COMPARISON OF SELECTED ALGORITHMS FOR FORCE IDENTIFICATION IN TIME DOMAIN

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Summary

In recent years one can observe significant growth of the interest in the structural health monitoring (SHM) systems development and applications. However many authors focuses on the damage detection and all the activities related with diagnosis of failure. Meanwhile, classical, full SHM system should have in addition to a diagnostic module also module for excitation monitoring. Excitation can be measured, but easier and cheaper is to identify it by measuring the response of the object. Often it is the only practical possibility to monitor the excitation. The authors took this often overlooked problem of SHM systems, comparing the most commonly used algorithms for the identification of excitation acting in the time domain in terms of their usefulness in SHM systems. Showing a description of each of the algorithms and simulation results. The following features were compared: accuracy of the excitation reconstruction, simplicity of the algorithm, including the amount and type of data needed to build the model.

Keywords: force identification, inverse problems.

PORÓWNANIE WYBRANYCH ALGORYTMÓW IDENTYFIKACJI WYMUSZEŃ DZIAŁAJĄCYCH W DZIEDZINIE CZASU

Streszczenie

W ostatnich latach obserwuje się znaczny wzrost zainteresowania budową i zastosowaniami układów monitorowania stanu obiektów (ang. Structural Health Monitoring - SHM). Jednakże większość autorów skupia się na wykrywaniu uszkodzeń i innymi czynnościami związanymi z diagnostyką. Tymczasem, klasyczny, pełny układ monitoringu powinien posiadać poza modułem diagnostycznym również moduł odpowiedzialny za rejestrację wymuszeń. Wymuszenia te mogą być mierzone, lecz taniej i łatwiej niejednokrotnie jest identyfikować je na podstawie pomiaru odpowiedzi. Często jest to jedyna praktyczna możliwość monitorowania wymuszeń. Autorzy podjęli ten często pomijany problem, dokonując porównania najpopularniejszych algorytmów identyfikacji wymuszeń działających w dziedzinie czasu pod kątem ich przydatności w układach SHM. Pokazano zarówno opis metod jak i wyniki ich symulacyjnej weryfikacji. Porównywano następujące cechy algorytmów: dokładność odtwarzania wymuszenia, prostota algorytmu z uwzględnieniem implementacji, czasu działania i rodzaju danych koniecznych do przygotowania algorytmu.

Słowa kluczowe: identyfikacja wymuszeń, zagadnienie odwrotne.

1. INTRODUCTION

Structural health monitoring (SHM) is a relatively new appearance in science. The first references to this subject appeared in world literature in the 1980s. SHM is a natural development of technical diagnostics and is also very closely connected with non-destructive testing. According its definition SHM is: the interdisciplinary field of science leading to the provision of, at any moment of the working life of the object, a diagnosis of the material integrity of successive elements, as well as the state of all elements together creating the tested object as a whole. This state must stay in the range defined during design of the object, although it may change as a result of normal usage, environmental effects or unexpected events. Thanks to the continuous monitoring, which allows an analysis of the complete history of the structural health, as well as the monitoring of operating conditions (loads), the SHM system should also provide a prognosis (damage development, remaining work time etc.) [1]. Many authors often forgets about the second part of the definition, which says about the excitation monitoring, and it is equally important as damage detection in the SHM systems. In Fig. 1. the classic, full SHM system block diagram is presented.

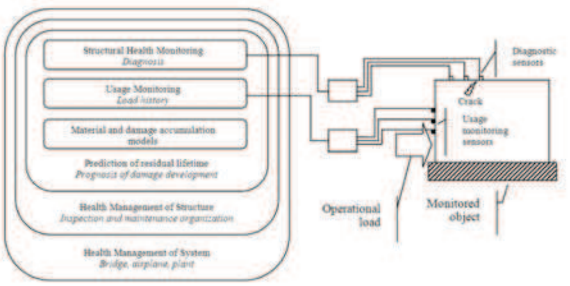

Fig. 1. Block diagram of SHM system

The presented block diagram depictures that each SHM system should be composed of three equally important modules:

- a diagnostics module,
- a module monitoring operating conditions,
- a database containing material models and damage accumulation models.

The first of these performs the basic task of SHM systems, in other words, it tests the integrity of particular sub-system elements. This allows (depending on the level that a given system represents – see the previous section) the detection, localisation and identification of damage developing in the object. When damage appears, the module automatically informs the operators about it, simultaneously sending information to higher management levels. The operators, helped by the diagnosis provided by the sub-system management level and system management level, take a decision regarding further actions. Possible actions include changing the work system parameters, turning off sub-systems or, as a last resort, turning off the whole system.

The second of the modules helps by monitoring exploitation conditions. Environmental conditions are measured, including temperature, humidity, pressure (depending on requirements), as well as the main forces present in the system. These are excitations or in the form of generalised forces or kinematic excitations, and can be measured directly or indirectly, or identified on the basis of response measurements. In cases where the recorded forces exceed the average due to inappropriate usage, or unfavourable external appearances, e.g. storms, hurricanes and earthquakes, this sub-system may send a warning to the operators, and administration of the object, which on this basis may or, in fact, should, conduct a more detailed analysis. This analysis aims at checking the influence of the exceeded force values on the object.

It is worth noting that the two modules discussed above use separate sensor networks. It sometimes occurs that both a change in force and structural changes occurring in the object as a result of damage cause a change in the system response. The independence of both measurement networks allows the differentiation of both sources of anomalies. Before placement of the sensors, an appropriate analysis is performed with the aim of finding the best sensor localisation for both groups of sensors. In the case of sensor networks for force identification transfer path analysis (TPA) is very helpful, while sensitivity analysis can be applied during the placement of diagnostic sensors.

The third module of execution level contains a database of material models suitable for monitoring sub-systems as well as damage accumulation models. Together with information from the two previously described modules, a prognosis concerning damage development and the remaining work time of sub-systems is generated. It is worth adding that this module may be located on execution levels or on one of the management levels depending on where greater computing power is accessible.

Last two of the above modules required the excitation monitoring. Unfortunately measurement of operational excitations is sometimes very difficult or even impossible. That is why the excitations are often monitored on the basis of structure response measurement. The actual excitation value is reconstructed with use of the inverse problem solution.

2. CLASSIFICATION OF LOAD IDENTIFICATION ALGORITHMS

An overview of the literature concerning the problems of force identification on the basis of signal response measurements allows the formulation of a few divisions of these methods.

The first of these is a division due to the number of forces present in systems. The next factor differentiating methods of force identification is their ability to identify whole force vectors (direction, sense and value) or only the values of forces present at known locations and directions of its activities. The most-well-known division of force identification methods is based on differences in the type of estimation algorithms [2]. According to this division, one can distinguish:

- methods based on deterministic dependencies:
  - methods operating in the time domain:
    - iterative methods,
    - single-step methods,
  - methods operating in the frequency domain:
    - methods based on frequency characteristics,
    - methods based on the mutual energy theorem,
    - methods based on modal filtration,
  - methods operating in the amplitude domain.
- methods based on statistical dependencies.
- methods based on intelligent algorithms:
  - methods using neural networks,
  - methods using genetic algorithms,
  - methods based on fuzzy reasoning.

A separate problem connected with the identification of forces is the separation of many sources present in systems [3, 4], for example, for the needs of transfer path analysis.

Since for the prognosis of remaining life of the system the time history of the excitations and loads are necessary, for the purposes of application in SHM the algorithms which operate in time domain were selected to the comparison.

3. COMPARISON DETAILS AND ASSUMPTIONS

As it was stated in the previous section the time domain algorithms were selected for further consideration. Among these methods the four most promising were chosen:

- quality function minimization method (QFM),
- method based on state and input observer (SO),
- method based on regressive parametric model inversion (PMI),
- method based on artificial neural network (ANN).

To test the method in the first step the simulation data were prepared. To do so the finite element model of the steel - aluminum frame was created. Next the model was imported to the Simulia Abaqus/CAE 6.10-1 software in order to simulate the dynamic responses in time domain. In Figure 2 the model of the object is presented.

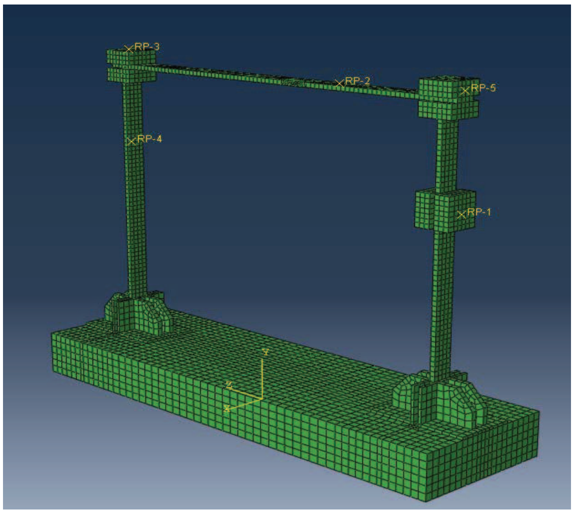

Fig. 2. Model of the simulated system

The excitation was placed in point RP1. The responses in form of vibration accelerations were virtually measured in points RP2 – RP5. Two simulations with two types of excitation signals were carried out:

- harmonic excitation with amplitude 50 N and frequency 5 Hz,
- random excitation with mean value 0.5, normal distribution and amplitude 1 N.

In the consecutive steps the data were used for verification of selected methods. Next each of the methods was classified and evaluated according to the following criteria:

- the accuracy of the signal reconstruction - which were taken into account two factors: Pearson's correlation coefficient and percentage fit of the signals expressed by the formula:

$$Fit = \left[\frac{1 - Norm\left(Y - \widehat{Y}\right)}{Norm\left(Y - \widehat{Y}\right)} \right] \cdot 100\% \quad (1)$$

  where: $Y, \widehat{Y}$ - normalized vectors of measured and estimated force
- the level of complexity in software/hardware implementation and computational,
- time of calculations,
- type and number of required training data.

For every of the above criteria the ranking of methods was done – the algorithms were ordered from the worst to the best one.

4. FORCE IDENTIFICATION WITH USE OF QUALITY FUNCTION MINIMIZATION

This method belongs to the most often used iterative methods [5, 6, 7, 8]. It may be used for reconstructing the force time history on the basis of knowledge of responses. In particular, it is suitable for the identification of impulse force. It is based on the minimization of the objective function as a measure of the fit between the measured response signal and the calculated one.

Using a reduced vector of state variables q we define the objective function as a difference between the measured response y and the calculated response q.

$$J\left(c, f_j\right) = \sum_{j=1}^{N} \left(q_j - y_j\right) D \left(q_j - y_j\right)^T + f_j E f_j^T \quad (2)$$

where: c – vector of initial conditions of motion,
f_j, q_j, y_j – force, calculated and measured state variables vectors at the time j,
D, E – weight matrices.

The introduction of the element $f_j E f_j^T$ to the objective function (1) is necessary due to the quality of the obtained force. This operation is the so-called regularisation. In order to obtain forces present in the system, J should now be minimised:

$$\min J \to f \quad (3)$$

With the objective function defined in this way, it is necessary to select the methods for its minimization. Here, methods based on dynamic programming [5], [6] or genetic algorithms [7] are applied. The advantage of these methods is their ability to be applied in non-linear systems, a drawback is the large calculation power and the long time required for calculations.

In the performed simulation the authors used the state space model identified for the system presented in Fig. 2. As the optimization algorithm the dynamic programming was applied. As it was stated in Section 3 the method was tested with use of two type of signals – harmonic and random. In Figure 3 the results of comparison between applied and estimated harmonic excitation signal are presented. In Figure 4, appropriate comparison for random signal is shown.

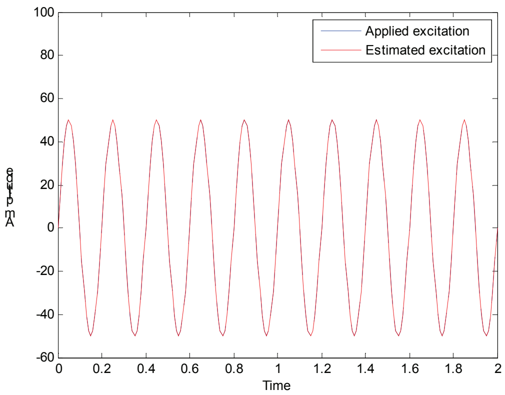

Fig. 3. Results of comparison between applied and estimated harmonic excitation signal

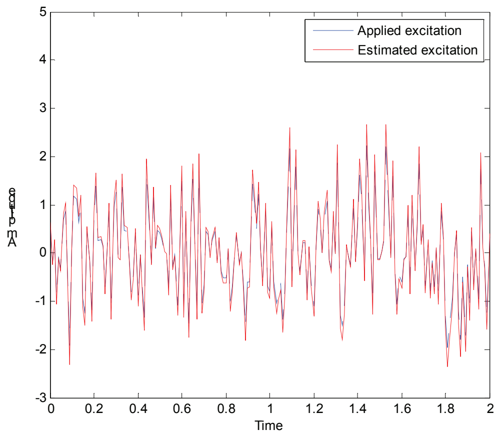

Fig. 4. Results of comparison between applied and estimated random excitation signal

The quantitative results of excitation signal estimation are gathered in Table 1.

Table. 1. Results of excitation estimation

Correlation coeff.		Signal fit		Calculation time [s]	
harm.	noise	harm.	noise	harm.	noise
0.999	0.95	99%	92%	165	640

As it can be observed from the above results the method is very accurate for both types of signals. Also it did not required many training data – only one set of time histories for the state space model identification. However its implementation was quite complex and time consuming and the time of calculation was very long. The latter is the biggest drawback of the tested algorithm.

5. FORCE IDENTIFICATION WITH USE OF STATE OBSERVER METHOD

The next method of force identification, which was imported from automatics, uses the state observer with unknown input signal [9]. This type of observer, on the basis of the system responses signals, identifies its states as well as input signals. The method of force identification using such an observer is resistant to measurement noise and may operate in real time. The design of the observer for non-linear objects begins with writing its mathematical model in the form of a state of equations:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + f((x,u),y) \\ y(t) &= Cx(t) + Du(t) \end{aligned} \tag{3}$$

where: $x(t)$ – vector of object state
$u(t)$ – vector of desired force
$y(t)$ – vector of measured outputs
$f((x,u),y)$ – element introducing non-linearity to the object.

This can be divided into two parts – known and unknown:

$$f((x,u),y) = f_L((x,u),y) + Wf_U((x,u),y) \tag{4}$$

where: $f_L((x,u),y)$ – known non-linear part
$f_U((x,u),y)$ – unknown non-linear part

The matrices A, B, C, D, and W are constant and have real values. The task consists of designing an observer, which, with the measured system responses, estimates both the state of the object and the forces present at input. Details of the design procedure for this type of observer can be found in [10] and require two assumptions to be met:
Assumption 1:
$f_L((x,u),y)$ must meet the inequality below with the Lipschitz constant:

$$\left\| f_L(\xi,y) - f_L(\hat{\xi},y) \right\| = \gamma \left\| \xi - \hat{\xi} \right\|, \wedge y \tag{5}$$

where: $\xi(t) = \begin{bmatrix} x(t) \\ u(t) \end{bmatrix}$

γ - Lipschitz constant – positive real scalar

Assumption 2:
The matrix $[D\ CW]$ has a full column rank. A necessary condition for meeting this assumption is for the number of system outputs to be greater than or equal to the sum of the number of inputs and the size of the non-linear part, which does not meet the Lipschitz condition.
In the tests the authors used the same state space model as in Subsection 4. The state observer implementation was performed with use of the Linear Matrix Inequality Toolbox from the Matlab

package. In Figure 5 the results of comparison between applied and estimated harmonic signal are presented. In Figure 6, the same comparison for random signal is shown.

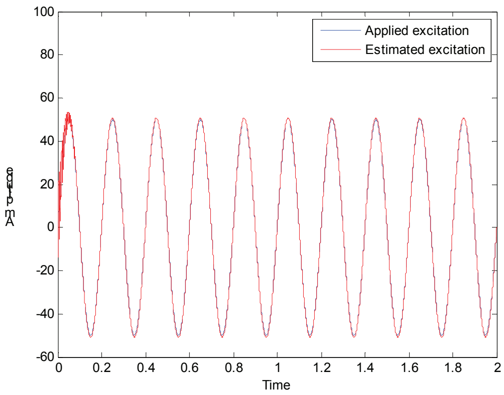

Fig. 5. Results of comparison between applied and estimated harmonic excitation signal

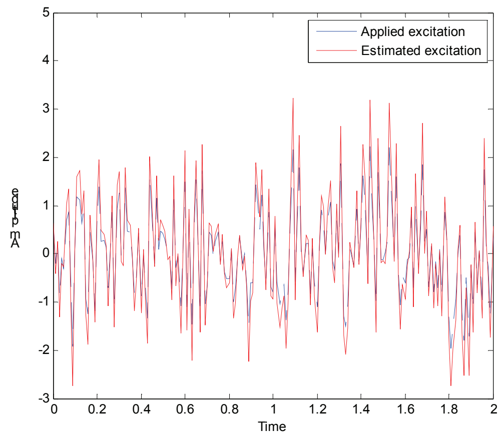

Fig. 6. Results of comparison between applied and estimated random excitation signal

The values of comparison indexes are presented in Table 2.

Table. 2. Results of excitation estimation

Correlation coeff.		Signal fit		Calculation time [s]	
harm.	noise	harm.	noise	harm.	noise
0.998	0.713	93%	77%	0.21	0.14

As it can be seen from the results the method is also very accurate. According to the training data its requirements are the same as previously presented QMF method – only one set of time histories. It also worked very fast. However its implementation was very complex and required such a sophisticated tools as LMI toolbox.

6. FORCE IDENTIFICATION WITH USE OF PARAMETRIC MODELS INVERSION

The use of regressive parametric models for the identification of input signals can be seen in automatics. Adaptation of this method for mechanical systems and force identification can be found in the works [11] and [12]. Its basic stages are: selection of the structure and identification of the regressive parametric model, then inversion of the model and input to the inverse model of the response signal, most often in vibration acceleration form, with the aim of calculating the forces causing the response. The basic problem for solutions is therefore inverting regressive models.

In order to generate responses for an inverse linear dynamic model, it is necessary for it to be proper or strictly proper [13]. A proper object is characterised by having a transmittance with a numerator order lower than the denominator order $nB < nA$, in the strictly proper object, however, the numerator order is equal to the denominator order $nB = nA$. When the numerator order is higher than the denominator order $nB > nA$, the object is physically unrealisable with regard to the required ideal differentiation. Besides this, the object should be linear, stationary and minimum-phase.

Physically realisable inversion for the object described by the continuous model is presented as a combination of the transmittance of the object with its inverse model with an identical structure $H(s)\cdot H_{inv}(s) = 1$. Ideal inversion requires the equality of the inputs $u_0(s)$ and $u(s)$ introducing the standard model $H_w(s)$ which allows the inverse model to be defined according to the dependency:

$$H_{inv}(s) = \frac{H_w(s)}{H(s)} = \frac{u(s)}{y_0(s)} = \frac{a_0 + a_1 s + \ldots a_{nA} s^{nA}}{\left(b_0 + b_1 s + \ldots b_{nB} s^{nB}\right)\left(1 + sT_w\right)^{(nA-nB)}} \tag{6}$$

where: nA, nB – polynomials order,
$u(s)$, $y_0(s)$ – estimated input and reference output,
T_w – time constant,

The scheme of procedures for inverting the model of the object is presented in Figure 7.

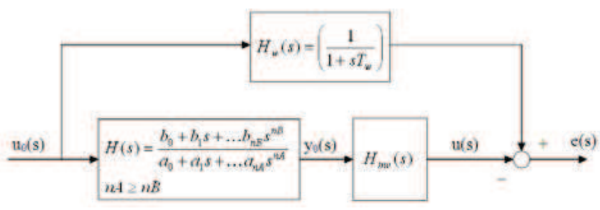

Fig. 7. Scheme of inverting a regressive parametric model of the object

In Figure 7 $e(s)$ designates the error between the reference force $u_0(s)$ multiplied by $H_w(s)$, and the estimated force $u(s)$, $H_{inv}(s)$ is the transmittance of the inverse model of the object.

An excessively large difference between the numerator order nB and the denominator order nA leads to greater inaccuracy of inversion. For large differences in the orders, the accuracy of inversion falls for increasing frequencies. This results from the possibilities of performing ideal integration (minimal value of T_w). A discrete inverse model is designated as follows:

$$H_{inv}(z)=\frac{H_w(z)}{H(z)}=\frac{u(z)}{y(z)}=\frac{a_0+a_1z+\dots a_{nA}z^{nA}}{\left(b_0+b_1z+\dots b_{nB}z^{nB}\right)}\left(\frac{1-c}{z-c}\right)^{(nA-nB)} \tag{7}$$

where: c – constant setting the accuracy of inversion.

for $c = 0$ we gain:

$$H_{inv}(z)=\frac{H_w(z)}{H(z)}=\frac{u(z)}{y(z)}=\frac{a_0+a_1z+\dots a_{nA}z^{nA}}{\left(b_0+b_1z+\dots b_{nB}z^{nB}\right)z^{(nA-nB)}} \tag{8}$$

In the case of discrete models, in order to maintain the physical realization of the system, an additional delay z^{-1} exciting causality of the impulse responses of the object is introduced. In other cases, the object would predict the future and the response would form before the force appeared.

In the conducted simulations the authors first identified the regressive parametric model with use of Identification Toolbox. Many different structures of models with different orders of polynomials were tested. In the figure 8 and 9 the harmonic and random signals are compared.

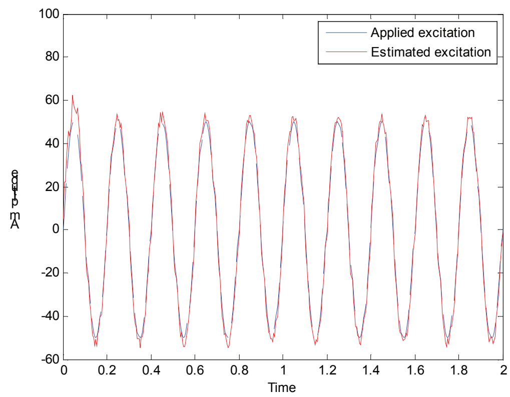

Fig. 8. Results of comparison between applied and estimated harmonic excitation signal

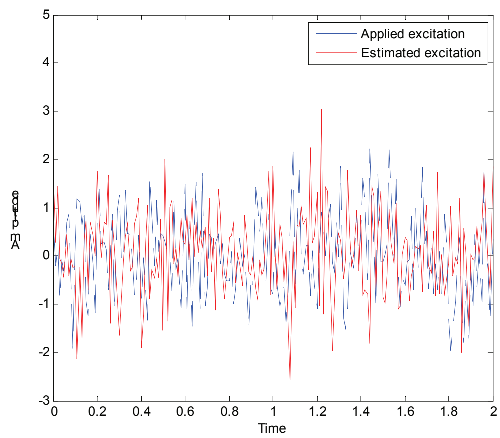

Fig. 9. Results of comparison between applied and estimated random excitation signal

The values of comparison results are placed in Table 3.

Table. 3. Results of excitation estimation

Correlation coeff.		Signal fit		Calculation time [s]	
harm.	noise	harm.	noise	harm.	noise
0.98	0.37	83%	33%	0.35	0.37

The best results for both harmonic and random data were achieved for the ARMAX model. The method worked very fast but the identification accuracy fro random signal was very poor. Also the amount of data required for the model preparation is bigger than in the two previous cases.

7. FORCE IDENTIFICATION WITH USE OF ARTIFICIAL NEURAL NETWORK

Artificial neural networks are constructed from a definite number of basic calculation units known as neurons. These neurons are connected with each other in a series-parallel way. Each of the neurons possesses its own activation function and weight value. A typical network has a structure of layers: the input layer with the number of neurons equal to the number of system inputs, one or a few hidden layers and an output layer. Each layer is built from one or more neurons. Particular types of neural networks differ in the architecture of neurons placement and the flow of information between them, activation functions, methods of learning, etc. and are widely discussed in the literature [14, 15].

The application of artificial neural networks for force identification is described, among others, in the works [16, 17, 18, 19]. Because a machine as a dynamic system may find itself in various phases of loading (run-up, work with full load, without load, run-down etc.), in order to accurately identify the exploitation forces, firstly the state in which the appliance is found should be recognized [31]. On the basis of the value of measured responses or process variables, using the decisive neural network, the load state of the machine is allocated to one of the groups. To do this, it is possible to use a "back-propagation" type network [14, 15] with the same number of input neurons as measured parameters. This process may be realized by a few neural networks in more difficult cases. It should be remembered that one undefined state should be added to the assumed machine work states, which allows qualification errors to be avoided. After performing classification of the loads states of the appliance, neural networks identifying exploitation forces on the basis of measured responses or process variables are constructed. For each load state there is a separate network. Such an approach considerably increases the accuracy of the identifying algorithm.

The universality of artificial neural networks combined with the classification of initial states allows the accurate identification of operational forces, conducted in real time. The difficulty of using neural networks is based on the lack of an unequivocal recipe for the type and size of networks which should be applied for a given problem.

To identify the forces acting on an object, it was decided to use a neural network with back-propagation of error, the feed-forward type. Input vector to the network was a set of responses of the object to the excitation contained in the output vector. During the trials, there were problems in the identification by the same network the harmonic and stochastic signals, due to their different characters. Therefore, it was decided to use two networks, one for the identification of sinusoidal excitation and the other for noise excitations. The allocation of one of the above networks the simple algorithm decides, on the basis of the number of peaks in a signal Fourier transform. If the number of peaks is more than ten, the signal is fed to the network devoted to the noisy signals. Otherwise, second network is used. In the figures 10 and 11 the harmonic and random signals are compared.

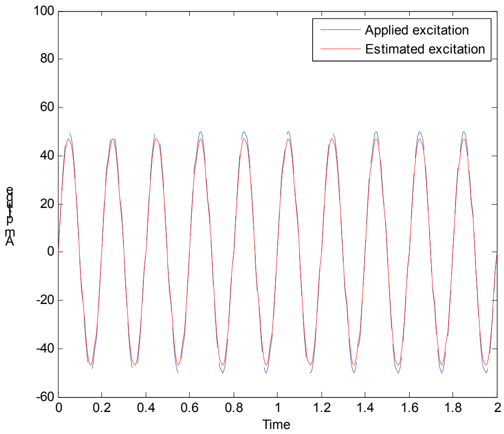

Fig. 10. Results of comparison between applied and estimated harmonic excitation signal

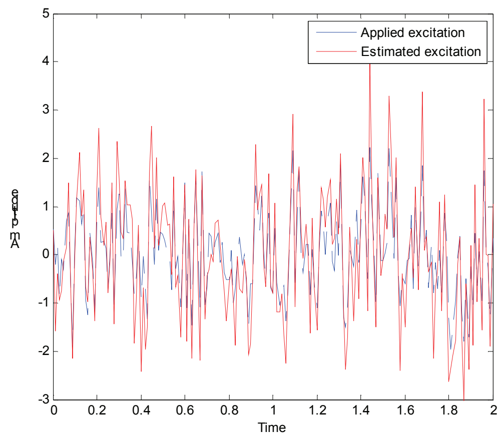

Fig. 11. Results of comparison between applied and estimated random excitation signal

The quantitative results of excitation signal estimation are gathered in Table 4.

Table. 4. Results of excitation estimation

Correlation coeff.		Signal fit		Calculation time [s]	
harm.	noise	harm.	noise	harm.	noise
0.999	0.62	89%	57%	0.45	0.47

Application of artificial neural network to the excitation identification for the considered case gave moderate results. It worked fast but the accuracy was worse than the one obtained in SO an QFM methods. Also the amount of training data was the biggest in this case.

8. SUMMARY

In the previous sections four time domain algorithms for excitation identification have been tested. They were verified on the same simulation data. In Table 5 the assessment of the methods efficiency is shown, according to the criteria presented in Section 3.

Table. 5. Assessment of excitation estimation algorithms

	SO	ANN	QFM	PMI
Estimation accuracy	1	3	1	4
Time of calculation	1	1	4	1
Training data	2	4	1	3
Complexity of implementation	4	2	3	1
TOTAL	**8**	**10**	**9**	**9**

The selected evaluation system showed that the method based on state observer seems to be the most versatile. If only the identification accuracy is considered the best choice would be the method based on quality function. When the model of the object is unknown and difficult for identification due to for example nonlinearities then ANN are the only case.

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