Chapter 1

Introduction and Literature Review

1.1 Introduction

The original goal of this thesis was developing new control procedures to control ship motions by means of non-traditional strategies. We started by exploring roll reduction using active fins controlled by a neural-network controller. As our work progressed, it became evident that, since the control methods we designed were based on general principles, it would be possible to adapt such methods to other engineering applications. Thus we decided to explore the world of seismic engineering, and in particular, control schemes applied to response reduction of civil-engineering structures under earthquake excitations. Though apparently very different issues, the seismic-engineering and ship-motion control applications hold many similarities, which made possible an adaptation of the ship-control strategies to the seismic-engineering applications. Furthermore, as our research progressed in both areas, a very enlightening mutual contribution developed between the two problems, which helped substantially the original research carried out for the ship-motion control, in addition to the constant new achievements obtained for the seismic-control application.

The first step of our research was developing a hydrodynamic model for the ship-motion control problem. This constituted an important achievement and a highly motivating starting point. In attaining this, two different hydrodynamic models were adapted to work interactively. Currently, one of the most useful tools for studying the motion of ships is the computer code called LAMP. LAMP, which stands for Large-

Amplitude-Motion Program, was developed by the Ship Technology Division, Science Applications International Corporation (SAIC), Annapolis, Maryland, USA (see Lin [50]). This program simultaneously and interactively predicts both the flowfield around and the motion of a ship in a seaway in the time domain. LAMP uses a source distribution on the instantaneous wetted surface of the hull, a practice that requires re-paneling the ship at each time step. The flow generated by the sources satisfies the linearized free-surface condition on the incident wave; consequently, it is implied that the motion of the ship creates a relatively small disturbance. But it is not assumed that the amplitudes of the motion of the ship and the waves are small. The nonlinear terms are retained in the equations of motion of the ship. Several comparisons have shown the numerical results to be in good agreement with the experimental data. The nonlinear effects predicted by some theoretical works have also been captured by this code. An example of this are the nonlinear rolling motion of ships in beam seas predicted by Nayfeh and Khdeir [73] and the coupling between roll and pitch motion discussed by Nayfeh *et al.* [72] and Nayfeh and Oh [74].

LAMP computes their various contributions to roll damping by several methods related to their source. The roll damping associated with the generation of radiated waves is computed as part of the solution of the general wave-body interaction problem. Roll damping forces associated with the rudder, anti-rolling fins, or other wing-like appendages are computed by using the FINS program or using low-aspect airfoil theory (see Comstock [14]).

The viscous contributions to roll damping are computed as part of a general viscous-force model. To this end empirically derived expressions for hull skin friction (Kato [41] and Himeno [30]), bilge-keel eddy-making (Kato [42]), skeg and foil eddy-making (Hoerner [31] and Ikeda, *et al.* [34]), and lift-induced drag (Bertin, *et al.* [5]), are incorporated. Because LAMP solves for general six-degree-of-freedom motions in the time domain, general expressions for viscous or other external forces, including those involving nonlinear dependency on the state variables, can easily be incorporated into the simulation.

In addition to this, user specified linear and quadratic roll damping coefficients can be implemented. These coefficients can be used as an alternative or supplement to the empirical viscous models mentioned above, and they are particularly useful for *tuning* the LAMP model to match roll-damping characteristics derived from complex viscous flow calculations or from experimental measurements. For the CG47 data used in following chapters, LAMP’s viscous model was *tuned* by simulating roll decay tests and adjusting the roll damping coefficients to match the empirically observed decay.

LAMP currently does not have the capability of modeling the flowfield around and predicting the hydrodynamic forces acting on fins attached to the hull of a ship (moving with six degrees of freedom). Thus, the influence of fins on the motion of the ship cannot be modeled. One of the achievements of this work was to extend the capabilities of LAMP to include fins so that, when the equations of motion are integrated in time, the hydrodynamic loads acting on the fins are included. The fins are modeled by a general unsteady vortex-lattice method, instead of sources. Thus, the complete simulation is based on a distribution of sources and vorticity. In addition, the problem is somewhat complicated by the fact that the grids needed to produce accurate estimates of the loads on the ship can be much coarser than those needed to produce accurate estimates of the forces acting on the fins. Different meshes require different time steps. As a result, the complete simulation consists of two interacting programs running different meshes with different singularities and different time steps. FINS has been completely developed as part of the present work. The predicted loads generated by the fins are functions of the motion of the ship, the motion of the fins relative to the ship, and the history of both motions. The no-penetration condition is imposed on the surfaces of the hull and the fins simultaneously and interactively. These numerical models have accurately predicted the motion of actual ships as well as the unsteady loads on the fins. In the process of adapting FINS to work for LAMP some improvements were made to the LAMP code by the team at S.A.I.C. and the team at Virginia Tech. One of the main contributions of the Virginia Tech team (mainly by Professor Preidikman[1]) to LAMP was the implementation of an

[1] Universidad Nacional de Río Cuarto, Provincia de Córdoba, Argentina.

alternative algorithm to solve the equations of motion. This was done by a predictor-corrector Hamming's method (see *e. g.* Carnahan *et al.* [9]). This procedure was chosen for two reasons: 1) the general unsteady vortex-lattice method performs better when the loads are evaluated at integral time steps; 2) the loads depend implicitly on the acceleration of the ship so that the acceleration appears on both sides of the governing equations. For both reasons, Runge-Kutta methods are not very accurate, though it was empirically observed that when taking sufficiently small time steps, Runge Kutta methods still perform well. The code FINS was adapted to work under such iterative conditions if required.

A neural-network control system and a fuzzy-logic control system were developed to govern the motion of the fins relative to the ship to reduce the rolling oscillations. These systems can also provide control signals for the rudder. One of the important achievements of this work was developing a novel training strategy to provide training either for the neural-network controller or the fuzzy-logic control system. This strategy is based on a load-matching procedure, which seeks to generate appropriate moments capable of canceling the moments acting on the ship, which are responsible for its rolling motion.

We also worked on more complex control systems that are appropriate for multi-input-multi-output controllers. To this end, we developed a new neural-network architecture, which can effectively handle such requirements. We call this new approach modal neural networks. Modal neural networks are based on combining the control modes involved in a multi-output controller in such a way that makes the training of the network efficient and expedient. Though this is part of our ongoing research, we show some results from such a controller capable of minimizing roll, pitch and heaving motions.

As mentioned above, we also explored the seismic engineering field to apply some of the concepts that were originally developed for naval applications. To this end, we first implemented a two-dimensional linear model of a multistory building. Later hysteretic characteristics were added to this model. In developing the structural part of the code, a member of the present advisory committee, Doctor Matheu, played an essential role. To control the response of the structure we modeled a tuned mass damper located on the roof of the building. Such devices are already in use and provide a good passive reduction. Once the passive device is tuned properly, active control is added to improve the already efficient passive damper. Control is achieved by means of a neural network. The same load-matching training strategies developed for naval applications were successfully adapted to train these hybrid devices. A new gradient-search approach was also implemented to train the neural-network controller, which yielded similar results. A significant advantage of the present approach is that it does not require a system-identification of the building.

Another innovation was the training-datum procedure used to train the building-vibration controller. This was done in terms of the seismic data to be used during the training process. Even if future seismic events may not be predicted, it came to our attention that, for many areas, detailed records of past seismic activity are available. In such cases, an average spectrum of past earth motions could be obtained for these areas. Based on this information, a set of training earthquakes could be synthesized which, on average, displays a characteristic spectrum similar to that of the building site. This information can be extracted from records of past earthquake activity registered in the area were the building is to be constructed. This is the criterion we adopted as the basis of our method. We cannot know in advance the earthquake motions or the corresponding spectra that a building may encounter in the future. But, in many cases, we can determine the characteristic spectrum of the building site; given this information we can generate a set of training earthquakes with a mean spectrum comparable with that of the building site. This set is then used to train the controller. After the training is completed, we can estimate the training efficiency and validate the training process by exciting the building with recorded seismic events of the area that were not part of the set used to train the controller. This procedure yielded very good results.

1.2 Literature Review

We divide our literature review into five major topics:

1) Research related to fin hydrodynamics

2) Research related to seismic engineering

3) Research related to neural-network control

4) Research related to fuzzy-logic control

5) Research related to reducing the rolling motion of ships by means of active fins

1.2.1 Previous Hydrodynamic Research Related to Fins

Some of the previous research related to the hydrodynamic approach used for the fins is presented in this section. Breslin [7] studied the wave-induced drag of a hydrofoil of finite span in shallow water. His model was based on the shallow-water potential theory developed for sources. Kaplan *et al*. [39] studied the downwash pattern produced by a hydrofoil with a two- and three-dimensional potential theory in the presence of a linearized free surface. Using a potential-flow model, Nishiyama [77] derived some expressions to compute lift forces and drag coefficients on fully submerged hydrofoils. To this end, he developed a potential model with linearized free-surface conditions and appropriate boundary conditions on the lifting surface. Later Wu [100] considered the extraction of flow energy by a wing oscillating in waves. He conceived a possible future application to control theory and the study of flutter. His study had its origins in Weinblum's [96] first approximate theory for the motion of heaving and pitching hydrofoils. Lloyd [61] showed how fins lose lift when they interact with bilge keels. He also showed the influence in sway and yaw that a pair of fins introduces when the mean planes of each fin are not mutually parallel. This can generate strong coupling between roll, sway and yaw motions. His work was related to the frequently detected considerable loss of lift with respect to cavitation-tunnel measurements. Using wing-section theory design, Shen and Eppler [84, 85] made some research regarding the performance of symmetric and non-symmetric hydrofoil profiles in terms of cavitation and other hydrodynamic characteristics. Leclerc and Salaün [47] developed an unsteady linearized lifting-surface theory for hydrofoils that included free-surface effects. Later Grue *et al.* [25] introduced a linear vortex sheet to model both an airfoil and its wake. Though unsteady, it was still a two-dimensional model. Eça and Falcao Campos [18] also developed a two-dimensional approach to consider the interaction of a potential flow with a boundary layer. Dallinga [16] experimentally analyzed fins interacting with real-ship hulls, which helped to validate the performance of our code FINS and the theoretical formulation behind it. Cheng *et al.* [11] made some studies of swimming three-dimensional waving plates, which have some similarity with our work. Cheng's research was related to the swimming performance of fishes. For the waving plates, he used an unsteady vortex-ring method. The symmetry of the problem allowed Cheng to use a half-space model. Other previous research has been done in this area. Wu [100, 101, 102, 103] was one of its pioneers with his theory of motion of two-dimensional waving plates. By using two and three-dimensional wing theory, many important contributions in this filed were also made by Lighthill [48, 49], Chopra [12, 13], Katz and Weihs [43], and others. Our novel contribution (Liut *et. al*, [57]) in this area is a three-dimensional model of fins, which can move with six degrees of freedom in a flowing fluid. We use an unsteady vortex lattice to model the fins, the fin-tip vortices and the wake shed from the trailing edge. We also model the interaction with the hull, or a neighboring portion of it, where the fins are attached. Our model can interact with a source/sink model for the hull. Both models can use grids of different resolution and run with different time steps; this results in an accurate and original approach. As we can see, our hydrodynamic model does not have restrictions on the degrees of freedom. Also the vortex method used in modeling the fins allows us to take into account viscous-related phenomena present in high Reynolds-number flows, such as predicting the rate at which vorticity is shed from the fin tips and trailing edges.

1.2.2 Seismic Engineering Considerations

We have explored different techniques to reduce the response of buildings excited by earthquakes. The model used for the building is a classic shear-force model. We have also implemented hysteretic characteristics based on the Bouc-Wen model [6, 62, 64, 97].

The controller we utilize in all cases is a tuned mass damper (TMD) located on the roof of the building. In order to optimize the performance of the already efficient passive tuned mass damper we add active control (for the TMD). Tuned mass dampers consist of moving masses, attached to the primary structure by means of a spring-damper connection. The seismic input energy is transformed into kinetic energy of the moving mass. Following Matheu [63], an antiresonance effect is generated at the frequency at which the device is tuned. Two smaller resonance peaks appear surrounding this frequency. The TMD damper plays an important role in reducing these peaks (Van de Vegte and Hladun [93]). Extensive research has been done to determine the frequency, tuning and damping characteristics capable to generate a good performance (Wang *et al.* [95]). Tuned mass dampers are most effective when the first mode contribution to the response is dominant (Soong [87]). This is generally the case for tall, slender structural systems. Multiple tuned-mass-damper configurations have been explored to improve the performance of wide frequency-band excitations (Igusa and Xu, [33]).

1.2.3 Neural-Network Control

Response reduction using active control constitutes a challenging and powerful design alternative in many engineering problems. In recent years, artificial neural networks have been gaining momentum as effective strategies to provide control actions for a wide diversity of applications. Different ways to train a neural-network controller have been proposed, and they are a subject of constant research and innovation. An important landmark in the development of neural-network research was Rosenblatt's [79] invention of the *perceptron*. The perceptron consists of a single artificial neuron designed to imitate, or *emulate*, pattern recognition tasks for biological visual systems. Rosenblatt found a simple but powerful algorithm capable of training the perceptron. He proved that his method would always converge to a desired set of weights (Perceptron Convergence Theorem). However, to attack linearly non-separable problems, Minsky and Papert [67] showed that multilayer perceptrons were required. Soon it became evident that Rosenblatt's training algorithm had serious limitations, which would preclude the development of multilayer perceptrons. These were related to the hard-limiter functions that Rosenblatt's perceptrons required. An alternative approach was suggested by Widrow-Hoff [98]. Widrow-Hoff's Adalines (adaptive linear elements) were similar to Rosenblatt perceptrons, but they had linear functions as output functions instead of the perceptron hard-limiters. Widrow-Hoff introduced an algorithm based on the so-called *delta rule* to train his Adalines. The delta rule had a clear intuitive interpretation, which was very reminiscent of Hebb's [29, 32] earlier studies of brain learning. But to attack complex nonlinear problems, multilayer, nonlinear neural networks were required, and since no efficient algorithm capable of providing training for such networks could be found, during the 1970's neural-network research stalled. This stalling was broken by Rumelhart [81, 82] and his backpropagation algorithm. Rumelhart redefined Rosenblatt's perceptrons replacing the hard-limiter output functions (used by perceptrons) by continuous sigmoidal functions. This allowed Rumelhart to handle neural networks in an analytical manner, which inspired him to develop his backpropagation training approach. Nonlinear, multilayer neural networks could finally be trained effectively, thus making it possible to attack a wide range of problems, which only nonlinear neural networks were capable of handling properly. Since then, the backpropagation technique constitutes a frequently used training approach for artificial neural networks in general. This technique was further explored and refined by many other researchers. It has also been proved that a neural network can reproduce any nonlinear function for a limited input set. This is a direct result of the application of the Universal Approximation Theorem [15, 23, 32]. This theorem also predicts that a single-layer (nonlinear) neural network would be enough to produce a desired output for a given training set, though one single layer does not guarantee an optimal implementation in terms of the number of neurons and learning speed.

In the field of control, standard supervised training associated with backpropagation demands *a priori* knowledge of the desired, but initially unknown, control law. A way to overcome this obstacle is to resort to an identification process that generates a parallel neural-network representation of the system to be controlled, in addition to the neural-network controller to be designed. The first efforts in this direction were carried out by Narendra and Parthasarathy [71], who proposed an identification and control method of dynamical systems using neural networks, and by Nguyen and Widrow [76], and their emulator multilayer neural network. For the control issues related to our work, this implied the need for an extra neural network to emulate the ship and fins or the building structure. In earthquake engineering, this particular technique has been explored with success by Faravelli and Venini [21], and Chen *et al*. [10]. Bani-Han *et al.* [1] developed a more refined approach whereby they could predict the future behavior of a system. They also made comparisons with experimental data. Joghataie and Ghaboussi [37] did a comparative study between this technique (which includes a neural-network emulator of the structure) and other control methods based on explicit mathematical functions. He and Wu [28] implemented a recursive neural-network controller, also using a system identification strategy to train the neural network.

In addition to the demand of more expensive computational efforts in developing a neural-network simulation of the building in order to train the neural-network controller, system identification strategies may be sensitive to unknown approximations embedded in the system identification process, especially when what is identified is not the real system but a model of it.

Two new backpropagation-based training approaches are introduced in this work: 1) the load-matching procedure (Liut *et al.* [51, 52, 53, 55, 56, 58, 60]); 2) an adaptive gradient search (Liut *et al.* [54, 56]), and Matheu *et al.* [64]). They do not require an overall identification of the system to be controlled, which eliminates the need for an extra neural network. For the case of control of building structures, a good reference with more classical approaches is given by the work of Singh *et al*. [86], more specifically in the area of sliding mode control. The results from that work were very valuable for this project since the controller device used there was also a TMD located on top of the building.

1.2.4 Fuzzy-Logic Control

To a lesser extent, fuzzy logic applied to control is another discipline we explored. First introduced by Zadeh [104] in the early 1960's, this discipline has been widely used for different applications. Our work extended the load-matching training procedure designed for neural-network controllers to fuzzy-logic control. Therefore, the concept of backpropgation is used here as well. Jang [35] produced an important contribution related to self-adapting, fuzzy-logic control systems. He developed the concept of adaptive-network-based fuzzy inference system, also know as ANFIS. Fuzzy-logic system identification was part of his approach. The fuzzy-logic defuzzification used by ANFIS is based on a zero-order Sugeno fuzzy model (or FIS, Fuzzy Inference System) [89, 90, 91]. Along with ANFIS, Jang introduced the concept of *universal approximator* [36] and using the Stone-Weierstrass Theorem [38, 80] he proved that when the number of rules is not restricted, a zero-order Sugeno model can match any arbitrary nonlinear function. He also related the Sugeno model with the Tsukamoto model [92]. An important issue that relates the neural-network world with fuzzy-logic models is the connection between FIS's and Radial Basis Function Networks (RBFN) [8, 68, 69, 78]. The latter are single-layer neural networks with Gaussian functions as squashing functions, with non-weighted input data. Kosko [45, 46] also describes the basis of the universal approximator used in Sugeno models. The same issue is addressed by Mendel [66].

1.2.5 Rolling Control of Ships by Means of Active Fins

Not much can be found in the literature related to fin-based control of ships by means of neural-network or fuzzy-logic controllers. As a matter of fact, there is not much related to fins and control in general. This does not come as a surprise since to attempt any involved study of this issue, a complex mathematical model is required to simulate ship-motions and the surrounding sea. In recent years, some attempts have been made in trying to materialize such a model as a computational tool. In this regard, LAMP is a state-of-the-art achievement, which has made possible the naval research done for this thesis. As a consequence of this, much of the work done for our dissertation in the field of ship-motion control is not only original but probably state-of-the-art as well.

We want to recognize the valuable help given by Sperry Marine Co., Charlottesville, Virginia, in giving us access to some of its technical data [88]. This contributed significantly to validate further our work in providing us with some clues of real-life limitations, especially regarding cavitation, as well as giving us some results obtained with PID-oriented controllers. An additional paper of two Staff Engineers of this company, Bennett and Johnson [4], provided further valuable extra information in this regard. An article of Wallace [94], also a Sperry Engineer, contributed with more data in the same field. Some articles describing the performance and characteristics of fin stabilizers systems designed for FFG-7-class ships of the US Navy also gave us valuable experimental data [17, 75]. Some features for stabilizer design developed for a SWATH type vessel as described by Fairlie-Clarke [20] provided further information, not only about the hydrodynamic characteristics and shape of the fins used in real-life implementations, but also about mechanisms used to actuate the fins.

1.3 Original Contributions and Major Achievements

The main contributions and achievements produced by this work are described as follows:

- We developed a hydrodynamic model of fin stabilizers by means of an unsteady, votex-sheet method. We implemented this model, called FINS, in a FORTAN 90 code.

- We adapted FINS to work interactively with a Green-function, source-distribution code, called LAMP, developed by the Ship Technology Division, Science Applications International Corporation (SAIC), capable of generating a hydrodynamic model of marine vessels and their interaction with the surrounding sea.

- We designed a neural-network controller to actuate the fins in order to reduce the rolling response of a ship.

- We developed a fuzzy-logic controller to actuate the fins to reduce the rolling response of a ship.

- We designed a neural-network controller to govern the actuation of a tuned mass damper on top of a building to reduce the seismic response of the structure.

- We developed a training technique based on a load-matching procedure, capable of providing training for a controller on line.

- We developed an adaptive gradient-search training method, which can be applied to neural-network and/or fuzzy-logic controllers.

- We introduced the concept of artificial modal neurons and modal neural networks, as suitable tools for multi-input-multi-output control systems.

1.4 Organization of the Dissertation

In Chapter 2, we explain the hydrodynamic model used for the fins, and the approach to combine this model with the sea-ship model. In Chapter 3 we discuss a building model to which active control is applied. In following chapters the behavior of this model is studied when it is subject to seismic excitations. In Chapter 4 we discuss some neural-network and backpropagation principles which are used in the next chapters in relation to active control. In Chapter 5 the moment-matching technique is introduced and a naval application is discussed to train a neural-network controller for roll stabilization of ships. To this end, we use the hydrodynamic models described in Chapter 2. In Chapter 6 we consider the same principles behind the moment-matching training procedure and we adapt them to a civil engineering application. This yields a force-matching training technique. For this discussion, we use the linear structural model described in Chapter 3. In Chapter 7 we explore a different training approach based on an adaptive gradient-search method. We illustrate this method with a seismic control example using the linear and hysteretic building models discussed in Chapter 3. In Chapter 8 we introduce the principles of artificial modal neurons and modal neural networks (MNN), as efficient tools suitable for multiple-input-multiple-output systems. We illustrate this by an application of a MNN controller designed to reduce pitch and rolling motion of ships. In Chapter 9 we discuss fuzzy-logic control; there the load matching training procedure described in Chapters 5 and 6 is furthered generalized and applied to fuzzy-logic controllers. This is illustrated with a naval application, similar to that used in Chapter 5. Finally, in Chapter 10, we give some final remarks and discuss some future work associated with this dissertation.

The figures related to each chapter are included at the end of the chapter. The references are shown at the end of this work, followed by the author's vita. The references appeared in alphabetical order, and they are numbered. When the same author is mentioned more than once, the corresponding articles are listed by date.

If a chapter contains tables, they appear after the figures.