COMPENSATION FOR UNBALANCES WITH AID OF NEURAL NETWORKS

Mathias Paul,[1] Wilfried Hofmann,[1] Hans Friedrich Steffani[1]

ABSTRACT

The aim of this paper is to provide an extended method to compensate remaining unbalances at magnetic bearings. The compensation signal will still be generated by a MLP-network. Only now, the network needs very few training data, other values will be learned during operation with the aid of a quality criterion.

INTRODUCTION

Active magnetic bearings have been used in high speed applications due to their durability, operating precision and the adjustability of the bearing stiffness. Unbalances are measureable by simple means and principally removeable with conventional methods. They cannot be eliminated completely though, and radial forces are still at work in the high speed range. So remaining unbalances can limit the maximum rotational speed. In principle there are two categories of methods for unbalance compensation: close loop control methods (Ahrens, et. al., 1996; Namerikawa et. al, 1996) and open loop methods (Knospe et. al., 1996). The main problem of the first technique is the stability of the control loops. Furthermore, a remaining disturbance has to be left for function. Disadvantage of the open loop method is that parameters have to be inserted any way. This paper describes a method tackling this problem with the aid of neural networks.
Figure 1 shows the complete test set-up. Basis is a common 75 kW induction motor. The time discrete controller is implemented on a TMS 320-C40 signal processor.

UNBALANCES

As mentioned above, remaining unbalances are inevitable for high speed rotors. A balanced shaft can be assumed as a stiff one in speed ranges below approximately the half of first resonant frequency. Further on an abstract level the shaft is subdivisioned into many very small disc (Fig.2).

[1]TU Chemnitz, Institute of Electrical Machines and Drives, 09107 Chemnitz, Germany.

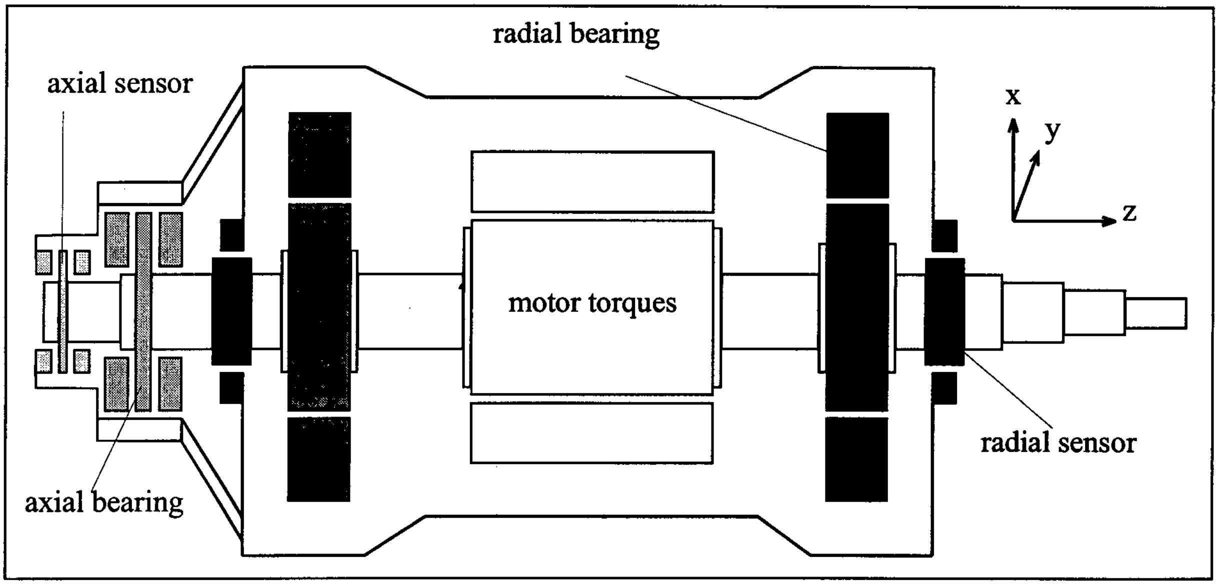

Figure 1: Active magnetic bearing

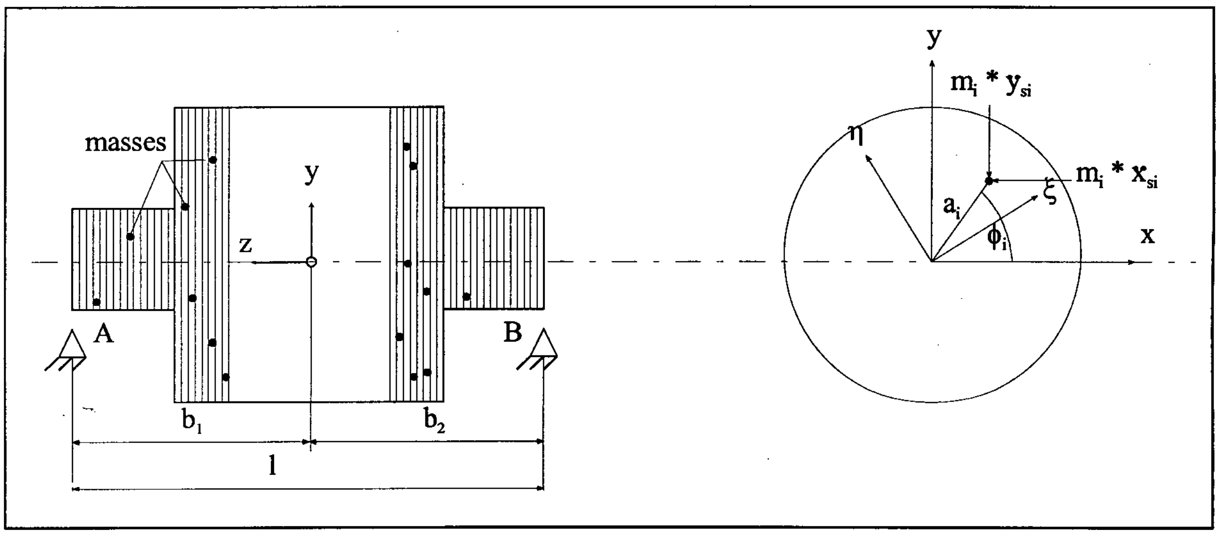

Figure 2: Subdivided shaft with masses

The projection of the centrifugal forces to the x-axis of the non rotating coordinate system of each axis

$$F_{xi} = \omega^2 a_i \cos(\omega t + \phi_i) \quad (1)$$

which leads to the total force

$$\begin{aligned} F_x &= \sum_i F_{xi} \\ &= \omega^2 a \cos(\omega t + \phi) \end{aligned} \quad (2)$$

The total moment of the unbalance forces in respect to the CoG

$$
\begin{aligned}
M_y &= \sum_i z_i F_{xi} = z_i\, a_i \cos(\omega t + \psi) \\
&= \omega^2 \Lambda \cos(\omega t + \psi)
\end{aligned}
\tag{3}
$$

To calculate the balance of forces and moments the bearing-forces $\hat{F}_{xA}$, $\hat{F}_{xB}$ and their moments, $-b_1\hat{F}_{xA}$ and $b_2\hat{F}_{xB}$ have to be respected. In compliance with the balance equations

$$
\begin{aligned}
F_{xA} + F_{xB} + F_x &= 0 \\
-b_1 F_{xA} + b_2 F_{xB} + M_y &= 0
\end{aligned}
\tag{4+5}
$$

we get

$$
\begin{aligned}
F_{xA} &= \frac{M_y - b_2 F_x}{b_1 + b_2} \\
F_{xB} &= -\frac{M_y + b_1 F_x}{b_1 + b_2}
\end{aligned}
\tag{6+7}
$$

for the balance forces. Both, the F_x and the M_y are sinusoidal signals where the frequency ω refers to the axis' rotational speed. Therefore, the bearing forces, which are a weighted sum of both F_x and M_y, are sinusoidal functions:

$$
\begin{aligned}
F_{xA} &= \omega^2 \hat{a}_A \sin(\omega t + \phi_A) \\
F_{xB} &= \omega^2 \hat{a}_B \sin(\omega t + \phi_B)
\end{aligned}
\tag{8+9}
$$

with the same frequency but different amplitudes and phases.

In the stator reference system these forces can be assumed as sinusoidal disturbances for the respective axis. This disturbance can neither be influenced nor measured. It's only possible to see the effects of the forces in the position of the shaft.

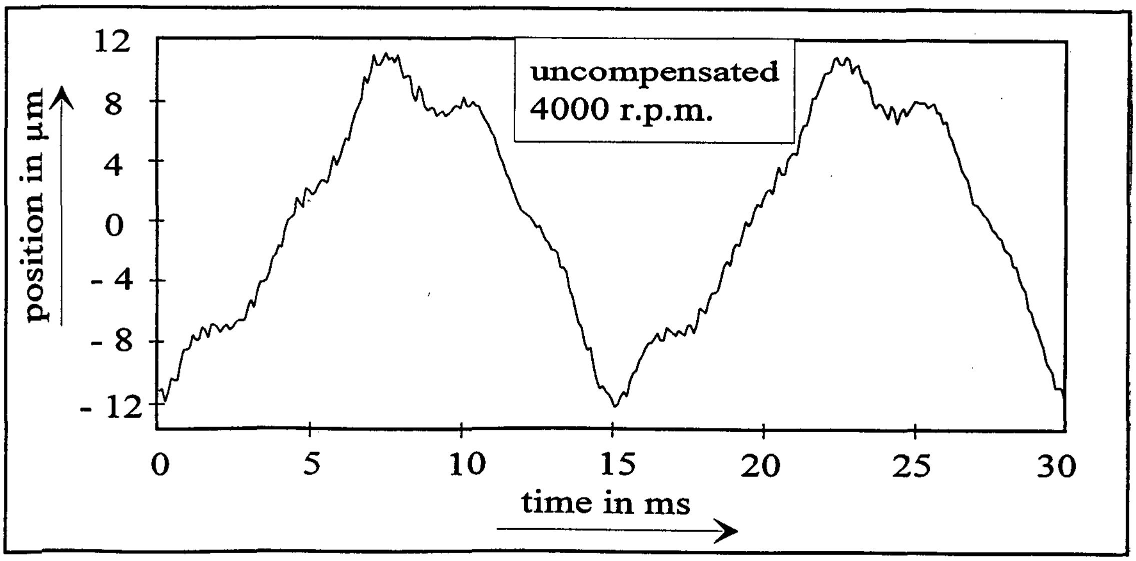

Figure 3:Effect of unbalances

In principle there are two categories of methods for unbalance compensation: close loop control methods (Ahrens, et. al., 1996; Namerikawa et. al, 1996) and open loop methods (Knospe et. al., 1996). The main problem of the first technique is the stability of the control loops. Furthermore, a remaining disturbance has to be left for function. In our open loop method the compensation signal

$$U_{comp} = A \cdot sin(\omega t + \varphi) \tag{10}$$

is added to the controller output. The compensation signal has to be chosen according to the speed such that the tolerance of cyclic running is as small as possible throughout the whole speed range. It will be generated by a sinus generator or by a digital signal processor. The position tolerance caused by the unbalances can be limited so to 10% of the uncompensated value. The great disadvantage of this methods of compensation is, that A and ϕ have to be insert manually.

PARAMETERS CALCULATED BY A MULTILAYER PERCEPTRON (MLP)

The test set-up, a magnetic beared turbo fan, works in a speed range from 0 to 6000 r.p.m. Considerable unbalances do not occur below approximately 3000 r.p.m. Further a neural net was trained with experimentally determined values of A and ϕ for the whole speed range.

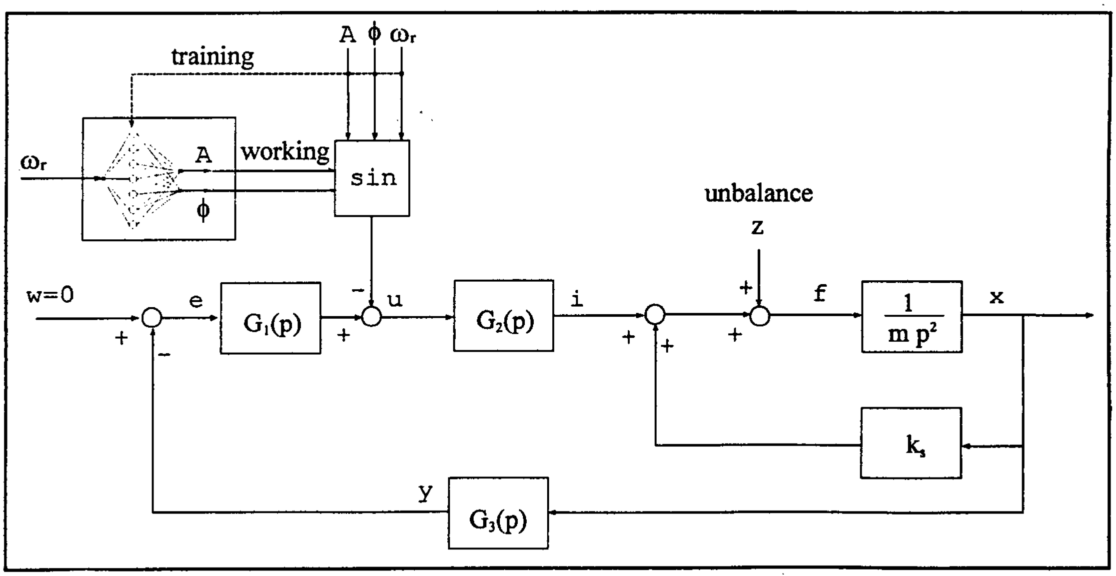

Figure 4: Block diagram bearing axis($G_1(p)$ = transfer function of controller; $G_2(p)$ = transfer function of amplifier; $G_3(p)$ = transfer function of sensor)

Figure 4 shows a block diagram of one independent bearing axis including the compensation for unbalances with the aid of neural network. The first tests served to find an optimal network topology. It must to be able to learn all values of A and ϕ for all possible working points. Therefore a dense net of amplitudes and angles was determined experimentally and fed to a network. The compensation was realized by the digital signal processor, A and ϕ were inserted manually. The aim is to learn the two nonlinear function A=f(ω) and ϕ=f(ω). The number of neurons must be sufficient to store the information. On the other hand the training time becomes longer with every neuron more. The root-mean-square rms of the remaining ripple can be used as a characteristic for the quality of compensation. Still, there is no definite connection between a too high rms and the single compensation parameter. It remains unclear whether the magnitude or the angle or both must be changed to improve the compensation.

NETWORK EMPLOYED

Multilayer - Perceptron networks combined with the backpropagation algorithm are able to learn every nonlinear function. Therefore the continuous differentiable sigmoid function was used as the activation function:

$$s(x) = \frac{1}{1+e^{-cx}} \tag{11}$$

The rotor speed is the input data. Magnitude and angle will be calculated as output data. Figure 5 shows the notational conventions.

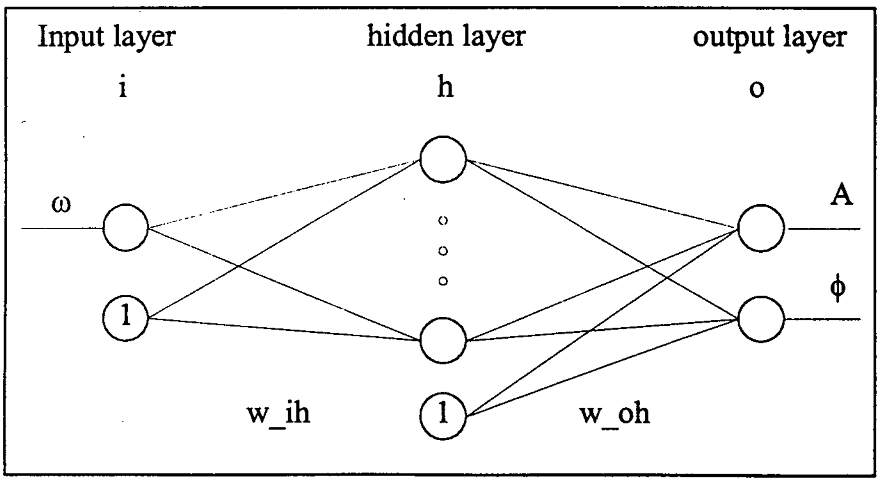

Figure 5: Multilayer perceptron employed

The neuron output values are calculated:

$$o_j^1 = s\left(\sum_{i=1}^{n+1} w_{ij}^1 \, \hat{o}_i\right) \tag{12}$$

Backpropagation is a simple gradient descent method. The aim is to look for the minimum of the error function. With further applications of the chain rule the weight changes of the neurons are calculated as follows:

$$\vec{\nabla}E = \left(\frac{\partial E}{\partial w_{11}^{1(2)}}, \ldots, \frac{\partial E}{\partial w_{i+1,h}^{1(2)}} \right) \tag{13}$$

Furthermore, some variations of backpropagation are implemented in order to improve the learning process:
a **momentum term** a D_m $w_{ij}(t-1)$ added to the weight change aiming at different learning speeds (on plateaus acceleration and in gorges delayal)
a **weight decay term** -d $w_{ij}(t-1)$ added to the weight change to limit the weights
a **quickpropagation** algorithm to speed up the training with backpropagation in general
flat-spot-elimination means that a constant value will be added to the sigmoid function.
The following network configuration was used to learn the training data:

- input layer - 1 input neuron (rotor speed) / 1 Bias
- hidden layer - 15 hidden neuron / 1 Bias
- output layer - 2 output neurons (magnitude, angle)

If the learning rate or momentum term were higher than indicated above, the weight corrections would soon become so high that the floating point overflow occurs.

To provide a real advantage to the conventional method, the network should need to be fed with only very few values of magnitudes and angles. The other values will be learned online during operation. Therefore the rms is used as a quality criterion.The network should learn further online with the help of the quality criterion. The simulation was started with only 3 learning objects (A and ϕ for 3 speeds). After the square error became under 0.0001 a new learning object was added.

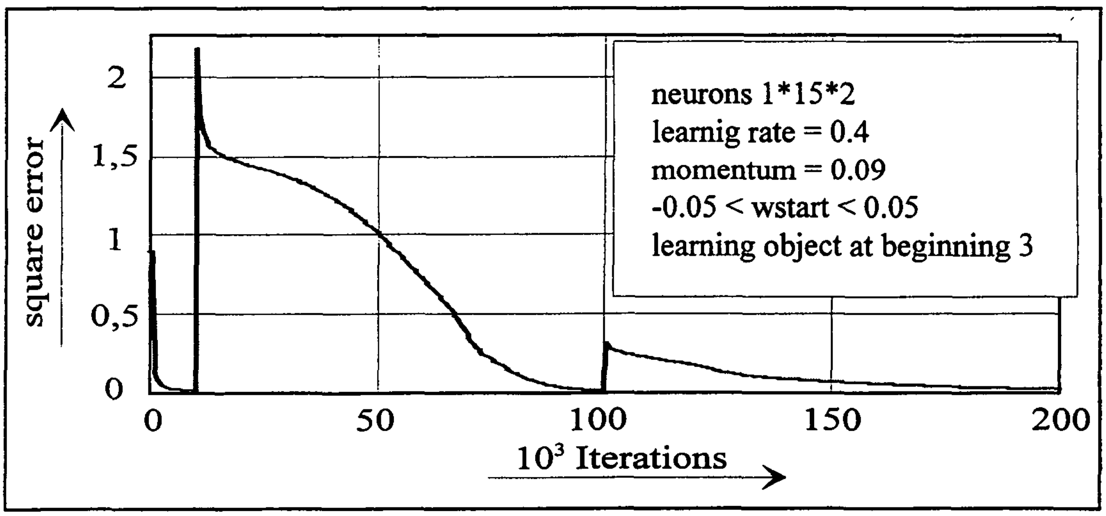

Figure 6: Adding learning objects

Figure 6 shows the behaviour of the square error adding new learning objects. It is thus possible to determine a dense net of correct compensation parameters, without leaving a safety operating area with the drive.

MEASURED RESULTS

Figure 7 shows a comparison between the behaviour of the uncompensated and the compensated system (one bearing). The position tolerance will be limited to roughly 6µm (pic-pic). The remaining noise (see enlargement) of the compensated positions is caused by magnetic forces of the the motor windings. The measured noise of the capacity measuring tool used is approximately 1,5 µm. That is the lower limit for a sensible compensation for unbalances.

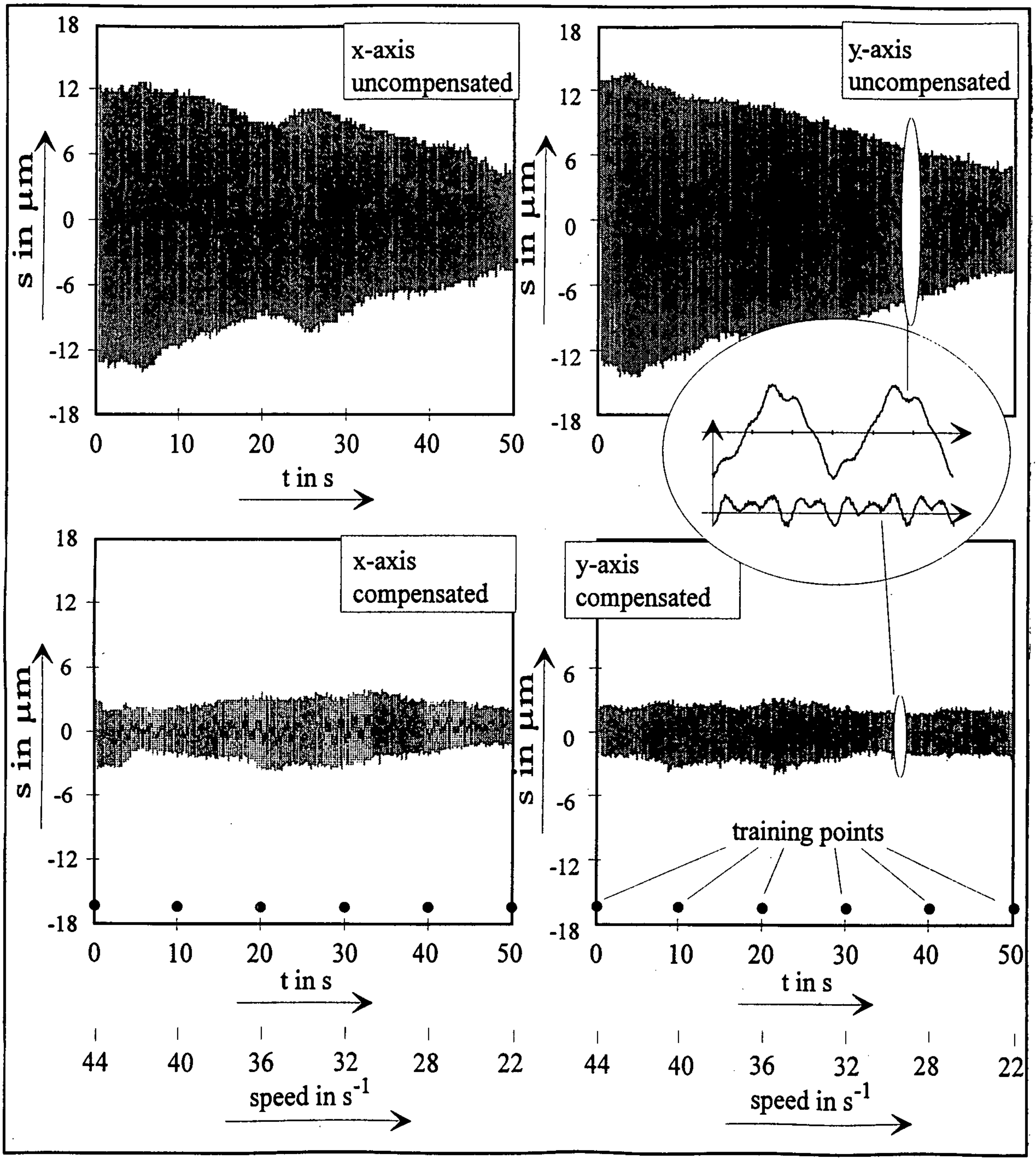

Figure 7: Comparison compensated-uncompensated

PROGRAMM STRUCTURE

The algorithms for the neural network are implemented in common C. They run with DOS on every system. The structure is completely dynamic not object orientated. It can be stopped at any definite point and continued later. The network data will be saved automatically. The backpropagation algorithm has optional variations.
Furthermore, all interesting information like square error, number of iterations and the input/output values of all neurons are graficaly retrievable.

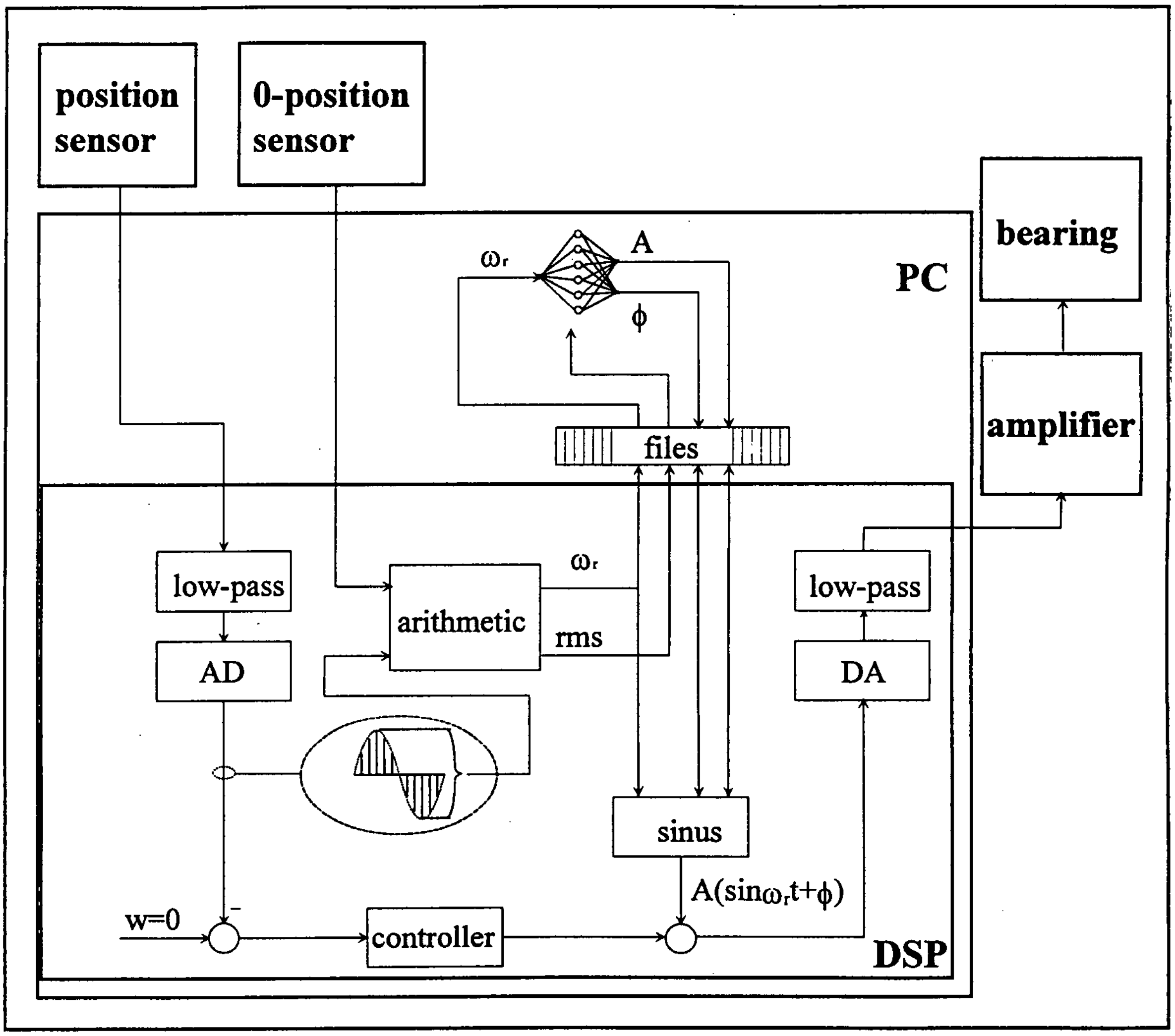

Figure 8: Hardware structure

The signal processor calculates the speed from of the 0-position data and writes the speed together with the actual magnitude and angle and the rms into files. The neural network, which is implemented on the personal computer, is able to read the files and learns with the aid of these data (Figure 8).

CONCLUSIONS

The neural net structure is realized as a dynamic one so it is possible to use it in other applications. The aim of secondary work is to control the whole bearing system including the compensation for unbalances future with the aid of a neural network.

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NOMENCLATURE

F = force
ω = rotor speed
a = unbalances
ϕ = angle
M = moment
Λ = moment of inertia
c = slope constant of sigmoid function
o = network output
w = weights
E = total Error