3. Applications of neural networks for identifications of loads in mechanical structures

3.1. Introduction

We are facing important shift in machinery management through different types of mechanical structures. The majority of industrial and transport facilities know about condition-based maintenance (CBM) and many of those are using or planning to implement in the near future [8]. This subject is especially important in power plants, aviation systems, high-speed trains, etc., where mechanical components are considered critical. In case of failure, the whole system is forced outage, which causes very high economical losses and even danger for users. Up to now, most of such systems operate with strictly followed overhaul programs. This attitude helped to decrease the number of failures but generated higher maintenance costs and did not guarantee failure avoidance. These goals can be better achieved with CBM. CBM requires that the operator should know the actual technical state of machinery and has the possibility to predict its safe operation live. One of the most important factors that influence safe operation is fatigue usage.

To determine fatigue usage of mechanical components at a given stage of their operations is one of the main tasks of the currently used monitoring and diagnostic system. The scheme of usage monitoring procedure is shown in figure 1.

![Fig.1. Scheme of usage monitoring system](image_url)

The process of predicting safe retirement times for critical machinery components essentially involves three steps, which include:
- generation of operation conditions profile,
- acquisition of fatigue load from measurements for given operation conditions,
- establishment of S-N curve at statistically reduced endurance limit on full scale specimens in the laboratory test.

All of these steps are very important for correct usage determination. First two steps are related to machinery operation but the last one is related to materials data. Due to
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these facts a new identification problem in diagnostics of mechanical structure can be formulated. In the literature there are described two typical approaches to identification of loads of mechanical systems:
- based on measurements of process data (movement data),
- based on structure responses measurements due to loads under identification.

These two approaches can be applied in different operation conditions. The first can be applied if the process data for machinery (driving data for vehicle, flight data for airplanes) are measured, and have influence on load of operating structures. But the second in a case if response on a loads under identification can be measured directly. Relations between process data and load cycles of structures are commonly nonlinear and very difficult to analytical modeling. These reasons are main in choosing neural networks as a basic tool for identification of loads based on process parameters measurements.

The second problem of load identification, based on direct measurements of system responses is a classical inverse identification problem. Some deterministic and intelligent algorithms can be applied in this case. The overview of these methods is shown in a next section of this work.

In this section methodology of load identification based on process data measurements and neural networks is considered.

3.2. Formulation of load identification problem

The main idea of the method of load identification [1] is shown diagrammatically in the figure 2.

![Fig.2. Scheme of presented load identification method.](image)

The relation between process data and load vector is approximated using regression model or neural network. The regression model parameters are estimated based on measurement results [6]. In a case of application of neural network to approximate this relation, neural network is learned based on experimental data [6]. It will be shown bellow that for many real structures such approach gives not enough accurate results. In such a case new approach based on neural network algorithms is proposed. This method includes the following steps:
- Identification of process state
- Identification of loads for particular state

The approach is diagrammatically shown in figure 2.
Both steps of identification can be perform using neural networks. The first step is a classification task, but the second approximation. The task for neural network in the first step is to recognize process state based on measured process data. This classification problem can be solved using deterministic algorithms also. The second step of the approach is an approximation of relation between process data, state of the process and loads of the structure. This approximation has not so complex structures than has procedure shown in figure 1. Modified identification procedure implemented using neural networks is shown in figure 3.

Two applied neural networks have commonly different structures, sometimes for classification of process state simple ADALINE type of neural network can be applied. Type of networks depends on form of surface, which is a boundary between particular process states. For load identification task, which can be formulated as approximation task backpropagation neural networks is commonly use. Realisation of loads identification procedure based on neural networks algorithms is beneficial for on line usage monitoring of complex structures that operate in various conditions. Identified loads can be an input data for procedures of fatigue life calculations and usage assessment.

Application of presented approach for identification of load of helicopter structures during flight is a subject of a next section.

3.3 Identification of helicopter loads during flight

A helicopter structure is subjected to severe loads due to the time varying flight conditions and mission profiles. These loads can result in fatigue damage of flight critical components that can accumulate and cause failure. If component loads can not be carefully monitored the classical maintenance procedures based on assumed operation time limitation has to be applied. But in many helicopter cases this time limit is overestimated due to safety reasons that cause of exploitation cost dramatically increase. Economical and safety reasons are motivations of usage monitoring in
helicopter structures. The most critical helicopter components that are subjected to fatigue loads is rotor system.

Rotor system’s component loads are not routinely measured during flight due to complexity of instrumenting in a rotating system. Several attempts have been made to predict rotor system loads from measurements in the fixed system using statistical approaches and intelligent algorithms. The approach based on regression model of relation between loads and flight data (data recorded using standard flight recorder) is presented in [6] and summarized in the section 5 of this text. Different approach, based on neural network algorithms is shown in [7]. There is shown a case study for SH-60B helicopter and three helicopter components have been under a test: the rotor blade pushroad, blade bending, main-rotor damper. Correlation coefficient between neural network approximation of loads of these component and measured loads has values from 84% to 95%. These values have been accepted by fatigue analyst. To improve quality of load prediction based on measured flight data the innovated approach is proposed and tested on SW-3 PZL Swidnik helicopter. The main rotor damper and bending of main rotor have been predicted using neural network algorithm. The measured loads in a form of strains time histories are shown in figure 4. The results of load measurements have been obtained with special helicopter instrumentation that is not installed as standard helicopter equipment. This data has been used to learn neural networks to predict helicopter load. As flight, data five parameters have been recorded using BUR-1-2 recorder: altitude, horizontal speed, yaw angle, pitch angle, slip angle.
All measurement results are synchronised with main rotor rotation. Due to fact that recorder data set is not continuous and has different sampling frequency for different flight parameters to apply its for neural networks learning data processing has to be done.

Discontinuities of recorded signals have been cancelled by gluing plots at the point of discontinuity, author tried to omit samples in that period of shaft rotation in which discontinuities occurred, also. ut this approach gave bad results and was not recommended.

The biggest amplitudes of loads are in frequency domain up to 20 Hz that recorded signals (recorded with many different frequencies 400 Hz, 100 Hz) have been resample using sampling frequency of 50 Hz. To resample recorded signal averaging procedures are used.

To compress data for neural networks learning only a mean value and maximum amplitude of signal in one rotation of main rotor have been used.

Two main tasks are solved using neural networks:
- classification of flight state,
- determination of stress amplitude for particular flight states.

The concept of neural network that solves such formulated tasks is shown diagrammatically in figure 4. For a state classification based on flight data backpropagation neural networks is applied. Input layer has five neurones but hidden layer has 6 neurones ( it is the best configuration with minimal dimension to solve formulated classification task). The neural network has 44 outputs each for particular flight state. The architecture of this network has been chosen based on numerical experiment. Learning process of such neural network is based on backpropagation mechanism. Particular output of the classification neural network is activated for particular flight state. Based on this decision the appropriate neural network for given flight state is chosen. This network is dedicated for load identification. Each neural network for load determination has five neurones in input layer and different number of neurones in hidden layer. This number depends on recognised flight state. As an output the main rotor damper load and bending loads of main rotor are obtained. The mean
value and amplitude of these loads are given. These two load characteristics are necessary to determine fatigue of helicopter critical components.

The architecture of classification neural networks is shown in figure 6. This neural network has complex structure, contains two types of networks: two state decision element which classify provisionally flight state for four groups and backpropagation type of neural network for classification of state within these groups. At a first step speed is a feature which has different value for different state, generally we can distinguish states with velocity 0 and velocity different then zero. Helicopter manufacturer as possible flight states finds this number applied neural network distinguishes 44 different flight states, for tested helicopter.

![Fig.5. Scheme of applied load identification procedure using neural networks.](image)

The output signal form state classification neural networks is used in proposed procedure to select neural network for loads identification. These neural networks are chosen as typical backpropagation neural networks with sigmoid type of activation function mean value and amplitude of damper load and bending load of main rotor are determined as an output of neural network. These data can be used for fatigue rest life calculation. The learning process is performed using backpropagation algorithm and SSE error as a quality criterion. The value of the error to stop learning procedure is set as 0.001. Very important step in neural networks learning is a choice of training data base. The training data set is the set of known input/output pairs that is used to train neural network. The training data set should be chose that captures all of the information required but not is biased to any given condition. If certain conditions are
over emphasised in the training data set, they will dominate the solution process and bias the model to perform well for that condition but poorly for others. A testing data set is also extracted from the flight measurements data base. This data set is not used during training of the network but rather data from different flight test should be chosen. It is possible for poorly trained network to predict training set well but will be probably unable to generalise results for a new data set. A history of learning of neural network for state classification is shown in figure 7. In this case, 2338 epoch was necessary to achieve limit value of SSE error.

Fig.6. Architecture of classification neural network applied for flight state classification.
Performance of neural network not only depends on the training data set but also on its physical design. Currently, the methodology to determine the optimum network design for given problem does not exist. A design sensitivity study was conducted in order to ascertain the appropriate number of hidden–layer nodes necessary for accurate performance. A single hidden layer design was chosen and the number of neurones in the hidden layer was varied from 5 to 20 in increment of 1. The neural network for load identification has been learned based on measurements load during flight for different flight conditions. The experiment was done for all 44 flight conditions and in data base used for learning all flight conditions have been represented. During the experiment, a strains at chosen points of helicopter structure have been measured. The backpropagation algorithm was applied for learning. The measured and predicted load...
are shown in figure 9 and in form of mean value of amplitude and maximum of amplitude in figure 10. To show convergence between predicted and measured load the correlation has been tested. Correlation test results are shown in figure 11. As we can notice from above plots designed neural networks gives a good approximation of helicopter component loads.

Fig. 9. Measured and predicted mean value of amplitude (normalized) of bending load of helicopter rotor.

Fig. 10. Maximum of amplitude of bending load of helicopter rotor.
3.4. Conclusions and final remarks

Neural networks seem to be a very effective tool in flight state classification and load identification of helicopter structures, but learning process is very time consuming process which strongly depends on used training data set. But load prediction process using neural networks approach is very effective and can be done on-line. Further research that is continuation of this study should go in direction of hardware realisation of trained neural network and direct application on helicopter board.

3.5. Literature for section 3