

Neural-Network and Fuzzy-Logic Learning and Control of Linear and Nonlinear Dynamic Systems

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(ABSTRACT)

The goal of this thesis is to develop nontraditional strategies to provide motion control for different engineering applications. We focus our attention on three topics: 1) roll reduction of ships in a seaway; 2) response reduction of buildings under seismic excitations; 3) new training strategies and neural-network configurations.

The first topic of this research is based on a multidisciplinary simulation, which includes ship-motion simulation by means of a numerical model called *LAMP*, the modeling of fins and computation of the hydrodynamic forces produced by them, and a neural-network/fuzzy-logic controller. *LAMP* is based on a source-panel method to model the flowfield around the ship, whereas the fins are modeled by a general unsteady vortex-lattice method. The ship is considered to be a rigid body and the complete equations of motion are integrated numerically in the time domain. The motion of the ship and the complete flowfield are calculated simultaneously and interactively. The neural-network/fuzzy-logic controller can be progressively trained.

The second topic is the development of a neural-network-based approach for the control of seismic structural response. To this end, a two-dimensional linear model and a hysteretic model of a multistory building are used. To control the response of the structure a tuned mass damper is located on the roof of the building. Such devices provide a good passive reduction. Once the mass damper is properly tuned, active control is added to improve the already efficient passive controller. This is achieved by means of a neural network.

As part of the last topic, two new flexible and expeditious training strategies are developed to train the neural-network and fuzzy-logic controllers for both naval and civil engineering applications. The first strategy is based on a load-matching procedure, which seeks to adjust the controller in order to counteract the loads (forces and moments) which generate the motion that is to be reduced. A second training strategy provides training by means of an adaptive gradient search. This technique provides a wide flexibility in defining the parameters to be optimized. Also a novel neural-network approach called modal neural network is designed as a suitable controller for multiple-input multiple output control systems (MIMO).

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