PROGNOSIS OF BEHAVIOUR OF MACHINE TOOL SPINDLES, THEIR DIAGNOSTICS AND MAINTENANCE

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The present article focuses on the use of neural networks to predict the behaviour of certain diagnostic parameters of spindles of machine tools. An online vibro-diagnostics is used, and from many specific measured parameters, the effective value of some variables in the time series. The results are used in the maintenance based on the technical condition, in particular, in preventive and proactive maintenance. This procedure is completely original and allows for better setting of maintenance policy, which is also beneficial for planning maintenance costs. The article also mentions the necessity to implement the steps described, also in the context of the Industry 4.0 initiative, and further, it briefly discussesprognostics, technical diagnostics, maintenance and maintenance systems. The used neural networks and the calculation procedure are also analysed. The conclusions obtained are evaluated.

KEYWORDS

neural networks, prognosis of diagnostic parameters behaviour, machine tool spindle, preventive and proactive maintenance, maintenance system, Industry 4.0

1 INTRODUCTION

The First Industrial Revolution took place at the end of the 18th century when labour was replaced by machines. An important tool in this process was the steam engine. A massive onset of mechanization in industry and agriculture was marked by a sharp rise in productivity,followed by population growth and significant social, cultural and political changes.

The Second Industrial Revolution began almost 100 years later when electrification and motorization took place. Important inventions included an electric bulb (ThomasAlva Edison), an electric transformer (Nicola Tesla) and an internal combustion engine (Gottlieb, Daimler). The Third Industrial Revolution began in the late 1960s with the emergence of computing technology that enabled the automation of a number of human activities and accelerated technical developments. The Fourth Industrial Revolution started to be discussed not earlier than in 2013. The idea is that it will result in almost complete automation of production, including control and management processes that are, today, still executed by humans. The factories in the Fourth Industrial Revolution will be completely self-managed.

The Industry 4.0 concept is a revolutionary and evolutionary summary of what machine manufacturers have been experiencing lately. Consideration of cyber-physical systems (CPS) can already have far-reaching consequences for the future. Machines, as part of the CPS system, are probably best prepared for the future. One of the primary indication of Industry 4.0 is digitization. This means that all the data from machine has common time links, based on faster data generation and accessible at all network levels. During organizing of the network, all data is displayed in one network according to the specified standard.[Heller 2016].

Maintenance management is in most companies at the very onset of applying the Industry 4.0 initiative. Maintenance managers are only being familiarised with the main ideas challenges of this initiative, i.e. the issues of digitization and automation of manufacturing, maintenance and service processes, using the principles of virtualization, decentralization, real-time work capabilities, service oriented approach, modularity and the Internet of things and services. The following text presents the ideas of prof. Legat, the long-time chairman of the Czech Maintenance Society, who in the interview for the journal All. For. Power stated that "The benefits of implementing the Industry 4.0 initiative to the maintenance processes to enhance the company competitiveness are evident." In addition, you can get acquainted with more detailed ideas mentioned in the above interview:

"Maintenance management in the light of the Industry 4.0 initiative should change significantly. There will be an increased pressure on the transition from the maintenance after failure and periodic maintenance to the predictive and proactive maintenance wherever technically feasible and economically beneficial. The most significant problem that I can see is in the absence of analyses of data in general and automated analyses in particular. There is a lack of sophisticated data analyses, artificial intelligence in the diagnostics of technical condition and failure states, algorithms to calculate predictions of limiting states for recovery, routine planning of preventive maintenance, shutdowns, assortment and stock of spare parts, etc. [Legat 2016].

While many activities are still at the beginning of their solution, some facts are certain. The above mentioned and described changes influence the maintenance policy" [Legat 2013].

Maintenance and deployment of technical diagnostics is also always about costs. It is generally stated that a reduction in maintenance costs of up to 30 % can be achieved.

As mentioned above, currently to meet industry 4.0 requirements, industrial practice increasingly addresses maintenance and related with it issues.

2 GENERAL FEATURES OF TECHNICAL DIAGNOSTICS AND MAINTENANCE

Technical diagnostics is the science of assessing the technical condition of the monitored object, i.e. machines or their parts. The basic concept is a diagnostic variable that carries diagnostic information about the condition of the machine. Depending on this variable, the technical diagnostics is also divided. The most common is for example:

1. Vibrodiagnostics
2. Thermodiagnostics
3. Electrodiagnostics
4. Noise diagnostics
5. Diagnostics of flow rate and surface height
6. Multiparametric diagnostics

These terms are generally known; therefore, they are not further explained.
For the needs of this article vibrodiagnostics as a diagnostic method and vibration acceleration as a diagnostic variable is used.
The main focus of each diagnostic task is to construct a diagnostic system, which is a set consisting of monitored diagnostic variables, a diagnostic object, diagnostic tools (a more common term is a diagnostic instrument), diagnostic methods and methodologies, and also a human factor (mostly a diagnostician).
In practice, it is also important to divide the diagnostics into off-line diagnostics (performed after machine shutdown) and on-line (it is performed when the machine is under operation, a higher level is monitoring when the machine is tracked - monitored for a long time).
Recently, the machine maintenance, in connection with the implementation of the Industry 4.0 initiative, has seen an onset of the use of methodology, which is also called diagnostics; this provides an overview of the datacollected from the machines (import or measurement of specific machines). These data are evaluated anddisplayed in control diagrams. The evaluation of the monitored process is shown both in value and graphically in the form of various indicators, such as total effectivity of device, mean time between failures, mean time of repair, etc. [Bilavcik 2017].
Maintenance is divided into basic types, as can be seen in the following figure.

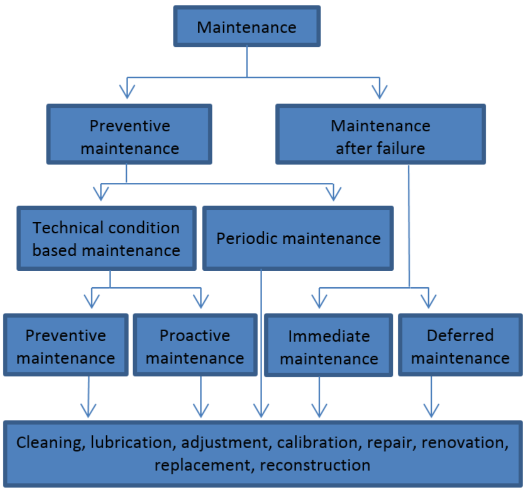

Figure 1. Basic division of maintenance [Legat 2013]

During the evolution of maintenance, various maintenance systems were developed. Their names mostly represented the essence of maintenance. These are, for example, the following systems:

1. System of after failure management
Maintenance is performed after a failure state has been detected. This is the oldest maintenance system that is still in use.
2. System of scheduled preventive repairs
A pre-inspection and, if necessary, a repair is performed after the scheduled time cycle (mostly determined by production). This system is very expensive but still used in some companies at present.
3.System of differentiated proportional care
It determines a degree of complexity of machines, their technical level and technical condition based on apparent manifestations of wear and tear. Maintenance is subjected to costs and failure rate. There is a feedback between the shop floor and other company departments.
4. System of diagnostic maintenance
The actual technical condition of the object is respected, the methods of technical diagnostics are used. Machines are decommissioned only when they have reached a certain wear limit. A limit of diagnostic variable is determined. This system has been commonly used up to the present day. However, it is gradually replaced by the following system.
5. System of prognostic maintenance
It is a continuation of previous diagnostic systems. Measured data on technical condition are also used for trending, which allows for prediction based on various mathematical procedures, such as the least squares method or artificial intelligence methods – neural networks, genetic algorithms, fuzzy systems, etc. It is also currently used regarding the development of Industry 4.0 initiative in maintenance.
6. System of automated maintenance
Efforts to maximize the maintenance performance and minimize costs. Maintenance is a closed system in the production system, which allows for real time control. This control is not possible without powerful computer technology. This current system is used relating to the implementation of the Industry 4.0 initiative in maintenance.
7. System of total productive maintenance (TPM)
It is concerned with maximizing the total efficiency and performance of machines by reducing:

- Number of failures
- Idle run
- Inconsistent products
- Adjustment, etc.

It is important to increase the skills and knowledge through teamwork and motivation of staff. TPM has its own goals, philosophy, strategy, and concept. At present, it is significantly deployed in many companies, each company has its own TPM system.
8. System of reliability centred maintenance (RCM)
This system allows for implementation of a preventive and predictive maintenance program to improve the overall safety and readiness. It allows for the use of a tree of logical reasoning. So far, it is not much used; however,its use is promising and economically beneficial. It is a part of research at our workplace.

3 EXPERIMENT ON MACHINE TOOL SPINDLES

This section describes a specific example of predicting the time series of RMS (Root Mean Square) value of vibrations of machine tool spindles. Based on the experience from several companies in analysing the failures, the spindle is one of the critical points of each machine tool. Also, the costs of its repair are not negligible.

Based on prognosis, it is possible to predict the technical condition of the spindles and thereby of the whole machine.

Vibrations of machine tool spindles were measured on-line in the engineering company.Measurement methodology, data evaluation and further is specified in [Hammer 2016].
The data contain vibration measurements within 60 days, every half an hour, during machining. Nine vibration-related parameters were measured: maximum vibration acceleration, RMS value of vibration acceleration, RMS value of vibration speed, amplitude of rotation frequency of vibration acceleration, and RMS value of vibration acceleration in the frequency bands of 0.2-1 kHz, 1-3 kHz, 3-6 kHz, 6-9 kHz, 9-10 kHz.The frequency range of vibration acceleration measurement is selected based on typical equipment failures.
Artificial intelligence, especially neural networks, and genetic algorithms have been used for prognosis of condition. Moreover, in total, three possibilities of using the neural network are described in the text.
An important general task in the prognosis of spindle vibration status is data pre-processing and optimization of neural network parameters. The measured data were averaged to remove noise and incidental phenomena and normalized in the range 0 to 1.

To predict the data, the forward neural network was first selected.The general scheme of this network is shown in the figure 2.

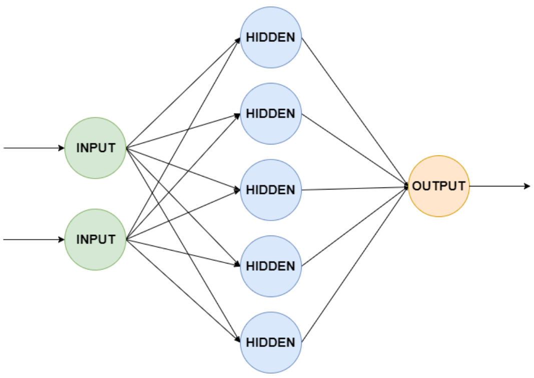

Figure 2. Forward neural network

The MAPE (mean absolute percentage error) criteria was used to assess the prognosis quality, which is described by:

$$M = \frac{100}{n} \sum_{i=}^{n} \qquad (1)$$

where M is MAPE, n is number of fitted points, Y_i is the actual value and P_i is the prognosis value.
A few neural network parameters cannot be determined before the beginning of neural network training. Optimal solutions can be found by systematically scrolling through all possible solutions. Such tasks with less time and computational demands can be solved by using a genetic algorithm. To optimize the neural network parameters and select the variables to predict the total RMS value of vibrations, the following genetic optimization algorithm was used by the authors:
We have the MAPE function criteria F = (x1, x2, x3, x4, x5) for evaluating the quality of the time series of vibration parameters, where:

x1 – length of measurement history from the last N points, based on which the prognosis is compiled.
x2 – number of output values of prognosis.
x3 – number of neurons in the first hidden layer.
x4 – number of neurons in the second hidden layer
x5 – 9-bit binary vector where 1 indicates the presence of a parameter in the data input set, 0 is its absence.
Further, the authors describe the used optimization algorithm in detail:
a. A random initial population of 30 individuals is generated (the value is determined empirically).
b. For each individual from the population, the quality function value (fitness function) is calculated.
c. With the selection operator, the individuals who may become parents can be selected from the population. The Tournament method was used as a selection method. Thus, four individuals are randomly selected. The winner of the tournament in the group will be the individual with the highest fitness value.
d. Then, a crossover operation is performed to obtain a new individual who can get each gene with the same probability from both the first parent and the other one.
e. For each individual of the next generation we go through the entire chromosome, and we are unlikely to add a random number to the values of some genes.The significance of the mutation is that in each generation a feature appears that no individual has ever had; therefore, it could not be passed on to the offspring.
f. The next step is to evaluate the new generations. If an individual appeared that meets the required features, the algorithm ends.
g. If an individual does not meet the required features, the current generation is replaced by a newly generated one.
h. If the termination criteria is not met, the algorithm repeats from the point b. The condition for terminating the genetic algorithm is that the MAPE criteria is less than 5% on the test set. Optimal results were obtained during 29 iterations of the genetic algorithm.
i. A block diagram can be seen in figure 3.
The optimal neural network model was selected using the crossover validation method. Parameters of the neural network that have been optimized: the number of neural network inputs, the number of output layer neurons, the number of hidden layers and the number of neurons in hidden layers. The structure of optimal neural network architecture is shown in Figure 4.

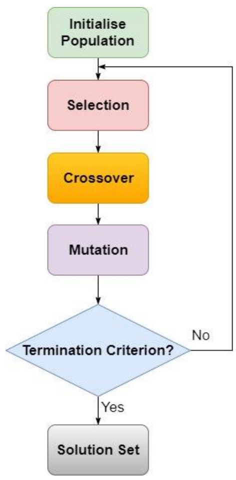

Figure 3. Block diagram of used genetic algorithm

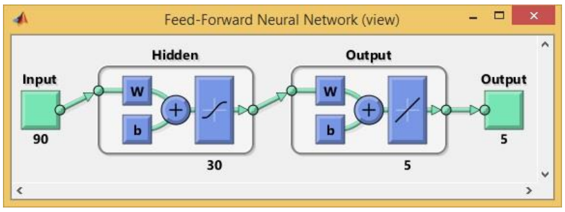

Figure 4. Structure of optimal neural network architecture

According to the outputs of the genetic algorithm for predicting the RMS value of spindle vibrations, the following parameters were chosen: RMS value of vibration acceleration, maximum value of vibration acceleration, and amplitude of speed frequency of vibration acceleration. The feature selection allows for reduction of the number of data on the neural network input, thereby increasing the learning speed of the neural network and reducing the number of irrelevant data and minimizing the likelihood of neural network overlearning.

At the input of the neural network, there are the last 30 measurements of total RMS value, maximum RMS value, and amplitude of rotation frequency of vibration acceleration. The network contains one hidden layer with 30 neurons. We have a prognosis for 5 more measurements of the RMS value of vibration acceleration at the output.

The results of prognosis are shown in figures 5 and 6.The MAPE prognoses are approximately 21.3 %.

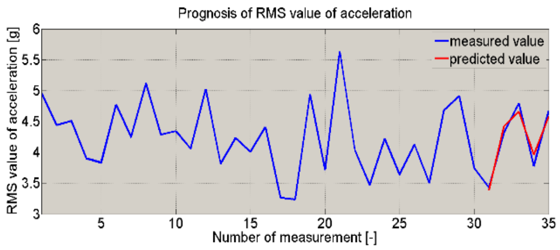

Figure 5. Results of prognosis of RMS value of vibration acceleration

The second method for data prognosis is the use of neural network ensemble. This is a learning paradigm where the final number of neural networks is trained for the same task; the block diagram is shown in figure 7.

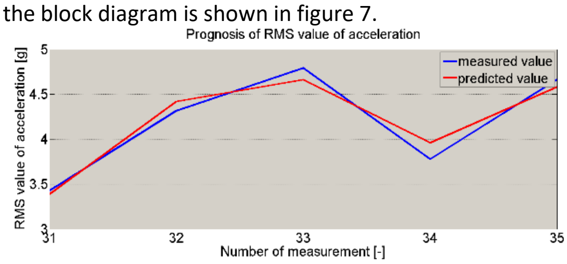

Figure 6. Results of prognosis of RMS value ofvibration acceleration

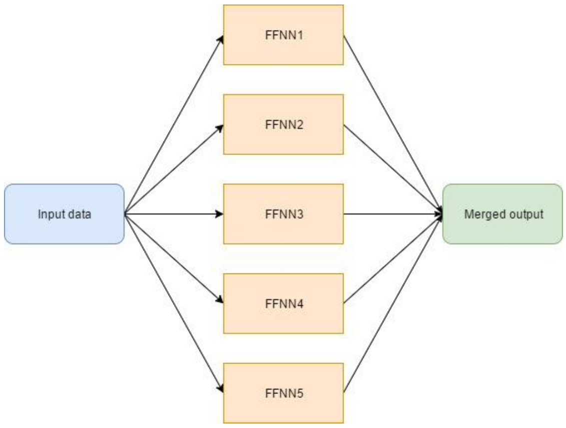

Figure 7. Block diagram of a neural network ensemble

The first step in designing of a neural network ensemble is to teach several neural networks to predict the condition of the machine. Furthermore, the results of the prognosis of neural networks are combined using an arithmetic mean. In the ensemble, forward neural networks with the same architecture as in the previous case and different initialization conditions were used. The optimal number of networks in the ensemble was selected on the validation set. The quality of the prognosis, depending on the number of networks in the ensemble, is shown in figure 8. According to this figure, it is obvious that the optimal number of networks in the ensemble is five.

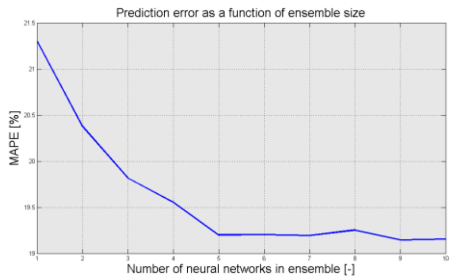

Figure 8. The quality of prognosis depending on the number of networks in the ensemble

When using an ensemble, the result of the prognosis is 19.2%, which is by 2.1% higher accuracy compared to a single neural network.

Following the neural network in figure 2, the RBF (Radial-Basis Function) network, the scheme of which is shown in figure 8, was used. The optimal network architecture was selected using the genetic algorithm: 90 input layer neurons, 341 neurons with RBF activation function of the hidden layer and 5 neurons of the output layer. The network structure is shown in figure 9.

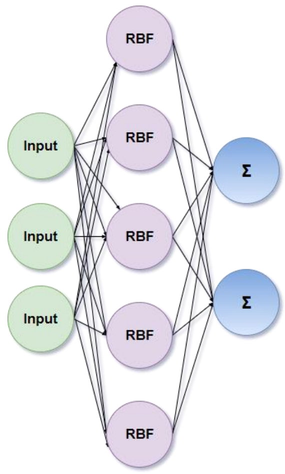

Figure 9. Structure of RBF network.

For our case, the MAPE prognosis using RBF neural networks is 20.4%.
Results were then compared and evaluated.

4 CONCLUSION

In this paper, the authors offer the methods of predicting vibration parameters for monitoring the condition of machine tool spindles. One of the proposed method is based on a multilayer perceptron. Another method is based on the ensemble of neural networks. The last approach of predicting the machine technical condition is based on RBF-neural networks. This article describes the use of a genetic algorithm for optimal selection of neural network parameters and the selection of prediction flags. This approach ensures the maximum accuracy of the machine technical condition prognosis.
For the duration of time series of 30 points and 4 input parameters, the accuracy of the prognosis using a multilayer perceptron for another five measurements is 21.3%. The highest accuracy of the prognosis shows the neural network ensemble – 19.2%. A comparison of prognostic methods is shown in Table 1. In a time-based analysis using last 60 hours of vibration measurements, we can predict the spindle condition for next 10 hours. This makes it possible to predict a possible worsening of the spindle condition.

Method	MAPE [%]
Multilayer perceptron	21.3
Ensemble of neural networks	19.2
RBF-neural network	20.4

Table 1. Comparison of prognostic methods

The results of prognoses show that the proposed methods predict the spindle condition with a feasible accuracy and estimate the development trend of diagnostic parameters. A prognosis of the spindle condition prevents the machine from sudden interruptions in operation and thus reduces the secondary costs associated with interrupting the production process on the production line. Maintenance can be carried out at the closest halt of production, for example, at the end of working hours or the working day. Therefore, we can easily find out the cause of defect with using of offline diagnostic methodology and remove it before this defect develops in a failure and the machine will be suddenly shutdown, with all the consequences.
In the present article, data from on-line vibration diagnostics of spindles of machine tools were used. Those data were obtained in a prestigious company in the Czech Republic. This article is not addressed to finding the cause of failures or diagnostics, but prognosis of diagnostic variables behavior with using of new approaches, namely neural networks and genetic algorithms. Prognosed values will be used as an input to the diagnostic system and subsequently to determine the maintenance procedure.
Of course, everything is also related to the specification of the maintenance policy for the given case at the relevant workplace.
The proposed solution is further elaborated at our workplace. Other machines are diagnosed and the results are evaluated. It is also verified as a part of the technical diagnostics and maintenance, and also deployment of other solutions that are related to the Industry 4.0 initiative, which we deal with at our workplace.

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