Force prediction in bolts of flange connections – elastic waves and soft computing approach

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Abstract

In this paper an idea of the force identification in bolts was proposed. It takes advantage of the elastic wave propagation phenomenon which are introduced and measured by piezoelectric transducers. An experimental test was performed on the bolt of flange connection. The connection was mounted in a static test machine and loaded with tension. It was noticed that force changes influence signals measured by sensors, what was reflected also in principal components calculated. The obtained patterns data base was then used for the training artificial neural networks (ANNs). Preliminary obtained results showed that ANNs are able to predict the force in bolts with reasonably well accuracy, but their generalization ability should be improved.

Keywords: artificial neural networks, elastic waves, force prediction, flange connection

1. Introduction

Force measurement in bolts is important in many industrial and engineering applications. Most often they are carried out during the structure assembly using a torque wrench. More precise devices are usually used in experimental tests of prototype connections, in order to study the behaviour of their individual components. The second area are non-destructive tests (NDT) and structural health monitoring (SHM) systems which enhance safety and reliability of structures.

There exists also a group of joints where a level of pretension force influence the strength of a slip resistance connection [2]. In this case, pretension force changes over time may become a very important issue, especially in cyclically-loaded constructions such as bridges, telecommunication towers or wind turbines.

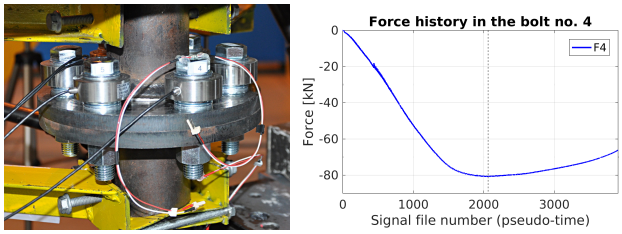
The idea proposed in this paper takes advantage of the elastic wave propagation phenomenon. It can be expected that even relatively small change in a bolt force will affect the signals measured (its time of flight, amplitude, frequency, etc.) [1, 3].

2. Laboratory tests

A flange connection consisted of six bolts M16 of class 5.8 was investigated in a static test machine. Four bolts were equipped with washer strain load cells. One of them was also instrumented with piezoelectric transducers (Fig. 1a) in order to excite and measure elastic wave signals. An axial force history measured on this bolt (no. 4) by washer strain cell was shown in Fig. 1b. The test was terminated at the time when some of the bolts have been torn off.

2.1. Laboratory equipment

The laboratory setup consisted of a signal generator (TTi) where an excitation was defined in the form of 2.5 sine wave modulated by Hanning window. Then the signal was amplified and split to the actuator and the synchronization channel. A digital oscilloscope (LeCroy) was used to store signals received from sensors. Two piezoelectric transducers were mounted on the bolt's head (actuator and sensor) and one at the end of its shank (sensor). The sensor wax was used do mount transducers, which enables their non-invasive recovery. Only sensor cables were temporary fixed in single points with adhesive applied hot.



(a) (b)

Figure 1: (a) The flange connection investigated; (b) force history received during the static test from a washer strain cell installed on the bolt no. 4.

2.2. Elastic waves

Elastic wave signals were excited and recorded with frequency close to 0.5 Hz. Until the connection was destroyed, 3902 signals were stored from each sensor. Exemplary signals received at both sides of the bolt for selected force levels were shown in Fig. 2. It can be noticed that force variations affect also the signals measured (mainly through amplitude changes).

The elastic wave signals were filtered and principal components analysis were performed in order to reduce the data size [4]. The calculated components and the force values measured have formed a pattern database used for ANNs training.

Preliminary simulations have shown that the ANNs training with data related with the sensor placed at the shank end have caused that the learning process was more stable and the standard deviation of results was lower than in case of the sensor on the bolt's head. Therefore, it was decided at this stage of investigation, that only pitch-catch signals will be used for the purpose of training the diagnosis system.

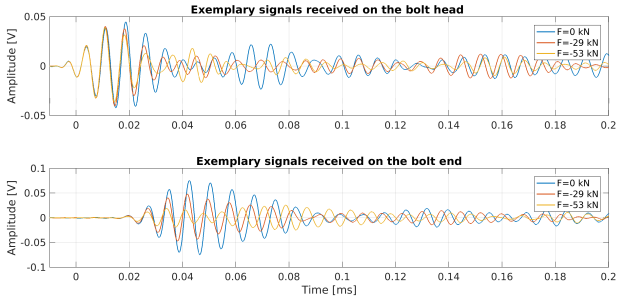


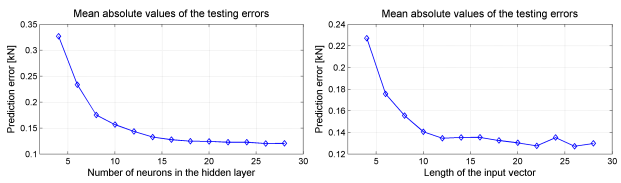
Figure 2: Elastic wave signals measured by piezoelectric transducers installed on the bolt's head end the shank's end.

3. ANNs and their architecture

A force identification provides information about the predicted value of that force with respect to parameters that are sensitive enough to its changes. The correct selection of these parameters is the most important issue in any identification task.

For the mentioned task feedforward ANNs are commonly used. They consist of an input (first) layer, usually one or two hidden layers and an output layer. The number of elements in the input/output layers is determined by the size of a pattern database. Improved accuracy of the neural algorithm may be obtained by tuning its architecture. Therefore, a series of simulations have been carried out to find the most appropriate length of the input vector and the number of neurons in the hidden layer.

First, the input vector consisted of 10 principal components, while the number of neurons in the hidden layer was varying from 4 to 28. From the set of 3902 patterns, 867 and 433 were selected with constant distribution for testing and validation vectors (together 1/3 of the patterns). For each variant simulations of ANNs training were repeated 50 times. The obtained results of mean testing errors were shown in Fig. 3a. It can be noted there that the value of 16 neurons in the hidden layer provided very accurate prediction results.



(a) (b)

Figure 3: Testing error variation with respect to (a) the number of neurons in the hidden layer and (b) the size of the input vector.

Next, the input vector length was varying from 4 to 28 principal components. The obtained results were shown in Fig. 3b. In this case, the testing error level has stabilized from length of 12 components.

Finally, it was assumed that in the studied case the recommended ANNs architecture should consist of 12 principal components on the inputs vector and 16 neurons in the hidden layer. Then the averaged error of the force prediction should be even lower than 0.15 kN.

4. Classification and force prediction

One of the SHM system applications is to warn against excessive loads and to count such the events in order to estimate remaining time of a safety usage. Detection of the operating phase (e.g. elastic or plastic) of the structural members or connections can be achieved using elastic waves and ANNs for the classification task.

Moreover, it can be seen in Fig. 1b, that the case, when an axial force in the bolt equals to -70 kN does not provide sufficient knowledge whether it is in the plastic or the elastic range. Therefore, it would be advantageous if the task of force prediction is combined with the classification of operating phases.

Therefore, based on the investigated connection, it was assumed that the measured signals will be divided into two groups at the point of a local force minimum (exactly for the argument 2061, see Fig. 1b). Next, two approaches were studied in order to assign the measured signal to the appropriate classes. Autoassociative neural networks were used in the first case and the ANN for regression tasks in the second case. Basically, it was possible to achieve a very accurate classification in both these cases.

Exemplary obtained ANNs training results were shown in Table 1, where testing errors of the force prediction and the classification of operating phases were collected. They confirm a relatively good agreement with the target values.

Table 1: Testing errors of the force prediction and classification

Output	MSE	R^2
Prediction	0.9994	0.9999
Classification	0.9886	0.9908

5. Conclusions and final remarks

The obtained results have showed that ANNs are able to find the relation between the changes in elastic wave signals and force variations. In the studied example, where the laboratory test on the single bolt were carried out, principal components seem to contain information suitable enough for precise identification of axial forces.

In the future work the set of training patterns is going to be extended with data related to experimental tests performed on the wider group of bolts. The usefulness of other signal parameters such as time of flight or wavelet coefficients are also worth checking out.

References

[1] Ding, X., Wu, X., Wang, Y., 2014. Bolt axial stress measurement based on a mode-converted ultrasound method using an electromagnetic acoustic transducer, *Ultrasonics*, 54, pp. 914âĂŞ920, 2014.

[2] Fric, N.T., Budjevac, D.V., Miskovic, Z.M., Veljkovic, M.B., Markovic, Z.A. and Dobric, J.D., Calibration of the high strenght bolts for measuring of the pretension force, *Eighth International Conference on Advances in Steel Structures*, 1–10, Lisbon, Portugal, July 22-24, 2015.

[3] Kim, N. and Hong, M., Measurement of axial stress using mode-converted ultrasound. NDT&E International, 42, pp. 164âĂŞ169, 2009.

[4] Nazarko, P., Soft computing methods in the analysis of elastic wave signals and damage identification, *Inverse Problems in Science and Engineering*, 21 (6), pp. 945–956, 2013.