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Composed Mathematical-Informational modeling of column-base connections

Abstract
Depending on the type of structural analysis required, any moment-rotation curve representation can be used; these include linear, bilinear, multi-linear and nonlinear representations. The most accurate representation uses continuous nonlinear functions. In this study, two distinct approaches are proposed to account for the complex hysteretic behavior of column-base connections. The performance of the two approaches is examined and is then followed by a discussion of their merits and deficiencies. To capitalize on the merits of both mathematical and informational representations, a new approach, a composed modeling framework, is developed and demonstrated through modeling column-base connections. In the composed framework, a conventional mathematical model is complemented by the informational methods. The role of informational methods is to model aspects that the mathematical model leaves out. The potential of the composed method is illustrated through modeling complex hysteretic behavior of column-base connections.

Keywords
Mechanical modeling, neural network, column-base connection, composed modeling.

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1 INTRODUCTION

Past researches demonstrated that semi-rigid connections may be effectively used for seismic design and the large spectrum of their behavior strongly influences frame stability and strength (Elnashai et al. (1998), Takanashi et al. (1993) and Faella et al. (1994)). In order to take advantage of semi rigid connections, it is necessary to represent the actual joint hysteretic behavior with reasonable accuracy in analytical assessment and analysis for design.

Most modeling approaches are based on well-established fundamental mechanical theories using material and geometric properties, referred to hereafter as mechanical approaches. On the other hand, informational approaches have been used in several applications and have shown clear promise as alternatives to mechanical approaches. By directly extracting a hysteretic relationship from the available collected data using a neural network or some other optimization technique, the behavior of complex systems may be accurately represented. Various modeling approaches for column-base connections exist in a mathematical modeling viewpoint, from a simplified global modeling method to a detailed finite element modeling method. Pinheiro and Silveira (2005) have presented computational details necessary for the nonlinear analysis of steel structured frames with semi-rigid connections.

Predictions by global models are performed through the determination of key parameters (e.g. initial stiffness, moment capacity, etc.) and fitting of a skeleton curve through these points. In the empirical global model, the key parameters can be retrieved from experimentally obtained data sets. These were commonly represented with simple expressions such as power functions, polynomials or combinations of the two. Such global models can be developed through simple analytical considerations, usually focusing on the response of one component, which is considered to be the only source of flexibility in the connection. After major deformation sources are identified, initial stiffness and moment capacity are directly determined from material and geometric properties. On the other hand, the detailed finite element models are capable of representing the contribution of each component as well as complex interactions between the components. However, finite element modeling methods are time-consuming and computationally intensive. All of the mathematical models involve some level of idealization by using mathematical representations based on mechanical properties. This idealization may lead the mathematical representations to exclude some aspects of physical behavior that may be significant.

The component-based method offers a practical method for modeling the complex behavior of connections without the very high computational overhead required with the detailed finite element models. The component-based approach arrives at the model of the overall connection by combining the analytical model of the individual sources of flexibility, including the nonlinear constitutive relationships of components. Eurocode 3 (1997) was the first code to adopt the concept of components to determine the design properties of bolted connections. However, the prediction of complicated hysteretic response has remained challenging.

An alternative approach is to represent the actual behavior based on the information contained in observed data. Informational neural network formulations may be viewed as equation-free global representation, since there is no need for a pre-defined mathematical expression, thus setting this approach apart from curve-fitting. The purpose of curve-fitting is to find some parameters for a given mathematical equation, while that of neural network modeling is to learn the background mechanics. Once this learning is achieved, the neural network is ready to be implemented into other structural analysis platforms without posing further simplification and calibration challenges. The information about the underlying mechanics is extracted from the observed data and stored in neural networks. This is referred to in this report as 'informational' models. Trained neural networks can then be used in computational simulations of the target system. Various material models using neural networks have been proposed to describe the complex behavior of materials (Ghaboussi and Sidarta, (1998); Gawin et al., (2001); Furukawa and Hoffman, (2004)). These informational approaches also have limitations.

In this article, two different approaches, mechanical and informational, are considered to model the complex hysteretic response of column-base joints. First, a new mathematical model is proposed with full conformance to the principles of mechanics. Second, a comprehensive neural network model is developed for the same problem solved using the mechanical approach. Finally, the comparative merits and drawbacks of the two approaches are highlighted. The corollary of the above treatment is that a composed formation that includes the most effective mathematical and informational aspects of the complex connection behavior would be a clear option worthy of investigation.

2 COMPONENT-BASED MECHANICAL APPROACH

There are different studies that have proposed various models to represent the non-linear M–θ behavior of the connections. Only a few of the past models adequately come close to characterizing some special M–θ behavior through the full range of loading/rotations and are discussed as follow.

Lorenz et al. (1993) show that due to the inherent oscillatory nature of the polynomial series, they may yield erratic tangent stiffness values. Furthermore, in these polynomial series functions, the implicated parameters usually have very little physical meaning. Due to their nature, the simplest form of power model does not represent the connection behavior adequately. It is unsuitable if accurate results are desired.

The multi-parameter exponential models (Lui–Chen function, (1986) and Kishi–Chen function, (1986)) can provide a good fit, they involve a large number of parameters. Therefore, a large number of data are required in their curve-fitting process; this fact makes their practical use difficult. This restriction has limited the application of the aforementioned models. Thus, a new M– θ model is derived in this paper.

By considering the conditions of a rigid connection, the model function should satisfy the following boundary conditions:

1. The M– θ curve should be passed through the origin: $M_{(\theta=0)} = 0$.
2. The M– θ curve should be passed through the ultimate point: $M_{(\theta=\theta_u)}$= Mu.
3. The slope of the M– θ curve at the origin is equal to the initial stiffness: $IF\ (\theta = 0) \rightarrow \frac{dM}{d\theta} = ki.$
4. As the rotation becomes large, the M– θ curve tends to the straight line, represented by M = M_n+ $(K_p)\,\theta$, where M_n is defined as the normalizing moment or the intercept constant moment and K_p is the strain hardening stiffness of the M– θ curve in the plastic zone, as shown in Figure 1.

In addition to above mentioned boundary conditions, the model function must have the ability to correlate with experimental results. Based on the current knowledge of connection behavior and modeling requirements, a proper model should be adopted. In this paper the following equation is proposed for predicting the nonlinear behavior of column-bases under monotonic loading:

$$M = (C_1 + C_2\theta) * \left(1 - e^{-(c_3(1+c_4\theta)\theta)}\right) + c_5\theta \tag{1}$$

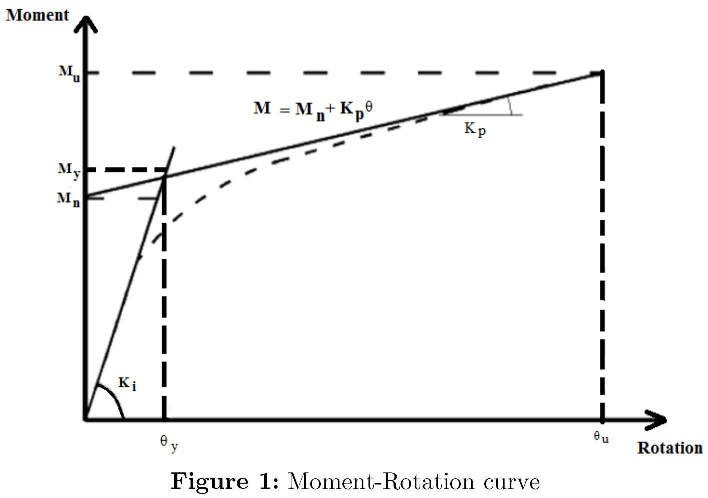


Figure 1: Moment-Rotation curve

Where c_1, c_2, c_3, c_4 and c_5 are the model parameters, which canbe obtained as follows:

For all values of model parameters, the first boundary condition is satisfied. Differentiating Eq. (2) and substituting for $\theta = 0$ yields:

$$if \quad \theta = 0 \quad \rightarrow \frac{dM}{d\theta} = c_1 c_3 + c_5 = K_i \tag{2}$$

For satisfying the third boundary condition, it can be written:

$$\lim_{\theta\to\infty} \frac{dM}{d\theta} = c_2 + c_5 = K_p \tag{3}$$

when rotation (θ) becomes large, the M– θ curve tends to the straight line, therefore:

$$\lim_{\theta\to\infty} M = c_1 + (c_2 + c_5)\theta = M_n + K_p * \theta \tag{4}$$

Therefore, parameter c_1 represents the intercept constant moment, M_n. If parameters, c_4 and c_5, are replaced by β and α*K_p, the other parameters are yielded and the function of the model is expressed as follows:

$$M = \alpha k_p\theta + \left(M_n + (1-\alpha)k_p\theta\right) * \left(1 - e^{\left(\frac{-(k_i-\alpha k_p)(1+\beta\theta)\theta}{M_n}\right)}\right) \tag{5}$$

Where M_n is the intercept constant moment, K_i is the initial stiffness, K_p is the strain hardening stiffness and finally α and β are the shape parameters obtained from calibration with the experimental data. The parameter, β, is introduced to manage the rate of decay of the slope of the curve. Moreover, K_p can be substituted as follows:

$$M_y = M_n + K_p\theta_y \to K_p = \frac{M_y - M_n}{\theta_y} \tag{6}$$

Then, substituting Eq. (6) into Eq. (5), the following form of the function can be obtained:

$$M = M_n \times \alpha \times m^* \times \frac{\theta}{\theta_y} + \left(1 + (1-\alpha)m^* \frac{\theta}{\theta_y}\right) \times (1 - e^{-(1+\beta\frac{\theta}{\theta_y})\frac{\theta}{\theta_y}} \tag{7}$$

Where m* is defined as $\left(\frac{M_y}{M_n} - 1\right)$.

The authors, through a parametric study, obtained the appropriate values of α and β for column-bases as zero and 0.25, respectively. Then, the function for column-base is expressed as follows:

$$M = M_n\left(1 + \left(\frac{M_y}{M_n} - 1\right)\frac{\theta}{\theta_y}\right)\left(1 - e^{-\left(1+0.25\frac{\theta}{\theta_y}\right)\frac{\theta}{\theta_y}}\right) \tag{8}$$

So: $c_1 = M_n, c_2 = (1-\alpha)k_p,\ c_3 = \frac{k_i - \alpha k_p}{M_n},\ c_4 = \beta \ and\ c_5 = \alpha * k_p\ in\ equation\ 1.$

2.1 Evaluation of the mathematical model parameters

In order to utilize this model for any connections, the corresponding parameters must be calculated. The three physical parameters can be derived through analytical procedures, as well as numerical parametric studies. In spite of the fact that there are two shape parameters in the presented function, the accuracy of the predicted curve is extremely affected by the precision of prediction of the physical parameters, which are evaluated as described in the sections to follow.

2.1.1 Evaluation of initial stiffness, K_i

For evaluating stiffness properties, such as initial stiffness, most of analytical studies have used component methods. In the context of the component method, whereby a joint is modeled as an assembly of springs (components) and rigid links, using an elastic post-buckling analogy to the bilinear elastic–plastic behavior of the each component, a general analytical model is proposed that yields the initial stiffness and the strain hardening stiffness of the connection. Consequently, the rotational stiffness of a connection is directly related to the deformation of the individual connection elements.

Component	Stiffness coefficient K_i
Concrete in compression	$K_{13} = \frac{E_c\sqrt{b_{eff} I_{eff}}}{1.275E}$ b_{eff} is the effective width of the T-stub flange I_{eff} is the effective length of the T-stub flange
Base plate in bending under tension (for a single rod row in tension)	With prying forces: $K_{15} = 0.85\frac{I_{eff} t_p^3}{m^3}$ Without prying forces: $K_{15} = 0.425\frac{I_{eff} t_p^3}{m^3}$ I_{eff} is the effective length of the T-stub flange t_p is the thickness of the base plate m is the distance according to Figure 6.8 EN 1993-1-8
Anchor rods in tension	With prying forces: $K_{16} = 1.6\frac{A_s}{L_b}$ Without prying forces: $K_{16} = 2.0\frac{A_s}{L_b}$ Lb is the anchor rod elongation length, taken as equal to the sum of 8 times the nominal bolt diameter, the grout layer, the plate thickness, the washer and half of the height of the nut.

Table 1: Stiffness coefficients for basic joint components according to Eurocode 3 (1997)

Generally, the behavior of the connection largely depends on the component behavior of the tension zone, the compression zone and the shear zone.

The basic components, which contribute to the deformation of the common column-base, are identified as: (1)The compression side - the concrete in compression and the flexure of the base plate.(2) The column member.(3) The tension side - the anchor rods and the flexure of the base plate. Table 1 shows Stiffness coefficients for basic joint components.

The rotational stiffness of a column-base joint, for a moment $M_{j,Ed}$ less than the design moment resistance $M_{j,Rd}$ of the joint, may be obtained with sufficient accuracy from:

$$S_j = \frac{Ez^2}{\mu \sum_1^i K_i} \quad (9)$$

Where:
$K_i$is thestiffness coefficient for basic joint of component i, z is the lever arm and μ is the stiffness ratio $\frac{S_{j,ini}}{S_j}$.

Type of connection	Welded	Bolted end-plate	Bolted angle flange cleats	Base plate connections
φ	2.7	2.7	3.1	2.7

Table 2: Value of the coefficient φ according to Eurocode 3

The stiffness ratio μ should be determined from the following:
If $M_{j,ED} \leq \frac{2}{3} M_{j,Rd}$: $\mu = 1$
If $\frac{2}{3} M_{j,Rd} < M_{j,ED} \leq M_{j,Rd}$: $\mu = (1.5\frac{M_{j,ED}}{M_{j,Rd}})^{\varphi}$
In which the coefficient φ is obtained from Table 2 and the basic components K_i are defined in Table 1.

2.1.2 Evaluation of intercept constant moment

The intercept constant moment, M_n, is selected as the moment corresponding to the intersection of the moment axis and the strain hardening tangent stiffness line, which passes through the ultimate point, as shown in Figure 1. Therefore, the intercept constant moment is highly dependent on the connection ultimate moment (Latour and Rizzano (2013)). For determination of the intercept constant in this paper, the ultimate moment is firstly evaluated. for evaluating the ultimate moment (M_u), the different components contributing to the overall response of general column-base are recognized as follows:

1. The tension zone deformation consists of the deformation of base plate and bolt elongation.
2. For the compression zone, deformation of base plate in bending and concrete in compression.

On the basis of these assumptions, the ultimate moment of column-base depends on the strength of the individual connection elements. The literature on column base connections offers no unified acknowledgment of what a preferred progression of damage is in a base plate connection, or what parameters could help in the selection of the progression of damage, or how to design a column base in order to produce a specific mechanism that is sought. Capacity design principles consistent with the AISC Seismic Provisions (2002) provides one means of controlling the progression of damage in the concrete, anchor rods, steel base and steel column.

The lowest ultimate component force value will present the amount of connection ultimate moment. Some possible options for the progression of failure are:

1. The base of the column is designed to fail first
2. The column base connection is designed to fail first
3. Combined mechanisms

The most common source of brittle behavior in column bases may be found in a poor performance of the welds, anchor rods, or concrete. However, after the Northridge Earthquake, the Northridge Reconnaissance Team (1996) reported an additional type of brittle behavior not reproduced in experiments, namely fracture of a thick base plate. Even though premature buckling of the column flanges was found to be another possible failure mode with low energy dissipation, the use of columns with compact sections eliminates the probability of this type of failure. The moment resistance of column bases ($M_{j,Rd}$) is obtained from Table 3.

The intercept-constant, M_n, can approximately be evaluated as a portion of the connection component ultimate moment. The equation that is used to evaluate$M_n$for column-base is:

$$M_{n=}0.08025 \times M_{j,Rd} \tag{10}$$

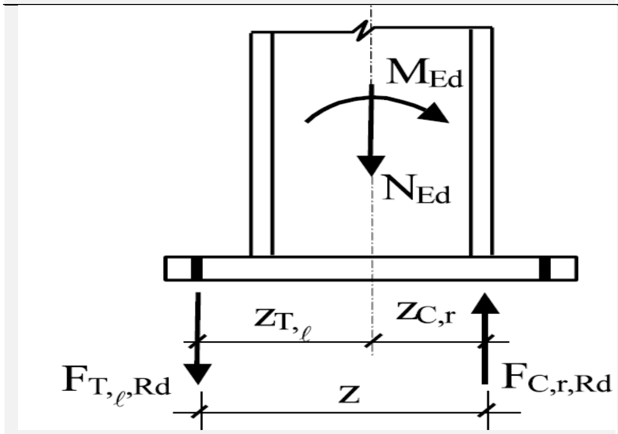
2.1.3 Evaluation of strain hardening stiffness

Empirically, after formation of plastic hinges in the connection components, the connection deformation can be calculated using the tangent modulus of elements. Yee and Melchers (1986) suggested that as strain hardening occurs subsequent to yielding, the shear modulus of the column web may be assumed to be approximated by4% of the elastic shear modulus of the column, and also the strain hardening modulus can be adopted by 2% of the elastic modulus. Shi et al. (1996) recommended that if the bolt tension stress reaches its yield stress, the tangent modulus of the bolt can be taken as 5% of the elastic modulus of the bolt. Genetic Algorithm procedure can be safely use to evaluate the required joint components postlimit stiffness. This concept was introduced after the works of Lima et al. (2005). In this study the ratio of $K_p/K_i$is approximated by 5%.

2.2. Verification

A component-based mechanical model is proposed as a macro element comprising rigid bars and one-dimensional springs. Each spring is formulated in the force displacement domain to represent the hysteretic response of the deformable component. Computer-based analytical simulations were performed to compare the experimental result of the column-base connection by Gomez (2010).

Loading	Lever arm z	Design moment resistance $M_{j,Rd}$
Left side in tension Right side in compression	$z = Z_{T,l} + Z_{c,r}$	N_{Ed}>0 and e >$Z_{T,l}$ $\quad$ $N_{Ed} \le 0$ and e ≤ $-Z_{c,r}$ The smaller of $\frac{F_{T,l,Rd}\cdot z}{Z_{c,r}/e+1}$ and $\frac{-F_{c,r,Rd}z}{Z_{T,l}/e-1}$
Left side in tension Right side in tension	$z = Z_{T,l} + Z_{T,r}$	1)N_{Ed}>0 and $0 < e < Z_{T,l}$ $\quad$ 2)$N_{Ed} > 0$ *and* $-Z_{T,r} < e \le 0$ 1)The smaller of $\frac{F_{T,l,Rd}\cdot z}{Z_{T,r}/e+1}$ and $\frac{F_{T,r},Rd.z}{Z_{T,l}/e-1}$ 2) The smaller of $\frac{F_{T,l}.Rd.z}{Z_{T,r}/e+1}$ and $\frac{F_{T,l,Rd}z}{Z_{T,l}/e-1}$
Left side in compression Right side in tension	$z = Z_{c,l} + Z_{T,r}$	N_{Ed}>0 and e≤ $-Z_{T,r}$ $\quad$ $N_{Ed} \le 0$ and $e > Z_{c,l}$ The smaller of $\frac{-F_{c,l,Rd}\cdot z}{Z_{T,r}/e+1}$ and $\frac{F_{T,r,Rd}\cdot z}{Z_{c,l}/e-1}$
Left side in compression and Right side in compression	$z = Z_{c,l} + Z_{c,r}$	N_{Ed} ≤0 and 0<e <$Z_{c,l}$ $\quad$ $N_{Ed} \le 0$ and $-Z_{c,r} < e \le 0$ The smaller of $\frac{-F_{c,l},Rd.z}{Z_{c,r}/e+1}$ and $\frac{-F_{c,r},Rd.z.}{Z_{c,l}/e-1}$
M_{Ed}>0 is clockwise, N_{Ed}>0 is tension $e = \frac{M_{Ed}}{N_{Rd}} = \frac{M_{Rd}}{N_{Rd}}$ and $F_{Ti}, F_{Ci}$from table 6.2 EN 1993-1-8.		



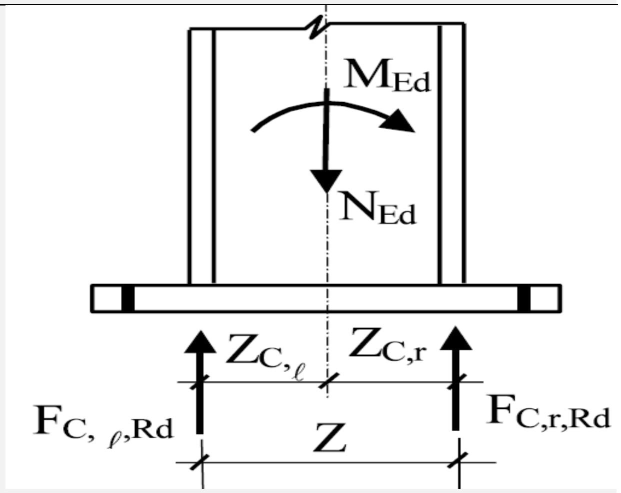


Table 3: Moment resistance of column bases (Ermopoulos and Stamatopoulos (2011))

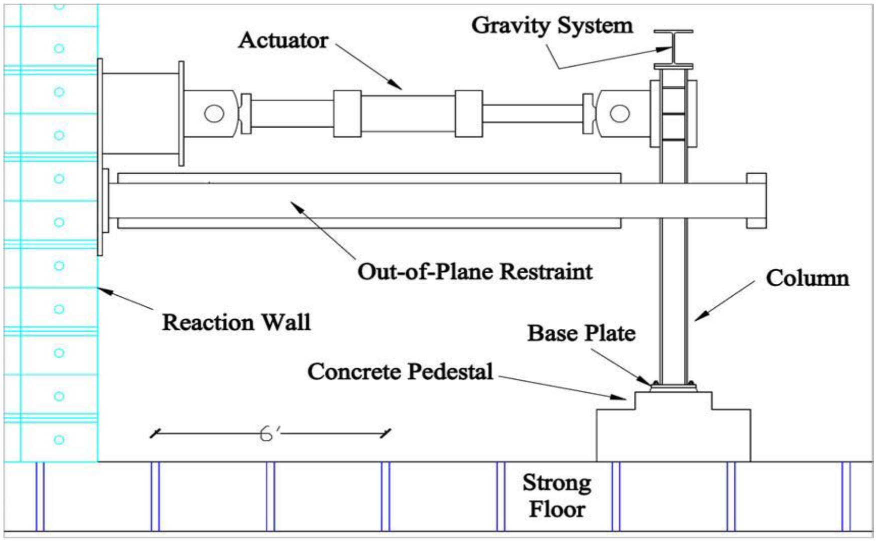


Figure 2: Typical moment transfer test setup (Gomez (2010))

Moment transfer test was conducted at the UC Berkeley Network for Earthquake Engineering Simulation (NEES) Structures Laboratory in Richmond, California. The test specimen features an A992 Grade 50 W8×48 cantilever column welded square and concentric to the center of the base plate. Figure 2 schematically illustrates the test setup. The cantilevered column specimen was loaded transversely to produce column major axis bending. This Test (1.0" thick base plate, four Grade 105 anchor rods) was loaded cyclically without any axial (gravity) load, and the resulting plot of the base rotation versus the base moment is shown in Figure 3.

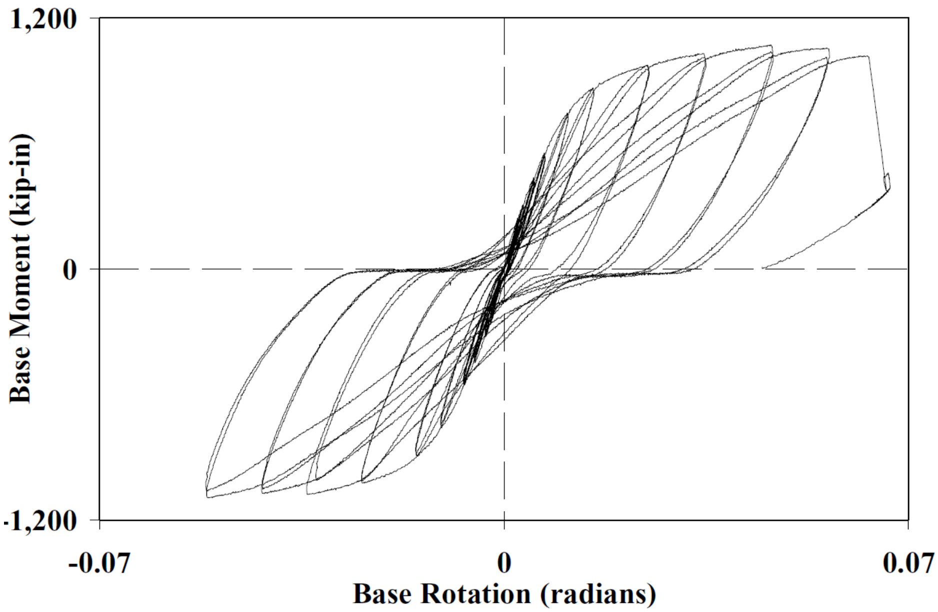


Figure 3: Base rotation versus base moment data (Gomez (2010))

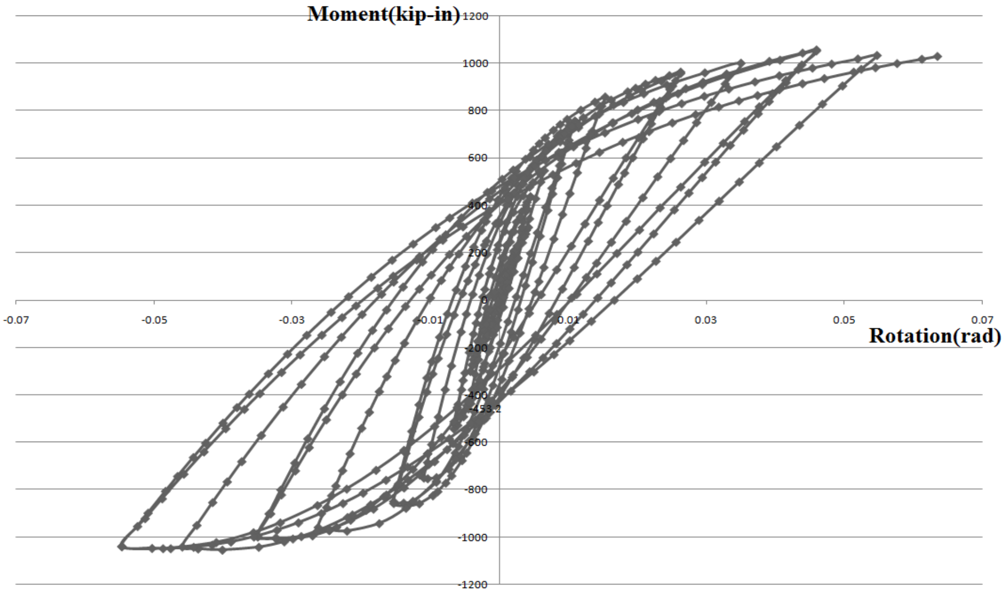


Figure 4: Mathematical model

The response of a selected connection shows highly pinched hysteresis loops. The moment- rotation curve of the mathematical model is presented in Figure 4. Although it displays reasonable agreement in terms of initial and unloading stiffness, the hysteretic loops of the mathematical model do not include the pinching effects. The correlation coefficient is calculated for comparing the experimental and mathematical data. Correlation coefficient is about 0.957. It shows the proposed mathematical model predicts the global behavior of column base connection with reasonable agreement.

3. INFORMATIONAL NEURAL NETWORK APPROACH

In this part the information obtained from Moment-Rotation curve is used for estimating the hysteresis curve. At the present, Feed-Forward neural networks are widely used in the field of engineering. These neural networks are usually constructed with multiple layers of artificial neurons: an input layer, output layer, and hidden layers.

In neural network architecture, the number of neurons in the input and output layers are determined by the formulation of the problem. The number of neurons in the input and output layers is related to the capacity of the neural network. The neural network requires sufficient capacity to represent the complexity of the underlying information in the training data. However, the degree of complexity of the problem cannot easily be quantified. Each neuron is linked with all of the neurons in the adjacent layers by weighted connections.

Back-propagation is a learning algorithm in Feed Forward networks. The back-propagation algorithm is a method of changing the connection weights so that the Feed-Forward network learns the input-output pairs in the training set. The learning rule is based on the gradient descent algorithm, which suggests changing each weight proportional to the gradient of cost function (error measure) at the present location. It necessarily decrease the error (or cost function) if the learning rate is small enough. In order to represent the behavior of the path dependency, multi-point models which employ additional input variables such as immediate previous states of variables or variables increments should be used.

The adaptive technique allows the new neurons to be automatically added to hidden layers during the training, which is shown schematically in Figure 5. In the process of training the neural network, the learning rate is monitored and new neurons are added to hidden layers if the current network reaches its full learning capacity.

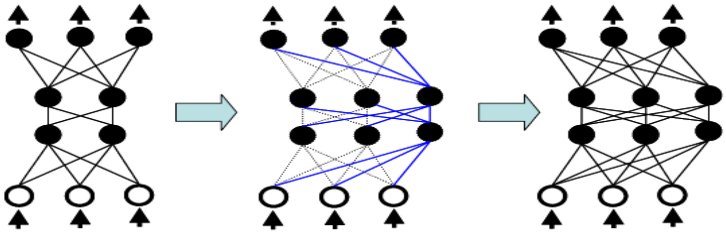


Figure 5: Adaptive feature (Yun et al. (2010))

3.1. Nonlinear hysteretic model

Classical plasticity models combine properties of isotropic and kinematic plasticity to explain the cyclic or dynamic behavior. However, those hardening rules have some difficulties in illustrating the Bauchinger effect in materials and hysteretic degradation in structural components because the shape of a yield surface is known to change during cyclic loading. In a typical cyclic response, one strain value is corresponding to multiple stresses, and vice versa. This is referred to as one-to-many mapping. The one-to-many mapping prevents the neural network from learning hysteretic behaviors. Introducing new additional variables in the input layer allow the neural network to create and learn a unique mapping between stresses and strains. Figure 6 shows a neural network hysteretic model developed by Yun et al. (2006).

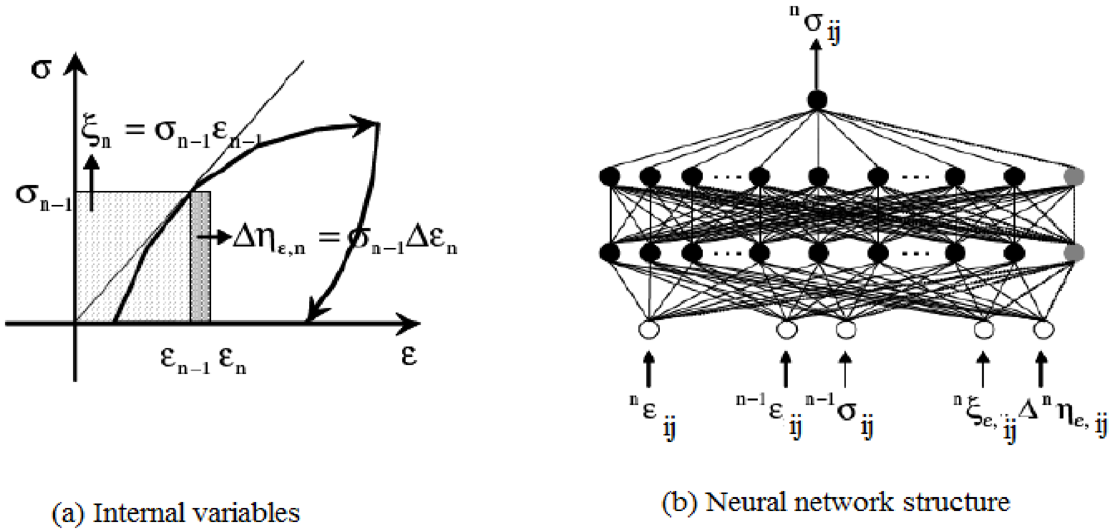


Figure 6: Neural network based cyclic model by Yun et al. (2008)

The proposed neural network model contain 5 input variables of $\varepsilon_{n-1}, \sigma_{n-1}, \zeta_n, \varepsilon_n$ and $\Delta\eta_n$ in strain control form. Two hysteretic parameters of ζ_n and $\Delta\eta_n$ were introduced to transform the one-to-many mapping to single valued mapping. These were defined as $\zeta_n = \sigma_{n-1}\,\varepsilon_{n-1}$ and $\Delta\eta_n = \sigma_{n-1}\,\Delta\varepsilon_n$, where the subscript n indicates the n-th incremental step. The variable ζ relates to strain energy in the previous step along the equilibrium path. The variable $\Delta\eta$ indicates the direction for the next step along the equilibrium path.

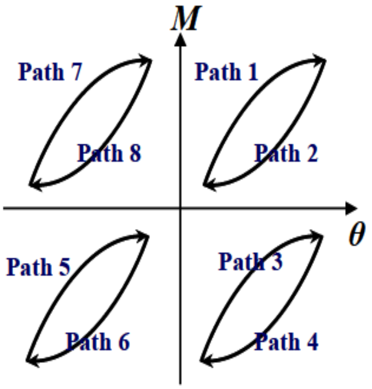
3.2. Neural network for hysteretic behavior of column-base connections

In this section, the neural network for modeling the cyclic behavior of column-base connections is made. The neural network is defined in the moment and rotation domain instead of the stress and strain domain, as can be seen in equation 11.

$$M_n = M_{NN}\left[\{\theta_n, \theta_{n-1}, M_{n-1}, \zeta_n, \Delta\eta_n, E_{n-1}\}\right] \quad (11)$$

Two hysteretic parameters are defined as $\zeta_n = M_{n-1}\,\theta_{n-1}$ and $\Delta\eta_n = M_{n-1}\,\Delta\theta_n$, where the subscript n indicates the n-th incremental step. These hysteretic parameters are key variables for unique mapping by determining the quadrant and path direction. Each path corresponds to the unique combination of the signs of the three variables $\Delta\eta_n$, ζ_n and θ_n as can be seen in Figure 7. In order to represent the degradation of stiffness and strength in consecutive cycles, a degradation parameter is introduced as an input variable and defined as $E_{n-1} = E_{n-2} + |M_{n-1}\,\theta_{n-1}|$.

The degradation parameter indicates the accumulated strain energy until the previous step. The combination of current rotation and the degradation parameter provides the neural network with information about the level of fatigue and relaxation. For example, input variables including a large value of degradation parameter predicts less moment than when input variables contain a smaller value degradation parameter. Figure 8 shows the unique mapping with degradation.



	ξ	$\Delta\eta$	θ
Path 1	+	+	+
Path 2	+	-	+
Path 3	-	+	+
Path 4	-	-	+
Path 5	+	+	-
Path 6	+	-	-
Path 7	-	+	-
Path 8	-	-	-

Figure 7: Unique mapping by hysteretic parameters and current rotation (Yun et al. (2010))

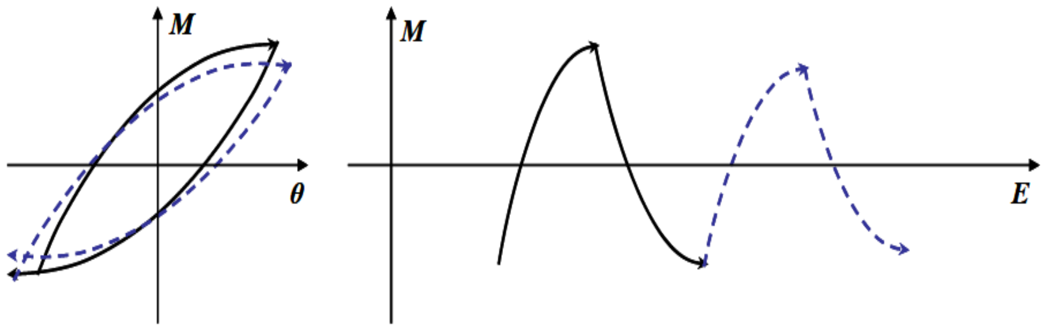


Figure 8: Unique mapping with degradation (Yun et al. (2010))

The trained neural network models should be verified with the target response in recurrent mode. In the recurrent mode, the output predicted by the trained neural network models is utilized in computing the input values in the next step, as can be seen in Figure 9. Therefore, the inputs in the current step such as the hysteretic parameters and previous states of forces and displacement are determined with the output of the neural network in the previous step. This mode suits for nonlinear analysis techniques.

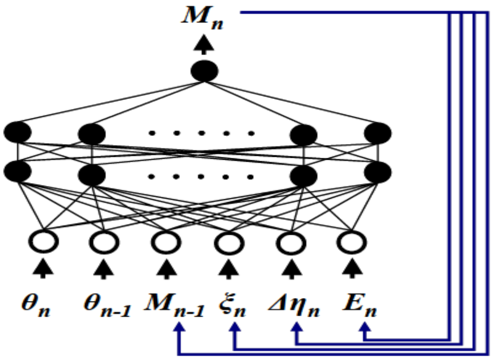


Figure 9: Neural network in recurrent mode (Yun et al. (2010))

The experimental results in Figure 3 exhibit a highly nonlinear response including pinching effects and light deterioration. These complicated phenomena are difficult to express with mathematical equations. From the experimental results, training data sets were collected and constructed with moment and rotation pairs digitized at random intervals to train the neural network. As seen in equation (11) for modeling the hysteresis behavior, 6 input variables are used. This network contains 2 hidden layers and 15 neurons per hidden layer. There are no explicit rules for determining the number of neurons in hidden layers. After training the network with 15000 epochs, neural network model is tested in recurrent mode. As can be seen in Figure 10 with using the outputs of the network the hysteresis curve can be drawn.

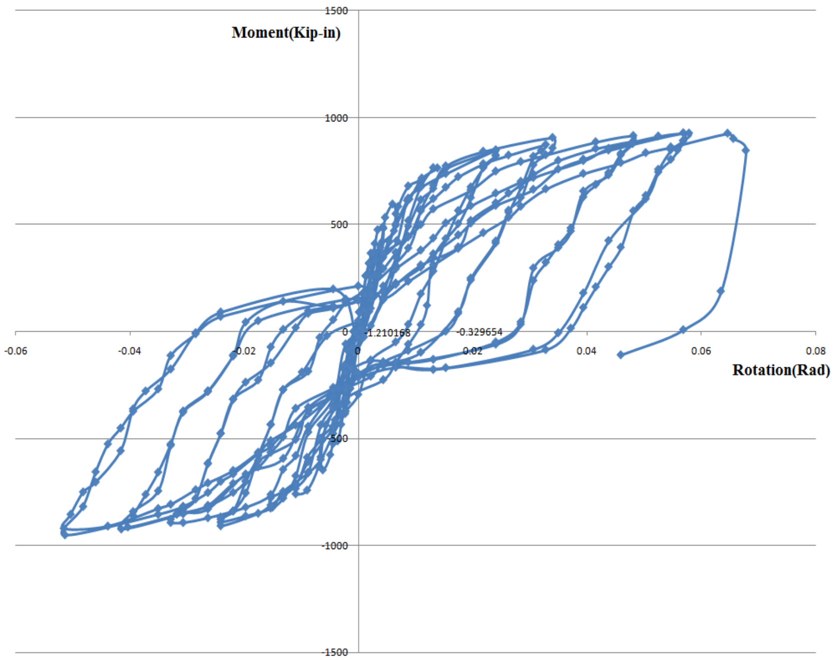


Figure 10: Neural network model trained with experimental data

4. COMPOSED MATHEMATICAL-INFORMATIONAL APPROACH

Idealization is the quantitative transition from complicated, experimental, or real life situations to ideal, theoretical, or limiting cases. This transition is always in danger of leaving out essential aspects of the situations. The idealized behavior is predictable only when a considerable number of factors have been eliminated or assumed.

Nature's problem solving strategies have evolved differently from mathematically based problem solving methods. Most problems that biological systems solve in nature are inverse problems, as are inherently most engineering problems. The biologically inspired soft computing methods have the potential to solve the inverse problem in engineering.

Constitutive modeling is an inverse problem, for example. In a typical experiment, input and output pairs are measured in the stress-strain domain, or in the force-displacement domain. The input and output are known and the system needs to be determined. This inverse problem is also referred to as system identification.

If the modeling complexity is of concern, the neural network model is an attractive approach because the primary benefit of neural networks is that they are capable of inferring a rule from the data with greater efficiency than developing a mathematical function, which in some cases may be entirely impractical.

The purpose of modeling is to increase the understanding of the real world. The validity of a model relies not only on its fit to the observations within given data (interpolation), but also on its ability to predict future situations outside of the observed data (extrapolation). Even if the non-universality of neural networks is in compliance with the characteristics of biological systems in nature, this feature prevents the neural network models from predicting ranges outside of the training data. The mathematical model, using well-estimated parameters established with as many data as the neural network model is trained with, could approximate future events with acceptable accuracy even if the mathematical model is too generic and does not fit a particular data set well enough.

A new composed modeling framework is proposed for the realistic simulation of natural and engineered systems. The composed framework employs the concept of component-based modeling. A mathematical model is built with mechanics-based components, and informational models complement the mathematical model by learning the information that the mathematical model leaves out. Therefore, a composed model is more effective in copying the reality and predicting similar future events.

In this example, the analytical results from the simulation were considered as reference data (moment-rotation pairs) by replacing a real experimental test. The mathematical components exhibit non-pinched hysteretic loops and this behavior is successfully modeled by using the composed formulation. In this chapter, real experimental test of column-base connections are used for reference data and validation purposes. The behavior of informational components in the moment-rotation domain will be extracted from the reference data in the moment-rotation domain. The network with a structure {6-20-20-1} is developed for composed model. The results of composed model after training with 20000 epochs are shown in figure 11.

Pinching is characterized by an increase in rotation without a significant increase in moments, thus resulting in a loss of stiffness in the connection. There are two main causes of pinching effects in bolted connections. One is the nonlinear contact between connecting and connected members, and the other is slippage due to the clearance of the bolt hole. The mathematical model exhibits only smooth hysteretic behavior without pinching effects, while the proposed composed model is capable of representing all important aspects including pinching effects and mild degradation in stiffness. The pinching effects are developed mostly by slip behavior. The correlation coefficient is calculated for comparing the composed model and experimental data.

Correlation coefficient is about 0.987. It shows the proposed composed model predicts the pinching and global behavior of column base connection with high accuracy.

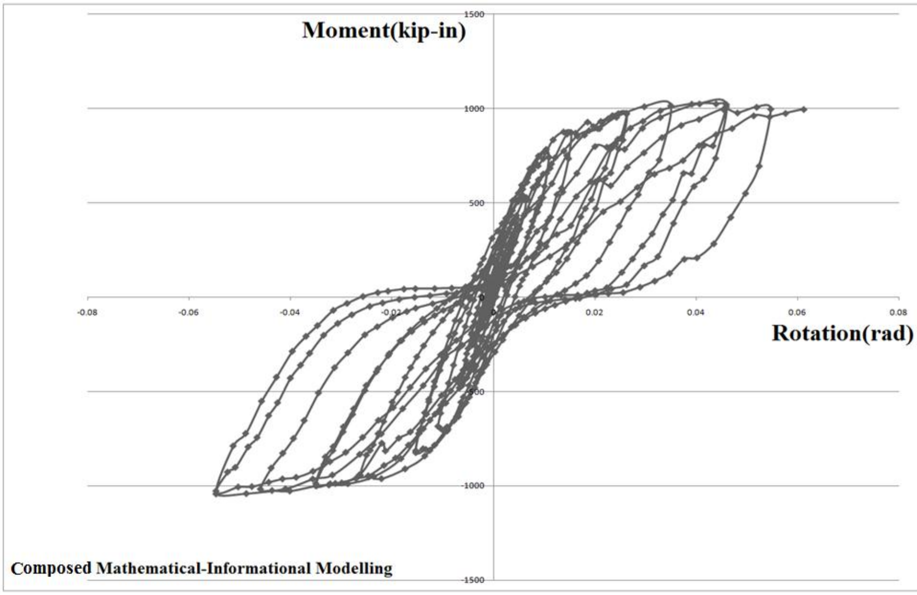


Figure 11: composed model trained with mathematical data

5. CONCLUSION

Two distinct modeling approaches were presented and examined to represent the complex hysteretic behavior of column-base connections in steel frames. First, column-base connections were modeled through a component-based mechanical approach, where the deformation sources were identified and formulated with individual force-displacement relationships. All constitutive relationships except slippage were derived on the basis of rigorous mechanical approach. The capability of predicting moment-rotation relationship under cyclic loads was investigated in comparison with the experimental test results. Although the highly pinched hysteretic response of column-base connection was predicted well by the completely mechanical model, the component-based model requires slip relationships, which are not amenable to mechanical modeling. In the second part of the article, neural network models were applied to learn mechanical rules directly from experimental data. The neural networks informational model demonstrated excellent agreement with the actual response. The results emphasize that the neural network model may be a good alternative to the mechanical model for predicting hysteretic behavior, where even considerable pinching is observed.

Finally, the limitation of two approaches was discussed. Since the mathematical expressions utilized in the component-based mechanical model are derived from the material and geometric properties, they are easy to extend to the general use for changing the configuration and material properties. However, there are components of the deformation that are not suited to mechanical representations. The component of deformation is slippage at and ovalization of bolt-holes are shown to be exceptionally challenging to model within an efficient representation for column-base connections in frames. They are, however, most suitable for informational models. The corollary of the above treatment is that a mixed formation that includes the most effective mechanical and informational aspects of the complex connection behavior and is developed in this paper.

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