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DEVELOPMENT OF A SYSTEM FOR PREDICTING FAILURES OF BAGGING MACHINES

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Abstract. *The reliability and effective operation of machines is a pressing problem for every enterprise, which requires labour intensive systematization of production processes. The goal is to develop an algorithm and a system for predicting failures of packaging machines based on the analysis of operational indicators. The scientific novelty lies in the integration of statistical data to assess the efficiency of machine operation and predict possible failures, which allows significantly improving maintenance processes and reducing the risks of unforeseen breakdowns. The practical value is the development of a forecasting system that collects the necessary statistical data and performs forecasting. Based on the collected data, an assessment of the efficiency of work and forecasting of possible failures is carried out. The forecasting system is demonstrated on the example of packaging machines LEMO INTERmat ST-SA 850 of "Tatrafan" LLC. Two research methods were used: calculation (mathematical) and forecasting system (least squares method). The forecasting system provides two ways of presenting data: tabular and graphical. Tabular presentation of data allows filtering information according to various criteria, while graphical display is implemented in the form of diagrams showing the operating time and downtime of machines. The main results are the determined range of probable failure of LEMO INTERmat ST-SA 850 packaging machines, which lies in the range from 9090.5 to 12736.5 hours of operation and almost coincides with the manufacturer's warranty period. With timely maintenance, it is possible to increase the lower limit of this interval.*

Keywords: forecasting, reliability, equipment failure

OPRACOWANIE SYSTEMU PROGNOZOWANIA AWARII MASZYN PAKUJĄCYCH

Streszczenie. *Niezawodność i efektywna praca maszyn stanowi palący problem każdego przedsiębiorstwa, wymagający pracochłonnego usystematyzowania procesów produkcyjnych. Celem jest opracowanie algorytmu i systemu prognozowania awarii maszyn pakujących na podstawie analizy wskaźników eksploatacyjnych. Nowością naukową jest integracja danych statystycznych w celu oceny efektywności pracy maszyn i przewidywania ewentualnych awarii, co pozwala znacząco usprawnić procesy utrzymania ruchu i ograniczyć ryzyko nieprzewidzianych awarii. Znaczenie praktyczne ma opracowanie systemu prognostycznego, który będzie zbierał niezbędne dane statystyczne i wykonywał prognozowanie. Na podstawie zebranych danych przeprowadzana jest ocena efektywności pracy i prognozowanie ewentualnych awarii. System prognozowania zaprezentowano na przykładzie maszyn pakujących LEMO INTERmat ST-SA 850 firmy Tatrafan LLC. W badaniach zastosowano dwie metody: obliczeniową (matematyczną) i prognostyczną (metodę najmniejszych kwadratów). System prognozowania umożliwia prezentację danych na dwa sposoby: w formie tabelarycznej i graficznej. Prezentacja danych w formie tabelarycznej pozwala na filtrowanie informacji według różnych kryteriów, natomiast prezentacja graficzna realizowana jest w formie diagramów, obrazujących pracę i przestoje maszyn. Głównymi wynikami jest określony zakres prawdopodobnej awarii maszyn pakujących LEMO INTERmat ST-SA 850, który mieści się w przedziale od 9090,5 do 12736,5 godzin pracy i niemal pokrywa się z okresem gwarancji producenta. Dzięki terminowej konserwacji możliwe jest podwyższenie dolnej granicy tego przedziału.*

Słowa kluczowe: prognozowanie, niezawodność, awarie sprzętu

Introduction

In modern industrial production, one of the most important factors of enterprise efficiency is ensuring reliability and uninterrupted operation of the machine [6]. Machine failures can lead to significant financial losses, reduced productivity and product quality, as well as downtime in production, therefore their prediction is a necessary tool for increasing the stability of production processes, which indicates the relevance of the research topic.

The novelty of this study lies in the development of an algorithm and a system for predicting failures of bag-making machines based on the analysis of operational indicators, in particular, the use of data on downtime and failures of LEMO INTERmat ST-SA 850 bag-making machines.

The uniqueness of the approach also lies in the combination of theoretical research and practical application on a real example of bag-making machines of the enterprise "Tatrafan" LLC, which allows you to identify the most likely failure times and optimize maintenance planning to extend the operational life of the machine.

Failure prediction of machines, in particular LEMO INTERmat ST-SA 850 batch machines, is one of the important elements in ensuring the smooth operation of production processes of "Tatrafan" LLC. This review is aimed at analysing the main approaches, methods and tools used for failure prediction, as well as their impact on the stability of technological processes.

1. Literature review

The basics of machine failure prediction are based on the use of data such as machine operation history, operating conditions and signals received from sensors.

Important aspects of forecasting are degradation modelling, in which the performance of a machine gradually deteriorates due to wear and aging, degradation models that allow assessing the state of the machine over time and predicting the moment of failure [12], data analysis methods that include statistical methods [9], machine learning and artificial intelligence for analysing large amounts of data and detecting hidden patterns [3, 15], monitoring systems in which the integration of IoT sensors and realtime data processing platforms allows for rapid monitoring of the state of the machine [1].

There are the following methods of failure prediction

Statistical methods, where reliability models, such as the Weibull distribution, estimate the probability of failure at a certain point in time [5]; regenerative analysis for predicting repeated failures [17]; machine learning (ML), where classification and regression, including algorithms such as decision trees, SVMs or gradient boosting, are used to assess failure risks [10] and neural networks, which allow processing complex signals and predicting failures based on multidimensional data [18].

Physical models include the analysis of degradation mechanisms such as corrosion or wear based on the physical properties of materials, etc. [4, 7, 13].

Hybrid approaches combine statistical methods and ML to improve the accuracy of prediction [2].

Paper [11] introduces an innovative approach to developing mechanisms for securing objects on the end effectors of technological equipment, thereby reducing operational failures.

Using prediction to improve process resilience such as reducing downtime (early detection of potential failures allows for repair or replacement of the machine before a critical moment), optimizing costs (effective prediction reduces emergency repair costs and losses due to production stoppages) and improving safety (avoiding unexpected failures helps reduce risks to personnel and the environment). Insufficient or poor quality data can limit the effectiveness of models. The combination of IoT, Big Data and artificial intelligence requires significant investment and knowledge. The diversity of machines and operating conditions makes it difficult to create universal solutions.

The goal is to develop and implement a system for predicting failures of packaging machines based on the analysis of operational data.

2. Objects and methods

As initial data (Table 1) for forecasting, we accept statistical data of LEMO INTERmat ST-SA 850 batchforming machines of "Tatrafan" LLC (Fig. 1), which were obtained during the operation of the machine [16].

Table 1. Forecasting for equipment before the first failure

Name of equipment for bag production machines	The number of hours of operation before the first failure
LEMO INTERmat ST-SA 850 #1	9225
LEMO INTERmat ST-SA 850 #2	10025
LEMO INTERmat ST-SA 850 #3	11140
LEMO INTERmat ST-SA 850 #4	12160
LEMO INTERmat ST-SA 850 #5	9030
LEMO INTERmat ST-SA 850 #6	13100
LEMO INTERmat ST-SA 850 #7	8120
LEMO INTERmat ST-SA 850 #8	10140
LEMO INTERmat ST-SA 850 #9	14025
LEMO INTERmat ST-SA 850 #10	12170

Fig. 1. LEMO INTERmat ST-SA 850 [16]

The warranty service life for this type of machine is 10,000 hours of operation.

Two methods were used for the study, calculation (mathematical) and creation of a forecasting system with the least squares algorithm [14].

Technical characteristics from the passport of the bagging machines and information about the current state of the machine are entered into the forecasting system manually. The card is given in Figure 2. Daily work shifts inspect the machines. Tasks related to repair, maintenance and inspection are recorded in the system. Thus, the accounting of machines is completely transferred from paper media and journals to electronic maintenance. As the machines are operated, statistical data accumulates in the forecasting system.

Fig. 2. Equipment card

To solve the problem of predicting machine failures, the following algorithm is implemented a group of machines of the same type is selected, namely LEMO INTERmat ST-SA 850 batch machines. Next, a query is constructed to obtain statistics on operation and the first failure for each machine from the selected group [19]. The mathematical expectation and variance [8] are found for the total machine operation time, after which the interval at which the failure of a new machine of this type is most likely is calculated. The number of operating hours until the first failure for each machine, the predicted failure interval, and the new machine that has not yet been inspected are displayed on the screen.

The time interval that reflects the most likely period of failure of a new machine, as well as the name of the machine that has not yet been inspected, is received as the initial information.

In the absence of a new machine that meets the forecast criteria, the message will be displayed: "There is no machine to undergo technical inspection".

If there are no statistical data for forecasting or their insufficient quantity, the message will be displayed: "Insufficient statistical data!".

To make a forecast, it is necessary to select statistical data of machine operation and failures. For correct calculation, it is necessary to select a group of machines of the same brand. In the absence of selected machines, the user will receive a message about the need to fill in the field.

Methods of obtaining statistical data

One of the most important indicators for the forecasting system is the collection of statistical data of machine failures. For their collection, information soft-ware was developed and implemented in the enterprise "Tatrafan" LLC.

Data updating was carried out automatically once a day according to the machine operation schedule. In the absence of an operation schedule, manual data entry is provided. To register a machine failure in the machine card, you must click the "Record machine stop" button. This will open a task creation window, in which the impossibility of continuing operation will be noted.

There are two methods of obtaining statistical data in the forecasting system: tabular and graphical. When using the tabular method of obtaining data, it is possible to filter by all criteria. This form is presented in Fig. 3.

Fig. 3. Statistical data in the form of a table [16]

The second way of presenting statistical data is a graphical method, which has the form of a pie chart (Fig. 4). The chart displays the operating time of machines and their downtime. By default, statistics of all machines for the entire period of operation will be displayed. There is an option to select the machine and the time period for which data is required.

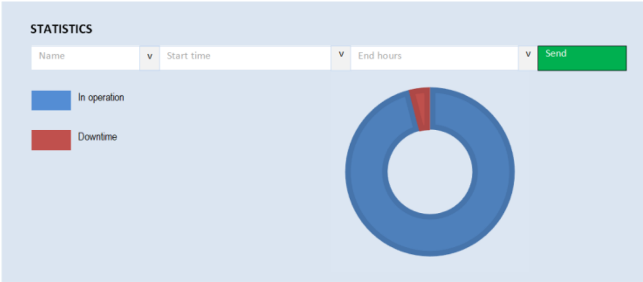

Fig. 4. Statistical data in the form of a diagram

Based on the provided statistical data, the efficiency of the bagging machines is predicted and assessed (Fig. 5).

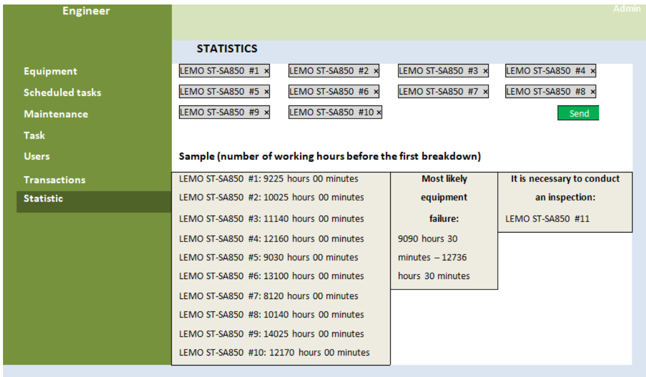

Fig. 5. Forecasting

When selecting a group of cars of the same brand, its prediction is calculated (Fig. 6).

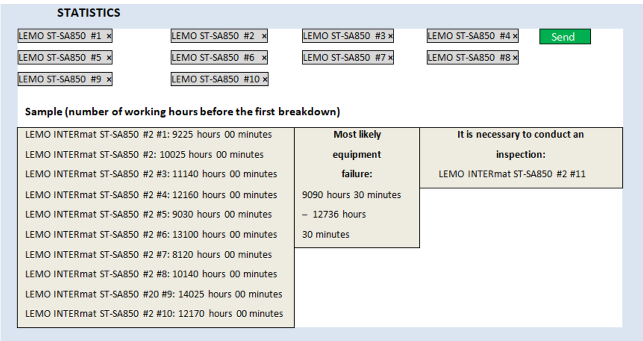

Fig. 6. Forecasting in the system

3. Results and discussion

As a result of an experimental study of predicting the first failure of a new machine, the following calculations were performed.

3.1. Forecasting method 1

We apply the calculation (mathematical) method and calculate the average value (mean time to failure):

$$M(x) = \frac{1}{n}\sum_{i=n}^{n} x_i \quad (1)$$

$M(x) = (9225 + 10025 + 11140 + 12160 + 9030 + 13100 + 8120 + 10140 + 12170) \div 10 = 10913.5$ hours

Then we find the variance:

$$D(x) = \frac{1}{n}\sum_{i=n}^{n} (x_i - M(x))^2 \quad (2)$$

$D(x) = M(x^2) - \left(M(x)\right)^2 = (92252 \times 0.1) + (100252 \times 0.1) + (111402 \times 0.1) + (121602 \times 0.1) + (90302 \times 0.1) + (131002 \times 0.1) + (81202 \times 0.1) + (101402 \times 0.1) + (140252 \times 0.1) + (121702 \times 0.1) - (109013.5)^2 = 10050062.5 + 8510062.5 + 12409960 + 14786560 + 8154090 + 17161000 + 6593440 + 10281960 + 19670062.5 + 14810890 - 119104482 = 3323605.5$ hours

We calculate the mean square deviation:

$$\sigma(x) = \sqrt{D(x)} \quad (3)$$

$\sigma(x) = 1823$ hours.

So, the most likely failure of the machine lies within 9090.5 to 12736.5 hours. This range generally confirms the warranty period of operation of the machines, and with proper technical inspections there is a probability of an increase in the lower limit of the interval.

3.2. Forecasting method 2

Let's conduct the following experiment in the forecasting system using the least squares method and compare it with the calculated (mathematical) one, predict the failure of the bagging machines.

The least squares method involves constructing a regression equation. To do this, we will compile Table 2, which contains the initial and additional data.

Table 2. The least squares method

(x)	(y)	x^2	y^2	x×y	x^3	x^4	x^2×y
1	9225	1	85100625	9225	1	1	9225
2	14240	4	202777600	28480	8	16	56960
3	18870	9	356076900	56610	27	81	169830
4	23960	16	574081600	95840	64	256	383360
5	26450	25	699602500	132250	125	625	661250
15	92745	55	1917639225	322405	225	979	1280625

The system of equations takes the following form:

$$\begin{cases} 5a + 15b + 55c = 92745 \\ 15a + 55b + 225c = 322405 \\ 55a + 225b + 979c = 1280625 \end{cases}$$

We get the parameter values:

$$a = 3003;\ b = 6384.14;\ c \approx -327.86$$

We calculate:

$$y = -327.86 \times x^2 + 6384.14 \times x + 3003$$

Let's perform failure prediction based on the obtained regression:

$y = -327.86 \times 6^2 + 6384.14 \times 6 + 3003 = -11802.96 + 38304.84 + 3003 = 29504.88$ hours

The failure line graph is shown in Fig. 7.

We will perform similar actions in the forecasting system. The forecasting result is presented in Fig. 8.

Thus, the resulting forecast for the next failure is 29504.88 hours.

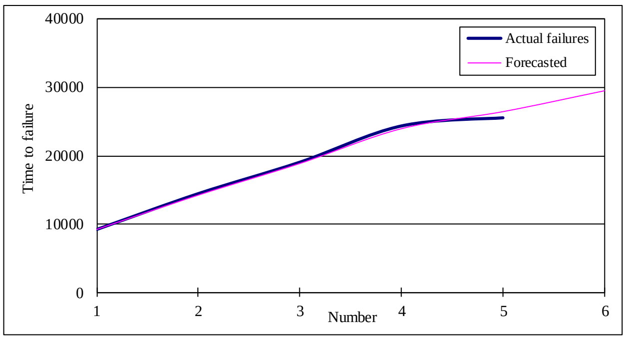

Fig. 7. Machine failure schedule

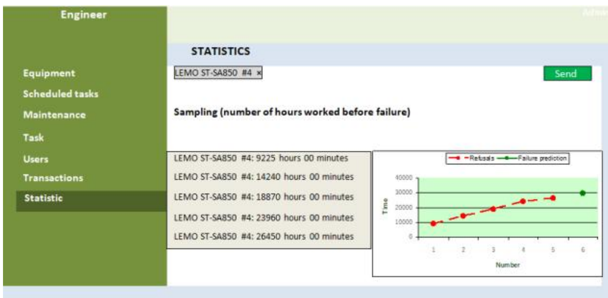

Fig. 8. Forecasting the next machine failure

4. Conclusions

As a result of the research, an effective system for predicting failures of bag-making machines was developed, based on the analysis of operational indicators, in particular, data on downtime and failures of bag-making machines LEMO INTERmat ST-SA 850 LLC "Tatrafan". According to the results of the forecasting, the following results were obtained, where the most likely failure of the machines lies in the range from 9090.5 to 12736.5 hours. These limits generally confirm the warranty period of use of the machine manufacturer, and with proper technical inspections there is a probability of an increase in the lower limit of the interval. This forecasting system can be used to assess the technical condition and efficiency of operation of any other machines. Forecasting allows you to reduce the frequency of machine downtime, increase their efficiency and optimize the maintenance process. The use of mathematical calculation methods and the least squares method allowed us to create a reliable forecasting model that is able to predict technical failures within the warranty period of the equipment.

The practical significance of the work lies in the integration of a forecasting system, which makes it possible to monitor the technical condition of machines and carry out maintenance in a timely manner, which, in turn, contributes to increasing the efficiency of equipment operation and reducing the risks of unforeseen breakdowns. The use of the system on the example of "Tatrafan" LLC bagging machines confirmed its ability to accurately predict the most likely failure times that meet warranty conditions, and also makes it possible to increase the service life of equipment with proper maintenance. Therefore, the results of the study have important practical significance for improving operational reliability and reducing maintenance costs for industrial equipment. As a result of conducting a scientific study, we determined the main indicators and criteria for assessing the technical condition of machines, on the basis of which the forecasting was carried out. As a result, it was found that the results obtained experimentally and the results of calculations in the system are practically identical. This indicates the correctness of the developed algorithms. We created a system for collecting and analysing statistical data on machine operation with the ability to visualize results in the form of tables and diagrams. We tested and evaluated the effectiveness of the proposed method for predicting LEMO INTERmat ST-SA 850 bag-making machines of "Tatrafan" LLC.

References

[1] Anozie U. C. et al.: Integration of IoT technology in lean manufacturing for real-time supply chain optimization. International Journal of Science and Research Archive 12(2), 2024, 1948–1957 [https://doi.org/10.30574/ijsra.2024.12.2.1498].

[2] Azevedo B. F., Rocha A. M. A. C., Pereira A. I.: Hybrid approaches to optimization and machine learning methods: a systematic literature review. Mach Learn 113, 2024, 4055–4097 [https://doi.org/10.1007/s10994-023-06467-x].

[3] Derogar S. et al.: Prediction of punching shear strength of slab-column connections: a comprehensive evaluation of machine learning and deep learning based approaches Mech. Adv. Mater. Struct. 31(6), 2024, 1272–1290 [https://doi.org/ 10.1080/15376494.2022.2134950].

[4] Falkenberg S. F., Spinler S.: The role of novel data in maintenance planning: Breakdown predictions for material handling equipment. Computers & Industrial Engineering 169, 2022, 108230 [https://doi.org/10.1016/j.cie.2022.108230].

[5] Fan L. et al.: Reliability analysis of computed tomography equipment using the q-Weibull distribution. Engineering Reports 5(7), 2023, e12613 [https://doi.org/10.1002/eng2.12613].

[6] Gajewski J., Vališ D.: Verification of the technical equipment degradation method using a hybrid reinforcement learning trees–artificial neural network system. Tribology International 153, 2021, 106618 [https://doi.org/10.1016/j.triboint.2020.106618].

[7] Huliieva N. M., Pasternak V. V.: Isothermal mechanical Cycling of Saponite–Titanium Composites in Conditions of Complex Stressed State. Latvian Journal of Physics and Technical Sciences 59(6), 2022, 12–21 [https://doi.org/10.2478/lpts-2022-0043].

[8] Kang R., Gong W., Chen Yu.: Model-driven degradation modeling approaches: Investigation and review. Chinese Journal of Aeronautics 33(4), 2020, 1137–1153 [https://doi.org/10.1016/j.cja.2019.12.006].

[9] Lieposhkina N. et al.: Statistical Methods for Decision-Making Regarding Technological Systems. Intelligent Systems in Production Engineering and Maintenance III, 2023, 293–305 [https://doi.org/10.1007/978-3-031-44282-7_23].

[10] Omar E. D. et al.: Comparative Analysis of Logistic Regression, Gradient Boosted Trees, SVM, and Random Forest Algorithms for Prediction of Acute Kidney Injury Requiring Dialysis After Cardiac Surgery. International Journal of Nephrology and Renovascular Disease 17, 2024, 197–204 [https://doi.org/10.2147/IJNRD.S461028].

[11] Prydalnyi B.: Creation of automatic clamping mechanisms for spindle assemblies of machine tools using a formalized description of structural elements. Eastern-European Journal of Enterprise Technologies 5(1(119)), 2022, 26–35 [https://doi.org/10.15587/1729-4061.2022.265191].

[12] Prydalnyi B., Kuznetsov Y., Lyshuk V.: Methodology and Tools for Computer-Aided Calculation of Characteristics of Electromechanical Clamping Drive Actuated by Induction Motor. ICIE 2021. Springer, Cham 2021, 256–266 [https://doi.org/10.1007/978-3-030-54817-9_30].

[13] Ruban A., Pasternak V., Huliieva N.: Prediction of the Structural Properties of Powder Materials by 3D Modeling Methods. Materials Science Forum 1068, 2022, 231–238 [https://doi.org/10.4028/p-18k386].

[14] Shi H. et al.: Robust Total Least Squares Estimation Method for Uncertain Linear Regression Model. Mathematics 11(20), 2023, 4354 [https://doi.org/10.3390/math11204354].

[15] Soori M., Arezoo B., Dastres R.: Artificial intelligence, machine learning and deep learning in advanced robotics, a review. Cognitive Robotics 3, 2023, 54–70 [https://doi.org/10.1016/j.cogr.2023.04.001].

[16] Tatrafan. Flexible [https://tatrafan.ua/Tehnologi/#acttech5] (available: 09.01.2025).

[17] Vago N. O. P., Forbicini F., Fraternali P.: Predicting Machine Failures from Multivariate Time Series: An Industrial Case Study. Machines 12(6), 2024, 357 [https://doi.org/10.3390/machines12060357].

[18] Vasiliauskaite V., Antulov-Fantulin N.: Generalization of neural network models for complex network dynamics. Commun Phys 7, 2024, 348 [https://doi.org/10.1038/s42005-024-01837-w].

[19] Yadav D. K., Kaushik A., Yadav N.: Predicting machine failures using machine learning and deep learning algorithms. Sustainable Manufacturing and Service Economics 3, 2024, 100029 [https://doi.org/10.1016/j.smse.2024.100029].

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