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Control of the electrodynamic shaker with additional force sources

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In vibration testing, the device under test (DUT) is usually connected to an electrodynamic exciter using a fixture. The connection needs to be as rigid as possible, such that it influences the acceleration exposition spectrum as little as possible. However, if the fixture is too heavy, then a more powerful exciter is required to be able to deliver sufficient force to achieve the requested acceleration magnitude. The unwanted vibrations are often dealt with using an active vibration absorber, such as [2] or more specifically a delayed resonator [3]. The issue with such approaches is that mass is added to the device. One possible solution to this problem is to use a light fixture with additional actuators that compensate for vibrations of the fixture itself.

A 3D CAD model of a small plastic tank with a fixture was constructed from aluminium extrusions connecting it to the steel plate of the main vibration exciter. Then a simulation model was developed and then its order was reduced using modal reduction. The positions of the accelerometers and the action of the actuators are collocated. The assembly is shown in Fig. 1.

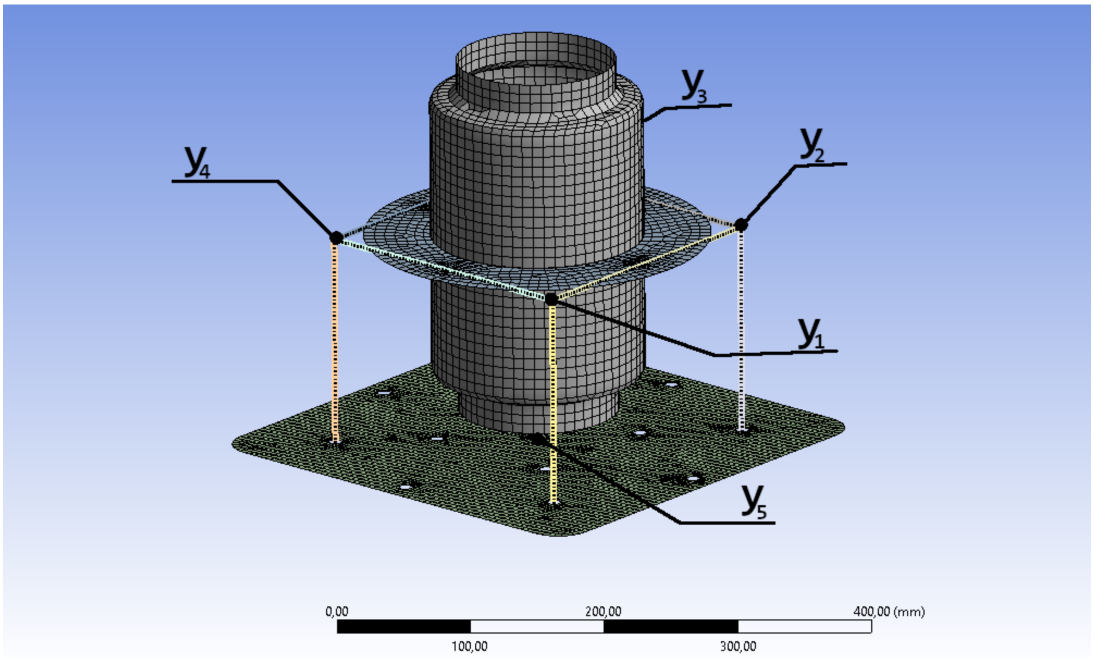

Fig. 1. DUT and the fixture. The positions of the accelerometers are marked – points y_1 to y_4 are located on top of the studs and the y_5 is located on the plate underneath the tank, which is suspended from the crossbars. The actuators points of action are collocated with the accelerometers

The control strategy is based on the adaptive inverse control [4] approach that utilizes an adaptive filter. In this work, this control strategy is realized using a Linear Neural Unit (LNU) with Levenberg–Marquardt (LM) learning algorithm, as described in [1].

The LNU input $\vec{x}$ consist of bias $x_0 = 1$ and delayed samples of the system output y_i

$$\vec{x}(t) = \begin{bmatrix} 1 & y_1(t-T) & \ldots & y_1(t-n_yT) & y_2(t-T) & \ldots & y_5(t-n_yT) & \end{bmatrix}^T,$$

where $T = 0.01$ ms is sampling period and n_y is the number of samples from each output that are included. The output of the LNU is then given by

$$\vec{y}_{\mathrm{LNU}} = \vec{w}^T\vec{x},$$

where $\vec{w}$ is the vector of neural weights. The LM algorithm optimizes the cost function

$$\mathrm{MSE}_j = \frac{1}{l}\sum_{i=1}^{l} e_j(t_i)^2,$$

where l is the batch length and e_j is the jth component of

$$\vec{e}(t) = \vec{y_D} - \vec{y}_{\mathrm{LNU}},$$

which is the difference between the desired output $\vec{y}_D$ and the optimized system output $\vec{y}$. The goal is for the LNU to be the inverse of the controlled system, so in this case

$$\vec{e}(t) = \vec{u}(t - T_D) - \vec{y}_{\mathrm{LNU}}(t),$$

where $\vec{u}$ is the controlled system input and $T_D = \left\lfloor \frac{n_y}{2} \right\rfloor$ is the delay used to eliminate the issues with causality. The weights' updates are then calculated as

$$\vec{w}(k+1) = \vec{w}(k) + \Delta\vec{w}(k) = \vec{w}(k) + \left(\mathbb{J}^T\mathbb{J} + \mu\mathbb{I}\right)^{-1}\mathbb{J}^T\mathbb{E},$$

where

$$\mathbb{J} = \begin{bmatrix} \vec{x}(t) \\ \vdots \\ \vec{x}\left(t - T(l-1)\right) \end{bmatrix}$$

is the Jacobian matrix, μ is the learning coefficient, $\mathbb{I}$ is the identity matrix,

$$\mathbb{E} = \begin{bmatrix} e(t) \\ \vdots \\ e\left(t - T(l-1)\right) \end{bmatrix}$$

and l is the length of the mini-batch. This update is calculated for every l time step. The diagram of the system is shown in Fig. 2.

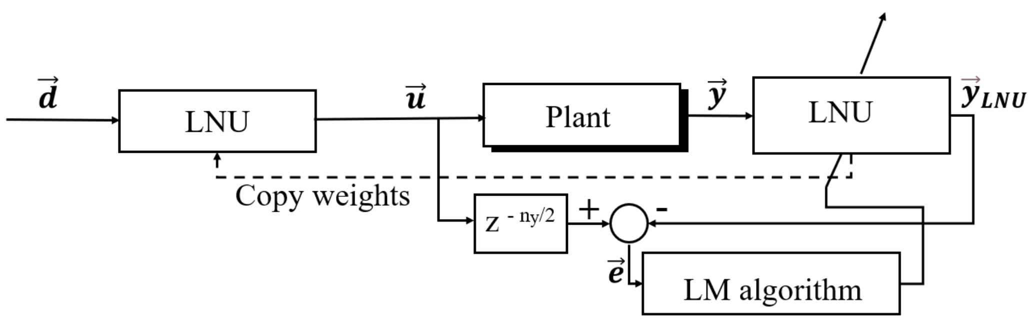

Fig. 2. Diagram of the control system. The LNU before the plant works as a controller. The LNU after the plant is learning the inverse of the plant and its weights. The weights are then used to update the controller LNU

The system has been simulated with parameters

$$
\begin{aligned}
n_y &= 200, \\
l &= 500, \\
\mu &= 0.1,
\end{aligned}
$$

and white noise with constant power spectral density in the frequency range 0 to 2000 Hz and with $d_{\mathrm{RMS}} = 1\ \frac{\mathrm{m}}{\mathrm{s}^2}{}_{\mathrm{RMS}}$ as input. The same waveform was used for all inputs. The results of the simulation are shown in Fig. 3.

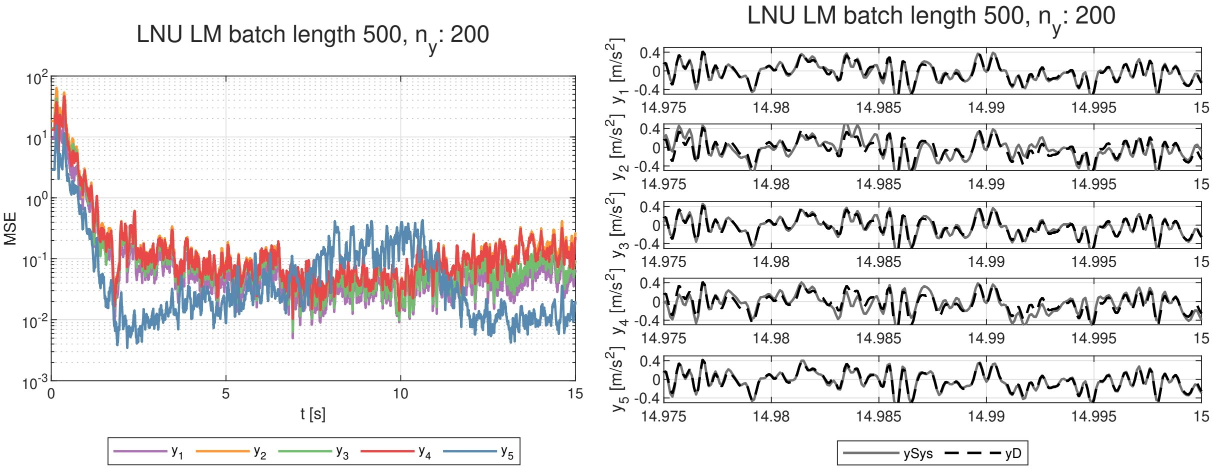

Fig. 3. (*Left*) The LNU is able to decrease the MSE significantly in the first 3 seconds; (*right*) the output acceleration follows the desired waveform

The simulation results are promising. Therefore, the following work will focus on the experimental evaluation of the algorithm on the specific real world test stand, which is currently being built.

Acknowledgements

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