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PREDICTIVE STUDY OF FIRE RISK IN BUILDING USING BAYESIAN NETWORKS

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ABSTRACT.

Morocco, like many countries, has experienced significant development in the construction sector. Recently, various types of buildings, including residential buildings, public structures, high-rise buildings, and workplaces, have been constructed.

Unfortunately, this development is accompanied by a significant increase in domestic risks. Some of these risks are associated with natural disasters such as floods, droughts, earthquakes, etc., while others result from human activities and errors like fires, gas leaks, electrical hazards, etc. The consequences include human losses, physical injuries, psychological traumas, and material damage, leading to substantial financial losses.

In this paper, we focus on the study of fire risk in buildings. We present a predictive study of fire risk in buildings using the Bayesian network method. The primary focus of the study is to calculate the probability of fire ignition in buildings, which can be triggered by various factors such as poor electrical installation, gas leaks, or the presence of flammable products. Additionally, the study considers human ignorance, inadvertence, or criminal acts as potential contributors to the fire risk.

The result obtained from this study identifies electrical problems, often linked to poorly maintain electrical installations or the use of degradable electrical equipment, as a potential source of the most fire ignition in buildings.

Keywords: *Fire Risk, Decision System, Bayesian Network, Fire Ignition Probability.*

1. INTRODUCTION

Nowadays, the study of fire safety has known a significant evolution in Morocco as in other countries [1]. It is integrated into various regulated areas such as construction and transportation.

The general process adopted to study fire risk involves identifying all events that may pose a risk, assigning occurrence probabilities to each sequence, and evaluating the adverse effects of this phenomenon based on a set of parameters.

Table 1 clearly presents the anticipated objectives of the fire safety study.

Table 1 : Fire Safety objectives

<table>
<tr><td rowspan="7">Objectives of fire safety</td><td rowspan="3">Stop fire ignition</td><td colspan="2">Control the combustible elements</td></tr>
<tr><td colspan="2">Control the heat source</td></tr>
<tr><td colspan="2">Control the interactions</td></tr>
<tr><td rowspan="4">Reduce fire effects</td><td rowspan="2">Control the fire</td><td>Stop the fire</td></tr>
<tr><td>Control the fire spread</td></tr>
<tr><td rowspan="2">Take care about people and property</td><td>Limit the rate of human losses and material damage</td></tr>
<tr><td>Protect people and property</td></tr>
</table>

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In the same context and to achieve the mentioned objectives, the proposed study aims to evaluate the fire ignition risk in a building by the identification of potential sources and calculating the probability of fire ignition based on the building's condition.

To illustrate the extent and severity of the damage caused by fires, statistics are provided regarding the human and material losses resulting from domestic fires in Morocco and other countries.

According to statistics shared by the Moroccan Civil Protection Directorate, there are 700 deaths reported each year due to domestic fires. In 2011, civil protection registered 16,723 domestic fires, while in 2012; more than 26,130 domestic fires were recorded, reflecting a growth rate of 36%

The figure below (Figure. 1) displays the number of deaths caused by fires in 2007, 2008 and 2009. These data were published in [2] According to these statistics, the United States holds the highest rank in the number of deaths, with 3,750 fatalities in 2007, 3,650 in 2008, and 3,300 in 2009. Japan secures the second position, recording 2,050 deaths in 2007, 2,000 deaths in 2008, and 1,950 deaths in 2009.

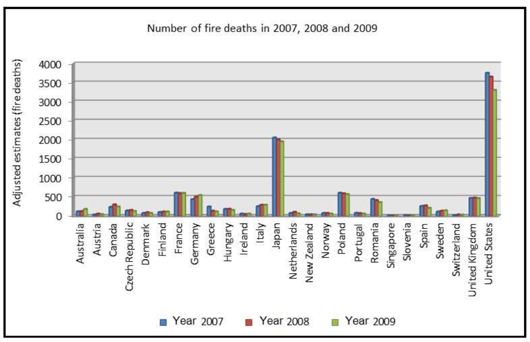

Figure. 1 : Number of deaths caused by fires in the period [2007-2009]

Based on the statistics published [2], multiple countries had immense losses in millions due to the fires between 2007 & 2009. Indeed, the situation was considerably more severe for Japan where the losses achieved billions. Japan recorded the highest value of losses in goods in 2008, reaching 615 billion Japanese Yen. All these statistics and others are represented in Table 2.

Table 2 : Cost of loss of property in millions in 2007, 2008 and 2009 (millions, except for Japan – billions)

Country	Devise	Direct losses		
		2007	2008	2009
Singapore	$S	110	110	115
Australia	$AUS	905	1000	945
Czech Republic	Kc	2450	3700	2450
Spain	€		910	
Poland	zl	900	1450	1150
United States	$US	16500	17500	14000
Japan	¥	600	615	605
New Zealand	$NZ	180	240	
Germany	€	2950	2850	3050
United Kingdom	£	1700	1950	1800
Finland	€	315	305	295
Netherlands	€	900	1050	925
Sweden	kr	5400	5950	5550
Denmark	kr	4050		
France	€	3400	4550	
Italy	€	2500	3150	3750

Considering the severity of the damage caused by domestic fires, it prompts the question: what is the primary factor behind such incidents, and what measures can be taken to prevent them ?

To respond to both questions, the paper begins with an introduction presenting the general problematic and various related works. Following with the method and tools that’s briefly illustrate the Bayesian networks method. Subsequently, applying our fire risk management method with the same technique and finalizing by describing and analyzing the obtained results

2. RELATED WORKS

Various techniques exist for managing fire risk in a building, including genetic algorithms, fuzzy logic [3], event trees, and Petri nets. Some of these techniques are employed to predict the damage caused by the spread of fire, while others focus on forecasting intervention scenarios.

In this study, Bayesian networks have been selected for their relevance and efficiency. They offer several advantages over other artificial intelligence techniques, including the acquisition, representation, and utilization of knowledge[4] [5] :

A Bayesian network is a probabilistic graphic model applicable in various stages of fire

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risk management, and as a result, numerous works have already been published on its utilization.

In this paper [6], the authors employed the Bayesian network technique to model fire spread in an office building, considering two distinct scenarios: the first involves calculating the probability of fire spread in an office building without the installation of sprinklers, and the second scenario incorporates the use of sprinklers. The results indicate that the installation of sprinklers significantly contributes to reducing the extent of fire spread.

In a subsequent paper [7], the authors introduced a method for dynamically modeling fire spread, considering both horizontal and vertical directions of propagation. The methodology involves proposing algorithms that simulate the fire spread process in buildings and subsequently calculating the dynamic fire spread probability for each compartment at each proposed simulation time step.

In this paper [8], the authors introduced a method for modeling a decision-making tool with the objective of estimating the magnitude of a fire in a building. This model considers a set of conditions and unexpected events that are possible to happen in case of an emergency.

In the same context, we have underscored a general method for analyzing the fire ignition risk in building. This method consists of identifying the precise source of fire ignition considering various existing triggers [9]. The technique adopted in these analyses is Bayesian network.

The choice of this technique is justified by several reasons as outlined by [4].

- ✓ The capability to gather and integrate knowledge of different natures into a single model.
- ✓ The representation of the knowledge using Bayesian networks is very simple. It consists of link causes and effects by arrows.
- ✓ The graphic representation of a Bayesian network is explicit, intuitive and understandable by a non-specialist, which facilitates the validation of the model, its possible evolutions and especially its use.
- ✓ The existence of a large range of software that processes Bayesian networks: commercial tools and other open sources.

3. MATERIALS & METHODS

3.1 Bayesian Network overview

A Bayesian network is a graphical probabilistic model for acquiring, representing and exploiting knowledge, it is a technique that combines artificial intelligence with statistics to represent information that is uncertain and make decision from data that are incomplete [10]

It consists of two components [11]:

- ✓ An acyclic oriented causal graph whose nodes are variables of interest of the domain and whose arcs characterize the relations of dependence between these variables. The set of nodes and arcs constitute what is called the Bayesian network structure. It is a form of qualitative representation of knowledge
- ✓ A set of local probability distributions that are the parameters of the network. For each node, we have a probability table that depends only on the state of its parents Figure. 2.

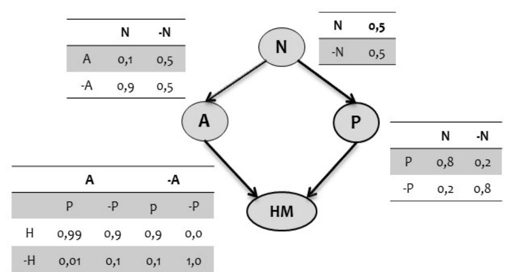

Figure. 2 : Example of a Bayesian network

3.2 Fundamentals of probability

Taking A and B two events, with P (A) is the probability that the event A will happen (A is true) and P (B) is the probability that the event B will happen (B is true)

3.2.1 Static independence

According to the probability theories [12]:

$P(A \cup B) = P(A) + P(B)$ (B and A two independent events) (1)

$P(A \cup B) = P(A) + P(B) - P(A \cap B)$ (B and A two dependent events) (2)

3.2.2 Conditional probability

A and B two events in a probabilistic space Ω with $P(B) \neq 0$

The conditional probability of the event «A if B» or «A knowing B», is the quotient [13]:

$$P(A|B) = \frac{P(A,B)}{P(B)} = \frac{P(A \cap B)}{P(B)} \quad \text{noted } P_B(A) \quad (3)$$

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- ✓ The probability P(A) is called the a priori probability and P(A\B) or PB(A) the posterior probability because its realization depends on the realization of B.
- ✓ The probability P(A,B) is called the joined probability

3.2.3 Total Probability

A1, A2… An form a complete system of events, if the parts A1, A2…, An of Ω constitute a partition of Ω as :

- ✓ $\forall i \ Ai \neq \emptyset$
- ✓ $\forall i \neq j \ Ai \cap Aj = \emptyset$
- ✓ $\cup_i \boldsymbol{Ai} = \Omega$

if {A1, A2, …., Ai, ….., An} is a complete system of events, regardless of the event B, so:
P (B) = P (B / A1) P (A1) + P (B /A2) P (A2) +…..+ P (B /An) P (An) (4)

Generally [6] :

$$P(B) = \sum_1^n \boldsymbol{P(B|Ai)P(Ai)} \qquad (5)$$

3.2.4 Equation de Bayes

if {A1, A2,…. , Ai,….., An} is a complete system of events, and regardless of the event B as P(B) ≠ 0, so:

$$P(Ai|B) = \frac{P(\mathbf{B|Ai}) * P(Ai)}{P(\mathbf{B|A1})*P(A1)+P(\mathbf{B|A2})*P(A2)+ \dots\dots +P(\mathbf{B|An})*P(An)} \qquad (6)$$

Generally :

$$P(Ai|B) = \frac{P(\mathbf{B|Ai})*P(Ai)}{\sum_1^n P(\mathbf{B|Ai})*P(Ai)} \qquad (7)$$

With :

- ✓ P(Ai|X) is the probability of Ai if we suppose that B is true.
- ✓ P(B|Ai) is the probability of the event B after considering the effect of Ai.
- ✓ P(B) is a priori probability of the event B.
- ✓ P(Ai) is the normalization.

3.3 Definition of a Bayesian network

Bayesian networks are graphical models that represent the probabilistic relationships between a set of variables.

A Bayesian network B = (G, θ) is defined by [14]:

- ✓ The set of observable random variables X = {X1, ……, Xn}
- ✓ G = (X, E), directed acyclic graph (DAG), where each node is associated with a variable of X.
- ✓ θ = {θi} = P(Xi|Pa(Xi))}, set of probability distributions of each node Xi conditionally to its immediate parents in the graph G.
- ✓ The joint probability of a set of Bayesian network variables is calculated as follows :

$$P(X1, X2, \dots, Xn) = \prod \boldsymbol{P(Xi|Pa(Xi))} \qquad (8)$$

4. PROPOSED METHOD

4.1 Algorithmic process

Our proposed method to manage the risk of fire ignition in a building is to use Bayesian Network method.

To implement this approach, we can follow the steps below :

- ✓ Analyze the building: This step involves examining the building to identify all parameters that could potentially lead to fire ignition.
- ✓ Build the Bayesian network: in this step, we define the general structure of the Bayesian network graph.
- ✓ Attribute initial probabilities (prior probabilities) to different nodes in the causal graph
- ✓ Calculate joint probabilities of the intermediate nodes and posteriori probabilities of the different possible causes by applying Bayes theorem.
- ✓ Diagnose the obtained results. In fact, the probability of the triggering event having the maximum value represents the main cause of fire ignition.

4.2 Parameters Identification

After a detailed analysis of all the buildings and extensive bibliography and webography research about fire phenomenon, its mechanism, its causes and its consequences, a list of causes is established and presented in Table 3.

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Table 3 : Parameters identification related to the fire risk.

Triggers	A1	Deficient electrical installation
	A2	Bad quality of electrical equipment
	A3	Contact between incompatible products
Activators	B1	Mishandling of electrical devices
	B2	Electrical overload
	B3	Power cut
	B4	Degradation of electrical wires
	B5	Excessive heating in the conductors
	B6	Insulation fault
	B7	Short circuit
	B8	Strong intensity electric
	B9	Combustion of electrical equipment
	B10	Appearance of electric arcs
	B11	Appearance of sparks
	B12	Chemical reactions
	B13	Heat release
	B14	Appearance of new products
Results	C1	Electrical equipment malfunction
	C2	Electrocution
	C3	Fire ignition
	C4	Poisoning
	C5	Asphyxia
	C6	Explosion

The Figure. 3 presents the general structure of the Bayesian network modeling the fire risk ignition in a building by integrating the triggers, potential results and intermediate events or activators (electrical overload, power cut, insulation fault, short -circuit, appearance of sparks, chemical reactions, appearance of new products, etc.).

A fire can be caused by a faulty electrical installation, the use of bad quality equipment or by contact between at least two incompatible products.

However, asphyxiation, poisoning, explosion, electrocution, malfunction of electrical equipment and fire outbreak represent the potential results.

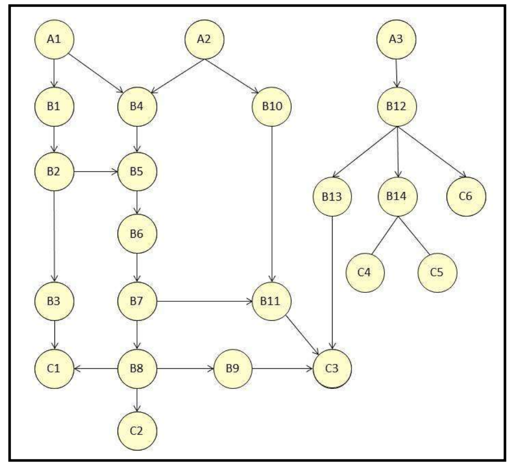

Figure. 3 : Bayesian network modeling the fire risk ignition in a building.

4.3 Priori probabilities attribution

The developed audit system is a generic tool designed for auditing various types of building. Consequently, distinct values are assigned to the initial probabilities of triggering a fire event.

Using the symbols outlined in Table 3, the initial probabilities P(A1), P(A2) and P(A3) of the trigger elements are denoted as αI, αE, αP respectively. These values are typically determined by experts through an analysis conducted for the specific building.

These experts may include urban planning professionals and civil protection actors. They conduct a comprehensive analysis of a building, generating a report based on the status of its equipment installation and the quality of its electrical equipment. Additionally, they assess the presence of incompatible products that could pose a danger.

In Figure. 6, the initial probabilities for different triggers are assigned based on expert opinions.

4.4 Total probabilities calculation

The next step is to calculate the total probabilities of all intermediate nodes of the Bayesian network graph. Given the large number of nodes and the complexity of the calculations, the Elvira tool is used [15].

The following figure (Figure. 7) shows the same Bayesian network with the integration of total probabilities calculated for every node for buildings having the following characteristics (it’s our case study) :

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- ✓ The degree of performance of the electrical installation is 30%.
- ✓ The quality of the equipment installed is 50%
- ✓ The organization degree of incompatible products is 70%.

Hence, as it is presented in the Figure. 7, the probability of fire ignition in building that have these characteristics is 76 %. This probability can change (increase or decrease according to the values of the initial probabilities introduced αI, αE, αP.

Based on the values chosen previously, this building is exposed to a set of risks (short-circuit, power cut, equipment malfunction, electrocution, intoxication, explosion, etc.) with different degrees and percentages grouped together in the figure presented below (Figure. 4).

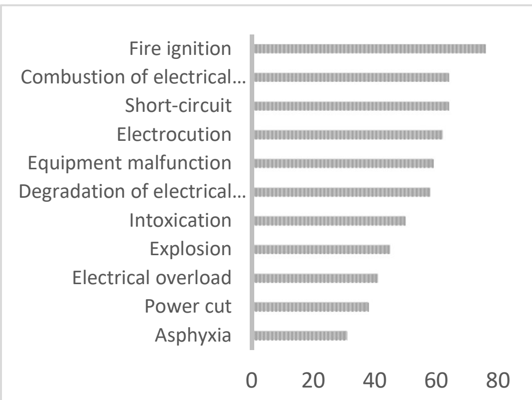

Figure. 4 : The probabilities of the various risks associated with buildings.

4.5 Calculation of a posteriori probabilities

After the construction of the Bayesian network that models the risk of fire ignition in the building chosen to be audited. The subsequent step is calculating the posteriori probabilities of the elements that trigger a fire (a faulty electrical installation, the use of poor quality equipment, and contact between incompatible products) taking into consideration different consequences (malfunction of electrical equipment, case of electrocution, fire outbreak, intoxication, case of suffocation, explosion). These posteriori probabilities are used to identify the elements representing a source of danger for our building.

The Bayesian inference algorithm adopted to calculate these probabilities is the junction tree [16]. To calculate the posterior probabilities illustrated in Table 4, the Matlab programming tool is used.

Table 4 : List of the probabilities to calculate for the diagnosis of the fire risk ignition

Probability Identifier	Description
P (A1= True)	The probability of the building having a faulty installation
P (A2= True)	The probability of the building being equipped with poor quality equipment
P (A3= True)	The probability of the building containing poorly organized flammable products.
P (A1= True |C3= True)	The probability of fire ignition resulting from a faulty installation in the building.
P (A2= True |C3= True)	The probability of fire ignition due to the presence of poor-quality equipment in the building
P (A3= True |C3= True)	The probability of fire ignition resulting from a contact between incompatible products in the building.
P (B1= True | C3= True)	The probability of a fire outbreak due to the improper handling of electrical equipment.
P (B2= True | C3= True)	The probability of a fire outbreak due to electrical overload
P (B4= True | C3= True)	The probability of a fire outbreak due to the degradation of electrical wires
P (B7= True | C3= True)	The probability of a fire outbreak due to a short circuit
P (B12=True | C3= True)	The probability of a fire outbreak resulting from the chemical reaction between incompatible products

5. RESULTS & DISCUSSION

After execution of the algorithm that calculate the posteriori probabilities for α_I = 30 %, α_E = 50 % and α_P= 70 %, the results obtained are presented in Figure. 5

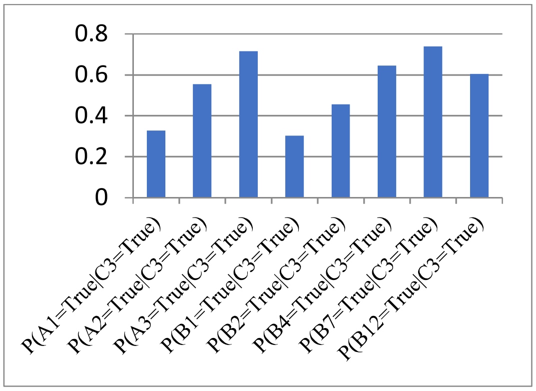

Figure. 5 : Posteriori probabilities of fire ignition

By analyzing the results illustrated in the Figure. 5, the maximum probability (73,88 %) is about short circuit event. So, the main cause of fire ignition in building is often related to electrical risk and particularly to short circuit problem

The second probability (71,50 %) is about the event « Contact between incompatible products ». In fact, the reactions between incompatible products are considered as a very dangerous factor which can give rise to fires.

The third source noticed is about degradation of electrical wires with a probability of 64,43 %.

After that, we execute the same algorithm for various values of αI, αE, αP. The calculated conditional probabilities are documented in Table 5. These results showcase the variation in percentages for different fire sources based on the input values from our graph. These values are selected by experts, considering the specific conditions of the building under audit.

The obtained results indeed enable the analysis of the risk of fire outbreaks, facilitating the identification of potential sources of this danger.

After analyzing the results presented in Table 5, it is evident that fire outbreaks are frequently caused by electrical problem, such as overload, degradation of electrical wires or a short circuits.

6. CONCLUSION

The present article provides a detailed illustration of a method for effectively managing fire risks in buildings through the application of a probabilistic approach based on Bayesian networks. In this process, we meticulously identified and compiled an exhaustive list of parameters that could potentially trigger a fire. These parameters were then visually represented in the form of a causal graph, termed the generic model of our Bayesian network. Utilizing the Bayes equation, we computed various posterior probabilities associated with the likelihood of a fire outbreak.

Upon analyzing the results obtained, our findings indicated that a significant proportion of home fires stem from electrical issues, either due to the deterioration of electrical equipment or a flawed electrical installation. The modeling framework presented in this article represents a crucial milestone in developing a decision support system for fire risk management in buildings. This system aims to evaluate the fire risk across three phases: predicting the likelihood of an outbreak, assessing the extent of propagation, and predicting the severity of material or human damage.

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Table 5 : Results of conditional probabilities

Probability	Values														
	α_I	α_E	α_P	α_I	α_E	α_P	α_I	α_E	α_P	α_I	α_E	α_P	α_I	α_E	α_P
	0,5	0,5	0,5	0,8	0,15	0,25	0,25	0,95	0,15	0,4	0,4	0,9	0,15	0,2	0,25
P(A1=True|C3=True)	0.533017			0.836680			0.259083			0.434171			0.181945		
P(A2=True|C3=True)	0.543866			0.164371			0.892470			0.443505			0.251100		
P(A3=True|C3=True)	0.516286			0.262373			0.156509			0.906565			0.27046		
P(B1=True|C3=True)	0.426217			0.610130			0.258817			0.367541			0.222804		
P(B2=True|C3=True)	0.499817			0.573299			0.420385			0.481624			0.464874		
P(B4=True|C3=True)	0.722330			0.773804			0.818294			0.633270			0.386996		
P(B7=True|C3=True)	0.786393			0.839751			0.813857			0.736596			0.637554		
P(B12=True|C3=True)	0.511100			0.396387			0.342085			0.691631			0.418539		

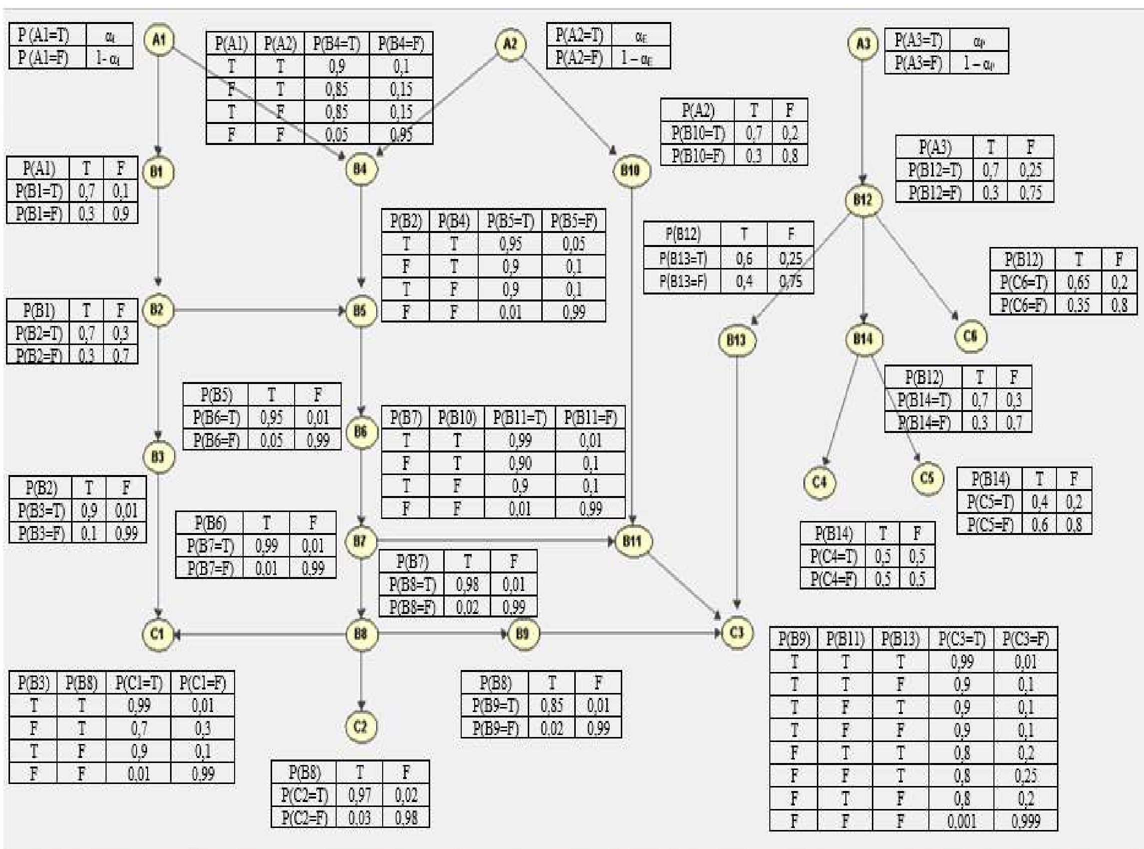

Figure. 6 : Bayesian network modeling the fire risk ignition in a building.

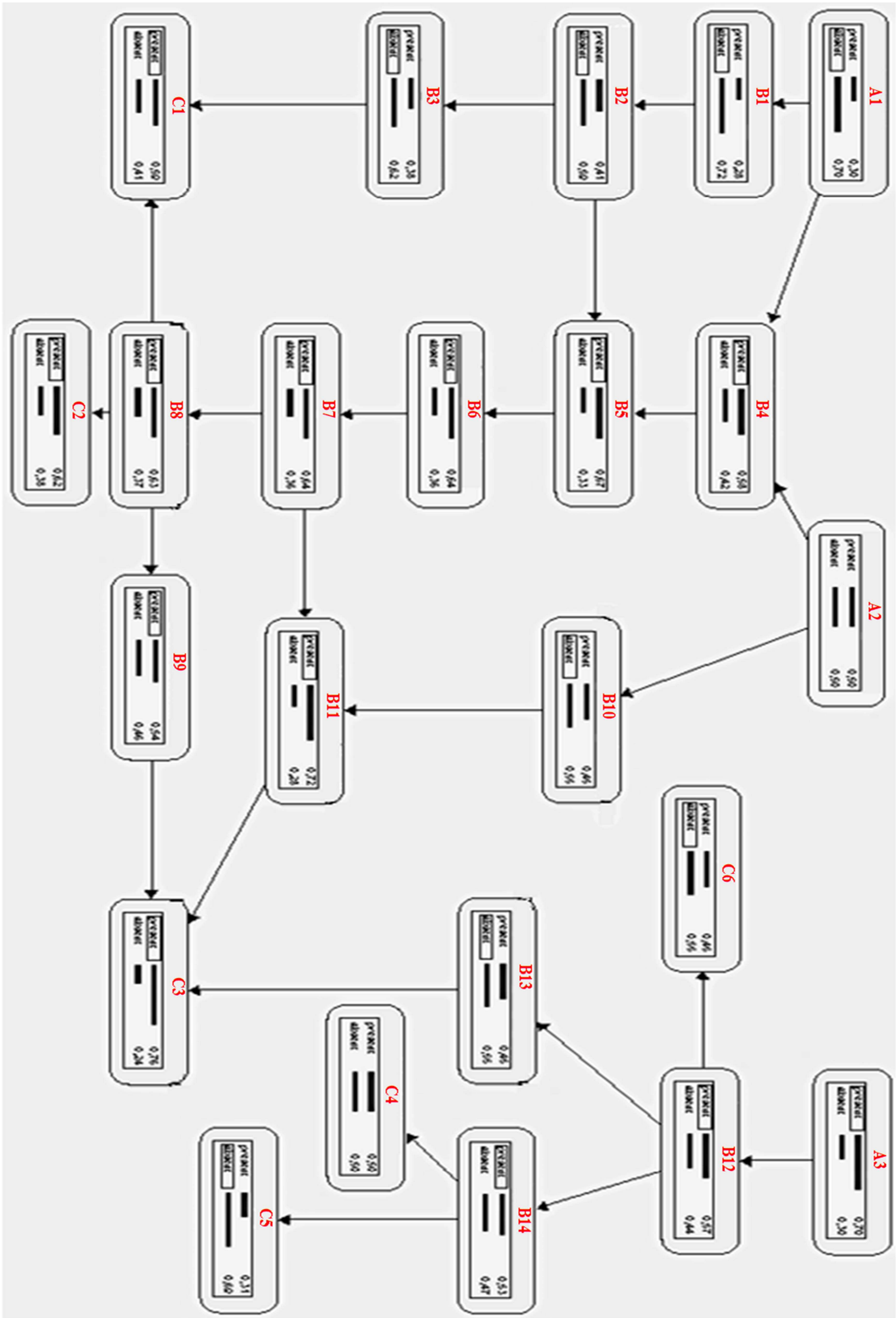

Figure. 7 : Bayesian network modeling the risk of fire ignition in a building made using the Elvira