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Application of the Computation Procedure in Bayesian Network in Estimation of Total Cost of Natural Stone Elements Production

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Summary. In the course of data collection and processing, an essential role is played by computation processes which can be performed automatically. Moreover, these processes should naturally allow for uncertainties. The article presents such a process realized with the aid of Bayes network technique. The model enables the user to monitor the total production cost of elements which are made of natural granite stone. Inference mechanisms built into the system make it possible to retrieve the information necessary for a rational production management. The basis for estimation is an approach based on a probability distribution defined over a set of values of decision variables representing parameters of the production process. It has been shown how to carry out a simulation research in a range of situations where inference mechanisms are applied.

Key words: production process, natural stone, granite, computation processes, production costs, Bayesian networks.

INTRODUCTION

Granite machining process consists of many operations affecting the overall course of the process as well as the final effect. Each operation is an integral part of the entire process, having an impact on the other stages of the process, or it is determined by them. It is not possible to determine causal links without the knowledge of proper complete course of the process [12]. Structural non-homogeneity, high variability of process parameters burdened with randomness, justify treating the process components as random variables and a probabilistic model as a natural way of representing them.

The necessity of taking uncertainty present in the process into consideration, makes Bayesian network a useful system of knowledge representation, when it is needed to clearly encode an uncertainty factor and understanding issue in terms of nondeterministic cause-effect relations. These network capabilities can be employed in creating production process predictability.

The possibility of automation of data collection process, as well as of data processing, is an essential aspect [5, 6, 9] whereas the computation processes are performed automatically basing on advanced cognitive modelling systems. The process stages and the states of objects used in specific processes are known within the accuracy of probability distribution. Cognitive modelling can be based on Bayesian network technique.

An important computation process in technical systems engineering, which needs to be embedded in the system, is the possibility of monitoring production costs. It is a multidimensional process, which refers to entire systems, their components (subsystems), and finally, specific groups and machine types. Production cost optimization forms the groundwork for effective technical systems utilization. Entire production cost estimation, based on the information obtained from database, allows comparing the technology of a particular production process to other production technologies. Computational procedures are based on a deterministic approach including financial ratio methods.

An alternative approach is the approach based on Bayesian network. Such an approach is justified by the uncertainty factor which is integrally related to production process. The essence of the offered approach is that each cost component and the factors which determine its size are represented by random variables.

Bayesian network has many applications where it is needed to explicitly encode uncertainty coefficient and reasoning in terms of nondeterministic causal link relations [13, 14, 23, 24]. They are therefore a useful tool to model uncertainties in production processes [17, 18, 19, 20], predictability of technical objects behavior [2, 3], computer-aided decision making processes [14, 20], and to express reliability knowledge both in terms of practical approach [4, 8, 15] as well as for theoretical analyses purposes [1, 25].

Another field of application of the Bayesian network is the problem of complex flowchart management [16, 22].

The aim of this study is to present a conceptualization method of computation process realizing a problem in Bayesian network language, by illustrating it with an example of estimation of the total cost of natural stone (granite) elements machining process. An assumption has been made during designing the model, according to which the process components are represented as random variables. Bayesialab program was used in building the model. This environment has built-in inference mechanisms allowing the model to operate as a prognostic and explanatory system.

MODEL CONCEPTION AND STRUCTURE

Natural stone machining process modelling is based on the analysis of the granite features which are important in terms of modelling, and the machining process elements which influence different costs, as well as operating-supervising time. Factors which influence the cost and operating-supervising time have been presented as variables and their values implemented in Bayesialab environment [10]. The variables are represented by nodes and their labels correspond to the process component represented by a specific node. It has been assumed that variables values can be continuous within a given range or they can be of a discrete type. Cause-effect relations are represented by arcs. They reflect relations which take place in the modelled process. Subsequently, a priori probability distributions have been assigned over the range of variable values, defining distribution type and its values.

Nodes can be divided into certain groups representing different aspects of the modelled process. All model elements have values and probability distributions assigned to them and basing on those, values of other variables are determined by arithmetic operations or logical operators.

A layer describing the features of the workpiece is distinguished in the network. Variables representing density, thickness and length of machined material (granite), as well as machining quality belong to this layer. The machined material density is an essential variable in natural stone machining process. It depends on the percentage of each mineral which the natural stone is composed of. The main minerals which granite consists of are: orthoclase, plagioclase, quartz, biotite and a whole series of other minerals in trace amounts. Granite density has an impact on unitary cutting tool consumption cost and feed rate. In the model, density is represented by a discrete random variable, which can have three values: low, average and high. Low density is within the interval from 2400 kg/m³ up to max. 2600 kg/m³, e.g. Kashmir White granite, whose density is 2470 kg/m³. The average density begins from above 2600 kg/m³ up to 2800 kg/m³. This interval contains most granite, including: Impala 2710kg/m³, Strzegom 2630kg/m³, Vanga 2635kg/m³. The high density category ranges from 2800 kg/m³ up to 3000kg/m³. This density group consists of the following granites: Azul Platino 2820 kg/m³, New Impal Red 2820 kg/m³, Star Galaxy 2830 kg/m³. These intervals include almost all granite densities.

Thickness of the machined granite workpiece is another continuous variable which was considered in the model. The workpiece thickness is based on a client's own taste, as well as on assembly and design capabilities. It was assumed that this variable ranges from 50 mm to 100 mm.

The variable length of the workpiece represents the sum of its side lengths. This variable is used to estimate the cycle time of machining the workpiece surface. It is a continuous variable and it can have values from 500 mm to 620 mm.

The quality of the machining process is a variable which represents a client's expectations concerning the final product quality. Machining parametres and required number of cycles are determined by defining a quality class. It is assumed in the model, that the variable representing quality is a discrete variable and it can take three different values: high, average and economic. The cutting disc feed rate is chosen according to the required quality. Slow cutting disc feed decreases labour consumption during the process of polishing.

The workpiece surface is a continuous-type variable and its values are found as the product of length and thickness variables. This variable can take values from the interval from 0,2 m² (minimal value) to 0,62 m² (maximal value). The value of this variable impacts on intensity of cutting tool consumption. The machined surface, after polishing, must undergo preservation and gloss finish treatment.

Feed rate is determined by the quality required, as well as by density of the workpiece. Its precise value is found using a logical formula. It was assumed that the values of the variable have normal distributions, an expected value of distribution corresponds to a particular rate and standard deviation is 0,001. Feed rate is a variable which determines cycle time.

Another process parameter is the number of cycles. It depends on the declared quality and it is 26 cycles for economic quality, 27 for average quality and 28 in case of high quality.

Water consumption in machining process is evaluated in the model as the product of unitary water consumption per minute related to the machining time. It was assumed that the variable of unitary water consumption per minute is a continuous variable and it ranges from 10-12 l/min.

Other variables enable estimation of operation time and their costs. They are continuous variables which represent: unitary machining cycle time, workpiece machining time, cutting tool exchange time and worker's work time. Unitary machining cycle time equals a complete cycle time of polishing machine operation. A workpiece machining time is estimated on the basis of information represented by nodes: workpiece length, cutting disc feed rate. In this manner, we obtain probability distributions over a set of estimated possible machining time values. Extending machining time has a significant impact on the final cost, since workload, water and electricity consumption increase.

Cutting tool exchange time is a variable whose values depend on the worker's experience, abilities, manual and motor coordination skills. In the model, this time is represented by a continuous variable of 20-25 min. A worker's worktime is a variable evaluated by the sum of a workpiece machining time and the time required for cutting tools exchange. This variable can range from 35 to 345 minutes.

The last group of variables considered in the model, are the variables which represent costs. Costs represent quantitative expenditure corresponding to the realization of a specific version of stone machining process. They include: unitary cutting tool consumption cost, preservation and gloss finish cost, as well as evaluated consumption costs of cutting tools, finishing elements, water, energy, utilities and labour. The range of each variable was either assigned or evaluated, according to possible versions of the process and current prices.

The final variable in the model is a continuous variable representing the total cost of machining a single workpiece. The total cost is evaluated as the sum of values of three nodes: finishing elements cost, utilities cost and labour cost. The node shows probability distribution over a set of cost values which can be reached during the machining process of natural stone.

A graphical form of the conceptualization presented above, and at the same time, the structure of a network allowing for the estimation of a single workpiece machining cost in Bayesian network technique, has been shown in the Fig. 1. The variables used in computations, representing machined pieces features, machining parameters, times and all constituent costs are represented by equally named variables in the network. Probability distributions over sets of the variables considered in the model are illustrated in a graphical form in the Fig. 2.

ESTIMATION OF TOTAL GRANITE ELEMENTS PRODUCTION COST

For the purpose of verification of the model, a computation concerning machining process of natural granite stone elements has been carried out. Inference mechanisms, typical in Bayesian networks, were applied in the verification.

The standard mechanism of the network working (prediction of the consequences of decisions) provides the process total cost according to the workpiece features, quality requirements and operator's competence.

In the analyzed problem, it has been assumed that the variables: the workpiece length –of 0.536*10 m, machining quality – average, cutting tool exchange time of 20.5 min, wage rate according to category equals 0.225 zł. per minute, the number of cycles is 27, and unitary water consumption has been fixed at 10.75 litres per min. The total cost has been evaluated for the workpiece thickness of 0.065m and various density values: low (A), average (B), high (C). Computation results as probability distribution over a set of total cost values have been presented in the Fig. 3.

The above calculations were repeated, assuming the workpiece thickness to equal 0,85 m. Calculations results are presented in the Fig. 4. In the first case (thickness of 0.65 m), the lowest total cost 48,893 was obtained for the low density of the workpiece, and the highest for the high density, and amounts to 164,317 zł. It should be noted that in case of low density with probability of 0,71, a possible outcome of costs can range from 39,7 to 62.9 zł. Whereas, in case of high density, the total cost can take values from intervals: 132.6-155.8, 155.8-179.2, 179.2-202.3 zł. practically, with equal probability (0.23, 0.29, 0.21, respectively). For average workpiece density the total cost is 106,228 zł.

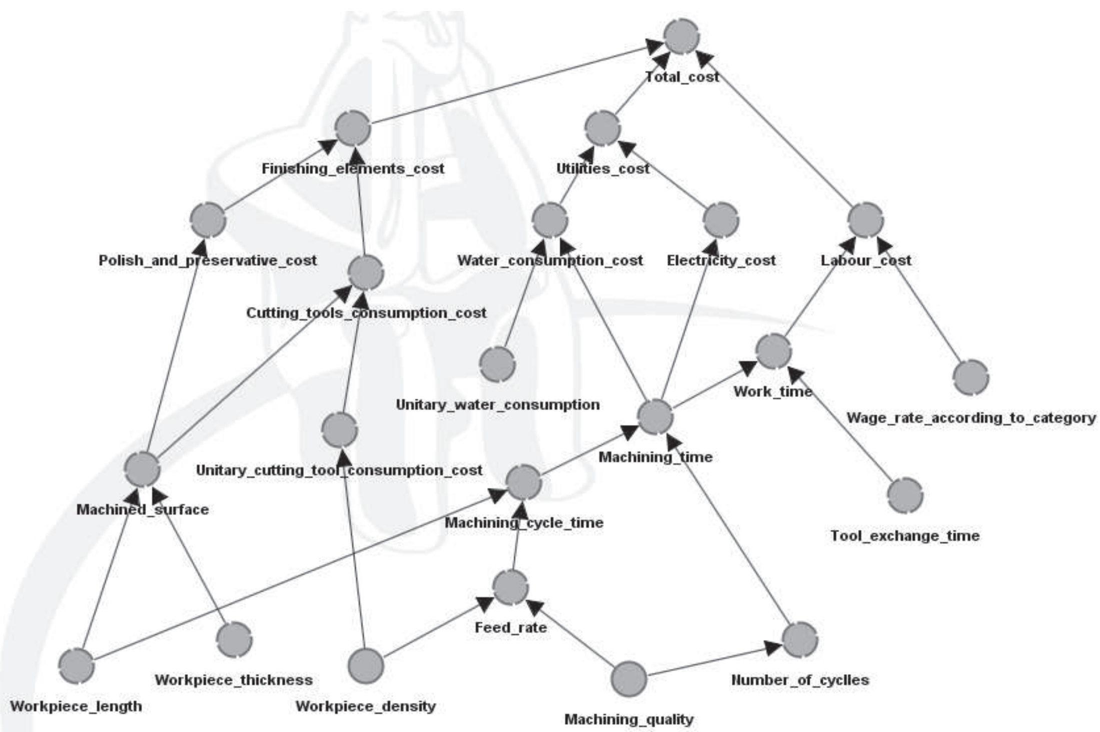


Fig. 1. Network structure used for estimation of natural stone machining process cost

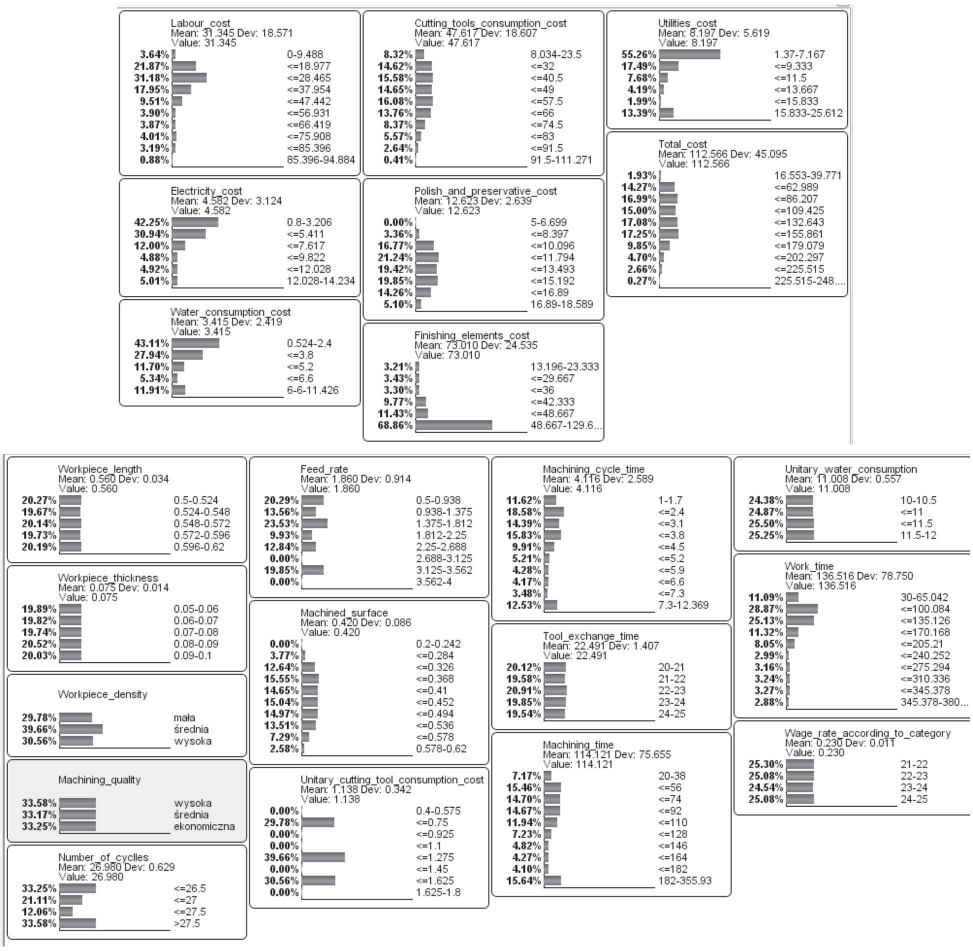
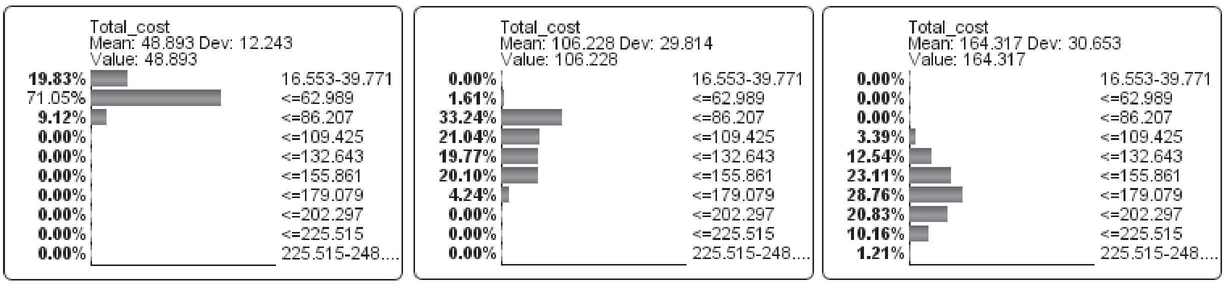
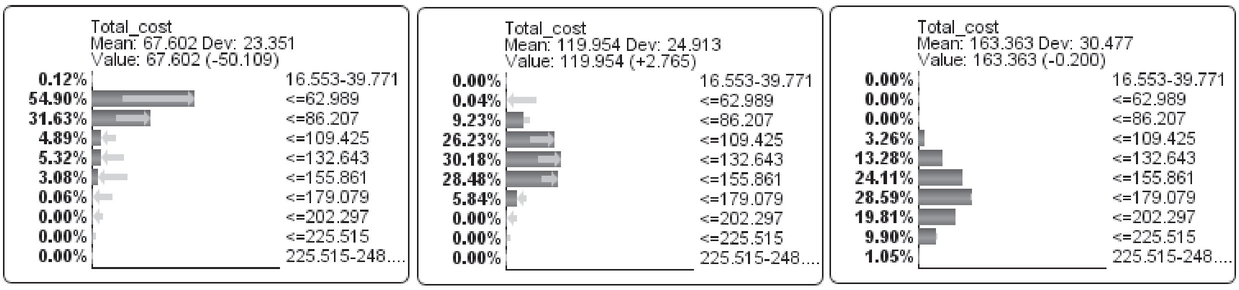


Fig. 2. Probability distributions over random variable values



A B C

Fig. 3. Total cost (thickness 0,065) depending on the density of the machined stone



A B C

Fig. 4. Total cost (thickness 0,065) depending on the density of machined stone

For the variable 'workpiece thickness' at the value of 0.85, the total cost obtained was 67.602 for low density, 119.95 for the average and 163.36 for the high. In this case, the knowledge of probability distribution allows for estimating the chance of getting a desired value of the total cost.

The diagnostic inference mechanism available in the network is useful in a situation when we want to determine conditions that must be satisfied in order to achieve the assumed level of the total cost. Fig. 5 shows points which correspond to constant total costs (K_1 = 144.252 and K_2 = 74.598) depending on thickness and length of the workpiece.

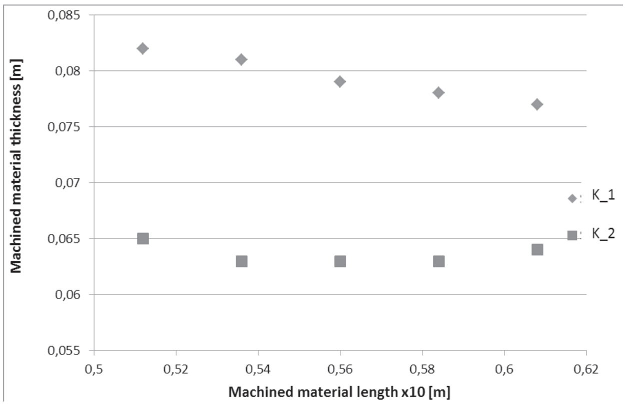


Fig. 5. Points corresponding to constant total costs of machining process depending on thickness and length of the workpiece

The working scheme of the model shown above can be applied to estimation of other cost components. Information possible to obtain by simulation experiments is of a great practical importance and can be used in the natural stone element production management.

CONCLUSIONS

The procedure of estimating the total cost of natural stone machining, which is implemented in Bayesian network, is an example of a computation process which can be entirely automated by virtue of embedded inference mechanisms. The convenience of input data which can be formed arbitrarily basing on available resources and predicted production conditions, account for its significant importance at the stage of design, planning, monitoring and analysis of production process with reference to natural stone elements in specific condition of realization.

Prognostic inference allows for analysing all possible versions depending on model input variables. A set of acceptable solutions can be determined, accurate to probability distribution. For expected values of the terminal variable (in this case, for total production cost), hypothetico-deductive inference (temporal backward projection) facilitates, with an accuracy of probability distribution, determination of requirements regarding variables representing each cost component and variables describing features of the workpiece, as well as machining process parameters.

Machine learning mechanisms which are available in the system [11] facilitate adaptability of the model, both in terms of topology (adjusting the model to object types) as well as in determination of a priori probability distributions.

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ZASTOSOWANIE PROCEDURY OBLICZNIWEJ W SIECI BAYESOWSKIEJ DO WYZNACZANIA KOSZTÓW CAŁKOWITYCH PRODUKCJI ELEMENTÓW Z KAMIENIA NATURALNEGO

Streszczenie: W Proces gromadzenie danych oraz ich przetwarzania istotna rolę odgrywają procesy obliczeniowe, które mogą być realizowane automatycznie a ponadto w naturalny sposób powinny umożliwiać uwzględnienie niepewności. W artykule przedstawiono przykład takiego procesu realizowanego w technologii sieci bayesowskich. Model umożliwia monitorowanie kosztów całkowitych produkcji elementów wykonanych z kamienia naturalnego granitu. Wbudowane w system mechanizmy wnioskowania pozwalają wydobywać informacje niezbędne do racjonalnego zarządzania produkcją Podstawą oceny jest podejście oparte o rozkład prawdopodobieństwa określony nad zbiorem wartości zmiennych decyzyjnych reprezentujących parametry procesu produkcyjnego. Pokazano w jaki sposób wykorzystując mechanizmy wnioskowania można prowadzić symulacyjne badania różnych wariantów sytuacyjnych.

Słowa kluczowe: proces produkcji, kamień naturalny, granit, procesy obliczeniowe, koszty produkcji, sieci bayerowskie.