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Technological Machines Operation by Identification Method

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Abstract
In order to effectively organize the process of agricultural enterprises, it is reasonable to involve management tools to build optimal models of interaction of individual components of the production process. The most significant part concerning the technical and economic efficiency is the technological process. However, the harvesting and postharvesting process is of the highest priority. The current stage of the management paradigm development includes the attraction of mathematical modeling in the organizational process. The construction of mathematical models is necessary at the stage of planning, organization, control, and is aimed at choosing such parameters of the technological process that will ensure the highest economic efficiency. At the same time, the validation process of the optimal parameters of machines and equipment that separate the grain receiving is of the most importance. While solving this problem, it is necessary to consider various efficiency criteria, the main of which are “loss volumes” and “reduced costs”. The criteria for the efficiency of the technical equipment of postharvesting grain process are the permissible values of agrotechnical requirements that consider the time of safe storage of freshly harvested grain mass without pretreatment and grain shatter losses due to its overripe. It is necessary to consider the maximum allowable volumes of losses during the postharvesting technological process. In order to define the best organizational solutions the iteration principle is used until a solution that meets the restrictions on the reduced costs level is found. The mathematical modeling in technological processes is carried out with the involvement of regression models that allow predicting the qualitative indicators of the operation of the pre-cleaning machine. As a result, it is possible to choose such a mode of equipment operation that ensures the production of grain that meets the regulatory requirements for the quality of the resulting product. The novelty of this study lies in the development of optimal ways for combine harvesters functioning. The article presents the methodology and procedure of optimizing the technological process during the postharvesting process of grain. The characteristics received as a result of experiments allow us to organize the technological process in an agricultural enterprise in the most optimal way so that it is economically and technically efficient.

Keywords- Grain postharvesting treatment,Technological process, Identification, Mathematical model, Efficiency, process modeling, Service reliability, Reduced costs, Process optimization.

1. Introduction

A modern approach of agricultural production is based on several technological solutions that allow to manage the process remotely. So, the basic technical and economic index of technological process is being planned and business processes are reengineered in order to optimize them. It is necessary to create an effective management process on each stage of technological production by risk-management tools due to the fact that agricultural industry has an elevated uncertainty of expected results. Therefore, mathematical models play a very significant role. This issue is of the highest interest. Some of its aspects are studied in research articles (Inskyi et al., 2001; Unger et al., 1999; Hemis et al., 2019). Some appliance results of specific types of models in agricultural sector are showed in the paper (Affholder et al., 2012; Parfenova et al., 2019; Parfenova et al., 2020).

The object of our research is such an element of agricultural industry as grain handling. Both a grain-cleaner and a grain harvesting complex in a whole are very complicated to manage. A statistic dynamic of functioning of these machines is not clearly studied. Besides, it is difficult to mathematically describe the processes and functions of grain cleaners (Meißner, 2015). So, the goal is to identify processes of grain postharvesting treatment, which explains the structure and parameters of technical equipment as technological system (Eickhoff, 1983; García-Lara et al., 2010).

In order to correctly solve this problem, we need to study the characteristics and peculiarities of grain-cleaners to manage them automatically and to increase its service reliability (Eickhoff, 1975; García-Lara et al., 2010). To achieve this goal, we need:

- To define the nature of random processes in input and output of grain cleaner during its regular operation;
- To define the level and type of connection between input and output processes;
- To define the degree of identity of the model with the technological machine;
- To define the possibility to estimate the characteristics of the grain cleaner by a linear operator and to evaluate the degree of nonlinearity of the model;
- To define the model operator estimation.

With the straight-lined grain postharvesting treatment, alimitative section of a technological process is a heating dehumidification (Kerimov et al., 1989; Meißner, 2015). Many different researchers studied this subprocess as the main element in the systematic implementation of the task of ensuring the technological reliability of grain harvesting machines (Aytasova, 2019; Price et al., 2013; Vanangamudi et al., 2017; Souza et al., 2019).

Another stage of the grain post harvesting treatment, which determines the stability of the functioning of the grain harvesting complex in general, is the grain receiving part, which includes a “car-dump-pit-precleaner”.

The technological requirements that must be considered when designing rational options for grain harvesting complexes are as follows (Kerimov et al., 1989; Hasanuzzaman, 2019; Liu et al, 2012):

1. Harvesting in the optimal agrotechnical terms, which helps to reduce grain losses due to standing corn dead ripe stage. The formula is the following:

$$E_1 = 1 - \frac{M_{n1}}{M} \tag{1}$$

where M_{n1} – the value of potential losses due to standing corn dead ripe stage; M – the value of biological yield, c/ha.

2. In-time treatment of freshly harvested grain heap in order to prevent its self-heating. The value of the grain harvesting process efficiency is shown as:

$$E_2 = 1 - \frac{M_{n2}}{M - M_{n1}} \tag{2}$$

where M_{n2} – losses due to spoilage of freshly harvested grain due to exceeding the permissible holding period without processing (self-heating).

3. The stream-line of the technological process of harvesting and post-harvesting treatment. If this requirement is not followed, losses are possible both due to standing corn dead ripe stage, and due to late grain treatment, if it has to be temporarily stored at reserve sites. The indicator of the flow rate of technological operations is written as follows:

$$E_3 = 1 - \frac{M_{n3}}{M - M_{n1}} \tag{3}$$

Where, M_{n3}– the amount of grain arriving for treatment, bypassing the reserve site.

It is obvious that the flow rate E_3considers $E_1$and E_2. This shows that the productivity of the machines and the capacity of the interoperational storage units that make up the "car-dump-pit-precleaner" complex must be coordinated in such a way that there is a condition $E_3 \to$min.

2. Methods

Let us consider the problem of the optimal parameters of machines and equipment of a grain receiving section with their joint operation.

The parameter of the optimal functioning of the considered complex is the "reduced costs" indicator.

The machine productivity over the time interval Δt is considered as a random process (stochastically).therefore, the requirement for the operation of the machine in optimal mode will be fulfilled only with a certain probability.

$$\begin{gathered} P\{x_i \leq f(\Delta t) \leq x_{i+1}\} = L_i\,; \\ P\{x_i \leq \varphi(\Delta t) \leq x_{i+1}\} = \beta_i\,; \\ i = 0, 1, \dots n\,; \end{gathered} \tag{4}$$

where $f(\Delta t)$ – a random variable characterizing the change ofacar productivity; $\varphi(\Delta t)$ – a random variable characterizing the change of a pre-cleaner productivity.

Experimental studies show that the distribution functions of these random variables can be approximated with a sufficient degree of accuracy by a normal distribution with the parameters (Wentzel, 1975; Handbook on rice cultivation and processing, 2007; Mir et al, 2019):

- Expected value $M = Q$;
- Standard deviation $\sigma = \delta(Q)$,

where Q – passportcapacityofthegrain cleaner; δ(Q) – functional dependence.

Consequently, random functions $f(\Delta t)$ and $\varphi(\Delta t)$ with probabilities L_i, $i = 0, 1, \dots n_1$; β_j, $j = 0, 1, \dots n_2$ take numerical values that are in the intervals (Parfenova et al, 2019; Parfenova et al, 2020):

$$\left[\left(i - \frac{1}{2}\right) a, \left(i + \frac{1}{2}\right) a\right] \text{ и } \left[\left(j - \frac{1}{2}\right) a, \left(j + \frac{1}{2}\right) a\right] \quad (5)$$

It is known that $L_i(Q_1, Q_2, N)$, $i = 0, 1, \dots n_1$ and $\beta_j(Q_1, Q_2, N)$, $j = 0, 1, \dots n_2$ – are the probabilities of the machines productivity, operating in the grain post harvesting treatment technological process are within the specified intervals.

The expected value of the amount of processed grain for Θ time intervals is the following (Yanushevsky, 1978; Vanangamudi et al., 2017):

$$C = \Theta \sum_{j=0}^{n_2} j\beta_j\,(Q_1, Q_2, W_a) \quad (6)$$

The reduced costs during receiving section operation are:

$$G = G_1 + G_2 + G_3 + G_4 + G_5 + G_6 \quad (7)$$

where $G_1 = \varphi_1(Q_1)$; $G_2 = \varphi_2(Q_2)$; $G_3 = \varphi_3(W_a)$

Here G_1, G_2, $G_3$are non-decreasing functions of losses due to operating costs for the considered machines and interoperable storage devices.

The design decisions task is formulated as follows:

$$G(Q_1{}^*, Q_2{}^*, W_a) = \min[G_1(Q_1) + G_2(Q_2) + G_3(W_a) + G_4(Q_1, Q_2, W_a) + \\ + G_5(Q_1, Q_2, W_a) + G_6(Q_1, Q_2, W_a)] \quad (8)$$

$Q_1 \in \Omega_1$
$Q_2 \in \Omega_2$
$Q_3 \in \Omega_3$

With the following conditions:

$$\Theta \sum_{j=0}^{n_2} j\overline{\beta_j}\,(Q_1, Q_2, W_a) > V \quad (9)$$

whereΩ_1, Ω_2, Ω_3 – the set of permissible values of the machines productivity and the volume of the dump pit; Q_1– passport capacity of the grain cleaner (defined as the amount of grain transported per 1 hour of operation); Q_2– passport capacity of precleaner, t/hour; W_a– dump pit capacity, m^3; $L(t)$ – the value characterizing the rate of grain inflow by grain cleaners into the dump pit; $\beta(t)$– the value characterizing the change in theprecleaner performance parameter.

To analyze the random processes, we use the method of discrete Markov chains with a finite set of states (Bikel & Doxam, 1983). So, we will consider a stochastic transition matrix A, which elements are the probabilities of changing the value of the grain volume in the dump pit during the time interval from $i_1$to i_2.

The set of states Ω_3 is the set of values of the grain stock in the dump pit. The elements of the A matrix are found from the relations:

$$a_i, i_2(L_j, \overline{\beta_k}) = \begin{cases} \sum_{k=0}^{m} \bar{L}_{k+i_2-i_1}\bar{\beta}_k + \sum_{k=0}^{m_1} \bar{L}_k \sum_{S=k=1}^{n_2+i_2-i_1} \beta_{S-i_2+i_1}, i_2 = 0; \\ \sum_{k=0}^{m} \bar{L}_{k+i_2-i_1}\beta_k \,, 0 < i_2 < W; \\ \sum_{k=0}^{n_2} \bar{\beta}_k \sum^{n_1+i_1-W} \bar{L}_{S-i_1+W} \,, i_2 = W, \end{cases} \tag{10}$$

where $m = min(n_2, n_1 - i_2 + i_1)$,$m_1 = min(n_1, n_2 - 1 - i_1 + i_2)$.

The probability of a change in the amount of grain in the dump pit at the *i-th* moment of time is described by the system of equations:

$$j_{i_2} = \sum_{i_1=0}^{W} Q_{i_1,i_2}(\bar{L}_i, \bar{\beta}_k) j_{i_1}, i_2 = 0,1, \dots W \tag{11}$$

The probabilities of changing the amount of grain delivered to the dump pit and processed by the machines over the time interval from $i_1$to i_2 are equal to:

$$\bar{L}_j = P\left\{I(\Delta t) \in \left[\left(j - \frac{1}{2}\right)a, \left(j + \frac{1}{2}\right)a\right]\right\} = P\left\{f(\Delta t) \in \left[\left(j - \frac{1}{2}\right)a \times \left(j + \frac{1}{2}\right)a\right]\right\} \cdot$$
$$\cdot P\left\{[W_a - S(\Delta t)] \in \left[\left(j + \frac{1}{2}\right)a, W_a\right]\right\} + P\left\{f(\Delta t) \in \left[\left(j + \frac{1}{2}\right)a, n_1 a\right]\right\} \cdot$$
$$\cdot P\left\{[W_a - S(\Delta t)] \in \left[\left(j - \tfrac{1}{2}\right)a \cdot \left(j + \tfrac{1}{2}\right)a\right]\right\} \tag{12}$$

or this can be written differently:

$$\bar{L}_j = L_j\left(\sum_{S=1}^{n_2} \beta_S + \sum_{S=0}^{min(n_2,j-1)} \beta_S \sum_{k=0}^{W-j+S} j_k\right) + \sum_{k=j+1}^{n_1} L_k \sum_{S=0}^{j} j_{W-S}\,\beta_{i-S}, j = 0,1, \dots n_1.$$

$$\bar{\beta}_k = P\left\{D(\Delta t) \in \left[\left(k - \frac{1}{2}\right)a, \left(k + \frac{1}{2}\right)a\right]\right\} = P\left\{\varphi(\Delta t) \in \left[\left(k - \frac{1}{2}\right)a, \left(k + \frac{1}{2}\right)a\right]\right\} \cdot$$
$$\cdot P\left\{S(\Delta t) \epsilon \left[\left(k + \frac{1}{2}\right)a, W_a\right]\right\} + P\left\{\varphi(\Delta t) \in \left[\left(k + \frac{1}{2}\right)a, n_2 a\right]\right\} \cdot$$
$$\cdot P\left\{S(\Delta t) \epsilon \left[\left(k - \tfrac{1}{2}\right)a, \left(k + \tfrac{1}{2}\right)a\right]\right\} \tag{13}$$

Or this way:

$$\bar{\beta}_k = \beta_k\left(\sum_{S=k}^{n} L_S + \sum_{S=0}^{min(n_1,k-1)} L_S \sum_{i=k}^{N+S} j_{i-s}\right) + \sum_{i=0}^{j} j_i L_{j-i} \sum_{k=j+1}^{n_2} \beta_k, k = 0,1, \dots n_2 \tag{14}$$

The system of nonlinear algebraic equations is solved by iteration methods. To define the values of the probabilities of stationary states of the considered complex of machines, it is sufficient to have the number of time intervals Θ_1, equal to 5…10 (Affholder et al., 2012; Kerimov et al., 1989).

The algorithm is based on the branch-and-bound method.It considers the splitting of the set of possible values of the productivity of machines and the capacity of the storage system $\Omega = \{\Omega_1 \times \Omega_2 \times \Omega_3\}$, where the sign × means Cartesian product, onUoverlapping subpopulations. This procedure allows you to choose from a subset of options $T(\Omega_v)$, v = 1, U, the one that is characterized by the minimum value of the reduced costs while meeting the given requirements.
The iteration process lasts until a random vector is defined satisfying the conditions, and the value of the function for the specified vector must be less than the lower limit of the reduced costs value (Lazor, 2013).

Let M_{1v}^{I}, M_{1v}^{II}, M_{1v}^{III}– be the minimum values of the productivity of machines and the volume of the dump pit in the subset of options Q_v;
M_{2v}^{I}, M_{2v}^{II}, M_{2v}^{III}–maximum values of machine productivity and volume of the dump pit in the subset of options Q_v.

Then the following equation is true:

$$Q_{T_v} = \{M^T{}_{1v}, M^T{}_{1v} + 1, \dots, M^T{}_{2v} - 1, M^T{}_{2v}\} \tag{15}$$

To define the lower limit of the values of the reduced costs in each subset of options, we use the property of optimal resolutions:

$$minG(L) = min \sum_{I=1}^{G} G_1(L) \leq \sum_{I=1}^{G} minG_1(L) \tag{16}$$

where $L = (Q_1, Q_2, W_a)$.

If $Q_1^{(1)} \leq Q_1^{(2)}$, then

$$\sum_{i=0}^{n_1} iL_i\left(Q_1^{(1)}\right) \leq \sum_{i=0}^{n_1} iL_i\left(Q_1^{(2)}\right) \tag{17}$$

Accordingly, if $Q_2^{(1)} \leq Q_2^{(2)}$then:

$$\sum_{k=0}^{n_2} K\,\beta_k\left(Q_2^{(1)}\right) \leq \sum_{k=0}^{n_2} K\beta_k\left(Q_2^{(2)}\right) \tag{18}$$

In case, when$Q_2^{(1)} < Q_2^{(2)}$and$N^{(1)} < N^{(2)}$, then:

$$\sum_{i=0}^{n_1} i\bar{L}_i\left(Q_1, Q_2^{(1)}, W\right) \leq \sum_{i=0}^{n_1} i\bar{L}_i\left(Q_1, Q_2^{(2)}, W^{(2)}\right) \tag{19}$$

In case, when $Q_1^{(1)} < Q_1^{(2)}$and $N^{(1)} < N^{(2)}$, then:

$$\sum_{k=0}^{n_2} K\,\bar{\beta}_k\left(Q_1^{(1)}, Q_2, W^{(1)}\right) \leq \sum_{k=0}^{n_2} K\bar{\beta}_k\left(Q_1^{(2)}, Q_2, N^{(2)}\right) \tag{20}$$

So, we have the following equation:

$$\min_{Q_1 \in \Omega_v} G_1(Q_1) = G_1\left(M_{1v}^{I}\right) \tag{21}$$

$$\min_{Q_2 \in \Omega_v} G_2(Q_2) = G_2(M_{1v}^{II}) \tag{22}$$

$$\min_{W \in \Omega_v} G_3(W) = G_3(M_{1v}^{III}) \tag{23}$$

$$minG_4(L) = G_4(M_{1v}^{I}, M_{2v}^{II}, M_{2v}^{III}) \quad L \in \Omega_v \tag{24}$$

$$minG_5(L) = G_5(M_{2v}^{I}, M_{1v}^{II}, M_{2v}^{III}) \quad L \in \Omega_v \tag{25}$$

$$minG_6(L) = G_6(M_{1v}^{I}, M_{2v}^{II}, M_{1v}^{III}) \quad L \in \Omega_v \tag{26}$$

For the specified subset, the following formula is used to determine the minimum values of the reduced costs:

$$T(Q_v) = G_1(M_{1v}^{I}) + G_2(M_{1v}^{II}) + G_3(M_{1v}^{III}) + G_4(M_{1v}^{I}, M_{2v}^{II}, M_{2v}^{III}) + \\ + G_5(M_{2v}^{I}, M_{1v}^{II}, M_{2v}^{III}) + G_6(M_{1v}^{I}, M_{2v}^{II}, M_{1v}^{III}). \tag{27}$$

Let us substitute in the formula the maximum values of the parameters of the productivity of machines and capacities of interoperable storage devices:

$$Q_1 = M_{2v}^{I}, Q_2 = M_{2v}^{II}, W = M^{III} \tag{28}$$

If this inequationis not fulfilled in this case, then it is also not fulfilled for other values of the vector L from the subset of options Q_v.

Since the group of machines that make up the receiving section has the greatest influence on the change in the quality parameters of grain in the process of its post-harvest treatment, then exactly these machines are the goal of further research, such as precleaner OVS-25.

3. Research Results

The entire set of parameters that characterize the state of the pre-cleaner can be represented in the following way (Figure 1): input $\overline{X}$, output $\overline{Y}$, state parameters F (which characterize the dynamics of the pre-cleaner), control $\overline{y}$(which are represented by kinematic and operational-technological parameters).

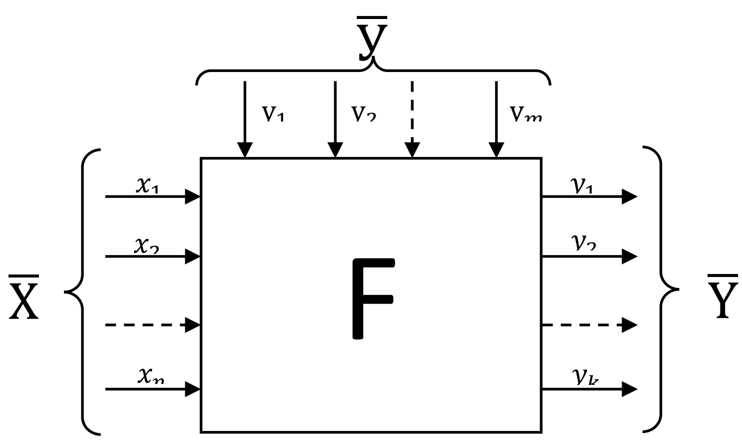


Figure 1. Information model of the OVS-25S grain pre-cleaner technological process.

Mathematically, the control parameters $\overline{Y}$ are independent variables; they ensure the efficiency of the system functioning by influencing the technological process.

The analysis of the internal structure of random processes in grain pre-cleaners is carried out on the basis of the correlation function $R_{xx}(t)$ and spectral density $S_{xx}(\omega)$, which are connected by the Fourier cosine transformation and accordingly are equal:

$$R_{xx}(\tau) = M\{[X(t) - m_x(t)][X(t+\tau) - m_x(t+\tau)]\} \tag{29}$$

where M – expectedvalue; $\tau = (t_2 - t_1)$ – time shift between ordinates; ω – wave circular frequency.

The graphs of the normalized correlation functions of input disturbances were obtained in the scientific-experimental facility of the St. Petersburg State Agrarian University during the harvesting seasons of 1985-2005 when processing oats for three modes of pre-cleaner (Hemis et al., 2019):

$Q_1(t) = 10\ t/h;$
$Q_2(t) = 15\ t/h;$
$Q_3(t) = 20\ t/h.$

The analysis of the experimental data shows that the pre-cleaner output processes are characterized by a similar structure (Feller, 1984; Handbook on rice cultivation and processing, 2007).

Based on the results of the dynamics of the pre-cleaners, it can be confirmed that an increase in delivery leads to a weakening of the correlation between the input and output parameters of the pre-cleaner technological process (Prokhorenko, 1976).

The correlation functions of the processes of changing the initial moisture of grain$W(t)$ and grain dockage $S(t)$are shown in Figure 2 and Figure 3.

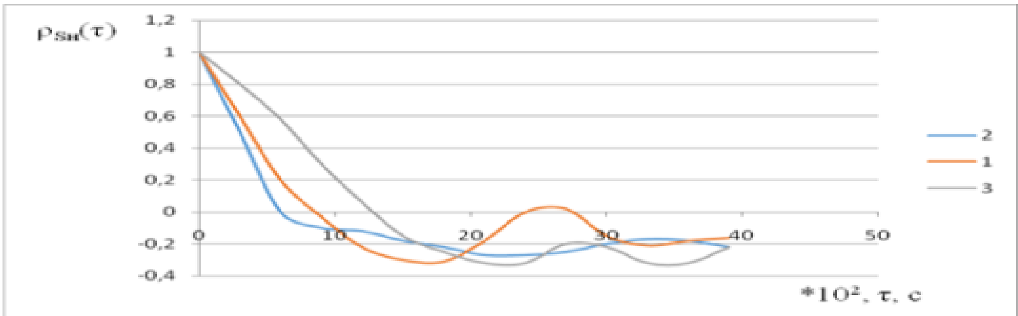
Fall time of the correlation functions vary significantly and is characterized by the values: $T_{W,S}$ = (9...14,7)*10^2C. So, the internal structure of the initial moisture and grain dockage is of a statistical nature, and these parameters are formed under the influence of many random factors.

With an increase in the grain supply to the pre-cleaner, the correlation function fall time decreases, which means there is a decrease in the stability of the technological process.

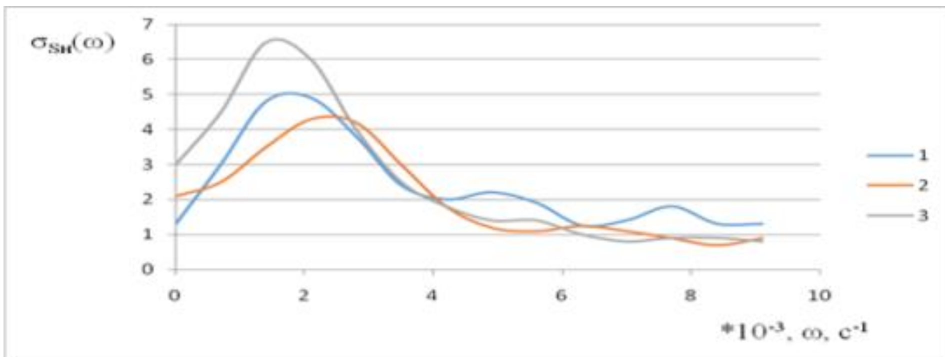
The experimental correlation functions were approximated using the formula:

$$\rho(\tau) = e^{-L[T]}(cos\beta[\tau] + sin\beta[\tau]) \tag{30}$$

where L– the fall rate of the correlation function coefficient; β–the vibrational properties of the correlation function coefficient.

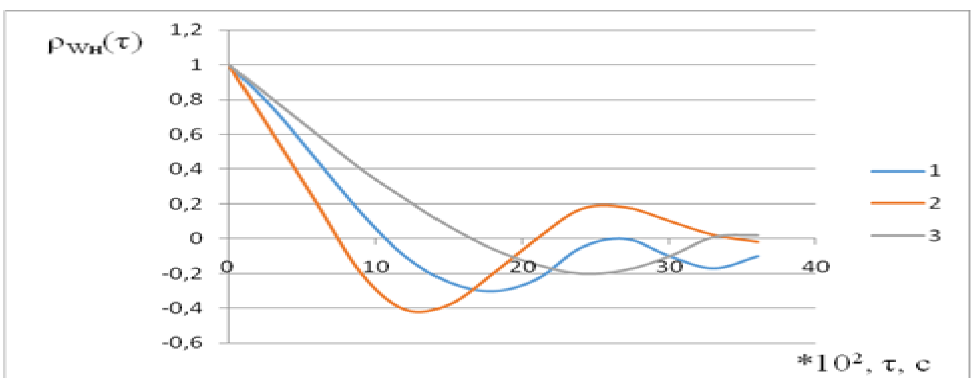


(a)

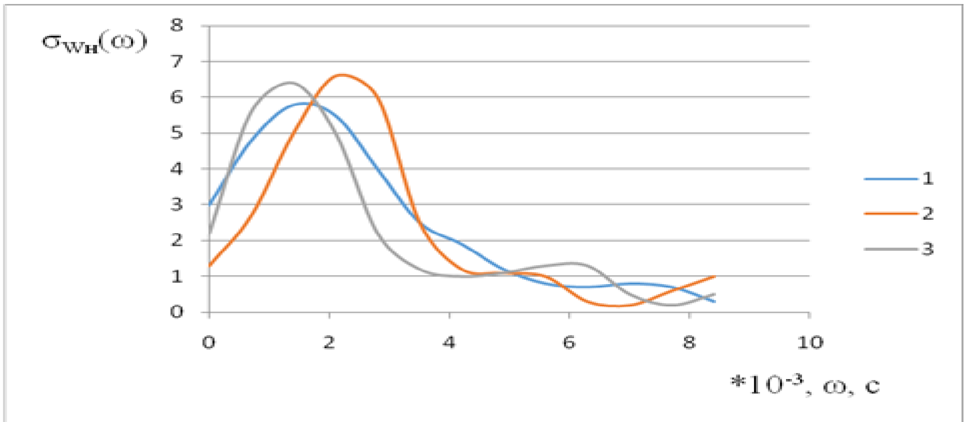


(b)

Figure 2. Correlation function (a) and spectral density (b) of the process of changing the initial grain dockage.



(a)



(b)

Figure 3. Correlation function (a) and spectral density (b) of the process of changing the initial grain moisture.

We used the least-square method for approximation. The obtained values of the L and β coefficients (for input and output processes) are presented in Tables 1 and 2 respectively.

Table 1. Approximation coefficients of the processes correlation functions of changing the delivery $Q(t)$, initial moisture $W_i(t)$ and initial dockage $S_i(t)$.

Implementation	Correlation functions coefficients	Numerical values of approximation coefficients, x10^{-3}, c^{-1}		
		Q(t)	$W_i(t)$	$S_i(t)$
1	L	0,59	0,57	0,98
	B	1,97	2,2	2,17
2	L	0,55	0,52	0,64
	B	1,52	1,27	1,21
3	L	0,6	0,27	0,29
	B	1,88	2,31	1,38

The characteristics of the output processes implementations are presented in the Table 2.

Table 2. Approximation coefficients of the processes correlation functions of changing the productivity of pre-cleaner, grain loss with waste $L(t)$ and final grain dockage $S_k(t)$.

Implementation	Correlation functions coefficients	Numerical values of approximation coefficients, x10^{-3}, c^{-1}		
		Q(t)	L(t)	$S_k(t)$
1	L	0,56	0,59	0,96
	B	1,88	2,13	2,09
2	L	0,54	0,51	0,69
	B	1,50	1,32	1,19
3	L	0,61	0,26	0,32
	B	1,89	2,37	1,36

According to the tables above, the L coefficients vary significantly, while the changes in the B coefficients are relatively small.

Changes in the frequency of the considered random processes were estimated using the normalized spectral density$\sigma_x(\omega)$:

$$\sigma_x(\omega) = \frac{S_x(\omega)}{D_x} \tag{31}$$

The analysis of the correlation functions and spectral densities indicates that in order to stabilize the mode of operation of the OVS-25Spre-cleaner, it is necessary to maintain the grain supply at the level of 10…15 t/hour.

To estimate the statistical relationships between input and output processes, we represent a multidimensional system, which is a pre-cleaner as a set of one-dimensional models characterized by correlation coefficients and the degree of nonlinearity.

The correlation between these processes at the input and output, as well as a low degree of nonlinearity, allow us to conclude that a linear operator must be used. The coefficients values characterizing the correlation (ρ) and the degree of nonlinearity (n) for various communication channels between the input and output values of the processes are shown in Table 3.

Table 3. The correlation coefficients and the degree of nonlinearity between the input and output processes of one-dimensional models.

“Input-output” communication channel	ρ	n
Moisture – efficiency	-0,37/0,52	0,30/0,35
Dockage – efficiency	0,15/0,22	0,18/0,24
Grain supply – losses	0,65/0,79	0,13/0,18
Grain dockage – losses	0,34/0,61	0,30/0,38
Moisture – losses	0,19/0,24	0,32/0,42
Grain supply – dockage	0,49/0,70	0,20/0,26
Dockage – dockage	0,49/0,62	0,30/0,39
Moisture – dockage	0,10/0,21	0,07/0,17

An important task of the identification of technological processes of grain cleaners is to define their dynamic models (Tsypkin, 1995). The dynamic model for the pre-cleaner, consideringthe static connection between the input and output processes, will be written in the following way:

$$W(S) = \{W_{QP}(S), W_{QD}(S), W_{QSi}(S)\} \tag{32}$$

We define the numerical values of the transfer function coefficients for linear one-dimensional models via the "grain supply - efficiency" communication channel, since these processes affect the entire course of the grain post-harvestingtreatment to the greatest extent.

To calculate the amplitude-frequency characteristic we use the dependence:

$$[A(\omega)]^2 = \left[\frac{S_{QP}^{(v)}(\omega)}{S_Q(\omega)}\right]^2 + \left[\frac{S_{QP}^{(i)}(\omega)}{S_Q(\omega)}\right]^2 \tag{33}$$

$S_{QP}^{(v)}(\omega)$ – realcomponentofthecross-spectraldensityalong the channel;

Q → P (“grain supply–efficiency”);

$S_{QP}^{(i)}(\omega)$ – imaginary componentofthecross-spectraldensityalong the channel Q → P (“grain supply–efficiency”).

We build an experimental curve with the values we have got.

The calculation of the transformation operators of input processes into outputs is carried out by the solution of the Wiener-Hopf equation:

$$R_{xj}(\tau) = \int^{\infty} h(t)\, R_j(\tau - t)dt \tag{34}$$

and its transformation in the frequency domain:

$$S_{xj}(\omega) = \overline{W}(i\omega)S_j(\omega) \tag{35}$$

$$S_x(\omega) = [A(\omega)]^2 \cdot S_j(\omega) \tag{36}$$

where h – pulse characteristic; x – input vector; j – output vector.

To approximate the experimental curves we use:

$$[A(\omega)]^2 = \frac{K^2}{\left(1 - T_1^2\omega^2\right)^2 + T_2\omega^2} \tag{37}$$

where T_1 – time constant characterizing the inertial properties of the precleaner;
T_2 – time constant characterizing the damping properties of the precleaner.
The assessment of the dynamic properties of the grain pre-cleaner as a system was carried out according to the following relationship:

$$\rho = \frac{T_2}{2*T_1} \tag{38}$$

where T_1 – time constant characterizing the inertial properties of the precleaner;
T_2 – time constant characterizing the damping properties of the precleaner.

Transfer function coefficients for different operating modes of the pre-cleaner by the “grain supply – efficiency” channel are shown in Table 4.

Table 4. The values of the transfer functionscoefficients for the three modes of operation of the pre-cleanerby the “grainsupply – efficiency” channel.

Operation mode	K	T_1; $*10^2$c	T_2; $*10^2$c	ρ
I	0,45	6,90	6,67	0,48
II	0,51	7,11	7,19	0,51
III	0,54	6,84	8,01	0,59

These transfer functions are used in the control systems of the pre-cleaner and during assessment of the quality of technical equipment operation of grain post-harvesting treatment in general. The regression model of the technological process of the grain pre-cleanerby the “grain supply – efficiency” channelis the following:

$$m_{xj} = m_x + \frac{\sigma_x \rho_{xj}}{\sigma_j} * \left(j - m_j\right) \tag{39}$$

where m_x and m_j – the respective average value of the input and output processes of the pre-cleaner; $\sigma_x$andσ_j – standard deviations; ρ_{xj} – correlation coefficient value.

If

$$\frac{\sigma_x \rho_{xj}}{\sigma_j} = b;$$
$$m_x - bm_j = a$$

Then we can rephrase it as a following:

$$m_{xj} = a + bjx \tag{40}$$

For the pre-cleaner technological process the formula (40) will be written as follows:

$$m_{P/Q} = a + b_{QP}Q \tag{41}$$

where a and b – linear regression coefficients determined by standard computer programs using the least square method (Bendat, & Pearsol, 1983).

This model allows using known inputs to predict the output processes of grain cleaners that implement a technological operation at the stage of preliminary grain cleaning.

The identity of these models to real technological processes is assessed by the expression:

$$\zeta = \frac{D\lfloor m_{P/Q} \rfloor}{D_y} \tag{42}$$

where $D\lfloor m_{P/Q} \rfloor$ – variance of the conditional expectation (regression function) relatively to fixed levels of the input vector; D_y – variance of output process.

The variance $D\lfloor m_{P/Q} \rfloor$ is actually a variance of the forecast.

The most accurate description of the pre-cleaner technological process is the one by the$Q \rightarrow$ Pchannel, where the degree of identity of the models is ζ = 0,5÷0,6. This channel shows the strongest correlation between the input and output parameters of the grain cleaning process.

To further increase the identity of the models, it is necessary to increase their dimension, taking into account two influences (parameters) at the input and one parameter at the output using the standard procedure (Eickhoff, 1975).

Then the model of the pre-cleaner can be showed as the following:

$$m_{xj} = \left| m_{P/QW}, m_{L/QS_i}, m_{S_k/QS_i} \right| \tag{43}$$

where L – grain loss in waste; S_i – initial grain dockage; S_k – final grain dockage.

The regression equation for these models is the following:

$$m_{xj} = a_0 + a_1 j_1 + a_2 j_2 + b_1 j_1^2 + b_2 j_2^2 + b_3 j_1 j_2 \tag{44}$$

The degree of identity of such models is 0,80…0,95.

Regression models allow us predicting the quality indicators of the pre-cleaner operation and depending on the initial characteristics of the grain to choose an operating mode that ensures the production of grain that meets the GOST requirements (national state standard) (Yanushevsky, 1978).

The values of the coefficients and the degree of identity of the one-dimensional regression models are shown in Table 5.

Table 5. Numerical values of the coefficients, band the degree of identity E_D for one-dimensional models.

Operation mode	Channel	Numerical values		
		a	b	E_D
I	Q – P	1,42	0,61	0,49
	Q – L	-0,61	0,59	0,37
	Q –S_k	0,81	0,44	0,29
II	Q – P	1,81	0,64	0,52
	Q –L	-1,49	0,57	0,49
	Q – S_k	0,69	0,39	0,37
III	Q – P	2,47	0,64	0,49
	Q –L	-2,13	0,73	0,54
	Q –S_k	-2,01	0,84	0,43

The values of the coefficients of the regression models with two inputs and one output are shown in Table 6.

Table 6. Numerical values of the coefficients and the degree of identity for two-dimensional models.

Model	a_0	a_1	a_2	b_1	b_2	b_3	E_D
QW – P	0,17	1,94	0,01	0,19	0,01	-0,11	0,71
QSi – L	1,93	-1,51	0,07	0,53	0,01	-0,01	0,77
QSi–S_k	-0,31	1,43	-0,54	-0,29	0,01	0,09	0,79

4. Conclusion

It is necessary to evaluate operationally the technological parameters of the harvesting complexes by the identification approach under the regular operation conditions of technical equipment, in particular, grain cleaners. For this purpose, we have developed an adjustable mathematical model that reflects the operation dynamics of the OVS-25S grain pre-cleaner. This model is a part of engineering the adaptive grain treatment technologies and post harvesting treatment and allows in operational mode to ensure the quality management of production processes.

The criteria for the technical equipment effectiveness of grain post-harvesting treatment are accepted values of agrotechnical requirements, that consider the time of safe storage of freshly harvested grain mass without preliminary processing and loss of grain by self-shattering due to its standing corn dead ripe stage.

We need to evaluate the quality of identification by residual vector, which corresponds to the actual conditions of technical equipment and its engineering parameters.

Thus, the process of post-harvest processing is optimal and is aimed at creating such parameters of grain harvesting equipment, which allows reducing losses and increasing the profitability of an agricultural enterprise accordingly.

Further development of the proposed model will improve the quality management processes in the agro-industrial complex, more optimally build interaction procedures in integrated grain harvesting systems. Achievement of this goal is envisaged by practical testing of the model elements at an agricultural concern in the Leningrad region.

Conflict of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

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