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NARX MODEL IN ROTATING MACHINERY DIAGNOSTICS

SUMMARY

Rotating machines are often described using linear methods with acceptable accuracy. Some malfunctions, however, are of non-linear nature. The most common examples of those malfunctions are loose bearings and rotor rubs. Accurate detection and identification of such malfunctions requires more accurate methods. One of such methods can be NARX – nonlinear systems identification. This method is based on neural networks approach and is especially efficient in modeling and diagnostics of nonlinear systems. Application of this method leads to shorter and less costly tuning of the model to the object, which is the key requirement when practical application of a method is concerned. The paper presents how NARX can be applied for modeling of rotating machinery malfunctions. Idea of the diagnostic algorithm based on such modeling is presented. The proposed algorithm was verified during research on a specialized test rig, which can generate vibration signals. The paper also presents results of an application of the NARX method for data collected at a wind turbine.

Keywords: *NARX model, rotating machinery diagnostics, wind-turbine damage detection*

ZASTOSOWANIE MODELU NARX W DIAGNOSTYCE MASZYN WIRNIKOWYCH

Maszyny wirnikowe są często opisywane przy użyciu metod liniowych z zadowalającą dokładnością. Niektóre awarie mają jednak charakter nieliniowy; jako przykład można wymienić m.in. takie usterki jak luźne łożyska i przytarcia wirnika. Precyzyjne wykrywanie i identyfikacja ww. usterek wymaga bardziej dokładnych metod. Jedną z takich metod może być NARX – model umożliwiający nieliniową identyfikację systemów. Metoda ta opiera się na sieciach neuronowych i jest szczególnie skuteczna w zakresie modelowania i diagnostyki układów nieliniowych. Zastosowanie tej metody prowadzi do krótszego i mniej kosztownego dostrajania modelu do obiektu, co jest kluczowym wymogiem w przypadku praktycznego zastosowania tej metody w diagnostyce. W artykule przedstawiono, jak modele NARX mogą być stosowane do modelowania awarii maszyn wirnikowych, a także ideę algorytmu diagnostycznego z wykorzystaniem takiego modelowania. Proponowany algorytm został zweryfikowany podczas badań na specjalnym stanowisku badawczym, które umożliwia generowanie sygnałów drganiowych oraz wprowadzanie symulowanych uszkodzeń. W artykule przedstawiono również wyniki zastosowania metody NARX dla danych zarejestrowanych w elektrowni wiatrowej.

Słowa kluczowe: *model NARX, diagnostyka maszyn wirnikowych, wykrywanie uszkodzeń turbin wiatrowych*

1. INTRODUCTION

Nowadays rotating machines play an important role in modern power plants. Most industrial processes where energy is processed are based on rotating machinery. Thus, it is increasingly important to maintain those machines in healthy technical state. Main drivers for final users of rotating machines are:

– avoidance of catastrophic failures,
– decrease of maintenance costs,
– increase of availability.

To achieve above goal new maintenance and health monitoring techniques are considered. Theoretical research is performed since decades, starting from a simplified, linear rotor model. With advances in rotor-dynamic research new processes were identified and described. Extensive review of theoretical description of rotordynamic phenomena can be found in (Gryboś 1994, Muszyńska 2005). In many cases those phenomena are of non-linear nature (Kiciński 2004,

Sanz *et al.* 2007). A rotor and its support consisting of hydrodynamic bearings, formulate a highly nonlinear closed-loop system (Kraemer 1993). Additionally, several faults have inherently nonlinear nature. Good examples are mechanical looseness or rotor rub. Such problems were also investigated and solved in the industrial practice. An interesting survey of rotating machinery malfunctions can be found in (Eisenmann 1997, Kiciński 2005).

In general case, to model a rotating object (with or without malfunctions), the system input may be defined as forces relating to rotor imperfections such as unbalance or overloads connected to external forces acting upon the shaft (Barszcz *et al.* 2004). The state vector includes velocities and displacements of nodes, where lumped physical models are focused. The equations describing system dynamics strongly depend on parameters, mainly on the rotational speed Ω. Parameters of an applied model for diagnostics to be identified from measured data should be very sensitive to the symptoms of malfunctions of rotating machinery.

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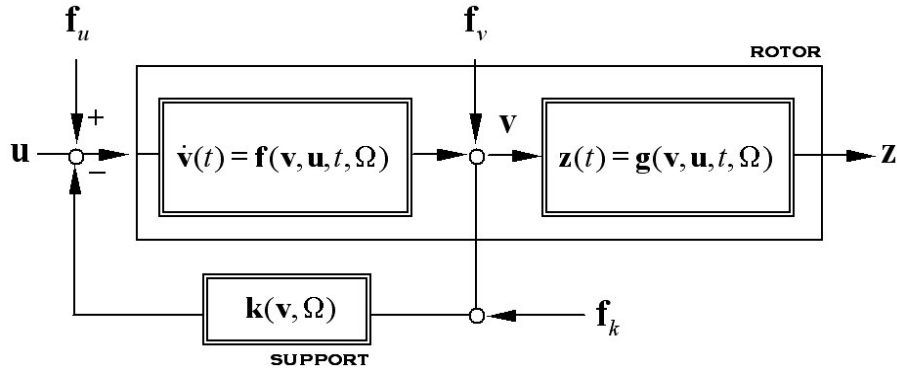
Fig. 1. A block scheme of rotor and support equations affected by faults in the form of state-space equations

The problem of the fault and system dynamics description (Fig. 1) of the supported rotors can be formulated based on nonlinear state-space equations as follows (Barszcz *et al.* 2004):

$$v(t) = f(t, v(t), u(t), w(t), f_{k,u}(t), \theta)$$
$$z(t) = g(t, v(t), u(t), w(t), f_v(t), \theta) \tag{1}$$

where:

$\quad t$ – continuous time domain,
$\quad z(t)$ – output signal vector,
$\quad u(t)$ – input signal vector,
$\quad v(t)$ – state vector,
$f_v(t), f_{k,u}(t)$ – faults vectors,
$\quad w(t)$ – disturbances vector affecting on states,
$\quad \theta$ – model parameters.

The parameters of the vector θ are physically significant and their changes correspond to faults (malfunctions) to be detected. A major problem with the rotor-dynamic system modeling is that equations strongly depend on parameters, especially the rotational speed.

The general problem presented above is often approached using linear system identification method. In many cases such an approach yields good results, allowing detection and identification of machinery faults. In some cases, linearization of a nonlinear model can also bring useful results (Barszcz 2005). In other cases, as mentioned previously, nonlinearities are inherent and linear models can be only used in a limited scope.

Mechanical looseness is an inherently nonlinear phenomenon. It is encountered when a stationary machine part (e.g. bearing pedestal) becomes loose. In such a case, the effective rotor stiffness is reduced. This often results in the rotor resonance shifting to a frequency, which is an even multiple (or fixed fraction) of rotating speed. Additionally, due to mechanical looseness synchronous motion of a part may become truncated, e.g. due to hammering of parts. Truncated sine waves exhibit a series of running speed harmonics. Those harmonics, in turn may induce resonances of other parts of the machine. Examples of practical cases of looseness can be found in (Eisenmann 1997). Proposal of

analytical model of this malfunction was given in (Muszyńska 2005). The model of the rotor lateral vibration mode with additional terms, due to coupling with the stationary part can be presented as follows:

$$MC + (D_m + vD_f)C + KC + vK_f(C - c) +$$
$$+ K_{XY}C\cos 2\psi - MC\varphi^2 = \tag{2}$$
$$= mr\Omega^2 \cos(\Omega t + \delta - \psi) + P\cos(\gamma - \psi)$$

$$MC\psi^2 + (D_m + vD_f)C^2\psi - K_{XY}C^2\sin 2\psi - 2MCC\psi =$$
$$= C[mr\Omega^2 \sin(\Omega t + \delta - \psi) + P\sin(\gamma - \psi)] + v(C + R_r)F_t \tag{3}$$

where:

$$v = \begin{cases} 1 & if \quad |W| \geq c \\ 0 & if \quad |W| < c \end{cases}$$

$\quad M$ – rotor/support modal mass,
$K_{XY} = (K_X - K_y)/2$ where: K_X, K_Y – bearings lateral stiffness,
$\quad C$ – polar coordinates,
$\quad D$ – rotor/support modal damping,
$\quad D_f$ – rotor radial damping,
$\quad K_f$ – rotor radial stiffness,
$\quad m$ – unbalance mass,
$\quad P$ – amplitude of radial force applied to the rotor,
$\quad \Omega$ – rotor rotational speed,
$\quad \gamma$ – angular orientation of force P,
$\quad \psi$ – polar coordinates,
$\quad r$ – unbalance radius,
$\quad \delta$ – unbalance angular location,
$\quad c$ – bearing radial clearance,
$\quad R_r$ – rotor bearing radius,
$\quad F_t$ – tangential force at the rotor/stator contact.

The main assumption of the model is discontinuous (and thus nonlinear) change of the stiffness. The same model can be applied for looseness and for rubbing. In the first case, change of stiffness is caused by pedestal/surface contact. In the latter one – by rotor/stator contact. In some systems,

when stiffness (and sometimes damping) varies between extreme discrete values, the system given in (2) and (3) may become chaotic. Basics of chaotic motion are described in (Lorenz 1963). The suspended rotor with looseness or rub is one of the examples, where such a chaotic motion can take place. As shown in (Goldman and Muszyńska 1994), the condition for such behavior is the discontinuous nonlinearity of the system, and its high sensitivity to deterministic external excitation. To model such nonlinear objects, neural networks (NN) can be applied.

2. FUNDAMENTALS OF NARX MODEL

The most general structure of nonlinear 'black-box' model is a neural input-output model (Norgaard 2000). It is recommended for modeling cases without a priori knowledge of structure and its nonlinearities. The neural network (NN) is a set of parameters called weights and biases. Various architectures of neural networks are described (Korbicz *et al.* 1994). The most often applied network structure is the multi-layer perceptron (MLP). An example of structure of two layers MPL is presented in Figure 2.

Mathematical description of this architecture of the NN can be given by the expression:

$$\hat{y}(t) = F_i \left[\sum_{j=1}^{nH} W_{i,j} f_j \left(\sum_{l=1}^{n\Phi} w_{i,l} \varphi_l + w_{j,0} \right) + W_{i,0} \right] \qquad (4)$$

where:

$\hat{y}(t)$ – predicted output vector,
φ – input vector,
nH – number of neurons in hidden layer of NN,
$n\Phi$ – number of NN inputs,
f – activation function,
$w_{j,l}$ – weights of the NN,
$W_{i,j}$ – biases of the NN.

The predictor $\hat{y}(t)$ consists of the past outputs and/or the past inputs and predicted output where θ denotes the parameter vector, which contains all the adjustable parameters of a network. Here, biases were presented as weights with second index 0. Usually sigmoid/tansig activation functions are applied in the hidden layer neurons, whereas linear – in the output layer. The structure given by equation (4) is considered. The weights are adjusted during the training process based on a training set of inputs and outputs. The learning criterion is the least mean square error between the given output and the predicted output. The formula for prediction error is given by equation:

$$PE = \frac{1}{2N} \sum_{r=1}^{N} \left[y(t) - \hat{y}(t \mid \theta) \right]^T \left[y(t) - \hat{y}(t \mid \theta) \right] \qquad (5)$$

where:

N – number of neurons,
$y(t)$ – output vector,
$\hat{y}(t \mid \theta)$ – predicted output vector,
θ – parameters vector.

The weights are found according to the learning algorithm. The basic one is based on the back-propagation. Detailed description of this algorithm and other ones are given in e.g. (Kiciński 2004). The multi-layer perceptron can be applied to identify or model a nonlinear system dynamic. The structure, which will be investigated here, is referred to as NARX – Nonlinear Auto Regressive model with eXogenous input (6) and (7). The NARX model (Barszcz *et al.* 2006, Basso *et al.*2005, Bednarz *et al.* 2005, 2006, 2007, Chen and Bilings 1989, Leonartis and Billings 1985a, 1985, Piroddi and Spinelli 2003) represents a wide class of non-linear systems and many well-known non-linear input-output models
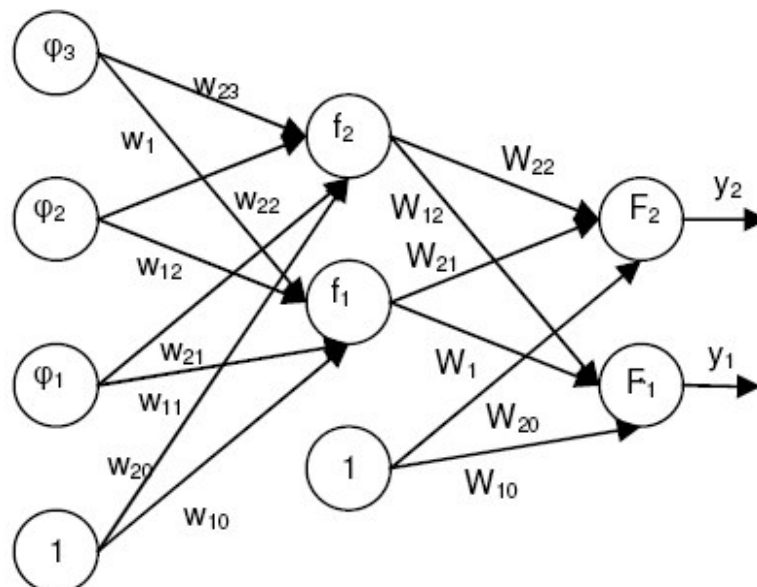

Fig. 2. The structure of 2 layer Multi Layer Perceptron

(Jing *et al.* 2007, Kerschen *et al.* 2006, Thouverez and Jezequel 1996) are specific cases of this model.

$$y(t) = \sum_{m=1}^{M} y_m(t) \qquad (6)$$

$$y_m(t) = \sum_{p=0}^{m} \sum_{k_1,k_{p+q}}^{K} c_{p,q}(k_1, ..., k_{p+q}) \times$$

$$\times \prod_{i=1}^{p} y(t-k_i) \prod_{i=p+1}^{p+q} u(t-k_i) \qquad (7)$$

where:

$y_m(t)$ – mth-order output of system,

$k_i = 1, ..., K,$

$$\sum_{k_1,k_{p+q}}^{K} (\cdot) = \sum_{k_1=1}^{K} (\cdot) ... \sum_{k_{p+q_1}=1}^{K} (\cdot)$$

For such a structure, we can define regression vector and predictor as:

$$\varphi(t) = [y(t-1) ... y(t-n_a)u(t-n_k) ... u(t-n_b-n_k+1)]^T \quad (8)$$

$$\hat{y}(t \mid \theta) = \hat{y}(t \mid t-1, \theta) \qquad (9)$$

The regression vector is used as the input to the neural network. After successful learning process, the network is capable to approximate behavior of the system.

NARX networks are applied for modeling and identification of dynamic systems (Kościelny 2001, Nalinaksh and Satishkumar 2001, Narenda and Parthasarathy 1990) yielding good results. Typical architecture of such application is presented in Figure 3.

Application of such a network for diagnostics of rotating machinery needs to solve two problems:

– unavailability of input signal,
– interpretation of results.

The input signals in rotating machinery are the forces loading on the structure. The majority of this force is the rotor unbalance force. After being transmitted through the object it produces vibrations, which are observed as system outputs. The rotor unbalance force is immeasurable and – even worse – it is nonstationary, for it depends on rotational speed, rotor temperature. In such a case either no input signal will be used, resulting in degradation of quality of the model, or another signal can be used as the input. In this approach we propose to use one of vibration signals or keyphasor as the input signal. In such an approach the NARX network will approximate a nonlinear filter, transforming vibration signal from one channel to the other one. Interpretation of results causes problems, because NN parameters (i.e. weights) do not have any physical interpretation. In the presented approach the output from the network is the predicted vibration signal (or signals, in more general case, but the paper is focused on one output), so there is no direct information about any malfunction. We propose to train the network and next calculate only "distance" between current set of input/output data and the set used to train the network. Good scalar estimate of this value is normalized sum of squares of prediction errors (NSSE – expressed by equation (10)), when new data is used to validate the NARX network trained with training data.

$$NSSE = \frac{1}{2N} \sum_{t=1}^{N} [y(t) - \hat{y}(t \mid \theta)]^T [y(t) - \hat{y}(t \mid \theta)] +$$

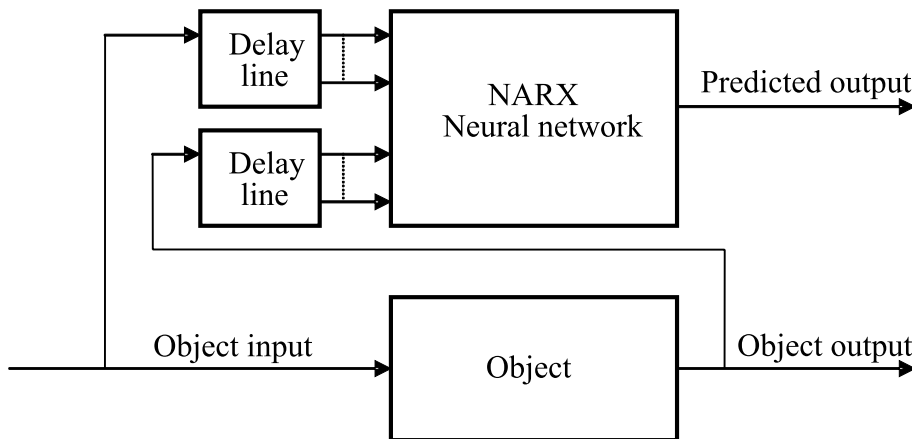$$+ \frac{1}{2N} \theta^T d\theta \qquad (10)$$

Fig. 3. The NARX network used for system identification

Thus, the output will be the set of numbers, showing how much the current state of the machine differs from selected reference states known previously. Proposed algorithm was verified based on the data from a laboratory test rig.

3. LABORATORY TEST RIG

The rotordynamics test rig (Fig. 4) was designed and installed in Department of Robotics and Mechatronics AGH University of Science and Technology. The main goal is development and verification of diagnostic techniques for rotating machinery.

The rotor – bearing system is assembled on the heavy steel plate. The rotor is driven by the 1.2 kW AC motor, controlled by the converter. The converter controls the rotational speed set manually or from a PC through a serial link. Various transient states can be easily tested. The driven system can consist of one 1200 mm or two 600 mm shafts assembled on bearings. The rig has exchangeable bearings, rolling and sliding ones. One of bearing supports can introduce controlled misalignment. Up to few disks can be assembly on shafts, to introduce static or dynamic unbalance. It is possible to introduce looseness and rotor rub. The rig is equipped with rotational speed controller and vibration measurement system, which consists of:

– keyphaysor,
– 8 vibration displacement eddy-current probes,
– 2 three-axial accelerometers,
– signal conditioning,
– analog input computer board,
– acquisition computer,
– software.

Vibration displacement sensors are installed on pedestals, two sensors per one (see Fig. 4). This allows to measure shaft vibration in any position, not only at the bearings. Acceleration sensors are installed on bearing covers. The sampling frequency initially can be set with the default value of 2 kHz. Apart of storage of raw vibration data, the measurement systems calculate following parameters of the vibration signals:

– root mean square,
– peak-peak amplitude,

– amplitude and phase of the first harmonic,
– amplitude and phase of the second harmonic,
– DC value (for eddy-current probes).

Recorded data can be exported for future processing (e.g. in Matlab environment). It can be also presented in one of following plots: time trend, waveform, spectrum, cascade, orbit, Bode, polar. The measurement system is very flexible and can be easily adapted to the particular experiment. It is possible to increase the sampling frequency (up to 20 kHz per channel) or to add more signal analysis procedures, like other high harmonics, or sub-synchronous components.

4. EXPERIMENTAL RESULTS

The results of proposed health monitoring algorithm tests are presented. In the first part of chapter the results of detection of the typical failures (unbalance, misalignment and mechanical looseness) in rotating machines by means of NARX signal models are presented. In the second part of the chapter the idea of using NARX model for prognosis of mechanical state of machines is presented. In the last part of chapter the possibility of using NARX model for blade crack detection is shown.

4.1. NARX model in failures detection

The goal of the experiment is verification of the algorithm dedicated to detect typical malfunctions of rotating machines. The looseness, unbalance and misalignment were chosen as main malfunctions which can be modeled using nonlinear approach. To reliably detect such a nonlinear behavior, the approach based on NARX neural network, proposed in chapter 2, has been used. The algorithm is applicable to small machines in power generation plants. Thus, it must fulfill the following requirements:

– the machine has rolling bearings (typical layout of smaller machines like fans and blowers),
– machine rotational speed is not constant,
– vibration is measured with accelerometers installed on bearing housings and displacement probes installed along the shaft.
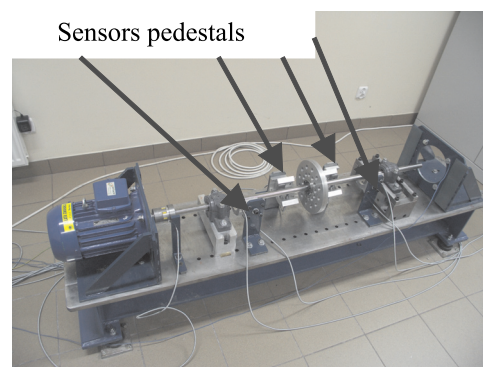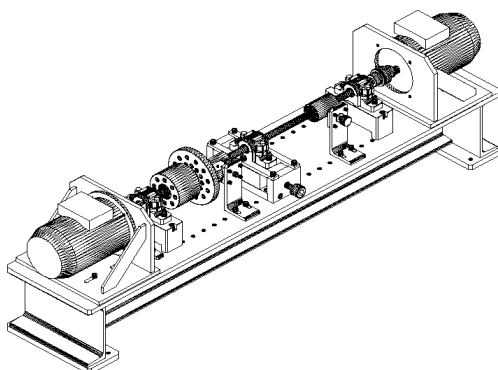

Fig. 4. Design (left) and photograph (right) of the rotordynamic research test rig

Data processing was performed with Matlab and dedicated toolboxes: System Identification, Neural Network and Neural Network Based System Identification v. 2.0 (Norgaard 2000). Keyphasor signal (rotating speed) was chosen as the input to the system. As a test signal a signal from eddy current sensor (vertical directions) at driven end was chosen (DEZ). Existing data were divided into separate sets, each having 2500 samples. Such sets were prepared for all states of rotating machine: undamaged, with unbalance, misalignment and two cases of loose bearing and for various rotational speed. Several attempts to determine the optimum network structure were performed. The analysis was started from the order of 10 inputs and 10 outputs. The initial network had 10 neurons in the hidden layer. All neurons in the hidden layer had hyperbolic tangent activation function. The single neuron in the output layer had linear activation function. After NN architecture optimization, the best results have been obtained for network having order of 3 inputs, 3 outputs and 5 neurons in the hidden layer. After network optimization phase, three networks have been trained, each one modeling dynamics in a different technical state (correct and loose bearing at driven end (DE) and non-driven end (NDE)). Those trained NN were later used as reference networks. The goal of the algorithm is to detect, if the set of currently acquired data can be classified to one of known states. To verify this idea, 3 sets of validation data (each one consists of 5000 input and 5000 output samples), each taken from measurement with different malfunction present, were presented to each network. The measure of distance between real data and predicted output was normalized sum of squared prediction error (NSSE). Thus, 9 estimates were obtained for every channel. The Figure 5 presents results for the channel DEZ.
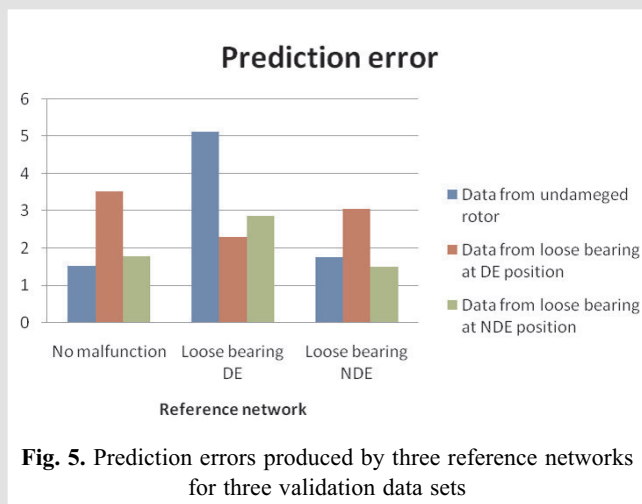
**Fig. 5.** Prediction errors produced by three reference networks for three validation data sets

The graph in Figure 5 shows differences between data from the same state, for which the network was trained and for different data. After these tests we have decided to use the reference network for undamaged rotor for detecting another malfunctions – unbalance and misalignment. The results of comparison are shown in Figure 6.
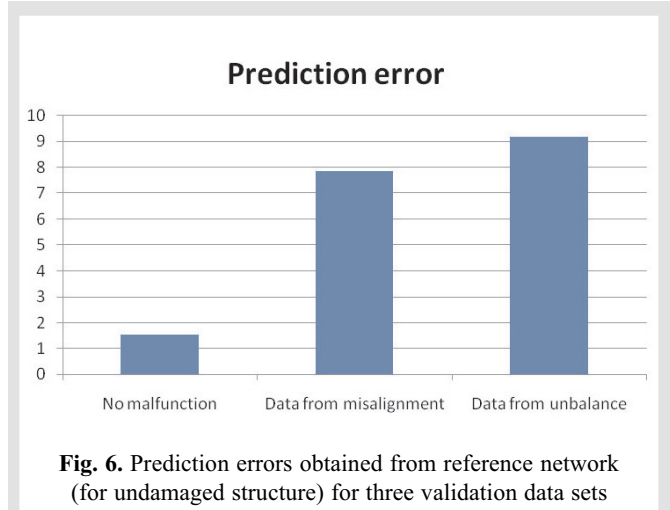
Fig. 6. Prediction errors obtained from reference network (for undamaged structure) for three validation data sets

### 4.2. Prognosis of health state of rotating machinery with NARX model

The next step of presented researches was focused on checking the influence of damage propagation for NSEE value. The experiment has been carried out for unbalance and misalignment for three different levels: small, medium and large. A new NN dedicated for analysis of experiment results has been introduced. The results of these experiments are presented in the Figure 7 and 8 for signals from accelerometers and in the Figure 9 and 10 for signals from eddy-current displacement sensors.
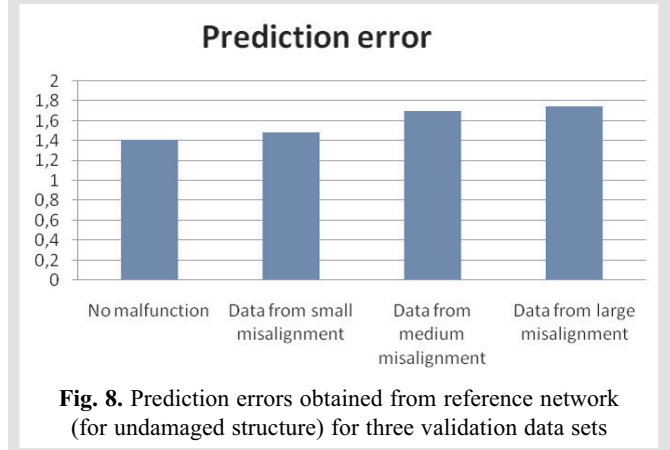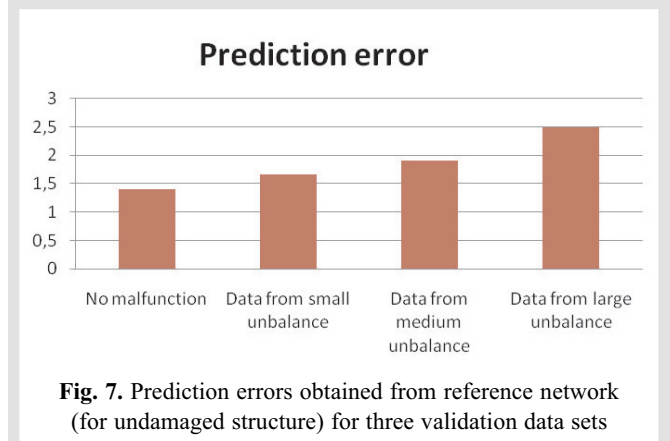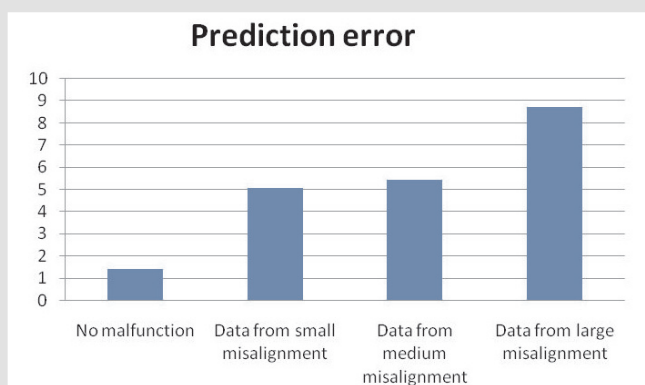

Fig. 7. Prediction errors obtained from reference network (for undamaged structure) for three validation data sets

Fig. 8. Prediction errors obtained from reference network (for undamaged structure) for three validation data sets
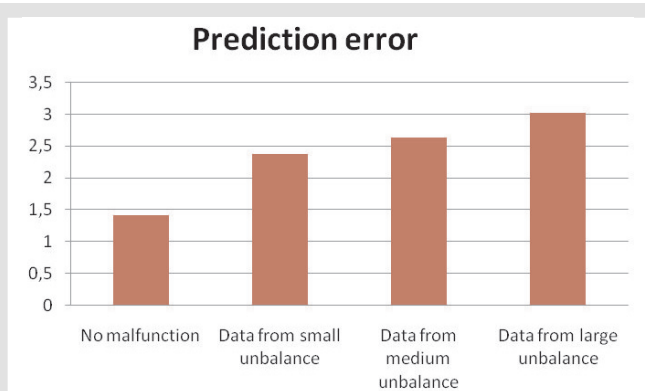
Prediction error

Fig. 9. Prediction errors obtained from reference network (for undamaged structure) for three validation data sets
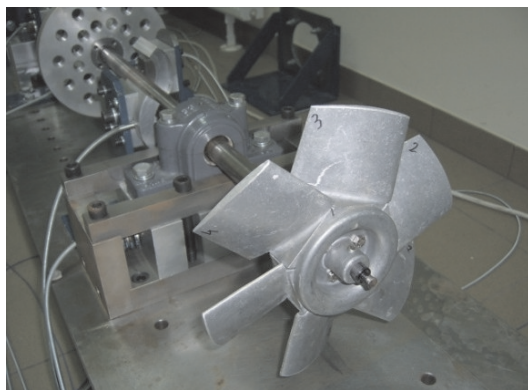
Prediction error

Fig. 10. Prediction errors obtained from reference network (for undamaged structure) for three validation data sets

Experiments results clearly show that NARX models can be successfully implemented in rotating machinery health monitoring. Value of prediction error for NARX approach increases for increasing damage. This means that ones can prognoses estimated time for normal operation of rotating machinery. Presented results proved applicability and advantages of NARX models in model based health monitoring of rotating machinery.

4.3. Blade crack detection

Blade cracks is one of the most dangerous damage in rotating machinery (Orłowski 2001) and numerous researches in this field were done (Oberholster and Heyns 2006, Peng *et al*. 2007, Smit and Heyns 2002, Stoisser and Audebert 2008). This chapter concerns detection and identification of turbine blade cracking by means of the NARX model based damage detection technique. For the tests described in this chapter the test rig has been modified by mounting the blades at the end of the shaft (Fig. 11). Then a crack of a blade was introduced (Fig. 12) by cutting of a blade in central section.

The goal of the experiment was to verify the algorithm for detecting of blades cracks in turbines. To detect such a damaged which assurance is joined with nonlinear behaviour, the approach based on NARX NN, proposed in chapter 2, was chosen.

In the NARX approach data processing was performed in Matlab and dedicated toolboxes: System Identification, Neural Network and Neural Network Based System Identification v. 2.0. As the input to the system the keyphasor signal was chosen. Two signals: a signal from eddy current sensor (vertical directions) at the driven end and a signal from accelerometer (vertical directions) at the driven end were chosen as test signals. Existing data was divided into separate sets, each having 10000 samples. Such sets were prepared for all the measured states: undamaged as well as with a cracked blade, separately for accelerometers and eddy-current sensors. Several attempts to determine the optimum network structure were performed. The analysis started from order of 4 inputs and 4 outputs. The initial network had 2 neurons in the hidden layer. All neurons in the hidden layer had hyperbolic tangent activation function. The single neuron in the output layer had linear activation function. After optimization, the best results were obtained for network having order of 3 inputs, 3 outputs and 5 neurons in the hidden layer. After network optimization phase, few networks were trained (two for accelerometers and two for eddy-current sensors) – each one modeling dynamics in a different technical state. Those trained networks were later used as reference networks. The goal of the investigation was to detect whether the set of currently acquired data could be classified to one of the known states. To verify this idea, 4 sets of validation data (each set consisted of 35000 input and 35000 output

Fig. 11. Experimental rig with blades

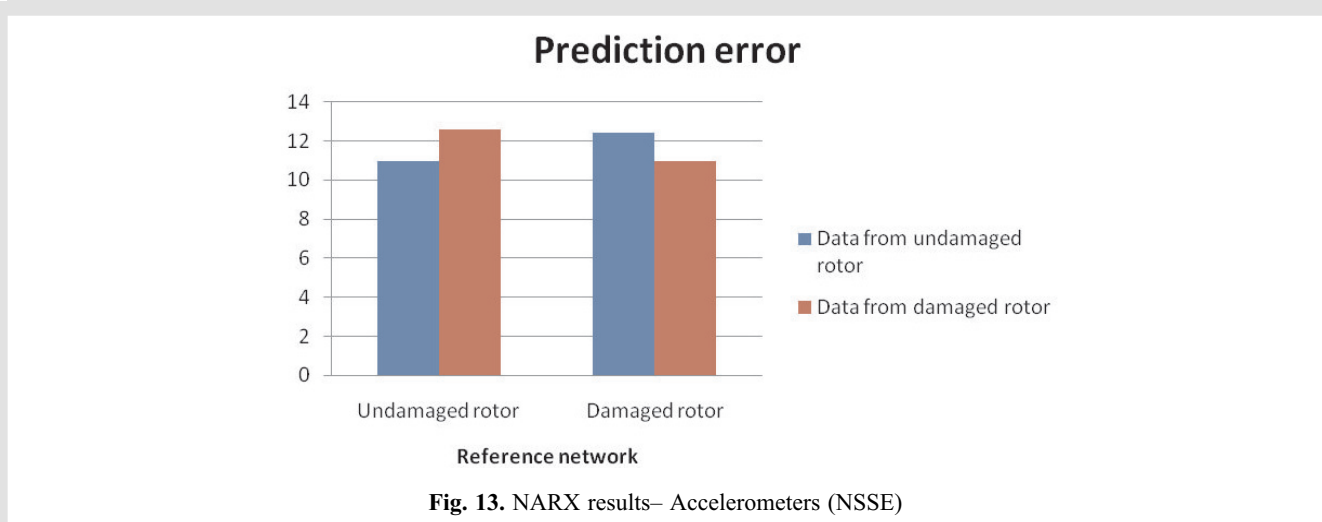**Fig. 12.** Simulation of crack at blade no 3

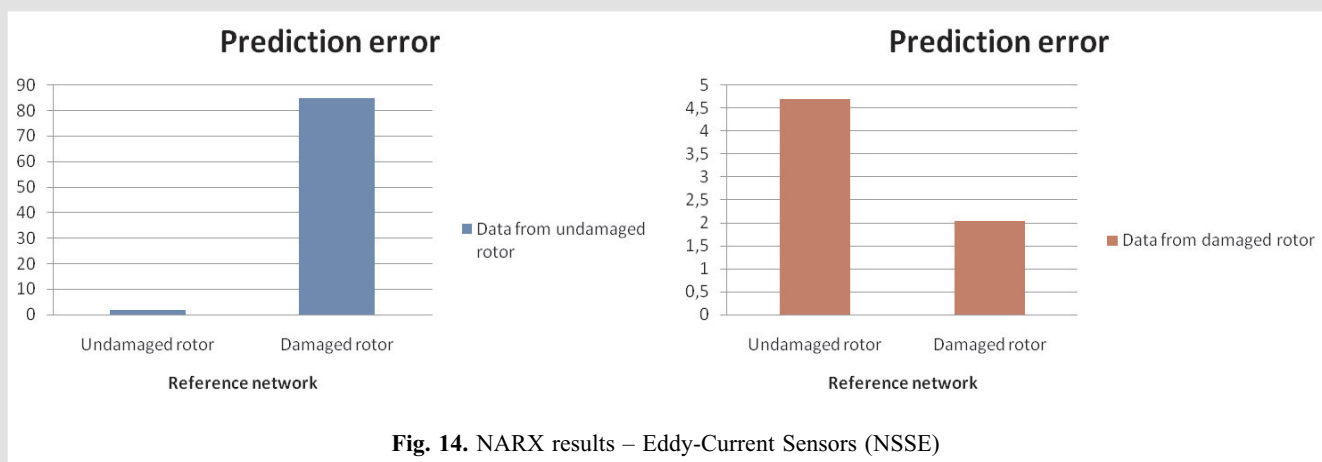**Fig. 13.** NARX results– Accelerometers (NSSE)

Fig. 14. NARX results – Eddy-Current Sensors (NSSE)

samples), resulting from measurements in the presence of different malfunctions, were used as inputs to the considered networks. As the measure of instance between real data and predicted output the normalized sum of squared prediction error (NSSE) was assumed. Thus, 4 estimates were obtained for every channel. In the Figure 13 there are presented results for the signals form accelerometers while in the Figure 14 for the signals form eddy-current displacement sensor.

Experimental results clearly show that value of NSEE error can be used as diagnostic symptom in turbine blades monitoring. Appearance of crack in the blade has significant influence for neural network prediction error especially for eddy-current sensors.

4.4. Application of proposed diagnostic algorithm for wind turbine damage detection

The last stage of proposed algorithms testing was done on real data collected on wind power plant turbine. The general view of wind power plant is presented in Figure 15.

Data were collected by a typical time signal recorder mounted at the object. Location of one of measurement point is presented in Figure 16. In Figure 17 there is presented the scheme of the considered system with the network of measurement points (P1, ..., P6).

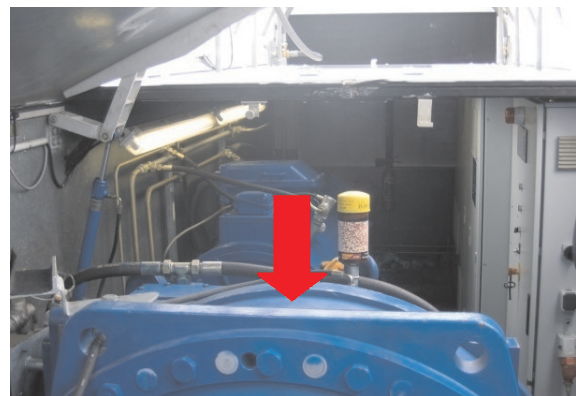**Fig. 15.** General view of wind power plant (www.wikipedia.pl)

Fig. 16. Location of one of measurement point
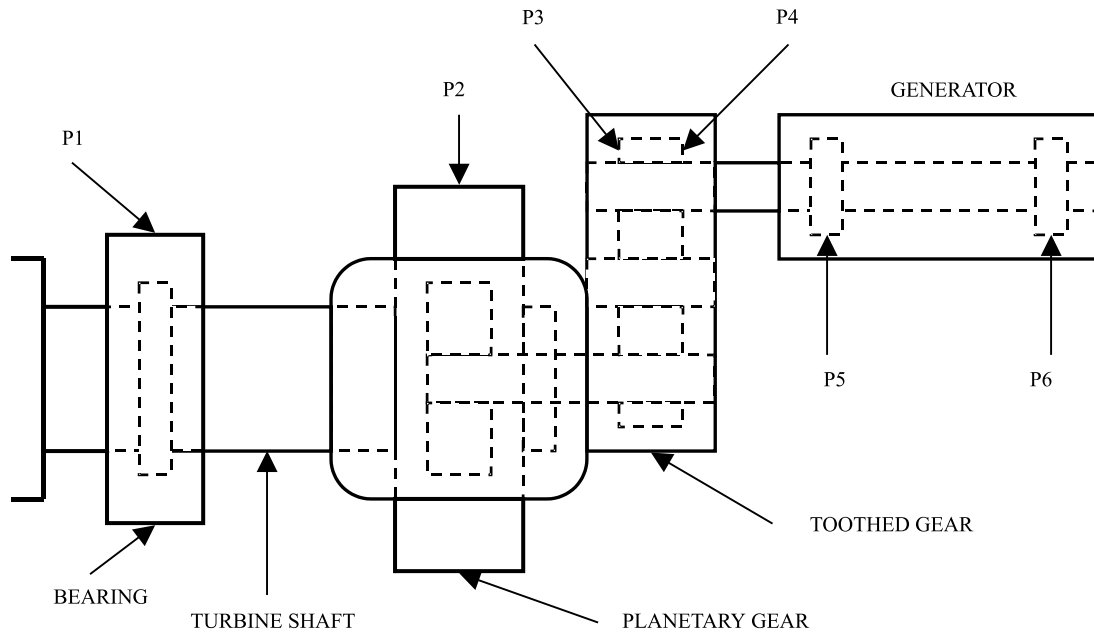
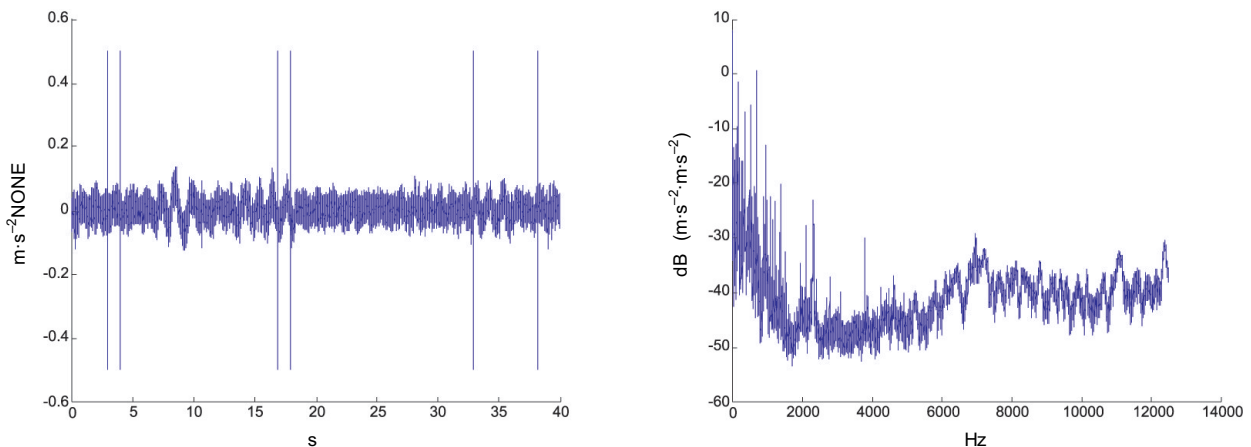**Fig. 17.** Scheme of measurements points location

Fig. 18. Example of data acquired from one vibration channel with its spectrum

In the Figure 18 the example of data acquired from one vibration channel with its spectrum is presented.

During the whole experiment the object was in the same condition so we can check only the reliability of proposed algorithms based on real data. In the NARX approach data processing was performed in Matlab and dedicated toolboxes: System Identification, Neural Network and Neural Network Based System Identification v. 2.0. As the input to the system the Keyphasor was chosen. As the training set the data collected at 2007-07-21 by sensor placed on turbine shaft bearing was chosen. Several attempts to determine the optimum network structure were performed. The analysis started from order of 7 inputs and 7 outputs. The initial network had 4 neurons in the hidden layer. All neurons in the hidden layer had hyperbolic tangent activation function. The single neuron in the output layer had linear activation function. After optimization, the best results were obtained for network having order of 2 inputs, 2 outputs and 4 neurons in the hidden layer. After network optimization phase a reference network based on data from 2007-07-21 was trained. The goal of the investigation was to detect whether the set of data acquired between 2007-07-21 and 2007-07-28 could be classified to one of the known states. Chosen data was recorded for different rotational speed of turbine main shaft and for various weather condition. To verify this idea, 8 sets of validation data (each set consisted of 10 000 input and 10 000 output samples) from various dates were used as inputs to the considered networks. As the measure of distance between real data and predicted output the normalized sum of squared prediction error (NSSE) was assumed. The results are presented in Figure 19.

After this analysis we decided to prepare data with simulated fault. As fault we decided to take into consideration an unbalance which is the most typical failure in wind turbine.
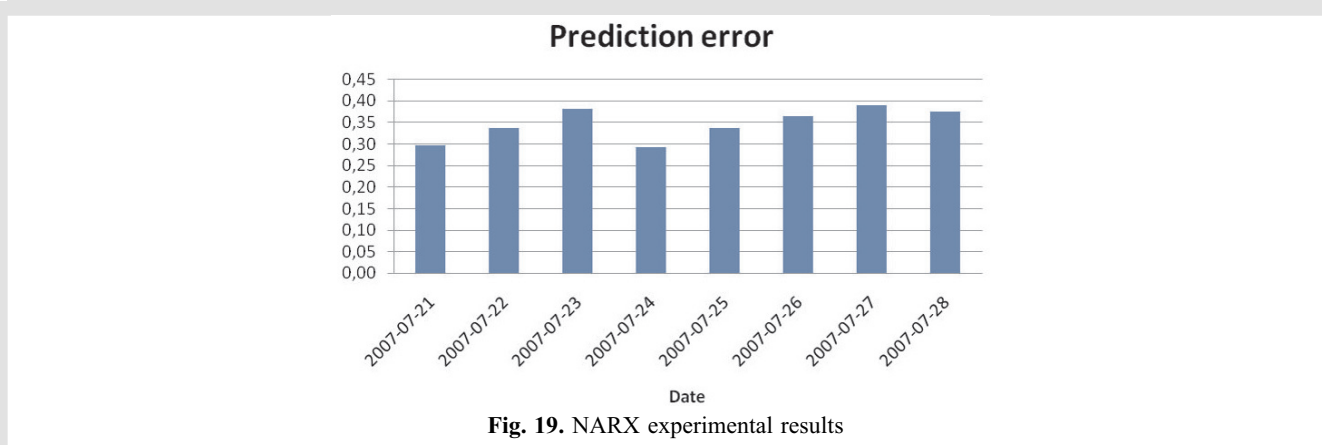
Fig. 19. NARX experimental results

We prepared 50 sets of validation data (each set consisted of 10 000 input and 10 000 output samples) from various value of unbalance were used as inputs to the considered networks. The unbalance was simulated as sinus with frequency equal to rotational frequency of turbine and amplitude increase from 0 to 0.009 [m/s²]. The value of amplitude was chosen based on the known history of turbine vibrations. This sinus was added to signals recorded at turbine main shaft. The example of spectra of prepared signals are presented in Figure 20. The results of NARX model testing for unbalance detection are presented in Figure 21. As the measure of distance between real data and predicted output the normalized sum of squared prediction error (NSSE) was assumed.

The results of experiment clearly show that NARX model can be successfully used for monitoring of wind turbine. NSEE value doesn't depend on the moment of measurements, rotatonal speed of turbine and weather conditions. The reliability of proposed algorithm is good enough to use it in on-line structural health monitoring of real object.
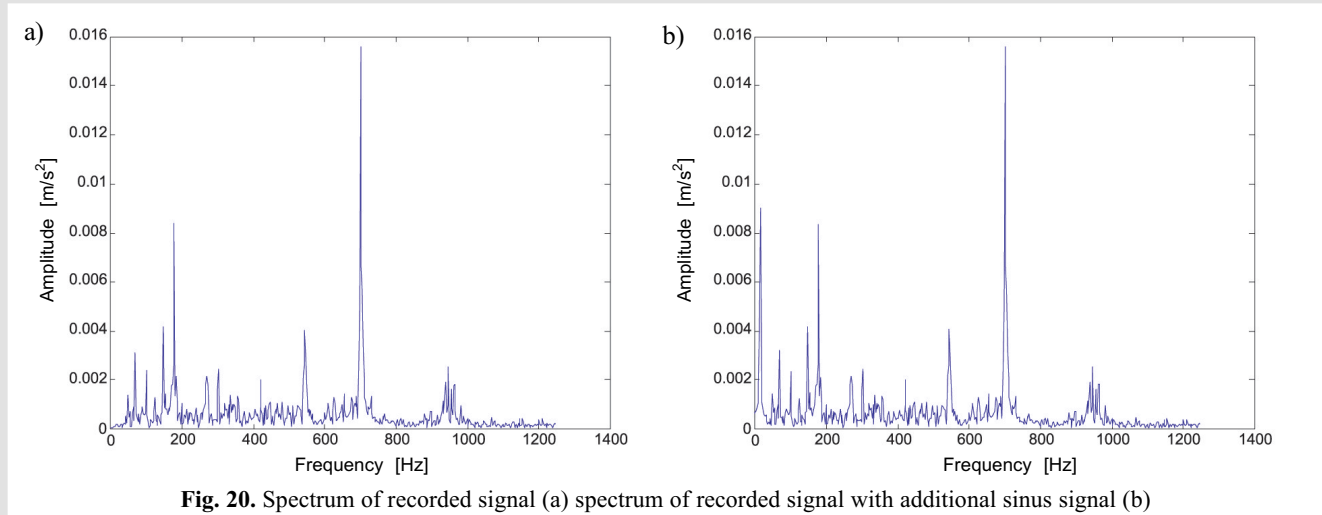

Fig. 20. Spectrum of recorded signal (a) spectrum of recorded signal with additional sinus signal (b)
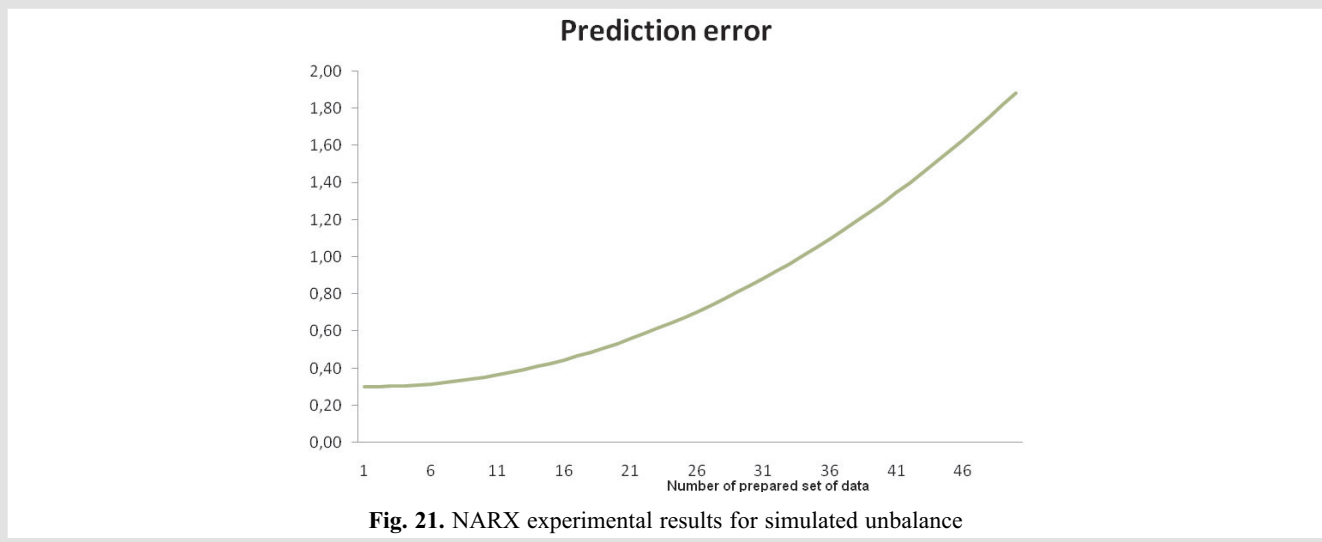

Fig. 21. NARX experimental results for simulated unbalance

5. CONCLUSIONS

The paper presents results of application of NARX networks for diagnostics of rotating machinery. There are other approaches, which could be investigated. Usage of perceptron networks is often proposed for such an application. The most promising application of perceptrons is its usage for classification of spectra, when spectral lines are used as inputs to the network. Though this approach is simple to present, it is much harder to implement it in reality. The most important limitation is very high number of inputs. To simplify the problem, one can use spectra of worse resolution, but the consequence is loss of ability to distinguish particular spectral lines. This can be important limitation for machines on rolling bearings, which have very rich spectra. On the other hand, one can use as inputs only selected harmonics (sometimes together with phase information), which are known to be sensitive for certain malfunctions. Due to the reasons given above, this method is better for machines with sliding bearings, where spectra have less components.

The proposed algorithm suffers from very high complexity – there must be a separate network trained for every malfunction. Then, after new data is acquired, prediction error for each reference network must be calculated. All these factors create huge demand for processing power. On the other hand, modern computers will process shown amounts of data in hundreds of milliseconds (as was tested during research on Pentium 4), which allows this algorithm to work even online, where it is sufficient to determine the technical state every few minutes – at most.

Important advantage of proposed method is ability to learn as new data with new malfunctions are acquired. To achieve this, the algorithm should be treated as supporting tool for a vibration expert. When new data with unknown failure are acquired, no similarity to an existing state is detected. In such a case, an expert should investigate the case, train new reference network on acquired data and label it with a meaningful name.

The paper presents application of NARX neural network to diagnostics of rotating machinery. The proposed method was verified at the test rig, where correct state and two cases of mechanical looseness failures were introduced. Performed research showed ability of proposed algorithm to detect introduced malfunctions. The algorithm was designed to work in the steady state only, for it should be applicable for machines working on a constant rotational speed for long periods of time. Proposed algorithm is very processing power demanding, but does not exceed capabilities of modern computers.

Acknowledgments

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