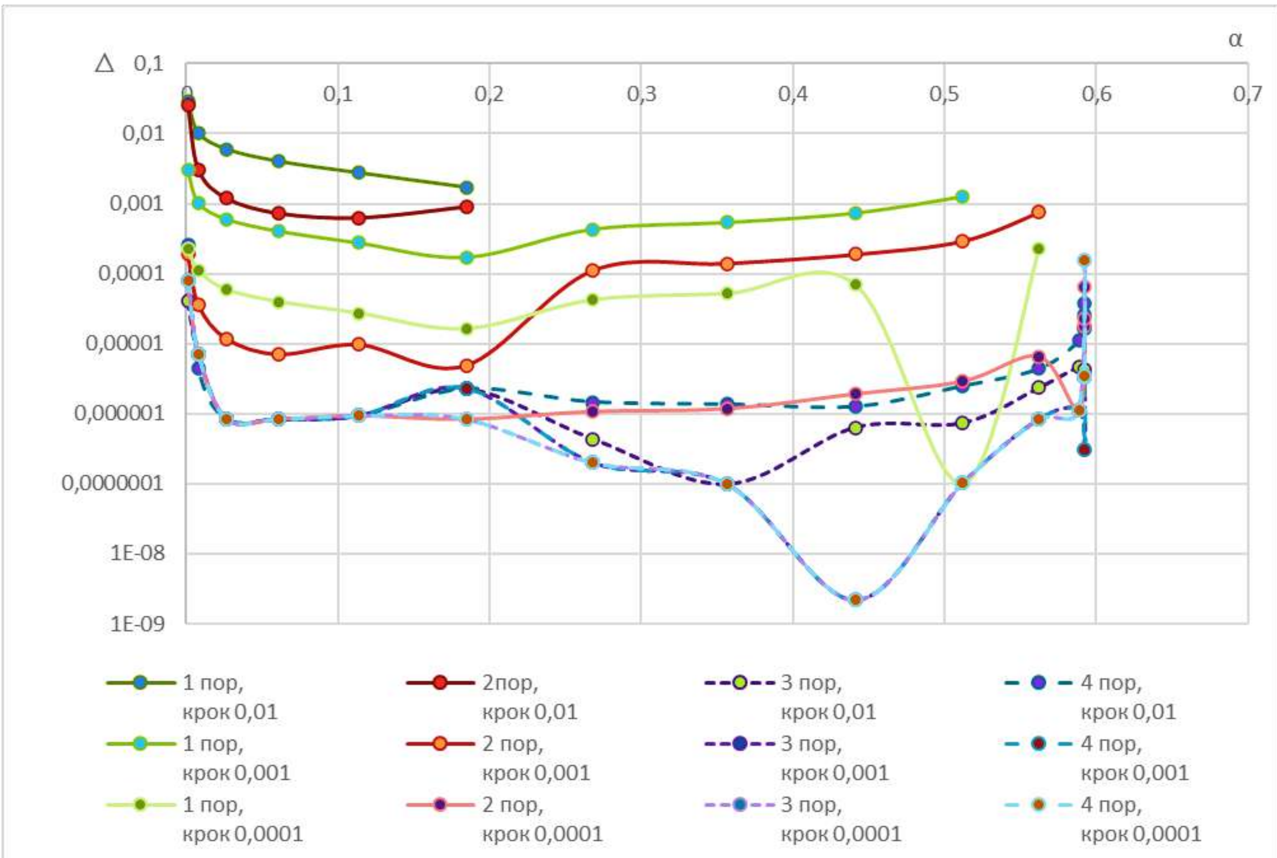

Рис. 2. Графічні залежності похибок обчислення радіусів обертових крапель числовими методами інтегрування

Дослідження проводились для методів Рунге-Кутти з постійним кроком інтегрування, отже методи зі змінним кроком інтегрування можуть бути темою майбутніх досліджень.

Література

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INTELLIGENT SYSTEM FOR CONTROLLING SURFACE ROUGHNESS PARAMETERS OF PARTS BASED ON MULTI-TASK NEURAL NETWORKS

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In modern high-tech instrument-making, ensuring a given surface roughness is a critically important stage that directly affects the operational reliability, wear resistance and fatigue strength of parts [1]. The traditional approach to controlling roughness parameters is usually based on post-processing analysis, when measurements are taken after the completion of the machining operation using contact profilometers or optical systems. This approach creates significant time delays and does not allow for a prompt response to deviations in the technological process, which often leads to the appearance of defects. The solution to this problem is the implementation of intelligent prediction methods that allow assessing the surface quality directly during cutting, using indirect physical features, such as vibration signals [2].

The proposed method is based on the use of deep learning, in particular, an improved Deep Belief Network (DBN) architecture, adapted for solving several tasks simultaneously. The scientific novelty of the approach lies in the integration of the evaluation of surface roughness parameters and the state of wear of the cutting tool into a single analytical model.

The physical justification of such a structure is based on the fact that the degradation of the cutting edge is the root cause of the change in the surface microgeometry. The use of common hidden layers of the neural network allows the model to more effectively extract invariant features from noise vibration signals, providing higher accuracy compared to isolated prediction algorithms [3].

The process of system operation begins with the stage of recording primary data. During machining on a CNC machine tool, a three-axis accelerometer installed on the spindle assembly records the dynamic characteristics of the process along the X, Y and Z axes.

The received signals are extremely complex and contain a significant amount of background noise from the operation of the machine tool drives and the cooling system. To increase the stability of the algorithm at the pre-processing stage, the data expansion method is used by adding controlled white Gaussian noise. This allows for the formation of a reliable training set that simulates different conditions of the shop floor environment and prevents overtraining of the model on specific random perturbations [4].

The central element of the method is the specific topology of the neural network, presented in fig. 1:

As can be seen from the diagram, the structure consists of an input layer, several consecutive hidden layers based on restricted Boltzmann machines (RBM) and a branched output cascade. Each RBM layer is trained iteratively, which allows the system to independently identify the most informative frequency and time patterns of vibration.

At the highest level, the network is divided into two parallel vectors: one is responsible for the discrete classification of roughness levels, and the other for monitoring the degree of tool wear. Such a separation allows us to take into account the mutual influence of these parameters through the common weighting coefficients of the lower layers [5].

To convert vibrations into an input feature vector, statistical parameters of the time domain are used. The most significant are the root mean square (RMS), which reflects the total vibration energy, and the kurtosis, which indicates the presence of peak impact loads characteristic of the initial stages of cutting-edge failure.

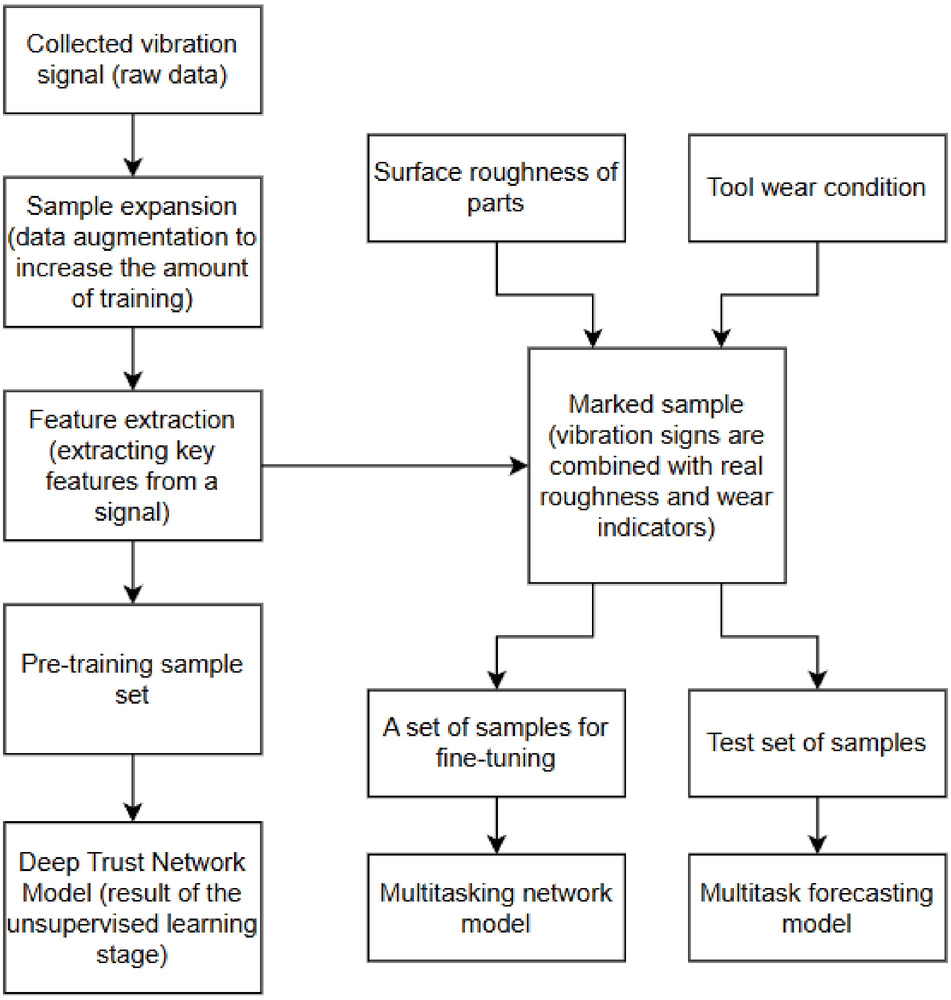

Fig. 1. Architecture of a multi-task forecasting model

The mathematical tuning of the model is carried out using a combined loss function that balances the errors of both tasks. This ensures that the system will not shift the focus to only one parameter, providing a comprehensive assessment of the technological state [6].

The implementation of such an intelligent system allows transforming the approach to quality management: from passive detection of defects to active prevention of their occurrence. Integration of the algorithm into the machine control system allows real-time correction of cutting modes (for example, reducing the feed when detecting signs of vibration instability) or automatically stopping processing to replace the tool. This ensures the stability of the technological process, minimizes the impact of the human factor and significantly increases the economic efficiency of production by reducing the number of defective parts and optimizing the cost of tool materials. Thus, the combination of deep learning and multi-task vibration analysis is one of the most promising areas of development of machining technologies within the framework of the Industry 4.0 concept.

Keywords: surface roughness parameters, neural network, tool wear control, vibration signal analysis.

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ДОСЛІДЖЕННЯ УМОВ ЗАСТОСУВАННЯ СФЕРИЧНОЇ АПРОКСИМАЦІЇ ЕЛІПСОЇДАЛЬНИХ РЕФЛЕКТОРІВ У ФОТОМЕТРИЧНИХ ПРИСТРОЯХ БІОМЕДИЧНОГО ПРИЗНАЧЕННЯ

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Еліпсоїдальні рефлектори (ЕР) широко застосовуються у фотометричних пристроях для вимірювання показника заломлення біологічних тканин методом повного внутрішнього відбиття (ПВВ) [1]-[3]. Принцип роботи ґрунтується на стигматичній властивості еліпсоїда обертання: всі промені, що виходять з одного фокуса F_1 та відбиваються від поверхні ЕР, збираються у другому фокусі F_2 незалежно від точки відбиття. Ця властивість є критичною для формування чіткого кільця ПВВ на CCD-сенсорі, розміщеному у F_2, положення якого однозначно визначає показник заломлення досліджуваної тканини n_2 [4], [5].

Еліпсоїд обертання з великою піввіссю a та малою піввіссю b описується рівнянням:

$$\frac{\rho^2}{b^2} + \frac{z^2}{a^2} = 1,$$