

# **BAYESIAN BELIEF NETWORK IN THE ANALYSIS OF DAMAGE TO PREFABRICATED LARGE-PANEL BUILDING STRUCTURES IN MINING AREAS**

**Janusz RUSEK \*, Karol FIREK**

Department of Engineering Surveying and Civil Engineering  
Faculty of Mining Surveying and Environmental Engineering  
AGH University of Science and Technology in Krakow  
al. Mickiewicza 30, 30-059 Krakow, Poland

## **Summary**

The paper presents a methodology for assessing the intensity of damage to the elements of building structures constructed in the large-panel technology, located in mining areas. Bayesian Belief Network was used, which allows to predict the intensity of damage to a building structure, and the probability of its occurrence was predicted. The article also presents the possibility of using the created model for the assessment of damage in the case of incomplete or uncertain decision data. The structure of the Bayesian Belief Network was built on the database regarding the construction, maintenance quality, and intensity of damage to 129 buildings, taking into account environmental effects in the form of mining impacts. The study demonstrates applications of the network for the diagnosis of the causes of damage and for predicting the impacts of mining activities on building structures.

**Keywords:** damage to large-panel building structures, mining impacts, Bayesian Belief Network

## **1. INTRODUCTION**

The technical condition of building structures located in mining areas, besides natural wear associated with the passage of time, is affected by a number of additional factors, which are random in the statistical sense, including the impacts of underground mining in the form of rock mass tremors and continuous surface deformation.

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\* rusek@agh.edu.pl

Assessment of mining impacts on building structures includes both prediction of the potential effects of exploitation at the approval stage for the plan of a mining plant, as well as the necessity to determine the causes of damage, reported to the department of mining damage, after mining the deposit. This assessment is a complex decision problem, with uncertainty as to the value of the factors, such as mining impacts, affecting the technical condition of the buildings.

The paper presents the methodology for evaluating the intensity of damage to elements of building structures located in mining areas. Bayesian Belief Network was used, which allows to predict the intensity of damage to a building structure, together with the determination of the probability of its occurrence. The authors demonstrated the possibility of applying the model created to predict the state of damage and to diagnose its causes.

The research was based on the database regarding the construction, maintenance quality, and intensity of damage to 129 multi-storey buildings of prefabricated large-panel structure, located in the mining area of Legnica-Głogów Copper District (LGOM).

## **2. RESEARCH METHODOLOGY**

### **2.1. General characteristics**

In decision support systems using traditional rules of a probabilistic approach, difficulties occur which are related to a mathematical presentation of the problems in the form of joint probability distribution for a large number of decision variables. Additional difficulties are associated with the need to collect a specified number of model data to determine all the parameters of the model in the process of adaptation, and to check it properly, as well as with determining conditional probability distributions for a large number of variables [1].

In 1988, in [2], while introducing the concept of conditional independence of events, a new representation of the joint probability distribution was proposed, which is known today as Bayesian networks. This proposal allowed to eliminate the original, enormous computational effort associated with modeling the joint probability distribution for all input variables treated as mutually dependent.

Bayesian networks are widely used in various fields of science and engineering, and their main advantages include (e.g. [3]):

- clear interpretation of the system structure in the context of the relationships between nodes representing attributes,
- high level of generalization of the acquired knowledge, and no effect of the so-called

overfitting,

- possibility to solve problems in which the number of learning patterns is smaller than the number of model parameters,
- possibility to infer in the case of uncertain and incomplete information about the decision attributes,
- effective methods of building the system, including evolutionary algorithms, based on the model data used in the learning process.

## 2.2. Mathematical bases

In general, belief networks are a combination of the *DAG* (*Directed Acyclic Graph*) method and the formalism of Bayesian inference (e.g. [4, 5]). The structure of the Bayesian network in the form of a directed acyclic graph  $G(N, E)$  consists of nodes ( $N$ ) representing the attributes, and the set ( $E$ ) consisting of the edges defining the cause-and-effect relationships between the attributes [6]. The introduction of conditional independence allows to eliminate from the network a number of relationships which do not exhibit cause-and-effect relationships, which in turn significantly reduces the computational effort. At each node of the network, *CPT* (*Conditional Probability Table*) is determined, in which for individual states of the attribute  $A_i = \{A_i^1, A_i^2, \dots, A_i^k\}$  their conditional probability  $A_i^j$  is determined, depending on the value of the attributes which comprise the set of  $par(A_i)$  (1). *Directed Acyclic Graphs* represent the structure of the cause-effect relationships between the attributes  $E = \{A_1, A_2, \dots, A_n\}$ , which form the basis for the inference in such systems (Fig. 1).

In general, the joint probability represented by the network can be written in the following form [3]:

$$P(A_1, A_2, \dots, A_n) = \prod_{i=1}^n P(A_i | A_{i-1}, \dots, A_1) = \prod_{i=1}^n P(A_i | par(A_i)) \quad (1)$$

where:  $par(A_i)$  – nodes of the graph which are directly preceding the node  $A_i$  (c.f. Fig. 1).

Basing on such a network with the conditional probability tables assigned to a given node, using the equation (1) and Bayes' theorem [6], in the evaluation of the condition of objects, it is possible to perform both the diagnosis of the causes for the observed effects, as well as the prediction of the effects for the assumed causes (Fig. 2).

When it is necessary to identify the most likely state of the decision attribute, all its possible categories are considered, and on the basis of *MAP* ranking (*Maximum-a-Posteriori*) [6], this one is determined for which the posterior probability takes the highest value.

Construction of Bayesian Belief Networks involves the determination of their structure

and calibration of the parameters affecting the values of conditional probabilities for each node. Both the determination of the topology as well as of the network parameters can be arbitrary, imposed by an expert, or it can be performed through optimization [3]. In this paper there is the division of the procedure into the expert one - in the selection of network topology, and the automatic one - in the case of adjusting the network parameters using the *EM* method (*Expectation-Maximization Algorithm*) [6] using learning data stored in the database.

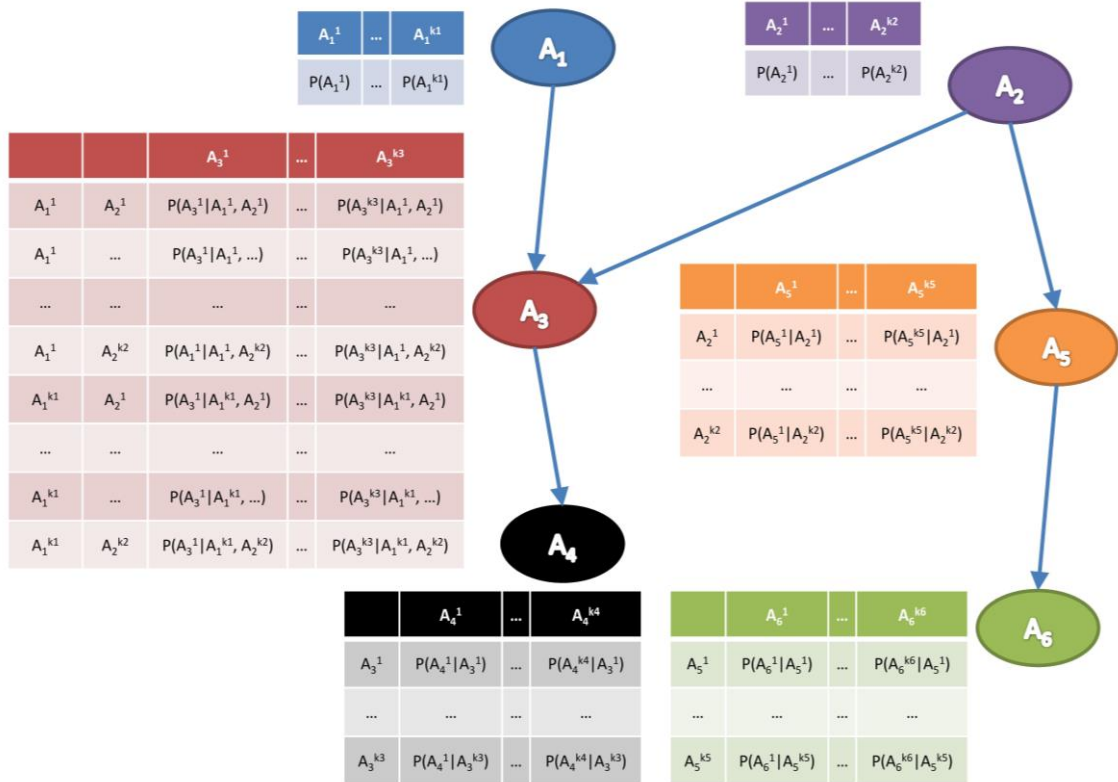


Fig. 1. Schematic diagram of the structure of the directed acyclic graph as a Bayesian network for the attributes  $A_1, A_2, \dots, A_6$ , together with conditional probability tables for each node

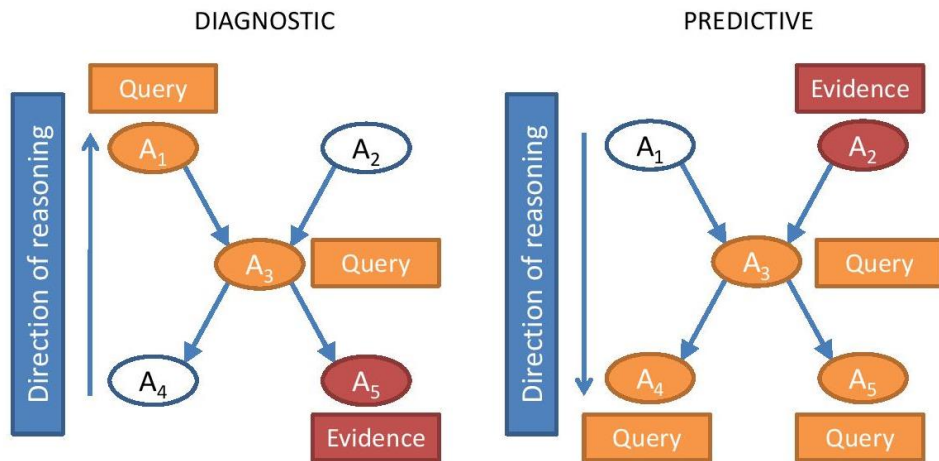


Fig. 2. Schematic diagram of the direction of inference for diagnoses and predictions [7]

### 3. DESCRIPTION OF VARIABLES USED FOR THE CONSTRUCTION OF BAYESIAN BELIEF NETWORKS

#### 3.1. The influence of continuous surface deformation

Basing on the data collected from mines, the values of the parameters characterizing the continuous surface deformations in LGOM were determined. The mining area category (**KT**) [8] was adopted as the index describing the threat of continuous surface deformation. The mining area category describes the intensity of continuous surface deformation, expressed by assigning values characterizing the slopes, curves, and horizontal deformation, to the specific ranges of these indices (0, I, II, III, IV and V).

#### 3.2. The impact of mining tremors

The impact of mining tremors, characteristic for the LGOM area, was taken into consideration using the factor  $a_{sg}$  of dynamic impacts on the technical wear [9]:

$$a_{sg}(x, y) = \sqrt{\sum_{k=1}^n a_{Hk}(x, y)^2} \quad ; \quad a_{Hk}(x, y) \geq a_p \quad (2)$$

where:  $(x, y)$  - coordinates of the object,

$a_{Hk}(x, y)$  - peak value of the horizontal component of the vibration acceleration in the frequency range up to 10 Hz, calculated at the point  $(x, y)$

$n$  - the number of tremors that occurred during the exploitation, for which the calculated peak value at the point  $(x, y)$  was higher than the threshold value  $a_p = 0.12 m/s^2$ .

This factor takes into account both the number and the individual intensity of all seismic phenomena, significantly affecting the building during the whole period of its use. The significance of the so-defined dynamic impact factor  $a_{sg}$  was positively verified in the course of the research on the technical wear of traditional development and buildings constructed in the industrialized technologies (e.g. [10]).

#### 3.3. Structure resistance to mining impacts

Structure resistance category (**KO**) [8] was adopted as the index of resistance of a building structure to mining impacts. It results from its geometrical, construction and material characteristics. Structure resistance category (0, 1, 2, 3, 4), understood as resistance to horizontal deformation and curvature of land, is adapted to the values of these indices defined in the mining area categories (**KT**). The structure is considered to be resistant to mining impacts when its resistance category (**KO**) is not smaller than the mining area category (**KT**).

#### 3.4. Quality of building maintenance

The analysis took into account the **REM** parameter (in a 4-point scale), which was

adopted as a qualitative categorical variable reflecting the extent of the repair work management for individual buildings. Gradation of the level of maintenance quality results directly from the frequency and scope of the performed modernization works.

### **3.5. State of damage to building elements**

For each building, a qualitative damage intensity index  $w_{ui}$  was determined, relating to the individual structural and non-structural components (eg. [10]). A total of 22 elements were distinguished, for which this index was defined in a 6-point scale, where  $w_{ui} = 0$  means that the damage does not occur,  $w_{ui} = 1$  - slight damage,  $w_{ui} = 2$  - moderate damage,  $w_{ui} = 3$  - intense damage  $w_{ui} = 4$  (and 5) - very intensive damage.

The study used the information collected during the survey conducted with the participation of the authors. On this basis, a database was established which included 129 multi-storey residential buildings and public utility buildings, up to 35 years old, located in the LGOM mining area. All the structures subject to the analysis were constructed in the large-block technology, in the systems of large blocks (WBL) and large blocks for school buildings (SzWBL).

Prior to the study, analysis of the input data was performed for their variability. It allowed to leave for further analysis the indices describing the damage to the following elements: basement load-bearing walls ( $w_{u2}$ ), overground load-bearing walls ( $w_{u3}$ ), ceilings and roofs ( $w_{u7}$ ), partition walls ( $w_{u11}$ ), internal plaster and wall coverings ( $w_{u12}$ ), floors ( $w_{u13}$ ), layers of cladding ( $w_{u17}$ ), damp insulation ( $w_{u18}$ ), roofing ( $w_{u19}$ ), flashings and guttering ( $w_{u20}$ ), as well as external elements such as platforms, trims ( $w_{u22}$ ).

In the analyzed group of objects, the values of the damage intensity index  $w_{ui}$  demonstrate that most of the buildings were damaged slightly or moderately.

## **4. STUDY RESULTS**

### **4.1. Verification of the quality of the created Bayesian Belief Network**

As a result of the analysis, a structure of the Bayesian Belief Network was obtained, which is presented in Figure 3. The model described in this paper was created using the *GeNIe* modeling environment developed by the Decision Systems Laboratory of the University of Pittsburgh (<http://dsl.sis.pitt.edu>).

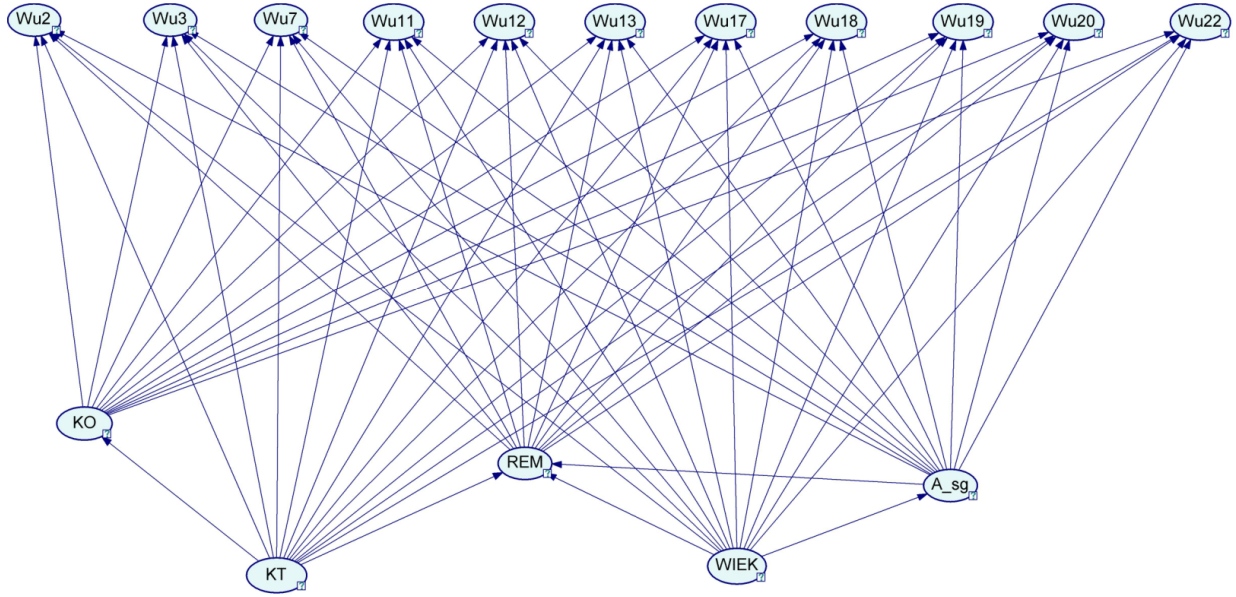


Fig. 3. Schematic diagram of the created Bayesian Belief Network

Source: own study based on the *GeNIe* program [11]

The structure of the network in terms of the predetermined relationships between the analyzed variables was created based on the knowledge and experience of the authors. Network parameters, in the form of Conditional Probability Tables (*CPT*) for each of its nodes, were determined using the *EM* method.

The resulting model was verified for its proper classification. The verification was carried out in two variants (**I** and **II**). The first one (**I**) was the prediction of the intensity level of damage indices ( $w_{ui}$ ), depending on the input mining impacts ( $KT$ ,  $a_{sg}$ ), design characteristics ( $KO$ ), maintenance quality ( $REM$ ) and the age of the building ( $WIEK$ ). In the second variant (**II**), basing on the specific values of the damage intensity indices, the network demonstrated the categories of potential causes. Table 1 illustrates the results of the conformity of these indications with the created model.

Tab. 1. Results of the conformity of indications of the created Bayesian Belief Network

Variant <b>I</b> - prediction	Variant <b>II</b> - diagnosis
Average conformity of the model for the prediction of all the analyzed damage intensity indices $w_{ui}$	Average conformity of the model in diagnosing the causes of the observed degree of damage to the building $w_{ui}$
86.37 %	85.66 %

The verification of the model quality, both in the case of predicting the degree of

damage to individual elements (variant **I**), as well as in the case of diagnosing the causes of damage (variant **II**), high levels of conformity were achieved. This is confirmed by the initial assumption of the suitability of the adopted methodology, both for estimating the extent of mining damage and for identifying the dominant factor influencing their occurrence.

#### 4.2. Example of the prediction of damage intensity indices - variant I

To illustrate the possibilities of using the Bayesian Belief Network to predict the damage intensity category, the case of inference was considered, in a situation of incomplete information about their causes (variant **I**). Assuming lack of information about the category of the dynamic impact factor  $a_{sg}$ , its value will be assessed during the inference on the basis of the cause-and-effect relationships with other attributes existing in the network (Tab. 2). Based on the values of conditional probabilities illustrated in Table 2, for all the damage intensity indices and for the attribute describing the intensity of mining tremors ( $a_{sg}$ ), it is possible to determine their most probable categories. For example, for the index  $w_{u2}$ , it is the category 2 with the probability equal to 0.66.

Tab. 2. Results of the predictions of the damage intensity index in the case of an incomplete set of input data (variant **I**)

Indices of potential causes of damage (input variables)												
Index name	WIEK		REM		KO		KT				$a_{sg}$	
Predetermined index category	4		3		2		2				-	
Damage intensity indices (output variables)											Index of tremors	
Index name	$w_{u2}$	$w_{u3}$	$w_{u7}$	$w_{u11}$	$w_{u12}$	$w_{u13}$	$w_{u17}$	$w_{u18}$	$w_{u19}$	$w_{u20}$	$w_{u22}$	$a_{sg}$
Resulting index category	Probabilities of categories of individual indices											
0	0.11	0.11	0.11				0.11	0.56	0.70	0.56	0.39	
1	0.11	0.11	0.11	0.36	0.29	0.15	0.11	0.15	0.15	0.29	0.25	0.43
2	0.66	0.52	0.66	0.64	0.56	0.70	0.39	0.29	0.15	0.15	0.11	0.57
3	0.11	0.25	0.11		0.15	0.15	0.39				0.25	

#### 4.3. Example of diagnosing the causes of the intensity of damage - variant II

In the case of diagnosing the causes of the observed extent of damage with the evidences, the categories of individual damage intensity indices were determined. Table 3 summarizes the values of conditional probabilities for the variables which according to the description of the phenomenon (e.g. [9]) may contribute to the occurrence of damage to building structures. As a result of the model simulation for the given values of the damage indices, the obtained response identified the category for the attributes describing the age,

maintenance quality, resistance of the building, continuous surface deformations and mining tremors. For example, the index *WIEK* was assigned category 4 with the probability equal to 0.65. All the variables (except the variable *REM*) are characterized by uniqueness of indications resulting from the high probability values for the dominant categories. A relatively low level of identifying the resulting category for the variable *REM* may be due to the dependence of this attribute of other variables in the model structure (c.f. Fig. 3).

Table 3. Results of the inference for diagnosing the causes of the observed damage intensity (variant II)

Damage intensity indices (input variables)											
<i>Index name</i>	$w_{u2}$	$w_{u3}$	$w_{u7}$	$w_{u11}$	$w_{u12}$	$w_{u13}$	$w_{u17}$	$w_{u18}$	$w_{u19}$	$w_{u20}$	$w_{u22}$
<i>Predetermined index category</i>	2	1	1	2	2	2	3	2	1	1	1
Wskaźniki potencjalnych przyczyn uszkodzeń (zmienne wyjściowe)											
<i>Nazwa wskaźnika</i>	<i>WIEK</i>		<i>REM</i>		<i>KO</i>		<i>KT</i>		$a_{sg}$		
<i>Resulting index category</i>	Probabilities of categories of individual indices										
0	0.02		0.26		0.51		0.19		0.64		
1			0.30				0.34				
2	0.05		0.20		0.39		0.41		0.36		
3	0.28		0.24		0.10		0.07				
4	0.65										

## 5. SUMMARY AND CONCLUSIONS

The paper demonstrates possibilities of inference regarding the technical condition of building structures with the use of Bayesian Belief Network. The research study was based on the database regarding the construction, maintenance quality, and intensity of damage to 129 multi-storey buildings of prefabricated large-panel structure, located in the mining area of Legnica-Głogów Copper District (LGOM).

The presented results prove that Bayesian Belief Networks allow to combine a formal uncertainty with the probability of occurrence of individual variables affecting the intensity of damage to a building. The result is the possibility to streamline the assessment of the condition of building structures in mining areas.

Based on the performed analyses, it was found that the proposed methodology can be used both to predict the effects of the planned mining exploitation and to diagnose the dominant external factor causing the observed extent of damage. In addition, inference can be performed basing on the incomplete information about the analyzed phenomenon.

The use of the probabilistic approach offered by Bayesian Networks may allow to combine the current results of the analysis of the technical condition with the field of structural reliability comprising the techniques based on strictly defined probability distributions.

The article was prepared as part of the AGH statutory research No. 11.11.150.005.

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