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SMART OPERATIONAL LOAD MONITORING USING DECISION TREES AND ARTIFICIAL NEURAL NETWORKS: A COMPARATIVE STUDY

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Abstract: *Operational Load Monitoring is an industrial process that allows to predict the remaining in-service life of a mechanical structure under variable loads. Data from sensors embedded or mounted on the structure is acquired and allows to estimate the number and amplitude of load cycles that the structure has withstood so far in its working environment. This process is especially important in the aerospace industry where mechanical structures of an aircraft are monitored in order to maximize their operating lifetime. Smart Operational Load Monitoring means implementation of artificial intelligence techniques to the process in order to make predictions based on measurements from reduced number of sensors. In this paper a composite lightweight structure of typical geometry used in aircraft structures is taken as an example for Smart Operational Load Monitoring. The predictions are made from measurements from six strain gauges mounted to the structure, using carefully prepared artificial intelligence-based models. Efficiency of the models is compared, in terms of their prediction accuracies and computational complexities.*

Keywords: Artificial intelligence, Decision trees, Operational load monitoring, Artificial neural networks, Lightweight structures.

1. Introduction

Operational Load Monitoring (OLM) is an industrial process of measuring and registering of the number and amplitude of load cycles that a mechanical structure withstood in its working environment. The purpose is to make predictions about the remaining in-service life of the structure, taking into account possible fatigue failure. This process is especially widely applied in aerospace industry to monitor the aircraft structure usage and maximize the time to replacement without compromising flight safety (Dziendzikowski et al., 2021).

Normally sensors should be mounted in all critical points of the structure (where stress or strain concentrations are possible). However, if the structure is loaded at different points and directions over time, the number of critical points might be too high to handle, making the OLM less accurate. The authors in their previous work (Mucha et al., 2020a) proved that if all possible load cases of the structure can be identified and simulated, Smart Operational Load Monitoring (SOLM) can be applied. It is most important to have an accurate, experimentally verified and validated, numerical model of the monitored structure. The structural behavior is described by a boundary value problem (Piasecka-Belkhayat and Korczak, 2020) therefore, finite element-based (Grzejda, 2021, 2014) software can be utilized to create the parametric numerical model. With such model, the state of the structure and sensor measurement values can be simulated for every possible load case. Based on such generated reference data, artificial intelligence techniques can be utilized to train a prediction model that will provide fast and quite accurate information about the current state of the structure from sensor measurements. In (Mucha et al., 2020a) the authors used an artificial neural network (ANN) to make the predictions of inversed safety factor of the structure based of measurements from strain gauges. ANNs are computing systems of connected artificial neurons,

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bioinspired on principles of data processing in animals' brains. An artificial neuron is basically a mathematical model of a biological neuron. It receives multiple input signals, processes it as weighted sum of inputs by linear or nonlinear function, and returns single output. Neurons in ANN are organized in layers where every neuron in a layer receives the same information from previous layer and processes it simultaneously (Livingstone, 2009).

This paper presents an investigation of the possibilities of implementing decision trees (DTs) as the predictor in SOLM. DTs are supervised learning methods used for classification and regression problems. They are based on tree-like model with nodes and branches. Every internal node is a test on an attribute and each connected branch represents the outcome of the test. The end nodes are leaves that represent the final decision based on the series of connected tests (Rokach and Maimon, 2014). DTs with different complexity levels were built and tested in SOLM task with experimentally measured input data. The accuracy and computational complexity of the DTs were compared with the ANN described in (Mucha et al., 2020a).

2. Considered structure

The considered structure is a hat-stiffened panel made of carbon woven / epoxy laminate, with overall dimensions of 597 x 204 x 29 mm, presented in fig. 1a. It is a structure of typical topology used in aerospace industry for aircraft skin (Pravallika and Yugender, 2016). Boundary conditions are presented in Fig. 1b: displacements on line BC1 are fixed in every direction, displacements on line BC2 are constrained in vertical (Y) direction, the panel can be loaded vertically (in -Y direction) at any point on line BC3. Three strain gauges are mounted on the top surface, and three on the bottom rib, as shown in Fig. 1b and 1c, respectively. Finite element model was created and presented in Fig. 1d, only surface elements were applied. Surfaces representing strain gauges locations and 31 points of load at line BC3 were separated where the mesh was refined.

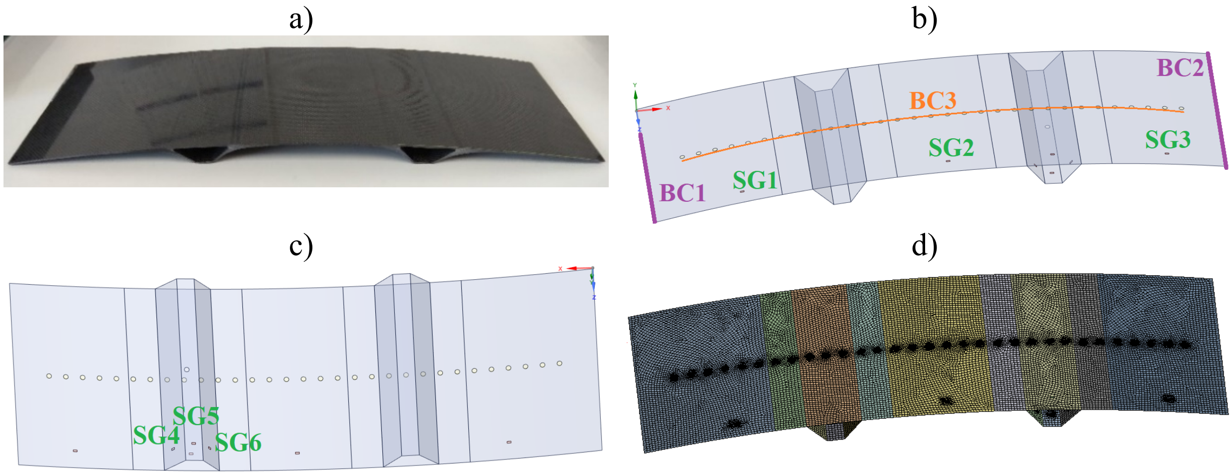

Fig. 1: Considered structure: a) photograph, b) boundary conditions and top strain gauges locations, c) bottom strain gauges locations, d) finite element model.

The finite element model was verified and validated experimentally, as described in (Mucha et al., 2020b). Then the model was parametrized, and 1241 analyses performed, corresponding to loads up to 20 N at every discrete load point at line BC3. For every analysis, average normal strains at surfaces SG1-SG6 and corresponding inversed safety factor (ISF) were acquired, making the reference data to the prediction model. Inversed safety factor was calculated as maximal from three criteria: maximal strains, maximal stresses, and Tsai-Wu failure criteria for composite materials. The schema of inputs and outputs to the prediction model is presented in Fig. 2a.

The requirements for the prediction model are high accuracy and low computational complexity, taking into account possible real time applications in industrial SOLM. All the presented models were trained with the numerically generated (from parametrical finite element model) reference data for all possible load cases. Then the models were tested using experimentally acquired data from strain gauges for a single load point, in the very middle of the panel. In the experiment, a universal testing machine and data acquisition systems (for applied force and resulting strain signals) were used. Photograph of the experimental setup is presented in Fig. 2b. In order to compare the trained models with each other, the root-mean-square error

(RMSE) between the predicted and actual ISF values, and computational time were measured when the models were introduced to 538 experimentally acquired data samples.

a) b)

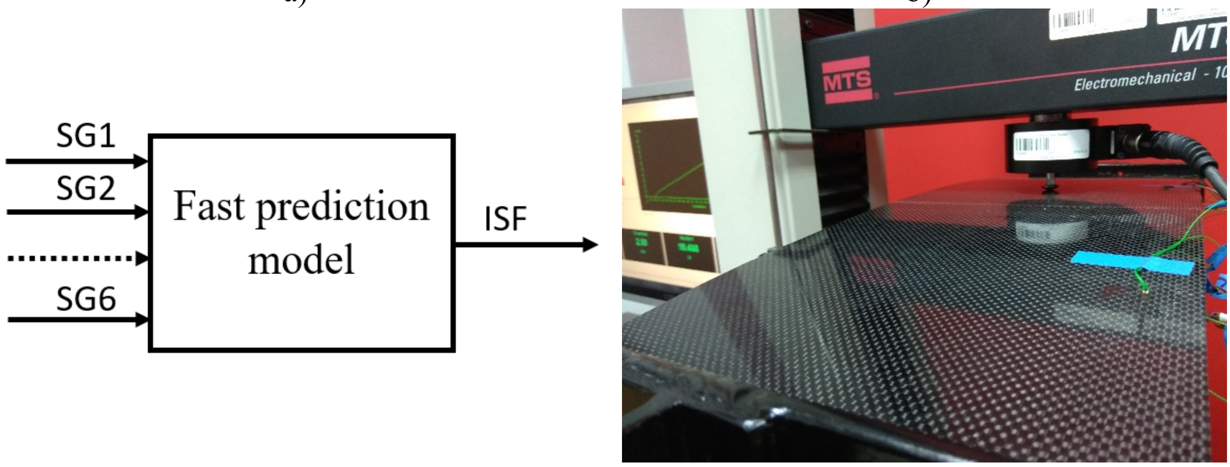

Fig. 2: Prediction model: a) schema of inputs and outputs, b) acquisition of data for model verification.

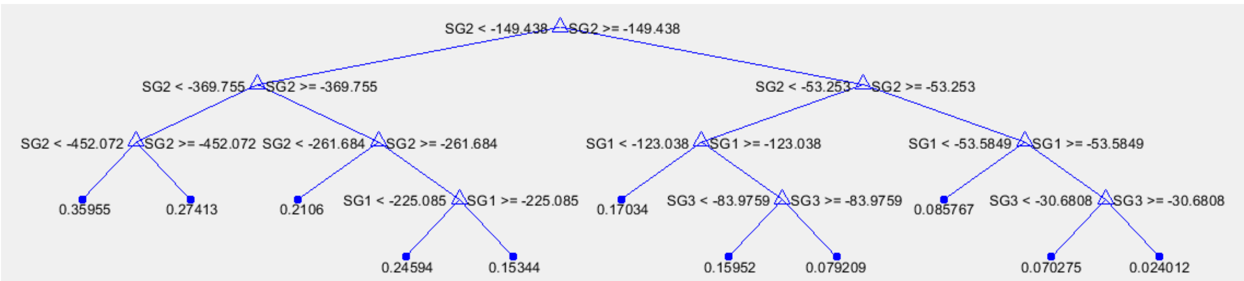

Fig. 3: Structure of DT1: decision tree with 10 splits (triangle nodes).

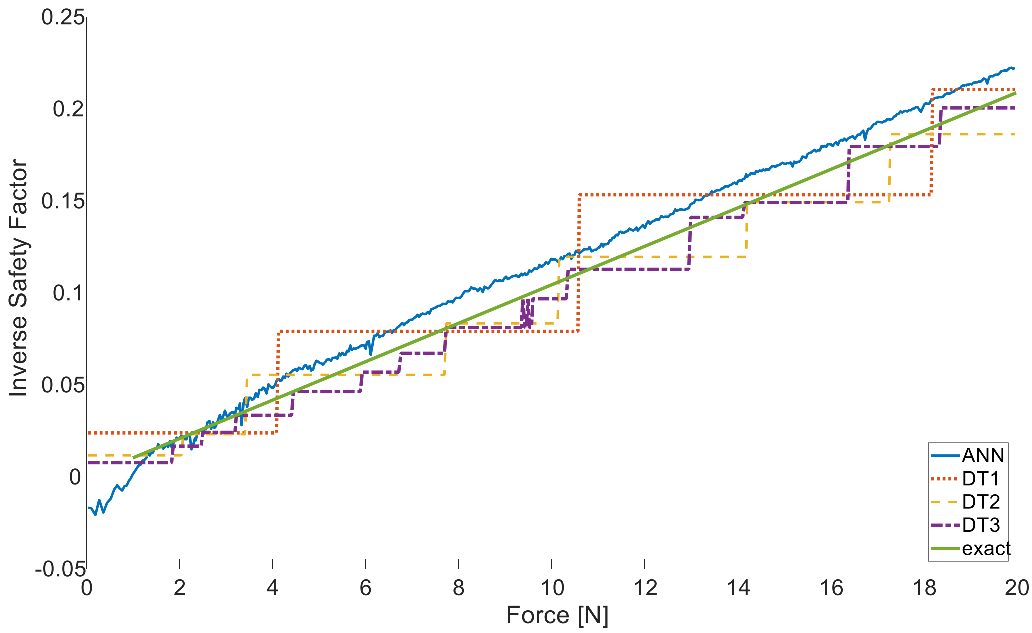

Fig. 4: Prediction results for experimentally measured input data, for considered prediction models

Tab. 1: Comparison of the obtained prediction models.

Criterion	ANN	DT1	DT2	DT3
RMSE []	0.0109	0.0190	0.0143	0.0077
comp. time [ms]	0.26	2.49	2.97	3.52

The reference prediction model is the ANN, described in (Mucha et al., 2020a). The ANN is two-layered feed-forward, with nine neurons of sigmoid activation function in the hidden layer, and one neuron of linear activation function in the output layer.

Three binary decision trees were fitted with the reference data. For each tree the maximum number of splits was fixed: 10 splits for DT1, 50 splits for DT2, and 100 splits for DT3. For each of the trees, 1000 attempts of fitting were made, from which the best tree was chosen based on RMSE. For each attempt, new random 70% of reference data was chosen as training data. The structure of DT1 is presented in Fig. 3.

Predictions of the considered models, when introduced to experimentally measured signals from strain gauges, compared to exact output results are presented in Fig. 4. Exact results are known, as the applied force was measured in the experiment and ISF could then be simulated from the FE model. Comparison of accuracy and numerical complexity of all the prediction models is presented in Tab. 1.

3. Conclusions

The accuracy of the decision trees was dependent on the complexity of their structure. The more splits were allowed in the fitting process, the more possible "boxes" of the outcome were obtained, as clearly indicated by the plots in Fig. 4, and the highest accuracy of predictions was achieved, as observed by RMSE values in Tab. 1.

When comparing ANNs and DTs, the important advantage of the latter was higher noise resistance. As one can see in Fig. 4a, for low strain values (where the noise was relatively high compared to the signal values), the predictions of ANN were negative and that does not have physical representation. This problem did not occur in any of the DTs.

On the other hand, the disadvantage of DTs comparing to ANNs is the numerical complexity. Rather small ANN (with only 9 hidden neurons) returned more accurate predictions that DT2 with 50 splits. Only DT3 with a high number of 100 splits was able to produce results with smaller RSME than the ANN, but at expenses of a higher computation time

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References

Dziendzikowski, M., Kurnyta, A., Reymer, P., Kurdelski, M., Klysz, S.; Leski, A. and Dragan, K. (2021) Application of Operational Load Monitoring System for Fatigue Estimation of Main Landing Gear Attachment Frame of an Aircraft. *Materials*, 14(21), 6564.

Grzejda, R. (2014) FE-modelling of a contact layer between elements joined in preloaded bolted connections for the operational condition. *Advances in Science and Technology Research Journal*, 8, 24, pp. 19-23

Grzejda, R. (2021) Finite element modeling of the contact of elements preloaded with a bolt and externally loaded with any force. *Journal of Computational and Applied Mathematics*, 393, 113534.

Livingstone, D. J. (2009) *Artificial Neural Networks: Methods and Applications*. Humana Press.

Mucha, W., Kuś, W., Viana, J.C. and Nunes, J.P. (2020a) Operational Load Monitoring of a Composite Panel Using Artificial Neural Networks. *Sensors*, 20, 2534.

Mucha, W., Kuś, W., Viana, J.C. and Nunes, J.P. (2020b) Experimental validation of numerical model of composite panel for aerospace structural applications, In: Fuis, V., ed., *Engineering mechanics 2020*, Brno University of Technology, Brno, pp. 358-361.

Piasecka-Belkhayat, A. and Korczak, A. (2020) Analysis of ultrashort laser pulse irradiation with 2D thin metal films using the fuzzy lattice Boltzmann method. *Journal of Theoretical and Applied Mechanics*, 58, 1, pp. 209-219.

Pravallika, K. and Yugender, M. (2016) Structural Evaluation of Aircraft Stiffened Panel, *International Journal of Science and Research,* 5, 10, pp. 753-759.

Rokach, L. and Maimon, O. (2014) *Data Mining with Decision Trees: Theory and Applications.* World Scientific.