TEKA. COMMISSION OF MOTORIZATION AND ENERGETICS IN AGRICULTURE – 2017, Vol. 17, No. 3, 93-102

Modeling Technology in Centralized Technical Maintenance of Combine Harvesters

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Received February 6.2017: accepted May 24.2017

Summary. In Ukraine and abroad in several sectors of industries, a system of informational support of products lifecycle. Which is based on the standardized representation of product data and assumes brand warranty and post-warranty service. Such technologies typically include control system reliability: the system collects information about failures, scheduled and emergency repairs, as well as about the technical condition detected with special test and diagnostic tools. Similar systems are being introduced in the high technology industries of our country, and in the sphere of technical maintenance of combine harvesters are being introduced separate elements of the system.

Analysis of the possible production situations with an organized enterprise centralized technical maintenance of combine harvesters on the technical condition of the units allows to make a conclusion on what to reduce in-plant losses is possible by reducing errors and detection of aggregates and their distribution.

Selection of artificial neural networks as a mathematical apparatus for the solution to reduce error detection of aggregates and their distribution for technological routes at the centralized maintenance of combine harvesters was justified by the ability of this mathematical tool to the study, analysis and retention results, as well as high adaptation to the solution of the problem.

When building a neural network classifier of the system of technical maintenance of combine harvesters, it is first necessary to determine the complexity of the division of objects into classes. To simplify the problem of classification of the system of technical maintenance of combine harvesters, it is necessary to achieve a linear separation of the objects of study.

Since the task involves more than two classes of system of technical maintenance of combine harvesters for the distribution of units between them, the most efficient method of forming output signals will be a set of vector components. In other words, every possible defect combine harvester will have its output signal, and the presence of a defect or lack of it will say 0 or 1 on the corresponding output. It is very important to achieve close as possible to 0 or 1 values, this requires preprocessing the input data.

Key words: modeling, technology, operation, maintenance, combine harvester.

INTRODUCTION

The use of monitoring was especially effective with acquisition of parts and assigning routes to restore worn parts, as the decision about the technical condition of a part, assembly or assembly of combine harvesters was carried out by computer, which allowed to reduce the influence of subjective factors in the allocation of maintenance fund for trails.

The functions of the majority of computerized control systems for maintenance of combine harvesters in the agricultural repair shops has been expanded by adding the possibility of inventory management and maintenance personnel.

Later, any system, EAM system (from the English. Enterprise Asset Management), which are mainly used to maintain production equipment and machinery in good technical condition. These systems can consistently manage the following processes:

- maintenance,
- manage inventory,
- logistics,
- management of finance, quality and human resources under a unified strategy.

When implementing data systems in the enterprise focus on reducing the cost of maintenance of combine harvesters without compromising the level of reliability, or to improve certain production parameters without increasing costs.

Of EAM-systems for the sphere of technical maintenance of combine harvesters appeared in the integrated management – MRO-system (from the English. Maintenance, Repair and Overhaul), whose main purpose is automation of the planning activities of personnel involved in the maintenance of combine harvesters, and provide them with the necessary resources. In addition, these systems involve functionality for informing and solving a number of problems:

- manage timing of service and cancellation of combine harvesters,
- optimization of structure and size of the Park of combine harvesters,
- storing information about each unit of the convoy of combines, failures in the process of operation, and also maintenance of combine harvesters,
- support the territorial subdivisions of the enterprise, engaged in technical maintenance of combine harvesters, in the framework of a unified strategy.

THE ANALYSIS OF RECENT RESEARCHES AND PUBLICATIONS

In Ukraine and abroad in several sectors of industries, a system of informational support of products lifecycle [1, 2]. Which is based on the standardized representation of product data and assumes brand warranty and post-warranty service [3, 4]. Such technologies typically include control system reliability: the system collects information about failures [5], scheduled and emergency repairs [6], as well as about the technical condition detected with special test and diagnostic tools [7]. Similar systems are being introduced in the high technology industries of our country [8], and in the sphere of technical maintenance of combine harvesters are being introduced separate elements of the system [9].

Currently in control theory the processes of technical maintenance of combine harvesters is popular techniques service-oriented reliability of machinery and equipment – known in the world as RCM (Reliability–centered Maintenance) [10, 11]. According to this method, the maintenance of all units of combine harvesters in immaculate condition not an end in itself, the main thing is the efficiency of the production system as a whole and not the performance of each unit [12, 13].

The goal of RCM is to ensure reliable operation of critical facilities [14], in accordance with their criticality [15], the failure of which will entail significant consequences [16]. In the assessment of impacts takes into account the various risks – disruption of the production plan, compliance with product quality, environmental disaster [17].

The main stages of the RCM analysis [18–20]:

• A – definition of the limits of the system and/or subsystem

• B – define all functions of the system and/or subsystem

• C – identification of functionally significant items (FSI),

• D – define the reasons of failures of functional elements, forecasting of failures and probability of their occurrence,

• E – use problem solving to classify the results of the failure of functionally important elements

• F – select operations for the initial maintenance program combines

• G – in case some operations for maintenance of combine harvesters can not be established, the set of operations is reviewed

• H – create a dynamic programme of technical maintenance of combine harvesters as a result of planned and systematic maintenance by monitoring (systematic monitoring), the collection and analysis of operational data.

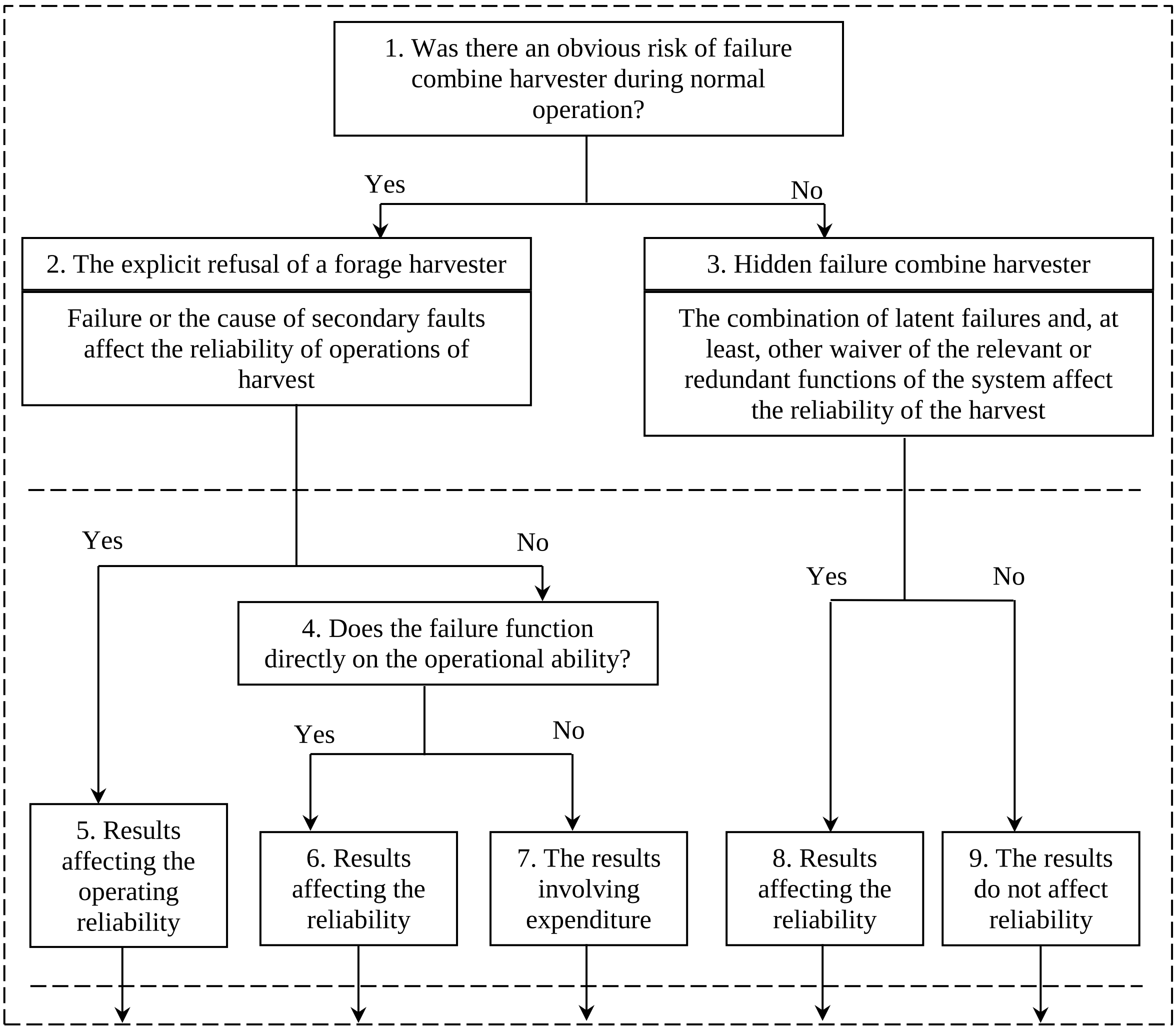

Fig. 1. The decision tree for maintenance of combine harvesters in the system of the RCM

OBJECTIVE

The article presents the analytical statements of methodological approaches to modeling technology in centralized technical maintenance of combine harvesters.

THE MAIN RESULTS OF THE RESEARCH

The first step when using the RCM methodology is to define the limits or boundaries of the subsystem. This means that the system is divided into subsystems of more than simple complexity.

The second step is the identification of functionally significant elements.

The next step involves identifying the causes of failures of functionally important elements and the prediction of the probability of their occurrence. Qualitative methods (based on the collective professional opinion and practical application) and quantitative methods (e.g., method of analysis of the nature and consequences of failures (FMEA–Failure Modeand Effect Analysis) or the method of risk analysis) can be used to identify the causes and results of failure elements. The average time to failure is based on competent analysis diagram cause – failure – effect.

Logical tree of decision-making shown in Fig. 1, is used to classify the results of failures.

Analysis of the nature and consequences of failures (FMEA) and logic tree decision making (FTA–Fault Tree Analysis) faults, can be a successful approaches in solving the tasks related to the prioritization of Troubleshooting in the first place.

If the probability of failure was predictable even during normal system operation, this denial is explicit, otherwise it is classified as hidden.

Centralized maintenance of combine harvesters according to the technical state based on the principles of the routing technology and information technology, a key factor in the question of its effectiveness.

In Fig. 2 presents a breakdown of technological and information support of the centralized maintenance of combine harvesters, which greatly determine its effectiveness.

However, in addition to the technological and information support and the efficiency of centralized maintenance of combine harvesters is also significantly affected by the human factor, which is the origin of the false defect of 1st kind and 2nd kind the pass of the defect at the stage of pre-repair diagnosis.

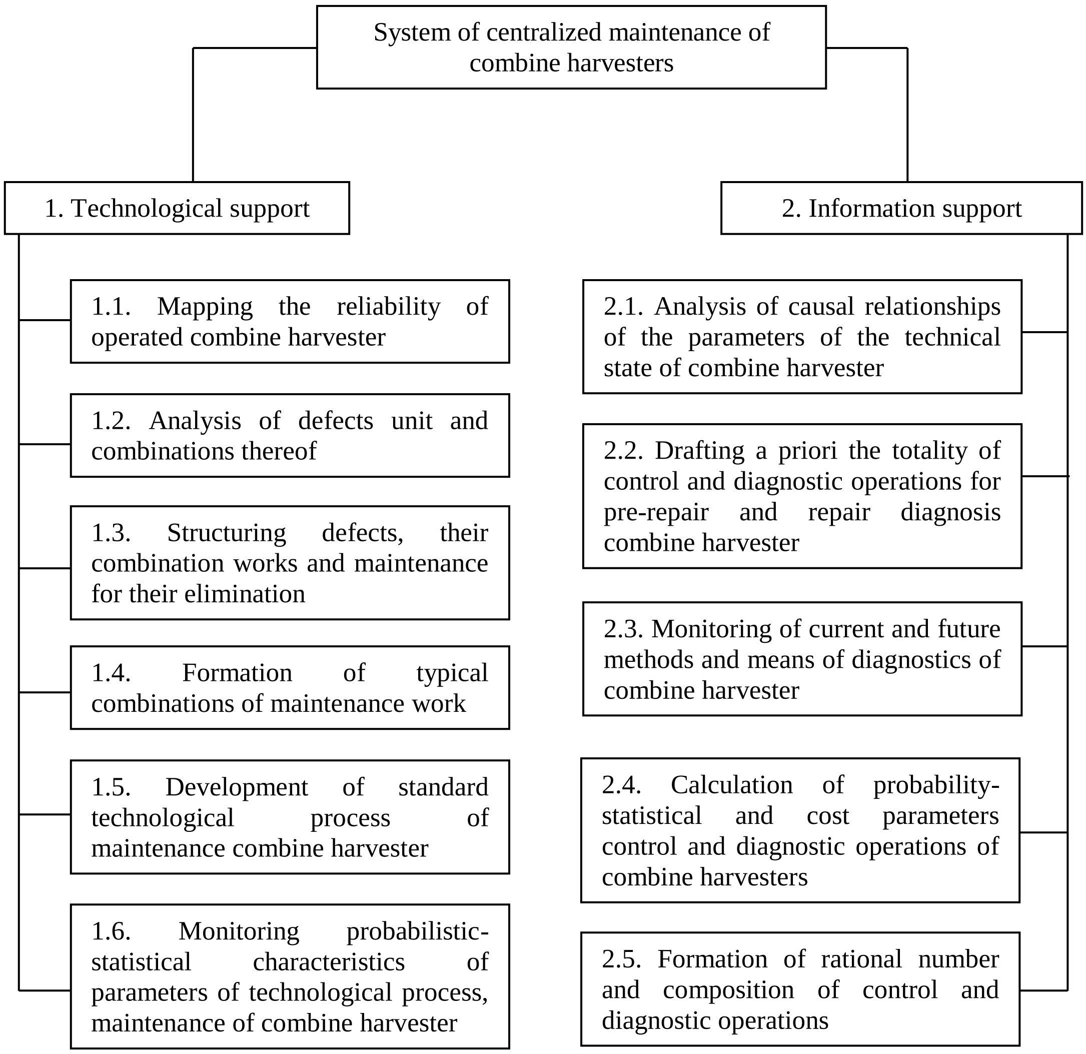

Fig. 2. Components of technological and information support of the centralized maintenance of combine harvesters

In Fig. 3 and Fig. 4 presents the dependence of the recognition errors of the 1st kind from the time of day (depending on shift) taking into account the category and age of the operator-diagnostician, where α is a recognition error of the 1st kind of false defect determination of the operator-diagnostician of repair works, P – working category of the operator-diagnostician, W – the age of the operator-diagnostician, years, L – shift working time pre-repair diagnosis, hour.

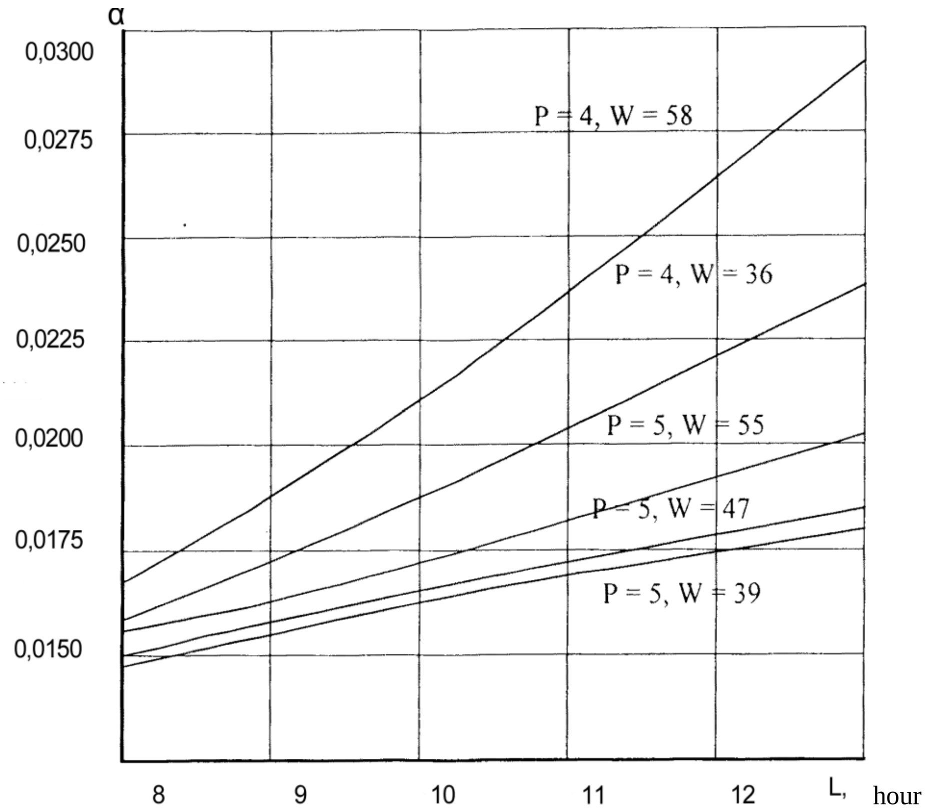

Fig. 3. The dependence of the probabilities of errors of the 1st kind, the first shift from time to time taking into account the category and age of the operator-diagnostician

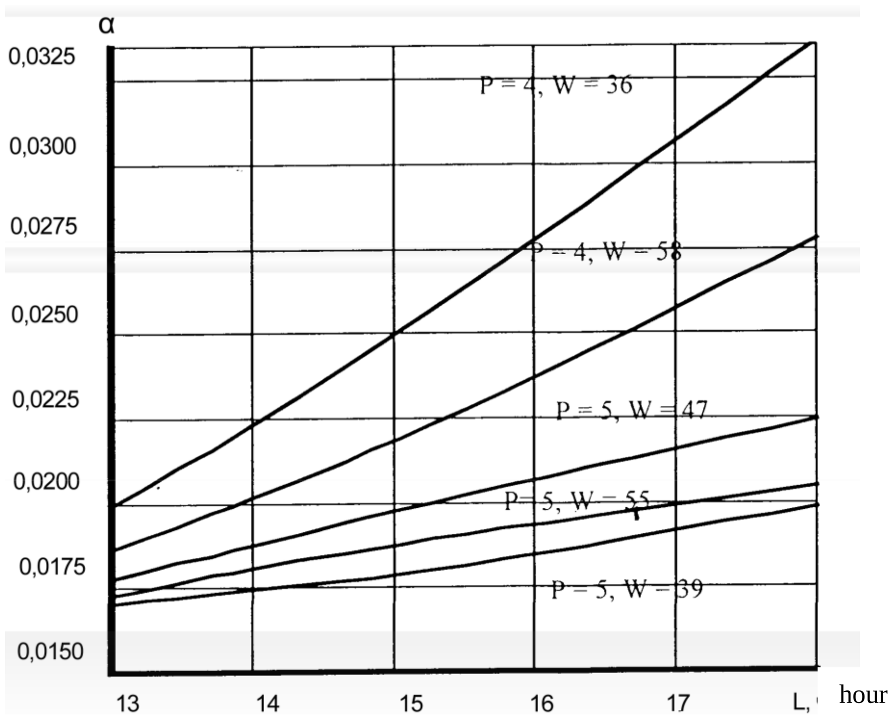

Fig. 4. The dependence of the probabilities of errors of the 1st kind the second shift from time to time, taking into account the category and age of the operator-diagnostician

In Fig. 5 and Fig. 6 are presented the dependence of the recognition errors of the 2nd kind from various factors, where β is the recognition error of the 2nd kind the pass of the defect in the definition of the operator - diagnostician of repair works, P – working category of the operator-diagnostician, W – the age of the operator-diagnostician, years, L – shift working time pre-diagnosis, hour, N – the time unit (mileage), hours.

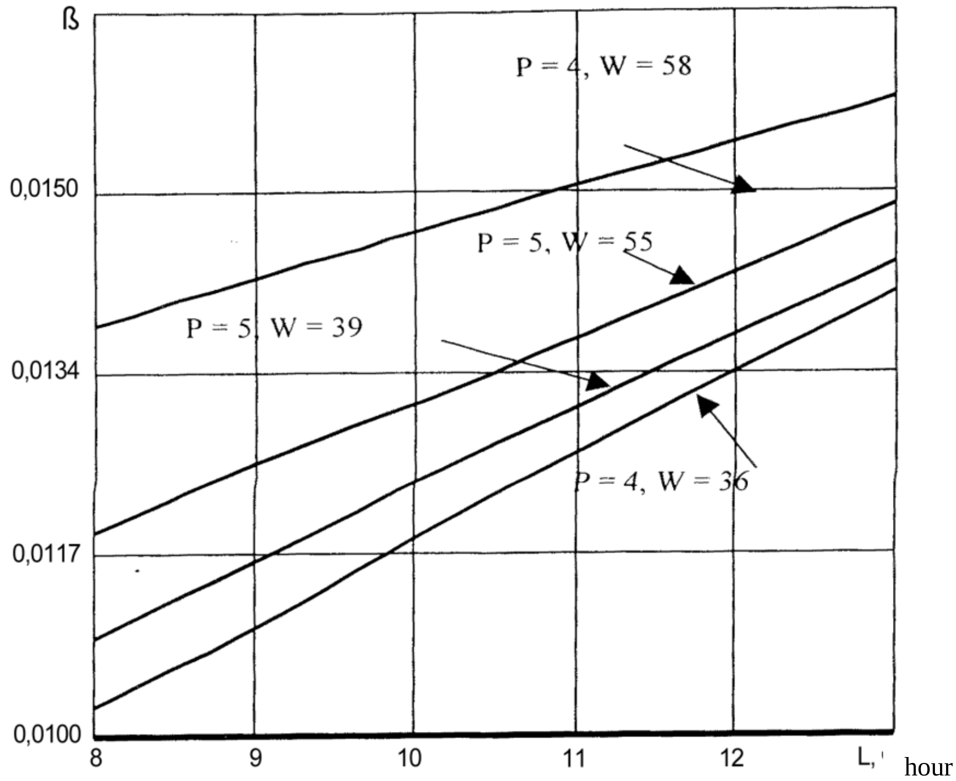

Fig. 5. Dependence of the probability of error of the 2nd kind from the time of the day taking into account the category and age of the operator-diagnostician

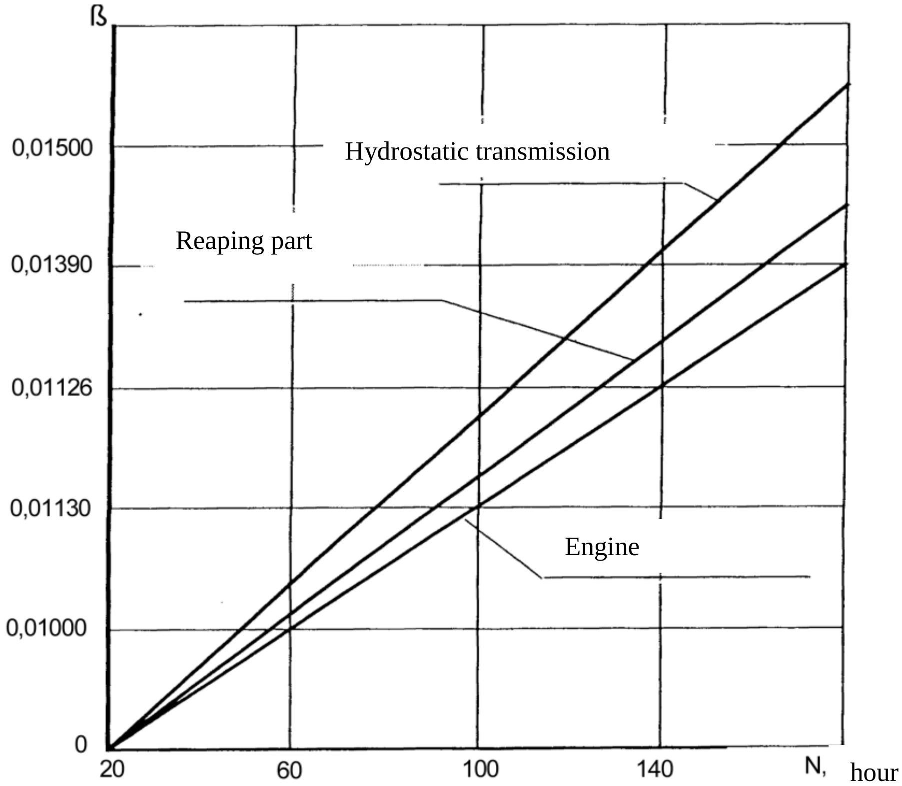

Fig. 6. Dependence of the probability of error of the 2nd kind from the achievements of the unit

The design process centralized maintenance of combine harvesters is due to the formation of the most efficient production-technical base, providing a significant reduction in internal losses of the agrarian enterprises. In this case external to the plant-specific factors, in accordance with the purpose and objectives of the present study can be considered a force majeure and to exclude them from further analysis.

Taking as a basis the classical form of organization of centralized technical maintenance of combine harvesters, where the process of disassembly $K = \{k: k = \overline{1, K}\}$ of units of combine harvesters is the set of installed in advance of typical combinations of repairs (more complex restoration work), the objective function of the study can be represented as an additive expression, which characterize current production losses:

$$C_{\sum VN} = \sum C_{\sum sh} = (C_{\sum obs} + C_{\sum prop} + C_{\sum dis})\, N_g \to \min,$$

where: $C_{\sum VN}$ – generalized loss of industrial repair business, UAH,

$C_{\sum sh}$ – loss of production generated by the error distribution of the repaired units to complex recovery operations, UAH,

$C_{\sum obs}$ – the costs of unnecessary work in eliminating erroneously detected defects, UAH,

$C_{\sum prop}$ – costs of executing the conditionally re-work when skipping erroneously detected defects, UAH,

$C_{\sum dis}$ – losses generated by errors in the allocation of the units on the technological routes of repair, hryvnia,

N_g – production program of the enterprise, units/year.

In addition, each set of reconstruction efforts represents some subset of $\{i\}_k$ repair (disassembly and assembly) operations, many $R = \{r: r = \overline{1, R}\}$ which is necessary and sufficient, to eliminate defects of any units among the repaired at this facility.

Component $C_{\sum sh}$ – the objective function (2.1) can be expressed functional:

$$C_{\sum sh} = f\,(C_{ij}, P_{ij}),$$

where C_{ij} – generalized cost of running works on revealing and elimination of the i-th defect the j-th repair of the unit, UAH,

P_{ij} – probability of the event consisting in the occurrence of recognition errors of the i-th defect the j-th repair of the unit.

The probability P_{ij}, taking into account the provisions of probability theory, you can define the following expression:

$$P_{ij} = \alpha_{ij} + \beta_{ij},$$

where a_{ij} – the recognition error of the 1st kind (false failure) of the i-th defect the j-th repair of the unit at the stage of pre-repair diagnosis,

β_{ij} – recognition error of the 2nd kind (omission faults) of the i-th defect the j-th repair of the unit at the stage of pre-repair diagnosis.

Introducing integer variables taking values:

$$\delta_{ij} = \begin{cases} 1 \\ 0 \end{cases},$$

where: 1 – where a_{ij} are the recognition error of the 1st kind (false failure) of the i-th defect the j-th repair of the unit if the i-th missing defect of the j-th repair of the unit is determined to be present,
0 – otherwise (false failure).

$$\mu_{ij} = \begin{cases} 1 \\ 0 \end{cases},$$

where: 1 – if the i-th present the defect of the j-th repair of the unit is defined as missing,
0 – otherwise (skipping faulty).

The probability P_{ij} can be written in expanded form:

$$P_{ij} = \{1-[\delta_{ij}\ (1-\alpha_{ij}) + \ \eta_{ij}(1-\beta_{ij})]\}.$$

In the general case due to an erroneous determination of the i-th defect the j-th engine, when in reality is no such defect (about fault – α_{ij}) any losses $C_{\sum obs}$. Costs $C_{\sum prop}$ – to conditionally re-run work generated errors β_{ij} resulting from crossing the i-th defect PD of the j-th repair of the unit (omission faults).

Analysis of the possible production situations allows us to represent the functional $C_{\sum VN}$ in the following form:

$$C_{\sum VN} = \sum C_{\sum sh} = (C_{\sum obs} + C_{\sum prop} + C_{\sum dis})\, N_g.$$

Thus, the achievement of the goal – reduction of internal losses in operation of the system of centralized maintenance of combine harvesters is possible only when solving the task of decrease of absolute values of errors at all stages of the production process restore functionality.

A set of methods for data mining object of research called Data Mining. Knowledge produced by these methods usually represent in the form of models.

One such class of models are the artificial neural network is a mathematical model that represents an ordered set of artificial neurons that are linked together in a certain way.

Selection of artificial neural network as a mathematical apparatus for the decision of tasks of recognition of defects the repair of units of the Fund and their distribution for complexes of repairs in a centralized technical maintenance of combine harvesters due to several reasons.

1. With the ability to learn and remember, and by changing the adaptive parameters of the artificial neurons of the network, it is possible to achieve a high degree of accuracy when solving this problem.

2. The use of artificial neural networks allows to avoid the process of accumulation of statistical information for calculation of probabilities of occurrence of defects (as does the method of organization and optimization of technological processes centralized maintenance of combine harvesters on standard combinations of repairs) for the optimal allocation of units for complexes of repairs.

3. Check the adequacy of the constructed on the basis of artificial neural network models is carried out using

test samples that are formed during the experiment the object of research, which ensures a high degree of reliability models.

In the application of artificial neural networks first of all the question of the choice of the network architecture (number of “hidden layers” and the number “artificial neurons” in each of them) for a specific task.

An artificial neuron is a node, artificial neural networks, modeled after the simplified principle of functioning of biological neuron. The first work that laid the theoretical foundations for creation of intelligent devices, is the article by W. Mac-Colloca and V. Pitts.

From a mathematical point of view, an artificial neuron is a function of a single argument – a linear combination of all signals at the input (this function called the activation function), which produces an output signal of the neuron.

In general, the mathematical model of artificial neuron is the weighted adder and has the form:

$$S = \sum_{i=1}^{n} x_i \cdot w_i + x_0 \cdot w_0 = \sum_{i=0}^{n} x_i \cdot w_i,$$

where: S – weighted sum of the input signals of the neuron,

x_i – value at the i-th input neuron,

w_i – weight of the i-th synapse,

n – number of inputs,

x_0 and w_0 – accordingly, the values of the additional input (X_0=1) and its weight.

The output value of the neuron is a function of its state:

$$Y = f(S),$$

where: $f(S)$ – activation function.

All layers of a neural network can be divided into three groups:

• the first layer of neurons in a multilayer neural network is called the input. It usually do not perform any computational operations, since it consists of neurons, which are used for receiving data (signals) and further transmission to the inputs of hidden layer artificial neural networks,

• hidden (intermediate) layers are the key, because often make up a large part of the structure of artificial neural networks,

• the output layer – the result of the operation of the network.

Choice sigmoid as the activation function because it is differentiable on the entire axis x and has a very simple derivative. When using the back-propagation algorithm errors, it accelerates the learning process of the network.

The output value of the neuron with sigmoidal activation functions, takes the following form:

$$Y = f(S) = \frac{1}{1+e^{-\alpha S}}.$$

In Fig. 7 graphically shows the model of an artificial neuron, where the number of input signals is denoted by X. Here multiple signals x_1, x_2, x_3, ..., x_j at the corresponding inputs (in the aggregate denoted by the vector X) have their weights (which reflect the strength of synaptic connections and their set is denoted by the vector W). The product of the signals and the corresponding weights is supplied to the summing unit, which algebraically adds the inputs.

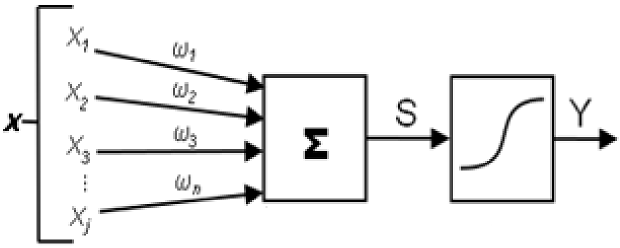

Fig. 7. Model of artificial neuron

The resulting sum, the value obtained is the argument of the activation function, which generates the output value Y.

Based on theoretical elaborations Hecht-Nielsen the question of the optimal number of hidden layers, as well as from the analysis of the practical applicability of artificial neural networks for different classification tasks, we can conclude that using more than two hidden layers in the network design are often inappropriate.

Formula, which is a consequence of the theorem of Arnold–Kolmogorov–Hecht-Nielsen, it is possible to calculate the required number of neurons for the hidden layer.

First there is the assessment of necessary number of synaptic weights when:

$$L = \frac{N_w}{N_x+N_y}.$$

However, as the practice of constructing artificial neural networks in this approach, one can argue that the number of neurons in the hidden layer was optimally matched to the task, in addition, usually the result is a large scale interval, which is the value of L.

Therefore, a consequence of the theorem of Arnold–Kolmogorov–Hecht-Nielsen will be used only to determine the upper limit values of the neurons (R) in the hidden layer. Dropping the lower bound of the interval, and equating the remaining N_w to the upper boundary and substituting in the formula, we get:

$$\frac{N_y \cdot Q}{1 + log_2 Q} \le N_w \le N_y \cdot \left(\frac{Q}{N_x} + 1\right) \cdot$$
$$\cdot \left(N_x + N_y + 1\right) + N_y.$$

where: N_y – number of neurons in the output layer,

Q – the number of values of the training sample,

N_w – the required number of synaptic weights,

N_x – number of neurons in the input layer.

After that, the number of neurons in the hidden layer will be determined by the formula:

$$R = \frac{N_y \cdot \left(\frac{Q}{N_x}+1\right) \cdot \left(N_x+N_y+1\right)+N_y}{N_x+N_y}.$$

Further, R is used as the upper limit to which the number of neurons will grow until it reaches the optimal values. As the experience of building models based on artificial neural networks, capacity of neurons in the hidden layer over the resulting limit R in most cases is impractical.

Technical condition of each of a plurality $O=\{O_i: i = 1, 2, 3, ..., M\}$ received at the repair Fund units of combine harvesters is characterized by a set of controllable parameters whose values are determined at the stage of pre-repair diagnosis with centralized technical maintenance of combine harvesters. Certain combinations of these parameters and their values imply the presence or absence of defects of the units.

We introduce the notion of the ability to generalization ability is acquired in the process of learning property of a neural network to give correct results for any new input combinations that did not participate in the learning process.

If an artificial neural network give a high percentage of correct results not only for training samples but also new, previously unknown examples, it is considered that it has acquired the ability to generalize.

In the case where a high percentage of correct results are ensured only for training samples and test samples is often wrong, it can be concluded that neural networks do not have the ability to generalize.

Let the number of complexes and rehabilitation works in the centralized technical maintenance of combine harvesters is known in advance the value of Z, and X is a combination of controlled parameters of the units, coming in repair fond. Deviations in parameter values from nominal indicate the presence of defects in the units Y. In this case, the task of neural network classification is reduced to the construction of the algorithm Θ, where the initial stage, the classification $\Theta : X \to Y$, based on acquired in the learning process, the ability of neural networks to generalize, and further there is a distribution of the aggregate units in the complex of restoration work on from the identified combinations of defects: $\Theta : X \to Y$, where $y \in Y$ and $y \in Z$.

When building a neural network classifier of the system of technical maintenance of combine harvesters, it is first necessary to determine the complexity of the division of objects into classes. To simplify the problem of classification of the system of technical maintenance of combine harvesters, it is necessary to achieve a linear separation of the objects of study.

Since the task involves more than two classes of system of technical maintenance of combine harvesters for the distribution of units between them, the most efficient method of forming output signals will be a set of vector components. In other words, every possible defect combine harvester will have its output signal, and the presence of a defect or lack of it will say 0 or 1 on the corresponding output. It is very important to achieve close as possible to 0 or 1 values, this requires preprocessing the input data.

CONCLUSIONS

1. Thus, the achievement of the goal – reduction of internal losses in operation of the system of centralized maintenance of combine harvesters is possible only when solving the task of decrease of absolute values of errors at all stages of the production process restore functionality.

2. Further, R is used as the upper limit to which the number of neurons will grow until it reaches the optimal values. As the experience of building models based on artificial neural networks, capacity of neurons in the hidden layer over the resulting limit R in most cases is impractical.

3. Since the task involves more than two classes of system of technical maintenance of combine harvesters for the distribution of units between them, the most efficient method of forming output signals will be a set of vector components. In other words, every possible defect combine harvester will have its output signal, and the presence of a defect or lack of it will say 0 or 1 on the corresponding output. It is very important to achieve close as possible to 0 or 1 values, this requires preprocessing the input data.

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МОДЕЛИРОВАНИЕ ТЕХНОЛОГИИ ВЫПОЛНЕНИЯ РАБОТ ПРИ ЦЕНТРАЛИЗОВАННОМ ТЕХНИЧЕСКОМ ОБСЛУЖИВАНИИ ЗЕРНОУБОРОЧНЫХ КОМБАЙНОВ

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Аннотация. В Украине и за рубежом в ряде отраслей промышленностей применяется система информационной поддержки жизненного цикла изделия. В основе которой лежит стандартизированное представление данных об изделии и предполагается фирменное сервисное гарантийное и постгарантийное обслуживание. Подобные технологии, как правило, включают в себя систему управления надежностью: осуществляется сбор сведений об отказах, плановых и аварийных ремонтах, а также о техническом состоянии выявляемых с помощью специальных контрольно-диагностических средств. Подобные системы активно внедряются в наукоемких отраслях промышленности нашей страны, а в сфере технического обслуживания зерноуборочных комбайнов внедряются отдельные элементы данной системы.

Анализ возможных производственных ситуаций при организованном на предприятии централизованном техническом обслуживании зерноуборочных комбайнов по техническому состоянию агрегатов позволяет сделать вывод о том, что добиться снижения внутрипроизводственных потерь можно при снижении возникающих ошибок распознавания дефектов агрегатов и их распределения.

Выбор искусственных нейронных сетей в качестве математического аппарата для решения задачи снижения ошибок распознавания дефектов агрегатов и их распределения по технологическим маршрутам при централизованном техническом обслуживании зерноуборочных комбайнов обоснован способностью данного математического аппарата к обучения, анализу и запоминанию результатов, а также высокой адаптации под решение поставленной задачи.

При построении нейросетевого классификатора системы технического обслуживании зерноуборочных комбайнов, прежде всего, необходимо определить сложность разделения объектов на классы. Для упрощения задачи классификации системы технического обслуживании зерноуборочных комбайнов, следует добиться линейного разделения объектов исследования.

Так как поставленная задача подразумевает более двух классов системы технического обслуживании зерноуборочных комбайнов для распределения агрегатов между ними, то наиболее рациональным способом формирования выходных сигналов будет являться совокупность компонентов вектора. Иными словами, каждый возможный дефект зерноуборочных комбайнов будет иметь свой выходной сигнал, а о наличии дефекта или его отсутствии будет говорить 0 или 1 на соответствующем выходе. При этом очень важно добиться как можно более близких к 0 или 1 значений, для этого необходимо провести предварительную обработку входных данных.

Ключевые слова: моделирование, технология, работа, техническое обслуживание, зерноуборочный комбайн.