Development of predictive maintenance based on artificial intelligence methods

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Abstract: *Artificial intelligence become more widespread in all manufacturing subjects. In manufacturing artificial intelligence deals with such tasks as quality control, robot navigation, computer vision, processes controlling, etc. The area of maintenance in machining is a great prospect for implementing artificial intelligence tools for analysis, prediction of monitored parameters, optimization, and improvement of the quality of the maintenance process. In particular, the article refers to predictive maintenance as a modern trend in mechanical engineering. In this article, a quick review of using methods of artificial intelligence and predictive analytics in maintenance and one practical implementation case of NAR network for time-series prediction was provided.*

Keywords*: ARTIFICIAL INTELLIGENCE, PREDICTIVE MAINTENANCE, MATLAB, NAR NETWORK*

1. Introduction

The industry is the part of the economy that produces materials and goods with a high degree of mechanization or automation to ensure the requirements for the quality of products and the productivity of the production process. Fundamental changes in technologies and methods of production, which were characterized by the introduction of new technologies at the whole stage of the development of industrialization, are now called industrial revolutions.

Nowadays, smart technologies, together with the massive introduction of information technology in the industry, large-scale automation of business processes, and the spread of artificial intelligence, create the basis for the future new industrial revolution called Industry 4.0.

When starting a new production process, a lot of attention is given to such points as the economic calculation of production efficiency, the choice of equipment, suppliers, and materials. The goal of any modern production is the productive, economical, and safe production of goods in the right volume while maintaining the desired level of quality.

At the same time, the progress of technology is causing the implementation of new highly productive machining methods, which also place higher demands on production machines and tools, their reliability, and the reliability of the production process itself.

Reliability is the ability of the equipment to perform required functions in the specified technical conditions over the operation. One of its most important features is faultlessness, which is defined as the ability of a machine to complete all specified conditions and parameters by the manufacturer's technical documentation and recommendations within the specified manufacturer's time.

And a reduction in the machine's ability to operate in a fault-free or operational mode leads to errors and defects in machine operation, production failures and can ultimately lead to faulty failures and emergencies.

2. Maintenance in the industry

The great importance of maintenance for the industry is difficult to underestimate, as its neglect is a major cause of failure and the associated costs and losses in the production process, as preventing failure is always cheaper in the end than eliminating its consequences.

The term "maintenance" according to the standard STN EN 13 306 means a summary of all activities (management, technical and administrative), the aim of which is to maintain, maintain the equipment in working order, or restore such conditions.

We often talk about maintenance strategies, which are divided into post-failure maintenance (reactive maintenance) and pre-failure maintenance. The main division of maintenance strategies is shown in Fig. 1.

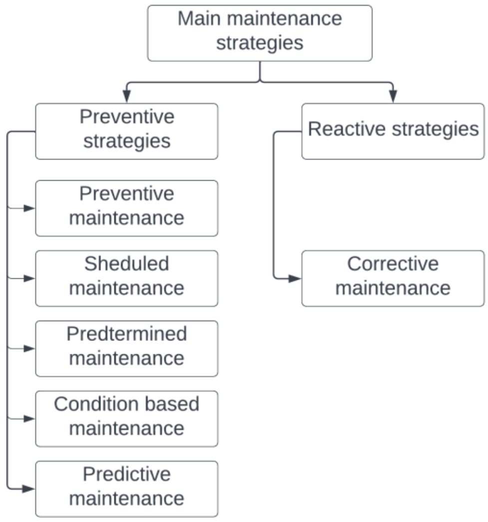

Fig. 1 *The division of maintenance strategies*

The main goal of maintenance is to maintain the operability of the machines, which means ensuring the smoothest possible operation of the production process, minimizing the time of production interruption, and eliminating the negative consequences of machine downtime. Maintenance goals also include achieving and extending the planned technical life of production machines, minimizing threats to environmental damage, and preventing occupational accidents and health [2].

3. Predictive maintenance as a modern trend

The obvious advantages of preventive maintenance over reactive maintenance are, for example, a lower risk of failures that will cause a long-term shutdown of the equipment, a reduction in the risk to the health and life of workers working with the equipment. The possibility of maintenance planning in connection with planned outages causes a significant reduction in maintenance costs. However, the maintenance interval specified by the manufacturer is not always optimal and appropriate for a particular operation, and the separate determination of such an interval may be associated with downtime risks and unforeseen costs.

Predictive Maintenance (PdM) deals with the problem of determining the correct length of maintenance cycles. The goal is to schedule maintenance at the most convenient and cost-effective time to optimize equipment life before the equipment will be damaged. Unlike preventive maintenance, the maintenance of each device is assessed and planned based on the current state of the device. The basis of predictive maintenance is perfect "condition monitoring" - using a summary of certain measured physical parameters (such as system pressure, temperature, vibration, etc.), the current state is determined continuously. Furthermore, based on these data, we use statistical and artificial intelligence methods to try to estimate the failure time. With this procedure, we enable a sharp reaction to a change in the condition of the equipment, and subsequently, depending on the real situation, it is possible to extend or shorten the maintenance cycle for a specific machine.

Predictive maintenance is a current trend in the industry, as predictive maintenance is in principle more effective than preventive maintenance because it is based not only on the actual current state of the equipment but also on the historical load and considers other factors. It also reduces the number of unplanned downtimes, increases productivity, reduces the cost of maintaining operability, and increases the safety of the production process

4. Artificial intelligence and machine learning in PdM

Unlike traditional maintenance procedures that rely on the life cycle of machine components, a predictive approach based on the principle of machine learning prevents the loss of resources and insufficiently optimized use of resources for maintenance tasks.

Artificial intelligence in predictive maintenance can adapt routine maintenance activities to the needs of each device. The implemented artificial intelligence system can be taught to visually identify errors and patterns in the device, can follow the instructions of a computer-aided design without further programming of the system, and even use the currently obtained data for subsequent training and real-time model improvement. Automatic anomaly detection reduces unplanned downtime and costs by quickly providing an estimate of when a device will fail. Successfully implementation of artificial intelligence for predictive analytics tasks is shown in [3-5].

In terms of predictive maintenance of machines and equipment, continuous monitoring has great importance. By using the sensor on the investigated machine, it is possible to create a mass of data on the state of the device continuously in time. These, in turn, together with the historical data after establishing the dependencies between the normal and faulty states of the system and the corresponding parameters, already allow the top of the prediction model.

The maintenance interval prediction task is essentially a time series prediction task. The time series is arranged according to the time of occurrence of the series of quantities of some investigated parameter. The values of the examined parameter are usually recorded in equally long-time intervals. The time series is used to monitor time changes and monitor trends in the development of the examined parameter. Furthermore, changes to any parameters are chaotic because they change randomly in the real world.

The most used in research and practice models for time series prediction are linear autoregressive models (AR and ARX). moving average model (MA), autoregressive moving average (ARMA), LSTM neural networks model, and nonlinear autoregressive (NAR and NARX) neural network models.

AR and ARX models were successfully implemented for example in [6,9] for regulation of the climate parameters in buildings and greenhouses. Among the main benefits of the ARX model is the simple structure of the model - a small number of model parameters, simplicity of interpretation of model parameters, and simplicity of possible integration of the model into the control system. However, ARX models are not able to estimate nonlinear dependencies.

The ARMA (autoregressive moving average) model class can be used to solve problems in engineering, economics, and the natural sciences, which have a large amount of data where the observed quantities are interdependent. The models can be used for both deterministic and stochastic modeling using historical data and prediction errors to generate forecasts, dynamic analyses, and other statistical information with a minimum number of parameters used to represent system dynamics.

Algorithms that use ARMA models for prediction show good results for short-term prediction and this can be seen in studies [8,10], but the accuracy of the model decreases significantly as the time for which parameter values need to be predicted increases. The response tends to over-reproduce the average of values observed in the past. In addition, these methods work with homogeneous time series, where input and prediction are within the same set of values.

All the above models can be used to construct the recurrent neural network (RNN) for time-series prediction. However, they have a problem storing and spreading errors in time. It happens because the backpropagated error either disappears quickly or increases sharply, as the magnitude of the error signal propagated back in time depends exponentially on the size of the scales.

This problem can be solved by using long-short time memory (LSTM) networks. The structure of the LSTM neural network consists of cells (Fig. 2), which are formed by an entrance gate, an exit gate, a forgetting gate, and a memory cell.

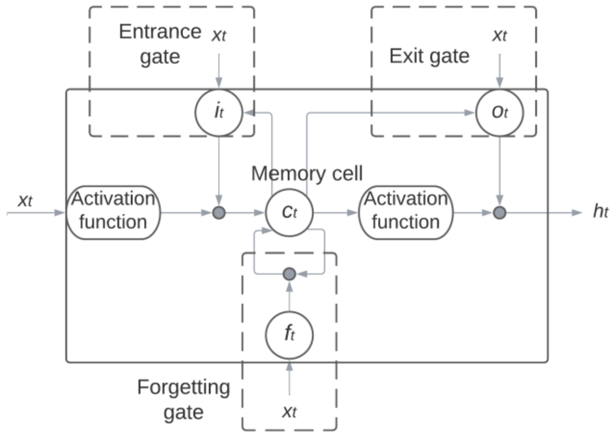

Fig. 2 *The LSTM cell structure*

Using the LSTM network allows tracking the dependencies of new observations with past (even very distant) ones. However, this capability, due to the tendency of the cell state values to increase linearly (especially when observing a continuous data flow), can cause the LSTM module to fall into a normal error backpropagation network. This means that the main ability - to keep the error in time will be eliminated. In general, LSTM models are complex and are rarely used to predict a single time series because they require a large amount of data to be estimated. However, they are commonly used when predictions are needed for many time series [1].

One of the modern and most widely used time prediction methods is prediction using NAR (Nonlinear AutoregRession) and NARX (Nonlinear AutoregRession with exogenous inputs) neural networks.

A NAR neural network is a type of dynamic neural network based on time series. The relationship between the input and output variables of the model is not just a static mapping, but the output of each moment is synthesized based on the dynamic results of the system before the current moment, so it has a feedback and memory function.

In the case of a neural network NAR, the delayed time series values are used as inputs to the neural network. The output from the neural network is a predicted value, corresponding to the value of the parameter that needs to be predicted at a certain point in time[5].

5. An example of time-series prediction using NAR network

To visually illustrate the predictive ability of a nonlinear autoregressive neural network to make predictions, a simple model was developed in the MATLAB software package to predict the magnitude of the output signal for acceleration data.

To generate a gyroscopic dataset an M5-StickC microcontroller (see Fig. 3) was used.

Fig. 3 *The M5-StickC microcontroller*

The M5-StickC microcontroller can read acceleration along the X, Y, and Z axes as well as gyroscopic data in the same axes at a frequency of 18 measurements per second. The created data set was then saved in .csv format.

Before entering the neural network, data must be pre-processed to eliminate error values and possible completion of missing points. The result is shown in Fig. 4.

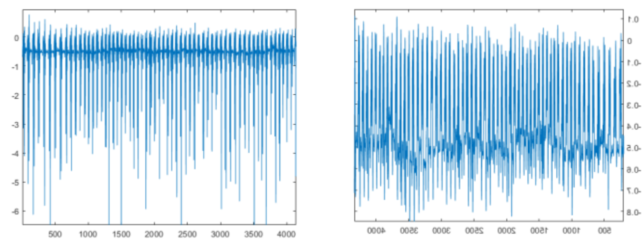

Fig. 4 *Data before pre-processing (left) and after pre-processing (right)*

The Designed NAR network consists of the input layer, 3 hidden layers with tangent sigmoid function as an activation function, and the output layer with linear function as an activation function. The structure of the neural network is shown in Fig. 5.

For time series prediction tasks, the NAR neural network architecture, unlike conventional recurrent networks, is designed as a time-delay neural network (TDNN). It means that the output of each moment is synthesized based on the dynamic results of the system before the current moment, so it has a feedback and memory function.

Fig. 5 *The structure of the designed NAR network*

After creating the training dataset, the neural network was trained, and a one-step-ahead prediction plot was built. In Fig. 6 prediction values (orange plot) and real-time values (blue plot) are shown for one-step prediction.

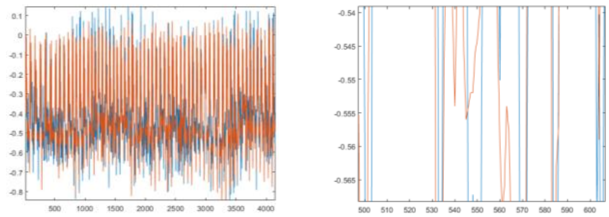

Fig. 6 *Predicted and real-time values*

6. Results and discussion

The proposed neural network model showed a high preliminary result for predicting the values of the time series. When predicting one step, the prediction accuracy reached 90%. This is illustrated by the regression plot (Fig. 7).

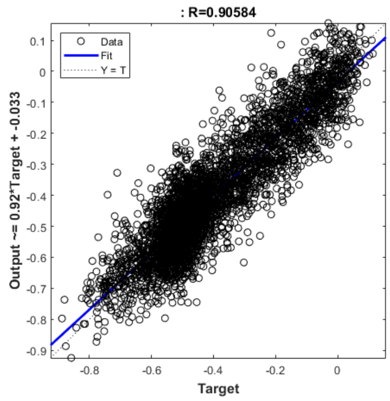

Fig. 7 *Regression plot for one step ahead prediction*

However, in the case of predicting more steps, the accuracy of the proposed model dropped significantly (see Tab. 1).

Tab. 1 *Accuracy of proposed neural network*

Number of ahead prediction steps	Correlation coefficient value
5	0,76
10	0,57
20	0,28

As can be seen from Tab. 1, the predictive accuracy for predicting 20 steps is approximately 28%, which means that the accuracy for using the proposed neural network in practice for predictive maintenance tasks is not suitable.

The decrease in accuracy can be due to the insufficient quality of the data taken - the data acquisition technique did not assume a cyclic change in the parameters, and because of this, the parameters were chaotic. It is possible to partially eliminate this disadvantage with the help of better data pre-processing. However, the methodology for obtaining data needs to be developed more carefully.

Another possible reason for poor prediction may be the architecture of the neural network itself. It is probably worth trying to use a different number of hidden layer neurons and the number of layers itself, as well as other activation functions.

7. Conclusion

In this paper, a brief analysis of artificial intelligence models used for predictive analytics in predictive maintenance tasks was made. A model was proposed, and an example was given of using a neural network with non-linear autoregression to predict the behaviour of acceleration data along with one of the axes.

Experimental data showed insufficient reliability of the proposed model for real practical problems. The presumably negative results were contributed by the chaotic nature of the data (the stable dependence of the microcontroller readings on the moment in time in the future) and the too simple structure of the neural network. In the future, it is planned to develop another neural network model with non-linear autoregression for a more accurate forecast and the possibility of using such a model in practice.

8. References

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