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Technological Machines Operation by Identification Method

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Abstract

To effectively organize agricultural enterprises, management tools are essential for optimizing the interaction of production components. The key concern is improving the technological process, especially the harvesting and post harvesting stages. This study proposes a mathematical model for optimizing machine parameters, focusing on reduced costs and minimizing loss volumes during post harvesting. By applying regression models, the study predicts the performance of pre-cleaning machines and identifies operational modes that meet quality standards. The novelty of the research lies in optimizing combine harvester functions to ensure technical and economic efficiency.

1. Introduction

In modern agricultural production, the ability to remotely manage and optimize processes is becoming increasingly crucial. The technological advancements in agricultural machinery and management systems are designed to enhance efficiency and minimize uncertainty in outcomes, which is particularly significant due to the high-risk environment in agriculture. Various uncertainties, such as weather conditions, crop diseases, and fluctuating market prices, make agricultural production unpredictable. Thus, the need for sophisticated management tools, including mathematical modelling, is emphasized to ensure operational effectiveness at each stage of the agricultural production process.

Mathematical models have proven to be powerful tools in optimizing various business and technical processes across industries, including agriculture. These models help in planning, organization, control, and decision-making processes, particularly for ensuring the technical and economic efficiency of the machinery involved. Recent research highlights the value of these models in agricultural production, focusing on improving grain handling processes, which form a crucial element of agricultural operations.

Grain harvesting and postharvesting operations involve complex machinery and require careful management to reduce losses and enhance quality. Both the grain-cleaning process and the entire grain harvesting complex involve intricate dynamic systems that are difficult to manage manually, primarily because the technical and functional behavior of these machines is not always well understood. The grain postharvesting process, in particular, presents numerous challenges due to the variability in inputs and the need for precise management to ensure minimal loss.

This study aims to address these challenges by identifying and analyzing the key processes involved in grain postharvesting treatment. Specifically, it focuses on the grain-cleaner, a complex machine critical to the postharvesting process, and attempts to optimize its performance by identifying patterns in its functioning and employing mathematical models. These models can help in the automatic control of grain-cleaners and enhance their reliability and efficiency.

The goals of the research include:

- Defining the nature of random processes involved in grain cleaning, both at the input and output stages.
- Determining the relationships between these random processes and the machine's operational parameters.
- Developing a reliable mathematical model that reflects the technological processes of grain-cleaners.
- Proposing optimal operational modes for grain-cleaners to minimize grain loss and maximize efficiency.

By focusing on these aspects, the study hopes to develop an effective mathematical framework that can be employed in real-world agricultural settings to improve grain-cleaning processes and reduce postharvest losses.

2. Methods

The method employed in this study involves developing a mathematical framework to model the grain postharvesting process, particularly focusing on the grain-receiving section, which includes equipment like pre-cleaners and dump pits. The study's primary objective is to optimize the operational parameters of the machines involved in this section to minimize operational costs while ensuring optimal performance.

The grain-receiving section's functioning is described as a stochastic process, where machine productivity varies randomly over time due to several unpredictable factors. Therefore, the research models machine productivity as a stochastic process and formulates the problem as one of optimizing performance under these conditions.

Table 1: Approximation Coefficients of the Processes' Correlation Functions

Implementation	Correlation Function	Coefficient (L)	Coefficient (B)
1	Q(t)	0.59	1.97
	Wi(t)	0.57	2.2
	Si(t)	0.98	2.17
2	Q(t)	0.55	1.52
	Wi(t)	0.52	1.27
	Si(t)	0.64	1.21
3	Q(t)	0.6	1.88
	Wi(t)	0.27	2.31
	Si(t)	0.29	1.38

The parameters of interest in this optimization problem include:

- Machine productivity, which is considered a random variable over time.
- The probability distribution of machine productivity and its variations under different operational modes.
- The reduced costs associated with operating the grain-receiving section, which include direct costs related to machine operation, grain losses, and costs associated with storage and maintenance.

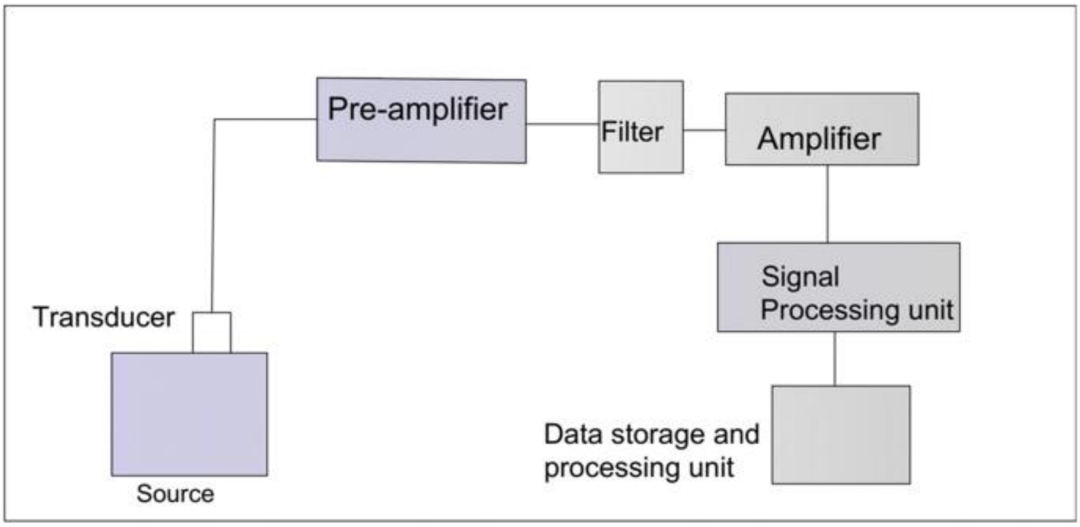

Figure 1: Information Model of the OVS-25S Grain Pre-Cleaner Technological Process

The optimization approach focuses on minimizing the "reduced costs" while ensuring that the machine's operational parameters meet certain technical constraints. The reduced costs are calculated as a sum of multiple cost components, including:

Table 2: Approximation Coefficients of Output Processes' Correlation Functions

Implementation	Correlation Function	Coefficient (L)	Coefficient (B)
1	Q(t)	0.56	1.88
	L(t)	0.59	2.13
	Sk(t)	0.96	2.09
2	Q(t)	0.54	1.50
	L(t)	0.51	1.32
	Sk(t)	0.69	1.19
3	Q(t)	0.61	1.89
	L(t)	0.26	2.37
	Sk(t)	0.32	1.36

Table 3: Correlation Coefficients and Degree of Nonlinearity Between Input and Output Processes

"Input-Output" Communication Channel	Correlation Coefficient (ρ)	Degree of Nonlinearity (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

- The operational costs of each machine.
- The costs of grain losses due to delayed processing or machine inefficiencies.
- Storage costs and other operational expenses related to the grain-receiving section.

The method used to solve this optimization problem includes:

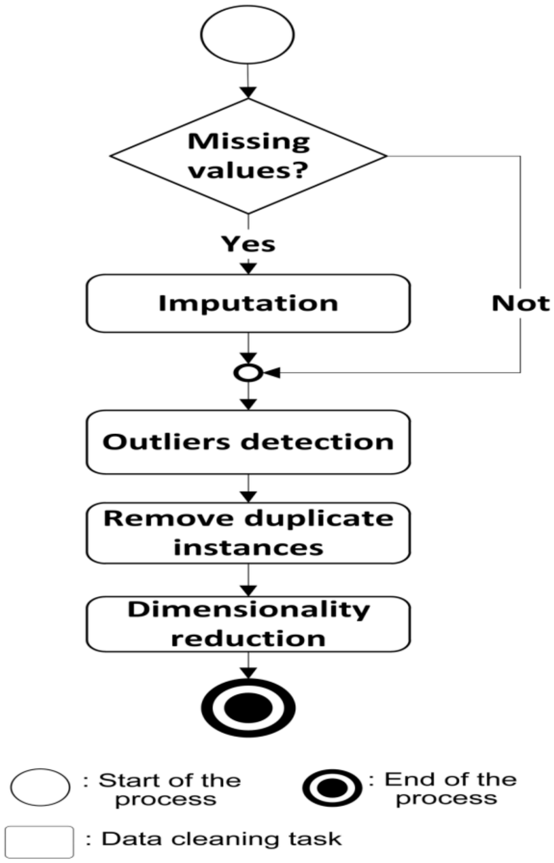

Figure 2: Regression Model of the Pre-Cleaner Technological Process

- **Markov Chains**: The study models the changes in the amount of grain in the dump pit over time using a discrete Markov chain, which allows for capturing the probabilistic nature of grain inflow and outflow from the storage unit.
- **Regression Models**: The performance of machines, particularly pre-cleaners, is modeled using regression techniques. These models allow for predicting machine performance under different operational modes by identifying key input-output relationships.
- **Correlation and Spectral Analysis**: The internal structure of random processes affecting the grain pre-cleaner's performance is analyzed using correlation functions and spectral density analysis. These statistical methods help in understanding how different input variables (such as grain moisture and dockage) influence the output variables (such as grain losses and machine efficiency).
- **Iteration Method**: The study applies an iterative optimization method that continuously adjusts machine parameters until a solution is found that minimizes costs while meeting performance constraints.

The experiment's goal was to identify and quantify the correlation between input disturbances (e.g., grain moisture, initial grain dockage) and output parameters (e.g., efficiency, losses). The study also employs dynamic models for assessing the pre-cleaner's performance and for designing control systems that can optimize machine performance in real-time.

4. Conclusion

The research conducted provides a mathematical framework for optimizing the postharvesting grain-cleaning process, particularly focusing on the OVS-25S pre-cleaner. The use of mathematical models, including Markov chains, regression analysis, and correlation functions, has allowed for a deeper understanding of how various operational parameters impact the efficiency and reliability of grain-cleaning machinery.

The study's key finding is that maintaining a stable grain supply rate (between 10-15 tons/hour) can significantly enhance the stability and efficiency of the pre-cleaning process. Furthermore, the regression models developed in this study enable the prediction of machine performance based on known inputs, allowing operators to choose the most efficient operational modes depending on the grain's initial characteristics (e.g., moisture content and dockage).

The optimization of machine performance is critical in reducing grain losses during the postharvest process, directly influencing the profitability of agricultural enterprises. By applying the proposed mathematical models, agricultural operations can minimize technical inefficiencies, reduce grain losses, and improve overall economic outcomes.

The proposed model not only provides a robust framework for optimizing the operation of grain-cleaning equipment but also lays the foundation for future improvements in agricultural machinery management. Further research and testing in real-world agricultural settings, such as the planned practical implementation in an agricultural concern in the Leningrad region, will help refine these models and extend their applicability to other types of machinery and processes within the agricultural industry.

In conclusion, this study highlights the importance of using advanced mathematical models to optimize technological processes in agriculture, particularly grain handling and postharvesting treatments. By employing these models, it is possible to significantly improve both the technical efficiency and economic profitability of agricultural enterprises.

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