Neural Network Control of a Magnetically Suspended Rotor System

Magnetic bearings offer significant advantages because they do not come into contact with other parts during operation, which can reduce maintenance. Higher speeds, no friction, no lubrication, weight reduction, precise position control, and active damping make them far superior to conventional contact bearings. However, there are technical barriers that limit the application of this technology in industry. One of them is the need for a nonlinear controller that can overcome the system nonlinearity and uncertainty inherent in magnetic bearings. At the NASA Lewis Research Center, a neural network was selected as a nonlinear controller because it generates a neural model without any detailed information regarding the internal working of the magnetic bearing system. It can be used even for systems that are too complex for an accurate system model to be derived. A feed-forward architecture with a back-propagation learning algorithm was selected because of its proven performance, accuracy, and relatively easy implementation.

The neural net plant emulator was first trained to emulate a theoretical model of the nonlinear plant. A discrete theoretical model of the plant dynamics in state-space notation was used to choose the present states of the plant (rotor displacement and velocity) and the plant input (control current) as the input to the emulator. The next states, the rotor displacement and velocity after one sample time, were chosen as the output. During the learning procedure, we minimized the errors between the actual network output and the desired values by upgrading the weights. After training, the neural emulator perfectly predicted the next states (delayed by one sample time) of the magnetic bearing system for the current states and control force, which were not in the training sample data.

Our second step was to use the trained neural emulator to train a neural net controller to make the whole system meet conventional performance specifications on such parameters as the bandwidth, settling time, and overshoot. We wanted the controller to take the current magnetic bearing states $\vec{x}(t)$ and demand r as input parameters, and to output a control force $u(t)$ to the magnetic bearing system. These current state values should make the magnetic bearing's next state vector

$$\vec{x}(t + 1)$$

be identical to that defined by the desired linear reference system, satisfying performance specifications in either the frequency or time domain.
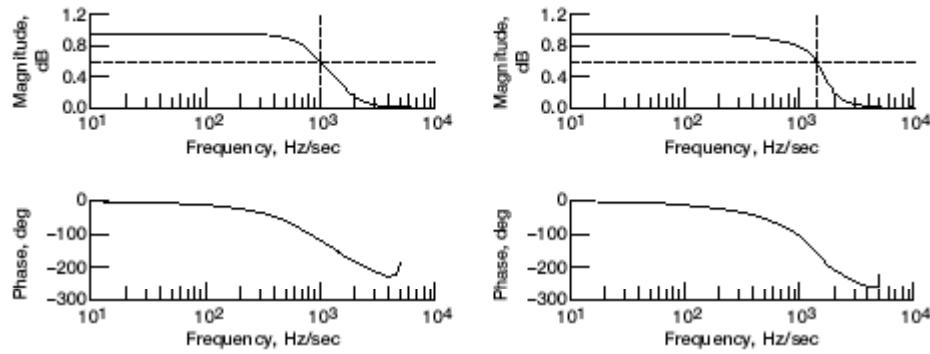
Bode plots of desired and neural network models in frequency domain, showing averaged transfer function. Left: Simple second-order linear reference model for a frequency domain of peak magnitude, m_p, 1.1, and cutoff frequency, w_c, 1000 Hz. Right: Trained closed-loop system.

The left side of the preceding figure is the Bode plot of a simple second-order linear reference model derived from frequency domain specifications; the right side shows the closed-loop magnetic bearing system after training. They are almost identical even after 200 training epochs. Another neural controller based on time domain specifications was trained and tested by simulating its response for the initial condition and comparing the results to the actual magnetic bearing response (see the following figure). The neural net controller was so accurate that it perfectly overlapped the magnetic bearing response (+ markers).
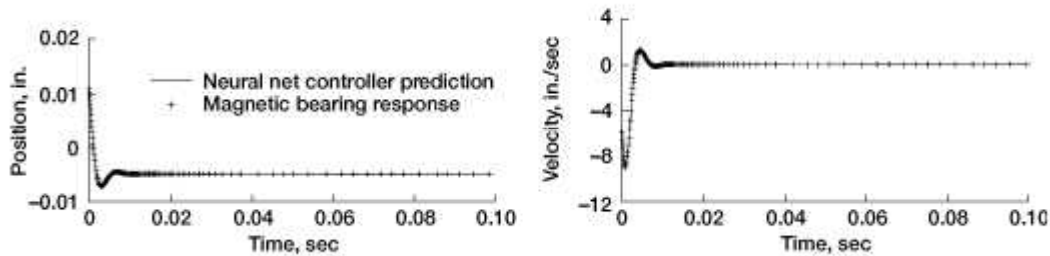
Desired and actual response in time domain. Left: Simple second-order linear reference model response for percent of overshoot, P_0, 4.3 percent, and settling time, T_s, 0.0001 sec. Right: Trained closed-loop system response for initial position, x_0, 0.0011 in.; initial velocity, $\bar{x}_0$, -6 in./sec; and reference position, r_f, -0.005 in.

In summary, a neural network controller that circumvents the magnetic bearing's nonlinearity was developed and successfully demonstrated on a small Bentley-Nevada magnetic bearing rig. The neural plant emulator and neural controller were so accurate that the neural network controller did a near perfect job of making the nonlinear magnetic bearing system act like the linear reference model. This novel approach demonstrated the feasibility of using it for advanced turbomachinery systems with large-scaled magnetic bearings with unknown dynamics.

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