

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

Daniel Armando Liut

Dissertation submitted to the Faculty of the
Virginia Polytechnic Institute and State
University in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy
in
Engineering Mechanics

Dr. Dean T. Mook, Chair

Dr. Owen F. Hughes

Dr. Enrique E. Matheu

Dr. Ali H. Nayfeh

Dr. Saad A. Ragab

Dr. Hugh F. VanLandingham

August 18th, 1999

Blacksburg, Virginia

Keywords: unsteady source-vortex-lattice hydrodynamics, ship-motion control with fins, linear and hysteretic building structures, tuned mass dampers, neural-network and fuzzy-logic control, load-matching procedure, adaptive gradient search, modal neural networks.

Copyright 1999, Daniel A. Liut

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

Daniel Armando Liut

(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).

Acknowledgments

First of all I want to recognize *Professor Dean T. Mook* for his constant support, trust and advice, which in many instances went far beyond his advisory duties.

Then I want to emphasize that the alphabetical order of the members of my advisory committee is not accidental. Each one of them played an **essential role**, which made possible the accomplishments of this work: *Professor Owen F. Hughes*¹ for his naval advice so important for our research; *Doctor Enrique E. Matheu*² for his seismic engineering experience and work in the seismic engineering code, which is an important part of our research; *Professor Ali H. Nayfeh*³ for his support and advice; *Professor Saad A. Ragab*⁴ for his experience in fluids and his personal advice; and *Professor Hugh F. VanLandingham*⁵ for introducing us to the fascinating world of neural networks and fuzzy logic.

Though not a part of my advisory committee, *Professor Mahendra P. Singh*⁶ played an important role, by contributing with his advice and experience in the writing of many of our papers.

I want to recognize the economic support given by the MURI⁷ project which, through *Professor Nayfeh's* initiative, made possible most of the research of this work.

I further want to thank *Mister Kenneth Weems*⁸ for the technical support he provided, which helped us implement the interaction between the programs FINS and LAMP.

I want to recognize the valuable contribution of the *Argentine Navy*, which made possible the first phase of this enterprise, and which provided me with a thorough and integral education, in line with its tradition of honor and excellence.

¹ Aerospace and Ocean Engineering Department.

² Engineering Science and Mechanics Department (assistant professor).

³ Engineering Science and Mechanics Department.

⁴ Engineering Science and Mechanics Department.

⁵ Electrical Engineering Department.

⁶ Engineering Science and Mechanics Department.

⁷ ONR under the MURI on Nonlinear Control of Dynamic Systems N00014-96-1-1123.

⁸ Ship Technology Division, Science Applications International Corporation, Annapolis, MD, USA.

I also want to recognize the important contribution of the *Universidad del Aire*, (*Argentine Air Force*), which put me in contact with *Professors Mook's* and *Nayfeh's* research team, and which gave me the first background needed for my studies at Virginia Tech. In this regard I want to mention especially *Professor Victor Torregiani*.

I want to thank *Professor Edmund G. Henneke*⁹ for his economic support in granting me different teaching assistantships during the years 1995 and 1996.

I want to recognize *Professor L. Glenn Kraige*¹⁰, an outstanding educator, who gave me invaluable support with his advice.

I want to thank *Professor Romesh C. Batra*¹¹ for his contributions and advice as a former member of my advisory committee.

I finally want to express my warm gratitude to the *United States of America*, which always treated me with high respect and generosity.

⁹ Department Head of the Engineering Science and Mechanics Department.

¹⁰ Engineering Science and Mechanics Department.

¹¹ Engineering Science and Mechanics Department.

Table of Contents

1	Introduction and Literature Review	1
1.1	Introduction	1
1.2	Literature Review	6
1.2.1	Previous Hydrodynamic Research Related to Fins	6
1.2.2	Seismic Engineering Considerations	8
1.2.3	Neural-Network Control	8
1.2.4	Fuzzy-Logic Control	11
1.2.5	Rolling Control of Ships by Means of Active Fins	12
1.3	Original Contributions and Major Achievements	13
1.4	Organization of the Dissertation	14
2	Fin-Hull Interaction: The Hydrodynamic Model	16
2.1	Introduction	16
2.2	FINS	18
2.3	Kutta Condition and Shedding	23
2.4	Pressure Computations	25
2.5	Time-Marching Procedure	33
2.6	Code Validation and Results	34

2.7	Final Remarks	39
3	Seismic Engineering: The Structural Model	63
3.1	Introduction	63
3.2	The Structural Model	63
3.3	Input Data and Numerical Examples	67
4	Neural Networks and the Backpropagation Technique	84
4.1	Introduction	84
4.2	Neural Networks	84
4.3	The Backpropagation Algorithm for a Two-Layer, Single-Output Neural Network	86
5	The Moment-Matching Procedure: A Marine Application	95
5.1	Introduction	95
5.2	The Dynamics of the Problem	97
5.3	The Control System	101
5.4	The Training Procedure	103
5.5	Convergence	108
5.5.1	Convergence Algorithm	108
5.5.2	Adapting to Changes in Sea, Structure and Ship Loads	111

5.6	Results	112
5.7	Concluding Remarks	114
6	The Force-Matching Procedure: A Civil Engineering Application	126
6.1	Introduction	126
6.2	The Neural-Network Controller and the Structural Model	129
6.3	Training the Neural Network	131
6.4	The Force-Matching Training Procedure	132
6.5	Numerical Results	139
6.6	Concluding Remarks	143
7	An Adaptive Gradient Training Approach for a Neural-Network Controller: A Civil Engineering Application	160
7.1	Introduction	160
7.2	The Structural Model and the Neural-Network Controller	161
7.3	Weight Adjustment Procedure	163
7.4	Numerical Results	173
7.5	Final Remarks	180
7.6	Complementary Example: Step-By-Step Training Procedure for a Three-Weight Neural Network during the First Six Epochs.	181

8	Modal Neural Networks: A Naval Application	212
8.1	Introduction	212
8.2	The Modal Neuron and Modal Neural Networks	213
8.3	Results	217
8.4	Concluding Remarks	220
8.5	Complementary Discussion: The Backpropagation Technique in Modal Neural Networks.	221
9	Control of Rolling in Ships by Means of Active Fins Governed by a Fuzzy-Logic Controller	236
9.1	Introduction	236
9.2	Fuzzy-Logic Control	237
9.3	The Training Procedure	240
9.3.1	The Backpropagation Algorithm	241
9.3.2	The Moment-Matching Procedure	244
9.3.3	Initial-Rule Initialization. Clustering Algorithm	246
9.4	Results	251
9.5	Concluding Remarks	253
10	Final Remarks	262
10.1	Concluding Discussion	262
10.2	Future Work	264

Bibliography 267

Vita 280

List of Figures

Chapter 2

2-1	Example of a vortex-lattice mesh defined over a fin, and the circulations associated with each element of the mesh.	40
2-2	Biot-Savart Law. Velocity field associated with a straight segment of vorticity.	41
2-3	Kutta condition: three-dimensional view. Vorticity shed from the trailing edge (T.E.) of an airfoil.	42
2-4	Kutta condition: two-dimensional view. Vorticity shed from the trailing edge of an airfoil; P_u is the pressure on the upper surface of the fin and P_l is the pressure on the lower surface of the fin.	43
2-5	Two-dimensional schematic of a vortex sheet.	44
2-6	Inertial, body-fixed, fin-fixed and flap-fixed reference frames.	45
2-7	A cross section of the vortex sheet (lattice) showing the path of integration, C_p , to evaluate $\Phi_u^P - \Phi_l^P$. Shadowed circles represent discrete span-wise vortices; point P represents the control point. $G_p = \Gamma_1 + \Gamma_2 + \Gamma_3 + \Gamma_4$ is the circulation for the closed loop of discrete vortex segments enclosing the element that contains the control point.	46
2-8	Δv produced by a segment of vorticity between two elements.	47
2-9	Ship and fin grids.	48
2-10	Time-marching procedure.	48

2-11	Fin mesh and vorticity in a free flow and in the presence of an infinite wall. Number of fin elements = 256. Aspect ratio = 0.8. Fin deflection = 10 degrees. Flap deflection = 10 degrees.	49
2-12	Top (a) and front views (b, c) of a fin mesh and vorticity of a fin attached to the hull. Number of fin elements = 256. Aspect ratio = 0.8. Fin deflection = 10 degrees. Flap deflection = 10 degrees.	50
2-13	C_L computations with and without the fin-tip influence, for a fin of aspect Ratio 2 at an angle of attack of 5 degrees.	51
2-14	C_L computations with and without the fin-tip influence, for a fin of aspect ratio 0.7 at an angle of attack of 5 degrees.	51
2-15	C_L computations with and without the fin-tip influence, for a fin of aspect ratio 2 at an angle of attack of 10 degrees.	52
2-16	C_L computations with and without the fin-tip influence, for a fin of aspect ratio 0.7 at an angle of attack of 10 degrees.	52
2-17	The experimentally obtained variation of unsteady aerodynamic loads with angle attack for the NACA 0012. $M_\infty = 0.3$, chord-based $Re = 4 \times 10^6$ $\alpha = 3^\circ + 10^\circ \sin(0.2 t)$, and solid lines denote increasing α . (Taken from McCroskey <i>et al.</i> [65]).	53
2-18	The computed variation of unsteady aerodynamic loads with angle of attack for a flat plate of infinite aspect ratio; $\alpha = 3^\circ + 10^\circ \sin(0.2 t)$	54
2-19	The computed variation of unsteady aerodynamic loads with angle of attack for a NACA 0012 airfoil; $\alpha = 3^\circ + 10^\circ \sin(0.2 t)$	55

2-20	A comparison of the numerical and experimental normal-force coefficients as functions of the angle of attack for a rectangular, unit-aspect-ratio fin in a steady airstream. (^ Scholz [83], * Belotserkosvkiy [2], * Ermolenko [19] and * Winter [99] experimental data).	56
2-21	Schematic representation of Dallinga's model. (Taken from Dallinga [16]).	57
2-22	Comparison of numerical and experimental lift coefficients. (Experimental data from Dallinga [16]).	58
2-23	Comparison of numerical and experimental drag polars. (Experimental data from Dallinga [16]).	59
2-24	(1) Heaving-induced lift with zero fin angle of attack, and (2) lift as a function of fin angle of attack with no heaving motion. The fins are attached to the (curved) hull of a CG47 cruiser.	60
2-25	Rolling motion for a beam sea. Speed 20 knots. Thin line: no fins are present. Thick line: fins are present.	61

Chapter 3

3-1	Schematic representation of a building equipped with an active TMD.	69
3-2	El Centro ground motion.	70
3-3	San Fernando ground motion.	71
3-4	Loma Prieta ground motion.	72
3-5	Ground motions for 10 artificially generated excitations.	74
3-6	Ground response spectrum of the El Centro earthquake (strong line), and of the average spectrum of the 10 synthesized earthquakes (thin line).	75
3-7	Ground response spectrum of the San Fernando earthquake (strong line), and of the average spectrum of the 10 synthesized earthquakes (thin line).	76
3-8	Ground response spectrum of the Loma Prieta earthquake (strong line), and of the average spectrum of the 10 synthesized earthquakes (thin line).	77
3-9	Ground response spectra for the 10 synthesized earthquakes (GTH= ground time histories).	79
3-10	Hysteretic cycle of base shear versus base drift for a six-story building. Part <i>a</i> , no control; part <i>b</i> , active control. El Centro ground motion.	80

3-11	Hysteretic cycle of base shear versus base drift for a six-story building. Part <i>a</i> , no control; part <i>b</i> , active control. San Fernando ground motion.	81
3-12	Elastic and hysteretic peak relative displacements for a six-story building. El Centro ground motion.	82
3-13	Elastic and hysteretic peak absolute accelerations for a six-story building. El Centro ground motion.	83

Chapter 4

- 4-1 Schematic representation of a two-layer neural network. Thick arrows account for a set of axons with their origin at each input datum. Functions ϕ are the squashing functions of each neuron. . . . 92
- 4-2 Schematic representation of a general two-layer neural network for a single-output system. 93
- 4-3 Local minima (A , B , and C) for a one-weight performance index Θ . If the weight adjustment Δw predicted by the training algorithm for weight w is too small, the training algorithm may get stuck at a local minimum. Numerical momentum helps backpropagation to overcome the local valleys at A , B and C 94

Chapter 5

5-1	System identification training process. In part <i>a</i> , NNE 1 is the LAMP neural-network emulator. By comparing the output vectors \mathbf{p} and \mathbf{p}' , an error is determined, which is backpropagated through NNE 1. When $\mathbf{p} \cong \mathbf{p}'$ for any input data, LAMP is considered identified by NNE 1, and the training process is stopped. Then the fin emulator NNE 2 is added (part <i>b</i>). The process is repeated; the error \mathbf{e} is backpropagated through NNE 1 and NNE 2 until $\mathbf{p} \cong \mathbf{p}'$, for any input data. Now only the weights of NNE 2 are adjusted. Finally the neural-network controller is added (part <i>c</i>). A new error \mathbf{e}' is defined as a subset of \mathbf{p} , which is minimized. When \mathbf{e}' is backpropagated through NNE 1 and NNE 2, only the weights of the neural-network controller are adjusted until \mathbf{e}' meets the desired average minimization values.	116
5-2	The two coordinate systems used to describe the motion of a ship.	117
5-3	Grids for hull, fins and wake.	118
5-4	Neural-network controller used in the present example. Thick arrows account for a set of axons with origin at each input data. Squashing functions are represented by $\boxed{\downarrow}$	119
5-5	(a) Roll angle as a function of time. (b) Roll rate as a function of time. Thin curve: no fins. Thick curve: passive fins. Random beam sea.	120

5-6	(a) Roll angle as a function of time. (b) Roll rate as a function of time. Thin curves: no fins. Thick curves: active fins. Random beam sea.	121
5-7	Points where sea-surface heights close to the hull are measured (•).	122
5-8	(a) Roll angle as a function of time. (b) Roll rate as a function of time. Thin curves: no control. Thick curves: active fins. Sea-surface information available for the controller. Random beam sea.	123
5-9	(a) Roll angle as a function of time. (b) Roll rate as a function of time. Thin curves: no control. Thick curves: active fins. Sea-surface information available for the controller; 45 degrees incoming random sea.	124
5-10	(a) Roll angle as a function of time. (b) Roll rate as a function of time. (c) Roll acceleration as a function of time. Thin curves: no fins. Thick curves: active fins. Sea-surface information available for the controller; 45 degrees incoming regular sea.	125

Chapter 6

6-1	Nine-neuron, two-layer neural-network controller used in this work. Thick arrows account for different sets of weighted input data.	144
6-2	(a) Neural-network and building schematic, (b) evolution of the controller error, and (c) evolution of the acceleration response error of floor i	145
6-3	Schematic representation of a building equipped with an active TMD.	146
6-4	Response spectra of El Centro, San Fernando and the average of the training set earthquakes.	147
6-5	Comparison of uncontrolled and acceleration-feedback-control base shear responses for (a) El Centro motion and (b) San Fernando motion.	148
6-6	Control-force time histories for (a) El Centro motion and (b) San Fernando motion for acceleration feedback.	149
6-7	Actuator-stroke time histories for (a) El Centro motion and (b) San Fernando motion for acceleration feedback.	150
6-8	Comparison of uncontrolled and velocity-feedback-control base shear responses for (a) El Centro motion and (b) San Fernando motion.	151
6-9	Control-force time histories for (a) El Centro motion and (b) San Fernando motion for velocity feedback.	152

6-10	Actuator-stroke time histories for (a) El Centro motion and (b) San Fernando motion for velocity feedback.	153
6-11	Comparison of acceleration- and velocity-feedback peak relative displacement responses for (a) El Centro motion and (b) San Fernando motion. The results are normalized with the uncontrolled case.	154
6-12	Comparison of acceleration- and velocity-feedback peak interstory drift responses for (a) El Centro motion and (b) San Fernando motion. The results are normalized with the uncontrolled case. ...	155
6-13	Comparison of acceleration- and velocity-feedback peak absolute acceleration responses for (a) El Centro motion and (b) San Fernando motion. The results are normalized with the uncontrolled case.	156
6-14	Response reduction for various levels of ground-motion intensities for (a) base shear and (b) top-floor accelerations for velocity feedback.	157
6-15	Nonlinear feature of the maximum control force required for various levels of ground-motion intensities for velocity feedback.	158

Chapter 7

7-1	(a) Ten-story and (b) six-story schematic representations of two buildings equipped with active tuned mass dampers.	194
7-2	Two-layer, five-neuron neural-network controller. Thick arrows denote different sets of weighted input data.	195
7-3	Ground-response spectra corresponding to the set of ground motions used for training (average) and validating earthquakes. . . .	196
7-4	Uncontrolled and controlled top-floor displacements for (a) El Centro and (b) San Fernando ground motions. Acceleration feedback.	197
7-5	Uncontrolled and controlled base-shear responses for (a) El Centro and (b) San Fernando ground motions. Acceleration feedback. . . .	198
7-6	Control-force time histories for (a) El Centro and (b) San Fernando ground motions. Acceleration feedback.	199
7-7	Uncontrolled and controlled top-floor displacements for (a) El Centro and (b) San Fernando ground motions. Velocity feedback.	200
7-8	Uncontrolled and controlled base-shear responses for (a) El Centro and (b) San Fernando ground motions. Velocity feedback.	201
7-9	Control-force time histories for (a) El Centro and (b) San Fernando ground motions. Velocity feedback.	202
7-10	Top-floor response spectra for a passive controller (Passive), velocity-feedback controller (VF), and acceleration-feedback controller (AF). El Centro (a) and San Fernando (b) ground motions.	203

7-11	Response-reduction factors for acceleration and velocity feedback for (a) peak relative displacements, (b) peak interstory drift, and (c) peak absolute accelerations. El Centro earthquake.	204
7-12	Response-reduction factors obtained for two different training cost functions, J, for (a) peak relative displacements, (b) peak interstory drifts, and (c) peak absolute accelerations. San Fernando earthquake.	205
7-13	(a) Peak base shear reduction factor and (b) peak control force as functions of peak ground acceleration, for a velocity-feedback controller.	206
7-14	(a) Loma Prieta ground-acceleration time history. (b) Ground response spectra of the training set of earthquakes (average) and Loma Prieta earthquake.	207
7-15	(a) Peak relative-displacement and (b) peak absolute-acceleration reduction factors for Loma Prieta earthquake. Six-story hysteretic building model. Velocity-feedback control (interstory velocities).	208
7-16	(a) Peak relative-displacement and (b) peak absolute-acceleration reduction factors for El Centro earthquake. Six-story hysteretic building model. Velocity-feedback control (interstory velocities).	209

Chapter 8

8-1	Neural-network controller for a MIMO system. The input represents the data fed to the controller. The two outputs δ_p and δ_s represent the port and starboard fin deflections for a fin-stabilizer system for ships. Thick arrows account for a set of axons with origin at each input data. Squashing functions are represented by \boxed{f} .	228
8-2	Four-mode rolling control by using a pair of fins and a rudder. . . .	229
8-3	Two-mode rolling control by using a pair of fins.	230
8-4	First-layer, four-mode, three-output modal neuron, j . Vector \mathbf{a} is the input vector to the system of dimension η . Squashing functions are represented by \boxed{f}	231
8-5:	Two-layer, two-mode, two-output MNN controller. The outputs are the port and starboard fin deflections (δ_p and δ_s) used to reduce the rolling motion of a system. The first layer has σ two-mode modal neurons. Subscripts and superscripts p and s stand for port and starboard, respectively. Vector \mathbf{a} is the input vector of dimension η . Squashing functions are represented by \boxed{f}	232
8-6	Roll reduction using a pair of fins controlled by a two-mode neural network.	233
8-7	Pitch reduction using a pair of fins controlled by a two-mode neural network.	234
8-8	Heave reduction using a pair of fins controlled by a two-mode neural network.	235

Chapter 9

9-1	Input/output membership functions. Five rules ($R = 5$); n input data.	254
9-2	Gaussian membership functions.	255
9-3	Singleton membership functions.	255
9-4	Fuzzy logic system.	256
9-5	(a) Roll angle as a function of time; (b) roll rate as a function of time. Thin curves: no fins. Thick curves: active fins, 58 rules. Random beam sea.	257
9-6	(a) Roll angle as a function of time; (b) roll rate as a function of time. Thin curves: no fins. Thick curves: active fins, 2790 rules. Random beam sea.	258
9-7	(a) Roll angle as a function of time; (b) roll rate as a function of time. Thin curves: no fins. Thick curves: active fins, 9 rules. Random beam sea.	259
9-8	(a) Roll angle as a function of time; (b) roll rate as a function of time. Thin curves: no fins. Thick curves: active fins, 87 rules; 135 degrees random sea.	260
9-9	(a) Roll angle as a function of time; (b) roll rate as a function of time. Thin curves: no fins. Thick curves: active fins, 2790 rules; 135 degrees random sea.	261

List of Tables

Chapter 2

2-1	Time-marching procedure.	62
-----	-------------------------------	----

Chapter 6

6-1	Response ratios (of controlled to uncontrolled response) for El Centro and San Fernando earthquakes for various control schemes.	159
-----	---	-----

Chapter 7

7-1	Response-reduction factors for different control schemes. Linear building model.	210
7-2	Response-reduction factors for different control schemes. Hysteretic building model.	211