Identification of loads in mechanical structures – helicopter case study

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This paper presents possibility of identification of loads in mechanical systems based on response measurements during operation. Information of loads is very useful in diagnostic process, if usage of structure is under investigation. State of the art in the field of loads identification is presented. The problem of load identification is defined, and some methods are presented. The paper is focused on the problem of loads identification based on measurements of process parameters or movement parameters for vehicles or airplanes. Two methods are applied to show applicability of this approach in industrial practice; neural network based method and regression model based method. A case study of identification of load of helicopter structure during flight is presented.

Keywords: Loads identification, neural networks application for loads identification, helicopter loads identification, regression model for load identification

1. INTRODUCTION

The aim of diagnostic procedure of mechanical structures is to determine its technical state and if is not satisfactory to localise faults and assess its dimension. One of the most commonly use diagnostics of rotating machinery is vibrodiagnostics that consist of vibration measurements during operation and estimation of chosen state symptom. As a state symptom some signal estimates like mean value of amplitude, spectrum, RMS, p-p value can be used. The vibration can be measured in continuous way by monitoring system or can be measured periodically with given state dependent period. When during testing vibration level exceeds given standards or manufacturer recommendations reasons should be identify. Proposed diagnostic procedure diagrammatically is shown in Fig. 1. There are two basic reasons of increasing vibration levels of operating machinery:

- too big excitation level caused by machinery faults,
- resonance of the structure.

The first case of machinery malfuntion is considered in this paper. In a case when main reason of decreasing vibration level is big excitation level the source of this excitation should be identify by means of localisation and assessment. This requires special procedures for identification of loading forces for operating structures based on response measurements. If loads of the structure is known an usage monitoring can be implemented. Sometimes it is impossible or impractical to use special transducers that are installed on a structure, then methods based on process parameters measurements are recommended. This approach is diagrammatically shown in Fig. 2. But in many industrial cases the relations between loads and process parameters are very complex and difficult to analytical formulation. 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.

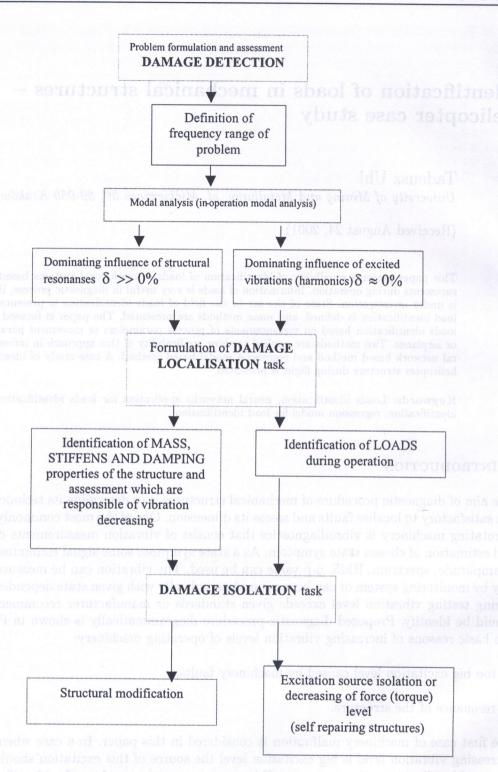


Fig. 1. The scheme of proposed diagnostic procedure

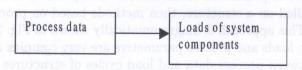


Fig. 2. Scheme of presented load identification method

To identify operational load based on process parameters or system response measurements many methods can be employed [1, 4, 5, 7, 9, 10, 13]. These methods are classified into three main categories:

- deterministic methods,
- stochastic methods,
- artificial intelligence based methods.

To deterministic methods of load identification belong two main techniques:

- frequency domain methods [7, 9, 10],
- time domain methods [1, 4, 13].

This classification is based on signal processing methodology applied for experimental data which are necessary to perform estimation of loads parameters process.

Basic methods of identification of excitation forces have been formulated for linear systems in which assumption about small damping and stationarity of parameters are valid. Methods in frequency domain require information about FRF (Frequency Response Functions) for investigated structures and spectrum of system responses measured during operation. Based on these information spectrum of excitation forces can be estimated.

Similar methods are formulated in time domain, using relation between excitation and system responses in a form of convolution. An iterative formula for calculation of excitation forces in mechanical structures is proofed based on properties of Toeplitz matrix [5].

Identification of excitation forces can be performed using mutual energy theorem formulated by Heaviside at 1892 [3, 16]. This method allows to identify spectrum of loads based on response (in a form of vibration velocity) measurements [7, 9].

Given above identification methods can be used for systems which are linear but not for nonlinear. For both linear and nonlinear systems, methods based on minimization of given objective function can be employed. Mainly a least square error between simulated and measured system response is used as objective function in this identification method. The dynamic programming optimization method formulated by Bellman [15] is commonly use for minimization of objective function to estimate excitation forces. Some examples of application of these methods are shown in [4, 15]. Similar approach based on genetic algorithms is presented in [18].

Statistical approach is formulated using statistical models of relation between system response or process parameters and operational loads of the structure. The approach based on regression model of relation between loads and flight data (data recorded using standard flight recorder) is presented for helicopter in [12, 19, 20]. The quantitative measure of quality of regression model is coefficient of determination R^2 that is, for many components of investigated helicopter type H-53, relatively low 78% [20]. It was a motivation to find better methodology of loads prediction and shows that linear model is not sufficient to find loads of particular helicopter components based on flight data. Proposal of application of neural networks for such data is shown in this paper. But, conducting regression analysis during the evolution of flight loads survey can be a valuable tool in providing the fatigue analyst with understanding of the process parameters that influence loads. Such information is not available from neural networks based approach.

2. FORMULATION OF LOAD IDENTIFICATION PROBLEM

The main idea of the method of load identification [17] is shown diagrammatically in Fig. 2.

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 [2, 8]. 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. In a case of application of neural network to approximate this relation, neural network is learned based on experimental data [2, 6]. This method includes the following steps:

- identification of process state
- identification of loads for particular state

The approach is diagrammatically shown in Fig. 3.

Both steps of identification can be performed using neural networks. The first step is a classification task, but the second approximation one. 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 for many industrial cases 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. Modified identification procedure implemented using neural networks is shown in Fig. 4.

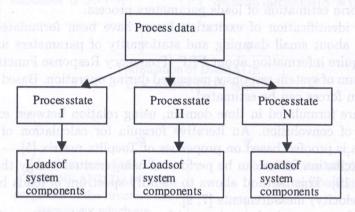


Fig. 3. Proposed identification procedure

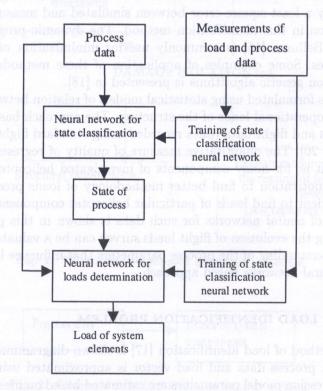


Fig. 4. Scheme of proposed neural network based realisation of load identification task

These 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 used [14].

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. IDENTIFICATION OF HELICOPTER LOADS USING NEURAL NETWORKS

A helicopter structure is subjected to severe loads due to the time varying flight conditions and different 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 are rotor and blades systems.

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 [12, 14, 20] and summarized in the paper. Different approach, based on neural network algorithms is shown in [6]. 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 results of load measurements have been obtained with special helicopter instrumentation that is not installed as standard helicopter equipment. This data has been taken to learn neural networks to predict helicopter load. As flight data, five parameters recorded using BUR-1-2 recorder: altitude, horizontal speed, yaw angle, pitch angle, slip angle are used. All measurement results are synchronised with main rotor rotation.

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

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 Fig. 5. For a state classification based on flight data backpropagation neural networks is applied. Input layer has five neurons, but hidden layer has 6 neurons (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 is chosen based on numerical experiment. Learning process of chosen neural network is based on backpropagation mechanism. Particular output of the classification neural network is activated for particular flight state, Based on this classification

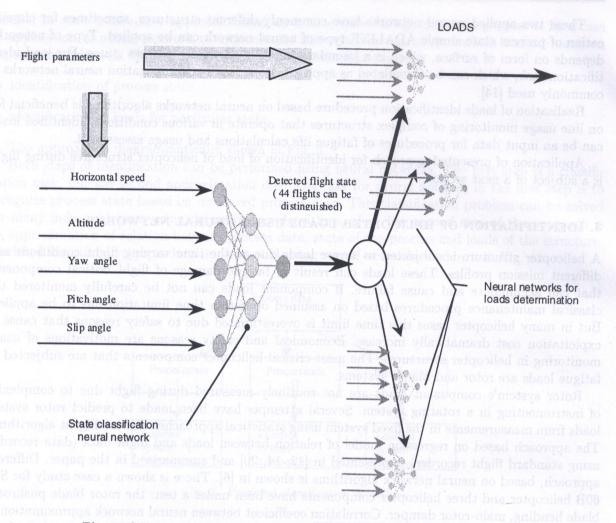


Fig. 5. Scheme of applied load identification procedure using neural networks

the appropriate neural network for given flight state is applied for load identification. Each neural network for load determination has five neurons in input layer and different number of neurons in hidden layer. This number depends on recognised flight state. As an output the main rotor damper load is obtained based on flight parameters treated as input to neural networks. The mean value and maximum of load are result of this identification procedure. These two load characteristics can be use to determine fatigue of helicopter critical components.

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 maximum amplitude of damper load 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 learn 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. Performance of flight state classification neural networks is shown in plot (Fig. 6)

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

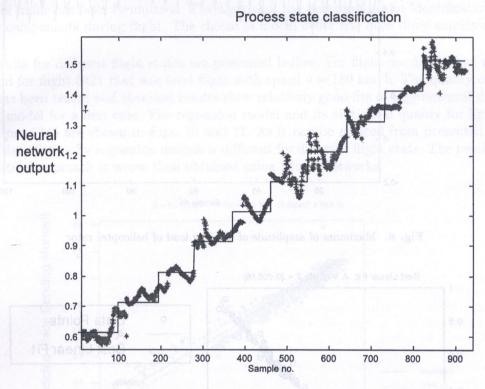


Fig. 6. Performance of state classification neural network

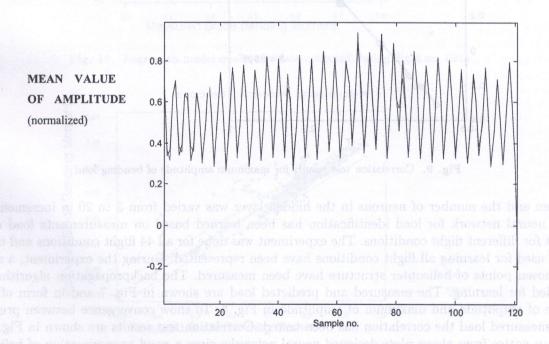


Fig. 7. Measured and predicted mean value of amplitude (normalized) of bending load of helicopter rotor

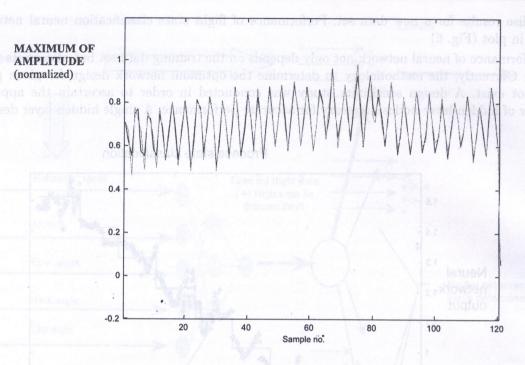


Fig. 8. Maximum of amplitude of bending load of helicopter rotor

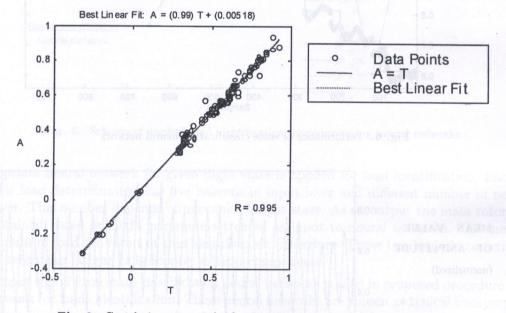


Fig. 9. Correlation test results for maximum amplitude of bending load

chosen and the number of neurons 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 Fig. 7 and in form of mean value of amplitude and maximum of amplitude in Fig. 8. To show convergence between predicted and measured load the correlation has been tested. Correlation test results are shown in Fig. 9. As we can notice from above plots designed neural networks gives a good approximation of helicopter component loads.

4. APPLICATION OF REGRESSION MODELS FOR HELICOPTER LOADS IDENTIFICATION

The idea of application of linear multiple regression for identification of loads in mechanical systems is based on approximation using regression model relation between process parameters and load vector. This method allows defining which process states have influence on load vector. For many different applications described above technique gave a promising results [2, 11, 18, 19].

To apply described above method for load identification the special MATLAB based procedure in a form of m.file has been formulated. The algorithm has been applied for identification of load of helicopter components during flight. The choice of model order has been done employing stepwise regression.

The results for different flight states are presented bellow. For flight no. 6245, that was vertical take off and for flight 6421 that was level flight with speed $v=180~\rm km/h$. The quality of regression function has been tested and obtained results show relatively good fits of experimental data by used regression model for a first case. The regression model and its statistical quality for light no. 6421 and flight no. 6245 are shown in Figs. 10 and 11. As it can be noticed from presented results the quality of data fitting by regression models is different for different flight state. The results obtained with statistical approach is worse then obtained using neural networks.

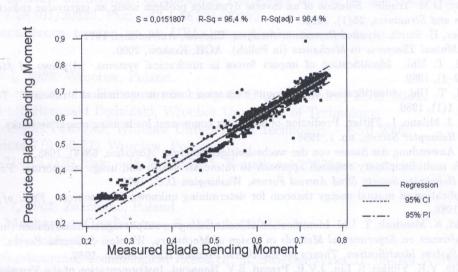


Fig. 10. Regression model quality for data collected during flight no. 6245

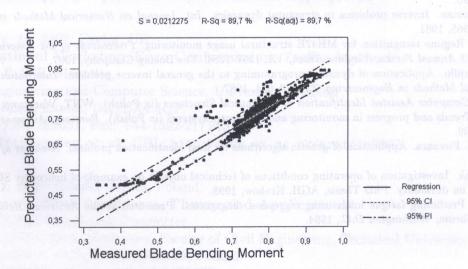


Fig. 11. The quality of regression model for flight no. 6421

5. 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. For particular flight states regression model is enough good approximation of relations between flight parameters and loads of helicopter structure.

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.

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REFERENCES

- [1] H.R. Busby, D.M. Trujillo. Solution of an inverse dynamics problem using an eigenvalue reduction technique. Computers and Structures, 25(1), 1990.
- [2] N.R. Draper, H. Smith. Applied Regression Analysis. Elsevier, Amsterdam, 1971.
- [3] Z. Engel. Mutual Theorems in Mechanics (in Polish). AGH, Kraków, 2000.
- [4] J. Giergiel, T. Uhl. Identification of impact forces in mechanical systems. Archives of Machine Design, XXXVI(2-3), 1989.
- [5] J. Giergiel, T. Uhl. Identification of the input excitation forces in mechanical structures. The Archives of Transport, 1(1), 1989.
- [6] D.J. Haas, J. Milano, L. Flitter. Prediction of helicopter component loads using neural networks. Journal of the American Helicopter Society, no. 1, 1995.
- [7] M. Hackl. Anwendung des Satzes von der wechselseitigen Energie. Acoustica, 58(4), 1985.
- [8] D. Hall. A multidisciplinary research approach to rotorcraft health and usage monitoring. Presented at the American Helicopter Society 52nd Annual Forum, Washington D.C., 1996.
- [9] J. Li. Application of mutual energy theorem for determining unknown force sources. Proc. of Internoise 88, Avignion, 1988.
- [10] W. Lisowski, K. Mendrok, T. Uhl. Identification of loads basing on output signal measurement (in Polish). Proc. of 5th Conference on Experimental Methods in design of Machinery, Wrocław-Szklarska Poręba, 2001.
- [11] L. Ljung. System Identification, Theory for the Users. Prentice Hall, London, 1987.
- [12] D.P. Schrage, Y.K. Yillikci, S. Liu, J.V.R. Prasad, S.V. Hanagud. Instrumentation of the Yamaha R-50/RMAX helicopter testbed for air loads identification and follow-on research. *Journal of the American Helicopter Society*, no. 3, 1996.
- [13] S.S. Simonian. Inverse problems in structural dynamics. Int. Journal on Numerical Methods in Engineering, 17: 357-365, 1981.
- [14] R. Teal. Regime recognition for MH47E structural usage monitoring. Proceedings of the American Helicopter Society 53 Annual Forum, Virginia Beach, VA, 1267-1284. The Boeing Company, 1997.
- [15] D.M. Trujillo. Application of dynamic programming to the general inverse problem. *International Journal on Numerical Methods in Engineering*, 23: 613-624, 1987.
- [16] T. Uhl. Computer Assisted Identification of Mechanical Structures (in Polish). WNT, Warszawa, 1998.
- [17] T. Uhl. Trends and progress in monitoring and diagnostic systems (in Polish). Pomiary, Automatyka, Kontrola, no. 4, 1999.
- [18] T. Uhl, J. Pieczara. Application of genetic algorithms for load identification problem. Archives of Transport (in print).
- [19] A. Wasilak. Investigation of operating conditions of technical objects on example of helicopter SOKOL and its influence on durability. PhD Thesis, AGH, Kraków, 1998.
- [20] L. Zion. Predicting fatigue loads using regression diagnostics. Presented at the American Helicopter Society Annual Forum, Washington D.C., 1994.