METHOD OF MACHINING CENTRE SLIDING SYSTEM FAULT DETECTION USING TORQUE SIGNALS AND AUTOENCODER

Damian AUGUSTYN*, Marek FIDALI*

*Department of Fundamentals of Machinery Design, Faculty of Mechanical Engineering, Silesian University of Technology, ul. Akademicka 2A, 44-100 Gliwice, Poland

damian.augustyn@polsl.pl, marek.fidali@polsl.pl

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Abstract: The sliding system of machining centres often causes maintenance and process problems. Improper operation of the sliding system can result from wear of mechanical parts and drives faults. To detect the faulty operation of the sliding system, measurements of the torque of its servomotors can be used. Servomotor controllers can measure motor current, which can be used to calculate motor torque. For research purposes, the authors used a set of torque signals from the machining centre servomotors that were acquired over a long period. The signals were collected during a diagnostic test programmed in the machining centre controller and performed once per day. In this article, a method for detecting anomalies in torque signals was presented for the condition assessment of the machining centre sliding systems. During the research, an autoencoder was used to detect the anomaly, and the condition was assessed based on the value of the reconstruction error. The results indicate that the anomaly detection method using an autoencoder is an effective solution for detecting damage to the sliding system and can be easily used in a condition monitoring system.

Key words: condition monitoring, torque signal, machining centre, anomaly detection, autoencoder

1. INTRODUCTION

Contemporary machining centres used in production are usually fully automated and complex mechatronic systems. Among many state-of-the-art systems that can be found in machining centres, sliding system plays a very important role. It is the mechanical system that enables the movement of the machine's table or spindle along the axes (X, Y, Z) to position the cutting tool precisely relative to the workpiece. The sliding system in contemporary machining centres plays a critical role in ensuring the precision and accuracy of the machining process. Fig. 1 presents an exemplary sliding system of a multi-axis machining centre.

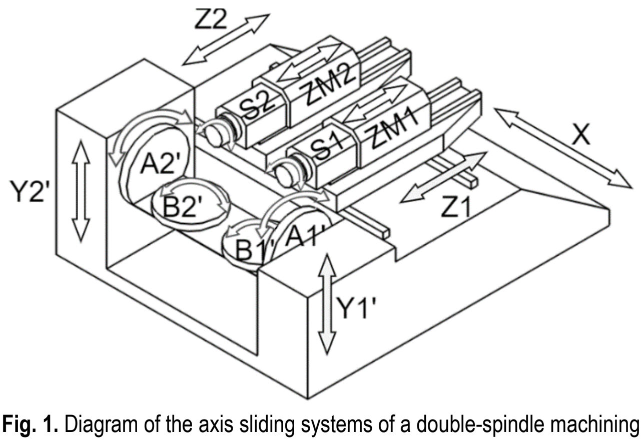

Fig. 1. Diagram of the axis sliding systems of a double-spindle machining centre

The sliding system is typically composed of several components, as shown in Fig. 2.

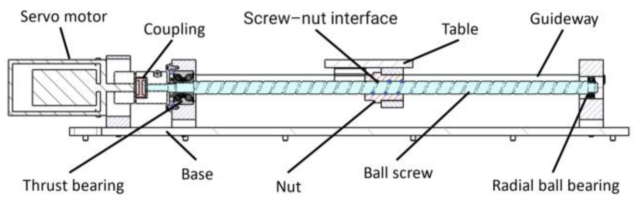

Fig. 2. Schematic diagram of the exemplary ball-screw drive system used in sliding system of machining centres

According to the different publications [1, 2] and reports of maintenance services, common faults of sliding systems are as follows:
– servomotor problems (bearings, electrical system);
– increased resistance to movement;
– decay of preload;
– increased clearance;
– ball screw damage;
– bearing damage.

Failures and damage to sliding systems can lead to serious problems and limitations in the operation of the machining centre, which can lead to loss of production, high repair costs and even the need to stop the production line. In recent years, much attention has been devoted to the development of various diagnostic methods for the sliding systems of the machining centre. Their goal is to enable the quick detection of failures and damages, which allows for quick intervention and minimising downtime.

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1.1. Condition monitoring and diagnostics of sliding systems

Condition monitoring of the sliding system in machining centres is an essential aspect of ensuring their operational efficiency and avoiding costly downtime due to unscheduled maintenance. There are various techniques available for condition monitoring, ranging from simple diagnostic signals from sensors and devices installed by the manufacturer to more sophisticated methods based on machine learning and deep learning.

Sliding system of machining centres could be monitored and diagnosed in different ways. Very often sliding systems are assessed indirectly by evaluating the quality of machining parts [3]. Direct assessment of the components of the sliding system can be performed using both off-line and on-line techniques, based on methods such as vibration analysis [4–7], laser interferometry [8, 9], noise analysis [10, 11], visual inspection [12, 13], temperature monitoring [14, 15], acoustic emission monitoring [16, 17], motor current signature analysis [18, 19] and thermal imaging [20–22].

One of the most commonly used techniques for condition monitoring of sliding systems is vibration analysis. This technique involves analysing the vibration signals generated by the sliding system and extracting various parameters based on time, spectral and time–frequency analysis [23, 24]. These parameters can be used to indicate the operating condition and mechanical performance of the sliding system.

Another technique for condition monitoring is torque signal analysis [25]. This technique involves analysing the torque signal generated by the servomotors of the sliding system and their controllers. The servomotor controllers measure and monitor various operational parameters such as temperature or electric current, which can be used to calculate a torque signal that is useful for assessing the condition of sliding systems. Servo torque signal analysis methods are based on long-term trends and short-term fluctuations, using signal models and the least squares method.

Methods based on machine learning and deep learning are also being used for condition monitoring of sliding systems. These methods can extract data from many available sensors and then fuse them to predict the remaining useful life (RUL) [26]. Convolutional neural networks consisting of two modules – feature extractor and classifier – are commonly used for this purpose [27–29].

More recently, deep adversarial networks and autoencoders [30, 31] have been used for fault detection and identification of sliding system. Deep adversarial networks have been used for RUL prediction with partial sensor malfunctions. Autoencoders have been used for fault detection and identification of sliding systems.

Overall, condition monitoring of sliding systems in machining centres is an active research area, with ongoing efforts to develop more accurate and reliable techniques for fault detection and identification. These efforts are aided by the availability of data acquisition systems, advances in machine learning and deep learning and the development of decentralised federated transfer learning methodologies.

2. SIGNALS OF SLIDING DRIVE TORQUE AND ITS ANALYSIS

During the research, we analysed the torque signals that were collected by our industrial partner from December 2019 to September 2022. Torque was measured during diagnostic tests on the sliding system drives of the X, Y, Z and A axes of machining centres. For the purposes of our research, we considered a set of 100,000 torque signals from 47 machining centres. The maintenance service reported that no faults were detected in the sliding systems during the signal collection period. The machining centre diagnostic test was performed periodically, at least once a day. This test involved performing a sequence of axis drive movements, during which the sliding travelled throughout the entire operating range and then returned to the initial position. Plots of exemplary torque signals for the X, Y, Z and A axes gathered during one of the diagnostic tests are presented in Figs. 3–6, respectively. We assumed that the torque signals acquired during the diagnostic test could be a source of information about the general condition of the entire sliding system, including the drive and sliding mechanisms. Therefore, we proposed a method for sliding fault detection based on these signals.

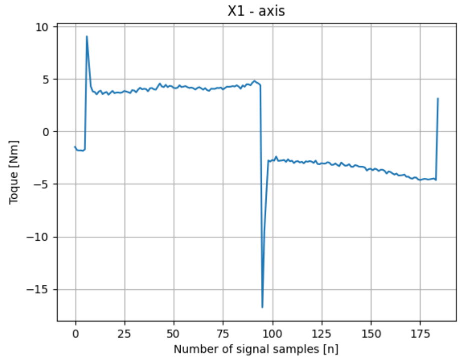

Fig. 3. Torque signal of the sliding servo drives for the X-axis

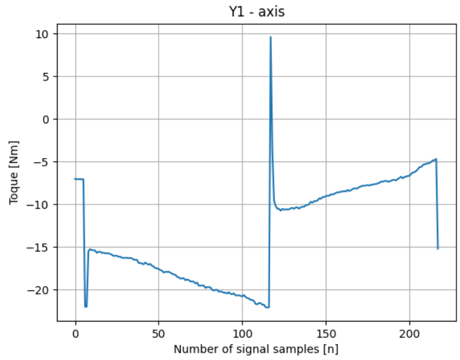

Fig. 4. Torque signal of the sliding servo drives for the Y-axis

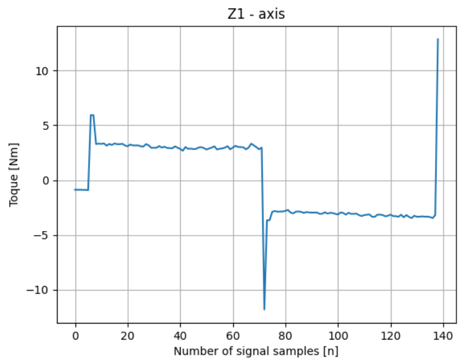

Fig. 5. Torque signal of the sliding servo drives for the Z-axis

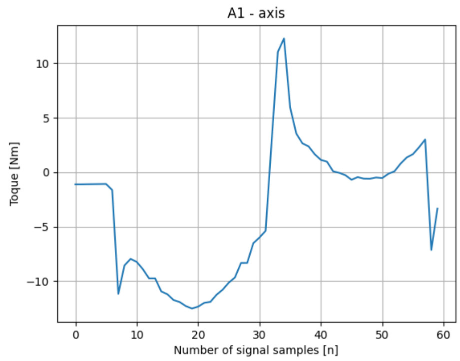

Fig. 6. Torque signal of the sliding servo drives for the A-axis

3. METHOD OF SLIDING FAULT DETECTION

The general idea of the method is based on detecting anomalies and deviations between the acquired torque signal and the model of the torque signal of a correctly operating sliding system. This is due to the fact that all collected signals represent good sliding system conditions. A flow of operations necessary to implement and verify the method is presented in Fig. 7. First, torque signals from the servo drives of individual axes are acquired and stored in a database after each periodic sliding system diagnostic test. In the next step, the recorded data are processed and analysed. Based on the properly recorded time series, anomalies are detected, and the value of the status indicator is calculated. The status indicator can be used to build long-term time series for trend analysis purposes. In the case of sliding system degradation, an increase in the value of the status indicator should be expected. By using the upper limit control method, it will be possible to detect the change in sliding condition and warn the maintenance services that additional inspection is necessary. The aim of this method is to improve efficiency, product quality and worker safety.

3.1. Anomaly detection and status indicator calculation

A crucial operation in the proposed method is the detection of anomalies in the torque signal and the calculation of the value of the sliding system condition indicator. There are several ways to detect anomalies in torque signals, such as model-based and residue analysis or feature extraction and neural models [32]. The second approach was tested during preliminary research and the results were very promising [33]. As part of the research continuation, it was decided to verify the potential of another type of feedforward artificial neural network called an autoencoder. This diagnostic method, based on the torque signal and using an autoencoder, is particularly useful in cases where there is a lack of data regarding the fault or where such data are rare or costly to obtain. This method can help to detect subtle and complex problems in sliding system of machining centre in real-time during diagnostic tests, allowing maintenance personnel to quickly respond and prevent further issues. Additionally, this method enables the evaluation and tracking changes of sliding system condition. In contrast to traditional diagnostic methods, the proposed method utilises the ability to learn complex data patterns and has the potential to detect subtle or difficult-to-identify faults using traditional methods. This method can be used in automated diagnostic systems and does not require extensive knowledge of technical diagnostics, making it more accessible and easier to implement in industry.

The threshold reconstruction autoencoder is the basic deep learning approach for anomaly detection. Autoencoders are used for an unsupervised learning process [34–36], while the developed method uses a supervised learning process [37], similar to a self-supervised process [38, 39]. The choice of the learning method was dictated by the unreliability of the assumption adopted in practice, which was revealed during the ablation studies [40]. The results of ablative studies showed the disadvantages of the method based on unsupervised learning compared to the applied method of supervised learning, which achieved higher performance. In unsupervised learning, where the training data may contain anomalous examples, the autoencoder could also reconstruct anomalies, which would reduce the ability to detect anomalies based on reconstruction errors. The autoencoder, for a set of input values, creates a hidden representation from which to recreate the batch data. The assumption of the developed diagnostic method is higher values of the reconstruction error for anomalous waveforms of the torque signal compared with normal waveforms.

It was assumed that the autoencoder is trained on the time series of the torque signals represented by sliding in good condition. The result of the autoencoder operation is the value of the reconstruction error, which can be treated as a status indicator. The application of autoencoder requires the preparation of input data. In the next step, torque signals were selected and pre-processed for further computation.

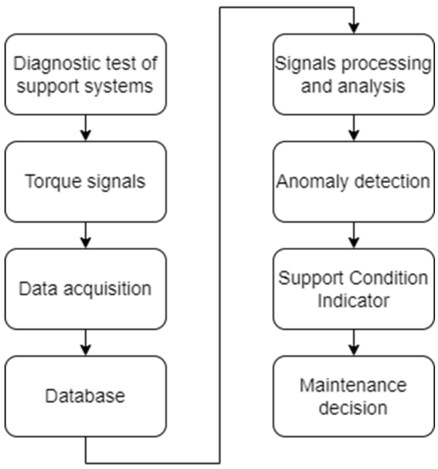

Fig. 7. Method of diagnosing a sliding system

3.2. Data preparation

The set of torque signals acquired during diagnostic tests of a sliding system of machining centres required verification and preprocessing. During the verification process, it was observed that some of the signals differed in the number of time points and time positions in relation to the beginning of the diagnostic test. Additionally, some signals were found to be cut off, most likely due to a lack of signal synchronisation. The cut-off signals were rejected. For the time-shifted signals, we developed a procedure to match them in time. In the next step, we divided the signals into two subsets: a subset of signals describing good conditions and a subset of signals with anomalies. To achieve this, a statistical analysis of the torque signal values was performed. The values of the torque variance were ordered in ascending order and 25% of

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the lowest and highest values were treated as outliers with probable anomalies (Fig. 8). Further analysis of the signals connected with the outliers allowed us to identify a small number of signals where anomalies were clearly visible (Fig. 9). The remaining 50% of feature values were assumed to be connected with torque signals describing good sliding system conditions and could be used for autoencoder training. The outliers were used for autoencoder testing. The process of selecting torque signals based on their feature values is presented in Fig. 8.

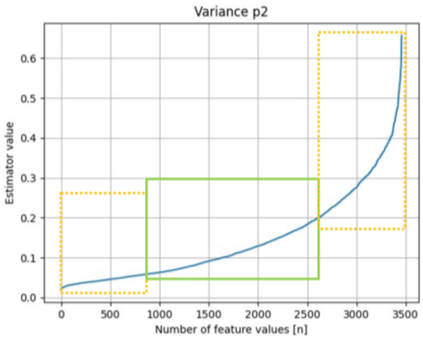

Fig. 8. Distribution of signal variance and way of values dividing into training (continuous line box) and testing (dotted line box) set

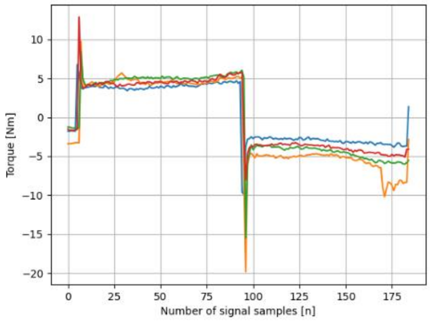

Fig. 9. Selected anomalous signals

The corrected torque signals, along with a small number of selected anomalous signals, were marked for the prepared training and test data sets. Both torque signal values in both data sets were then normalised. Fig. 10 shows the normalised torque signals for both good operation and anomalous sliding system operation. However, the reason for the detected anomalies was not identified by the maintenance personnel.

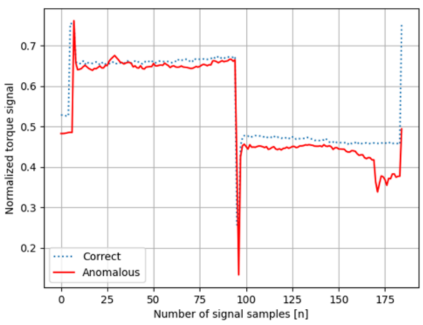

Fig. 10. Comparison of normalised torque signals for correct and anomalous sliding system operation

3.3. Anomaly detection using autoencoder

Pre-processed signals were utilised to train and test an autoencoder using a Python environment with TensorFlow and Keras libraries. A deep autoencoder with a symmetrical architecture was employed to detect anomalies. The autoencoder is composed of two components: an encoder and a decoder. The encoder part comprises three layers that utilise the Rectified Linear Unit (ReLU) activation function for ease of neural network optimisation. The decoder part also has three layers, with the ReLU activation function applied to the first two layers and the Sigmoid activation function applied to the final layer. The Adam optimisation method and Mean Absolute Error (MAE) [41] loss function were used for the autoencoder learning process, which was run only on the correct torque signals. A limited number of recorded anomalous torque signals were used to test the developed autoencoder model. The autoencoder model was trained over 30 epochs, and Fig. 11 shows the learning curve consisting of the training and validation loss.

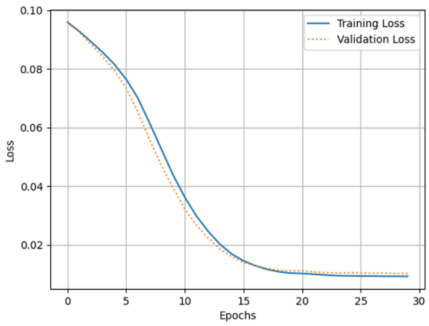

Fig. 11. Learning curve of the autoencoder model

4. ANOMALY DETECTION RESULTS AND DISCUSSION

The developed autoencoder was tested on data that was not used during the training process. The model was able to determine the good condition of the machining centre sliding systems with an average accuracy of 99% for the selected threshold values. Fig. 12 shows the performance of the autoencoder model on an example of a correct torque signal (represented by the blue dotted line). The reconstructed torque signal is shown in red, while the reconstruction error is shown in light red. As one can see, error is very small and almost not visible on the plot.

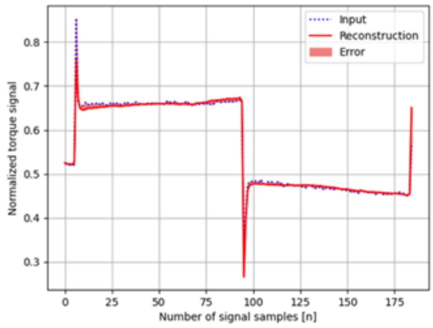

Fig. 12. Reconstruction error graph for a normal torque signal

In Fig. 13, the effect of the developed autoencoder model for an exemplary anomalous torque signal is shown. In this case, error is clearly visible and is close to 0.022.

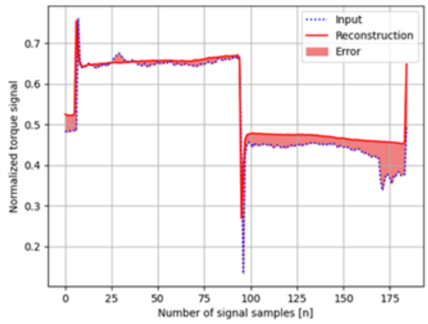

Fig. 13. Reconstruction error graph for an anomalous torque signal

The developed autoencoder allows for the visual representation of the reconstruction error in diagrams. For the purpose of the developed diagnostic system, anomaly detection is based on the reconstruction error, for which the average reconstruction error for the training set and the test set was calculated, as shown in Fig. 14.

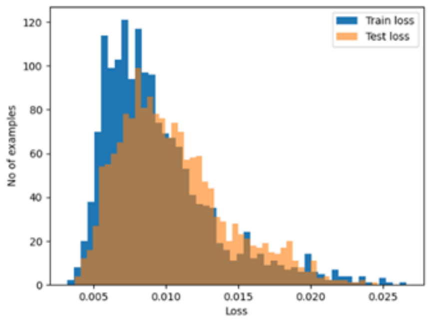

Fig. 14. Reconstruction error graph for torque signals from training set (blue) and test set (orange)

Based on the reconstruction error, graphs are generated to show the changes for the recorded time series. To make the system resistant to single isolated values of increased reconstruction error that may not be related to changes in the conditions of the sliding system drives, a moving average was used. This enables observation of the reconstruction error trend and prediction of the condition of the machining centre drives. Fig. 15 shows the reconstruction error for the time series from the training set.

Fig. 16 shows the reconstruction error for the test set. Time series in the test set were ordered according to ascending order of variance values (Fig. 9) of outliers.

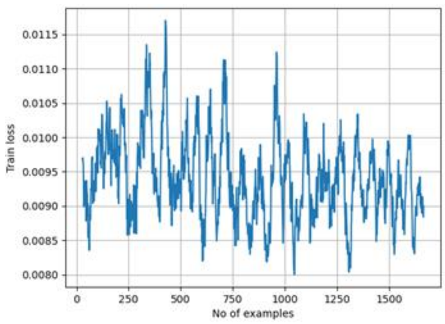

Fig. 15. Reconstruction error changes for the training set

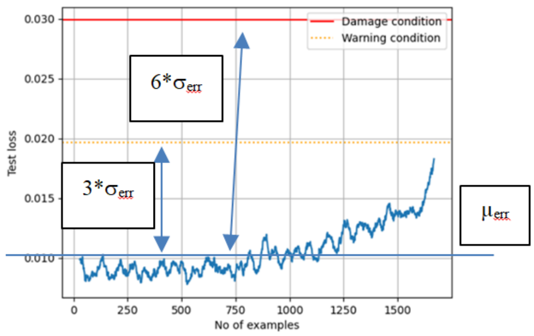

Fig. 16. Reconstruction error changes for the test set

Two threshold values were determined based on the analysis of the time series of reconstruction errors. The first threshold was determined by three standard deviations above the mean reconstruction error. The diagnostic system warning state has been assigned to it. The warning status is information for the maintenance department about the need to observe a given axis of the machining centre and control changes in its condition. The second was determined by six standard deviations above the mean reconstruction error. The fault condition of the machining centre servo drive was assigned to the second threshold. Exceeding the value of the second threshold determines the need for repair or accelerated maintenance of the machining centre sliding drive.

5. CONCLUSIONS

The use of servo drive torque signal measurement is an interesting alternative to assess the condition of the machining centre sliding system. This article presents an anomaly detection method which uses the autoencoder and allows the assessment of the conditions of the sliding system based on the reconstruction error value, which could be treated as a sliding system condition indicator. The autoencoder was trained based on the torque time series of the machining centre sliding systems. The training process was supervised, resembling a self-supervised process. Based on the selected error thresholds of the autoencoder reconstruction, it enables the assessment of the condition of the sliding system. The developed anomaly detection method enables the detection of registered anomalies in time series and the determination of the sliding system condition of the machining centre. Compared to the artificial neural network developed during earlier research, the method based on the autoencoder is characterised by greater efficiency and effectiveness in assessing the condition of sliding systems. The plans for future research include extending the ablative tests for the developed method in order to fully use its potential and capabilities.

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Damian Augustyn: https://orcid.org/0000-0002-4896-4090

Marek Fidali: https://orcid.org/0000-0002-3667-5582