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Serhii Kovalov[1], PhD ped. sci., **Viktor Aulin**[1], Prof., DSc., **Andriy Grynkiv**[1], PhD tech. sci., **Yuriy Kovalov**[2], PhD tech. sci.
[1]*Central Ukrainian National Technical University, Kropyvnytskyi, Ukraine*
[2]*Ukrainian State Flight Academy, Stepana Chobanu Street 1, 25005, Kropyvnytskyi, Ukraine*
e-mail: aulinvv@gmail.com, kovalyovserggr@ukr.net

Modeling the Stochastic State Matrix of a Production Line for Optimize its Operational Reliability Using Reinforcement Learning

The development of a production line state determination model aims to create a universal tool for evaluating and optimizing industrial systems. The proposed approach enables real-time analysis of equipment states, prediction of potential failures, and enhancement of overall operational efficiency.

The use of Markov chains allows for precise modeling of the sequence of production line states and the probabilities of transitions between them. This stochastic approach improves adaptability to real-world manufacturing conditions, surpassing the capabilities of traditional deterministic methods.

The formation of a stochastic state matrix optimizes production processes through advanced data analytics and AI integration. This enables manufacturers to minimize downtime, enhance resource allocation, and improve overall productivity while maintaining operational stability.

Transition probability estimation is based on both historical databases and real-time sensor measurements, allowing the model to adapt to various equipment types and operating conditions. AI-driven optimization enhances failure prediction accuracy, ensuring the production line remains efficient under diverse scenarios. By integrating Markov chains with data-driven insights, the approach supports proactive failure prevention and strategic resource management, ultimately improving the reliability and performance of industrial systems.

production line, Artificial Intelligence, production automation, Markov chain theory, stochastic matrix

Problem Statement. The theory of reliability is a crucial component in the implementation of various technical processes, particularly in the functioning of production lines. High reliability ensures the continuity of the production process and minimizes the risks of failures and downtime [1]. One of the effective approaches to studying reliability is the Markov chain theory, which allows for accurate description of the states of production lines and modeling processes to assess their reliability [2]. The use of Markov chains helps identify potential failure points and optimize maintenance, significantly improving the overall efficiency of the production system.

The optimization of modern production lines requires the implementation of advanced technologies, particularly artificial intelligence. AI can significantly enhance the productivity and flexibility of production processes. Reinforcement learning (RL), as one of the most powerful AI techniques, allows systems to learn independently and make decisions based on received feedback [4, 5, 6]. This is particularly useful in production lines where rapid adaptation to changing conditions and optimization of operating parameters are necessary.

Modeling production lines based on the RL method allows achieving high reliability and stability. Thanks to the self-learning capability of RL algorithms, the system can not only maintain an optimal operating mode but also continuously improve its performance. Thus, the integration of artificial intelligence (AI) into the production process opens up new horizons for improving the efficiency and reliability of modern production lines.

Analysis of Recent Research and Publications. The reliability of an object is defined by its ability to maintain within specified limits the values of all parameters that characterize the object's ability to perform required functions under given operating modes and conditions, maintenance, repair, storage, and transportation [1, 2]. Reliability is a complex property that depends on the product's purpose and application conditions. It consists of a combination of properties: reliability, durability, maintainability, and storability.

Durability, reliability, maintainability, and storability are the main parameters that determine the reliability of a production line. These parameters account for various aspects of equipment operation and help assess its ability to perform assigned functions over a long period. According to stochastic theory, these parameters are considered random variables that follow certain probabilistic distribution laws. Reliability can be evaluated by the probability of no failure over a specified period, typically described by an exponential distribution [1]:

$$P(t) = \exp(-\lambda t), \tag{1}$$

where $P(t)$ - is the probability of no failure by time t,

λ - is the failure rate.

Maintainability is evaluated by the equipment's ability to quickly recover after a failure occurs. The mean time to repair is a critical metric in this context and is defined as the average time required to repair and restore the system to operational status. Durability describes the overall operational lifespan of the equipment until significant wear necessitates replacement or major overhaul. Storability reflects the equipment's ability to maintain its operational characteristics during prolonged storage or transportation. All these parameters are considered in stochastic reliability models, where, for example, the time to failure can be described by a gamma distribution [1]:

$$f(t) = \frac{\lambda^k t^{k-1} \exp(-\lambda t)}{(k-1)!} \tag{2}$$

where $f(t)$ - represents the probability density function,

t - is the time,

λ - is the rate parameter, and

k - is the shape parameter.

Such an approach allows predicting the behavior of the production line and optimizing processes to improve its reliability. In the context of Markov chains, the reliability of a production line is determined through modeling the system states and transitions between them. The main idea is that the state of the system at any given moment depends only on its previous state and does not depend on how the system reached the previous state. This simplifies the analysis and evaluation of reliability [1, 2].

When applying Markov models to assess the reliability of a production line, possible states of the equipment, such as operational state, partial or complete failure, and transitions between these states are considered. The probabilities of transitions between states are determined based on statistical data on the reliability of components and the system as a whole.

Markov models allow determining such characteristics as mean time to failure, mean time to repair, and other reliability indicators. These models are also used to predict the system's behavior over time, which helps in planning maintenance and repairs [3].

As a result, Markov chains provide an effective tool for analyzing and modeling the reliability of production lines, enabling informed decisions to improve the efficiency and reliability of production processes [10].

RL allows systems to learn through interaction with the environment, receiving rewards for correct actions and penalties for mistakes [11]. The main components of this method are the agent, environment, actions, states, and rewards. The agent makes decisions (actions) based on its current state in the environment and receives feedback in the form of rewards or penalties, allowing it to learn an optimal strategy.

The conceptual implementation of the RL method in a production line includes the following aspects:

Agent - this is the production line management system that makes decisions regarding its operation. For example, it could be a program that controls the operation of robotic manipulators or conveyor belts.

Environment - this is the production process, which includes all components and operations performed on the production line. This can include both physical processes (movement of parts, assembly) and logistical processes (inventory management, production planning).

Actions - these are specific operations or commands that the agent performs to achieve the goal. For example, changing the speed of the conveyor, adjusting equipment parameters, or initiating additional processes.

States - these are the current conditions or configurations of the production line, such as equipment status, inventory levels, or the number of produced products. Each state provides the agent with information about the current situation on the line.

Rewards - these are metrics that reflect the efficiency of the production line. They can include the amount of produced products, production speed, waste minimization, or downtime reduction.

Modeling a production line using RL allows the agent to optimize processes, increasing the reliability and efficiency of operations. The agent learns through trial and error, receiving feedback in the form of rewards or penalties, and gradually improving its management strategy for production processes.

Task Definition. The research methodology for assessing the reliability of a production line by integrating Markov theory and the RL method consists of several key stages (Fig. 1).

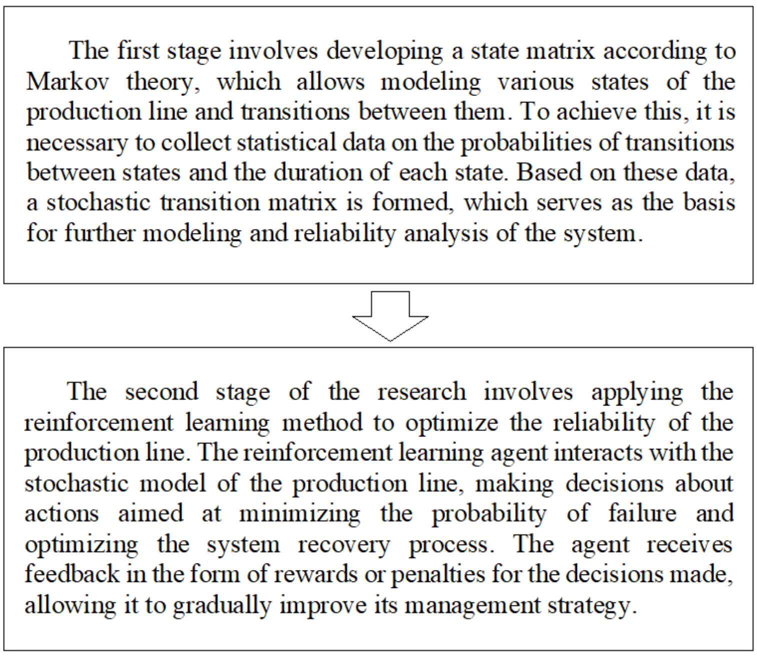

Figure 1 - Diagram of the methodology for assessing the reliability of the production line

Source: developed by the authors

In the course of the research, a model for determining a stochastic matrix has also been proposed, which assumes that the system consists of elements whose states are described by a stochastic distribution. Some elements of the system can be described using the classical approach, which takes into account databases and statistical regularities, while other elements can be described by parameters that correlate with reliability. This allows for more accurate formation of the stochastic matrix and considers all aspects of the production line's reliability.

Presentation of the Main Material. Thus, the methodology of this study includes data collection, development of Markov models, application of RL methods for reliability optimization, and formation of stochastic matrices for comprehensive system analysis. This approach provides a detailed understanding of the production line's functioning and develops recommendations for enhancing its reliability.

To determine the stochastic matrix, a model is proposed that represents the production line as a system consisting of various nodes. Each node of this system can be described in terms of classical reliability concepts, which include the analysis of reliability, durability, maintainability, and storability. For such nodes, a standard approach is used, based on collecting statistical data on failures and calculating reliability indicators from historical data.

Another type of node in this model involves a more modern approach, which includes measuring the operational parameters of nodes that directly correlate with reliability. This allows obtaining up-to-date data on the condition of each node in real-time. Using these data, stochastic state matrices are formed, reflecting the probabilities of transitions between different states of the nodes. This enables more accurate modeling of the production line's behavior and making decisions regarding its reliability optimization.

Thus, the proposed model provides a comprehensive approach to assessing the reliability of the production line, combining classical analysis methods with modern monitoring and data processing techniques. This not only allows predicting possible failures but also actively influencing management and maintenance processes to improve the efficiency and stability of the production line.

One of the approaches considered for finding parameters that correlate with the reliability of system nodes is acoustic spectral analysis, including ultrasonic. This method is a powerful tool for determining parameters that correlate with the reliability of production line nodes. The algorithms of this method include collecting sound data from equipment components using sensors that measure acoustic vibrations. Spectral analysis is performed by transforming the time signal into the frequency domain using mathematical methods such as polynomial regression and discrete Fourier transform [15]. This allows identifying characteristic spectral components that reflect the node's state.

The idea behind determining the state of a node based on its characteristic spectra is that different equipment states have unique acoustic signatures. For instance, a normally functioning bearing generates a specific sound spectrum, while a bearing with defects produces additional harmonics or noises at certain frequencies. Ultrasonic analysis enables the detection of high-frequency components that might be undetectable by traditional acoustic methods. This is particularly useful for diagnosing microscopic cracks, wear, or other initial damages that slightly affect the overall sound signal but are crucial for predicting future failures.

Using acoustic spectral analysis, one can create a model that includes stochastic state matrices of nodes, which reflect the probabilities of transitions between different states based on the obtained acoustic characteristics. Such models allow for the timely identification of potential problems and optimization of maintenance schedules, significantly enhancing the reliability and efficiency of the production line.

To conduct acoustic spectral analysis on production line nodes, it is necessary to integrate appropriate equipment that allows for high-precision measurements of acoustic characteristics. This includes installing sensors and transducers capable of capturing both sound and ultrasonic vibrations. Sensors are typically placed on key components of the production line where mechanical failures or wear are possible. Proper sensor placement is crucial for obtaining the most accurate data.

After collecting acoustic data, spectral analysis is performed using mathematical algorithms. One of the most common methods is the Fourier transform, which converts a time-domain signal into a frequency spectrum:

$$X(k) = \sum_{n=0}^{N-1} x(n) \exp(-j(\frac{2\pi}{N}/kn)) \quad (3)$$

where $x(n)$ - is the input signal,

(k) - is the output spectrum,

N - is the number of points in the signal, and

j - is the imaginary unit.

The Fast Fourier Transform is a more efficient implementation that reduces computational complexity. Additionally, approximation methods such as wavelet transforms can be used, allowing the analysis of signals with varying frequency resolutions.

The physical and technical aspects of implementing acoustic spectral analysis include the high sensitivity of sensors to vibrations and noise, as well as their ability to operate under conditions of high temperature and humidity. Ultrasonic sensors have the added advantage of detecting microscopic defects that are not accessible by conventional acoustic methods.

The results of spectral analysis allow the creation of node state models used for predicting failures and optimizing maintenance. This ensures increased reliability and efficiency of production lines.

Acoustic spectral analysis can be conducted at various frequencies, depending on the research purpose and the type of object. Ultrasonic analysis is particularly effective in detecting defects that do not yet affect the overall performance of the equipment but may cause serious problems in the future.

Here is the algorithm for forming a stochastic state matrix of a node based on acoustic spectral analysis is shown in Fig. 2.

This algorithm helps in forming a stochastic matrix that accurately reflects the probabilities of transitions between different states of the node based on acoustic data. The formula for the stochastic transition matrix is shown in (4).

Let P={Pij} be the stochastic matrix, where Pij is the probability of transitioning from state i to state j:

$$P_{ij} = \frac{N_{ij}}{\sum_{j=1}^{n} N_{ij}} \quad (4)$$

where Nij - is the number of observations of the transition from state i to state j,

n - is the total number of states.

In addition to acoustic spectral analysis, there are several other methods that allow measuring parameters correlated with the reliability of production nodes. One such method is temperature field measurement. This method helps detect overheating or uneven temperature distribution in individual equipment nodes, which can indicate wear or malfunctions. Temperature sensors are placed at critical points on the equipment, and the obtained data are analyzed using thermography or other mathematical methods to identify anomalies and their causes.

Video surveillance and motion pattern recognition is another important method. High-resolution cameras are installed at key points of the production line, allowing real-time tracking of node movements. Special image processing algorithms, particularly machine learning methods, are used to recognize motion patterns and detect deviations from normal operating conditions. This enables timely identification of potential failures and decisions regarding their resolution.

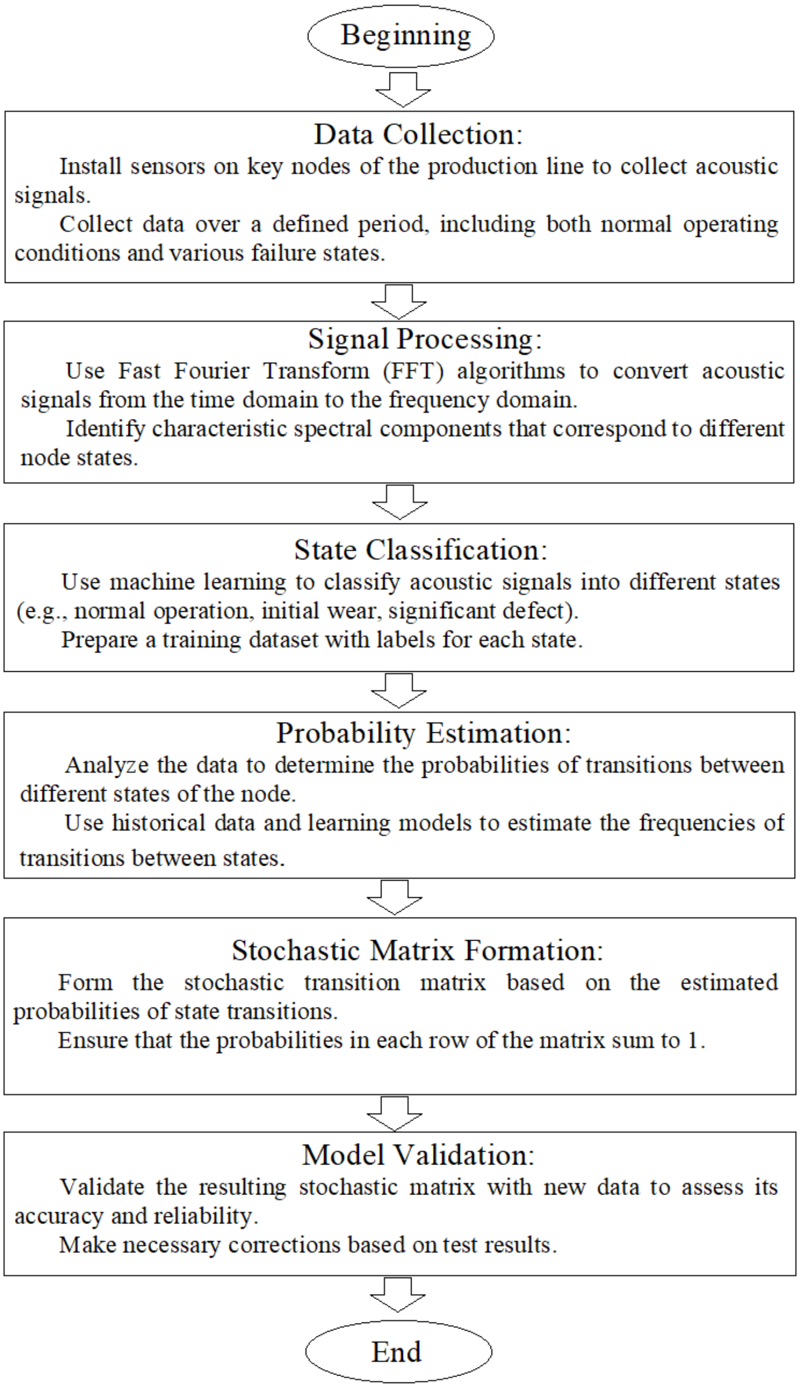

Figure 2 - Diagram of the algorithm for forming a stochastic state matrix

Source: developed by the authors

The method of current dipoles involves measuring the electrical characteristics of the equipment, such as resistance, inductance, and capacitance. These parameters can change depending on the condition of the nodes, allowing the identification of defects or wear. The application of current dipoles is particularly effective for diagnosing electromechanical systems and identifying potential problems at early stages.

Hardware neural networks, or embedded AI systems, are used to analyze large volumes of data collected from various sensors. These networks can detect complex dependencies and patterns correlated with the equipment's reliability. Thanks to self-learning algorithms, neural networks can continuously improve their predictions and recommendations, enhancing the overall efficiency and stability of the production line.

These methods allow for a comprehensive assessment of the state of production nodes and making informed decisions regarding their maintenance and repair, significantly increasing the reliability of production processes.

Conclusions.

1. A comprehensive approach to assessing and optimizing the reliability of production lines, based on a combination of Markov models and RL methods, has been applied.
2. A model has been developed that represents the production line as a system composed of nodes, each of which can be described using classical methods and stochastic models/
3. It has been shown that the use of Markov chains allows for accurate determination of the probabilities of transitions between the states of nodes, which contributes to a more detailed analysis and prediction of reliability.
4. It has been found that the application of the RL method allows optimizing the operation of production lines through agents' self-learning based on the data obtained about their states and operation. This enables effective responses to changing operating conditions and improves management strategies, thereby enhancing the overall stability and efficiency of the production process.
5. Various methods for measuring parameters correlated with reliability, such as acoustic spectral analysis, temperature field measurement, video surveillance and motion pattern recognition, the method of current dipoles, and the use of hardware neural networks have been proposed. These methods allow creating detailed state models of nodes, ensuring accurate and timely identification of potential failures.

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С. Г. Ковальов[1], канд. пед. наук, **В. В. Аулін**[1], проф., д-р техн. наук, **А. В. Гриньків**[1], канд. техн. наук, **Ю. Г. Ковальов**[2], канд. техн. наук
[1]*Центральноукраїнський національний технічний університет, м. Кропивницький, Україна*
[2]*Українська державна льотна академія, м. Кропивницький, Україна*

Моделювання стохастичної матриці станів виробничої лінії для оптимізації її експлуатаційної надійності за допомогою навчання з підкріпленням

Основною метою розробки моделі визначення стану виробничої лінії було створення універсального інструменту, здатного аналізувати та оптимізувати будь-яку промислову виробничу лінію. Модель розроблена для ефективної оцінки робочих станів виробничого обладнання, прогнозування потенційних збоїв та рекомендацій щодо коригувальних дій для підвищення надійності та ефективності. Завдяки використанню математичних методів та методів на основі штучного інтелекту, підхід забезпечує адаптивність до різних типів виробничих систем, що робить його застосовним у різних галузях промисловості.

Модель використовує ланцюги Маркова для точного представлення послідовності виробничих станів, включаючи ймовірнісний характер переходів між операційними фазами. На відміну від традиційних детерміністичних моделей, запропонований підхід враховує реальні невизначеності, властиві виробничим процесам, що дозволяє точніше прогнозувати поведінку системи. Інтеграція стохастичного аналізу розширює можливості моделювання складних робочих процесів, покращуючи прийняття рішень та оцінку ризиків у промисловому середовищі.

Метод формування матриці стохастичних станів забезпечує комплексну систему оптимізації для виробничих систем, використовуючи сучасну аналітику даних на основі штучного інтелекту. Цей підхід надає виробникам інструмент для покращення часу безвідмовної роботи, скорочення простоїв та більш ефективного розподілу ресурсів. Адаптивність моделі в режимі реального часу гарантує, що промислові системи залишаються чутливими до динамічних умов, оптимізуючи продуктивність та мінімізуючи перебої.

Модель успішно оцінює ймовірності переходу на основі як історичних баз даних, так і даних датчиків у реальному часі, що дозволяє їй адаптуватися до широкого спектру типів обладнання та умов експлуатації. Ця адаптивність підвищує точність прогнозування потенційних збоїв та оптимізації виробничих робочих процесів. Крім того, методи навчання з підкріпленням допомагають покращити продуктивність системи шляхом постійного вдосконалення операційних стратегій, зниження ризиків та підтримки безперебійної роботи навіть за змінних виробничих сценаріїв.

Завдяки інтеграції ланцюгів Маркова та аналітики на основі даних, запропонований підхід дозволяє ранньо виявляти потенційну неефективність та систематичні збої. Він допомагає виробникам прогнозувати критичні інциденти та оптимізувати процеси прийняття рішень, що призводить до підвищення продуктивності, зниження витрат на обслуговування та підвищення надійності на виробничих лініях. Зрештою, модель сприяє розробці високостійких промислових систем, забезпечуючи стабільну роботу та ефективність за різних умов експлуатації.

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