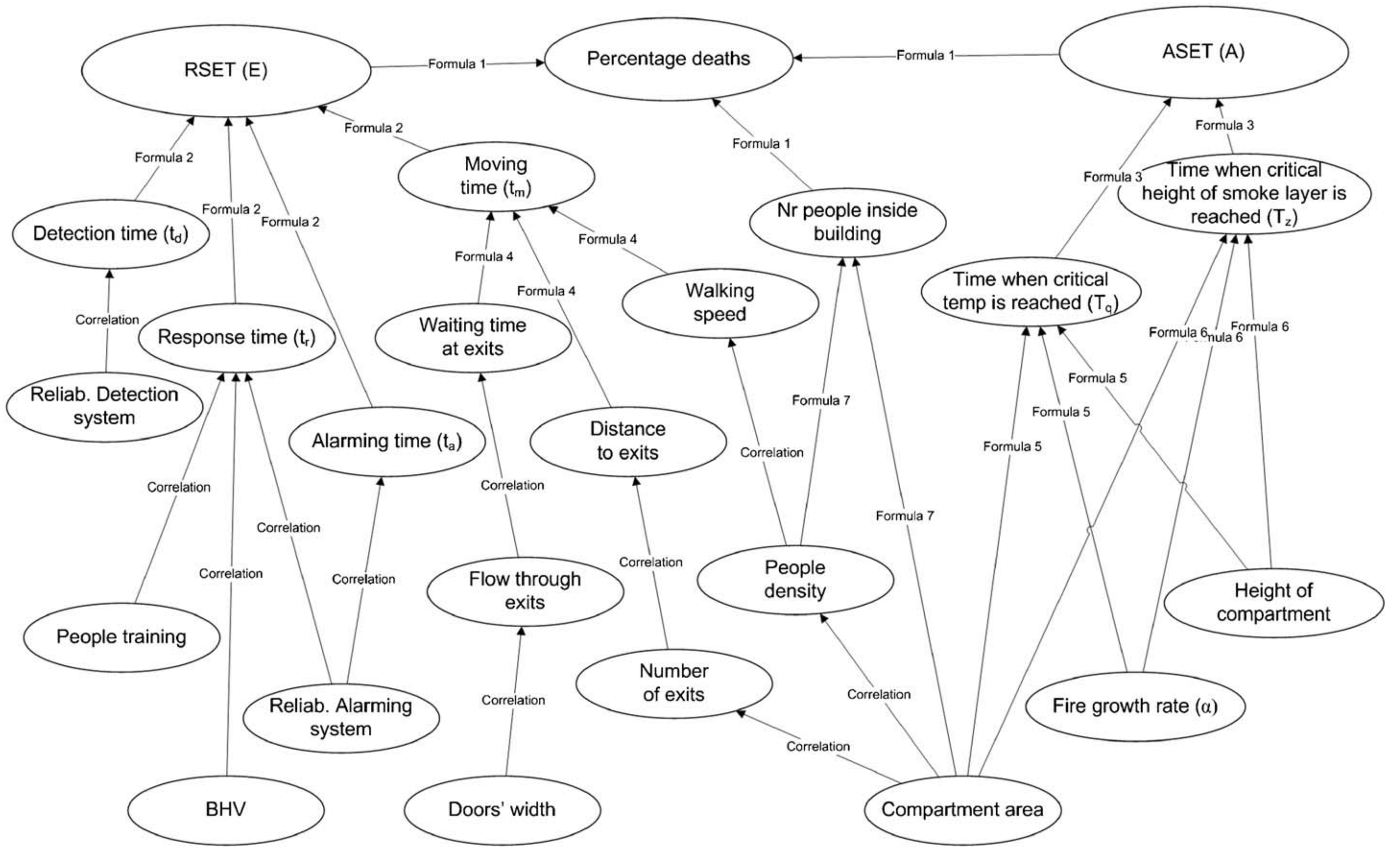


Fig. 2. Model for human fatalities in a fire.

Table 1
Four scenarios based on people training and BHV.

People training	BHV	
	0.03	0.07
1095	Base Case	Scenario 2
365	Scenario 1	Scenario 3

the Base Case and a 91.7% chance that there is no victim for Scenario 1. There is also a probability of 3.7% that more then 90% of the people died for Base Case, while for Scenario 1, the same probability is 3.1%. Of course, the difference is small, but when talking about human lives, any tenth part of a percent is important. The conclusion is that, definitely, performing more frequent evacuation exercises improves the level of fire safety for people inside the building, as expected.

On the other hand, increasing the percentage of people with special training, who can coordinate the evacuation, does not produce a reduction in the percentage of fatalities, especially if one thinks of cases with small consequences, which are more probable. This can be seen by comparing Base Case with Scenario 2. For human damages less then 10% of the people inside the building, Base Case is a better choice. However, if high-consequence accidents are the main concern of the decision makers and they are ready to take the risk of small consequences, Scenario 2 is considerably better. There is a probability of 3.7% that the outcome of the fire is higher then 90% for the Base Case, while for Scenario 2, the same probability is only 3.2%.

The ideal Scenario 3, in which both people training and percentage of BHV people are increased, is better for low-

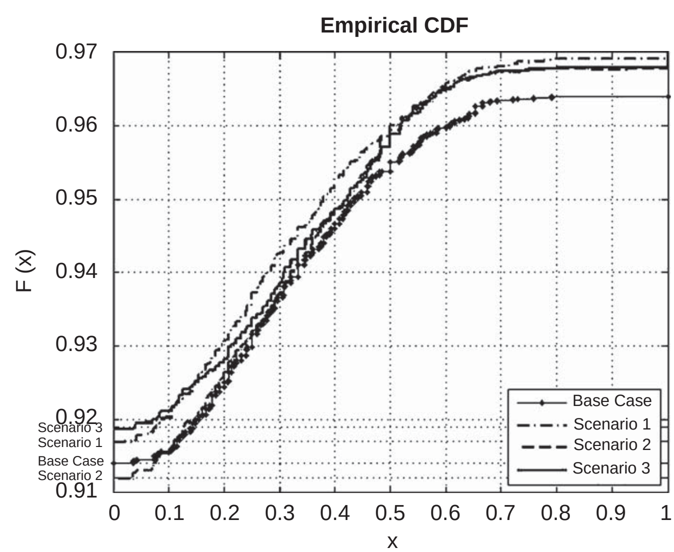


Fig. 3. Probability distribution of percentage of deaths for scenarios from Table 1.

consequences accidents, but it is not better then Scenarios 1 and 2 for high consequences. The probability to have no victims is equal to 91.9% for Scenario 3, but there is a probability of 3.2% that the percentage of deaths is larger then 90% for this scenario.

This is only an example of what-if analysis that can be performed using the model proposed in this paper. Some other analyses, such as finding the scenarios with the highest consequences, can also be performed by conditioning on the value of percentage of deaths variable.

4. Conclusions

In current society with a rapid rate of development, with new and modern architecture that involves more and more people, it seems to be very clear that there is need for a comprehensive model that can be used to estimate the extent of a possible fire in a building. The model should take into consideration all the factors involved in a complex system such as fire in a building, and especially interactions between them.

The use of BBNs in general and in particular in the field of fire safety is developing rapidly mainly due to its capability to represent complex systems with multi-dependencies between variables.

This paper shows the feasibility of the BBN approach to produce results that fulfil the need of those in authority in taking decisions about the acceptability of fire risk in a building. The main characteristic of this model is that it can be used in the planning phase of a new structure or of a new area of a city, without having historical data of past accidents in such a building. The model can be used to compare the behaviour of alternative designs in fires, in normal conditions, or in some extreme, unforeseen conditions. The results produced show not only the average risk, but also provide information about the probability of having some extreme consequences of fire. In this way, the model can be used to decide if the proposed design satisfies criteria of maximum level of risk.

The BBN approach for the problem of fire safety proposed in this paper can be extended in several directions, as follows: first, it can be used in a cost-effectiveness analysis, or in a multi-criteria analysis, combining the criterion of low damage with other criteria, like low costs for example. On the other hand, a more complex structure of the network can be obtained, by adding more variables, or extending the model to some other types of buildings, with some other specific problems. However, it is known that by adding more details, the model becomes more particular for a problem and less applicable to other problems. Therefore, equilibrium between details and general applicability of the model has to be maintained.

There are also some problems with the applicability of the BBN approach. The most difficult problem with the complex networks is the validation of both the structure of the network (as so-called "qualitative" validation) and quantitative results. The problem consists of the lack of complete and objective data needed for validation. However, validation studies for parts of the model can be performed, as well as sensitivity analysis of the model [33].

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