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Prediction of Shear Strength and Ductility of Cyclically Loaded Reinforced Concrete Columns Using Artificial Intelligence

Nicholas Gordon
University of Nevada, Las Vegas, gordonn3@unlv.nevada.edu

PREDICTION OF SHEAR STRENGTH AND DUCTILITY OF CYCLICALLY LOADED REINFORCED CONCRETE COLUMNS USING ARTIFICIAL INTELLIGENCE

By

Nicholas P. Gordon

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Ally M. Said, Ph.D., Committee Chair

Pramen P. Shrestha, Ph.D., Committee Member

Neil Opfer, M.B.A., Committee Member

Matt Pedersen, Ph.D., Graduate College Representative

Kathryn Hausbeck Korgan, Ph.D., Interim Dean of the Graduate College

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Abstract

The shear strength and deformation capacities of reinforced concrete (RC) columns are governed by a multitude of variables related to material properties of the steel and concrete used in the design and construction of the columns. Predicting performance of RC columns using design variables is a complex, non-linear problem. The prediction of shear strength and ductility for these types of structural members has historically been performed using empirically or semi-empirically derived formulae based on experimental results. The introduction of cyclical lateral loading, such as the forces imposed on a structure during an earthquake, can result in severe degradation of shear strength and ductility as load cycles continue. This can increase the complexity of predicting performance even further, as shear failure of the column occurs at relatively low deformations and can significantly affect the ability of the structure to resist lateral loading. Most existing models consider monotonic loading only and do not address this at all, which can result in extremely poor structural performance in a seismic event when compared to performance predictions.

Acknowledgments

I would like to express my gratitude to my research advisor, Dr. Aly Said, for providing me with direction, guidance, and the initial suggestion of applying my particular background of interests in artificial intelligence to structural engineering early in my educational endeavors. This journey has been a long one with many external interruptions, and I appreciate his patience and support along the way.

I have many other people that have assisted along the way, including friends, fellow students, and family members that have continually encouraged me and supported me throughout my academic career. Thank you to each and every one of them.

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List of Acronyms

ANN	Artificial Neural Network	GA	Genetic Algorithm
RC	Reinforced Concrete	NSC	Normal Strength Concrete
HSC	High Strength Concrete	ACI	American Concrete Institute
ATC	Applied Technology Council	FRP	Fiber Reinforced Polymer

Nomenclature

a	=	shear span, equal to distance from center of concentrated load to either: (a) face of support for continuous or cantilevered members, or (b) center of support for simply supported members
A_e	=	effective shear area
A_g	=	gross section area
A_v	=	total transverse reinforcement area per layer
b_w	=	base width of column perpendicular to transverse loading
c	=	concrete compression-zone depth
d	=	distance from extreme compression fiber to centroid of longitudinal tension reinforcement
D	=	diameter of column
D'	=	internal lever arm, core distance from centerline to centerline of outer transverse reinforcement hoops
f'_c	=	concrete compression strength
f_{yl}	=	yield strength of longitudinal reinforcement
f_{yt}	=	yield strength of transverse reinforcement

h	=	rectangular column depth, or diameter
P	=	factored axial force normal to cross section; to be taken as positive for compression and negative for tension
s	=	spacing of transverse reinforcement along member axis
μ	=	displacement ductility factor, taken as the ratio of ultimate displacement at failure to the displacement at yield
ρ_t	=	transverse volumetric reinforcement ratio
ρ_w	=	longitudinal reinforcement ratio

Chapter 1

Introduction

The shear strength and deformation capacities of reinforced concrete (RC) columns are governed by a multitude of variables related to material properties of the steel and concrete used in the design and construction of the columns. Predicting performance of RC columns using design variables is a complex, non-linear problem due to the interaction of these variables. The prediction of shear strength and ductility for these types of structural members has historically been performed using empirically or semi-empirically derived formulae based on experimental results. Typically, the reliability of semi-empirical approaches depends on the dataset used to calibrate it. The introduction of cyclical lateral loading, such as the forces imposed on a structure during an earthquake, can result in severe degradation of shear strength and ductility as load cycles continue. This can increase the complexity of predicting performance even further, as shear failure of the column occurs at relatively low deformations and can significantly affect the ability of the structure to resist lateral loading. Most existing models consider monotonic loading only and do not address this at all, which can result in extremely poor structural performance in a seismic event when compared to performance predictions.

1.1 Background and Motivation

Existing approaches for the analysis of RC columns subjected to seismic forces have more recently been defined in terms of deformation capacity and deformation demand in a seismic event as opposed to traditional force-based design procedures. Recent iterations of codified design procedures related to the rehabilitation of older structures have made this an explicit requirement. However, most existing models for the prediction of shear strength ignore the degradation of capacity when subjected to cyclical loading. Because of the high probability of shear failure at low deformations, overly conservative results are obtained at low levels of displacement and highly un-conservative results are seen at higher levels of deformation.

More recently, new models have been developed that include the shear strength degradation correlated with displacement and cyclical loading. These models often address the degradation of shear strength by defining a coefficient affecting the concrete contribution to shear strength based on experimental results. This coefficient defines the displacement ductility of a structural member, usually as a ratio of displacement at yield to ultimate displacement at failure.

Past research in the literature has presented empirically derived equations for predicting shear and deformation capacity of RC columns using "best fit" solutions to experimental data sets. These new models have provided solutions with significant but acceptable margins of error. With different methods of modern data analysis, more accurate solutions and additional confidence in the results can be obtained. This increased level of confidence has a direct correlation to the optimal use of construction materials and increased levels of safety. In areas of high seismicity, this higher level of safety for new construction or the rehabilitation of older structures is extremely important. While empirically derived equations have improved over time in their accuracy, additional improvement is necessary and possible using these non-traditional approaches.

1.2 Research Goals and Approach

As computing power has increased in recent times, the use of techniques applied in the field of artificial intelligence have been used for the analysis of data to find solutions to extremely complex and non-linear problems. These techniques are very effective in finding consistent and accurate global solutions to problems that may have locally defined minima or maxima in domain of the solution set. This research applies two such techniques to a data set of experimental results compiled from the literature and other sources.

The two particular techniques explored in the research are artificial neural networks (ANN) and genetic algorithms (GA). ANNs are effectively used for finding solutions to very complex non-linear multi-variable problems that are difficult to define in terms of restrictive domains. An ANN is a model that is 'trained' using a data set consisting of inputs and outputs. Based on the data, the ANN learns over time what outputs should be expected from a certain set of inputs. ANNs can be continuously revised over time by providing new training data which increases their accuracy. This is particularly valuable for solving the problems addressed in this research. No mechanical model for predicting shear strength exists that also addresses the shear strength degradation as a result of cyclical loading. Existing solutions are all empirically derived from experimental data. As more data becomes available through testing, the ANN can immediately process the new information and produce new, more accurate results.

Genetic algorithms (GAs) provide a different approach when compared to ANNs. GAs are used to solve problems of optimization rather than develop completely new models. This research aims to find the most reliable equations and models in the literature and apply further optimization to the coefficients defining their performance. Existing equations that do not account for the degradation of shear strength can be optimized using the test data of cyclically loaded RC columns, providing more accurate results in that domain.

This research aims to investigate the viability of using these knowledge-based analytical techniques to define models of shear strength prediction and the prediction of deformation capacities of RC columns subjected to cyclical loading. The goal of these new models is to exceed the accuracy and reliability of existing analytical techniques while providing a basis for further research and expansion of these goals. Further deep learning techniques could be applied in the future to address secondary coefficients and step functions that have defined existing models and, to a certain extent, the models presented in this research.

The data set used for the training of ANNs and optimization of existing models consists of a variety of RC column test specimens that are cyclically loaded and have hysteretic force-displacement data available. Specimens vary widely in terms of their material properties and physical dimensions. However, the data set is relatively small as this type of testing data is difficult and expensive to obtain. Training ANNs to a degree of very high accuracy requires a large data set. Thus, this research is presented as an investigation of the viability of using these techniques rather than the production of recommended models for determining shear strength and ductility of cyclically loaded RC columns.

1.3 Thesis Outline

This thesis consists of six chapters and is a presented as a compilation of articles written by the author, with contributions from thesis advisor, Dr. Said, which are either published or pending publication. Each article addresses topics discussed above. Chapter 1 addresses the motivation and goals of this particular research and provides some necessary background on the methodology. Chapter 2 provides a review of recent literature addressing these topics and the various approaches of previous research in determining solutions to these problems.

Chapters 3-5 are individual articles that have been previously published or submitted for publication covering the topics in greater detail. Chapter 3, "New Equation for Estimation of RC Columns Shear Capacity Using GAs", addresses the use of genetic algorithms for optimizing existing equations to predict shear strength of cyclically loaded RC columns. Chapter 4, "Predicting Shear Strength of RC Columns Using Artificial

Neural Networks”, addresses the viability of ANNs to build a model that can reliably predict shear strength performance of cyclically loaded RC columns. Chapter 5, “Estimating Ductility of RC Columns Using Artificial Neural Networks”, investigates the viability of using ANNs for directly determining ductility and deformation capacity of cyclically loaded RC columns.

Chapter 6 is a discussion on the results obtained from the research and provides conclusions and summary and the recommendations of the author. This chapter also includes possible future goals of this research and available areas of expansion.

Chapter 2

Literature Review

Existing literature covering topics related to or influencing this research spans decades into the past. However, only within approximately the last 20 years has the literature addressed some of the more important issues covered by this research. In the early 1990s, following several large seismic events in the US, a significant amount of research addressed the capacity of RC structures subjected to cyclical loads imposed during seismic events.

Several references cited by this research are related to previous applications of artificial intelligence in civil and structural engineering problems. These and other references address the theory, functionality, and application of artificial neural networks and genetic algorithms. While these documents provide an important foundation for this type of research, their content is outside of the scope of what this research addresses and will not be discussed in detail.

The following sections will review previous research providing significant contributions to the articles contained within this thesis. Important topics include establishing, verifying, and quantifying the degradation of shear strength in RC columns subjected to cyclical loading, existing models for evaluating shear strength and ductility of RC columns, prescriptive requirements of design procedures for cyclically loaded RC columns, and establishing the value and importance of this research.

2.1 Shear Strength Degradation in Cyclically Loaded RC Columns

Before many modern fundamentals of reinforced concrete design were established, a significant number of concrete structures were constructed using details and design procedures that made them vulnerable to damage and collapse in earthquakes. As discussed by Ascheim & Moehle, failures discovered after many intense seismic events could be attributed to inadequate column shear strength (Ascheim & Moehle, 1992). This research provided a review of RC bridge columns damaged during previous earthquakes and was some of the first research to establish the shear strength capacity of failed bridge columns using construction details and mode of failure. The authors evaluated existing methods for determining column shear strength and discussed the adequacy as applied to shear strength determined from the failed structures.

Code-based design procedures did not address this reduction in shear strength. Priestley, et. al. established a database of RC column test specimens that exhibited well-substantiated shear failures and evaluated existing models that showed a relationship between shear strength and ductility (Priestley, Verma, & Xiao, 1994). These authors established a predictive model for shear strength of RC columns correlated with the flexural ductility of the member. They established a model that incorporated the effect of axial load to the concrete contribution to shear strength and showed that shear strength was reduced as flexural ductility increased.

More recently, significantly larger databases of test specimens have been compiled and it has become clearer that an extremely strong correlation exists between flexural yielding and the reduction in shear capacity in reinforced concrete members (Biskinis, Roupakias, & Fardis, 2004). They were also able to establish an upper bound to the shear strength degradation as a function of displacement ductility.

The research produced and evaluated by these authors have established a clear connection between flexural yielding caused by cyclical loading and the reduction in shear capacity in reinforced concrete members. They have also brought to light the issues with current code design equations and their inability to accurately predict shear strength when not accounting for flexural yielding.

2.2 Existing Models

Existing models for the prediction of shear strength in RC columns come from several different sources. Of the most prominent in the US is ACI 318 by the American Concrete Institute, which governs codified design procedures for reinforced concrete columns. The models evaluated in this research address shear strength as a function of axial load contribution, steel reinforcement, and concrete strength (ACI Committee 318, 2008; Priestley, Verma, & Xiao, 1994; Biskinis, Roupakias, & Fardis, 2004). Some of the earliest models to account for the displacement ductility of RC structural members use a factor that is either applied to the concrete contribution alone or to both the steel and concrete. Assuming that as the member yields in flexure, both the steel and the concrete will be less able to resist shear due to the loss of aggregate interlock (Priestley, Verma, & Xiao, 1994). This factor, typically called k in the research, is an empirically determined factor that is a function of the member displacement ductility. However, models in ACI 318 do not account for such a factor and do not explicitly address the reduction of shear strength as a function of ductility.

Existing models that do account for member ductility in predicting shear strength are empirically derived based on large sets of test specimens that have been compiled over many years (Biskinis, Roupakias, & Fardis, 2004). These empirically derived equations are founded in mechanical principles related to the performance of concrete structures (Priestley, Verma, & Xiao, 1994). However, their accuracy is dependent on this empirically derived factor that attempts to simultaneously account for a multitude of variables and is applicable only to the set of test specimens used for the regression.

These existing models are evaluated against the database of test specimens compiled for this research to determine their performance. The accuracy of these existing models is used as a basis to determine the viability of the approaches presented by this research.

2.3 Summary

The literature has shown that there is a strong correlation between the ductility of RC columns and the shear strength. Current design procedures do not explicitly address this, while prescriptive models from the Applied Technology Council and other authors highlight the importance of considering member ductility when predicting shear strength.

The interaction between ductility and shear strength is a very complex and non-linear problem that is best determined through experimentation and evaluation of existing structures that have experienced shear failure after flexural yielding. However, traditional analytical techniques have shown that there is still room for improvement as the amount of available data expands (Biskinis, Roupakias, & Fardis, 2004).

Previous research in the field of applying artificial intelligence to problems in structural and civil engineering has been effective, especially in situations of high complexity and multiple independent variables (El Chabib, Nehdi, & Said, 2006).

Chapter 3

New Equation for Estimation of RC Columns Shear Capacity Using GAs

Columns are crucial members to the stability of a structure and hence the design philosophy imposes a strong-column-weak-beam strength hierarchy. Accordingly, it is important to accurately estimate the capacity of the column, whether for new construction or to assess the need for rehabilitation of an old structure. Currently, the estimation of the capacity of reinforced concrete members relies on formulae that are often empirical or semi-empirical. For RC columns, several parameters involving steel and concrete define the capacity. The interaction between such parameters renders the behavior complex, and as a result, estimation of a column's capacity becomes problematic. This study investigates the potential use of genetic algorithms to introduce a formula for shear capacity estimation of cyclically loaded RC columns. A database from experimental results in the literature was used to formulate and optimize the proposed equation. Results from the proposed equation are evaluated with values calculated using semi-empirical and empirical formulae from the literature. Two optimized equations are presented that produce improved results. The results provide a basis for the use of genetic algorithms in shear strength prediction.

3.1 Introduction

When designing a structure to withstand design seismic loads, it is important to ensure that the deformation capacities of the structure exceed the deformation demands. Capacity-based procedures address this implicitly, while displacement-based design procedures are heavily based on this fact. By standard seismic provisions, structures are designed with high ductility and large deformation capacities. Shear failure of reinforced concrete (RC) members occurs at low deformations, causing a large drop in lateral load resistance. This results in poor seismic performance of the structure.

Numerous studies have shown that cyclic loading causes shear strength of RC members to degrade significantly when compared to the flexural strength of the member (Ascheim, et al., 1992; Biskinis, et al., 2004; Moehle, et al., 2001; Priestley, et al., 1994). For this reason, it is apparent that the design of newer RC structures should take into account the reduction of shear strength due to seismic-induced cyclic deformation.

However, in many cases, due to the fact that the shear strength is dependent on several independent variables in the member, empirical equations that have been developed in analytical manners are often proposed to predict the shear strength of these members. These empirical models have improved significantly upon their predecessors as shown by Biskinis et al. (2004). However, there is room for improvement.

Recent procedures issued by FEMA for seismic evaluation of existing structures (Federal Emergency Management Agency, FEMA-356, 2000) and seismic design of new structures (Federal Emergency Management Agency, FEMA-368, 2000) involve member verifications explicitly in terms of member deformations. These procedures provide a strong motivation for an accurate dependable quantification of the load and deformation capacities of RC members. Quantification of load and deformation capacities of RC members is a difficult task due to their nonlinear and complex behavior under seismic loading. Accordingly, the existing equations in the literature need to be reexamined and verified utilizing a large amount of experimental data, more recent information in the literature and modern analytical techniques. The information derived from this study is critical for all RC structures but especially for structures in Nevada since it has the third highest seismic activity in the country.

3.2 Objectives

This goal of this study is to optimize an already existing equation for predicting shear strength of RC members, while taking into account the effect of cyclical loading. Several existing equations were evaluated, and the equation with the best performance was chosen for optimization. The equation was then calibrated with new empirical coefficients by performing genetic optimization on the equation with experimental data from the database. Individual equations were developed for both circular and rectangular columns. The database has been compiled and consists of column specimens that have been loaded cyclically and failed in shear or in shear after flexural yielding (flexure-shear).

The data was obtained from the Pacific Earthquake Engineering Research Structural Performance Database (PEER-SPD). PEER-SPD was chosen as the hysteresis of load-displacement data was readily available for nearly all column specimens in the database. This was necessary to form the load-displacement envelopes to determine column displacement and lateral loads at yield and ultimate failure, as well as the experimental values for the shear resistance, V_r. The experimental values of the shear resistance V_r were obtained by analyzing the force-displacement data for the column, determining the maximum loading, and using a value of 75% of the maximum load. This 75% is an average determined by empirically analyzing the force-displacement loops, and following the suit of Biskinis et al. (2004), a yield point was defined as the corner point of a bilinear envelope of the first loading cycle on the load-deflection diagram. The value of the force at this point is defined as V_r by Biskinis et al. (2004), but for the purposes of consistency and simple identification, an average of all specimens was taken at this point to be 75% of the peak resistance. Software was written to automatically determine these points from the hysteresis and source code is available upon request.

3.3 Introduction to Genetic Algorithms

Genetic algorithms (GA) are a form of artificial intelligence best suited for solving problems with complex nonlinear solutions, multiple variables, or extraneous noise. The method is based on finding the global minimum of a function by using the concepts of evolution and natural selection.

GAs find solutions to these functions by generating an initial set of random individual solutions called the population. Each individual solution, called the "chromosome," consists of values for each variable in the function, called "genes". These initial numbers are selected from ranges specified by the builder of the model, and are case specific to the problem. Each chromosome is tested for fitness, and the best performing chromosomes are selected to spawn the next generation of chromosomes through genetic operators such as crossover, mutation, and selection. In this manner, each generation of chromosomes should be superior to the generation before it, and thus closer to the final solution of the problem. After several generations, the algorithm will show little to no improvement between generations, indicating a convergence of the function.

Building a model for genetic algorithms and choosing the proper parameters such as mutation, selection, and recombination rates is case-dependent. It is also beyond the scope of this article to go into greater depth of setting up a genetic algorithm model to solve a problem. However, the models presented in this article are available at request of the author.

3.4 Previous Models of Shear Strength Prediction

Three previous models have been evaluated for their accuracy in predicting the shear strength of cyclically loaded members. The models evaluated are the ACI 318-08 simplified shear strength model (ACI Committee 318, 2008; Priestley et al., 1994; Moehle et al. 2001).

ACI 318-08

ACI 318-08 presents the same shear strength prediction model as has been provided by code standards in ACI 318-05 as well (ACI 318, 2005). Along with many of the other equations, it recognizes a contribution to the shear strength by the steel (V_S) as well as a contribution by the concrete (V_C).

$$V_r = V_C + V_S \tag{3-1}$$

$$V_c = 2\left(1 + \frac{N_u}{2000A_g}\right)\lambda\sqrt{f'_c}b_w d \tag{3-2}$$

$$V_S = \frac{A_v f_{yt} d}{s} \tag{3-3}$$

(Units: psi, in). For spirally reinforced columns, V_s is multiplied by ($\sin\propto + \cos\propto$) where $\propto$ is the angle between inclined stirrups and longitudinal axis of the member.

Priestly et al (1994) Model

Priestley et al., 1994 present another model that takes into account the displacement ductility, defined by ratio of the ultimate displacement at failure to the displacement at yield. This ratio is used to define a modification factor that reduces the predicted strength of the column. Priestley et al. (1994) have split the equation into three parts, a concrete contribution, V_C, a steel contribution, V_S, and an axial load contribution, V_P.

$$V_r = V_C + V_P + V_S \tag{3-4}$$

$$V_C = k\sqrt{f'_c}A_e \tag{3-5}$$

$$V_P = \frac{h-c}{2a}P \tag{3-6}$$

$$V_S = \frac{A_v f_{yt} D'}{s}\cot 30° \tag{3-7}$$

where k depends on the member displacement ductility level and the system of units chosen (MPa or psi); as well as on whether the column is expected to be subjected to uniaxial or biaxial ductility demand.

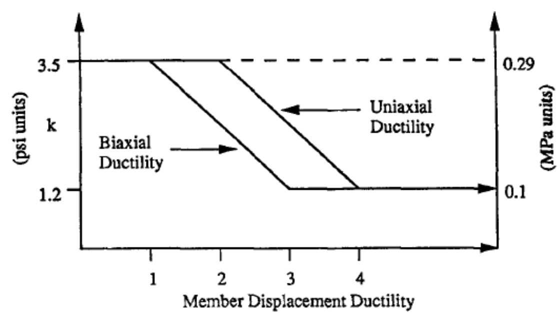


Figure 3-1 Degradation of Concrete Shear Strength with Ductility
(Priestley, Verma, & Xiao, 1994)

In (3-5), the effective shear area is taken as $A_e = 0.8A_g$ for both circular and rectangular columns. A figure is provided by Priestley et al. (1994) to determine k values (Figure 3-1). In (3-7), D' is taken as the distance between the very outer peripheral loops or spirals of transverse reinforcement, center to center, or $d - d'$ by some notation. For circular columns V_S is multiplied by $\frac{\pi}{2}$ and h is taken as the overall diameter.

Moehle et al (2001) Model

The third model evaluated for its capacity to predict shear strength is a model recently proposed by Moehle et al. (2001). This model also recognizes a degradation of shear strength as a result of cyclic loading. However, dissimilar to presentation by Priestley et al. (1994) this model applies the shear degradation factor to both the concrete and steel contributions to shear strength. Doing so results in a more accurate model as is evidenced by the data. Moehle's equations recognize steel and concrete contributions as separate as well, with the axial load contribution taken into account in the concrete contribution term.

$$V_r = k(V_C + V_S) \tag{3-8}$$

$$k = 0.7 \leq 1.15 - 0.075\mu \leq 1.0 \tag{3-9}$$

$$V_c = 0.5\sqrt{f'_c}\left(\sqrt{1 + \frac{P}{0.5\sqrt{f'_c}A_g}}\right)\left(A_g\frac{d}{a}\right) \tag{3-10}$$

$$V_S = \frac{\pi}{2}\frac{A_v f_{yt} D'}{s}\cot 45° \tag{3-11}$$

In circular columns, D' in (3-11) is taken as (diameter – 2 * cover).

The above models were tested on a database of 120 columns consisting of 65 spirally reinforced circular or octagonal cross-sections and 55 rectangular sections. Octagonal cross-section columns were approximated as circular sections as the small difference in the concrete area is negligible.

The graphs in Figure 3-2 and statistical data in

Table 3-1 show the performance for the three equations. Even though there is no account for the shear degradation under cyclic loading in ACI 318-08, results are split fairly evenly between over prediction of strength and being conservative. However, there are many cases where shear strength has been significantly over-predicted.

Table 3-1: Statistical Performance of Shear Strength Equations

	Rectangular Columns				Circular Columns			
		$V_{rexp}/V_{rCalculated}$				$V_{rexp}/V_{rCalculated}$		
Method	AAE (%)	Average	SD	CoV (%)	AAE (%)	Average	SD	CoV (%)
Moehle et al. (2001)	46.6%	1.76	0.92	52.4%	42.1%	2.12	3.33	157.5%
Priestley et al. (1994)	99.3%	0.63	0.27	42.8%	82.4%	0.71	0.40	56.9%
ACI-318-08 e. [11-4]	46.5%	0.85	0.35	40.5%	28.2%	1.14	0.35	30.5%
Proposed Equation	22.3%	1.09	0.32	29.1%	25.5%	1.15	0.33	28.5%

Statistical Evaluation of Existing Models

In the case of Priestley et al. (1994) the equations greatly over-predict the strength of almost all specimens. This could be due to the lack of application of the shear degradation factor to the steel contribution, or the over-estimation of exactly how much concrete is contributing to the shear resistance.

Moehle’s return to the classical Ritter-Mörsch truss analogy of a 45 degree angle seems to be the most conservative, especially with the shear degradation factor applied to the steel contribution. This causes a significant source of scatter and reduction of confidence.

Of the three proposed equations, ACI-318-08 eq. [11-4] evaluates the shear strength with the best performance. For this reason, this equation has been chosen as the basis for optimization in prediction of shear strength as affected by cyclical loading.

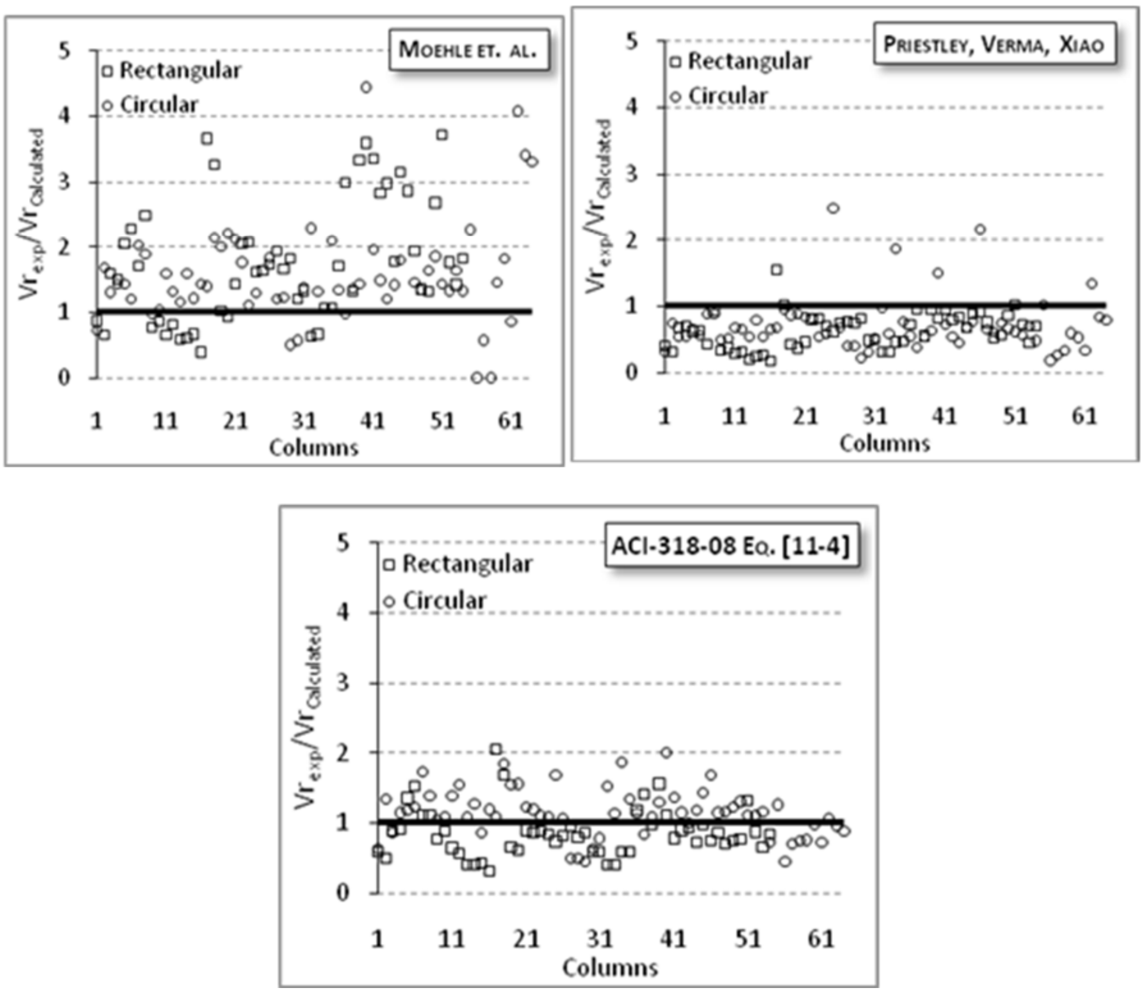


Figure 3-2 Performance of shear design equations
in calculating capacity of cyclically loaded RC columns

Genetic Algorithm Model

The approach for using genetic algorithms in this case is to optimize an already existing, high performance equation for predicting shear strength. The equation will be optimized for predicting the shear strength of cyclically loaded columns by using the data from these tests for optimization. This is done by inserting new coefficients into the existing equation, and testing the performance of the individuals against one-half of the data set. The other half is reserved to evaluate the performance of the optimization. The genetic algorithm will attempt to minimize the cumulative error of the data by choosing new coefficients each generation. As the algorithm converges, a set of 3 coefficients are generated, offering a more accurate model as applied to the test results.

In this case, as mentioned previously, the ACI-318-08 eq. [11-4] has been chosen for optimization. The original equation is outlined in equations (3-1), (3-2), and (3-3) above. The modified version is equation (3-12) below with the new coefficients C_1, C_2, and C_3 in bold.

$$V_r = 2\boldsymbol{C_1}\left(1 + \frac{N_u}{\boldsymbol{C_2}2000A_g}\right)\sqrt{f'_c}b_w d + \boldsymbol{C_3}\left(\frac{A_s F_{yt} d}{s}\right) \tag{3-12}$$

Each of the new coefficients serves a specific purpose. C_1 is positioned to modify the contribution of the concrete strength and axial load to the shear strength. C_2 is located specifically to modify the axial load contribution. C_3 is to estimate the proportion to which the steel contribution affects shear strength.

3.5 Proposed Models of Shear Strength Prediction

The model function for the genetic algorithm was optimized using two different data sets. Circular and rectangular columns were kept separate. This is due to the fact that circular columns under axial compression exhibit greater concrete shear strength contribution due to uniform concrete confinement under circular or spiral transverse reinforcement. For this reason, two separate sets of coefficients have been produced for rectangular and circular columns respectively. Equation (3-13) is for rectangular columns, and equation (3-14) is for circular columns.

$$V_r = 2.78\left(1 + \frac{N_u}{2760A_g}\right)\sqrt{f'_c}b_w d + 0.24\left(\frac{A_s F_{yt} d}{s}\right) \qquad (3\text{-}13)$$

$$V_r = 2.39\left(1 + \frac{N_u}{862A_g}\right)\sqrt{f'_c}Dd + 0.436\left(\frac{A_s F_{yt} d}{s}\right) \qquad (3\text{-}14)$$

3.6 Results and Discussion

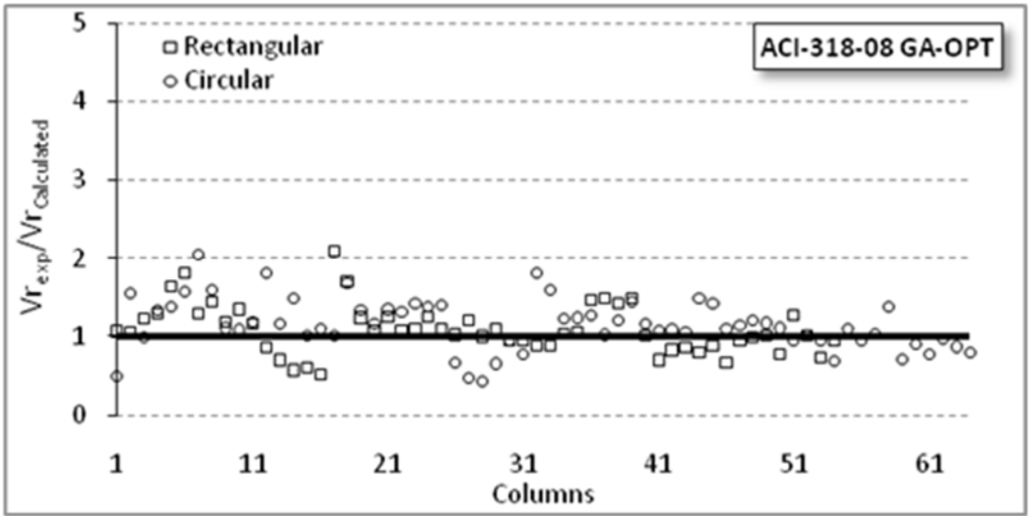


Figure 3-3 Performance of proposed equation on data

Figure 3-3 and Table 3-1 show that the performance of the proposed equations exceeds that of previous equations for the prediction of shear strength of RC columns under cyclical load. It is also interesting to note that when developing the equation for circular columns, the effect of axial load on the shear strength increased, while the opposite occurred for rectangular specimens. This could be due to the fact, as mentioned before, that the circular transverse reinforcement causes greater concrete confinement under axial load, and thus a greater shear resistance. On another note, the steel contribution in cyclical loading seems less of an issue than is the case with non cyclical loading, because in both equations, the optimum solution is only taking a certain percentage of this contribution. However, it is nearly double in circular columns, perhaps due to confinement reasons once again.

3.7 Conclusion

The proposed equations show greater performance than existing equations for predicting shear resistance of RC columns under cyclic loading. The study also shows that genetic algorithms could prove to be a very useful tool for strength prediction of RC members under unique circumstances. Existing equations can be optimized for specific performance by using experimental data sets to calibrate and breed the genetic algorithm and generate superior results.

Chapter 4

Predicting Shear Strength of RC Columns Using Artificial Neural Networks

A primary objective in the seismic design of structures is to ensure that the capacity of individual members of a structure exceeds the associated demands. For reinforced concrete (RC) columns, several parameters involving steel and concrete material properties control behavior and strength. Furthermore, it is unrealistic to simply consider the shear strength calculation as the sum of concrete and steel contributions while accounting for axial force when, in fact, all those parameters are interacting. Consequently, it is challenging to reasonably estimate the shear capacity of a column while accounting for all the factors. This study investigates the viability of using artificial neural networks (ANN) to estimate the shear capacity of RC columns. Results from ANN are compared with both experimental values and calculated values, using semi-empirical and empirical formulas from the literature. Results show that ANNs are significantly accurate in predicting shear strength when trained with accurate experimental results, and meet or exceed the performance of existing empirical formulas. Accordingly, ANNs could be used in the future for analytical predictions of shear strength of RC members.

4.1 Introduction

In the seismic design of structures, it is essential to ensure that the deformation capacities of a structure and its components exceed the associated deformation demands. This concept is implicitly addressed in capacity-based design procedures, and is an explicit core requirement of displacement-based design procedures. Thus, it is desirable that structures are designed with high ductility and large deformation capacities according to seismic provisions. Shear failure of reinforced concrete (RC) members is inherently brittle, resulting in a significant drop in lateral load resistance at low deformation; this is highly undesirable in seismic design. Several studies have demonstrated that the shear strength of RC members degrades substantially under cyclic loading when compared to the flexural strength of the member (Ascheim *et al.*, 1992; Priestley *et al.*, 1994; Moehle *et al.*, 2002; Biskinis *et al.*, 2004). Accordingly, existing seismic design guidelines for RC structures require special reinforcement for zones where plastic hinges are expected to form in order to ensure that brittle modes of failure are avoided.

Nonetheless, in many cases, due to the complex interaction between the parameters that affect shear strength of a member, empirical equations formulated based on analytical reasoning are often proposed in order to predict the shear strength of these members. These empirical models have been continuously and significantly improved, as shown by Biskinis *et al*. (2004). Recent procedures issued by the U.S. Federal Emergency Management Agency (FEMA) for seismic evaluation of existing structures (FEMA-356,

2000) and for the seismic design of new structures (FEMA-368, 2000) involve member verifications explicitly in terms of member deformations. These procedures provide a strong motivation to develop an accurate, dependable quantification of load and deformation capacities of RC members. Quantification of load and deformation capacities of RC members is a difficult task due to their non-linear and complex behavior under seismic loading. Accordingly, existing equations in the literature need to be reexamined and verified using a large amount of experimental data, the more recent information available in the literature, and modern analytical techniques.

4.2 Objectives

This study aims to improve upon existing empirical equations and models by implementing artificial intelligence algorithms to predict the shear strength of RC columns based on a number of different variables. Artificial neural networks (ANN) have been developed and trained to predict the shear resistance for rectangular and circular RC columns under axial load and cyclic lateral loading. A database has been compiled that consists of column specimens that have been loaded cyclically and failed in shear or in shear after flexural yielding (flexure shear).

4.3 Experimental Database

The experimental database used was obtained from the Pacific Earthquake Engineering Research Structural Performance Database (PEER-SPD). PEER-SPD was chosen because the hysteresis of load-displacement data was readily available for nearly all column specimens in the database. This was necessary to form the load-displacement envelopes in order to determine column displacement and lateral loads at yield and ultimate failure as well as to determine the experimental values for the shear resistance, V_r. By applying a uniform approach for evaluating shear strength of RC columns, the authors believe that the database that was used will have a more consistent dataset. The experimental values of the shear resistance, V_r, were obtained by analyzing the force-displacement data for the column, determining the maximum loading, and using a value of 75% of the maximum load. This 75% is an average determined by systematically analyzing the force-displacement loops; following the approach of Elwood (2002), a yield point was defined as the corner point of a bilinear envelope of the first loading cycle on the load-deflection diagram. The value of the force at this point was defined as V_r by Elwood (2002); however, for consistency and simple identification, an average of all specimens was taken at this point to be 75% of the peak resistance. Software was written to automatically determine these points from the hysteresis. The source code is available upon request.

4.4 Artificial Neural Networks

Artificial neural networks (ANN) are powerful computational tools inspired by the understanding and abstraction of the structure of biological neurons and the internal operation of the human brain (Haykin, 1994). The most important concept of ANNs is the way in which data is processed. Each ANN is composed of highly interconnected nodes or neurons used to process information. This structure allows ANNs to closely model the way that the human brain forms connections to solve problems and learn by example, or trial-and-error. A neural network must be "trained" for their specific application. This training process is accomplished by providing a network with a large amount of data to build connections between neurons. This is analogous to the same process that occurs in biological systems during the learning process. Synaptic connections between neurons are built and reconfigured over numerous generations of training. Increasingly, neural networks are applied to real-world applications where problems are too complex to solve by means of conventional methods or for problems where an algorithmic solution would be too complex or undefined. They also can be used where algorithmic solutions have been developed, but do not yield high accuracy in the results. Many applications of ANNs have shown superior accuracy to empirical algorithms in these cases.

Several types of neural networks exist, the most common of which is the continuous multi-layer perceptron (CMP). This type of network is based on recursive generational evaluation, consisting of various layers of neurons passing information between each other. The first layer, called the 'input layer', has the same number of neurons equal to the number of variables. Each successive layer is called a 'hidden layer', and may contain more or less neurons than the preceding layer. A final layer, called the 'output layer', contains the same number of neurons as the number of outputs expected by the response. In the case of no hidden layers, a neural network can only act on linear tasks. All problems that are capable of a solution with a CMP can be solved with only one hidden layer; however, more layers can be used, and may result in more accurate responses. A sample of a neural network architecture is shown in Figure 1.

Each neuron in a hidden layer first creates a linear combination of the outputs of the previous layer and a bias to introduce variation. These combinations and biases are called the weights. The neurons in the hidden layer then create a non-linear function based on the inputs. The most commonly used function is called the logistic function. This function varies from 0 to 1, and maps to a real value that may be positive or negative as well as large or small. As a requirement of using this function, all input data must first be normalized into a range from 0 to 1. One of the methods of normalizing the data input is by using the following equation:

$$x_t = \frac{(x - x_{min})}{(x_{max} - x_{min})} \tag{4-1}$$

where x_t is the scaled value of variable x, and x_{min} and x_{max} are the minimum and maximum values for the dataset, respectively. This normalizes any input data to a percentage value of the range of the data used.

The training is based on making the mean squared error (MSE) in the network as small as possible. This is done over many training cycles, because when the network is initially presented with a large seemingly random distribution, the MSE will be very large. The training process modifies the 'weights' of each neuron in an attempt to decrease the MSE of the net to a global minimum over each cycle. Once the training process is complete, another set of testing data is presented to the network, and the results are compared with experimental results.

In order to evaluate the performance of the ANN model, the absolute average error (*AAE*) of the ratio of the calculated shear capacity, $Vr_{calculated}$, to the experimentally measured shear capacity, $Vr_{experimental}$, was used to measure how accurately the network predicts the shear capacity relative to the experimental data. The *AAE* was calculated using the following equation:

$$AAE = \frac{1}{n}\sum \frac{\left|Vr_{experimental} - Vr_{calculated}\right|}{Vr_{experimental}} \times 100 \tag{4-2}$$

Furthermore, to determine the coefficient of variation among the ratio of $Vr_{experimental} / Vr_{calculated}$, the following equation was used:

$$COV = \frac{\sigma(Vr_{experimental} / Vr_{calculated})}{\mu(Vr_{experimental} / Vr_{calculated})} \tag{4-3}$$

where μ and σ are the mean and standard deviation, respectively.

4.5 Existing Shear Strength Models

Three previous models were evaluated for their accuracy in predicting the shear strength of cyclically loaded members. The models evaluated were the ACI 318-08

(2008) shear strength model and the models developed by Priestley *et al.* (1994), and Moehle *et al.* (2002).

The ACI 318-08 model presents the same shear strength prediction model as has been provided by code standards in ACI 318-05 (2005). Along with many of the other equations, this model recognizes a contribution to the shear strength by the steel (V_S) as well as a contribution by the concrete (V_C), as described in Equations 4-7 (units: psi, in).

$$V_R = V_C + V_S \tag{4-4}$$

$$V_c = 1.9\lambda\sqrt{f'_c} + 2500\rho_w \frac{V_u d}{M_m} b_w d < 3.5\lambda\sqrt{f'_c} b_w d\sqrt{1 + \frac{P}{500A_g}} \tag{4-5}$$

$$M_m = M_u - P\frac{4h - d}{8} \tag{4-6}$$

$$V_S = \frac{A_v f_{yt} d}{s} \tag{4-7}$$

In the case that M_m is negative, it is permitted to use the upper bound of V_c as the concrete contribution. For spirally reinforced columns, V_s is multiplied by (sin α + cos α), where α is the angle between inclined stirrups and longitudinal axis of the member.

Priestley *et al.* (1994) presented a model that takes into account the displacement ductility, defined by the ratio of the ultimate displacement at failure to the displacement at yield. This ratio is used to define a modification factor that reduces the predicted shear strength of the column. Priestley *et al.* (1994) divided the strength calculation into three parts: a concrete contribution, V_c; a steel contribution, V_s; and an axial load contribution, V_p. These equations are presented as follows:

$$V_R = V_C + V_P + V_S \tag{4-8}$$

$$V_C = k\sqrt{f'_c}A_e \tag{4-9}$$

$$V_P = \frac{h-c}{2a}P \tag{4-10}$$

$$V_S = \frac{A_v f_{yt} D'}{s}\cot 30° \tag{4-11}$$

where k depends on the member displacement ductility level and the system of units chosen (megapascals or pounds per square inch) as well as on whether the column is expected to be subjected to uniaxial or biaxial ductility demand. In Equation (9), the effective shear area is taken as $A_e = 0.8\ A_g$ for both circular and rectangular columns. Figure 2, provided by Priestley *et al.* (1994), is used to determine k values. In Equation (11), D' is taken as the distance between the very outer peripheral loops or spirals of transverse reinforcement, center to center, or $(d\ -\ d)'$ by some notation. For circular columns, V_S is multiplied by $\frac{\pi}{2}$, and h is taken as the overall diameter.

The third model, evaluated for its capacity to predict shear strength, is a model recently proposed by Moehle *et al.* (2002). This model also recognizes a degradation of shear strength as a result of cyclic loading. However, in contrast to the presentation by Priestley *et al.* (1994), this model applies the shear degradation factor to both the concrete and steel contributions to shear strength. Doing so results in a more accurate model, as is evidenced by the data. Moehle’s equations recognize steel and concrete contributions as separate as well, with the axial load contribution taken into account in the concrete contribution term.

$$V_R = k(V_C + V_S) \tag{4-12}$$

$$k = 0.7 \leq 1.15 - 0.075\mu \leq 1.0 \tag{4-13}$$

$$V_c = 0.5\sqrt{f'_c}\left(\sqrt{1 + \frac{P}{0.5\sqrt{f'_c}A_g}}\right)\left(A_g \frac{d}{a}\right) \tag{4-14}$$

$$V_S = \frac{\pi}{2}\frac{A_v f_{yt} D'}{s}\cot 45° \tag{4-15}$$

In circular columns, D' in Equation 15 is taken as (diameter – 2 × cover).

The above models were tested on a database of 120 columns consisting of 65 spirally reinforced circular or octagonal cross-sections and 55 rectangular sections. Octagonal cross-section columns were approximated as circular sections, since the small difference in the concrete area is negligible.

Evaluation of the existing shear strength models for RC columns is shown in Figures 3 through 5 as well as Table 1. Despite the fact that ACI 318-08 does not account for shear degradation under cyclic loading, results are split fairly evenly between over-prediction of shear strength and a conservative prediction, as shown in Figure 4-3. However, there are several cases where shear strength has been greatly over-predicted, for example, in the case of Priestley *et al.* (1994), where the equations greatly over-predict the shear strength of almost all specimens, as shown in Figure 4. This may be attributed to the lack of application of the shear degradation factor to the steel contribution or to the over-estimation of the concrete contribution to shear resistance. Moehle’s return to the classical Ritter-Mörsch truss analogy of a 45-degree angle seems to be the most conservative, especially with the shear degradation factor applied to the steel contribution, as illustrated in Figure 5.

The statistical performance of the three approaches presented in this paper, shown in Table 1, indicates that the ACI approach is quite acceptable, taking into account that it is a design standard that needs to conform to a wide range of applications.

4.6 ANN Model

Hundreds of neural network architectures were created and tested, and the top performing networks for circular and rectangular columns were selected. Selection criteria were based on the best fit to the data as well as the lowest absolute mean error. The networks were trained with a subset of the original data. This subset, chosen at random by a Gaussian distribution function, consisted of half the specimens available in the database. The other half was reserved to test the performance of the network. Figures 6(a) and 6(b) illustrate the networks for rectangular and circular columns, respectively.

For rectangular columns, seven input variables were provided to predict the shear strength of the member. These variables are shown in Table 2. Table 3 illustrates relevant statistical data for each of the top ANN models for rectangular columns. Network NN-321 had the best correlation to the results, and an error mean that leaned more towards the conservative side of prediction, which is preferable.

For circular columns, the same input variables were used to train the networks, with the exception of b_w and d, and the addition of the column diameter, D, bringing the total number of input variables for circular columns to six. Table 3 illustrates the pertinent properties and information about the structure and statistical data of the top ANN model for circular columns. The ANN models used for predicting the shear strength of circular columns were not as robust and efficient, and did not achieve the same confidence in the results as did the rectangular ANNs. However, the confidence was still significantly greater than the previously presented empirical equations.

ANN model NN-149 performed the best out of a large number of evaluated ANN models. However, NN-149 had trouble predicting shear strength for columns identified as high outliers. This is typical for many of the properties, especially in ANN modeling, where confidence in the results becomes dependent on the number of test specimens from the database used for training within that range. For that reason, it is recommended that the models are only used within the range of parameters that they are used in training.

4.7 Results and Discussion

In the prediction of shear strength for RC columns under cyclic loading, neural networks prove to be a very valuable tool due to the extremely non-linear nature of the parameters involved contributing to shear strength and the complexity of their interaction. Neural networks extend beyond the typical realm of empirically based equations, but have the important requirement of computing power and a meaningful database to predict the shear strength of columns. Neural networks can be retrained when new data become available, and actually 'learn' how to predict the shear strength based on all available information, just as humans can. Such capacity makes ANNs very beneficial in the seismic design of structures.

Rectangular Columns

For rectangular columns, the best performing ANN model was capable of predicting the shear strength of concrete columns significantly better than existing models in the literature. Results displayed in Figure 7 shows data points mostly around the 45° line; this is in clear contrast to the results shown in Figures 3 through 5. Results listed in Table 3 show the capacity of the network to estimate the shear strength of columns accurately for the wide range of parameters studied. Figure 9 shows the ratio of experimental to calculated column shear strength plotted against the range of several parameters. While most data points are close to the unity line, point clustering is quite common. Accordingly, it is recommended that new tests target new values of parameters, thus improving the performance of ANN models as well as other models in the literature.

Circular Columns

For circular columns, the ANN model performance was hindered by the limited number of data points provided. Nonetheless, the ANN model was able to outperform other formula in the literature, as seen in Figure 8. Furthermore, Figure 10 shows clustering of data for several parameters indicating that some parameters are repeatedly used at the same value, similar to rectangular columns. Figure 10(c) illustrates the need for high strength concrete column testing, since most tested column are below 40 MPa. It is also noteworthy that the majority of the estimated results were an underestimation.

4.8 Conclusion

In the prediction of shear strength for RC columns under cyclic loading, neural networks proved that it can be a very valuable tool due to the extremely non-linear nature of the parameters involved contributing to shear strength of RC columns. Neural networks extend beyond the typical realm of empirically based equations, but have the necessary computing power to predict the shear strength of the column. Neural networks can be retrained when new data become available, and can actually ‘learn’ how to predict the shear strength based on previous information, just as humans can. This makes ANNs very beneficial in the seismic design of structures.

For the prediction of the shear strength of rectangular RC columns, the ANN model NN-321 proved to be the best candidate with the best fit to the data, while ANN model NN-149 was the best model for circular columns. Both models outperformed the existing models in the literature examined in this study.

Nonetheless, neural networks have inherent limitation to their capability to predict shear strength of RC columns. ANN models are most accurate within the range of parameters used to train the network and accordingly, they should be applied cautiously outside the ranges of parameters.

Table 4-1 Statistical Performance of Existing Shear Strength Equations

Method	Rectangular Columns AAE (%)	$Vr_{experimental} / Vr_{Calculated}$ Average	SD	CoV (%)	Circular Columns AAE (%)	$Vr_{experimental} / Vr_{Calculated}$ Average	SD	CoV (%)
Moehle et al. (2001)	46.6%	1.76	0.92	52.4%	42.1%	2.12	3.33	157.5%
Priestley et al. (1994)	99.3%	0.63	0.27	42.8%	82.4%	0.71	0.40	56.9%
ACI-318-08 eq. [11-4]	46.5%	0.85	0.35	40.5%	28.2%	1.14	0.35	30.5%

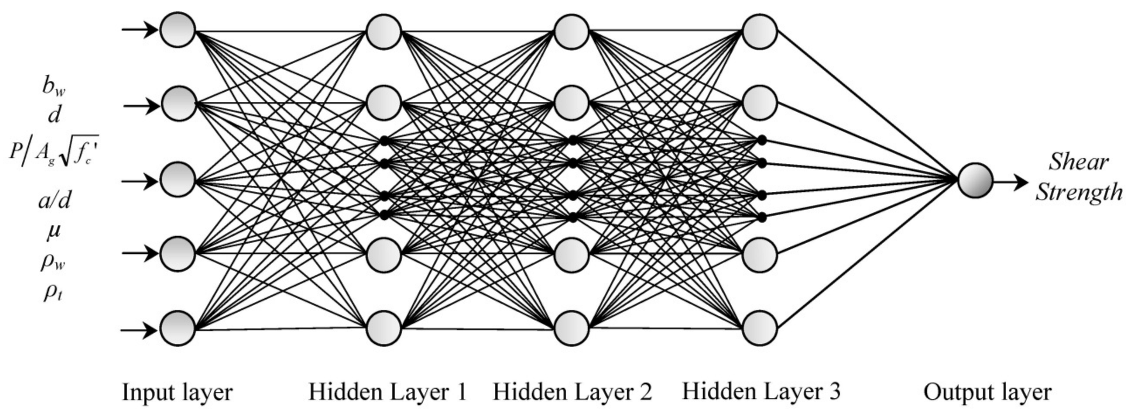


Figure 4-1 An example of the structure of an artificial neural network (ANN).

Table 4-2 ANN Input Variables for Rectangular Columns

Input Variable	Notation	Units	Comments
Column Base	b_w	length	
Effective Depth	d	Length	Distance from extreme compression fiber to centroid of longitudinal tension reinforcement
Axial Load Contribution	$\frac{P}{A_g\sqrt{f'_c}}$	unitless	
Aspect Ratio	$\frac{a}{d}$	unitless	
Displacement Ductility	μ	unitless	Ratio of ultimate displacement at failure to displacement at yield
Longitudinal Reinforcement Ratio	ρ_w	unitless	Area of longitudinal reinforcement divided by gross concrete area
Volumetric Transverse Reinforcement Ratio	ρ_t	unitless	

Table 4-3 ANN Properties and Performance for Rectangular and Circular Columns

Network	NN-321 (**Rectangular Columns)**	NN-149 (**Circular Columns)**
Data Mean	158.7418	253.68
Data S.D.	113.2625	130.08
Error Mean	2.325053	2.133
Error S.D.	14.703	29.609
Abs E. Mean	9.635623	21.719
S.D. Ratio	0.129813	0.974
Correlation	0.991577	2
# of Hidden Layers	2	10
# Hidden Units, Layer 1	15	7
# Hidden Units, Layer 2	13	---

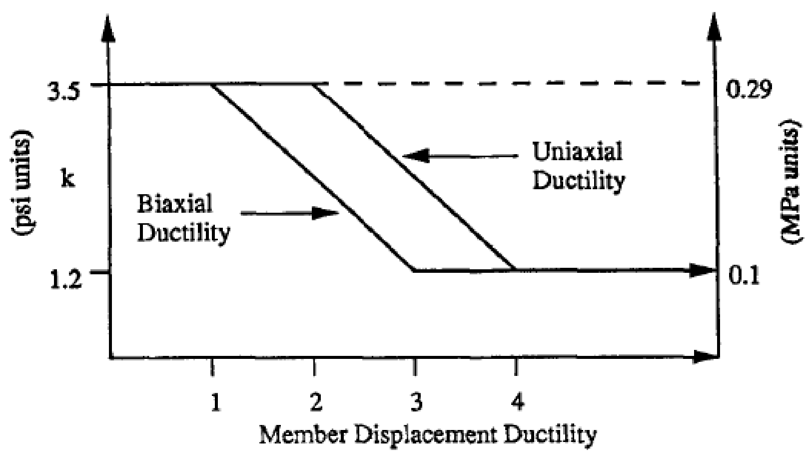


Figure 4-2 Degradation of concrete shear strength with ductility
(Priestley, et al., 1994)

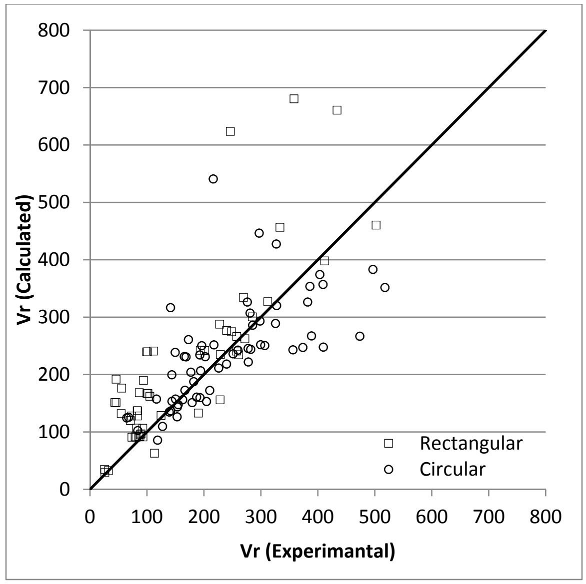


Figure 4-3 ACI 318-08 experimental vs. calculated column shear strength, according to Equation 11-4.

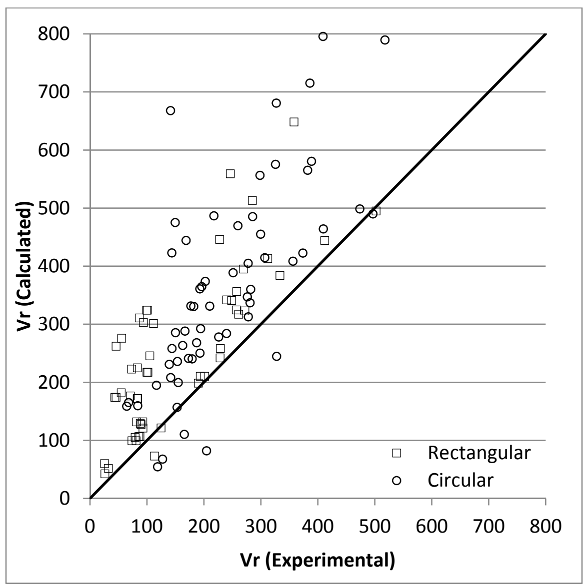


Figure 4-4 Priestley experimental vs. calculated column shear strength according to the Priestley et al. (1994) model.

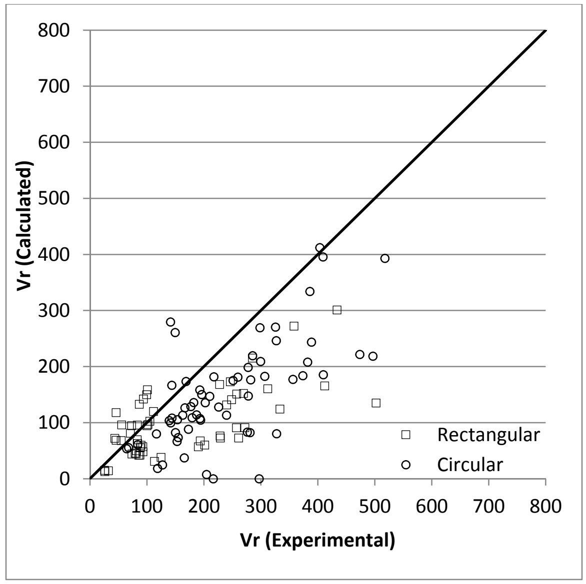


Figure 4-5 Moehle experimental vs. calculated column shear strength according to the Moehle et al. (2002) model.

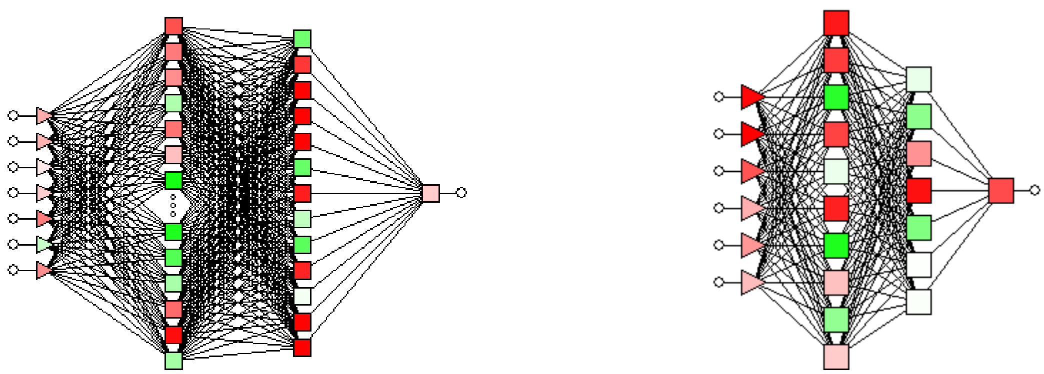


Figure 4-6 ANN model architecture for (a) NN-321 (rectangular columns) and (b) NN-149 (circular columns).

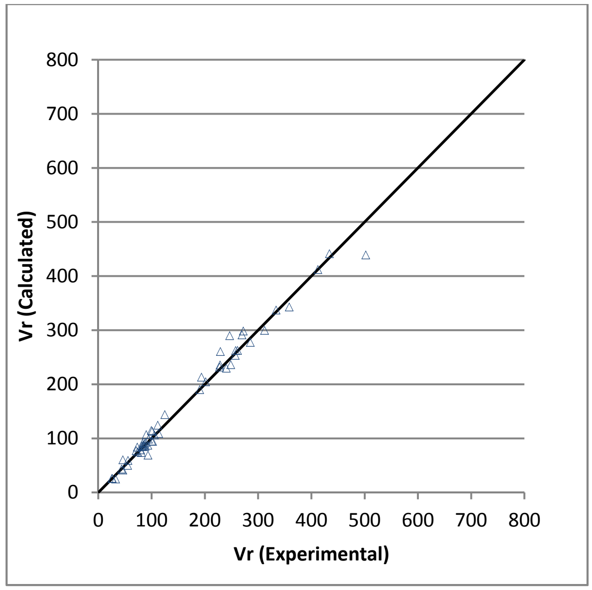


Figure 4-7 Rectangular ANN model experimental vs. calculated column shear strength

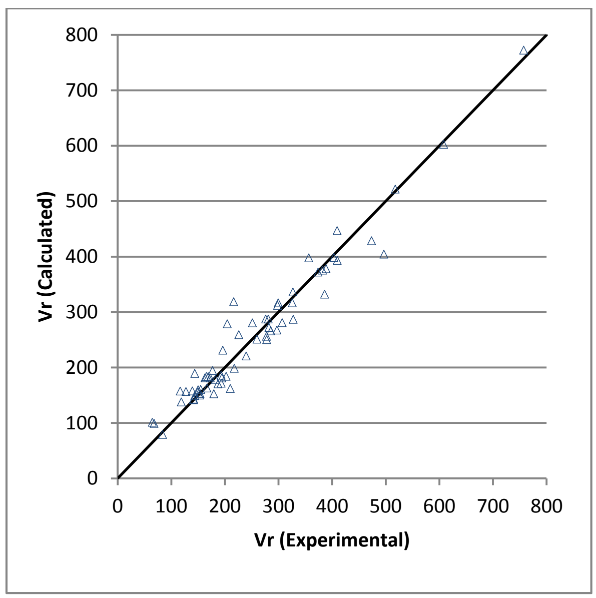


Figure 4-8 Circular ANN model experimental vs. calculated column shear strength

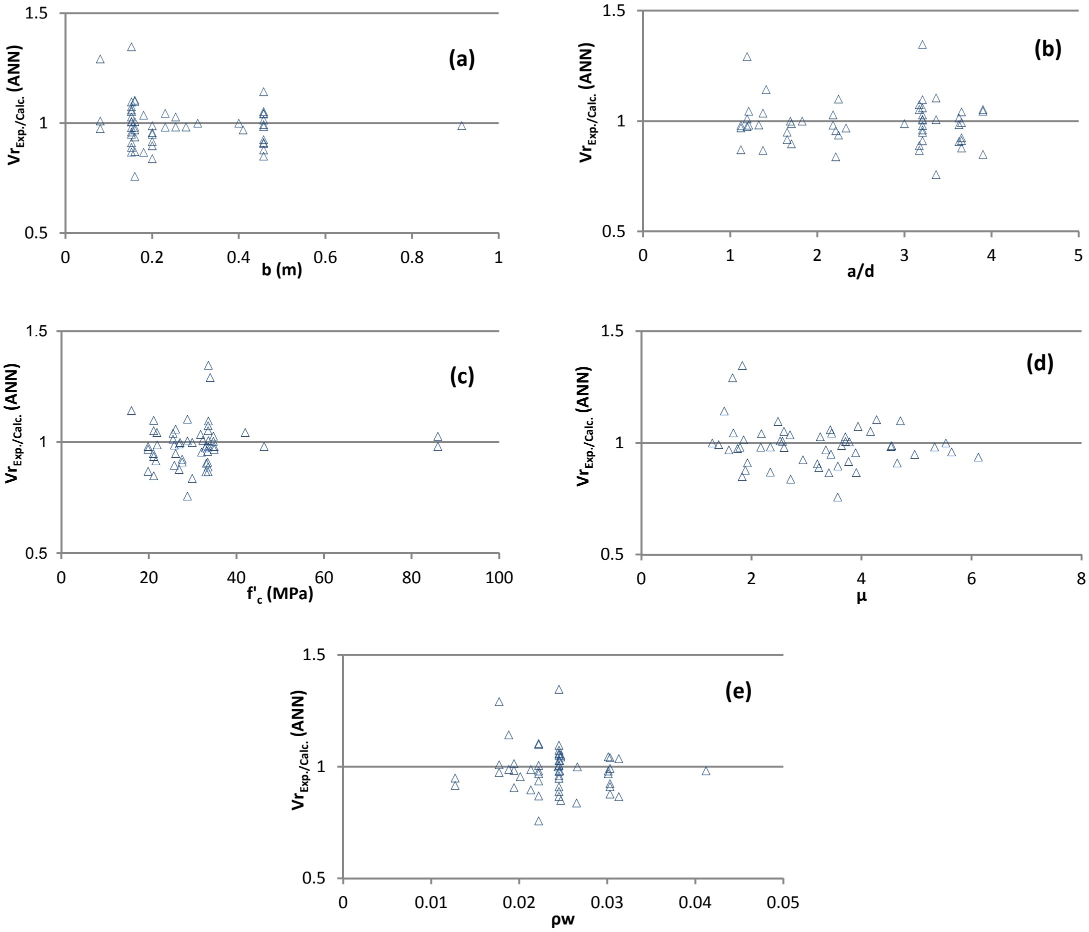


Figure 4-9 NN-321 parametric analysis (rectangular columns)

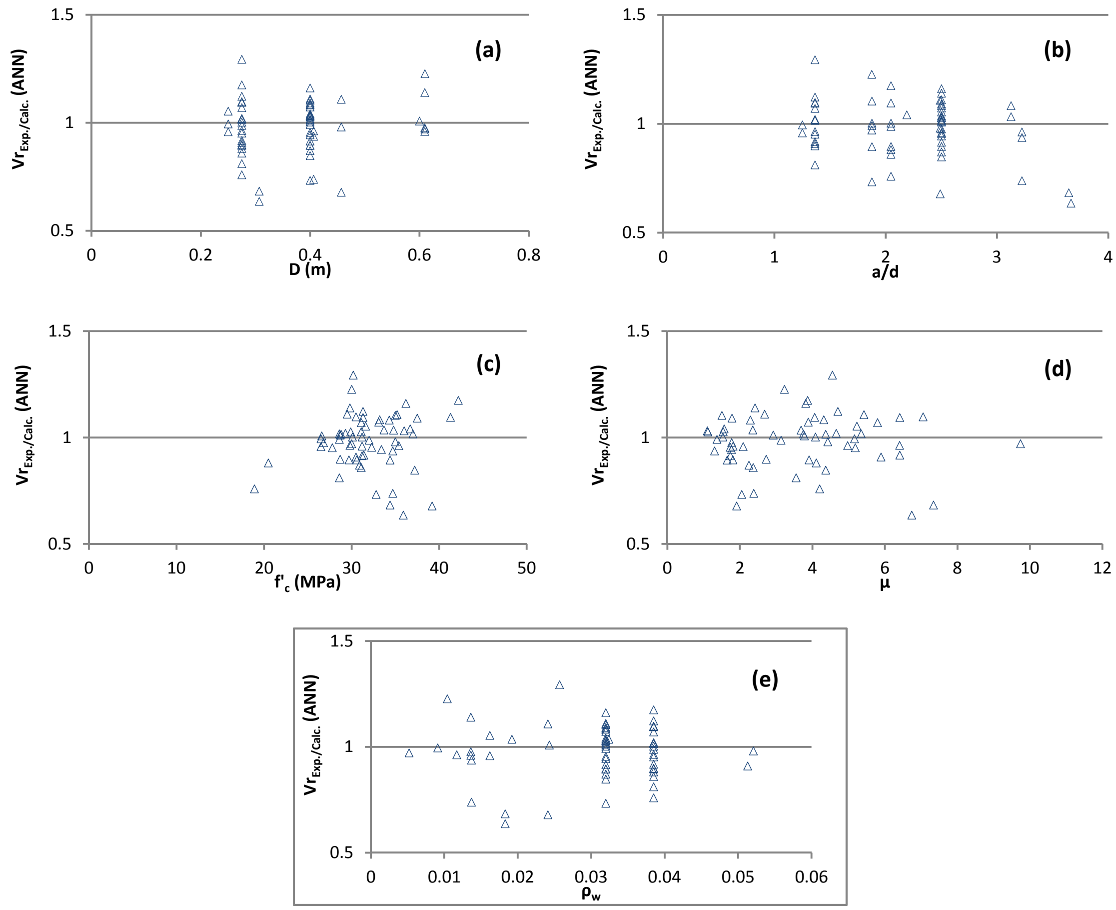


Figure 4-10 NN-149 parametric analysis (circular columns)

Chapter 5

Estimating Ductility of RC Columns Using Artificial Neural Networks

In seismic design of reinforced concrete (RC) structures, it is highly desirable to have a more ductile structure to dissipate energy during the occurrence of a seismic event. The ductility of a particular concrete member is often determined through full-scale testing or empirical models to ensure the drift capacity is within certain code-prescribed limits or displacement-based design limitations. Estimating the ductility of RC members is a complicated task due to the multitude of factors that influence the behavior of the member. Experimental data has been used numerous times to create and test analytical models that are empirical. This research shows the feasibility of using artificial neural networks (ANN) to predict the drift capacity of RC columns. An experimental database of results from the literature was used to train and test various networks, and the results are compared to existing models used to predict drift capacity. The results show that ANNs can be used successfully to provide more accurate results for the prediction of drift capacity of RC columns than existing methods.

5.1 Introduction

In seismic design of structures, it is important that the structure have the ability to withstand large deformations without collapse. Ductile structures are highly desired for their ability to withstand significant inelastic deformation without collapse. Ductile structures dissipate large amounts of energy through the yielding of the materials used in their construction. Specifically, in reinforced concrete (RC) structures, relevant correlations have been shown between the ratio and configuration of transverse reinforcement (Lam, et al., 2003; Elwood & Moehle, 2005), the strength of the concrete (Oehlers, Ali, & Griffith, 2009), the longitudinal reinforcement ratio, the shear span, axial loads, and the member size. As the relationship between these variables is non-linear and often unpredictable when looked at as a whole, very accurate empirical models are difficult to develop. For the same reason, these models often have limitations imposed on the range of the variables which the models can be used with reasonable confidence.

Recent building codes implement more stringent requirements for the seismic design of structures, especially on the ductility and drift capacity of a structure (Federal Emergency Management Agency, FEMA-356, 2000; Federal Emergency Management Agency, FEMA-368, 2000; Applied Technology Council, 1996). As a result, there is a strong motivation to find accurate and dependable methods to quantify the load and deformation capacities of structural members without costly testing. As mentioned, this is a difficult task due to the nonlinear behavior exhibited during seismic loading. Existing models and empirical equations need to be re-evaluated and verified using large amounts of data and more modern analytical techniques.

This study uses a collection of tests that were obtained from the Pacific Earthquake Engineering Research Structural Performance Database (PEER-SPD). This database is comprised of columns tested with cyclical horizontal load until failure. The data has been split into two subsets: rectangular columns and circular columns. All specimens included raw hysteresis data which was important to the research. An application was developed to programmatically determine the displacement ductility as defined by Elwood et. al. (Elwood & Moehle, 2005). This data was then used to develop and train several artificial neural networks (ANN) to predict the displacement ductility based on parameters of the column.

5.2 Objectives

The objective of this research is to develop an accurate and reliable method to determine the ductility of arbitrary concrete columns utilizing several properties of the column. This research creates a model that will provide a measure of how ductile a column is by predicting the displacement ductility. The displacement ductility is taken as the ratio of the displacement at shear failure to the displacement at yield.

Several ANNs are trained and evaluated for performance in predicting this value using a large database of test specimens. These results are analyzed against experimental results to determine if this approach provides more accuracy.

5.3 Methodology

Initially, a large database of test specimens was compiled from the PEER-SPD. These test specimens were required to have raw load-displacement values from the test. These values were then analyzed by a program called DISPLFIND written specifically for this task. DISPLFIND programmatically builds an envelope around the hysteresis curves. Building this envelope is critical to determining the displacement ductility as defined by Elwood et. al. The displacement ductility is defined as $\Delta s/\Delta y$ where Δs is the displacement after shear resistance dropped below 80% of the maximum shear, and Δy is the displacement at the point of intersection of a horizontal line at the peak shear, and a line formed by the origin and the point on the force-displacement envelope where the shear is at 70% of its peak value.

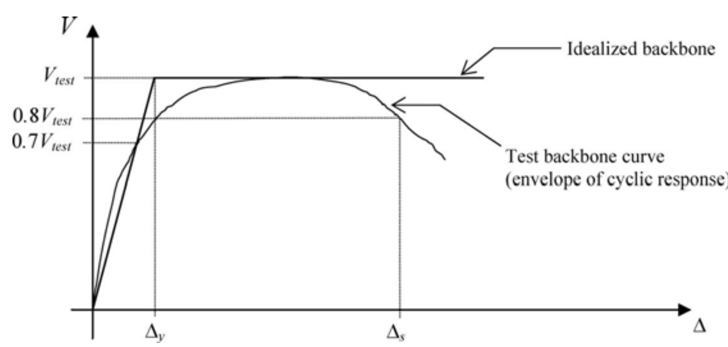


Figure 5-1 Definition of displacement ductility
(Elwood & Moehle, 2005)

Once the data had been prepared, it was used to train several ANNs of varying size and parameter. The data is split into rectangular columns and circular columns, as behavior is slightly different for each in terms of ductility. These results from the ANN were then compared against experimental results to evaluate their accuracy.

5.4 Introduction to Artificial Neural Networks

Neural networking is a technique of information and data processing built to model biological nervous systems such as the brain. The most important concept of ANNs is the way in which data is processed. Each ANN is composed of highly interconnected nodes or neurons used to process information. This structure allows ANNs to closely model the way that the human brain forms connections to solve problems and learn by example, or trial-and-error. A neural network must be "trained" for their specific application. This training process is accomplished by providing a network with a large amount of data to build connections between neurons. This process is analogous to the same process that occurs in biological systems during the learning process. Synaptic connections between neurons are built and reconfigured over numerous generations of training. Neural networks are applied more and more often to real world applications where problems are too complex to solve via conventional methods or problems where an algorithmic solution would be too complex or undefined. They can also be used where algorithmic solutions have been developed, but do not yield high accuracy in results. Many applications of ANNs have shown superior accuracy to empirical algorithms in these cases.

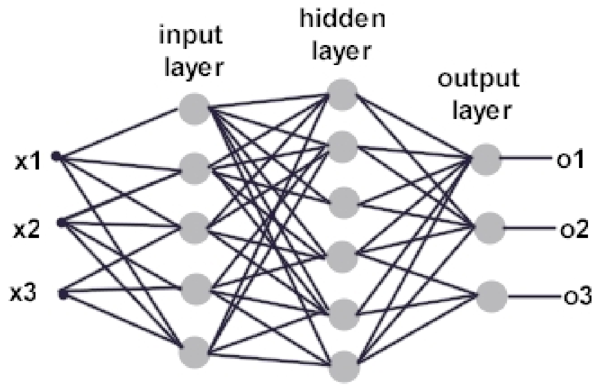


Figure 5-2 Example Structure of an ANN

There are several types of neural networks, the most common of which is the continuous multi-layer perceptron (CMP). The network is based on recursive generational evaluation, consisting of various layers of neurons passing information between each other. The first layer, called the “input layer”, has the same number of neurons equal to the number of variables. Each successive layer is called a “hidden layer” and may contain more or less neurons than the previous. A final layer, called the “output layer”, contains the same number of neurons as the number of outputs expected by the response. In the case of no hidden layers, a neural network can only act on linear tasks. All problems which are capable of solution by a CMP can be solved with only one hidden layer, but more layers can be used and may result in more accurate responses.

Each neuron in a hidden layer first creates a linear combination of the outputs of the previous layer and a bias to introduce variation. These combinations and biases are called the weights. These neurons in the hidden layer then create a non-linear function based on the inputs. The most commonly used function is called the logistic function.

This function varies from 0 to 1 and maps to a real value which may be positive or negative, and large or small. As a requirement of using this function, all input data must first be normalized into a range from 0 to 1. One of the methods of normalizing the data input is through the following equation:

$$x_t = \frac{(x - x_{min})}{(x_{max} - x_{min})}$$

Where x_t is the scaled value of variable x, and x_{min} and x_{max} are the minimum and maximum values for the dataset, respectively. This normalizes any input data to a percentage value of the range of the data used.

The training is based on making the mean squared error (MSE) in the network as small as possible. This is done over many training cycles, because when the network is initially presented with a large seemingly random distribution, the MSE will be very large. The training process modifies the "weights" of each neuron in an attempt to decrease the MSE of the net to a global minimum over each cycle. Once the training process is complete, another set of testing data is presented to the network, and the results are compared with experimental results.

However, other approaches to neural networking do not require this approach of normalization to the dataset, and are much more adaptive. This is a result of the technology improving and computing power becoming greater and allowing for a more robust simulation of a neural network.

5.5 Results

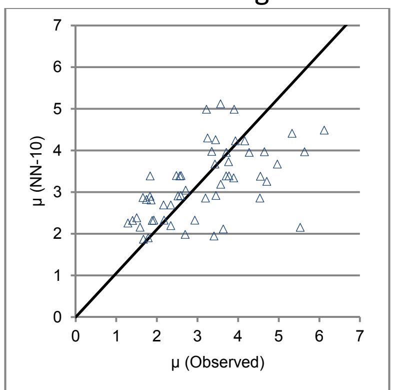
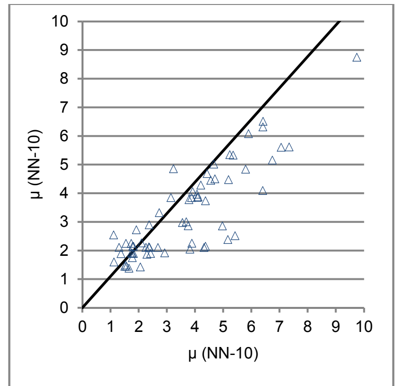
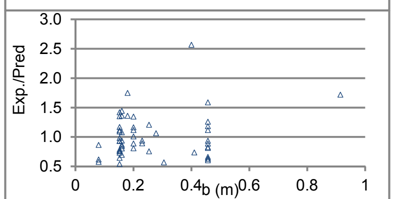
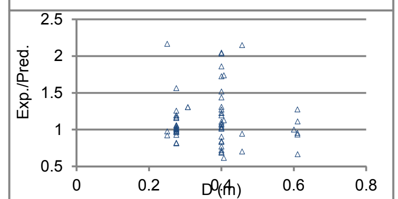
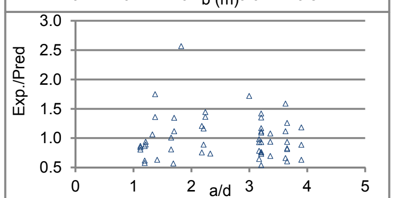
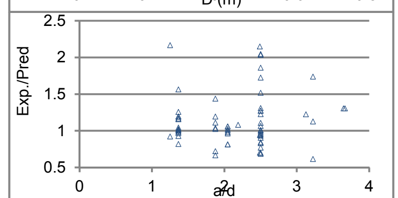
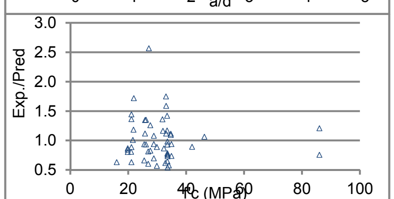
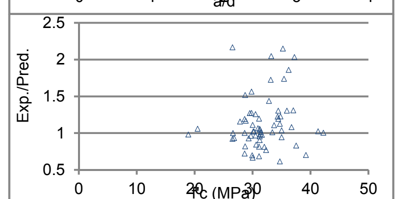
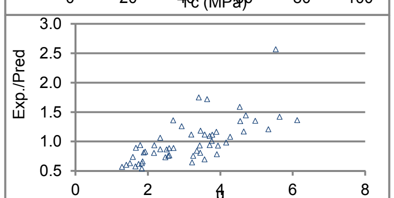
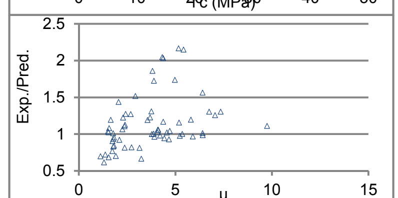
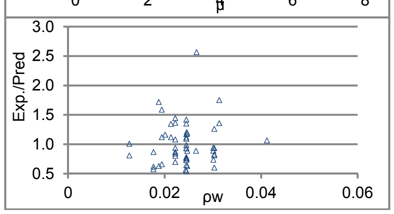
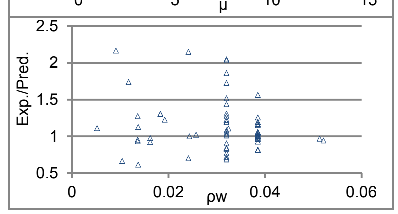
Hundreds of neural network configurations were trained and tested, and the top network for circular and rectangular columns was selected. Selection criteria are based on the lowest absolute mean error and lowest standard deviation on the testing subset. Networks were trained with a subset of the original data. This subset is chosen at random by a Gaussian distribution function and consists of half the specimens available in the database. The other half is reserved to test the performance of the network. The network illustrations can be found below.

For each neural network, six input variables are provided to train the network. They are as follows:

Table 5-1 ANN Input Variables

Input Variable	**Notation**	**Units**	**Comments**
Column Base or Diameter	b_w or D	meters	
Effective Depth	d	meters	Distance from extreme compression fiber to centroid of longitudinal tension reinforcement
Axial Load Contribution	$\frac{P}{A_g\sqrt{f'c}}$	unitless	
Aspect Ratio	$\frac{a}{d}$	unitless	
Longitudinal Reinforcement Ratio	ρ_w	unitless	Area of longitudinal reinforcement divided by gross concrete area
Volumetric Transverse Reinforcement Ratio	ρ_t	unitless	

Table 5-2 Results and Parametric Evaluation

	NN-10 Rectangular	NN-28 Circular
Experimental vs Predicted		
Column base dimension		
Aspect Ratio		
Concrete Strength		
Experimental Displacement Ductility		
Longitudinal Reinforcement Ratio		

The following table illustrates various properties of each neural network.

Table 5-3 ANN properties

Network Name	**NN-10 Rectangular**	**NN-28 Circular**
Mean of Experimental/Predicted	1.007	1.125
Standard Deviation	0.367	0.366
Coefficient of Variance	0.364	0.325
Number of hidden layers	1	2
Number of neurons in hidden layer	10	(1) – 30, (2) - 22

The parametric evaluation of the parameters used to train the network show a few important correlations. The first shows that in both the circular and rectangular networks, the predictions were accurate when the concrete strength was within the 27-32MPa range. This could be due to the fact that there were not many specimens well outside the range with which to train the network. The second important trend is shown when viewing the experimental displacement ductility. At lower measured levels of displacement ductility, the network tends to overestimate the ductility. As the actual ductility, is higher, the networks tend to be more conservative by over estimating the ductility.

Overall, the results are promising. The circular network performed better than the rectangular network. This could be due to a larger sampling set being available. The rectangular column data set was only comprised of 54 test specimens, whereas the circular column database contained 64.

5.6 Conclusion

Neural networks prove to be a very valuable tool to predict the ductility of a column. Neural networks extend beyond the typical realm of empirically-based equations, but have the important requirement of requiring computing power to make predictions. Neural networks can be retrained when new data become available, and actually “learn” how to make predictions the based on previous information, just as humans can. This makes ANNs very beneficial in the seismic design of structures.

Both models presented in this paper provide accurate predictions of the displacement ductility of a particular column based on many parameters of the column’s construction. However, it is the opinion of the author that the networks be re-evaluated using larger datasets before recommendation of real-world usage. As indicated in the literature, neural networks can provide more accurate results if larger datasets are available (El Chabib, Nehdi, & Said, Evaluation of Shear Capacity of FRP Reinforced Concrete Beams Using Artificial Neural Networks, 2006; Lee, 2003).

Chapter 6

Conclusions and Recommendations

As the research has shown, ANN models are viable methods for predicting shear strength and ductility of RC concrete columns. Compared to existing models, lower margins of error were achieved and statistically significant improvements were shown.

This research also demonstrates the viability of using genetic algorithms to optimize existing design equations in a particular domain of data. In this case, existing design equations were optimized using a data set of cyclically loaded RC columns subjected to flexural yielding and shear failure. These optimized equations demonstrated superior performance to existing models when used to predict shear strength in cyclically loaded conditions.

However, ANNs and GAs both exhibit better performance with larger data sets, and accordingly, these models should be used to predict structural performance when they are trained or optimized using significantly larger data sets. As ANNs can be continually trained using new test data, a model that exhibits favorable performance using smaller sets of data can be advanced by providing more experimental data.

Future research into this field could be expanded by providing this type of ANN model to other researchers as the body of test data grows. Providing an interface for other researchers would increase the value and accuracy of the model as it is continuously re-trained. However, as these approaches are trained using test data, they best suited as verification within the same range of variables encompassed by the training data rather than a model that could be used to predict shear strength and ductility in all RC columns.

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Curriculum Vitae

Nicholas Gordon, P.E., LEED AP BD+C

Department of Civil and Environmental Engineering and Construction

University of Nevada, Las Vegas

Las Vegas, NV 89154

Cell: (702) 460 – 5944

Email: gordonn3@unlv.nevada.edu

Education

University of Nevada, Las Vegas

B.S., Engineering, August 2008