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IMPLEMENTATION OF COMPUTATION PROCESS IN A BAYESIAN NETWORK ON THE EXAMPLE OF UNIT OPERATING COSTS DETERMINATION

IMPLEMENTACJA PROCEDURY OBLICZENIOWEJ W SIECI BAYESOWSKIEJ NA PRZYKŁADZIE WYZNACZANIA JEDNOSTKOWYCH KOSZTÓW EKSPLOATACJI*

In technical systems understood in terms of Agile Systems, the important elements are information flows between all phases of an object existence. Among these information streams computation processes play an important role and can be done automatically and also in a natural way should include consideration of uncertainty. This article presents a model of such a process implemented in a Bayesian network technology. The model allows the prediction of the unit costs of operation of a combine harvester based on the monitoring of dependent variables. The values of the decision variables representing the parameters of the machine's operation and the intensity and the conditions for its operation, are known to an accuracy, which is defined by a probability distribution. The study shows, using inference mechanisms built into the network, how cost simulation studies of various situational options can be carried out.

Keywords: *agricultural machinery operation, computing processes, unit operating costs, Bayesian networks.*

W systemach technicznych rozumianych w kategoriach Agile Systems istotnym elementem są przepływy informacyjne pomiędzy wszystkimi fazami istnienia obiektu. Pośród tych strumieni informacyjnych istotną 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 bayesowskiej. Model umożliwia predykcję jednostkowych kosztów eksploatacji kombajnu zbożowego na podstawie monitorowania wielkości zmiennych od których one zależą. Wartości zmiennych decyzyjnych reprezentujących parametry pracy maszyny oraz intensywność i warunki jej eksploatacji są znane z dokładnością do rozkładu prawdopodobieństwa. W pracy pokazano w jaki sposób wykorzystując mechanizmy wnioskowania wbudowane w sieci można prowadzić symulacyjne badania kosztów w różnych wariantach sytuacyjnych.

Słowa kluczowe: *eksploatacja maszyn rolniczych, procesy obliczeniowe, jednostkowe koszty eksploatacji, sieci bayesowskie.*

1. Introduction

The technical systems of today can be understood in terms of Agile Systems. This means that their existence is not a series of separate phases: design, manufacturing, operation and recycling. The "agile paradigm" assumes the simultaneous presence of all these phases. For example, the design works are carried out all the time and are aimed at continuous adaptations of technical systems to changing requirements [1, 22, 23]. The manufacturing process implements these adaptations and translates them into the operating features.

In such a system, an important role is played by intensive information flows manageable in Big Data information technology. The process of this data collection and its processing is automatic and takes place in a semantic data network technology [6,7,10]. Computational processes are performed automatically using advanced systems of cognitive modeling [8.22]. This modeling should take into account uncertainty factors. The states of processes and objects used in specific processes are known with an accuracy of the probability distribution. Cognitive modeling can therefore be based on probabilistic network technology.

In engineering of technical systems, in particular bio-agrotechnical [15], one of the important computational processes that must be embedded in the system is the ability to monitor operating costs. This is a multidimensional process of entire systems, their components (subsystems), and finally specific groups and types of machines. Optimization of operating costs forms the basis of the effective use of technical systems in agriculture. In the literature, and increasingly in the databases one can find information about the cost of the actions that make operational processes for the selected category of objects. Determining unit operating costs, being the cost of one hour of operation of a tractor or other machine, which is the sum of the unit costs of maintenance and use [24], based on information obtained from databases, allows for comparison of a particular technical object with other objects having the same purpose. This is essential during selection and purchase of a particular object. The possibility of feedback information from a particular class of objects allows designers to estimate the critical unit operating costs that cannot be exceeded if the designed object is to be competitive with the current market offer.

A wide commercial range of tractors and other machinery makes the rational selection of specific technical solutions, depending on the size of the farm and production profile, a difficult task from the point of view of their effective use. Principles of analysis and operational evaluation of an object [29] are defined by the methodological frameworks of determining the cost, depending on the intensity of use. The

(*) Tekst artykułu w polskiej wersji językowej dostępny w elektronicznym wydaniu kwartalnika na stronie ***www.ein.org.pl*** proposed computational procedures are based on the deterministic approach [28], with consideration of the indicative methods [24].

An alternative approach to the methods described above is an approach based on the Bayesian network. The use of the network is justified by the uncertainty factor integrally associated with the operation process of technical objects. The essence of the proposed approach is predicated on the fact that the individual cost elements and factors determining their size, such as the operating parameters of technical objects, conditions and intensity of using the equipment, and other factors such as maintenance costs, loan interest rates, etc. are represented as random variables.

Bayesian networks have been widely used in situations where in the explicit way the factor of uncertainty and inference in non-deterministic categories of cause–effect relationships should be encoded [13, 14, 27]. They are a useful tool for modeling uncertainty in agricultural production processes [18, 19], the prediction of the technical condition of the object in order to plan preventive measures [3, 4], computer-supported decision making processes [14, 21], and representation of the reliability knowledge, both in practical terms [4 , 8.15] and for the purpose of theoretical analysis [2.30].

Another application of Bayesian networks is the problem of managing complex networks of activities [17]. This approach makes possible the inclusion in the model of the relationship between the time of carrying out a particular activity and the conditions of its implementation and currently available production resources.

This study aims to provide a method of conceptualization in the language of Bayesian networks of the computation process on the example of determining the unit operating costs of agricultural machinery. The unit operating cost is determined as the average value of the cost per unit of measure of the work done in the lifetime of an object [24,29]. An important element of the methodology is the consistency with the demands of knowledge engineering, which assumes the possibility of using machine-learning methods to build a network. The possible scenarios for the functioning of the model are based on inference methods typical for Bayesian networks [27].

2. Conceptualization of determining the operating costs of agricultural machinery

Substantive knowledge of the operation of technical object, including the computation process, provides qualitative knowledge that is necessary to build the correct semantics of process models. In the case of Bayesian networks, this knowledge is used to establish the topology and thus the factorization of the total probability distribution, or presenting it as the product of the conditional probability distributions. At the stage of network usage, substantive knowledge is essential for choosing the significant paths of inference and interpretation of outcomes of the inference process.

As a basis of reference for the calculation of unit operation costs, one hour of the machine's operation was chosen [24]. The general rule is to calculate the cost of machines operation based on the reconstruction price regardless of whether the calculations concern a new machine or the one already used. In addition, this approach allows for consideration of the situation when, while planning the purchase of a particular machine, the limited time of its operation can be taken into account, assuming that after a certain time the machine can be sold off. Such an interpretation of the price is justified by the fact of its representation as a random variable, and the range of variation of this variable should be determined based on the difference between the purchase price and the expected selling price. Similarly, the lifetime of the machine (i.e. the normative, or pre-determined amount of "work" that it can perform from the purchase to its cassation or resale) and the hourly use of the machine per year (h / year) in the specific conditions of use, are represented as continuous random variables with a determined probability distribution established on the basis of learning data.

The adoption of these assumptions means that the individual components of the operating costs will be represented in the model as conditional random variables and the determination of unit operating costs in a particular case boils down to using these variables.

Graphical form of this conceptualization and simultaneously the structure of the network enabling the determination of operating costs in Bayesian network technology, is shown in Fig. 1 [11]. Network topology results from the structure of the calculation process. The network can be divided into nodes representing the raw input data, nodes representing the operations on these data and, finally, the final node that represents the unit operating costs. The nodes, which collect data from the data stream, represent the values of the data. Probability distributions on the set of values of these nodes are determined automatically based on the data obtained from the history of operation of the machine. The values assigned to nodes representing operations on random variables are also random variables. The value of the final variable is also determined with an accuracy of the probability distribution.

The parameters of the machine operation and the individual cost components adopted for the calculations are represented by the variables having the same name.

A machine's lifetime is represented by the variable Z. This variable represents the assumed time of use of the machine. The model assumes that this variable is expressed in hours of operation. It can

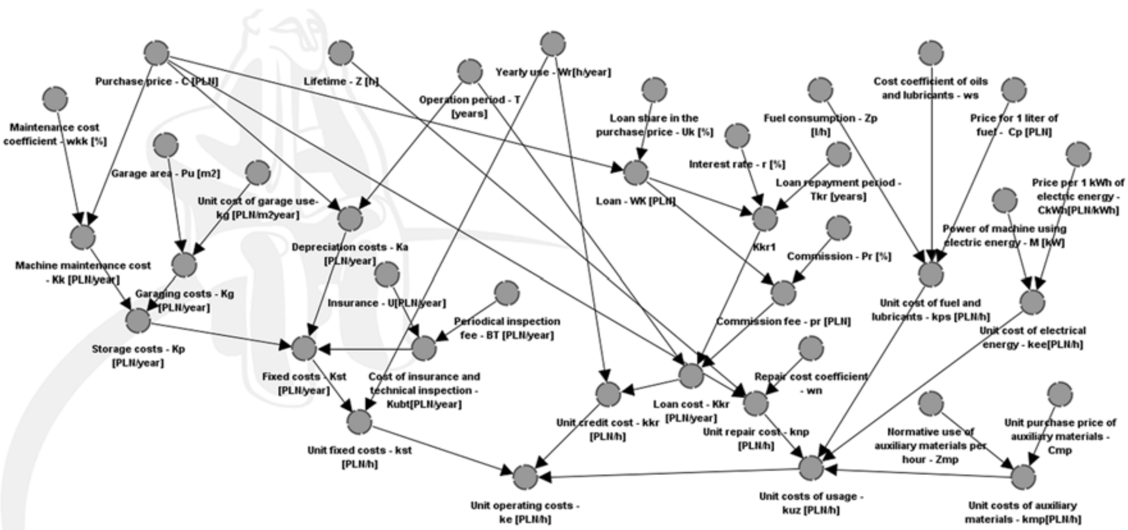


Fig. 1. Structure of the network for determining unit operating costs (own analysis)

also be expressed in other units such as the amount of work done. The hourly use of the machine per year W_r (h / year) is a random variable depending on the intensity of machine's operation in the specific conditions of its use. Another variable T represents the machine's operational time in years. The maximum value of this variable can be estimated by dividing the machine 's life time Z by the assumed time of its use per year W_r.

Amortization cost K_a is the expression of financial reduction in value of machines per year:

$$K_a = \frac{C}{T}, \tag{1}$$

where: C- purchase price in PLN
T- operation time in years

The cost of storing the machine K_P (PLN / year) is calculated as the sum of the garaging cost K_g and maintenance cost K_k. The garaging cost K_g (PLN / year) is calculated as the product of usable area P_u (m^2) of the garage or shed, and the unit cost of operation of the object i.e. the garage or the shed k_g (PLN / m^2year):

$$K_g = P_u \cdot k_g. \tag{2}$$

The maintenance cost of the machine K_k (PLN / year) includes the value of non-cash outlay and labor costs that are associated with post-season cleaning of the machine and securing it for the time of storage. This cost can be determined on the assumption that there is known distribution of working time, depending on the type of machine, the method and extent of maintenance, and the type of machine; or by using the simplified method as the product of the purchase price and the coefficient of maintenance cost w_{kk}. It is assumed that the w_{kk} coefficient, depending on the complexity level, is 0.5% – 1% of the machine's price. In the current procedure, the second method has been implemented.

The distribution of the variable representing the costs of insurance and technical inspections (if obligatory) K_{ubt} is estimated based on the current tariffs of insurance companies and the applicable rates.

The above cost components are independent of the intensity of operation of the machine. The total cost of this group K_{st} is the sum of the costs K_a, K_g, K_{ubt}. The sum of these components divided by the time of the operation of the machine per year W_r determines the unit fixed costs k_{st} per 1 hour of operation:

$$k_{st} = \frac{K_a + K_g + K_{ubt}}{W_r}. \tag{3}$$

When the purchase of the machine is associated with taking a loan, the user incurs additional costs. They include the interest on the loan, including additional charges, (although it does not apply to the loan's capital repayments, which are part of the depreciation costs). This cost is known in advance, but may vary due to conditions for granting loans for investments (e.g. interest, commission, repayment period and the grace period) by individual banks, the type of credit line, or the credit-worthiness of a borrower and loan collateral. Assuming that the cost of the loan K_{kr} (PLN / year) is spread over the period of the machine's use T, this cost can be determined on the basis of a simplified formula:

$$K_{kr} = \frac{1}{T}\left[\frac{U_k \cdot C \cdot r \cdot (T_{kr}+1)}{2} + pr\right], \tag{4}$$

where: T- machine's operation time (years)
U_k - loan share in the purchase price (%/100),
T_{kr} - loan repayment period (years),
r - interest rate (% / 100),
pr - commission and other fees associated with the loan facility (PLN)
C – price (PLN).

In the above considerations, the cost of interest on capital as an alternative method of gaining revenues in cases when the cost of the investment is financed from one's own resources, has been omitted. Currently, there is a prevailing opinion that the value of the cost of interest on capital is compensated by calculating the depreciation cost each time from the current price.

The loan cost K_{kr} divided by the time of the machine use per year W_r determines the unit cost component k_{kr} (in PLN / h)of work resulting from servicing the loan:

$$k_{kr} = \frac{K_{kr}}{W_r}. \tag{5}$$

The next category of cost includes the costs directly related to the machine's use. These costs include the cost of repairs, fuel and lubricants, the cost of electricity and any additional materials. The total value of these costs in a year depends on the amount of work done. In the model, the average values of these costs over the entire operation period are represented, because in principle, with the increase in machine wear, the unit cost of its use, especially repairs, will be higher than in the first year of its operation.

There are two alternative approaches to determine the cost of repairs. The first one is used when we have reliable statistics of operating history on the basis of which the actual distributions of normative cost of repairs, emergency repairs, maintenance and other tasks for the whole operation period can be estimated. The second approach (implemented in this model) assumes that the cost of repairs over the total operation period is from 0.4 to 1.5 of the purchase price, depending on the machine, and then the unit cost of repairs k_{np} in PLN per hour of operation is calculated as:

$$k_{np} = \frac{w_n \cdot C}{Z}, \tag{6}$$

where: w_n - repair cost coefficient,
Z- lifetime in hours
C- price.

Depending on the conditions of the machine's use, skills of technicians and quality of repairs and maintenance, repair costs k_{np} can vary considerably and this is taken into account by the fact that the coefficient w_n is represented as a random variable.

The unit cost of fuel and lubricants k_{ps} (PLN / h of work) is the product of unit fuel consumption Z_p (l / h of operation), of the engine and the price of 1 liter of fuel C_p, while the value of oils and lubricants used is determined in relation to the value of fuel consumed by an indicative method. The total unit cost of fuel and lubricants is:

$$k_{ps} = w_s \cdot Z_p \cdot C_p, \tag{7}$$

where: w_s – coefficient of lubricants cost to fuel cost.

The unit cost of electricity k_{ee} consumed by the devices is estimated as the product of the nominal capacity of the machine (M) and the price (C_{kWh}) of 1 kWh of electricity:

$$k_{ee} = M \cdot C_{kWh}. \tag{8}$$

The unit cost of auxiliary materials k_{mp} (PLN / h of work) is only present in the case of some machines, such as string or mesh for binding bales of straw in harvesting press, film for wrapping bales or silage etc. This cost is the product of the normative consumption of these materials Z_{mp} for 1 hour of the operation of the machine and the unit purchase price C_{mp}.

$$k_{mp} = Z_{mp} \cdot C_{mp}. \tag{9}$$

The total unit costs of machine use k_{uz} per 1 hour of operation are:

$$k_{uz} = k_{np} + k_{ps} + k_{ee} + k_{mp}. \tag{10}$$

The unit cost of operation k_e (PLN / h), (i.e. the cost of one hour of work of the tractor or machine) is the sum of unit costs independent of the amount of work, loan costs and operating costs:

$$k_e = k_{ST} + k_{kr} + k_{uz}. \tag{11}$$

Unit cost of operation of a set comprising tractor and machines is the sum of unit costs of operation of the machine and the associated tractor. This cost can also be expressed per unit of work performed (e.g. for 1 hour of work per 1 hectare) as the ratio of the cost per hour of operational performance of the tractor-machine set or the self-propelled machinery.

The above algorithm for determining unit operating costs based on Bayesian network technology is general in nature. The terminal node represents the unit cost of operation. The value of this variable in accordance with the methodology set out above is determined as the sum of unit costs (fixed, loan and the cost of use). These costs are represented in the network as three basic modules. The application of this model to assess a specific machine requires its "concretization". This concretization takes place in two stages. In the first stage, the network topology should be matched to a particular situation. Network topology takes into account the form of purchase of the machine (cash or credit) and energy sources (self-propelled machine, trailed or stationary electric- motor driven). Matching of the network involves activation of its respective modules. If the purchase is financed by a loan, the module for determining the *unit cost of loan* is activated. Similarly, depending on the energy source, a module for determination of the *unit cost of fuel* is activated (in the case of self-propelled or trailed machinery) or a *unit cost of electricity* module (in the case of stationary machines driven by electric energy). The second step of problem concretization involves assigning prior-conditional probability distributions to network nodes and specifying domains of nodes variability values.

3. Determination of unit operation costs of a combine harvester

In order to verify the model, calculations were carried out concerning combine harvesters with a working width of 4.5 – 5.0 meters. Network topology takes into account the possibility of buying the machine for cash or with part credit. A priori probability distributions were estimated using catalog data and the literature [24]. The purchase price was assumed at C = 322 500 PLN, lifetime Z = 2440 h, the operation time T = 15 years, the annual use W_r = 158 h / year; fuel costs and insurance and other components correspond to currently applicable prices. The first example analyzed assumes that the purchase was covered by one's own funds.

The typical mechanism of operation of the network (i.e. prediction of the decision effects) enables determination of the unit costs depending on the form of purchase, the assumed parameters of a combine harvester, projected costs of service and projected intensity of its use.

Calculations were performed for two scenarios of cost: optimistic and pessimistic. The optimistic variant (Fig. 2) implies that the components of the cost determined by an indicative method adopt minimum values. The pessimistic scenario assumes that these costs are maximised.

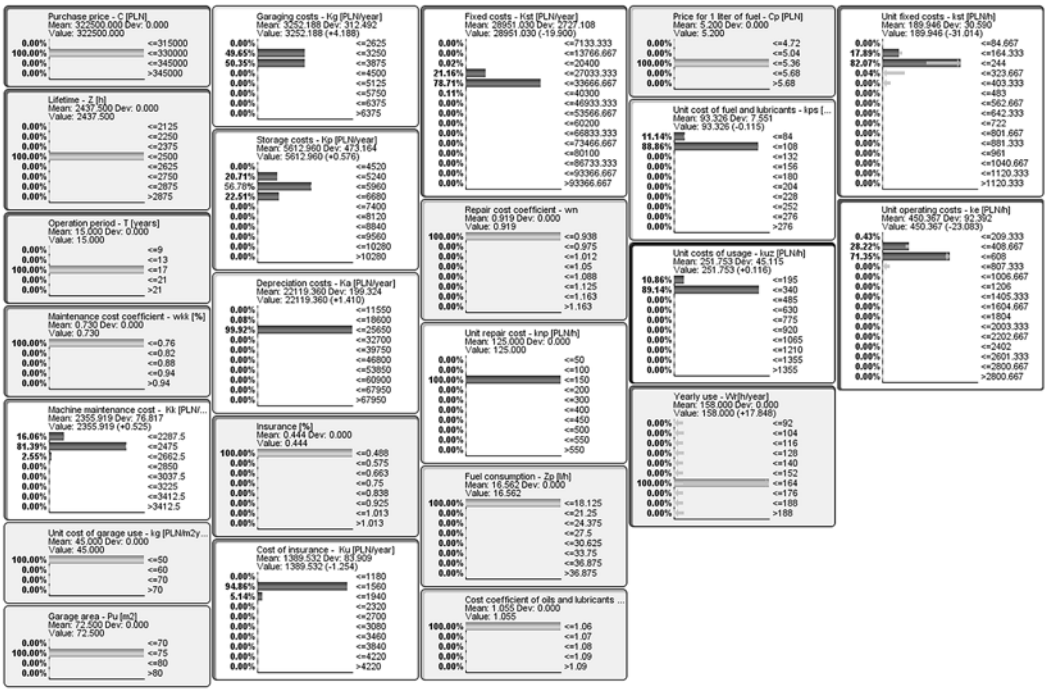


Fig. 2. Predictive inference optimistic scenario (own analysis)

If the variable is known to an accuracy of probability distribution (i.e. soft evidence) our knowledge of the terminal variable is fuzzy. As shown by the calculations, the expected values of variables representing the unit cost of operation, fixed costs and the use, amount to (in PLN per hours of operation) respectively: 456.1 (standard deviation 89.4), 191.3 (standard deviation 29.4), 254.3 (standard deviation 41.8).

In the case of a pessimistic scenario (Fig. 3), the unit cost of operation is a random variable with an expected value of 636.3. The expected values of the individual components are as follows (in PLN per hours of operation: the unit fixed cost 214.3 (standard deviation 28.6), and the unit cost of operation 411.0 (standard deviation 14.6).

Fig. 3 shows the probability distributions over a set of variables representing the unit operating costs, in the optimistic (W_1) and the pessimistic scenario (W_2).

Fig. 4 shows the relationship between unit cost of operation k_e (PLN/h) and the time of use of combine harvester per year (W_r) determined by using the network for both variants analyzed.

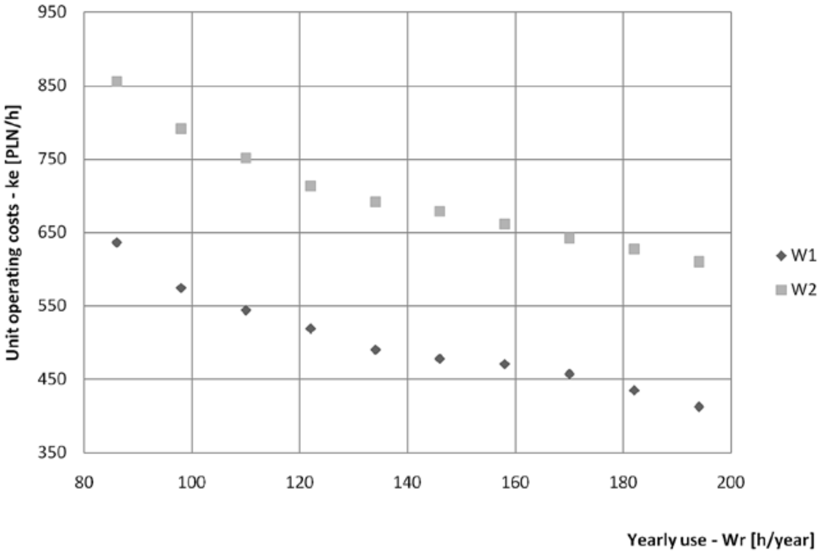


Fig. 5. Unit operating costs depending on the use of combine harvester per year (the purchase with 50% loan)

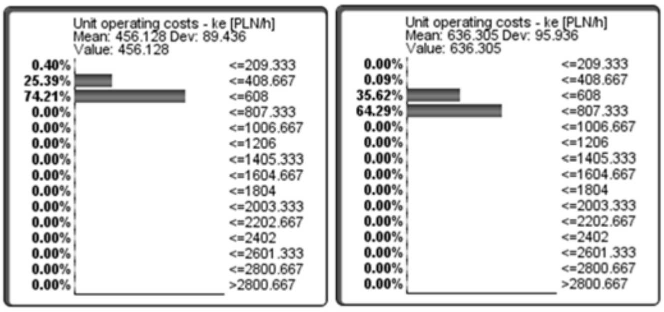


Fig. 3. Probability distributions for unit operating costs (own analysis)

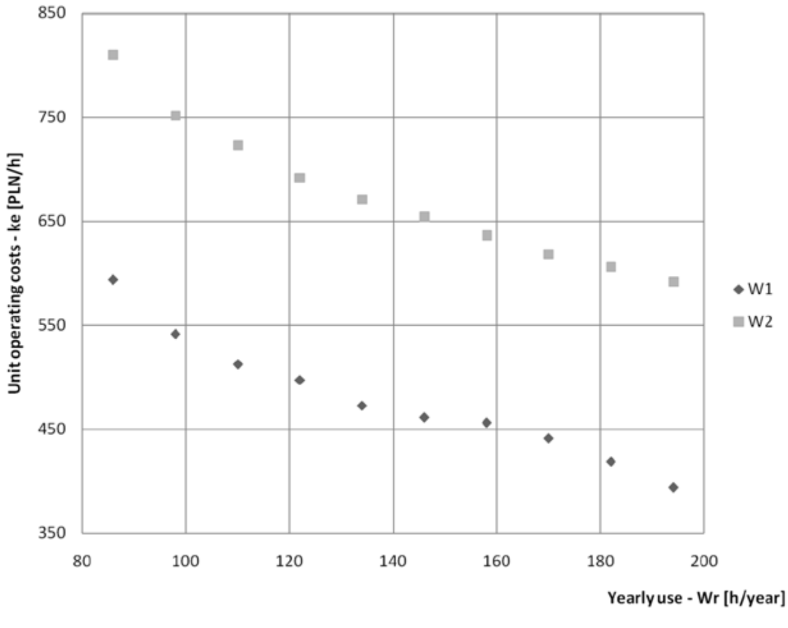


Fig. 4. Unit operating costs depending on the use of combine harvester per year

Similar calculations were performed when the purchase was half-financed by a loan, assuming optimistic scenario of the individual cost components. The adopted loan repayment period was T_{kr} = 3.5 years. In the variants analyzed the following interest rates and commissions were assumed: r = 11.4 (W_1) and r = 14.2 (W_2). Commission was assumed to be 0.7% (W_1) and 1.9% (W_2) of the loan amount. Based on the calculations, the unit operation cost depending on the use of the combine harvester per year for both analyzed variants was determined (Fig. 5).

The diagnostic inference mechanism available in the networks (i.e. time projection backwards) is useful when we want to specify conditions that must be met in order to achieve a particular level of unit costs. Fig. 6 shows the points corresponding to the fixed costs per unit, depending on the lifetime and yearly use of the object with no credit for investment and two analyzed variants, the optimistic and pessimistic scenarios.

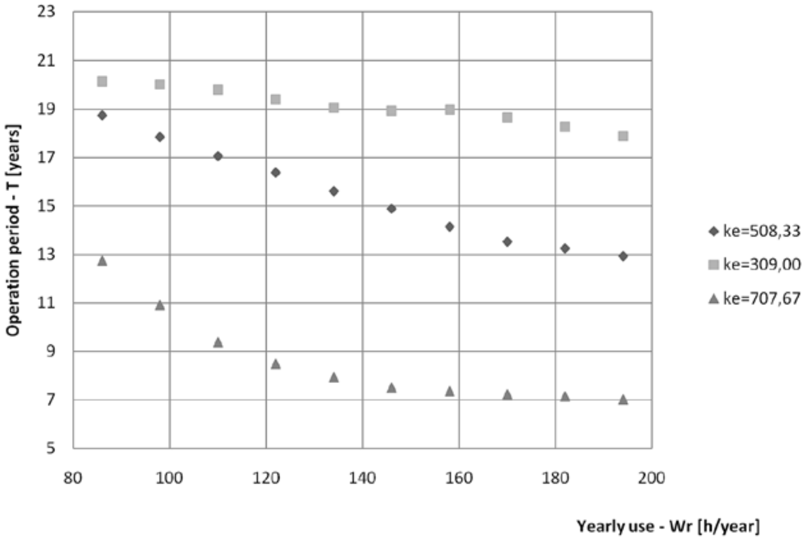
The above scenarios of the model's operation, by analogy, can be used for determining other cost components. Information that is possible to achieve with the model have great practical significance and can be used in the operational management process.

Summary

The implemented in Bayesian network procedure of calculating the unit operation costs is an example of the computation process, which due to the built-in inference mechanisms, can be completely automated. Easy changes of input data depending on the available financial resources and the expected conditions of use means that the proposed method can be of great significance in the design, planning, monitoring and analysis of the operational process of a specific object in its specific conditions of use.

Predictive inference allows for analyzing all possible solutions depending on the operating environment. With the accuracy of probability distribution, a set of mutually acceptable solutions can be determined. Hypothetical-deductive inference (time projection backwards) allows for the preset terminal variable value (in this case, the unit costs operation) determining the requirements for the variables representing the individual components of the cost, and the variables characterizing the machine parameters and its conditions of use.

The machine learning mechanisms available in the system [12] ensure adaptability of the model at both the level of topology (adaptation of the model to a particular type of object) and at the level of determining ‚a priori, the probability distributions of individual variables.



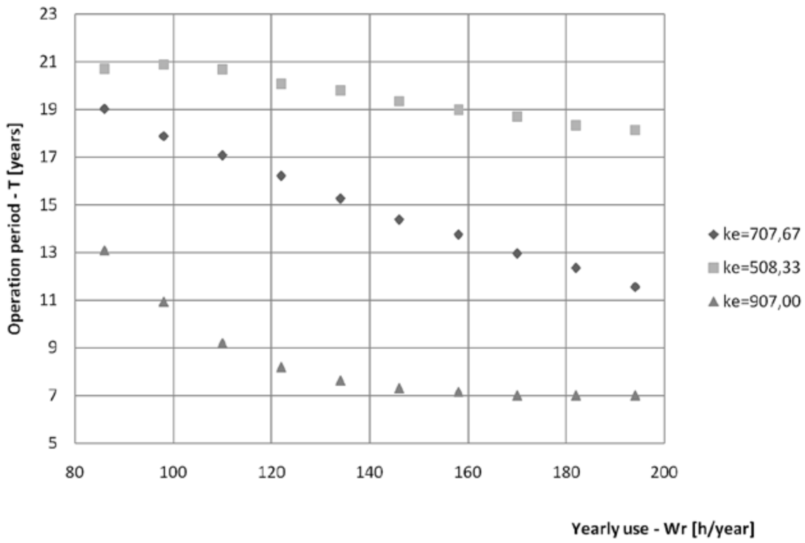


Fig. 6. The points corresponding to fixed unit operation costs, depending on the operation period (T) and the yearly use of W_r (optimistic scenario: upper graph, pessimistic scenario: bottom graph)

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