SEISMIC RESPONSE PREDICTION OF SELF-CENTERING CONCENTRICALLY
BRACED FRAMES USING GENETIC PROGRAMMING

A Dissertation

Presented to

The Graduate Faculty of The University of Akron

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

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May, 2015

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ABSTRACT

One of the commonly used earthquake-resistant structural systems is the conventional concentrically braced frame (CBF) system, which is widely used in the US. However, CBFs have limited drift capacity prior to a brace buckling occurrence. Self-centering concentrically braced frame (SC-CBF) systems have been recently developed to increase drift capacity prior to initiation of damage and to minimize residual drift. SC-CBF systems have more complex behaviors than conventional CBFs: the seismic response of SC-CBF systems depends on many new parameters such as rocking behavior, post-tensioning bars, and energy dissipation elements. Additionally, uncertainty of earthquake properties affects the system response.

An accurate prediction of roof drift is essential to the design of SC-CBF systems. In this study, a robust modelling tool, genetic programming, is used to predict the peak roof drift response under seismic loading. At first, the design and analysis procedure of the SC-CBF is automated in this study, as is not available in current design software. Three levels of complexity are considered for the numerical models:

- i. Linear materials and geometry
- ii. Nonlinear materials and linear geometry
- iii. Nonlinear materials and nonlinear geometry

where nonlinear materials capture yielding of the structural members and nonlinear geometry is considered by modelling buckling in the braces. Using these three levels of nonlinearity, the effect of nonlinearity on SC-CBF response is also investigated in this study.

Several SC-CBF systems are designed based on the design basis earthquake using a variety of mechanical and geometrical parameters. Then, the peak roof drift is predicted and formulated in two ways. First, the statistical parameters of peak roof drift (mean and standard deviation) are formulated based on the design variables (mechanical and geometrical parameters) in three different nonlinearity levels. Second, the peak roof drift response of each earthquake is formulated based on the design variables and selected ground motion intensity measures. To select the prediction parameters, particularly the ground motion intensity measures, evolutionary correlation coefficients are introduced in this study. There are many parameters involved in the formulation of the peak roof drift response of an individual earthquake. Therefore, a multi-objective strategy is also used in this study to maximize the accuracy and minimize the complexity of the model.

The results of this study can then be used in future designs to implement more efficient SC-CBF systems with a more accurate roof drift prediction.

DEDICATION

To my beloved parents, all accolades belong to you ...

ACKNOWLEDGEMENTS

The research presented in this dissertation was conducted at the University of Akron, Department of Civil Engineering, in Akron, Ohio.

I would like to thank my research advisor and chair of my thesis committee, Dr. David A Roke, for his constant guidance, support, direction, and advice for the past couple of years. I would also like to thank the following people for their contributions to my research: the civil engineering department staff, particularly Ms. Kimberly Stone for their support, and fellow students Amir H. Alavi and Parvin Arjmandi for their helps.

Most importantly, I would like to extend my sincerest thanks to my friends and family who have offered help and inspiration along the way. I extend a special thanks to my parents their counsel and immense contribution throughout my academic life.

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CHAPTER I

INTRODUCTION

1.1 Problem Statement

Steel concentrically-braced frame (CBF) systems, shown schematically in Figure 1.1, have been widely used in the United States as an earthquake-resistant structural system. The CBF has good stiffness and strength, and its ease of implementation makes it an economical seismic resistant steel frame system. However, CBFs have often exhibited limited system ductility capacity prior to brace buckling, which may lead to member failure, especially in braces (e.g., the failure shown in Figure 1.1(b)).

Figure 1.1 (a) Schematic of a conventional CBF system, (b) CBF brace buckling

The ductility capacity of CBF systems can be increased using buckling-restrained braced frames (BRBFs) (e.g., Fahnestock *et al.* 2003); however, BRBF systems may exhibit significant residual drift after earthquakes.

Generally, conventional seismic lateral force resisting systems such as CBFs dissipate energy through damage distributed to structural elements, which often causes residual drift of the structure. Damage and residual drift of the conventional systems usually result in socio-economic losses due to business downtime and repair costs (Chancellor *et al.* 2014a). Therefore, new seismic lateral force resisting systems, called self-centering systems, have been proposed recently.

1.2 Self-Centering Concentrically-Braced Frame

Self-centering concentrically-braced frame (SC-CBF) systems have recently been developed by Roke *et al.* (2006); similar rocking systems have also been studied by others (e.g., Holden *et al.* 2003). The SC-CBF system not only has good stiffness and strength but also has more ductility and drift capacity than CBF systems, while also reducing the residual drift. The SC-CBF system is shown schematically in Figure 1.2. It has two elements that do not appear in conventional CBF systems: post tensioning (PT) bars and energy dissipation elements. The SC-CBF systems have vertically-oriented PT bars, anchored at the center of the SC-CBF at the roof and base, to provide self-centering behavior and restoring forces; their main role is reduction of potential residual drift. Ideally, all SC-CBF members are designed to remain elastic under the design basis earthquake (Roke *et al.* 2010). In an SC-CBF system, SC-CBF columns do not carry gravity loads and, therefore, they are separate from the gravity columns. SC-CBF columns and adjacent gravity columns are connected via lateral-load bearing elements. The lateral-load bearings develop friction forces in the vertical direction and dissipate energy. These forces occur due to the relative vertical motion between the SC-CBF columns, which uplift from the foundation as shown in Figure 1.3, and the adjacent gravity columns, which do not uplift. The lateral-load bearing elements, in addition to dissipating energy through friction, reduce the peak response of the SC-CBF system.

Figure 1.2 Schematic of an SC-CBF system.

Figure 1.3 Schematic of SC-CBF rocking behavior

One of the main structural responses, which should be controlled in the structural design process, is maximum roof drift of the system. Due to complex rocking behavior of the SC-CBF system, particularly under lateral earthquake loading, prediction of its drift response is challenging. Seo (2005) proposed a relationship based on energy dissipation, strength of the structure and period called μ -R-T to predict the median design value of roof drift specifically for self-centering systems. Roke *et al.* (2010) used this strategy for designing the SC-CBF systems and approximation of the median roof drift in the design stage. However, Roke *et al.* (2010) found this method is not accurate enough to predict the median design value of the maximum roof drift. There is no analytical solution to estimate the drift response and only empirical and semi-empirical models can be used in this case. As this system is relatively new, there are very limited studies in this field and there is lack of appropriate drift response predictions.

1.3 Genetic Programming for Response Modelling

Genetic programming (GP) (Koza 1992) is a data driven approach to formulate prediction equations. GP is a more recent specialization of genetic algorithms (GAs), in which the solutions, instead of binary strings, are computer programs. The main advantage of GP-based approaches over other modeling tools is that GP is flexible and can generate predictive equations or formulas without any prior assumptions regarding relationships between input parameters. A GP-based equation is generally simple and easily used in practice. Gene expression programming (GEP) (Ferreira 2001) is a new variant of GP. GEP solutions are computer programs of different shapes and sizes that have been encoded in fixed-length linear chromosomes (Gandomi *et al.* 2011). Recent

research has applied GEP to structural engineering modeling (e.g., Gandomi and Alavi 2013, Gandomi *et al.* 2012). Any GP can be hybridized with regression analysis (RA) to provide a more precise model. A hybrid GP with RA, called multi-gene genetic programming (MGGP), was recently proposed by Searson *et al.* (2010) and successfully applied to structural engineering problems (Gandomi and Alavi 2012).

1.4 Outline of Research

In this study, at first, the SC-CBF design process is automated in MATLAB® based on the defined SC-CBF design procedure (Roke *et al.* 2010) at the design-basis earthquake (DBE) level. OpenSEES software (Mazzoni *et al.* 2006) is used for nonlinear static and dynamic finite element analyses. Then 75 SC-CBF systems with different mechanical and geometrical parameters are designed for use in this study.

Next, the dynamic responses of the structures for fifty DBE-level earthquakes are determined through nonlinear time history analyses using OpenSEES. Then, an algorithm is used to formulate the statistical parameters (mean and standard deviation) of the roof drift response. Equations based on genetic programming results are developed to predict the mean and standard deviation of the responses for three different model complexities. The resulting equations are simple and correlate well with the numerical analysis results.

Predicting the exact response of a structure under a specific earthquake is another part of this study that involves additional uncertainties. In addition to the mechanical and geometrical parameters of the SC-CBF system, earthquake intensity measures (IMs) are very important in predicting structural response. An evolutionary coefficient (Re2) is

proposed here to select the IMs that are most correlated to the peak roof drift response.

Then the selected IMs and mechanical and geometrical parameters of the SC-CBF system are used as the variables in model development. MGGP is used here to formulate the response, as it is particularly accurate when there are several input variables. The results show that the MGGP-based formula can predict the response of each earthquake with a high degree of accuracy.

CHAPTER II

RELEVANT PRIOR RESEARCH

Conventional seismic lateral force resisting systems dissipate seismic energy through distributed damage to primary structural elements, which can result in residual drift and significant socio-economic losses due to repair costs and business downtime (Chancellor *et al.* 2014a). A new class of seismic lateral force resisting systems, self-centering systems, has been developed to address these issues.

The SC-CBF system was initially proposed by Roke *et al.* (2006), and its design procedure (Roke *et al.* 2009, 2010) is a performance-based design procedure that employs friction-based energy dissipation. As this system is very new, only some limited studies have been done on it. Initially, Sause *et al.* (2006), Ricles *et al.* (2006), and Roke *et al.* (2008) performed analytical pushover and dynamic analyses on six-story SC-CBF systems with different configurations to evaluate the responses during earthquakes and to determine optimal system configuration.

Large-scale structural testing (0.6-scale) of a four-story SC-CBF system was conducted in ATLSS Engineering Research Center at Lehigh University by Sause *et al.*

(2010a). A schematic of the selected configuration and a photograph of the experimental test structure are shown in Figure 2.1. The results showed that the SC-CBF performance objectives under the design basis earthquake (DBE) were achieved, and only minor structural damage (in the form of PT bar yielding) occurred. Chancellor *et al.* (2011) performed experimental tests on the same SC-CBF setup during intense earthquake and aftershock ground motions. The results showed that the SC-CBF system performs well in intense earthquake ground motions at the maximum considered earthquake (MCE) level, and also during a DBE-level aftershock, even after the PT bars yield and the initial PT force is lost.

Figure 2.1 Frame configuration for large scale experimental test: (a) schematic; (b) experimental test structure (Sause *et al.* 2010b).

Roke and Jeffers (2012) studied different friction coefficient values and Roke and Hasan (2012) studied SC-CBF systems with three different bay widths to determine the

effects of these parameters on the design and response of SC-CBF system. Using numerical studies, Chancellor *et al.* (2013) demonstrated that the difference between the median peak story drift and median peak roof drift generally increases with increasing building height over SC-CBF bay (h/b) called aspect ratio (shown in Figure 2.2). This means that the SC-CBF response is less dominated by rigid-body rotation as it becomes taller, because the effect of the higher modes is increased. Akbas *et al.* (2014) showed that with increasing the height of the SC-CBF, higher modes effects on responses increase. They also found high correlations between modal responses in SC-CBF system.

Figure 2.2 Aspect ratio in the SC-CBF systems

Eatherton *et al.* (2012) demonstrated that steel braced frames with controlled rocking are reliable systems and can improve the conventional structural systems. In addition to gravity loads and PT bars, overturning can be resisted by replaceable structural fuses that

dissipate earthquake energy. Alternative configurations of structural fuses in SC-CBF systems are shown in Figure 2.3.

Figure 2.3 Alternative configurations of structural fuses in SC-CBF systems (Eatherton *et al.* 2012). (a) Single frame; (b) dual frame; (c) alternate fuses; (d) fuses at columns; (e) PT at columns; (f) PT and fuses at columns.

Eatherton and Hajjar (2014) they reviewed different rocking system (shown in Figure 2.4) and performed hybrid simulation testing for two different types of fuses for a self-centering rocking steel braced frame system. This experimental study demonstrated

that nondegrading butterfly fuse plates can undergo multiple large ground motions without deterioration of their stiffness or strength. Through all hybrid simulation tests, they also found residual drifts close to zero, which shows that the rocking steel frames have excellent self-centering ability.

Figure 2.4 Different configurations of rocking structural systems (Eatherton and Hajjar 2014). (a) jointed precast concrete wall; (b) rocking precast concrete wall; (c) rocking steel frame with friction dampers; (d) single steel frame; (e) multiple rocking hinges.

Kafaeikivi *et al.* (2013) studied seismic performance of a dual system combining CBFs and SC-CBF systems using fragility curves in different performance levels. They found that the dual system is less vulnerable than a conventional CBF system. Dyanati *et al.* (2013, 2014) compared CBF and SC-CBF systems using their fragility curves and found that an SC-CBF system is less likely to exceed a given performance level than a conventional CBF system.

The SC-CBF system's rocking behavior is expected to amplify higher mode effects. Roke *et al.* (2009) have shown that the force demands on the braces of a six-story SC-CBF system at the DBE level can be several times larger than those determined by applying a first-mode distribution of lateral forces. Another study on a six-story controlled rocking frame by Eatherton and Hajjar (2010) found that the median force in the first-story brace at the MCE level was more than three times the design force. They also found that the median force in that brace at the DBE level was more than twice the forces determined by allocating the design base shear forces based on an inverted triangular force distribution.

Wiebe *et al.* (2013) proposed two new techniques for controlled rocking steel frames. First, they added one or more controlled rocking joints above the base rocking joint. Then, a nonlinear self-centering energy dissipative brace at the first-story level was proposed to limit the peak base shear. Their experimental and numerical results show that the proposed mechanisms can provide better capacity by reducing the variability of peak seismic force demands without causing excessive displacements.

Chancellor *et al.* (2014b) showed that foundation flexibility is an important parameter in median drifts of short SC-CBF systems. They also found that roof drift predictions for high-rise SC-CBF systems are likely to overestimate median response.

Eatherton *et al.* (2014) examined the design concepts of SC-CBF systems and contrasted them with other conventional and self-centering seismic force resisting systems. They investigated the limit states and ways of controlling them. A six-story prototype structure was designed as a case study to demonstrate the applicability of these design concepts.

Chancellor *et al.* (2014) recently reviewed the latest developments in self-centering seismic lateral force resisting systems and outline current research challenges such as changes in friction surfaces and coefficients, isolating deformations related to gap opening, higher mode effects, collapse safety assessment of self-centering systems, and efficiency and strategic use of self-centering systems considering life-cycle cost. They describe the self-centering seismic lateral force resisting systems as:

“High performance structures for the city of tomorrow”

CHAPTER III

SELF-CENTERING CONCENTRICALLY BRACED FRAME SYSTEM

3.1 SC-CBF System Behavior

The idealized behavior of an SC-CBF system is shown schematically in Figure 3.1. The SC-CBF system is comprised of beams, columns, and braces in a conventional arrangement (as shown in Figure 3.1(a)), with column base details that permit the columns to uplift at the foundation (Figure 3.1(b)). Self-weight and post-tensioning (PT) forces (from PT bars arranged vertically at midbay in Figure 3.1(a)) counteract the column uplift and provide a restoring force after uplift. The beams, columns, and braces are intended to remain inherently elastic (damage-free) under the design basis earthquake (DBE); column uplift provides a softening mechanism that helps to restrict the force levels that develop in the frame under earthquake loading. The SC-CBF includes a distribution strut in the uppermost story to transfer the PT bar force to the braces.

Figure 3.1 SC-CBF system: (a) schematic of members and loads; (b) rigid-body rotation after column decompression and uplift.

The SC-CBF deforms elastically like a conventional CBF under low levels of lateral force. However, under higher levels of lateral force, the overturning moment at the base of the frame becomes substantial enough for one SC-CBF column to decompress, uplifting from the base as shown in Figure 3.1(b). After column decompression and uplift, the lateral displacement of the frame is dominated by rigid body rotation of the SC-CBF (i.e., rocking response) about the base of the SC-CBF column that is still in contact with the foundation, although some additional forces and deformations develop in the frame members. The PT steel elongates from the uplift of the frame, leading to an increase in PT force, thus providing a positive stiffness to the lateral force-lateral drift behavior after column decompression and uplift.

3.2 SC-CBF Configurations

Several SC-CBF configurations have been studied (Roke *et al.* 2006, 2009) to develop a final configuration (shown in Figure 3.2(a)) to use for a detailed study (Roke *et al.* 2010). This configuration consists of an SC-CBF positioned between two additional columns that are attached to the gravity load system of the building. These two “gravity columns,” which do not uplift, isolate the gravity load carrying function from the rocking of the SC-CBF. Friction-bearing dampers are located at each floor level to dispel energy through the relative vertical displacement between the gravity columns and the SC-CBF columns. Each friction-bearing damper has a small initial gap between the gravity column and SC-CBF column, which is then closed by the transfer of floor diaphragm inertial forces in bearing between the gravity column and the SC-CBF column. The normal force on the friction surface is equal to the floor diaphragm inertial force transferred to the SC-CBF at each individual floor level. Steel knuckles and brass plates are used as the friction surface to achieve a relatively high friction coefficient (0.45).

To reduce the elongation demand on the PT bars, the PT bars are located at midbay. As the tension column uplifts, a gap opens at the column base; the elongation demand of the PT steel is equal to half of the gap-opening displacement of the uplifting column. A vertical distribution strut is located in the upper story. This strut then distributes the force of the midbay PT bars to the braces over multiple stories.

Figure 3.2 SC-CBF schematics: (a) frame configuration; (b) free body diagram at column decompression.

A free-body diagram of the SC-CBF at column decompression is shown in Figure 3.2(b). The applied overturning moment (from the lateral forces F_i) is equal to the overturning moment at decompression (OM_D) and is resisted by the initial PT bar force (PT_0), the self-weight of the SC-CBF members (W), and the friction forces at the friction-bearing damper at each floor (F_{EDi}). By definition, at column decompression, only a single SC-CBF column transmits vertical loads (F_c) to the foundation. Further increases in the applied overturning moment will cause the SC-CBF column with zero vertical reaction to uplift from its base and will thus elongate the PT bars.

Elongation of the PT bars increases the PT bar force, providing a positive stiffness to the post-decompression lateral force-lateral drift behavior, as shown schematically in Figure 3.3. Rocking and the associated rigid-body rotation dominate the roof drift

response after column decompression because the elastic stiffness of the SC-CBF is much greater than the post decompression stiffness. Therefore, the increases in elastic deformations and internal forces in the SC-CBF members are limited by the rocking behavior, and thus resulting in a larger lateral drift capacity prior to the initiation of structural damage.

Figure 3.3 Schematic of hysteretic response of an SC-CBF system (Roke *et al.* 2010).

Cyclic loading of an SC-CBF results in the hysteretic behavior shown in Figure 3.3. The dashed lines indicate the hysteretic behavior of a bilinear elastic system with equal strength (OM_D) under cyclic loading to the same peak roof drift. The solid lines indicate the hysteretic behavior of an SCCBF with friction-based energy dissipation. Note that at the friction-bearings the friction increases the post decompression stiffness of the SC-CBF with respect to that of the bilinear elastic stiffness. The flag-shaped hysteresis that is

presented by the SC-CBF is characteristic of self-centering structural systems. The height of the hysteresis loop is equal to twice the overturning moment resisted by the friction in the lateral-load bearings (OM_{ED}) and is a function of the magnitude of the applied forces F_i that can be expressed as follows:

$$OM_{ED} = \sum_{i=1}^{ns} F_{EDi} \cdot b_{ED} = \mu \cdot \sum_{i=1}^{ns} F_i \cdot b_{ED} \quad (3.1)$$

where ns is the number of stories, μ is the coefficient of friction at the lateral-load bearings, and b_{ED} is the distance between the centerline of the adjacent gravity column where F_{EDi} acts and the centerline of the compression column of SC-CBF, as shown in Figure 3.4.

Figure 3.4 Moment arm (b_{ED}) used to compute the overturning moment resisted by the friction in the friction-bearing dampers (OM_{ED}).

3.2.1 Prototype Structures

In this study, several prototype structures were designed using SC-CBF systems for the lateral load resisting system. The prototype structures in this study are office buildings designed for a stiff soil site near Los Angeles, California. As shown in Figure 3.5, a typical floor plan for the prototype structure is symmetric and has six bays in each direction.

Figure 3.5 Typical floor plan of the prototype building.

The prototype structures designed in this study were four, six and eight-story buildings. Elevations of SC-CBF systems with these heights are shown in Figure 3.6.

Figure 3.6 Three different elevations of SC-CBF systems.

The estimated gravity loads and seismic masses for the prototype structure are as follows. The dead loads include the concrete floor slab, steel floor deck, mechanical equipment, floor and ceiling finishes, fire proofing, vertical projection of exterior wall and an estimated weight per square foot of structural steel. The assumed dead loads and are presented in Table 3.1. The seismic mass of each floor is taken as the dead load plus an approximated partition load, as per ASCE7 (2010). The “tributary” gravity loads are

the ones carried by the gravity-load-bearing columns that are laterally braced by the SC-CBF, indicated by the shaded area in Figure 3.5.

Table 3.1 Assumed dead load values for the prototype structure.

Weight, psf (kPa)	Roof	Other floors
Slabs	-	43 (2.099)
Weight of decks	-	3 (0.1465)
Ceiling material	5 (0.244)	5 (0.244)
Mechanical equipment	20 (0.9765)	10 (0.488)
Steel/Structural steel	10 (0.488)	15 (0.7324)
Floor finish	2 (0.0976)	2 (0.0976)
Fireproofing	2 (0.0976)	2 (0.0976)
Exterior wall	7 (0.3718)	25 (1.221)
Roofing material	6 (0.293)	-

3.2.2 SC-CBF Design Matrix

In order to formulate the statistical parameters (mean and standard deviation) of the response, a database of different parameters is required. In this study, two mechanical and two geometrical parameters have been considered as model variables:

3.2.2.1 Mechanical parameters

A prior experimental study (Roke *et al.* 2010) evaluated the seismic response of an SC-CBF with brass-on-steel lateral-load bearings with coefficient of friction (μ) equal to 0.45. In a more recent study by Roke and Jeffers (2012), three values of μ (0.30, 0.45, and 0.60) were used to determine the effect that friction has on the design and response of the SC-CBF system. An additional important mechanical property in this system is the yield stress of the structural steel (F_y), which has a significant effect on the selection of

steel sections in the member design phase. The yield stresses used in this study are 36, 50 and 60 ksi (248, 345, and 414 MPa).

3.2.2.2 Geometric parameters

Roke and Hasan (2012) studied SC-CBF systems with three different bay widths (b) to study the effect of various frame geometries on the seismic response of SC-CBF systems. In this study, three different bay widths were considered: 22.5, 30, and 40 ft (6.9, 9.1, and 12.2 m). Also an important geometric parameter is the height of the building (h). In this study, three different building heights were considered: 52.5, 77.5, and 102.5 ft (16, 23.6, and 31.2 m) by varying the number of stories.

The mechanical and geometric values used for structural design are shown in Table 3.2. Three values have been implemented for each variable. From this design matrix, a total of 81 possible SC-CBF systems were designed. However, the design of six eight-story buildings with low F_y and μ values did not converge, so they were removed from the design matrix, leaving a total of 75 converged designs in this study.

Table 3.2 Summary of design values

Geometrical		Mechanical	
b , ft (m)	h , ft (m)	F_y , ksi (MPa)	μ
22.5 (6.9)	52.5 (16)	36 (248)	0.30
30 (9.1)	77.5 (23.6)	50 (345)	0.45
40 (12.2)	102.5 (31.2)	60 (414)	0.60

CHAPTER IV

SC-CBF DESIGN

The design of each SC-CBF is based upon the performance-based design procedure for SC-CBF systems with friction-based energy dissipation (Roke *et al.* 2010). This design method is iterative and has two primary phases: member design and PT bar design. The adjacent gravity columns have additional vertical loads due to the forces that develop in the friction bearing dampers due to the relative vertical motion between the SC-CBF columns and the adjacent gravity columns. Therefore, first, these columns are statically designed based on their dead, live, and friction loads. Then, the SC-CBF members are designed according to a modification of the standard response spectrum analysis procedure, in which PT bar yielding limits the first mode response. In the member design phase, the SC-CBF members are resized until their capacities exceed the member force design demands. Initially, the center-to-center spacing between each adjacent gravity column and the SC-CBF column is set as 1.5 ft (0.46 m). After designing the members, the required edge-to-edge spacing between adjacent gravity columns and SC-CBF columns is 5 in to 10 in (0.13 m to 0.25 m) to allow space for the friction-

bearing dampers. If this required spacing is not satisfied, the SC-CBF bay width is changed and SC-CBF members are redesigned.

In the PT bar design phase, the system's drift capacity at PT bar yielding is compared against the estimated DBE drift demand. The drift capacity at PT yield is determined by the rigid-body rotation of the SC-CBF (after column decompression) and also the elastic deformation of the SC-CBF at PT yield. The rigid-body rotation elongates the PT bars, while the elastic deformation does not. A sample of PT bar design iterations is shown in Figure 4.1. The design is iterated until the roof drift capacity at PT bar yielding exceeds the DBE demand. Each new iteration increased the area of the PT bars, and member design was completed before the final drift check for that iteration (shown in Figure 4.1) was conducted.

Figure 4.1 A sample of PT bar design iterations.

In addition to the drift capacity exceeding the drift demand, the initial stress in the PT bars (σ_0) must be high enough for the SC-CBF's decompression strength OM_D to resist column uplift under common lateral loads (e.g., wind loading) (Roke *et al.* 2010). The initial stress is chosen to satisfy this constraint from the range where the roof drift capacity at PT bar yielding exceeds the DBE drift demand. Uplifting of structure under non-seismic lateral loads is checked using RA, which expresses the strength of the system with respect to the force demands based on linear elastic response (Roke *et al.* 2010). RA can be formulated using following equation:

$$R_A = \frac{OM_{elastic}}{OM_D} = \frac{R}{\alpha_D} \quad (4.1)$$

where $OM_{elastic}$ is the overturning moment demand based on linear elastic response to the DBE, R is the response modification coefficient (assumed equal to 8 in this study), and α_D is the ratio of OM_D to the overturning moment demand determined from the equivalent lateral force procedure (OM_{ELF}). Here, $R_A \leq 10$ (Roke *et al.* 2010), which means $\alpha_D \leq 0.8$.

A schematic of the design procedure is shown in Figure 4.2. Note that in each iteration, the PT bars, SC-CBF members, and SC-CBF bay width are redesigned after any changes in the system.

Figure 4.2 Simplified flowchart of the design procedure.

CHAPTER V

SC-CBF ANALYSIS

5.1 Numerical modeling

In this study, the entire numerical analysis process was automated using MATLAB®. OpenSEES (Mazzoni *et al.* 2006) is used for nonlinear static and dynamic numerical analyses of the SC-CBF systems.

For the purposes of this study, the SC-CBF structural members are initially modeled as linear elastic. Then, material nonlinearity is modeled by a material with isotropic strain hardening, and the nonlinearity in geometry is modeled by introducing small initial out-of-plane deformations to model brace buckling (Uriz and Mahin 2004).

A lean-on column is used to model the tributary gravity system of the SC-CBF. The lean-on column is connected to the adjacent gravity columns at each floor level. The bases of the lean-on column and the adjacent gravity columns have pin conditions, in which displacements are restrained but rotation is allowed. The vertical gap opening behavior at the SC-CBF column bases was modeled using zero-length gap elements that resist compression but not tension.

In design, the PT bar force is modeled using a concentrated force; however, the actual PT bars must be modeled in the analysis step to get more accurate results. For this purpose, nonlinear beam-column elements with post-yielding stiffness equal to 2% of their elastic stiffness are used to model the PT bars. The PT bars should only carry tension loads, as they will buckle under any compression loads due to their length; therefore, a zero-length tension-only element is used at the base node where the PT steel is anchored to the ground. This element also allows for a gap to form when the permanent deformation in the PT bars becomes large enough to eliminate the tension in the bars (Chancellor *et al.* 2013). To accurately apply the computed initial stress to the PT steel bars, an iterative process using the Nelder-Mead simplex optimization method (Lagarias *et al.* 1998) is implemented.

The friction behavior at the friction-bearing dampers was modeled using contact friction elements, which are gap elements that develop a friction force perpendicular to the applied compressive force. After modelling the PT bar initial stresses, floors may have some lateral expansion or contraction. Therefore, the initial lateral gaps between SC-CBF columns and adjacent gravity column should be corrected after the PT bar modelling step.

The SC-CBF analysis is a time consuming part of this research study, as it uses time history analysis to determine the structural response for each earthquake record. Therefore, this step was programmed for parallel processing using the MATLAB® parallel computing toolbox. The brief numerical modelling procedure including the parallel processing seismic analyses for N parallel processors is shown in Figure 5.1.

Figure 5.1 Numerical modelling flowchart

5.2 Subjecting the SC-CBF systems to ground motions

In this study, SC-CBF seismic response was determined using two different suites of ground motions. The first is a suite of 30 recorded ground motions, scaled to the design-basis earthquake (DBE) level, which had been previously used with SC-CBF systems by Roke *et al.* (2010). Table 5.1 presents the summary of these ground motions.

Table 5.1 Summary of ground motion characteristics of the first suite

Event	Station	M ^a	R ^b (km)	T ^c (s)	SF ^d
1994 Northridge	Santitasana	6.69	16.74	57.25	2.49
1995 Northridge	Santitasana	6.69	16.74	57.25	2.49
1990 Manjil	Manjil	7.37	12.56	53.52	1.36
1991 Manjil	Manjil	7.37	12.56	46	1.36
1994 Northridge	Arleta	6.69	8.66	40	1.40
1995 Northridge	Arleta	6.69	8.66	40	1.40
1976 Friuli	Tolmezzo	6.50	15.82	36.35	1.46
1977 Friuli	Tolmezzo	6.50	15.82	36.35	1.46
1989 Loma Prieta	Capitola	6.93	15.23	39.96	0.83
1990 Loma Prieta	Capitola	6.93	15.23	39.96	0.83
1989 Loma Prieta	Corralitos	6.93	3.85	39.95	0.73
1990 Loma Prieta	Corralitos	6.93	3.85	39.95	0.73
1980 Victoria	Cerro Prieto	6.33	14.37	24.45	1.28
1981 Victoria	Cerro Prieto	6.33	14.37	24.45	1.28
1979 Imperial Valley	Sahop Casa Flores	6.53	9.64	15.71	1.75
1980 Imperial Valley	Sahop Casa Flores	6.53	9.64	15.71	1.75
1999 Chi-Chi	HWA059	7.62	49.15	90	2.26
2000 Chi-Chi	HWA060	7.62	49.15	90	2.26
1994 Northridge	Hollywood Storage FF	6.69	24.03	40	1.55
1995 Northridge	Hollywood Storage FF	6.69	24.03	40	1.55
1994 Northridge	Sun Valley	6.69	10.05	30.28	1.28
1995 Northridge	Sun Valley	6.69	10.05	30.28	1.28
1995 Kobe	Shin	6.90	19.15	40.96	1.37
1996 Kobe	Shin	6.90	19.15	40.96	1.37
1989 Loma Prieta	San Jose	6.93	14.69	50.02	1.79

1990 Loma Prieta	San Jose	6.93	14.69	50.02	1.79
1994 Northridge	UCLA Grounds	6.69	22.49	60	2.35
1995 Northridge	UCLA Grounds	6.69	22.49	60	2.35
1989 Loma Prieta	Waho	6.93	17.47	25.01	1.55
1990 Loma Prieta	Waho	6.93	17.47	25.01	1.55

^aM = earthquake magnitude; ^bR = distance from the source to the station; ^cT = earthquake duration; ^dSF = DBE scale factor

The second suite of ground motions is the SAC database (Somerville *et al.* 1997), which has 140 recorded and synthetic ground motions. These ground motions are separated into three different seismic zones: Los Angeles (LA), CA (Zone 4); Seattle (SE), WA (Zone 3); and Boston (BO), MA (Zone 2). These records are also scaled to model different probabilities of exceedance: 2% in 50 years (approximately the maximum considered earthquake (MCE)), 10% in 50 years (approximately the DBE), and 50% in 50 years (called a frequently occurring earthquake (FOE)). A summary of the SAC ground motions in the DBE, MCE and FOE levels are presented in Tables 5.2, 5.3, and 5.4, respectively.

Table 5.2 Summary of DBE level ground motion characteristics of the second suite

City	Record	M	R (km)	T (s)	SF
LA	Imperial Valley, 1940, El Centro	6.9	10	39.38	2.01
LA	Imperial Valley, 1940, El Centro	6.9	10	39.38	2.01
LA	Imperial Valley, 1979, Array #05	6.5	4.1	39.38	1.01
LA	Imperial Valley, 1979, Array #05	6.5	4.1	39.38	1.01
LA	Imperial Valley, 1979, Array #06	6.5	1.2	39.08	0.84
LA	Imperial Valley, 1979, Array #06	6.5	1.2	39.08	0.84
LA	Landers, 1992, Barstow	7.3	36	79.98	3.2
LA	Landers, 1992, Barstow	7.3	36	79.98	3.2
LA	Landers, 1992, Yermo	7.3	25	79.98	2.17

LA	Landers, 1992, Yermo	7.3	25	79.98	2.17
LA	Loma Prieta, 1989, Gilroy	7	12	39.98	1.79
LA	Loma Prieta, 1989, Gilroy	7	12	39.98	1.79
LA	Northridge, 1994, Newhall	6.7	6.7	59.98	1.03
LA	Northridge, 1994, Newhall	6.7	6.7	59.98	1.03
LA	Northridge, 1994, Rinaldi RS	6.7	7.5	14.945	0.79
LA	Northridge, 1994, Rinaldi RS	6.7	7.5	14.945	0.79
LA	Northridge, 1994, Sylmar	6.7	6.4	59.98	0.99
LA	Northridge, 1994, Sylmar	6.7	6.4	59.98	0.99
LA	North Palm Springs, 1986	6	6.7	59.98	2.97
LA	North Palm Springs, 1986	6	6.7	59.98	2.97
SE	Long Beach, Vernon CMD Bldg.	6.5	1.2	39.08	0.49
SE	Long Beach, Vernon CMD Bldg.	6.5	1.2	39.08	0.49
SE	Morgan Hill, 1984, Gilroy	6.2	15	59.98	2.84
SE	Morgan Hill, 1984, Gilroy	6.2	15	59.98	2.84
SE	West. Washington, Olympia, 1949	6.5	56	79.98	1.86
SE	West. Washington, Olympia, 1949	6.5	56	79.98	1.86
SE	West. Washington, Seattle Army B., 1949	6.5	80	66.68	5.34
SE	West. Washington, Seattle Army B., 1949	6.5	80	66.68	5.34
SE	North Palm Springs, 1986	6	6.7	59.98	1.71
SE	North Palm Springs, 1986	6	6.7	59.98	1.71
SE	Puget Sound, Wa., Olympia, 1949	7.1	80	81.82	4.3
SE	Puget Sound, Wa., Olympia, 1949	7.1	80	81.82	4.3
SE	Puget Sound, Wa., Federal OFC B., 1949	7.1	61	74.08	5.28
SE	Puget Sound, Wa., Federal OFC B., 1949	7.1	61	74.08	5.28
SE	Eastern Wa., Tacoma County, 1949	7.1	60	59.98	8.68
SE	Eastern Wa., Tacoma County, 1949	7.1	60	59.98	8.68
SE	Llolleo, Chile 1985	8	42	99.98	1.24
SE	Llolleo, Chile 1985	8	42	99.98	1.24
SE	Vinadel Mar, Chile, 1985	8	42	99.98	1.69
SE	Vinadel Mar, Chile, 1985	8	42	99.98	1.69
BO	Simulation, hanging wall	6.5	30	29.99	0.39
BO	Simulation, hanging wall	6.5	30	29.99	0.39
BO	Simulation, foot wall	6.5	30	29.99	0.54
BO	Simulation, foot wall	6.5	30	29.99	0.54
BO	New Hampshire, 1982	4.3	8.4	19.23	10.75
BO	New Hampshire, 1982	4.3	8.4	19.23	10.75
BO	Nahanni, 1985	6.9	9.6	20.34	0.09
BO	Nahanni, 1985	6.9	9.6	20.34	0.09
BO	Nahanni, 1985	6.9	6.1	18.76	0.2
BO	Nahanni, 1985	6.9	6.1	18.76	0.2

BO	Nahanni, 1985	6.9	18	19.02	0.92
BO	Nahanni, 1985	6.9	18	19.02	0.92
BO	Saguenay, 1988	5.9	96	17.74	1.57
BO	Saguenay, 1988	5.9	96	17.74	1.57
BO	Saguenay, 1988	5.9	98	29.57	3.21
BO	Saguenay, 1988	5.9	98	29.57	3.21
BO	Saguenay, 1988	5.9	118	39.05	3.25
BO	Saguenay, 1988	5.9	118	39.05	3.25
BO	Saguenay, 1988	5.9	132	33.24	3.34
BO	Saguenay, 1988	5.9	132	33.24	3.34

Table 5.3 Summary of MCE level ground motion characteristics of the second suite

City	Record	M	R (km)	T (s)	SF
LA	1995 Kobe	6.9	3.4	59.98	1.15
LA	1995 Kobe	6.9	3.4	59.98	1.15
LA	1989 Loma Prieta	7	3.5	24.99	0.82
LA	1989 Loma Prieta	7	3.5	24.99	0.82
LA	1994 Northridge	6.7	7.5	14.95	1.29
LA	1994 Northridge	6.7	7.5	14.95	1.29
LA	1994 Northridge	6.7	6.4	59.98	1.61
LA	1994 Northridge	6.7	6.4	59.98	1.61
LA	1974 Tabas	7.4	1.2	49.98	1.08
LA	1974 Tabas	7.4	1.2	49.98	1.08
LA	Elysian Park (simulated)	7.1	17.5	29.99	1.43
LA	Elysian Park (simulated)	7.1	17.5	29.99	1.43
LA	Elysian Park (simulated)	7.1	10.7	29.99	0.97
LA	Elysian Park (simulated)	7.1	10.7	29.99	0.97
LA	Elysian Park (simulated)	7.1	11.2	29.99	1.1
LA	Elysian Park (simulated)	7.1	11.2	29.99	1.1
LA	Palos Verdes (simulated)	7.1	1.5	59.98	0.9
LA	Palos Verdes (simulated)	7.1	1.5	59.98	0.9
LA	Palos Verdes (simulated)	7.1	1.5	59.98	0.88
LA	Palos Verdes (simulated)	7.1	1.5	59.98	0.88
SE	1992 Mendocino	7.1	8.5	59.98	0.98
SE	1992 Mendocino	7.1	8.5	59.98	0.98
SE	1992 Erzincan	6.7	2	20.78	1.27
SE	1992 Erzincan	6.7	2	20.78	1.27
SE	1949 Olympia	6.5	56	79.98	4.35

SE	1949 Olympia	6.5	56	79.98	4.35
SE	1965 Seattle	7.1	80	81.82	10.04
SE	1965 Seattle	7.1	80	81.82	10.04
SE	1985 Valpariso	8	42	99.98	2.9
SE	1985 Valpariso	8	42	99.98	2.9
SE	1985 Valpariso	8	42	99.98	3.96
SE	1985 Valpariso	8	42	99.98	3.96
SE	Deep Interplate (simulation)	7.9	65	79.98	3.84
SE	Deep Interplate (simulation)	7.9	65	79.98	3.84
SE	1978 Miyagi-oki	7.4	66	79.98	1.78
SE	1978 Miyagi-oki	7.4	66	79.98	1.78
SE	Shallow Interplate (simulation)	7.9	15	79.98	0.94
SE	Shallow Interplate (simulation)	7.9	15	79.98	0.94
SE	Shallow Interplate (simulation)	7.9	15	79.98	1.49
SE	Shallow Interplate (simulation)	7.9	15	79.98	1.49
BO	simulation, foot wall	6.5	30	29.99	0.99
BO	simulation, foot wall	6.5	30	29.99	0.99
BO	simulation, foot wall	6.5	30	29.99	0.84
BO	simulation, foot wall	6.5	30	29.99	0.84
BO	simulation, foot wall	6.5	30	29.99	0.63
BO	simulation, foot wall	6.5	30	29.99	0.63
BO	Nahanni, 1985 Station 1	6.9	9.6	20.34	0.27
BO	Nahanni, 1985 Station 1	6.9	9.6	20.34	0.27
BO	Nahanni, 1985 Station 2	6.9	6.1	18.76	0.56
BO	Nahanni, 1985 Station 2	6.9	6.1	18.76	0.56
BO	Nahanni, 1985 Station 3	6.9	18	19.02	2.63
BO	Nahanni, 1985 Station 3	6.9	18	19.02	2.63
BO	Saguenay, 1988	5.9	96	17.74	4.48
BO	Saguenay, 1988	5.9	96	17.74	4.48
BO	Saguenay, 1988	5.9	98	29.57	9.21
BO	Saguenay, 1988	5.9	98	29.57	9.21
BO	Saguenay, 1988	5.9	118	39.05	9.3
BO	Saguenay, 1988	5.9	118	39.05	9.3
BO	Saguenay, 1988	5.9	132	33.24	9.58
BO	Saguenay, 1988	5.9	132	33.24	9.58

Table 5.4 Summary of FOE level ground motion characteristics of the second suite

City	Record	M	R (km)	T (sec)	SF
LA	Coyote Lake, 1979	5.7	8.8	39.38	2.28
LA	Coyote Lake, 1979	5.7	8.8	39.38	2.28
LA	Imperial Valley, 1979	6.5	1.2	39.08	0.4
LA	Imperial Valley, 1979	6.5	1.2	39.08	0.4
LA	Kern, 1952	7.7	107	78.6	2.92
LA	Kern, 1952	7.7	107	78.6	2.92
LA	Landers, 1992	7.3	64	79.98	2.63
LA	Landers, 1992	7.3	64	79.98	2.63
LA	Morgan Hill, 1984	6.2	15	59.98	2.35
LA	Morgan Hill, 1984	6.2	15	59.98	2.35
LA	Parkfield, 1966, Cholame 5W	6.1	3.7	43.92	1.81
LA	Parkfield, 1966, Cholame 5W	6.1	3.7	43.92	1.81
LA	Parkfield, 1966, Cholame 8W	6.1	8	26.14	2.92
LA	Parkfield, 1966, Cholame 8W	6.1	8	26.14	2.92
LA	North Palm Springs, 1986	6	9.6	59.98	2.75
LA	North Palm Springs, 1986	6	9.6	59.98	2.75
LA	San Fernando, 1971	6.5	1	79.46	1.3
LA	San Fernando, 1971	6.5	1	79.46	1.3
LA	Whittier, 1987	6	17	39.98	3.62
LA	Whittier, 1987	6	17	39.98	3.62

The first suite of records and the Los Angeles DBE-level records from the second suite are used in this study with the goal of predicting the mean and standard deviation of the SC-CBF peak roof drift response (θ) as a function of the structural parameters indicated in Table 3.2. Therefore, each of the 75 designed SC-CBF systems is analyzed under these 50 earthquake records, and the mean and standard deviation of the maximum roof drifts are considered as the dependent values (outputs) for the gene expression programming (GEP) prediction function.

Four-story SC-CBF response for the DBE-level Manjil earthquake record (from the first suite of records) is shown Figures 5.2 to 5.4. The roof drift is shown in Figure 5.2(a); the peak roof drift occurs at about 11 seconds. Figure 5.2(b) shows that the inter-story drifts for all stories have similar response histories, and that they are also similar to the roof drift response; this result is caused by the rigid body rotation of the SC-CBF system during rocking response. Figure 5.3 shows the column base gap opening response of the SC-CBF. As shown in Figure 5.3, the gap openings are not symmetric, as the applied earthquake record (and resulting response) is not symmetric. Figure 5.4 shows the PT force response; the PT bars have an initial force that is increased during rigid body rotation of the frame. It should be noted that the PT force increases by uplifting either the left or the right SC-CBF column; therefore, the PT force response is proportional to the envelop of the gap opening responses (as shown in Figure 5.3).

(continued)

Figure 5.2 Four-story SC-CBF response to Manjil earthquake record: (a) roof drift, (b) inter-story drift.

Figure 5.3 Four-story SC-CBF response to Manjil earthquake record: column base gap opening.

Figure 5.4 Four-story SC-CBF response to Manjil earthquake record: PT force.

The second ground motion database (the entire SAC suite) is applied to each of the designed SC-CBF systems to provide a database of earthquake responses in different hazard levels, so that SC-CBF response to individual earthquakes can be predicted. In addition to the structural design parameters, earthquake intensities are important to predict to predict an individual earthquake response. Therefore, several normalized intensity measures (IMs) are considered as candidates for the final model. These IMs are presented in Table 5.5 (Huang *et al.* 2010). It should be noted that spectral acceleration S_a is computed for the first mode period, $S_a(T)$, and for double the first mode period, $S_a(2T)$, with 5% damping. Additionally, the normalized IMs, strong ground motion duration (T_D), based on the time between 2.5 and 97.5% of the Arias intensity (Trifunac and Brady 1975), is also considered as an input candidate.

Table 5.5 Candidate normalized IMs to predict the maximum roof drift

IM	Symbol	Normalized formula
Elastic spectral acceleration	S_a	$\frac{S_a}{g}$
Elastic spectral velocity	S_v	$\frac{S_v T_1}{h}$
Elastic spectral displacement	S_d	$\frac{S_d}{h}$
Peak ground acceleration	PGA	$\frac{PGA}{g} = \frac{\max \ddot{u}_g(t) }{g}$
Peak ground velocity	PGV	$\frac{PGV \cdot T_1}{h} = \frac{\max \dot{u}_g(t) \cdot T_1}{h}$
Peak ground displacement	PGD	$\frac{PGD}{h} = \frac{\max u_g(t) }{h}$
Cumulative absolute velocity	CAV	$\frac{CAV \cdot T_1}{h} = \frac{\int_0^D \dot{u}_g(t) dt \cdot T_1}{h}$
Cumulative absolute displacement	CAD	$\frac{CAD}{h} = \frac{\int_0^D u_g(t) dt}{h}$
Arias intensity	I_A	$\frac{I_A \cdot T_1}{h} = \frac{\pi}{2g} \frac{\int_0^D [\ddot{u}_g(t)]^2 dt \cdot T_1}{h}$
Velocity intensity	I_v	$\frac{I_v}{h} = \frac{1}{\dot{u}_{g,\max}} \frac{\int_0^D [\dot{u}_g(t)]^2 dt}{h}$
Root mean square acceleration	A_{rms}	$\frac{A_{rms}}{g} = \frac{1}{T_D} \frac{\int_0^{T_D} [\ddot{u}_g(t)]^2 dt}{g}$
Characteristic intensity	I_c	$\frac{I_c \cdot T_1}{h} = \frac{A_{rms}^{1.5} \cdot T_D \cdot T_1}{h}$

D is the duration of a ground motion record.

All 140 SAC records are applied to the designed SC-CBF systems and the 10500 data points are gathered for model development for predicting the peak roof drift

response for individual earthquakes. All the IMs are also calculated and appended to the provided database as possible input variables.

Some six-story SC-CBF responses for the Tabas earthquake record in DBE level are shown Figures 5.5 to 5.7. The roof drift is shown in Figure 5.5(a) and the peak roof drift is pointed in this figure at about 16 second. Figure 5.5(b) shows the inter-story drift for all floors have similar pattern and they are also similar to the roof drift pattern, which is caused by the rigid body rotation of the system. Figure 5.6 shows the column base gap opening response of the SC-CBF. As shown in Figure 5.6, the gap openings are not symmetric which is natural as the applied earthquake record is not symmetric. Figure 5.7 illustrates that PT bars have initial force, and the force is increased after rigid body rotation of the frame because of the elongation. It should be noted that PT force can increase by uplifting both left and right column, therefore PT force pattern is similar to envelop of vertical/summation of gap opening responses (as shown in Figure 5.6). However, for this earthquake, with maximum roof drift more than 2%, the PT bar force does not converge to its initial value and it converges to a lower value, which shows the system lost some of its vertical stiffness after the peak.

Figure 5.5 SC-CBF drift response: (a) roof drift response, (b) inter-story drift responses.

Figure 5.6 Column base vertical gap opening response to Tabas earthquake record.

Figure 5.7 PT force response to response to Tabas earthquake record.

5.3 Effect of nonlinearity on SC-CBF response

An accurate prediction of roof drift under earthquake loading is essential for the design of SC-CBF systems. One of the main parameters for more accurate modelling is the consideration of nonlinearities in the materials (as materials may yield) and geometries (as structural members may buckle). In this study, three levels of complexity are considered to evaluate the effect of material and geometric nonlinearities: linear materials with linear geometry (LM/LG), nonlinear materials with linear geometry (NLM/LG), and nonlinear materials with nonlinear geometry (NLM/NLG).

- i. LM/LG: This is a basic model without any nonlinearity in the materials or geometries. This model can be accurate in some cases, as the SC-CBF members are intended to remain elastic and unbuckled during an earthquake. However, there are probabilities of yielding and buckling for the members during an earthquake, which increases for severe earthquakes. If yielding or buckling would occur, this model cannot capture those effects.
- ii. NLM/LG: Although the SC-CBF members are designed to remain elastic, all structural members have the potential to yield under seismic loading, especially when the system is rocking. Therefore, a nonlinear steel material model with isotropic strain hardening, called the Giuffre-Menegotto-Pinto material model (Filippou *et al.* 1983), is used to model material nonlinearity. Figure 5.8 shows a schematic of the stress-strain behavior of the material model. The parameter (r) that controls the transition between the elastic behavior and the hardening branch should be between 10 and 20. In this

study, r is equal to 15 for all models except when buckling in the members is modeled it is considered equal to 10. Although it doesn't have any significant effects on the response, it helps solve the convergence issue when both nonlinearities in materials and geometries are considered. The elastic modulus (E) is 29000 ksi, and the strain hardening ratio ($b = E_p/E$) is equal to 0.03. Figures 5.9(a) and 5.9(b) show the hysteretic behavior of this steel material model with isotropic hardening in compression and tension, respectively which are also used in this study.

Figure 5.8 Material parameters of monotonic envelope for the Giuffre-Menegotto-Pinto material model¹.

¹ <http://www.ce.berkeley.edu/~filippou/Research/Fedeas/steel.pdf>

Figure 5.9 (a) Hysteretic behavior with isotropic hardening in compression; (b) hysteretic behavior with isotropic hardening in tension¹.

- iii. NLM/NLG: In this model, nonlinear materials capture yielding of the structural members and nonlinear geometry is considered by modelling buckling in the braces. It should be noted that the other structural members may buckle, but their buckling probabilities are far less than those of the braces, as brace buckling is the main member failure mode for the SC-CBF system. For this purpose, an additional node is defined in the middle of each brace with an initial in-plane displacement of 1% of the brace length (Uriz and Mahin 2004), as illustrated in Figure 5.10.

Figure 5.10 Initial in-plane displacement used to model buckling in SC-CBF braces

Using these three levels of nonlinearity, the effect of nonlinearity on SC-CBF response can be investigated. The responses of an SC-CBF system under two different earthquakes are shown here for comparison. The first ground motion is from the Imperial Valley earthquake of 1979, which is not severe and causes a peak roof drift less than 1% for a four-story SC-CBF. The roof drift is shown considering different nonlinearity levels in Figure 5.11. There is no significant difference between the response histories regardless of the degree of nonlinearity in the models: there is only a slight difference in the value of the peak roof drift. The PT force time history during the earthquake is shown in Figure 5.12. There are significant differences in the PT force histories and peak values, so nonlinearity is shown to have an effect on the PT force response of the SC-CBF system, even with low roof drift response. After the peak PT force responses, the PT force of the NLM/LG model converges to a value less than the initial PT force. This shows that the some structural members may have yielded, and the system has a reduced vertical stiffness. The results show that considering nonlinearities in the materials and the nonlinearity in the geometry is essential.

Figure 5.11 SC-CBF roof drift response

Figure 5.12 PT force response

The second ground motion is from the Loma Prieta earthquake of 1989, in which the peak four-story SC-CBF roof drift is approximately 2.5%. The roof drift is shown considering different model nonlinearity levels in Figure 5.13. From the results, it can be seen that there are significant differences between the response histories that model yielding in the members and buckling in the braces. The history of PT force during the earthquake is shown in Figure 5.14. From this figure, it can be seen that the PT force histories and peaks are completely different. After peak responses, PT forces of the NLM/LG and the NLM/NLG models converge to values less than the initial PT force. This shows that the some braces or columns have yielded, and the system has a reduced vertical stiffness. The LM/LG model did not converge to a final value within the same timeframe. The results shows that the LM/LG model is not reliable and that nonlinearities, particularly geometric nonlinearity, must be considered for seismic analysis of SC-CBF systems.

Figure 5.13 SC-CBF roof drift response

Figure 5.14 PT force response.

CHAPTER VI

GENETIC PROGRAMMING

6.1 Overview

Genetic programming (GP) was introduced by Koza (1992) as a useful predictive tool. GP follows Darwinian principles to create computer programs that calculate relationships between input parameters and output values. Most of the genetic mechanisms commonly implemented in genetic algorithms (GAs) can also be used in GPs. However, an important difference between GPs and GAs is the representation of the solution: GP results are computer programs that can be represented as tree structures and declared in a functional programming language, but GA results are binary strings. This means that an evolving GP program (individual) is a parse tree that can be varied in length during a run rather than a fixed-length binary string. The classical GP approach that uses a tree structure is called tree-based GP, in which an individual member is a hierarchically-structured tree including terminals and functions (Gandomi *et al.* 2013), as depicted schematically in Figure 6.1.

Figure 6.1 Graphical representation of $y = \tan(cx)$ using a tree-based GP model

6.2 Gene Expression Programming

Gene expression programming (GEP) is a natural development of GP originally proposed by Ferreira (2001). GEP has five main components: (1) a function set, (2) a terminal set, (3) a fitness function, (4) control parameters, and (5) a terminal condition.

Unlike the parsing tree representation in traditional GP, GEP uses fixed-length character strings to represent solutions. These strings are consequently expressed as parse trees of different sizes and called expression trees (ETs). The advantage of this methodology is that the creation of genetic diversity is remarkably simple, due to the genetic mechanisms that work at the chromosome level. One of the strengths of GEP is its multi-genic nature, which allows for evolutions of more complex and nonlinear programs composed of several subprograms (Gandomi *et al.* 2012).

Each GEP gene contains a list of symbols with a fixed length, composed of the terminal set (e.g., $\{A, B, C, 7\}$) and the function set (e.g., $\{+, -, \times, /, \log\}$). Capable of representing any parse tree, GEP can inherently be the invention of chromosomes. To read and express the information encoded in the chromosomes, a new language has been

developed called Karva (Ferreira 2001). A sample GEP gene in Karva language can be expressed in the following form:

$$+. \times. \log . A. -. +. +. \times. B. A.C. 7.B.C \quad (6.1)$$

where A , B , and C are the problem variables and 7 is a constant. Eq. (6.1) is in Karva notation or K-expression (Ferreira 2006). The models can also be parsed into visually accessible ETs, although GEP evolved models are expressed in Karva code. For example, the gene of Eq. (6.1) can be expressed as the ET shown in Figure 6.2, which more clearly represents the mathematical and logical intricacies of the gene (Sadat Hosseini and Gandomi 2012).

Figure 6.2 Expression tree representation of Eq. (6.1)

The conversion of the K-expression to an ET starts from the root, and reads through the string sequentially, which is the first position in the K-expression. The GEP gene shown in Figure 6.2 and Eq. (6.1) can be expressed in a mathematically simple form as:

$$A ((C+ 7) - (B \times C)) + \log(B+A) \quad (6.2)$$

As previously stated, each GEP gene has a fixed length, which is predetermined for a given problem. However, in a GEP algorithm, the size of each ET varies due to redundant elements in ETs, which are not useful when applied to genome mapping (Alavi and Gandomi 2011). Therefore, the valid length of a K-expression may be less than or equal to the length of the GEP gene. A simplified representation of the GEP algorithm is illustrated in Figure 6.3 (Gandomi *et al.* 2011).

Figure 6.3 Schematic of the GEP algorithm.

6.2.1 Genetic Operators

In GEP, the best genes (programs) are selected using roulette wheel sampling with elitism and duplicated into the next generation based on fitness. This promotes the survival and propagation of the best individual to the next generation. By conducting one or more genetic mechanisms on the selected program, variations in the population are introduced. The genetic operators include crossover and mutation (as basic evolutionary mechanisms), and also rotation. The rotation operator rotates two subparts about a randomly chosen point of the element sequence in a genome. It can intensely reshape the ETs. For example, Eq. (6.3) shows the gene development of the gene by rotating the first five elements of the gene presented in Eq. (6.1) to the end.

$$+.+. \times .B.A.C. 7.B.C. +. \times. \log . A. - \quad (6.3)$$

Note that the rearrangement of terms creates redundant elements: the first seven elements are used to construct the solution function $(B + A) + (C \times 7)$, and the remaining seven elements are redundant. The corresponding ET expression of Eq. (6.3) is shown in Figure 6.4.

Figure 6.4 Expression tree representation of Eq. (6.3).

6.3 Multi-Gene Genetic Programming

Symbolic regression is typically carried out through the traditional (standard) GP for a population of trees to evolve. Each tree encodes a mathematical expression. The evolved expressions predict an $N \times 1$ output vector (y) using the corresponding $N \times M$ matrix of inputs (X), where N is the number of observations of the response variables and M is the number of input variables (Searson et al 2010).

In contrast to traditional GP, each symbolic model (and each member of the GP population) in multi-gene genetic programming (MGGP) is a weighted linear combination of the outputs from multiple GP trees. These trees may each be considered a “gene.” A typical model of multi-gene expression is shown in Figure 6.5. Using three input variables, this model predicts an output variable (A , B , and C). This model is linear with respect to the coefficients d_0 , d_1 and d_2 although the structure contains nonlinear terms (e.g., the tangent function). In practice, the maximum allowable number of genes (G_{max}) for a model and the maximum tree depth (D_{max}) for any gene may be user specified. . Therefore, the user may exert a high degree of control over the maximum complexity of the evolved models. In particular, enforcing rigid tree depth restrictions (e.g., maximum depths of 4 or 5 nodes) typically results in the evolution of relatively compact models. The models that have evolved are linear combinations of low order nonlinear transformations of the predictor variables (Searson et al 2010).

Figure 6.5 Expression tree representation of a typical multi-gene GP model.

For each model, the linear coefficients are derived using ordinary least squares method from the training data s . Multi-gene symbolic regression can be more accurate and computationally more efficient than standard GP for symbolic regression (Searson et al 2007, 2010). Furthermore, Searson *et al.* (2007) showed that the multi-gene approach can successfully be embedded within a nonlinear partial least squares algorithm. In MGGP, by creating individuals containing GP trees with different quantities of genes (between 1 and $G_{\max}$) generated at random, the initial population is constructed. During an MGGP run, genes are acquired and deleted using a tree crossover operator called the two-point high-level crossover. This is used in addition to the traditional GP recombination operators and allows the exchange of genes between individuals. If the i th gene in an individual is labeled G_i , then a two-point high-level crossover is performed as in the following example. The first parent individual of this example is composed of three genes (G_1 , G_2 , and G_3) and the second is composed of four genes (G_4 , G_5 , G_6 , and G_7). Two randomly created crossover points are selected for each individual. The genes within the crossover points are denoted by square brackets in Equation (6.4):

$$(G_1 [\mathbf{G}_2] G_3) (G_4 G_5 [\mathbf{G}_6 \mathbf{G}_7]) \quad (6.4)$$

Thereafter, the genes within the crossover points are exchanged, resulting in the creation of the following new individuals:

$$(G_1 G_6 G_7 G_3) (G_4 G_5 G_2) \quad (6.5)$$

The acquisition of new genes for both individuals is allowed by the two-point high-level crossover operation. Gene removal is also permitted. If an exchange of genes results in an individual containing more genes than $G_{\max}$, genes are randomly deleted from that individual until its number of genes reaches $G_{\max}$.

In the MGGP algorithm, standard GP sub-tree crossover is referred to as low-level crossover. In low-level crossover, a gene is chosen at random from each parent individual. Then, the standard sub-tree crossover is applied, in which the created trees replace the parent trees in the next generation in the otherwise unaltered individual.

The other main evolutionary mechanism is mutation. There are six different methods of mutating trees in MGGP: (1) sub-tree mutation, (2) mutation of constants using an additive Gaussian perturbation, (3) substitution of a randomly selected input node with another randomly selected input node, (4) set a randomly selected constant to zero, (5) substitute a randomly selected constant with another randomly generated constant, and (6) set a randomly selected constant to one (Searson et al 2010).

The probabilities of each of the recombination processes (mutation and crossover) can be then set by the user. The processes are grouped into categories called events.

Hence, the probabilities of crossover events, reproduction events, and mutation events can be specified. These probabilities must sum to one. The probabilities of event subtypes can also be defined by the user. For instance, it is possible to specify the probability of a two-point high-level crossover taking place given that a crossover event has been selected (Searson et al 2010). MGGP has been successfully applied to complex structural and geotechnical engineering problems (Gandomi and Alavi 2012).

6.4 Model Optimization

GP tries to find the best model with the best model structure for variables and constant coefficients. However, after developing a GP model, coefficient optimization can increase model accuracy. Therefore, an optimization strategy is used in this study to optimize the model by updating its coefficients while maintaining the model structure. For example, the final GP model shown in Figure 6.6(a) is optimized using a model with variable coefficients as variables (x_1 and x_2) (as shown in Figure 6.6(b)).

Figure 6.6 Coefficient optimization of a GP model (a) original GP model, (b) optimization model with variable coefficients.

To optimize the GP model, three different optimization algorithms have been used: direct search method (Hooke and Jeeves 1961), interior search algorithm (Gandomi 2014; Gandomi and Roke 2014a), and genetic algorithm (Goldberg 1989). The original interior search algorithm code is used in this study for model optimization, as it had been developed by the author (Gandomi 2014). For the other methods, direct search method and genetic algorithm, the implementations in MATLAB® Global Optimization Toolbox are used in this study.

6.5. Fitness Function

After developing the GP structures, the constant coefficients should be optimized. The objective function for both GP modeling and coefficient optimization is as follows (Gandomi and Roke 2013):

$$\rho = \frac{RRMSE}{R + 1} \quad (6.6)$$

where RRMSE is the relative root mean square error, and R is the correlation coefficient, calculated as follows:

$$RRMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - t_i)^2}{n}} \times \frac{1}{|\bar{y}_i|} \quad (6.7)$$

$$R = \frac{\sum_{i=1}^n (y_i - \bar{y}_i)(t_i - \bar{t}_i)}{\sqrt{\sum_{i=1}^n (y_i - \bar{y}_i)^2 \sum_{i=1}^n (t_i - \bar{t}_i)^2}} \quad (6.8)$$

where y_i and t_i are the i^{th} experimental and predicted outputs, respectively; $\bar{y}_i$ and $\bar{t}_i$ are the average values of the experimental and predicted outputs, respectively; and n is the number of samples.

Higher R values and lower $RRMSE$ values result in lower ρ and, subsequently, indicate a more precise model. It should be noted that ρ varies from 0 to ∞ and that ρ values close to 0 generally indicate the model fits very well to the actual values.

6.5.1. Model Complexity

In practice, the simplest possible model is most desirable. In addition, increasing the complexity of the model increases the model's overfitting potential. When the number of inputs for model development is low, model complexity can be easily controlled by the user. However, with an increasing number of input parameters, model complexity can become an issue. Therefore, the best models should be selected considering both model correlation and model complexity. In other words, a multi-objective optimization is necessary to find the best models in terms of both complexity (in general term) and performance (Searson 2015).

Expressional complexity of the model is measured using the expression structure, which is more easily quantified than a response surface, especially when a tree-based structure is used. The strategy proposed by Smits and Kotanchek (2005) is used to measure the complexity of a GP model. This methodology depends on tree depth, tree nodes, component function nonlinearity, number of variables, and combinations of these

parameters. This multi-objective genetic programming algorithm was implemented using a MATLAB based software platform (Searson 2015).

These best models are determined using a trade-off surface called the Pareto front. Figure 6.7 shows an example of the Pareto set during optimization. The green spots in Figure 6.7 are the Pareto set, which are the models that have the best combinations of high correlation and low complexity.

Figure 6.7 Example of GP models and the Pareto set.

6.6. Model Selection

It is better to test the derived models based on a validation (and/or testing) set to find a better generalization to avoid overfitting. Therefore, an objective function was constructed to measure how well the model developed (Gandomi *et al.* 2011). The best GP models were selected by minimizing the following function:

$$Objective = w_T \rho_T + w_V \rho_V \quad (6.9)$$

where

$$w_T = \frac{n_T - n_V}{n} \quad \text{and} \quad w_V = 2 \frac{n_V}{n}$$

where the subscripts T and V are related to the training and validation (and/or testing) sets, respectively. In addition, this objective function considers the effects of different data divisions. Since $w_T + w_V = 1$, *Objective* values close to 0 generally indicate the model is well trained, similar to ρ values.

6.7. Evolutionary Coefficient

When there are too many independent variables, a variable/feature selection method is necessary to select the most effective variables and reduce the dimensionality of data. Methods, such as sequential feature selection, have been published in the literature for this purpose. The easiest and most popular feature selection method is selecting the variables based on correlation to the output. In this study, a new method is proposed to evaluate the correlations between variables and output.

The correlation coefficient (R) or coefficient of determination (R^2) only show linear relationships between parameters. However, two parameters can have nonlinear relationships that cannot be captured by R or R^2 . Evolutionary computations can be used to find nonlinear relationships between two variables; therefore, an evolutionary algorithm is proposed herein to find the highest possible correlation between two parameters. A new coefficient, called the evolutionary coefficient (R_e^2), is proposed using GP. For the j^{th} variable (x_j), the R_e^2 value is the highest R^2 value found after developing a GP model using R^2 (or $|R|$) as the fitness function. R_e can be mathematically expressed as:

$$R_e = \frac{\sum_{i=1}^n (y_i - \bar{y}_i) \left(f(x_j)_i - \overline{f(x_j)_i} \right)}{\sqrt{\sum_{i=1}^n (y_i - \bar{y}_i)^2 \sum_{i=1}^n \left(f(x_j)_i - \overline{f(x_j)_i} \right)^2}} \quad (6.10)$$

where $f(x_j)_i$ is the i^{th} correlated output of the function for x_j and $\overline{f(x_j)_i}$ is the average value of $f(x_j)_i$.

For parameter selection, Ratner (2012) suggested using GP functions as variables to determine the most effective parameters. He tried to predict the response and used a combination of the original variables and the best GP models as the new variables. In his

similar study, he also proposed a new model called GenIQ as an alternative to the statistical ordinary least squares and logistic regression models².

² <http://www.geniqmodel.com/What-Is-The-GenIQ-Model.html>

CHAPTER VII

PREDICTION OF STATISTICAL PARAMETERS OF RESPONSE

7.1 Simulation Data

The statistical parameters of roof drift are very important, for reliability and performance based analysis and for the design of SC-CBF systems. In this section, arithmetic means (μ_θ) and standard deviations (σ_θ) of peak roof drift responses of SC-CBFs with different mechanical and geometrical parameters are modeled using GEP. It should be mentioned that roof drift response distribution can be reasonably approximated with a log-normal distribution (Roke *et al.* 2010), which can be defined using μ_θ and σ_θ .

Here, two levels of complexity are considered for analysis under seismic loadings:

1. linear materials with linear geometry (LM/LG),
2. nonlinear materials with nonlinear geometry (NLM/NLG).

LM/LG has been used in the most studies of SC-CBF system (e.g. Ricles *et al.* 2006; Roke *et al.* 2006, 2008, 2009, 2010; Sause *et al.* 2006) up to now, therefore it is used as

the benchmark. NLM/NLG is used as a more accurate modeling technique that includes possible nonlinearities, as discussed in Section 5.3.

To estimate the mean and standard deviation of the response for these two levels of model nonlinearity, two databases are generated from the responses of the 75 different configurations subjected to 50 DBE-level ground motions in Los Angeles area (3750 time-history analysis for each complexity level). The databases are then used to compute μ_θ and σ_θ of the 50 peak roof drift responses for each configuration. Out of each database, 80% of the data is used for training, and the remaining 20% is used for validation and testing. yield stress of structural members (F_y), coefficient of friction (μ), height of the structure (h), bay widths (b) and aspect ratio (h/b) are used in this study as the predictors (input values) to predict the μ_θ and σ_θ (output values).

7.2 Model development considering linear materials with linear geometry

At first all analysis are done considering linearity in materials and geometry to be used as a benchmark for other analysis with nonlinearity.

7.2.1 Sensitivity Analysis

Distributions of the responses, for LM/LG simulations, as functions of the input variables are shown in Figure 7.1. The results show that the roof drift decreases slightly with increasing b , h , and μ , but the response is not very sensitive to changes in F_y (which only changed the member sizes (for the LM/LG model, the numerical models effectively have an infinite yield stress, though the yield stress is used in the design process to determine member capacity)).

Figure 7.1 Distribution of peak roof drift response as functions of input variables: (a) bay width b ; (b) building height h ; (c) structural steel yield stress F_y ; and (d) coefficient of friction μ .

7.2.2 Model development for mean value

The first output value to be predicted by the GEP model in this study is the mean (μ_θ) of the DBE-level response of the designed SC-CBFs with LM/LG modeling. The corresponding GP trees for the best GEP-based model are presented in Figure 7.2, where d0 to d4 are input parameters h/b , b , h , F_y and μ , respectively, and c0 to c9 are constant coefficients. The GP trees in Figure 7.2 can be interpreted to a mathematical form by multiplying the sub-ETs together as:

$$\mu_\theta = \sqrt[4]{\frac{h}{b}} \cdot (c1 + c4) \cdot c1^2 \cdot c6 \cdot c3 \cdot \frac{c7}{c9} \cdot \sqrt[3]{h} \cdot (c1 + c1)(c4 + \mu) \frac{c3}{h} \quad (7.1)$$

Figure 7.2 Expression trees for the best GEP model. ETs = Π (Sub-ET i)

The best GEP model does not include F_y , which is expected as it is not very sensitive to this variable (shown in Figure 7.1) due to the linear material modeling. The final GEP model is optimized using the direct search method to improve accuracy. After simplification and optimization of the coefficients, the final equation is:

$$\mu_{\theta} = 7.7 \frac{2.8 - \mu}{b^{0.265} h^{0.433}} \quad (7.2)$$

In a preliminary study (Gandomi and Roke 2014b), μ_θ was predicted by GEP for four story buildings with different story heights using LM/LG modeling. The formula from this preliminary study was optimized using direct search method for the current database for four to eight story buildings as:

$$\mu_\theta = 0.036 \frac{F_y^{0.088}}{b^{0.075} H^{0.642}} \left(\frac{H}{b} + 9.79 \right) (\mu - 5.3)(\mu - 4.74) \quad (7.3)$$

The coefficient of variation (CV) and correlation coefficient (R) of Eqs. (7.2) and (7.3) (with respect to the numerical analysis results) are respectively presented in Figure 7.3 to indicate the accuracy of these prediction models. The prediction results show that these two GEP base formulas can estimate μ_θ accurately. Although Eq. (7.3) slightly outperforms Eq. (7.2) (lower CV and higher R), Eq. (7.2) is simpler than Eq. (7.3). Therefore, Eq. (7.2) can be selected as the best model to predict the μ_θ .

Figure 7.3 Comparison of GP predictions and numerical analysis (experimental) results for μ_θ prediction: (a) Eq. (7.2); (b) Eq. (7.3).

7.2.3 Model development for standard deviation value

After predicting the mean μ_θ , the standard deviation σ_θ must also be predicted by the GEP model. The same database and input variables are used to predict μ_θ and σ_θ . The expression trees for the best GEP-based model for σ_θ prediction are presented in Figure 7.4. This can be interpreted to a mathematical form by multiplying the sub-ETs together as:

$$\sigma_\theta = \sqrt[5]{\frac{h}{b}} \cdot \sqrt[5]{\frac{h}{b}} \cdot \sqrt[5]{h} \cdot \frac{c6}{h} \cdot \sqrt[5]{c2} \cdot \sqrt{c4} \cdot c0^2 (\mu + c7) \sqrt[5]{c5} \cdot e^{c3} \quad (7.4)$$

As with the GEP model for μ_θ , the final GEP model for σ_θ is optimized using the direct search method to improve accuracy. After simplification and optimization of the coefficients, the final equation is:

$$\sigma_\theta = 6.62 \frac{2.48 - \mu}{(bh)^{0.392}} \quad (7.5)$$

Again the GEP model did not consider F_y in its best model. Interestingly, GEP reached similar structures for the formulations of μ_θ and σ_θ .

Figure 7.4 Expression trees of the best GEP model for predicting σ_θ . ETs = Π (Sub-ET i).

Computing the coefficient of variation from the models ($CV_\theta = \sigma_\theta / \mu_\theta$), CV_θ is found to be essentially constant for the entire results database. Therefore, σ_θ can be approximated from the predicted mean as follows:

$$\sigma_\theta = \mu_{CV} \times \text{Eq. (7.2)}. \quad (7.6)$$

where μ_{CV} is the mean of CV_θ and is equal to 0.5757.

The prediction results of Eqs. 7.5 and 7.6 are presented in Figures 7.5(a) and 7.5(b), respectively. These results show that these two GEP base formulas can estimate σ_θ accurately; when σ_θ is calculated directly, the results are only slightly better (lower CV and higher R) than when μ_{CV} is used to approximate σ_θ . This confirms that the response distribution is similar for different SC-CBF configurations and σ_θ can be computed from μ_θ based on μ_{CV} .

Figure 7.5 Comparison of GP predictions and numerical analysis (experimental) results for σ_θ prediction: (a) direct calculation of σ_θ ; (b) estimated σ_θ based on average CV.

7.2.4 Parametric analysis

A parametric analysis was performed, for further verification of the GP models, which is required for engineering problems (Gandomi and Roke 2015). A parametric analysis is a useful tool to evaluate the effect of individual parameters on the peak roof drift response and to compare the trends observed in the GP results with those observed

in the simulated data. Figure 7.6 shows the predicted values of the mean peak roof drift response acquired by GP models as a function of each input parameter (b , h , F_y , and μ) where the solid black line shows the μ_θ and the dashed lines indicate $\pm\sigma_\theta$ predicted by GP-based formula. Each experimental result (from nonlinear analysis of a single ground motion) is shown as a grey O in Figure 7.6, and the experimental means (of the 50 ground motion results) are shown as red $\times$'s. The tendency of the GP models to the variations in b , h , F_y and μ can be determined according to the figures. The tendencies correlate to those presented in Figure 7.6, validating these results. Additionally, the GP predictions accurately capture the characteristics (μ_θ and σ_θ) of the distributions of the experimental results.

(continued)

(continued)

Figure 7.6 Parametric analysis of the GP models predicting the SC-CBF peak roof drift response characteristics. (a) b ; (b) h ; (c) F_y ; and (d) μ

7.2.5 Variable Importance

The variable importance of each variable in the GEP models can be computed by randomizing its input value and computing the decrease in the R^2 - value. The results are then normalized so that they add up to one³. The variable importance of the predictor variables (h/b , h , and μ) for the μ_θ and σ_θ models are displayed in Figure 7.7. As shown, the building height h is most important variable in each model and the aspect ratio h/b is the next most important variable. From this figure, the least important variable among these three parameters is the coefficient of friction μ . This analysis generally shows that the geometrical parameters are more important than the mechanical parameters in

³ <http://www.gepsoft.com/GeneXproTools/AnalysesAndComputations/VariableImportance.htm>

predicting the statistical parameters of peak roof drift of SC-CBF system considering LM/LG, which matches the expected result.

Figure 7.7 Contributions of the variables in the GEP models

7.3 Model development considering nonlinearity in materials and geometry

In this section both nonlinearity in materials and geometry are considered for developing models.

7.3.1 Sensitivity Analysis

Distributions of the responses as functions of these variables are shown in Figure 7.8. The results shows that the roof drift decreases slightly with increasing b , h , and μ , but the response is not very sensitive to changes in F_y (which changed the member sizes). The trend is generally very close to the trend in the LM/LG models.

Figure 7.8 Distribution of peak roof drift response as functions of input variables: (a) bay width b ; (b) building height h ; (c) structural steel yield stress F_y ; and (d) coefficient of friction μ .

7.3.2 Model development for statistical parameters

As with the prediction of the LM/LG response, the mean DBE-level roof drift response μ_θ of the NLM/NLG model will be predicted by GEP. The corresponding GP trees for the best GEP-based model are presented in Figure 7.9, where d0 to d4 are input parameters h/b , b , h , F_y and μ , respectively; and c0 to c9 are constant coefficients. This can be interpreted to a mathematical form as:

$$\mu_\theta = \sqrt[5]{c7} \cdot \frac{c3}{h} (c0 - \mu) \cdot (c3 \times b) \cdot \frac{h}{b \cdot F_y} \cdot (\mu - c4) \cdot \sqrt[4]{b} \cdot \frac{c0}{h} \cdot \sqrt[3]{\frac{h}{b}} \cdot \sqrt[5]{\frac{h}{b}} \cdot \sqrt[5]{c2} \quad (7.7)$$

Figure 7.9 Expression trees for the best GEP model. ETs = Π (Sub-ET i)

Unlike the GEP model for LM/LG, NLM/NLG includes F_y in its best model (shown in Figure 7.9 and Eq. (7.7)), which is expected as nonlinear material properties are included in the NLM/NLG models.

After predicting μ_θ , σ_θ can also be predicted for the DBE-level responses. As with the results discussed in Section 7.2.3, μ_θ and σ_θ are highly correlated and the $CV_\theta = \sigma_\theta / \mu_\theta$ is essentially constant for the entire results database. Therefore, from μ_θ predicted by the GEP model, σ_θ can be approximated by multiplying μ_{CV} by the predicted μ_θ for SC-CBFs with NLM/NLG. The value of μ_{CV} slightly changes from the LM/LG results, and it is equal to 0.5779 for the NLM/NLG model.

The final GEP model for μ_θ and approximated σ_θ are simultaneously optimized using the a multi objective optimization algorithm called nondominated sorting genetic algorithm II (NSGA-II) (Deb *et al.* 2002) to simultaneously improve the accuracy of μ_θ (objective 1, with fitness function ρ_1) and the accuracy of σ_θ (objective 2, with fitness function ρ_2). The Pareto front of the optimization results is shown in Figure 7.10.

Figure 7.10 Nondominated solutions using NSGA-II

After simplification and optimization of the coefficients, the final equation for predicting μ_θ is :

$$\mu_\theta = 8.2445 \frac{F_y - 3.6936}{b^{0.2833} h^{0.4667} F_y} (1.6756 - \mu)(1.9736 + \mu) \quad (7.8)$$

To improve the accuracy of the model, a correction coefficient (a function of secondary design parameters). However, the improvement was negligible even with a complex equation, because Eq. (7.8) is so accurate and its correlation is very close to one.

In Section 7.2.2, μ_θ was predicted for LM/LG models using Eq. (7.2). This formula can also be applied to the current database for NLM/NLG models without changing constants. The coefficient of variation (CV) and correlation coefficient (R) of Eqs. (7.2) and (7.8) are presented in Figure 7.11(a) and 7.11(b), respectively. The prediction results show that these two GEP base formulas can estimate μ_θ accurately. Eq. (7.8) only slightly outperforms Eq. (7.2) (with a lower CV and a higher R), which shows that the NLM/NLG modeling does have a significant effect on μ_θ .

Figure 7.11 Comparison of GP predictions and numerical analysis (experimental) results for μ_θ prediction: (a) Eq. (7.8); (b) Eq. (7.2).

The prediction results of σ_θ from Eq. (7.8) (Eq. (7.9)) are presented in Figure 7.12. These results confirms that the response distribution patterns are similar for different SC-CBF configurations and that σ_θ can be directly computed from μ_θ even when NLM/NLG modeling is considered in the analysis step.

$$\sigma_\theta = \mu_{CV} \times \text{Eq. (7.8)} \quad (7.9)$$

Figure 7.12 Predictions and numerical analysis (experimental) results for σ_θ prediction considering NLM/NLG modeling.

7.3.3 Parametric analysis

For further verification of the GP models, a parametric analysis was performed. A parametric analysis is useful as a tool to evaluate the effect of individual parameters on the peak roof drift response and to compare the trends observed in the GP results with those observed in the simulated data. Figure 7.13 shows the predicted values of the mean peak roof drift response obtained by GP modeling as a function of each parameter. Each experimental result (from nonlinear analysis of a single ground motion) is shown as a grey O in Figure 7.13, and the experimental means (of the 50 ground motion results) are shown as red X's. The trends in the GP models with respect to variations in b , h , F_y , and μ match the trends in the experimental data, validating the GP modeling results. Furthermore, as shown in Figures 7.13(a) to 7.13(b), the GP predictions accurately capture the characteristics (mean and standard deviation) of the distributions of the experimental results.

(continued)

(continued)

Figure 7.13 Parametric analysis of the GP models predicting the SC-CBF peak roof drift response characteristics.

7.3.4 Variable Importance

The variable importance of the input variables (h/b , b , h , F_y and μ) in the final GP model of μ_θ is presented in Figure 7.14. As shown, h/b is the most important variable and F_y is the least important variable. Like SC-CBF systems considering LM/LG, this figure generally shows that the geometrical parameters (h/b , b , and h) are more important than the mechanical parameters (F_y and μ) in predicting μ_θ for SC-CBF systems with NLM/NLG modeling.

Figure 7.14 Contributions of the variables in the GEP model for μ_θ

7.4 A case study

Although, the method proposed by Seo (2005) has been used in literature for designing this system, the initial SC-CBF studies found that it is not accurate enough (Roke et al 201). Assuming that roof drift follows a log-normal distribution, the median (θ_m) can be computed from basic statistical parameters (μ_θ and σ_θ) using the following formula (Ang and Tang 2007):

$$\theta_m = \frac{\mu_\theta}{\sqrt{1 + \left(\frac{\sigma_\theta}{\mu_\theta}\right)^2}} \quad (7.10)$$

From the GP results of this study, θ_m is computed from μ_θ (Eq. (7.8)) and σ_θ (Eq. (7.9)).

For one specific set of design values ($b = 30$ ft, $h = 77.5$ ft, $F_y = 50$ ksi, and $\mu = 0.45$), Figure 7.15 shows the peak roof drift (θ) versus the normalized initial stress in the

PT bars (σ_0 / σ_Y). There is a significant difference between the θ_m value assumed in design and the actual θ_m value. However, the drift predicted using the GP formulation (Eq. (7.8) and Eq. (7.9)) is an accurate approximation of the experimental θ_m . The GP formulation is more accurate than the previous method and may be used in SC-CBF design, though more research would be necessary to determine drift demand as a function of σ_0 .

Figure 7.15 Comparison of the actual and predicted θ_m in SC-CBF design.

CHAPTER VIII

INDIVIDUAL EARTHQUAKE RESPONSE

8.1 Simulation Data

After prediction of the statistical parameters of the response, the next stage of this research is the prediction of the maximum response to a specific earthquake record. For this purpose, GP has been used to formulate the maximum roof drift prediction as a function of structural parameters and earthquake intensity measures (IMs). Again, two modeling tiers are used: LM/LG (linear materials and linear geometry) and NLM/LG (nonlinear materials and linear geometry). The NLM/NLG model had convergence issues and is excluded from this study.

Two databases are developed using seismic analysis of the 75 designed SC-CBFs subjected to the 140 ground motions of the SAC ground motion suite (Somerville *et al.* 1997), so 10,500 time history analyses have been performed to create each database. For the LM/LG database, multi-gene genetic programming (MGGP) has been used to find the best prediction model (Searson *et al.* 2010). For the NLM/LG database, however, a multi-

objective strategy is used to find the best model, optimizing both accuracy and complexity at the same time.

The variables used to predict the peak roof drift of each individual earthquake are the mechanical and structural properties of the SC-CBF system and normalized IMs of the ground motion record. It should be noted that the natural logarithm of the roof drift response ($\ln(\theta)$) is used here, as the drift approximately follows a log-normal distribution, and this improved the modeling results. Out of 10,500 datasets in each database, 8,400 datasets (80% of the data) are used for training and the remaining 2,100 datasets (20%) are used for validation and testing.

8.2 IM selection

Before formulation, the three most effective IMs are selected based on their evolutionary coefficient (R_e^2) (as described in Section 6.4), determined with respect to peak roof drift response. Higher R_e^2 values indicate better correlation of an IM to the peak roof drift. This reduces the number of IMs considered in the model, accelerating the process of finding a simple prediction equation. As these simulations are only for finding the most effective IMs, the data with constant b , F_y , and μ are used, set as the middle values presented in Table 3.2. The associated R_e^2 values and the rank for thirteen normalized IMs and T_D are presented in Table 8.1 and the correlation results are also visualized in Figures 8.1(a) to 8.1(n).

Table 8.1 Evolutionary correlation and correlation rank of IMs

IM	Symbol	R_e^2	Rank
Elastic spectral acceleration	$S_a(T)$	0.7975	3
Elastic spectral acceleration	$S_a(2T)$	0.8680	2
Elastic spectral velocity	S_v	0.7938	4
Elastic spectral displacement	S_d	0.7761	5
Peak ground acceleration	PGA	0.5359	10
Peak ground velocity	PGV	0.9022	1
Peak ground displacement	PGD	0.7222	6
Cumulative absolute velocity	CAV	0.5694	11
Cumulative absolute displacement	CAD	0.6729	7
Arias intensity	I_A	0.6612	8
Velocity intensity	I_v	0.6454	9
Root mean square acceleration	A_{rms}	0.3235	13
Characteristic intensity	I_c	0.3305	12
Strong ground motion duration	T_D	0.0881	14

Figure 8.1 Correlation between transformed IMs and peak roof drift. (a) $S_a(T)$; (b) $S_a(2T)$; (c) S_v ; (d) S_d ; (e) PGA ; (f) PGV ; (g) PGD ; (h) CAV ; (i) CAD ; (j) I_A ; (k) I_V ; (l) A_{rms} ; (m) I_C ; (n) T_D .

The R_e^2 values of these parameters and their related rank are also presented in Table 8.1. As shown in Table 8.1, normalized PGV , $S_a(2T)$, and $S_a(T)$ have the highest R_e^2 values (ranked from 1 to 3, respectively); therefore, these IMs have been selected for model development in addition to the structural parameters used in Chapter VII.

8.3 Model Development using MGGP

Twenty MGGP models based on the four structural variables and the three selected IMs are developed. The best MGGP model has two genes and multiple linear regression analysis has been used to connect the genes. The mathematical formulations of these two genes are as follows:

$$\text{Gene 1: } \ln \left| \ln \left(4.365 \frac{PGV \cdot T_{n,1}}{h} \tanh(S_a(2T)) \right) \right|$$

$$\text{Gene 2: } \ln \left(\left(\frac{h}{b} + S_a(2T) \right) (\mu - 1.561) \right) - e^{\ln|\ln(S_a(T))|}$$

The MGGP-based formula is also optimized using the interior search method (Gandomi 2014). After simplification and optimization of all coefficients, the final formula is:

$$\begin{aligned} Ln(\theta) = & 2.35 + 1.925 \ln \left| \ln \left(5.146 \frac{PGV \cdot T_{n,1}}{h} \tanh(S_a(2T)) \right) \right| + \\ & 0.29 \ln \left(\left(\frac{h}{b} + S_a(2T) \right) (1.176 - \mu) \right) - 0.37 |\ln(S_a(T))| \end{aligned} \quad (8.1)$$

The prediction of Eq. (8.1) is accurate, with correlation $R = 0.9709$ for $\ln(\theta)$. However, as expected, the actual θ value is not as accurate as $\ln(\theta)$, and the correlation decreases to $R = 0.8847$ for θ . It is because, the dispersion of error increases with increasing θ . It should be noted that such large roof drifts are rarely happen in practice. The prediction results of the best MGGP model for both $\ln(\theta)$ and θ are shown in Figure 8.2. This figure also confirms that the MGGP base formula (Eq. (8.1)) can accurately estimate the peak structural response.

Figure 8.2 Comparison of MGGP predictions and numerical analysis (experimental) results for peak roof drift prediction: (a) $\ln(\theta)$; (b) θ .

8.4 Model Development using multi-objective MGGP

Multi-objective MGGP (MOGP) is used in this section to develop models with the basic mechanical and geometric variables of SC-CBF systems and three selected IMs (PGV , $S_a(2T)$ and $S_a(T)$). MOGP is utilized to not only model this highly nonlinear

problem but also to attempt to find a very simple model. The best MOGP run is selected from 50 different runs with different random initial populations. In this run there are 25,000 models in total; and out of the 25,000 possible models, 26 models are on front (nondominated solutions). All the solutions, with the Pareto set highlighted, are presented in Figure 8.3.

Figure 8.3 Solutions using MOGP

The final model should be selected from the Pareto set. All models in the Pareto set are presented in Table 8.2, which shows complexity and performance characteristics of the models on the Pareto front. Table 8.2 is sorted based on the models' accuracy.

Table 8.2 Pareto front models for the best run

R²	Complexity	Model
0.754	1	$66.1 PGV - 1.46$
0.781	2	$53.0 PGV + 0.383 Sa(T) - 1.56$
0.886	3	$1.2 \ln(PGV) + 4.98$
0.912	4	$0.573 Sa(2T) + 0.978 \ln(PGV) + 3.74$
0.926	6	$0.5 \ln(Sa(2T)) + 11.7 PGV^{1/2} - 1.1$
0.931	15	$4.93 \exp(PGV^{1/2}) + 0.433 \ln(PGV Sa(2T)) - 3.43$
0.931	11	$10.3 PGV^{1/4} - 1.58 PGV^{1/2} Sa(2T) - 3.3$
0.931	12	$0.425 \ln(PGV Sa(2T)) + 5.95 PGV^{1/2} + 1.38$
0.931	9	$0.436 \ln(Sa(2T)) + 9.08 PGV^{1/4} - 2.85$
0.932	16	$2.97 \tanh(Sa(2T))^{1/4} + 8.89 PGV^{1/4} - 5.5$
0.932	20	$2.96 \tanh(Sa(2T))^{1/4} - 1.61 \ln(\ln(PGV)^2) + 2.24$
0.935	24	$0.343 \ln(Sa(2T) \tanh(\tanh(Sa(T)))) + 11.2 \tanh(PGV)^{1/2} - 0.926$
0.935	21	$0.343 \ln(Sa(2T) \tanh(\tanh(Sa(T)))) + 11.2 PGV^{1/2} - 0.925$
0.936	26	$0.366 \ln(Sa(2T) \tanh(2.08 Sa(T))) + 11.5 PGV^{1/2} - 1.09$
0.936	29	$11.8 \tanh(PGV^{1/2}) + 0.363 \ln(Sa(2T) \tanh(2.09 Sa(T))) - 1.13$
0.937	31	$42.6 PGV + 0.413 \ln((h/b) Sa(2T) Sa(T)) - 42.6 (h/b) PGV Sa(T) + 0.556$
0.939	41	$10.5 PGV^{1/2} - (0.457 \ln(Sa(2T)))/(Sa(T)^{(1.0 Sa(2T)^{1/2}) (PGV - 1.0 \exp((h/b))))) - 0.901$
0.941	44	$25.9 PGV + 0.615 \ln(Fy^{1/2} \tanh(2.0 Sa(T)) (Sa(2T) + (h/b)^2)) - 1.08$
0.942	54	$0.525 \ln(Fy^{1/2} \tanh(2.0 Sa(T)) (Sa(2T) + (h/b)^3)) + 31.6 PGV^{1/2} (Sa(T)^{PGV}) - 1.03$
0.942	48	$0.54 \ln(Fy^{1/2} \tanh(2.0 Sa(T)) (Sa(2T) + (h/b)^2)) - 12.3 PGV^{1/2} PGV + 10.9$
0.943	62	$0.533 \ln(Fy^{1/2} \tanh(2.0 Sa(T)) (Sa(2T) + (h/b)^2)) - 13.6 PGV^{1/2} (PGV^{1/2} (Sa(T)^{PGV})) + 12.2$
0.944	80	$0.43 \ln(Fy^{1/2} ((h/b) + Sa(2T)) (Sa(2T) Sa(T)^2)^{1/2}) + (49.6 PGV \tanh(\tanh(Sa(T))) \exp((2.0 Sa(T))/Fy))/Sa(T) - 0.931$

0.944	147	$0.15 \ln(0.478 F_y P G V S a(2 T)^2 S a(T)^2 ((h / b)+P G V)((h / b)+S a(2 T))^2)+80.5 P G V S a(T) \exp (-1.0 \exp (-1.0 S a(T))(S a(T)-1.32)) \exp (-1.0(h / b)-1.0 S a(T))+0.417$
0.944	131	$0.363 \ln(P G V^{1 / 2} S a(2 T) \tanh (S a(T))((h / b)+P G V)^{(\mu S a(2 T))}(F_y-1.0 S a(2 T)^2))+\left(1.52 e 16 \tanh (\tanh (P G V^2))\right) /\left(5.5 e 12(h / b)+2.75 e 12 S a(T)+1.48 e 13 F_y P G V\right)-0.0536$
0.945	152	$0.164 \ln ((0.989 F_y P G V S a(2 T)^2 S a(T)^2((h / b)+P G V)((h / b)+S a(2 T)) / \mu)+82.0 P G V S a(T) \exp (-1.0 \exp (-1.0 S a(T))(S a(T)-1.32)) \exp (-1.0(h / b)-1.0 S a(T))+0.172$
0.945	157	$0.15 \ln ((0.479 F_y P G V S a(2 T)^2 S a(T)^2((h / b)+P G V)((h / b)+S a(2 T))^2 / \mu)+81.3 P G V S a(T) \exp (-1.0 \exp (-1.0 S a(T))(S a(T)-1.31)) \exp (-1.0(h / b)-1.0 S a(T))+0.289$

The selected model, which is highlighted in Table 8.2, has two genes, and their related trees are presented in Figure 8.4. As shown in Figure 8.4, μ does not contribute to the final model. It should be noted that there are some models that contain μ , but they did not dominate the final model in terms of accuracy and simplicity.

The final mathematical formulation of the model selected by MOGP is as follows:

$$L n(\theta)=25.9 P G V+0.615 \ln \left| \tanh \left(2 S_a(T) \right) \left(S_a(2 T)+\left(\frac{h}{b} \right)^2 \right) \sqrt{F_y} \right|-1.08 \quad (8.2)$$

Figure 8.4 Related trees to the selected model from Pareto front.

The prediction of Eq. (8.2) is very accurate and simple, with $R=0.9700$ and complexity of 44. As expected, like Eq. (8.1), the prediction of θ is not as accurate as the prediction of $\ln(\theta)$, and the correlation decreases to $R=0.8684$. This is because the dispersion of error increases with increasing θ . It should be noted that such large roof drifts rarely happen in practice, and are difficult to predict accurately regardless of method. The prediction results of the best MOGP model for both $\ln(\theta)$ and θ are shown in Figure 8.4, which confirms that the MOGP can provide an accurate formula to estimate the peak structural response.

Figure 8.4 Comparison of MGGP predictions and numerical analysis (experimental) results for peak roof drift prediction: (a) $\ln(\theta)$; (b) θ .

CHAPTER IX

SUMMARY AND CONCLUSIONS

9.1 Motivation

Conventional concentrically braced frame (CBF) systems have been widely used as an earthquake-resistant structural system. The CBF has good stiffness and strength, and its ease of implementation makes it an economical seismic resistant steel frame system. However, CBFs often exhibit limited system ductility capacity prior to brace buckling, which may lead to member failure and residual drifts.

Self-centering concentrically braced frame (SC-CBF) systems have been developed recently. SC-CBFs not only have good stiffness and strength but also have more ductility and drift capacity than CBF systems, while also reducing the residual drift. Therefore, SC-CBFs are suitable alternatives for CBF systems.

SC-CBF systems have some special elements, such as PT bars and friction-bearing dampers. These systems also exhibit rocking behavior under the action of lateral loads, particularly under earthquake loading, during which their columns decompress and uplift.

Due to this complex behavior of the SC-CBF system, and its unique structural elements, prediction of its seismic response is challenging.

One of the main structural responses, which must be estimated in the structural design process, is maximum roof drift of the system. However, the method used in initial studies for designing this system is not accurate enough. Furthermore, there is no analytical solution to estimate the drift response; only empirical and semi-empirical models can be used. As this system is relatively new, there are very limited studies in this field and there is a lack of appropriate drift response predictions. In addition, this system has not been defined in the available commercial software, so it is difficult to design and study different SC-CBF systems with different parameters. Therefore, there is no comprehensive study in the literature that considers the basic geometrical and mechanical parameters of SC-CBF systems.

9.2 Summary

In this study, the SC-CBF design process has been automated using MATLAB® to provide a tool for structural design and analysis of this system. In the developed code, OpenSEES software is called for structural analysis and finite element analysis. For the time-consuming nonlinear dynamic analysis, parallel processing is used to accelerate the simulation.

To create a comprehensive study about different SC-CBF systems, 75 systems with different mechanical and geometric properties are designed. Then the designed structures are numerically analyzed considering different levels of model complexity (with respect

to nonlinearities in materials and geometry). For time history analysis of the SC-CBF systems, two suites of earthquake records, including a total 170 ground motions, are used.

To formulate predictions of the peak drift response of SC-CBF systems, two recent variants of the genetic programming (GP) technique, called gene expression programming and multi-gene genetic programming, have been proposed. GP models have been developed to predict the statistical parameters (mean and standard deviation) of the roof drift of SC-CBF systems at the design-basis earthquake (DBE) level using mechanical and geometric properties of the system. The equations have been obtained for different levels of model complexity, with and without considering nonlinearities in materials and geometry.

After predicting the statistical parameters, peak roof drift of an SC-CBF for an individual earthquake record is also formulated using multi-gene genetic programming (MGGP). In addition to structural design variables, three normalized earthquake intensity measures are selected for these models. A new evolutionary method is proposed in this study to find the intensity measures most correlated to the peak roof drift response.

Because of the high degree of complexity in this problem, the obtained equations are usually not simple. Therefore, two different strategies have been used to find the best models. At first, the MGGP seeks the most accurate model, which is a relatively complex and long equation. Then, a multi-objective strategy is used to find the best model in terms of both accuracy and simplicity. The final model in this strategy is selected from the

nondominated solutions. Not only is the selected model, but it is also very accurate and can successfully predict the response of each specific earthquake.

9.3 Findings

The findings of current research are presented in this section as follows:

- The first contribution of this research is the development of a MATLAB® code to automate the design of the SC-CBF system, as the current codes and software have not included this system. The code can generate all the input files, including finite element input files, itself. Only the basic mechanical and geometric parameters are needed to run this code. This provides a tool to comprehensively evaluate different SC-CBF systems with different mechanical and geometric properties.
- One of the main problems in time-history analysis of structures during earthquakes is that it is a very time consuming process, especially for complex behavior like the rocking behavior of SC-CBF systems. In addition, SC-CBF systems have some specific elements (e.g., friction-bearing dampers) that cause problems in its convergence and make the analysis very slow such. To solve these problems and accelerate the analysis process, the OpenSEES software package is used (called from within MATLAB®) for structural and finite element analysis. Then for the time-history analysis of the system, parallel processing is used, which very effectively accelerates the nonlinear dynamic analysis. Seventy-five different SC-CBF systems with

different mechanical and geometric properties are designed here as a comprehensive design matrix for the SC-CBF system.

- Different levels of complexities in the modelling have been used here to see the general effects of nonlinearities in materials and geometry of the SC-CBF system. This comparative analysis indicates that there is no significant effect on the maximum roof drifts of the systems designed based on DBE hazard level and subjected to the same hazard level earthquakes. However, only modeling material nonlinearity may cause some problems, as it shows the PT force has potential to converge to a value less than the initial PT force.
- In this study, about 28,500 time-history analyses have been conducted on the designed SC-CBF systems, and valuable databases are provided for the accurate analysis and modeling of the peak dynamic responses.
- GPs have been used in this study to predict the peak roof drift response of the SC-CBF systems. GP is selected as a modeling tool due to the lack of available data on the system response, as the GP models are based purely on experimental data instead of on assumptions regarding system behavior. As these models also rely on simulated earthquake response data, modeling uncertainties that were not considered in the initial design procedure proposed in the literature because of by simplifications and assumptions may be reduced. GP has not been used for formulating the design process of any structural system in the literature; therefore, GP can be considered a new tool in this field.

- Simplified GP-based equations for predicting the statistical parameters (mean and standard deviation) of SC-CBF peak roof drift response have been proposed. These equations have high correlation with the simulated experimental data. These equations are simpler than other processes in the literature to predict such a response. A case study for a designed SC-CBF system also shows how GP results are accurate in terms of predicting the median value of peak roof drift response in comparison to the method initially used in the SC-CBF design procedure. These results can be used to improve the design of SC-CBF systems based on more accurate estimates of DBE roof drift response characteristics.
- From variable importance analysis of the statistical parameters models, it can be concluded that geometric properties are more effective in the maximum roof drift response in comparison with mechanical properties.
- The trends of the effects of changing the basic geometric and mechanical parameters are also investigated. The results shows that the roof drift decreases with increasing coefficient of friction, height of the structure and bay widths, and it is not very sensitive to changes in yield stress of structural members
- The effects of ground motion intensity measures (IMs) on the SC-CBF system response are ranked using a new feature selection strategy proposed in this study called the evolutionary correlation coefficient approach. The three most effective IMs and the structural (geometric and mechanical) parameters

are used to formulate the response of SC-CBF systems under individual earthquakes.

- Multi-objective GP is introduced as a modeling tool to formulate engineering systems when the purpose is finding a simple but accurate model. The Pareto fronts of the MOGP are presented in this study, and the best model is selected to satisfy both simplicity and accuracy needs. This strategy can be extended for use in other complex engineering problems as well.

9.4 Future works

Future work in this field should incorporate the following:

- Although nonlinearities in materials and geometry have been considered to more accurately model the system, the model may also be improved by using 3D models to capture out-of-plane buckling, which was approximated using in-plane buckling in this study.
- Here, four-, six-, and eight-story prototype structures are studied. The responses of SC-CBF systems in taller buildings should also be investigated.
- The effect of a few first modes are considered for designing the SC-CBF systems in this study, as it is assumed that the rocking response is dominated by rigid body rotation. However, SC-CBF design may need to incorporate additional higher modes, especially for taller structures.
- This study only considered structures in which the lateral load system is entirely composed of SC-CBFs. Future study may incorporate hybrid

systems, such as the dual SC-CBF/CBF system that is currently under development.

- Future work in this field should also incorporate additional structural parameters into the GP models to predict the drift as a function of the initial stress in the PT bars. This would improve the current proposed roof drift prediction for use in the SC-CBF design process.
- Predictions of SC-CBF column decompression and PT bar yielding, which may affect the peak roof drift response, could be studied in future research.
- Member yielding and structure collapse can be also investigated as additional limit states to consider in the design of SC-CBF systems.

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