HYBRID MATHEMATICAL AND INFORMATIONAL MODELING OF BEAM-TO-COLUMN CONNECTIONS

BY

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DISSERTATION

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ABSTRACT

The analysis of steel and composite frames has traditionally been carried out by idealizing beam-to-column connections as either rigid or pinned. Although some advanced analysis methods have been proposed to account for semi-rigid connections, the performance of these methods strongly depends on the proper modeling of connection behavior. The primary challenge of modeling beam-to-column connections is their inelastic response and continuously varying stiffness, strength, and ductility. In this dissertation, two distinct approaches—mathematical models and informational models—are proposed to account for the complex hysteretic behavior of beam-to-column 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 hybrid modeling framework, is developed and demonstrated through modeling beam-to-column connections.

Component-based modeling is a compromise spanning two extremes in the field of mathematical modeling: simplified global models and finite element models. In the component-based modeling of angle connections, the five critical components of excessive deformation are identified. Constitutive relationships of angles, column panel zones, and contact between angles and column flanges, are derived by using only material and geometric properties and theoretical mechanics considerations. Those of slip and bolt hole ovalization are simplified by empirically-suggested mathematical representation and expert opinions. A mathematical model is then assembled as a macro-element by combining rigid bars and springs that represent the constitutive relationship of components. Lastly, the moment-rotation curves of the mathematical models are compared with those of experimental tests. In the case of a top-and-seat angle connection with double web angles, a pinched hysteretic response is predicted quite well by complete mechanical models, which take advantage of only material and geometric properties. On the other hand, to exhibit the highly pinched behavior of a top-and-seat angle connection without web angles, a mathematical model requires components of slip and bolt hole ovalization, which are more amenable to informational modeling.
An alternative method is informational modeling, which constitutes a fundamental shift from mathematical equations to data that contain the required information about underlying mechanics. The information is extracted from observed data and stored in neural networks. Two different training data sets, analytically-generated and experimental data, are tested to examine the performance of informational models. Both informational models show acceptable agreement with the moment-rotation curves of the experiments. Adding a degradation parameter improves the informational models when modeling highly pinched hysteretic behavior. However, informational models cannot represent the contribution of individual components and therefore do not provide an insight into the underlying mechanics of components.

In this study, a new hybrid modeling framework is proposed. In the hybrid framework, a conventional mathematical model is complemented by the informational methods. The basic premise of the proposed hybrid methodology is that not all features of system response are amenable to mathematical modeling, hence considering informational alternatives. This may be because (i) the underlying theory is not available or not sufficiently developed, or (ii) the existing theory is too complex and therefore not suitable for modeling within building frame analysis. The role of informational methods is to model aspects that the mathematical model leaves out. Autoprogressive algorithm and self-learning simulation extract the missing aspects from a system response. In a hybrid framework, experimental data is an integral part of modeling, rather than being used strictly for validation processes. The potential of the hybrid methodology is illustrated through modeling complex hysteretic behavior of beam-to-column connections. Mechanics-based components of deformation such as angles, flange-plates, and column panel zone, are idealized to a mathematical model by using a complete mechanical approach. Although the mathematical model represents envelope curves in terms of initial stiffness and yielding strength, it is not capable of capturing the pinching effects. Pinching is caused mainly by separation between angles and column flanges as well as slip between angles/flange-plates and beam flanges. These components of deformation are suitable for informational modeling. Finally, the moment-rotation curves of the hybrid models are validated with those of the experimental tests. The comparison shows that the hybrid models are capable of representing the highly pinched hysteretic behavior of beam-to-column connections. In addition, the developed hybrid model is successfully used to predict the behavior of a newly-designed connection.
To my lovely family
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1.1 PROBLEM DESCRIPTION AND MOTIVATION

In steel and composite frames, welded beam-to-column connections are conventionally used for seismic designs. Welded connections in frames have been idealized as being infinitely rigid, since the response of the connections supposedly exhibits full strength and negligible relative rotational flexibility. Unexpected brittle failure has been observed in beam-to-column welded connections in the Northridge (USA) earthquake in 1994 and in the 1995 earthquake in Hyogo-ken Nanbu (Japan). Bolted connections have been extensively investigated as alternatives for seismic resistance in high seismicity zones. Recent research has demonstrated that bolted connections may be used effectively for seismic design and that their behavior strongly influences the frame stability and strength (Elnashai et al., 1998; Takanashi et al, 1993). In order to take advantage of semi-rigid connections, it is necessary to represent their actual hysteretic behavior with reasonable accuracy in analytical assessment and analysis for design.

Most modeling approaches of beam-to-column connections are based on well-established mechanical principles using material and geometric properties. In this thesis these methods are referred to as “mathematical” models. Various modeling approaches for bolted beam-to-column connections exist in a mathematical modeling viewpoint, from a simplified global modeling method to a detailed finite element modeling method. In general, the simplified global models represent the overall behavior of connections with only a few key parameters such as the initial stiffness and moment capacity of the
most critical component (Frye and Morris, 1975). 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. With regard to accuracy and efficiency in a modern computational environment, a component-based approach is a compromise between the simplified global modeling and the detailed finite element modeling methods (Rassati et al., 2004). 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.

An alternative approach is to represent the actual behavior based on the information contained in observed data. This is a fundamental transition from field equations to data that contain the required information of the physical behavior. Computational intelligence methods have made this approach possible and effective. The information about the underlying mechanics is extracted from the observed data and stored in neural networks. This is referred to in this thesis 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 et al., 1991; Ghaboussi et al., 1998; Gawin et al., 2001; Furukawa and Hoffman, 2004). Some applications of neural networks have been reported on monotonic behavior of beam-to-column connections (Anderson et al., 1997; Stavroulakis et al., 1997) and an inner product-based concept has been developed
for the application to cyclic models (Dang and Tan, 2005; Yun et al., 2008). However, these informational approaches also have limitations.

The corollary of the above treatment is that a hybrid formation that includes the most effective mathematical and informational aspects of the complex connection behavior would be a clear option worthy of investigation.

1.2 OBJECTIVES AND SCOPE OF RESEARCH

Two main goals of this doctoral research are to formulate a hybrid mathematical and informational modeling framework for realistic simulation, and through using this developed hybrid modeling framework, provide advanced beam-to-column connection models capable of predicting complex hysteretic behavior. To achieve these objectives, the following tasks have been completed.

- Development of a component-based mechanical model of beam-to-column connections
- Evaluation of an informational neural network model of beam-to-column connections
- Criticism of existing mathematical modeling and informational modeling approaches
- Verification of autoprogressive algorithm and self-learning simulation to obtain information for the hybrid modeling
- Development of a hybrid modeling framework for realistic computer simulation
• Characterization of the hybrid modeling framework for beam-to-column connection
• Application of the hybrid framework to model complex behavior of bolted beam-to-column connections

In the hybrid modeling framework, a mathematical model is complemented by an informational method. The role of the informational method is to model the aspects of the system that the mathematical model does not capture. The aspects that are not amenable to the mathematical modeling would be represented by neural networks, which are storing the information extracted directly from available data through autoprogressive algorithm and self-learning simulation. The established hybrid models are ready to use in analysis.

This hybrid modeling framework is developed to be applicable to a wide-range of fields in computational mechanics—for example, constitutive modeling in material to structure level, computational fluid mechanics, bio-medicine, and others—for the purpose of realistic simulation. This research, however, focuses on illustrating the potentials of hybrid modeling framework by using it to model complex hysteretic behavior of beam-to-column connections. The extended applications of the hybrid modeling framework is reserved for future work.

1.3 THEESIS ORGANIZATION

This thesis contains eight chapters. CHAPTER 1 introduces the research objectives and scope.
CHAPTER 2 presents literature reviews on connection behaviors, their effects on frame response, and the existing modeling methods of connections. Also discussed are the merits and drawbacks of global analytical modeling, finite-element modeling, and component-based modeling.

CHAPTER 3 illustrates a component-based mechanical modeling approach of bolted beam-to-column connections. Major sources of excessive deformation are identified; including yielding of connecting angle/plate and bolts, yielding of column panel zone, nonlinear contact, slippage, and bolt hole ovalization. Each deformation source is modeled as a one-dimensional spring component with a force-displacement relationship by using fundamental theory of elasticity and plastic mechanism. Then, a mechanical model is developed as a macro-element with a combination of rigid bars and springs formulated by material and geometrical properties. Finally, the proposed mechanical connection model is simulated in computers and compared with available experimental test results.

CHAPTER 4 evaluates an informational modeling approach with neural networks. The fundamental concepts of neural computation are reviewed. Overall connection behaviors are modeled with neural networks and these models are compared with available experimental test results. In addition, the performance of the trained neural network model is assessed in terms of different loading incremental steps and different loading history.

CHAPTER 5 describes a hybrid mathematical and informational modeling framework. First, mathematical modeling and informational modeling methods are respectively criticized to identify the need for a hybrid formulation. In the hybrid modeling framework,
the role of the informational approach is discussed in order to define the hybrid modeling. Component concepts are adopted to incorporate both approaches. Furthermore, autoprogressive algorithm and self-learning simulation are introduced to illustrate how local training data for an informational method can be obtained from global experimental data.

CHAPTER 6 characterizes the developed hybrid formulation into an application of modeling beam-to-column connections. The autoprogressive algorithm and self-learning simulation are applied to compute difference between a mathematical model and measurement of an overall connection response. Some techniques including stiffness control and updating skills of constitutive quantities and load pass are presented to increase the performance of self-learning simulation.

CHAPTER 7 illustrates examples of the hybrid modeling framework. Hybrid models are developed to predict complex hysteretic behavior of bolted connections—two angle connections and one flange-plate connection. The hybrid models are verified through comparison with experimental test results.

CHAPTER 8 summarizes the concluding remarks from this thesis research. Potential applications and recommendations are presented for future studies.
CHAPTER 2 : BACKGROUND AND LITERATURE REVIEWS

2.1 CONNECTION BEHAVIOR

2.1.1 Connection deformation

The behavior of a beam-to-column connection is considerably complex because it is associated with the material and contact nonlinearity between different members and connecting fasteners, and because internal actions are coupled interactively with each other. In general, the forces and displacements at the nodes of a given element are represented by two vectors as follows:

\[
\{ \mathbf{F} \} = \begin{bmatrix} N, V_y, V_z, M_x, M_y, M_z \end{bmatrix}^T
\]

\[
\{ \mathbf{D} \} = \begin{bmatrix} u_x, u_y, u_z, \theta_x, \theta_y, \theta_z \end{bmatrix}^T
\]  

(2.1)

The construction of the stiffness matrix for a beam-to-column connection is simplified especially in a global frame analysis. The axial deformation \( u_x \) and two shear deformation \( u_y \) and \( u_z \) are negligibly small in the construction of steel buildings and bridges (Celikag and Kirby, 1989). In addition, the stiffness of the horizontal floors is large enough to restrain the deformability of out-of-plane rotation \( \theta_y \) and torsional twist \( \theta_z \). Consequently, the response of a beam-to-column connection is simply described by means of the in-plane moment and rotation relationship as can be seen in Figure 2.1. Therefore, it is necessary to establish moment-rotation relationship in a convenient form so that the global structural analysis includes the effect of semi-rigid connection behavior.
It is worth noting that other actions—especially shear force \((V_y)\)—influences the behavior of a connection due to the interaction of moment and shear force.

(a) Internal actions in connection \hspace{1cm} (b) In-plain moment-rotation relationship

Figure 2.1 Internal actions in connections

2.1.2 Global analysis and joint classification

A global structural analysis on the basis of joint behavioral properties, i.e., the properties of the moment-rotation relationship, is presented in Table 2.1. There are three methods of global analysis on the basis of the classification of joints—elastic analysis, rigid-plastic analysis, and elastic-plastic analysis. First, the elastic analysis is performed with linear moment-rotation relationship of connections. The rotational stiffness of a connection is only of concern in the carrying out of frame analysis. Second, the rigid-plastic analysis is based on the design moment resistances of connections, provided that they are able to develop sufficient rotation capacity. The moment resistance and rotational capacity of a connection is of concern. Third, the elastic-plastic analysis is based on the nonlinear modeling of the moment-rotation relationship of connections. All of the rotational
stiffness, moment resistance and rotational capacity of a connection are of importance. Hence, the classification of joints is illustrated in terms of the concepts of stiffness, strength, and ductility.

(a) By stiffness

(b) By strength

Figure 2.2 Connection classification (Eurocode 3, 1993)

<table>
<thead>
<tr>
<th>Method of global analysis</th>
<th>Type of connection model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Simple</td>
</tr>
<tr>
<td>Elastic</td>
<td>Nominally pinned</td>
</tr>
<tr>
<td>Rigid-Plastic</td>
<td>Nominally pinned</td>
</tr>
<tr>
<td>Elastic-Plastic</td>
<td>Nominally pinned</td>
</tr>
</tbody>
</table>
Figure 2.2 (a) qualitatively illustrates that connections are classified by criterion of rotational stiffness, such as a nominally pinned connection (indicated by 1), a rigid connection (indicated by 3), and a semi-rigid connection (indicated by 2). Rigid connections transfer all end reactions with negligible deformations and their stiffness is close to infinite. Nominally pinned connections are assumed to transfer shear force from a beam to a column without developing significant moments and their stiffness may be negligible. Semi-rigid connections develop their own deformation and result in the change of moment distribution in the structure. Their stiffness falls in between a nominally pinned connection and a rigid connection and therefore it may be argued that all types of connection are considered to be semi-rigid. The stiffness criterion is of concern when elastic or elastic-plastic analyses are carried out.

In Figure 2.2 (b), connections are classified by the criterion of flexural resistance, such as a full strength and a partial strength connection. This classification was adopted in Eurocode 3 (CEN, 1993). A full strength connection has design resistance at least equal to that of the connected members, i.e., beams. Columns are not considered in classifying connection strength since strong-beam and weak-column necessitates that they are stronger than the beams. Connections belonging to type A have sufficient overstrength to prevent early yielding, whereas in connections belonging to type B, plastic hinges are formed in both the connection and the connected beams. A partial strength connection has less resistance than that of the connected members. A plastic hinge is formed only in a connection, not connected beams. A connection belonging to type D presents sufficient rotational capacity in a ductile manner, whereas a connection belonging to type C is undesirable in structural design. The strength criterion is of concern when rigid-plastic or
elastic-plastic analyses are carried out. The other classification criterion of connections is rotational ductility. This criterion is of concern also when rigid-plastic or elastic-plastic analyses are performed.

The AISC-LRFD specification (2003) divides types of connections by two, such as type FR (fully restrained) and type PR (partially restrained). If type PR connections are used, the flexibility of connections has to be considered in the analysis and design process of a structure.

2.1.3 Connection types and their behavior

Various types of connections present different rotational characteristics that influence frame responses. Figure 2.3 shows commonly used steel or composite beam-to-column connections. There are two main physical factors that influence connection behavior—the method of fastening and the kind of connecting components. Various fastening methods including butt welding, fillet welding, bolting, and riveting, may be employed in practical construction sites, either individually or in combination. Riveting is not used any more in the practical field due to the need to use highly skilled technicians at a comparably higher cost. A fully welded connection has traditionally been considered as rigid in a structural design and analysis, and welding tends to give simple and smooth hysteretic loops. On the other hand, use of bolts brings about complex responses between two adjacent members and bolting tends to present pinched hysteretic loops. In addition to connecting methods, the connecting components also influence connection behavior. Angles, plates, and T-stubs are used to connect two adjacent members. Each member has different response characteristics in a pull and push test, provided they are connected to the
column and beam with mechanically different configurations and different fastening (bolting or welding). Angle connections have more chances to give rise to nonlinear contact issues than plate connections because the assembly configuration provides less constraint.

Figure 2.3 Connection types
Ballio, et al. (1987) investigated the influence of detailing on the connections. In this study, 14 specimens with different splices and stiffeners were tested with the ECCS recommended testing procedure for short tests. Figure 2.4 illustrates four selected hysteretic loops. From left to right the following are shown: (a) fully welded connections, (b) end-plate connections, (c) flange-plate connections, and (d) angle connections. It is observed that the hysteretic loops get more complicated because pinching and degradation effects increase. The response of fully welded connections shows very stable hysteretic loops with low strength deterioration, while that of the angle connection exhibits the most pinched hysteretic loops including various deformation sources, which will be discussed later. In the case of welded connections, a column panel zone deformation is dominantly of interest. The response of the end-plate connection is smooth, like that of the fully welded connection, except small pinching effects, which result from
a nonlinear contact problem between an end-plate and a column flange. In the case of the flange-plate connections, flange-plate yielding causes excessive deformation and slippage, and ovalization of the bolt hole are additional deformation sources. In the case of the angle connection, all the deformation sources such as angle yielding, column panel zone yielding, nonlinear contact problem, slippage, and ovalization are combined; leading to the most complex hysteretic loops.

The smooth hysteretic loops of the welded connection can be presented by a relatively simple model, which can be characterized by the initial stiffness and yielding strength, while the angle connection requires a more refined model to represent the highly pinched hysteretic loops. In this research, focus will be on the angle connections since their hysteretic loops are most pinched and they have diverse components of deformation. The angle connections have more chances to give rise to nonlinear contact issues because the assembly with angles and bolts provides more flexibility than other types of connections.
2.2 EXISTING MODELS

Various modeling approaches of bolted beam-to-column joints exist in the mechanical modeling field; from simplified global models to detailed finite element idealizations. The prediction of connection responses by a global model is performed through the determination of key parameters (e.g. initial stiffness, moment capacity, et cetera) and fitting a skeleton curve through these points. The key parameters can either be retrieved from test data sets or can be evaluated through simple analytical considerations regarding the response of usually one component, which is considered to be the only source of flexibility in the connection. To overcome the limited theoretical background of the global models, the component-based approaches rely on the analytical modeling of individual sources of flexibility (angles, bolts, shear panel, et cetera), arriving at the overall connection response by assembling the components’ contributions. Finally, modeling by finite elements can simulate the three-dimensional nature of connection components as well as the interaction between them. By increasing the degree of detail, this approach accounts for sources of flexibility that are difficult to model explicitly. Hereafter, a classified review of available modeling approaches is given.

2.2.1 Simplified global modeling

2.2.1.1 Empirical models

In the empirical global model, the key parameters can be retrieved from experimentally-obtained data sets. These were commonly represented with simple arithmetic expressions such as power functions, polynomials, or combinations of the two.
Moncarz and Gerstle (1981) proposed tri-linear relationships, fitting the initial and strain hardening slopes of the moment-rotation curve with the addition of an intermediate linear branch between the elastic limit and yield moment. Using the same parameters, the resulting model under monotonic loading was then generalized for cyclic cases.

The model by Frye and Morris (1975) uses the odd power polynomial given,

$$\varphi = C_1(KM) + C_2(KM)^3 + C_3(KM)^5 \quad (2.2)$$

where K is a parameter that depends on the connection type and geometrical properties, and parameters $C_1, C_2, C_3$ are curve-fitting constants. This method may sometimes yield negative values of connection stiffness, which is physically unacceptable.

The four-parameter power model, suggested by Ang and Morris (1984), is capable of representing strain hardening effects. Its mathematical expression, given in equation 2.3, is a Ramberg-Osgood (1943) type of function,

$$\frac{\theta}{\theta_0} = \left[1 + \left(\frac{KM}{(kM)_0}\right)^{n-1}\right] \quad (2.3)$$

where k is a parameter that depends on the connection type and geometrical properties.

Another Ramberg-Osgood type of expression was proposed by De Martino et al (1984) to determine the moment-rotation curve of a connection under cyclic loading. This model also accounts for bolt slippage when bolted connections are considered.
Mathematical expressions that are based on calibration to the data generated by finite element analysis, were proposed by Krishnamurthy et al. (1979) in Figure 2.5 and Kukreti et al.(1987) for extended and flush end-plate connections as a power model.

2.2.1.2 Analytical models

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, the initial stiffness of the connection is calculated by an elastic analysis of usually one connection component (e.g. top angle), which is assumed to be the only source of flexibility. Subsequently, the connection moment capacity is calculated by a plastic mechanism analysis of the same key component. A final moment-rotation curve is established by a fitting of mathematical relationships to two previously determined quantities. This method is mainly used for the prediction of the most flexible types of connections, involving top and seat or web angles. This is usually employed by accounting for
deformations only at the connecting elements and neglecting the flexibility of the components of the connected members.

Johnson and Law (1981) proposed a method for the prediction of the initial stiffness and plastic moment capacity of flush end-plate composite connections. The elastic stiffness of a joint is determined by superposition of the stiffness provided by the steel components (end-plate, bolts, and column flange) and reinforced concrete slab. Based on the same approach, Yee and Melchers (1986) developed a method for the analysis of steel extended end-plate connections. The initial rotational stiffness of the connection is calculated by superposition of the flexibilities of individual components, and the plastic moment capacity is determined while assuming the yielding of the column web panel zone. Additionally, the hardening stiffness of the connection is derived from the post buckling resistance of the column web. The final moment-rotation relationship for the connection is obtained by fitting an exponential relationship to the three analytically derived quantities and experimental results.

Chen and Kishi (1989) and Kishi et al. (1990) developed models for the prediction of the moment-rotation response of double web angle connections, combined with top and seat angles. The initial stiffness and moment capacity were calculated by Equations 2.4 and 2.5, where all parameters come directly from material and geometrical properties. Figure 2.6 illustrates the geometrical properties of top and seat angle with double web angles connections.

\[
K_\varphi = \frac{3EI_{wa}d_1^2}{g_1(g_1^2 + 0.78t_{wa}^2)} + \frac{3EI_{wa}d_3^2}{g_3(g_3^2 + 0.78t_{wa}^2)}
\]  

(2.4)
\[ M_{j,u} = f_y \frac{L_{sa} t_{sa}^2}{4} + \frac{V_{pt} (g_1 - k_1)}{2} + V_{ps} d_2 + V_{pa} d_4 \]  

(2.5)

Figure 2.6 Connection configuration (Chen and Kishi, 1989)

2.2.2 Component-based modeling

The component-based modeling is a compromise between the global modeling and the finite element modeling. To overcome the limited theoretical background of the global models, the component-based approach relies on analytically representing individual sources of flexibility (angles, shear panel, etc.), arriving at the overall connection response by assembling the components’ contributions. To increase the accuracy and versatility, the approach takes advantage of nonlinear constitutive relationships of components instead of numerous elements.
Wales and Rossow (1983) developed a component-based model for double web angle connections. The approach idealizes the connection as two rigid bars, linked by a homogeneous continuum of independent nonlinear springs, which simulate infinitesimal double web angle segments as illustrated in Figure 2.7. The parameters defining the trilinear load-deformation relationships for the springs are determined from an analysis of the double web angles, when these are subjected to simple tension or compression. The angle and column flange flexural deformations as well as the bolt elongations are accounted for under tension, while the column web is the only component assumed to contribute under compression. The model is also capable of representing the coupling effects between bending moment and axial force applied to the connection. The simulation results of this model were compared with only one test by Lewitt et al. (1969), which yielded satisfactory results. The ability of this approach to account for the presence of axial force is an important novel feature, since it may influence the characteristics of the moment-rotation curve. This model was extended by Richard et al. (1988) to predict the response of top and seat angle connections with double web angles. The disadvantage
of this approach is that the validity of the results is again restricted to the range of the calibration data.

Tschemmernegg and Humer (1988) proposed a component-based model for welded connections and end-plate connections. Three nonlinear spring sets were introduced in this model as seen in Figure 2.8; where spring set A accounts for the load introduction effect from the beam to the column; spring set B simulates the shear flexibility of the column web panel zone; and spring set C represents deformability of connecting members. The spring properties are described by mathematical relationships, calibrated to test data retrieved from experimental investigations. The final moment-rotation curve is obtained by superposition of the response of three sets of springs.
Madas and Elnashai (1992) proposed component-based models for angle and end-plate connections. The model consists of a rigid parallelogram surrounding the panel zone and springs representing connecting elements such as angles and end-plate as shown in Figure 2.9. The constitutive relationship of each component is carefully formulated with mechanical properties. The shear panel zone is represented by a tri-linear curve with kinematic hardening rule, and the angle is done by an unsymmetrical multi-linear curve, where the contact between column flange and angle/end-plate is taken into account. However, this model did not consider the pinching effects and degradation effects in stiffness and strength.

**2.2.3 Finite element modeling**

Finite element modeling can be placed at the other extreme of mechanical modeling methods. In fact, some detailed finite element models have good potential to account for the complex behaviors of connections. Representation by finite elements can provide information on the deformational behavior of components, accounting also for their complex interaction. However, accurate prediction of a moment-rotation curve essentially requires the use of spatial and continuum nonlinear finite element analyses, which calls
for significantly more time and effort. Concentrated efforts are especially necessary to represent still sophisticated effects such as bolt slippage, interaction between beam and concrete slab, bolt preload, friction resistance subjected to monotonic or cyclic loads, contact zone nonlinearity, welds, and so on. This micro-scale approach is impractical for large structures such as building frames.

2.3 SUMMARY AND DISCUSSION

In the previous sections, existing models for predicting moment-rotation relationship of beam-to-column connections were presented. Herein the four categories of models are compared and their merits and drawbacks are discussed. Although simplified global models can closely fit virtually any shape of the moment-rotation curve, they suffer from the disadvantage that they cannot be used outside of the range of calibration data. In addition, they are unable to predict the substantially different behavior due to possible change of failure mode, when connections with different geometrical and material properties are considered. Notwithstanding, most of the presently available connection models belong to this category. The simplified global models are very effective for design purposes as well as for implementation in frame analysis programs.

On the other end of the complexity spectrum, the prediction of connection behavior by finite element analysis can produce accurate results when welded connections are considered. The challenge of modeling the behavior of bolted connections is in the inelastic response of individual components and their interactions. A detailed three-dimensional nonlinear finite element model may be capable of representing the complex behavior of bolted beam-to-column connections, including friction, slippage,
contact, initial imperfection, and residual stress. However incorporating the detailed finite element models of many connections in the dynamic analysis of large frame structures during the design process becomes impractical.

A component-based model can predict the moment-rotation response without restraining it to predetermined response patterns, far from the simplified global models. This model can be easily implemented into frame analysis, far from the finite element models. In addition, the accuracy and versatility of the method is increased as the number of components taken into account increases. Once an acceptable number of components is identified and formulated to individual constitutive relations, the modeling framework is ready to be applied to different configurations of connections by only changing the dimension and/or material properties.
CHAPTER 3 : COMPONENT-BASED MECHANICAL APPROACH

3.1 INTRODUCTION

In this research, the term ‘mechanical modeling’ specifies a modeling method based on material and geometric properties. A component-based modeling method is a compromise to span two extremes in the field of mechanical modeling: simplified global modeling and finite element modeling. To overcome the limited theoretical background of the global models, the component-based approach relies on an analytical representation of individual deformation sources to arrive at an overall connection response by assembling the contributions of the components. To increase the accuracy and versatility, the approach takes advantage of the nonlinear constitutive relationships of components instead of numerous elements. A comprehensive literature review on existing modeling methods of steel and composite beam-to-column connections is given by Nethercot and Zandonini (1989) and Faella et al (2000).

3.1.1 Simplified hysteretic modeling of beam-to-column connections

There are various mathematical models with varying degrees of complexity to represent hysteretic behavior of beam-to-column connections. Typical bilinear and tri-linear models cannot express the degradation of stiffness and strength, and nor can they express the pinching phenomenon. However, in a multi-linear model (Deng et al., 2000), both stiffness and strength degradation and pinching are expressed as functions of damage
state variables. This model is applied to unstiffened extended end plate connections and is illustrated in Figure 3.1. A nonlinear model developed by De Martino (1984) can take into account both pinching and degradation of stiffness and strength as a Ramberg-Osgood type model. Although a simplified model can be developed for a global behavior, it is not derived from the knowledge of the local behavior of each component. In this research, the mechanical modeling method will be used to build a global behavior from local contributions.

Figure 3.1 Multi-linear skeleton model by Deng et al. (2000)

### 3.1.2 Component-based hysteretic modeling of beam-to-column connections

The component-based approach uses the combination of rigid and deformable elements (springs) that can represent a deformation source of a single component. The components are generally modeled mechanically with material and geometric properties. Madas and Elnashai (1992) proposed a component-based analytical model by which the overall moment-rotation relationship is assembled from component contributions. De Stefano et al. (1994) proposed a mechanical model of double web angle joints by using only
geometric properties and a bi-linear inelastic stress-strain relationship. They adopt spring (beam element) and gap element, which is shown in Figure 3.2, but slip effects were not considered. Shen and Astaneh-Asl (2000) extended this model with the introduction of slip effects. In this study, pull-and-push tests of double web angles were carried out to develop the hysteretic force-displacement relationship of a single component.

Moreover, Eurocode 3 Annex J (CEN, 1997) was the first code to adopt the concept of components to determine the design properties of bolted connections. However, predicting a complicated hysteretic response continues to be a challenge.

Figure 3.2 Modeling of a double web angle by De Stefano et al. (1994)
3.2 MECHANICAL MODELING PROCEDURE

The mechanical approach uses only material and geometric properties, and theoretical mechanics considerations. The component-based mechanical model of a joint represents a moment-rotation relationship through superposition of the contribution of key components. Each component represents a deformation source by a mathematical expression. For this reason, it is necessary to first identify all sources of deformation and potential failure in the joint. Subsequently, the constitutive relationship of each component is derived to capture its deformational characteristics. Finally, an effective assembly of all components that respects equilibrium and compatibility is important in
order to achieve the desirable accuracy and robustness of the component-based model. This process will be illustrated with applications to bolted beam-to-column connections.

3.3 IDENTIFICATION OF DEFORMATION SOURCES

A component-based model represents a moment-rotation curve of a connection by superposing the contribution of the key deformation sources. Identifying connection components as sources of deformation and potential failure is necessary.

In a fully welded connection, the simplest combination of deformable components is employed because only the beam and column are involved in the connection. In fact, while welds could be actual connecting components in beam-to-column connections, they do not contribute to the overall rotational deformability of the connection due to their considerably limited deformability. Since welds do exhibit brittle failure mode, the design process must avoid their fracture. For this reason, the welds are not considered as a component, provided that a welded connection is designed with sufficient overstrength of welds. The shear deformation of a column panel zone is a major component of deformation sources. In addition, the flange bucking in a column and beams bring about excessive deformation.
Due to the variety of connecting elements and fasteners that are used between a beam and a column, a bolted connection has more deformation sources than a fully welded connection. Bolting imposes fewer constraints on a beam, a column, and connecting elements, than does welding; hence bolted connections have more flexibility than welded ones. The deformation potential of connecting elements such as angles is the most critical component in determining the whole connection behavior. Five important deformation sources of a top-and-seat angle connection with web angles are illustrated in Figure 3.4 and described below.

- The top and seat angles yield first and are the main energy dissipative component, provided that the shear strength of the bolts is sufficient. Since bending of bolts is coupled with that of angles, both angles and bolts are mechanically considered as a single component.
- If it is not excessively stiffened by continuity or doubler plates, the column panel zone is the other major source of deformation as well as a source of energy dissipation.
• The contact and separation between the face of the column flange and connecting angles introduces pinching effects into the joint behavior.

• Slippage between angles and beam flanges causes pinching.

• One face of the bolt hole deforms and becomes ovalized if excessive stresses are concentrated on it. Because of ovalization, the slip deformation increases.

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.

In addition, Figure 3.5 illustrates all possible deformation sources in steel and composite beam-to-column connections. These components have been adopted in Eurocode 3.
Figure 3.5 Deformation sources in steel and composite beam-to-column connections
3.4 CONSTITUTIVE RELATIONSHIPS FOR COMPONENTS

A mechanical model is based on the superposition of the component deformation contributed by each deformable component. Hence, the constitutive relationships of all deformable components have to be defined in a reliable way in order to represent the actual nonlinear response of a connection. In this section, each component of angle connections, which is investigated as a major deformation source in the previous section, is idealized with a one-dimensional nonlinear spring. All springs are formulated to represent a hysteretic force-displacement relationship. The following components are modeled accounting for their own monotonic and cyclic characteristics.

- Angle and bolts—top, seat, and web angles
- Column panel zone
- Nonlinear contact and detachment
- Slippage between two bolted plates
- Bolt hole ovalization
3.4.1 Connecting components–angles

Provided that the thickness of an angle is relatively small, angles are the most flexible components among connecting elements due to their L-shape geometry. Responses of angles including top, seat, and web angles can be considered as responses of pull and push test specimens. Applied moments in the end of a beam can be divided into couple forces and these couples are applied as a pull and push loading condition at the top and bottom flange of the beam, respectively. In this situation the top and seat angles can be considered as a pull and push test specimen with double angles in Figure 3.6, as the beam web is restrained by both top and seat angles that provide enough constraints to prevent displacement out of the loading direction. In the case of double web angles, since they undergo non-uniform deformations along their length, they are subdivided into a finite number of layers corresponding to each bolt. Each layer is assumed to undergo uniform deformation and is considered as a pull and push test specimen in the same way as top
and seat angles. This pull and push specimen is idealized two beam-bending elements and adequate support conditions by using symmetric configuration \cite{Shen and Astaneh-Asl, 2000}. Hereafter, the force-displacement relationship of the idealized angle will be formulated by means of an analytical method with reasonable assumptions.

![Figure 3.7 Tri-linear force-displacement relationship](image)

In order to represent the force-displacement relationship for a bolted angle, a tri-linear curve is employed as seen in Figure 3.7. It is divided into four stages corresponding to a deformation mechanism: an elastic stage, transition stage, mechanism stage, and post-yielding stage. Figure 3.8 shows idealized models for bolted angles and expresses key values to define each stage. The experimental tests of bolted angles \cite{Shen and Astaneh-Asl, 1999} showed two major deformation patterns depending on the location of a plastic hinge. Thereby, the key values are obtained by different equations in stages 2 and 3. First, the initial stiffness ($K_0$) is calculated by using simple elastic analysis. In this elastic stage, small deformation elasticity is assumed and the axial deformation of beams is ignored. At the end of this elastic stage, when the bending moment at node A reaches elastic moment.
capacity \( (M_y) \), the first yielding load \( (P_y) \) is obtained. Second, the transition stage continues until another plastic hinge forms in node C. In this stage, the transition stiffness \( (K_t) \) is obtained by using an elastic analysis of diagram 2. Once another plastic hinge is formed in node C, the plastic mechanism develops. In this mechanism stage, the plastic analysis of diagram 3 gives the second yielding load \( (P_s) \). After the plastic mechanism occurs, the small deformation assumption is no longer valid and the change in the geometry of an angle originates from the strain hardening of material. In this post-yielding stage, the post-yielding stiffness \( (K_u) \) is defined with steel hardening coefficient and initial stiffness.
Diagram | Pattern 1 | Pattern2
--- | --- | ---

Stage 1. Elastic stage – $K_0$ and $P_y$

$$K_0 = \frac{12EI}{g_1^3} \left[ 1 - \frac{3g_1}{4(g_1 + g_2)} \right]$$

$$P_y = \frac{4g_1 + g_2}{g_1(2g_1 + g_2)} M_y$$

Stage 2. Transition stage – $K_t$

$$K_t = \frac{12EI}{(g_1 - t)^2} \left[ \frac{1}{4(g_1 - t) + 3g_2} \right]$$

$$K_t = \frac{12EI}{(g_1 + bh/2)^2} \left[ \frac{1}{4(g_1 + bh/2) + 3g_2} \right]$$

Stage 3. Mechanism - $P_s$

$$P_s = \frac{2M_p}{g_1 - t}$$

$$P_s = \frac{2M_p}{g_1 + bh_0 + bh/2}$$

Stage 4. Post yielding – $K_u$

$$K_u = 0.03 \times K_0$$

Figure 3.8 Idealized models and expression of key values for bolted angles
3.4.2 Column panel zone

Shear deformation in the column panel zone provides a significant contribution of joint rotational behavior. In this study, the tri-linear model developed by Krawinkler et al. (1971; 1975) is employed to represent shear force versus shear deformation behavior of the column panel zone. The initial rotational stiffness ($K_i$) and shear strain ($\gamma_i$) corresponding to the first yielding is given;

$$K_i = \frac{G h_c t_{pc} h_b}{\beta} \quad \text{and} \quad \gamma_i = \frac{f_y}{(\sqrt{3}G)} \quad (3.1)$$

where $G$ is shear modulus and $h_c$, $h_b$ and $t_{pc}$ are the column depth, the beam depth, and the thickness of column web, respectively. $\beta$ is assumed to be 1 in the case of an external joint. After the yielding of the column web, the rotational stiffness of the column panel zone can be ascribed to the bending of the column flange. The post-yielding stiffness ($K_p$) is expressed;

$$K_p = \frac{24EI_{fc}}{5t_{fc}\beta} \quad \text{and} \quad I_{fc} = \frac{b_c t_{fc}^3}{12} \quad (3.2)$$

where $I_{fc}$ is the inertia moment of the column flanges and $t_{fc}$ and $b_c$ are the thickness and the width of the column flanges, respectively. This post-yielding behavior continues until the column flanges yield. It is assumed that the yielding of the column flanges occurs when the shear deformation reaches $4\gamma_i$. In the final stage, the rotational stiffness is expressed by the strain hardening of the material as follows;

$$K_h = \frac{E_h}{E} K_i \quad (3.3)$$
3.4.3 Slippage and bolt hole ovalization

In the existing cyclic tests of bolted connections it has been observed that bolt hole slip profoundly influences hysteretic behavior in severe cyclic loading cases (Shen and Astaneh-Asl, 1999; Swanson and Leon, 2000). The contact configuration between bolted double web angles and beam web is identical to the configuration of symmetric butt splices. The contact configuration between a top or seat angle and a beam flange is similar to the configuration of lap splices. In contrast with symmetric butt splices, lap splices have inherent eccentricity, resulting in additional bending moment. However, the bending moment may be ignored since the beam web and the other leg of the angle stiffen the contact splices to prevent bending behavior. In this section, a slip component is simplified on the basis of the slip mechanism in a symmetric butt splice.
The slip mechanism has three idealized stages which are before-slip, slip, and after-slip, illustrated in Figure 3.10. The deformation in the before-slip stage may be negligible and the slip occurs when the slip load is reached. Then, elastic displacement increases proportionately with the bearing force in the after-slip stage. Although bolt holes may ovalize to increase slip displacement if excessive stresses are concentrated on the edge of the bolt holes, the ovalization is ignored in the current slip model. The slip response is controlled by three parameters: slip load, slip displacement, and bearing stiffness. First, the slip load is computed by the slip coefficient \((k_s)\) and the clamping force \((T_i)\) as follows:

\[
P_{slip} = k_s m n T_i
\]  

(3.4)

where \(m\) and \(n\) are the number of slip planes and bolts, respectively. The clamping force is determined by bolt tension (pretension) depending on different tightening methods and variations in the mechanical properties of the bolts. The slip coefficients are affected with the condition of the faying surface, the number of bolts, alignment of the bolts to loading
direction, and loading types. A basic slip coefficient of 0.33 has been suggested in the condition where there are clean mill scale surfaces with monotonic tests of symmetric butt joints. However, it is worth noting that the slip load in the dynamic cases is different from that in the static cases because cyclic loading may give rise to bolt relaxation and alter the surface condition.

Second, the major slip is theoretically defined as being equal to two bolt hole clearances. High-strength bolts are usually placed in holes that are nominally 1/16 in. larger than the bolt diameter. Therefore, the maximum slip that can occur in a joint is equal to 1/8 in. However, in practical situations it is observed to be less than this, provided that more than 2 bolts are used in more than 2 bolt-lines. This might be due to small misalignments inherent in the fabrication process.

Third, the bearing stiffness of bolt holes is computed by:

$$K_{bearing} = K_{br} = 120F_y t_p d_b^{0.8}$$

(3.5)

where $F_y$, $t_p$, and $d_b$ are the yielding strength, thickness of faying plates, and diameter of bolts, respectively (Rex and Easterling, 1996; 2003).
3.4.4 Contact and detachment

![Diagram of pinched hysteretic loop and contact nonlinearity](image)

Figure 3.11 (a) Pinched hysteretic loop and (b) Contact nonlinearity

The contact and detachment between a column-flange face and connecting elements introduces pinching effects in overall joint behavior. Figure 3.11(a) shows a general pinched hysteresis loop and (b) shows associated contact configurations in the points noted on the hysteresis loop, where the column flange face and the beam end are illustrated by rigid solid lines and rigid dotted lines respectively, and the applied moment is diagramed in terms of the amount and the direction. In steps 1, 4, 5, and 8, the column web resists the rotation in the direction of applied moment but not in steps 2 to 3 and 6 to 7. The latter steps bring about stiffness reduction and the reduced stiffness influences rotational behavior until the beam end contacts the column flange face. Therefore, a component of the contact and detachment ion is based on the stiffness and strength of the column web in compression. It can explain one source of the pinching effects. The elastic stiffness of the contact and detachment component employs the formulation by Faella et al. (2000) as follows.
\[ K_{w_c} = E \frac{b'_{w_c}\text{w}_c t_{w_c}}{d_{w_c}} = E \frac{[2t_{sa} + 0.6r_{sa} + 2(t_{cf} + s)]t_{w_c}}{(h_c - 2t_{cf} - 2r_c)} \]  

(3.6)

where \( t_{sa}, r_{sa}, t_{cf}, \) and \( d_{w_c} \) are the thickness of the seat angle, the fillet radius of the seat angle, the thickness of the column flange, and the depth of the column, respectively. The value of \( s \) is equal to \( r_c \) for a rolled section or \( 2a_c \) for a built-up section. \( r_c \) and \( a_c \) are the web-to-flange radius of the column and the throat thickness of the welds, respectively.

### 3.5 COMPUTER IMPLEMENTATION

In the previous section, each of the components for all the deformation sources has been modeled as a one dimensional spring representing their own force-displacement relationship. In this section, a mechanical model is developed as a macro-element with a combination of rigid bars and springs formulated by material and geometrical properties.

![Figure 3.12 Macro-element for a fully welded connection](image-url)
Figure 3.12 illustrates the assembly of the simplest connection type, the fully welded connection. To perform the computational simulation effectively, three control points are placed as seen above. The distance between A and B is initially zero, and the shear panel zone is directly modeled with rotational spring instead of the rigid box. The bar going through control point A represents the beam end and is assumed to be a rigid element. The $k_1$, $k_2$, and $k_0$ represent angle springs and panel zone springs and they are connected with rigid bars. The connection analysis is ready to be carried out provided that support conditions are defined at C or A. Figure 3.13 shows the flow chart for computer simulation of the proposed connection model.

This computer simulation is similar to fiber element analysis with non-linear algorithm. First unbalanced force is calculated and then the unknown displacements are solved at the
control points, which are called the macro element level routine. The displacements in the control points are transformed to local points corresponding to component springs and then the internal spring forces are computed by spring force-displacement relationship, which is called component level routine. Then, equilibrium checks are performed at the control points. In this study, the Newton-Rapshon iterative scheme is employed to solve the nonlinear equations.

3.6 VALIDATION AND COMPARISON

In this section, the proposed mechanical model is compared to experimental results in both monotonic and cyclic cases. First, the experimental test data by Elnashai et al. (1998) is compared in the monotonic cases. Second, the experimental test data by Kukreti and Abolmaali (1999) and Calado et al. (2000) are used in the cyclic cases.

3.6.1 Monotonic cases

Elnashai et al. (1998) tested eight two-story frames—two rigid and six semi-rigid. In this section, the moment-rotation test results for the four selected semi-rigid connections are compared to the simulation results of the proposed mechanical model. The connection type used in these frames is top and seat angle connection with double web angles and the design details are presented in Table 3.1. Figure 3.14 shows the mechanical model for top and seat angle connection with double web angles. Three kinds of springs are idealized and used in this model—angle springs, column web compression springs, and a panel zone shear spring.
Table 3.1 Design details in top and seat angle connection with web angles

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<th>Web angles</th>
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<th>b</th>
<th>c</th>
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</tbody>
</table>

Table 3.2 presents the difference between experimental and analytical results in terms of initial stiffness, post-yielding stiffness, and moment capacity. The mechanical model tends to overestimate initial stiffness, but the difference is reduced at post-yielding stiffness. The comparisons of the moment capacity at 3% radian give reasonable agreement except in the case of SRB01, where the ultimate moment capacities are closer to each other. Figure 3.15 plots the connection responses of experimental tests and analytical simulations. The comparison between these demonstrates that the mechanical model captures the overall monotonic behavior well. It is noteworthy that the case CS03
has different yielding mode from other cases and the analytical model in pattern 2 was used.

Table 3.2 Experimental and analytical results

<table>
<thead>
<tr>
<th>Connection reference</th>
<th>SRB01</th>
<th>CS01</th>
<th>CS02</th>
<th>CS03</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Initial stiffness</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(kN m/rad)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experimental test</td>
<td>8500</td>
<td>4300</td>
<td>7500</td>
<td>9800</td>
</tr>
<tr>
<td>Mechanical model</td>
<td>8400</td>
<td>5000</td>
<td>9000</td>
<td>11000</td>
</tr>
<tr>
<td>Difference</td>
<td>1.2</td>
<td>14</td>
<td>16</td>
<td>11</td>
</tr>
<tr>
<td><strong>Post-yielding stiffness</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3% rad) (kN m/rad)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experimental test</td>
<td>250</td>
<td>200</td>
<td>550</td>
<td>800</td>
</tr>
<tr>
<td>Mechanical model</td>
<td>400</td>
<td>220</td>
<td>560</td>
<td>790</td>
</tr>
<tr>
<td>Difference (%)</td>
<td>37</td>
<td>9.1</td>
<td>1.8</td>
<td>1.2</td>
</tr>
<tr>
<td><strong>Moment capacity</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3% rad) (kN m)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experimental test</td>
<td>40</td>
<td>30.5</td>
<td>55</td>
<td>67</td>
</tr>
<tr>
<td>Mechanical model</td>
<td>50</td>
<td>30</td>
<td>53</td>
<td>71</td>
</tr>
<tr>
<td>Difference (%)</td>
<td>25</td>
<td>1.7</td>
<td>3.6</td>
<td>5.9</td>
</tr>
</tbody>
</table>
Figure 3.15  Comparison between experimental and analytical results
3.6.2 Cyclic cases

3.6.2.1 Calado et al. (2000)

Full scale experimental tests were carried out at the Material and Structures Test Laboratory in Lisbon by Calado et al. (2000). Specimen geometry and connection details are illustrated in Figure 3.16 (a). The tested specimen consisted of an IPE300 beam section and HEB160 column section by means of bolted top, seat, and web angles. As connecting angles, an L section 120 x 120 x 10 was employed. Both top and bottom angles were connected by means of 4 bolts (M16), located on two rows, on both column and beam flanges. Similarly, 3 bolts (M16), located on one bolt row only, were used for double web angles, for both the beam web and column flange. Continuity plates (12 mm thickness) were used in the column panel zone. As far as material properties are concerned, the beam, columns, and angles were of steel grade S 235 JR, and 8.8-M 16 bolts, pre-tensioned by a pre-loading equal to 88 kN, were also used. Two preliminary
coupon tests were performed for each section type and for both web and flange elements. The obtained results are summarized in Table 3.3, where the average value for each mechanical property is reported. Figure 3.16 (b) illustrates the component-based mechanical model of the top-and-seat angle connection with double web angles. The model (b) contains three different components: (spring 1), nonlinear contact components (spring 2), and shear panel zone (spring 3). The parameters of the angle components varies in the dimension of the angles; in top and seat angles, in the upper and lower layers of double web angles, and the middle layer of double web angles. Spring 2 is based on a column web compression component to represent the nonlinear contact behavior.

<table>
<thead>
<tr>
<th>Member section</th>
<th>Section element</th>
<th>Yielding strength (MPa)</th>
<th>Strain at yielding (%)</th>
<th>Ultimate strength (MPa)</th>
<th>Strain at ultimate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HEB160</td>
<td>web</td>
<td>348.63</td>
<td>0.53</td>
<td>490.31</td>
<td>31.5</td>
</tr>
<tr>
<td></td>
<td>flange</td>
<td>303.43</td>
<td>0.84</td>
<td>453.12</td>
<td>44.5</td>
</tr>
<tr>
<td>IPE300</td>
<td>web</td>
<td>315.67</td>
<td>0.66</td>
<td>451.26</td>
<td>41.1</td>
</tr>
<tr>
<td></td>
<td>flange</td>
<td>304.71</td>
<td>0.68</td>
<td>452.63</td>
<td>42.7</td>
</tr>
<tr>
<td>L120x10</td>
<td>-</td>
<td>252.23</td>
<td>0.52</td>
<td>420.14</td>
<td>44.5</td>
</tr>
</tbody>
</table>
The experimental and analytical results are presented and compared in Figure 3.17. The comparison demonstrates that the mechanical model predicts the pinching response and provides reasonable agreement in terms of stiffness, strength, and pinching. In fact, the overall hysteresis loops are hardly improved although slip components are added to the top and seat angles. This indicates that the pinching behavior in this example is more significantly influenced by nonlinear contact components, rather than slip components. In addition, this is compatible with the physical investigation in that the use of double web angles restrains the top and seat angles from undergoing slippage. However, adding bolt hole ovalization components leads to a better agreement with the experimental response by exhibiting the delay effects of stiffening point at each cycle, as seen in Figure 3.18.
Figure 3.18 Comparison of hysteretic responses of the experimental test (Calado et al., 2000) and the third mechanical model
3.6.2.2 Kukreti and Abolmaali (1999)

Kukreti and Abolmaali published the experimental test results for 12 top and seat angle connections in 1999. Figure 3.19 and Table 3.4 illustrate the geometry and design details for one of the tested connections. The response of a selected connection shows the highly pinched hysteretic loops and is expected to have all deformation sources described in the previous sections.

![Configuration of tested connection](image)

Figure 3.19 Configuration of tested connection

The mechanical model of Figure 3.20 (a) includes angle springs, a panel zone shear spring, and column web compression springs. The analytical results of the first mechanical model demonstrate reasonable agreement in the loading and unloading stiffness, but the pinching effects are too small. By adding slip components serially connected with the angle springs, the analytical results exhibit more pinched hysteretic loops and approach the experimental test results as seen in Figure 3.20 (b). In order to formulate the force-displacement relationship of the slip components, the slip coefficients are adjusted to 0.15 for this cyclic loading case instead of 0.33 for monotonic cases. If
bolt hole ovalization components are added as seen in Figure 3.20 (c), the agreement between experimental and analytical responses is further improved. The mechanical model is able to reveal that the starting point of stiffening at each cycle is delayed because the bolt holes are deformed until they are ovalized. Finally, the overall hysteretic response of the mechanical model shows excellent agreement with the experimental test results.

Table 3.4 Geometrical and material properties

<table>
<thead>
<tr>
<th>Unit</th>
<th>$l_h$</th>
<th>$l_v$</th>
<th>t</th>
<th>$d_b$</th>
<th>$g_c$</th>
<th>d</th>
<th>$f_y$ (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>mm</td>
<td>152</td>
<td>152</td>
<td>19</td>
<td>22</td>
<td>64</td>
<td>400</td>
<td>345</td>
</tr>
</tbody>
</table>
(a) Step 1 - without slip

(b) Step 2 - with slip

(c) Step 3 - with slip and ovalization

Figure 3.20 Comparisons of hysteretic responses at each mechanical modeling step with experimental test (Kukreti and Abolmaali, 1999)
3.7 SUMMARY AND DISCUSSION

In this chapter, the hysteretic behavior of angle connections is predicted by using a component-based mechanical modeling approach. Component-based modeling is a compromise to span two extremes in the field of mechanical modeling: simplified global modeling and finite element modeling. The method basically takes advantage of only material and geometric properties, and theoretical mechanics considerations. In order to represent the highly pinched behavior of angle connections, critical five deformation sources are identified. Constitutive relationships of an angle, a column panel zone, and contact between angle and column flange, are formulated on the basis of a complete mechanical approach, while those of slip and bolt hole ovalization are simplified by empirically suggested parameters and expert’s opinions. A computer module that integrates all components and performs nonlinear analysis, is written by using Matlab.

To validate this method, the moment-rotation curves of the mechanical models are compared with those of experimental tests. In the case of a top-and-seat angle connection with double web angles, the highly pinched hysteretic response is predicted quite well by the complete mechanical model, because the pinching behavior in this example is significantly influenced by contact between angle and column flange. This is compatible with the observation that the use of double web angles restrains the top and seat angles from undergoing slippage. On the other hand, in the case of a top-and-seat angle connection without web angles, the mechanical model requires slip components to represent the pinching effects. In fact, the slip component is not amenable to complete mechanical modeling, and this issue will be discussed in later chapters.
CHAPTER 4 : INFORMATION-BASED NEURAL NETWORK APPROACH

As an alternative approach to modeling complex material and structural behavior, which are not easily approximated by conventional methods, is the informational approach using neural networks. This alternative approach is based on the information contained in the observed data, which is a fundamental transition from using mathematical equations to using data that contain the required information of the physical behavior. Computational intelligence methods including neural networks have made this approach possible and effective. The information about the underlying mechanics is extracted from the observed data and stored in neural networks. Trained neural networks can then be used in the simulations.

4.1 INTRODUCTION OF NEURAL NETWORK

“Anyone can see that the human brain is superior to a digital computer at many tasks. A good example is the processing of visual information: a one-year-old baby is much better and faster at recognizing objects, faces, and so on than even the most advanced AI system running on the fastest supercomputer (Hertz et al., 1991).”

It is known that the human brain is the real motivation for studying neural computation. Although neural computation is biologically inspired, its potential applications lie mainly in computer science and engineering.
McCulloch and Pitts (1943) proposed a simple model of a neuron as a binary threshold unit. This model of the neuron computes a weighted sum of its inputs from other units, and passes that through step functions to determine the output, 1 or 0. 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, an 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 hidden 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. The signals are entered into the neurons of the input layer. These signals then travel through the connections, pass the hidden layers, reach the output layer, and produce the output of the neural network.

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 decreases the error (or cost function) if the learning rate is small enough. The update rules are used incrementally (pattern by pattern) and the steepness parameter (temperature) of the activation function is 1 or 0.5. The back-propagation may be
modified for the purpose of making convergence faster, avoiding local minimum, and improving generalization ability.

4.2 NEURAL NETWORK MATERIAL MODEL

Neural networks are massively parallel computational models that are very effective in engineering applications because of their characteristics of robustness, self-organizing and adaptive features, and the capability of generalization. Neural networks have been successfully applied to broad areas including pattern recognizing, system identification, financial applications, data mining, and many others. More recently, informational methods using neural networks were proposed in constitutive modeling as an alternative to conventional mathematical approaches. Ghaboussi et al. (1990; 1991) first proposed a new method using neural networks to model material constitutive behavior.

The data generated from experimental observation are used to directly train the neural networks, which have the unique capability of learning the complex nonlinear relationships. The simplest form of a neural network material model consists of the current total strains as input variables and current total stresses as output variables. However this form is not suitable for representing the path dependency for the constitutive behavior of materials. In order to represent the behavior of the path dependency, multi-point models which employ additional input variables such as immediate previous states of stress and strain, or stress and strain increments, are applied to a number of materials.

While neural networks are applied in a wide range of fields in mechanics and engineering, selected examples are presented as follows. Neural networks have been
successfully used in the constitutive modeling of plain concrete (Ghaboussi et al. 1991; Wu and Ghaboussi, 1993; Zhang, 1996), geomaterials (Ghaboussi et al.,1994; Ellis et al., 1995; Sidarta and Ghaboussi, 1998), advanced composite materials (Zhang, 1996; Pidaparti and Palakal, 1993; Ghaboussi et al., 1998), strain softening material models in reinforced concrete (Kaklauskas and Ghaboussi, 2001), rate dependent material behavior (Jung and Ghaboussi, 2006a; Jung and Ghaboussi, 2006b), and the hysteretic behavior of materials (Yun et al. 2008a; 2008b; 2008c).

4.2.1 Nested adaptive neural network

Nested Adaptive Neural Networks (NANN) have two desirable features for especially complex problems, such as being literally “nested” and “adaptive.” The former is related to the structure of the information in the training data and the latter is related to the size of the neural network (Ghaboussi, et al. 1997; Ghaboussi and Sidarta, 1998). The nested structure of the information in the training data is constructed hierarchically with data subsets. For example, the data from one-dimensional constitutive material behavior is a subset of the data from two-dimensional constitutive material behavior and this is in turn similarly applied to the three-dimension constitutive material behavior. This nested structure of training data is reflected in the structure of neural networks. A base module neural network is trained with the subset of one-dimensional behavior and a second module is added to the base module to represent the information of two-dimensional behavior. Similarly a third module can be added to represent three-dimensional behavior. Another example of the nested structure is in modeling the path dependency of material behavior.
The previous studies illustrated that several past states of stresses and strains with a current state of strains were capable of predicting the current state of stresses in path-dependent responses. Figure 4.1 shows the schematic diagrams of the “nested” feature in NANN, where several neural network modules are nested. A base module is first created and history modules are added in a hierarchical order. Each nested neural network module is fully connected within itself, but the newly-added module is connected to the existing modules in only one way. This one-way connection is a unique feature in NANN and it fits the fact that the past states influence the current state, but the current state does not influence the past states.
It was mentioned earlier that the relationship between the number of neurons in the hidden layers, the capacity of the neural network, and the degree of complexity in a given problem cannot be easily quantified. The adaptive technique allows the new neurons to be automatically added to hidden layers during the training, which is shown schematically in Figure 4.2. 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. When training continues, only new connections weights are modified, while the old connections are kept frozen. This process allows the new connections to learn the portion of the knowledge that has not been learned by the previous network. For a local adaptive learning, the RPROP (Resilient Back-propagation) algorithm is adopted in NANN (Riedmiller and Braun 1993).

4.2.2 Nonlinear hysteretic model

Even if great advances have been made in the inelastic modeling of materials and structural components, nonlinear analysis remains challenging, especially in the case of cyclic or dynamic loading. Classical plasticity models combine properties of isotropic and kinematic plasticity to explain the cyclic or dynamic behaviors. However, those hardening rules have some difficulties in illustrating the Bauschinger effect in materials and hysteretic degradation in structural components because the shape of a yield surface is known to changes during the cyclic loading.

It has been proposed that neural network based constitutive modeling methods serve as an alternative method for modeling the complex behavior of materials and structural components (Ghaboussi, et al., 1991; Ghaboussi and Sidarta, 1997).
Sufficiently diverse information contained in the training data set enables the neural network model to reasonably represent the behavior of materials or structural components. However, it may not always be possible that experiments generate sufficient data to train the neural network (Ghaboussi, et al., 1998). The prediction of the complicated cyclic responses remains especially challenging because of the inherent characteristics of the neural network.

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 4.3 shows a neural network hysteretic model developed by Yun et al. (2006). The proposed neural network model contains 5 input variables of \( \varepsilon_n, \varepsilon_{n-1}, \sigma_n, \xi_n, \) and \( \Delta \eta_{e,n} \), in strain control form. Two hysteretic parameters of \( \xi_n \) and \( \Delta \eta_{e,n} \) were introduced to transform the one-to-many...
mapping to single-valued mapping. These were defined as $\xi_n = \sigma_{n-1} \varepsilon_{n-1}$ and $\Delta \eta_{\varepsilon,n} = \sigma_{n-1} \Delta \varepsilon_n$, where the subscript $n$ indicates the $n$-th incremental step. The variable $\xi$ 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. The smooth closed hysteresis is subdivided into six segments and each segment corresponds to the unique combination of the signs of the three variables $\varepsilon_n$, $\xi_n$, and $\Delta \eta_{\varepsilon,n}$. These two variables can be used on their own, or in combination with one or two history points, as can be seen in Figure 4.3 (b). In addition, these parameters have been found to be effective not only in one-dimension but also in multi-dimension.

4.3 NEURAL NETWORK CONNECTION MODEL

4.3.1 Neural network for hysteretic behavior of beam-to-column connections

In this section, the neural network of hysteretic material constitutive modeling is adjusted and improved for modeling the cyclic behavior of beam-to-column connections. As previously mentioned, the focus is on the pinched hysteretic behavior of steel bolted beam-to-column connections.

The neural network is defined in the moment and rotation domain instead of the stress and strain domain, as can be seen in Equation 4.1. Two hysteretic parameters are defined as $\xi_n = M_{n-1} \theta_{n-1}$ 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 $\theta_n$, $\xi_n$, and $\Delta \eta_n$ as can be seen in Figure 4.4. One history point of the moment and rotation in the previous step helps to express the path dependency. 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 degradation parameter predicts less moment than when input variables contain a smaller value degradation parameter. Figure 4.5 illustrates the unique mapping with degradation.

$$M_n = \hat{M}_{NN} \{ \{\theta_n, \theta_{n-1}, M_{n-1}, \xi_n, \Delta \eta_n, E_{n-1}\} : \text{NN architecture} \}$$  \hspace{1cm} (4.1)

<table>
<thead>
<tr>
<th></th>
<th>$\xi$</th>
<th>$\Delta \eta$</th>
<th>$\theta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Path 1</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Path 2</td>
<td>+</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>Path 3</td>
<td>-</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Path 4</td>
<td>-</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>Path 5</td>
<td>+</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>Path 6</td>
<td>+</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Path 7</td>
<td>-</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>Path 8</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Figure 4.4 Unique mapping by hysteretic parameters and current rotation
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 4.6. Therefore, the inputs in the current step such as the hysteretic parameters and previous states of force and displacement are determined with the output of the neural network in the previous step. This mode suits stepwise nonlinear analysis techniques. In this section, this neural network is extended for use in approximating the hysteretic moment-rotation relationship of beam-to-column connections.
4.3.2 Training data from a mathematical function

The performance of the proposed neural network model is validated against two types of training data: (1) the data generated from a mathematical function and (2) the data generated by digitizing experimental test data. These two data sets have different characteristics as training sets for neural networks. Hereafter, these two examples are provided and discussed.

The behavior of a specimen is assumed to follow a Ramberg-Osgood type function as can be seen in Figure 4.7. A training data set for the first loading phase is generated by Equation 4.2 (a) and consecutive training data sets for unloading and reloading are generated by Equation 4.2 (b), where $M_y$, $K_0$ and $r$ are the yielding strength, the initial stiffness, and the shape parameter and $(M_i, \theta_i)$ represents turning pairs of unloading and reloading.

\[
\begin{align*}
(a): \theta &= \frac{M}{K_0} \left[ 1 + \left( \frac{M}{M_y} \right)^{r-1} \right] \\
(b): (\theta - \theta_i) &= \left( \frac{M - M_i}{K_0} \right) \left[ 1 + \left( \frac{M - M_i}{2M_y} \right)^{r-1} \right]
\end{align*}
\] (4.2)

![Figure 4.7 Ramberg-Osgood cyclic model](image-url)
The input-output relationship of the neural network is illustrated in Equation 4.3, which consist of 5 input variables and 1 output variable. Neural networks are trained with both directions of loading and reverse loading. Figure 4.8 shows the comparison between the target experimental and the neural network results using different neural network structures. In these cases, the shape parameter $r$ is equal to 7. The two trained neural networks have 10 and 30 neurons, respectively, in each of the two hidden layers. The green line with circles and the blue line with dots represent target responses and the neural network outputs, respectively. Both comparisons show excellent agreement between the target and neural network responses, which are simulated in recurrent mode.

In the first case in Figure 4.8 (a), the use of the comparatively small number of neurons required the larger number of training cycles of 30000 epochs in order to predict the cyclic response. On the other hand, the comparatively larger neural network in Figure 4.8 (b) predicted the same target response with the significantly smaller number of training cycles of 2000 epochs. It can be concluded that the neural network with 5 input variables including 2 hysteretic variables can represent the smooth hysteretic responses with sufficient accuracy. Moreover, although there is no explicit rule in selecting the number of epochs and neurons in each hidden layer, a proper combination of those allows for the neural network model to effectively store the information generated from the mathematical function and to predict the cyclic response well. The following examples will demonstrate a neural network’s general capability to learn the background mechanics of the actual hysteretic behavior of connections.

$$M_n = \hat{M}_{NN}[^{\{\theta_n, \theta_{n-1}, M_{n-1}, \xi_n, \Delta \eta_n\}}]$$  \hspace{1cm} (4.3)
Figure 4.8 Comparison between target and neural network responses

(a) NN structure: 5-10-10-2, 30000 epochs     (b) NN structure: 5-30-30-1, 2000 epochs
4.3.3 Training data from experimental tests

In the previous section, the performance of the proposed nonlinear hysteretic neural network model is validated by modeling the cyclic response generated by a mathematical function. The following examples will present neural networks’ capability for learning the complex response from experimental tests.

4.3.3.1 Validation in experimental tests

A top and seat angles beam-to-column connection with web angles is shown in Figure 4.9 (a), which is tested by Calado (2000). The experimental results in Figure 4.9(b) 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. They include another symmetric data set with respect to origin to account for reverse loading direction. The data sets from experimental
tests contain inherent scatters caused by the physical experimental process and are arrayed with random step sizes. This makes a difference between actual experimental test data and mathematically generated data in the previous case.

\[ M_n = \hat{M}_{NN} \{ \theta_n, \theta_{n-1}, M_{n-1}, \xi_n, \Delta \eta_n, E_{n-1} \} : \{6 - 15 - 15 - 1\} \]  \hspace{1cm} (4.4)

A neural network model of the angle connection employed one additional input variable of \( E_{n-1} \) to effectively represent more complex hysteretic behavior, as seen in Equation 4.4. The hysteretic parameters and the degradation parameter are computed by the digitized values at every load step. The preliminary parametric studies were carried out to determine the number of neurons in the hidden layers and then the neural network was consequently constructed with 2 hidden layers and 15 neurons per hidden layer. After
training with 12000 epochs, the trained neural network model is tested in recurrent mode and the results are compared to the target response. As can be seen in Figure 4.10, the comparison demonstrates that the neural network model predicts overall pinched hysteresis loops very well, and it could be said that the neural network model with 6 input variables are an adequate alternative for the more complicated cases. To summarize, this example indicates that the informational model, when using a properly designed neural network, may be capable of learning the complex behavior of a bolted connection directly from the experimental data.

4.3.3.2 Application to a different loading pattern

The training pairs in the training data sets are digitized at random intervals, while numerical simulation is usually carried out by using fixed increments. In this section, the performance of the trained neural network is briefly investigated in different structures of the neural networks under a new loading pattern. The new loading pattern is defined within the boundary of the digitized data as can be seen in Figure 4.11. The new pattern completes 5 cycles at -0.05 radian and the total experienced deformation is 0.3 radian. On the other hand, the digitized pattern completes the same number of 5 cycles at -0.057 radian and the total experienced deformation is approximately 0.35 radian. In addition, the new pattern is applied with a fixed increment between load steps.

Figure 4.12 presents a complex hysteretic response (a) obtained from an experimental test, and predictions (b,c,d) of trained neural networks with different architectures. If only two hysteretic parameters and previous states of moment and rotation are used for the input vector, the trained neural network exhibits approximated
behavior with a certain envelope curve. The neural network model with an architecture of \{5-7-7-1\} shows smooth cyclic behavior with only slightly smaller pinching effects in Figure 4.12 (b). When the neural network is trained with a bigger architecture of \{5-15-15-1\}, the outputs of the neural network model contain more pinching effects, but the hysteretic loops depict approximate enveloped-curve without stiffening delay effects at cycles, as can be seen in Figure 4.12 (c). Introducing one more input variable of $E_{n-1}$ gives better results than the cases using 5 input variables. In Figure 4.12 (d), the neural network model with a structure \{6-20-20-1\} shows acceptable results in terms of initial and hardening stiffness and strength. It exhibits the stiffening delay effects at consecutive cycles thanks to the degradation parameter, which seems to give proper information to the neural network about hysteretic degradation effects. In addition, the models (b) and (c) take relatively large numbers of epochs, 30000 and 50000 epoches, respectively; but the model (d) takes only 20000 epoches in spite of the large size of the neural network. These examples demonstrate that the neural network model with six input variables would show better learning efficiency than those with five input variables.
Figure 4.11 Static time-history loading patterns

Figure 4.12 Neural network responses under different loading history
4.4 SUMMARY AND DISCUSSION

In this chapter, a neural network informational modeling approach is employed to represent the highly pinched hysteretic behavior of beam-to-column connections. This alternative approach is based on the information contained in the observed data rather than mechanical properties. The information about the underlying mechanics is extracted from the observed data and stored in neural networks. Neural networks have been successfully applied to broad areas of structural engineering and mechanics.

To validate this approach in representing the hysteretic behavior of beam-to-column connections, two different training data sets; analytically-generated and experimental data are given, and the tested results are compared with the actual hysteretic responses. The neural network models show acceptable agreement in both cases. Adding the degradation parameter improves the performance of the neural network model when modeling highly pinched hysteretic behavior. It would conclude that the neural network model may be a good alternative to the mechanical model for predicting hysteretic behavior, even where considerable pinching is observed.

However, the neural network model of the top-and-seat angle connection can not represent the contribution of the individual component and hence does not provide an insight into the underlying mechanics of the components. This also poses problems for extended applications to differently designed connections.
CHAPTER 5: HYBRID MODELING FRAMEWORK

5.1 INTRODUCTION

The field of mechanics is concerned with the behavior of physical bodies subjected to external stimuli. A new data set is generated and collected from a physical event. The information contained in the data set is then conveyed to a proper mathematical model, which is capable of representing that specific event or other similar events. Mathematical models have normally been accepted as the only possible modeling approach that can describe the physical behavior of the event. However, there are other alternatives. Neural network modeling is involved with extracting and storing information from the data. This approach differs greatly from the development of mathematical models. In this chapter, the fundamentals of mathematically based methods and biologically inspired methods will be presented. It will continue to examine the characteristics and limitations of mathematical modeling and informational modeling, which will imply that there is a need to combine the two approaches for greater efficacy. Finally, the hybrid modeling will be formulated and the details will be illustrated by using simple examples.

5.1.1 Problem solving methods

5.1.1.1 Mathematically based methods

As mathematically based methods are literally based on mathematics, they inherit the unique characteristics of mathematics, which are precision, universality, and functional
uniqueness (Ghaboussi, 2009). Mathematically based methods always require precise values at every parameter. The mathematically-based modeled system considers all of the input parameters to be precise—no matter how those parameters are estimated and provided. Similarly, all values including outputs are also precise within round-offs in computation. It should be noted that the input-output relation computed with a high degree of precision may represent only the modeled system, and not the actual physical event.

The mathematically based methods use mathematical functions that are defined universally for all the possible values of their variables. However, it is the universality of the functions being used that is often not compatible with the actual physical behavior that is to be described. Mathematical functions are also unique in that each function provides a unique mapping.

These three characteristics of precision, universality, and functional uniqueness make the mathematically based methods only suitable for forward problems. In a forward problem, the model of the system and the input to the system are known, and the output needs to be determined. Although most engineering problems are inverse problems, they are normally solved as forward problems because most computational software have been developed based on forward problem solving methods. The mathematically based methods are not suitable for directly solving the inverse problems because the inverse problems do not have unique solutions (Ghaboussi, 2009).
5.1.1.2 Biologically inspired methods

“Soft computing methods are the class of methods which have been inspired by the biological computational methods and nature's problem solving strategies. Currently, these methods include a variety of neural networks, evolutionary computational models such as genetic algorithm, and linguistic based methods such as fuzzy logic. These methods are also collectively referred to as Computational Intelligence Methods. These classes of methods inherit their basic properties and capabilities from the computing and problems solving strategies in nature (Ghaboussi, 2009).”

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. In another type of inverse problem, a system and outputs of the system are known, and the inputs to the system need to be determined.
The inherent characteristics of the biologically inspired methods are imprecision tolerance, non-universality, and functional non-uniqueness (Ghaboussi, 2009). For example, a neural network allows for the scatter of training data, as can be seen in Figure 5.1. This imprecision tolerance offers generalization capability for the neural network. As for non-universality, a neural network can only learn to approximate a linear function within a range of training data, while the mathematical equation is valid for all possible input values. While mathematical functions are unique, many neural networks with different architecture can represent the same associations with satisfactory levels of approximation. In addition, the imprecision tolerance and random initial state of neural networks introduces random variability in the modeled systems. This feature coincides with the fact that a system in the real world should involve inherent random variability and uncertainty.
5.1.2 Modeling classification

Modeling processes are classified as mathematically based approaches and biologically inspired approaches, as can be seen in Figure 5.2. A modeling process would be determined by how much \textit{a priori} knowledge is available about the system. All necessary \textit{a priori} knowledge is available in a mathematically based approach, while a biologically inspired approach allows for a lack of \textit{a priori} knowledge. For example, a conventional modeling approach takes advantage of \textit{a priori} knowledge to employ the most acceptable mathematical functions and their parameters. \textit{A priori} knowledge may include given physical rules as well as expert’s opinion, intuition, or experience.

![Figure 5.2 Classification of modeling process](image)

5.1.2.1 Mathematically based modeling: mathematical modeling

The physical response of a natural or engineering system is traditionally expressed in terms of mathematical field equations by using proper physics. The mathematically based
modeling methods contain the information about the response of the physical system in mathematical functions, which is referred to as ‘mathematical modeling’ in this study.

In a mathematical modeling process, a decision is made about which parts of the system to model closely and which parts to ignore or account for indirectly. The selected parts normally have features that govern the behavior of the system. Through representing mathematical deduction, the messier aspects of the real-world system are transformed into mathematical representations of the essential features in the modeled system. This is idealization. If the idealized model is a good one, then the results of the mathematical calculations should say something about the actual behavior of the system. If the model's predictions do not match reality, then it may be necessary to refine the model and repeat the process until a satisfactory level of real-world agreement is reached. However, deciding how to represent a system in mathematical formulations is often the most difficult step of the modeling process, especially in modeling complicated systems. Moreover, the refinement of some parts may not be always feasible.

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.

5.1.2.2 Biologically inspired modeling: Informational modeling

As an alternative, the information about the system based on the underlying mechanics is directly extracted from available analytical and/or experimental data, and stored in connection weights of the neural network which is referred to as ‘informational
modeling’ in this study. Using neural networks implies that there is no need for a priori knowledge such as a pre-defined mathematical expression and/or empirically estimated parameters. 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.

In addition, the informational model using neural networks would not provide insight into the underlying mechanics of the observation. For example, a global response of a system is measured and a neural network is trained with information from the global response. This neural network model does not capture the local behavior of the system or the response of components in the system. Likewise the model only gives information about the overall system, and not about the interaction between the components within the system. It seems that a neural network model trained with entire information,
including all responses of components and interactions, could describe all features on the component level as well as on the system level. However, this is not quite possible because considering the additional variety of dimensional properties on the component level requires an enormous amount of training data sets, and it is arguable whether the available data sets are rich enough and comprehensive enough to train the neural networks. It is also particularly difficult to obtain data sets for interactions between components in the system due to economical and technical reasons.

In summary, mathematical modeling involves idealization. The idealization may often result in a mathematical formulation that excludes some aspects of the physical phenomenon that may be significant. An alternative approach is informational modeling, which is a fundamental transition from mathematical equations to data that contain the required information about the physical system. Computational intelligence methods (e.g. neural networks) have made this approach possible and effective. However, the informational approach also has limitations.
5.2 DEFINITION OF HYBRID MODELING

Hybrid mathematical and informational modeling is a modeling approach that uses the combination of mathematical models and informational models to perform realistic simulation. Hybrid modeling is effective especially in modeling the complicated behavior of a physical system; when the system or components of the system have inherent inelastic or nonlinear behavior; when the system is subjected to extreme loadings such as an earthquake; or when the system behaviors are considerably influenced by interaction between components and materials of the system. A mathematical model produces exact outputs of the idealized system. It is noted that the response of the mathematical model moves further from reality as the degree of simplification and assumption increases. In a hybrid model, a conventional mathematical model is complemented by informational methods. The role of the informational method is to model aspects that the mathematical model leaves out. Finally, a hybrid model of the system is more effective in copying the reality and predicting similar future events.
As an example of pushover analysis in Figure 5.3, the mathematical model of a bare-bone frame of a building is combined with the informational model of non-structural elements such as curtain-wall systems. The frame model consists of conventional mechanical models of beam-column elements and idealized joints, while the non-structural elements are modeled with neural networks, as non-structural elements are too complicated to model mechanically in the structure-scale modeling. As a result, the pushover response of the hybrid model might be improved over that of the conventional frame model. The purpose of the hybrid modeling is to get a realistic, and consequently accurate, response of the building, rather than the response of an idealized frame.
The framework of the proposed hybrid modeling is schematically shown in Figure 5.4. A system is typically modeled and simulated on computers when it is either impossible or impractical to create experimental conditions in which scientists can directly measure outcomes. Direct measurement of outcomes under controlled conditions always is more accurate than the modeled estimates of outcomes. In the hybrid modeling framework, one of the key ingredients is the direct use of measurements with computational intelligence by complementing mathematical equations. Some parts of the system are modeled with mathematical formulations as mathematical models; as shown on the left side of Figure 5.4, because those allow scientists and engineers to easily understand the fundamental behavior of the system. Others are modeled by neural networks as informational models, as shown on the right side. The neural networks store information that is contained in
experimental data or that the mathematical models do not capture. The tripartite relationship in the lower and middle parts of the flowchart is a unique feature of hybrid modeling that schematically describes how the informational model can learn the realistic behavior of the system. The details will be illustrated in the following sections.

Figure 5.5  Simple 1-D example of hybrid approach
Figure 5.5 illustrates a uni-axial modeling of a complex module in a mechanical system. A force and displacement curve in a compression test of the module is shown in (a). A bilinear model can be established by using the conventional mechanical approach as shown in (b). Since the module consists of many small mechanical parts, it may develop several different modes in yielding and failure. Such complicated behavior proves that it is very difficult to characterize post-yielding behavior even if the linear-elastic behavior is predicted within an acceptable range. Consequently, the hybrid modeling approach is an attractive alternative to the conventional modeling approach. As can be seen in (c), a mathematical model as a linear model can well represent linear-elastic behavior, and then the difference between the linear representation and measurement is obtained in (d), to create data sets to train neural networks. Finally, a hybrid model, in which the linear model is complemented by the neural networks, is able to predict inelastic behavior with acceptable accuracy as seen in Figure 5.6 (a). In addition, the neural network model can be launched after yielding because the difference vanishes in the linear-elastic range. The latter hybrid model shows better prediction, as can be seen in Figure 5.6 (b). Indeed, in most modeling processes, \textit{a priori} knowledge determines what properties of a modeled system are amenable to an informational approach. Therefore in this example, the information from the difference might mean nonlinear interaction among the small parts, which would be represented by the neural network model.
Figure 5.6 Two patterns that demonstrate a working hybrid model
5.3 CLASSIFICATION OF COMPONENTS

In past studies the informational neural network modeling method has been proven effective in modeling material constitutive relationship. There have been efforts to extend the benefit of informational methods to the modeling of systems (structures) or system components. However, increasing physical properties such as geometric properties leaves room for much improvement in the application to force-displacement domain. Ideally, the hybrid modeling method would bridge these difficulties and be an attractive alternative for modeling realistic behavior on both the system and component level.

In the hybrid modeling formulation, it is important to establish how a mathematical model is complemented by informational methods or how both models are combined. This greatly influences implementation in current analysis tools, such as finite element analysis. In essence hybrid modeling adopts the concept of a component-based modeling approach. A component could be defined as not only a part, but also a group of parts, that comprise the system to be modeled. Components have their own constitutive relationships and their behaviors should critically affect the behavior of the system they comprise. Therefore, identifying deformation sources is the initial step in the modeling process. Depending on the characteristics of each deformation source, components are classified to mechanics-based or information-based components.
Figure 5.7 is a two-dimensional chart that shows the classification of components. The x-axis refers to the modeling complexity of the component. The left side reflects less complicated models because underlying mechanics are well-developed, and efficient mathematical formulations exist. The right side indicates that the background theory is not fully developed, or the available representations are too complex to be implemented with the current computational power. The y-axis is the extent to which the deformability of a component is influenced by the mechanical properties. The top indicates that the constitutive relationship of a component can be determined by only mechanical properties. The bottom implies that other circumstances such as temperature, size effects, or correlation between components may considerably influence the deformability of the component. Therefore, the upper and left-hand side suggests a mechanics-based approach while the lower and right-hand side suggests an information-based approach. A bare-bone frame, soil, and cladding systems are, for example, placed in the classification chart in
Figure 5.7. The bare-bone frame is composed of basic beam-column elements and is therefore suitable for mathematical modeling. However, the cladding systems are too complicated to model mechanically in the structure-scale analysis and the soil behavior is sensitive to on-site information. They are rather suitable for informational modeling. Table 5.1 summarizes the characteristics of both mechanics-based and information-based components.

Table 5.1 Mechanical-based and informational-based components

<table>
<thead>
<tr>
<th>Mechanics-based</th>
<th>Information-based</th>
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<tbody>
<tr>
<td>The identified deformation source should be described by well-built mechanics theories and expressed with ready-to-use mathematical formulation. Examples: Bare-bone frame, beam, column, etc.</td>
<td>The identified deformation source may not be suited to mechanical representations. This may be due to: (i) underlying theory is not available or not sufficiently developed, (ii) existing theory is too complex and is therefore not suitable for modeling within system analysis. Examples: soil, cladding system, etc.</td>
</tr>
</tbody>
</table>
5.4 COMPONENT AND SYSTEM MODELING

After all components are classified as either mechanics-based or information-based, a mathematical model of the system is built first with the mechanics-based components. A mathematical model is based on the superposition of the contribution of the mechanics-based components, of which constitutive relationships are defined in mathematical formulations. Though the mathematical model is expected to keep main stream or backbone trend of the system behavior, it inevitably involves a certain level of abstraction. It is modeling information-based components that can bridge the gap between the abstraction and the reality. Details are given strictly within structural analysis.

5.4.1 Mathematical modeling

A mathematical model in structural analysis consists of a set of physical laws and mathematical equations required to study and predict the behavior of structures. There are three approaches in mathematical modeling in structural analysis: the strength of materials, elasticity theory, and the finite element approach.

The strength of materials method is the simplest, and is available for simple structures subjected to relatively simple loadings. This approach can be used either for structural members such as bars and beams; or for entire structures in conjunction with statics. For example method of sections and method of joints for truss structures, moment distribution for small rigid frames, and portal frame and cantilever method for large rigid frames. The solutions are based on linear elasticity and the superposition principle. This
is sufficient for solving many useful engineering problems such as small structures and the preliminary design of large structures.

The theory of elasticity method is available for structural elements of general geometry under general loading conditions. Individual members such as beams, columns, shafts, plates, and shells may be modeled. The analytical solution, however, is limited to relatively simple cases. For complex geometries, a numerical solution method such as the finite element method is necessary.

The finite element method stands on three legs: its mathematical models are based on the above two mechanics theories; it incorporates the matrix formulation of the discrete equations; and it uses computing tools to do the numerical work. This method is generally available for highly complicated geometry and loading conditions as well as linear and non-linear analysis. This is sophisticated enough to handle about any system as long as sufficient computing power is available.

![Mathematical model-based simulation in computer](image)

**Figure 5.8** Mathematical model-based simulation in computer
Figure 5.8 schematically illustrates the process of computer simulation with a mathematical model (Felippa, 2000). A system in the real world is converted to a mathematical model through idealization by using one of the above three methods. The mathematical model is discretized as a series of numerical formulations for computational simulations. The more simplification and assumptions are involved, the further the model strays from reality. The strength of materials and theory of elasticity methods make a variety of assumptions and simplify modeling processes. Consequently, modeling error increases and the solutions become less useful. As mentioned, the finite element method is applicable to any problems without limits, including linear and nonlinear analysis, solid and fluid interaction, and static and dynamic effects. This, however, does not imply that the computed solution will automatically be reliable, as the finite element method also takes over the assumptions of mechanics theories, and the solution strongly depends on the model and the reliability of the data input. Moreover, the finite element analysis is done using numerical approximation and therefore numerical errors always exist. Therefore, effective and reliable use of these mathematical modeling methods requires a solid understanding of their limitations.

5.4.2 Informational modeling

The informational components are modeled by using computational intelligence like neural networks. The general idea and scope of neural networks has been presented in chapter 4. Extended applications of the neural networks and information modeling process during the hybrid modeling framework are presented as follows.
Neural networks are the most useful biologically inspired methods in the engineering fields. In the area of computational mechanics, an informational method using neural networks was first proposed by Ghaboussi et al. (1990, 1991) in constitutive modeling as an alternative to conventional mathematical approaches. A new nested adaptive neural network was developed to deal with path dependency and to take advantage of the nested structure of the given data (Ghaboussi, et al. 1997; Ghaboussi and Sidarta, 1998). However, general neural network modeling of material constitutive relationships requires a large number of experiments to produce comprehensive data that contains information about all aspects, especially when the material behavior is quite complex. Additionally it is very difficult to keep the experimental test specimen in homogeneous conditions at the macroscopic level. Even state-of-the-art technology and equipment cannot guarantee these conditions when the specimens are subjected to complicated loads such as multi-axial or unloading/reloading cases. To overcome this drawback, Ghaboussi et al. (1998) introduced an entirely different method, called autopgressive algorithm. In this method, the neural networks are trained by global response information from a structural test. If the structural test is set up to generate comprehensive patterns of stress and strain, the autopgressive algorithm extracts the rich stress-strain information from the global structural response. The extracted information is stored in neural networks and the neural network material model could represent the complex material constitutive behavior. The significance is that the autopgressive algorithm showed the possibility of training a neural networks material model directly from experimentally determined structural response. A series of studies have extended the autopgressive algorithm to a more robust strategy and enable it to be incorporated in finite element codes. By using a self-
learning concept, Shin and Pande (2000) proposed a robust framework for the training of material constitutive models with an interactive correction method of stress and strain. Self-learning simulation has been applied to demonstrate the feasibility of extracting geomaterial constitutive behavior from site measurement (Hashash, et al.2003; Hashash, et al.2006).

The back propagation algorithm is a supervised learning method in feed-forward neural networks. The supervised learning process is summarized in Table 5.2, where the mathematical modeling process is also summarized for comparison. The supervised learning has four steps. The first step is to determine the type of training targets. Before doing anything else, an engineer should decide what kind of data are to be used. The second step is to gather training data sets, which characterize the real world behavior. Thus, a set of inputs and the corresponding outputs are gathered, usually from measurements. The third step is to determine input representation. The accuracy of the learned neural networks strongly depends on how the input vector is represented. In this step, the structure of the neural networks is determined. Finally, the engineer runs the learning algorithm on the gathered training data set. Parameters (connection weights of the neural networks) may be adjusted by optimizing performance on the training data set. After parameter adjustment and learning, the performance of the trained neural networks may be measured on a test set that is separate from the training set.
Table 5.2 Mathematical modeling and supervised learning process

<table>
<thead>
<tr>
<th>Mathematical modeling</th>
<th>Supervised learning</th>
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<tbody>
<tr>
<td>• Identify the physical law.</td>
<td>• Determine the type of training targets.</td>
</tr>
<tr>
<td>• Represent formulation.</td>
<td>• Gather training sets.</td>
</tr>
<tr>
<td>• Represent mathematical deduction from the messier aspects of physical reality to</td>
<td>• Determine the input representation and the structure of the learning algorithm.</td>
</tr>
<tr>
<td>essential features of the modeled system.</td>
<td>• Adjust parameters.</td>
</tr>
<tr>
<td>• Refine the model.</td>
<td></td>
</tr>
</tbody>
</table>

As can be demonstrated in Table 5.2, every step in the mathematical modeling process involves a priori knowledge and consequent idealization. In general, physical laws are effective in idealized conditions with proper assumptions, and mathematical representation requires more a priori knowledge and simplification with fundamentals of mathematics. In supervised learning processes, less a priori knowledge is needed only to determine the architecture of neural networks and the simplest functions are enough for representation of artificial neurons in computers. In fact, the best quality and quantity of data is important to both processes. There is, however, a difference in conveying the underlying information to a representation form. In mathematical modeling, the a priori knowledge from data analysis is idealized into mathematical equations, while the information contained in data is directly stored in neural networks during a supervised learning process. This direct use of the data enables the supervised learning method to perform more realistic simulation.
5.4.2.1 Training data set

There are two methods used to obtain training data for informational components. First, training data sets are obtained directly from experiments involving the components that are to be modeled. This is the common way. Secondly, the information for the components is extracted from global responses. In this case, the training data is built with the difference between a mathematical model and the global response of the real system. Two examples for both cases will be presented, and then the latter will be highlighted.

Figure 5.9 (a) shows a soil failure under a building. Various kinds of numerical modeling have been applied to account for soil-structure interaction. Although a large soil domain has been modeled to get accurate results in some studies, many practical approaches are widely accepted due to limited computational power. Instead of full modeling of a soil-structure system, the practical models ignore inertial interaction and are idealized as simple springs to apply only surface ground motion. However, the simplified models are not typically able to capture the complex soil behavior. Herein informational modeling is an attractive alternative to model complex soil behavior. Data generated from experiments with the similar soil foundation allow for the direct training of neural networks, which can be implemented like a simplified spring model in the simulation.
Real time structural health monitoring devices have been recently applied to a variety of industries including bridges, tall buildings, windmills, oil rigs, and more. The devices are capable of measuring and responding to both natural and man-made events including earthquakes, wind, explosions, and accidental heavy impacts. Figure 5.9 (b) shows an example of a monitoring experiment for high-rise buildings. The installed devices on the top—Global Positioning System (GPS) receiver, accelerometers, wind vanes, and anemometers—are capable of measuring real time building responses: horizontal displacement, torsional displacement, and acceleration. These global measurements on the top can yield useful information for local components of the buildings by using inverse analysis techniques like autopropgressive algorithm and self-learning simulation.
Since the informational approach is related to supervised learning, outcomes are strongly dependant on the quality of training data sets. Given experimental data are initially used for validation processes of mathematical models. In Figure 5.10, data flow in the hybrid modeling framework is enlarged from Figure 5.4. The two-way arrow $\alpha$ demonstrates refinement of mathematical models through comparison with each other. Some informational components may be trained directly by given experimental data as seen in the arrow $\beta$, while others may be trained by the difference between the results of a mathematical model and given data as seen in the arrow $\gamma$. The difference, which is usually extracted by using autoprogressive algorithm and self-learning simulation, represents the aspects that the mathematical model leaves out. Those aspects may imply either a deformation source or a group of sources, depending on the set-up of components in the hybrid model. *A priori* knowledge would help identify the characteristics of the difference, even if informational modeling approaches like neural network models themselves do not take advantage of this *a priori* knowledge.
5.4.2.2 Autopressive algorithm

The autopressive algorithm (Ghaboussi et al., 1998) extracts the rich stress-strain information from the structural response. Extending this methodology provides a method to generate approximate constitutive information of components from the measured response of a system. The training data built with the difference between a mathematical model and the measured response (the arrow $\gamma$ in Figure 5.10) in hybrid modeling formulation is also obtained.

In the autopressive algorithm, global deformation is measured with corresponding known external loads. A numerical simulation is developed with unknown constitutive models like a stress-strain material model. The unknown constitutive relationship is modeled with neural networks. This neural network is pre-trained with available a priori
knowledge, which may not accurately represent the material behavior. In the autoprogressive cycles, two forward analyses of inputting a discrete load and displacement yield approximate (but presumably improved) stress-strain training cases. The neural network material model is trained and updated with newly collected stress-strain training pairs. These forward analyses and training are iterated at each load step until the structural level response is predicted accurately enough. This process, called autoprogressive iteration, is repeated through the full range of applied loads. Care should be exercised in choosing the number of autoprogressive training cycles. Covering the full range of loads is referred to as a load pass. To complete training of neural network material models with satisfaction, several load passes may be required. The components of the autoprogressive algorithm—load control forward analysis, displacement control forward analysis, autoprogressive iteration, and several load passes—are also called self-learning simulation. The data flow from global measurements in the force-displacement domain to neural network material models in the stress-strain domain is illustrated in Figure 5.11.

Forward analysis

In the autoprogressive training, two analyses (A and B) are performed with the neural network material model. These analyses are called ‘forward analyses’. The forward analysis is a conventional structural analysis, but the distinctiveness is that the neural network material model is used in the same way as other material models. The forward analysis is performed in order to train and update the neural network model during the autoprogressive training phase, as well as in order to predict responses of similar systems after the training has been completed.
**Pre-training**

To initialize the neural network, the neural network model is pre-trained to represent linear elastic behavior. This initialization is necessary to perform the forward analyses and is achieved by using approximate Young’s modulus. The pre-trained neural network model is able to exhibit linear elastic behavior, which does not have to be exact. As the neural network gets trained, the initial pre-training data sets are incompatible with the updated neural network model. In this case, the pre-training data set should be controlled or excluded from the training database.

**Algorithmic tangent stiffness**

The trained neural network constitutive model can be used in the same way as the conventional constitutive model in analysis platforms. To implement a neural network material model to general finite element analysis, a material stiffness matrix should be formulated in a numerical way. The algorithmic tangent stiffness may be approximated in the following form by Hashash et al. (2004):

\[
K_{NN}^{n+1} = \frac{\partial^{n+1} \sigma_i}{\partial \varepsilon_i^{n+1}} \\
= \frac{S_j^e}{S_j^e} \beta^3 \sum_{k=1}^{NC} \left( \left( 1 - (\sigma_i^{NN})^2 \right) \omega_{ik}^{\text{NC}} \right) \times \left[ \sum_{l=1}^{NB} \left( 1 - (\sigma_j^{NN})^2 \right) \omega_{lk}^{\text{CB}} \left( 1 - (B_j)^2 \right) \omega_{lj}^{\text{BE}} \right]
\]

(5.1)

The symbolic letters stand for the following: \( K_{NN} \): algorithmic tangent stiffness; \( \beta \): steepness parameter; \( S_j^e \) and \( S_j^p \): scale factors of input and output variables; \( C_k^{NN} \): activation values from the second hidden layer; \( B_j \): activation values from the first hidden layer; \( \omega_{ik} \): connection weight between neuron \( i \) and \( j \); \( NB \): the number of first
hidden layer nodes B; \( NC \): the number of second hidden layer nodes C; \( \varepsilon_i \): strain vector in input layer; and \( \sigma_i \): stress vector in output layer. The algorithmic tangent stiffness can be used in implicit methods such as the Newton–Raphson method in a general finite element analysis.

5.5 SUMMARY AND DISCUSSION

Conventional modeling and computational simulation in mechanics and applied science are based on the mathematical equations that have been developed to represent the observation of the system behavior. This is referred to as ‘mathematical modeling’. In mathematical modeling process, systems are modeled at different levels of idealization. Idealization may often lead mathematical equations that exclude some aspects of physical behavior that may be significant. An alternative approach is ‘informational modeling’, which demonstrates a fundamental transition from mathematical equations to data that contain the required information about the system behavior. In mathematical modeling process, experimental data are narrowly used to validate the performance of mathematical models. On the other hand, they are actively used within informational modeling process. Computational intelligence methods have made the informational approach possible and effective. For instance, the information about the underlying mechanics is extracted from the experimental data and stored in neural networks. However, the informational approach also has limitations.

A new hybrid modeling framework is proposed for the realistic simulation of natural and engineered systems. The hybrid framework employs the concept of
component-based modeling. The components are classified as either mechanics-based or information-based, which are suitable for mathematical modeling or informational modeling, respectively. 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 hybrid model is more effective in copying the reality and predicting similar future events.
CHAPTER 6 : APPLICATION OF HYBRID MODELING
FRAMEWORK TO BEAM-TO-COLUMN CONNECTIONS

6.1 MOTIVATION FOR HYBRID MODELING

Steel frames are traditionally modeled with beams, columns and idealized connections. This conventionally-modeled system is practical and effective in an elastic analysis. However, the modeled system may be no longer effective; 1) if the components or material of the system undergo considerable inelastic behavior; 2) if it is subjected to extreme loadings such as earthquakes; 3) if the connecting system has substantial flexibility. In comparison to beam and column elements, beam-to-column connections represent more complicated behavior due to the assembly of discontinuous components with different material properties. In order to take account of the complex behavior, realistic models of connections are essential and hybrid models can provide an option.

6.1.1 Issues of modeling bolted connections

The primary challenge of modeling bolted beam-to-column connections are their highly inelastic response and continuously varying stiffness, strength, and ductility under severe earthquake. Connected elements such as beams and columns are linked with different connecting elements and fasteners instead of simple welds. The connecting elements include angles, plates, T-studs, and more. The bolt-fastening process needs high-strength bolts and bolt holes, and they apparently reduce the resistance of the connected member.
Moreover, bolting introduces substantial inelastic effects as follows. Contact between the connecting and the connected element is related to friction and slippage. The friction depends on the preload of bolting and the surface condition in the connected plates. The slippage develops bearing force that ovalizes the bolt holes. All hot-rolled connecting and connected elements contain uneven residual stresses. In some cases contact/detachment issues and prying effects arise, especially in angle connections. Therefore, the combination of these effects produces the highly complex behavior of bolted beam-to-column connections, exhibiting pinching effects, and stiffness or strength degradation.

6.1.2 Criticisms of mechanics-based and information-based hysteretic modeling

In chapters 3 and 4, a component-based mechanical model and an informational neural network model are developed to represent the behavior of steel bolted beam-to-column connections. The features of the two distinct approaches are compared and contrasted herein.

6.1.2.1 Mechanics-based hysteretic modeling

The finite element modeling method can be placed at the extreme end of mechanical modeling methods. The detailed finite element models have good potential to account for the complex behaviors of connections. The finite element models may represent idealized friction, slippage, contact, initial imperfection, and residual stress. However, accurate prediction of a moment-rotation curve requires computationally intensive and time
consuming 3D continuum nonlinear finite element analyses that are impractical in the analysis of large frame structures.

The component-based mechanical method offers a practical method for modeling the complex behavior of connections without the very high computational overhead that is required of the detailed finite element models. In the component-based mechanical model, the constitutive relationships of all components and their mechanical assembly are based on only material and geometric properties with theoretical mechanics considerations. The effectiveness of a component-based approach depends on the number of components and the accuracy of component constitutive relationships. Once an acceptable number of components is identified and idealized from the observed physical behavior to mathematical equations, the modeling framework is ready to be applied to different configurations of connections by only changing the dimension and/or material properties. However, the mathematical idealization of components and their assembly may often exclude some aspects of physical behavior that may be significant but are insufficiently understood. In the example of the top-and-seat angle connection with double web angles in chapter 3, the pinched hysteresis loops were effectively approximated by using the contact nonlinearity component, which was based on a completely mechanical approach. In the other example of the top-and-seat angle connection without web angles, even adding simplified slip components resulted in considerable errors because the idealized model might leave out some aspects that influence pinching effects.
6.1.2.2 Information-based hysteretic modeling

The conventional mechanical modeling process, including detailed finite element modeling and component-based modeling, involves idealization in the transition from the observed behavior to the mathematical equations representing that behavior. Idealization may often result in equations that exclude some aspects of the physical behavior that may be significant. An alternative approach is to represent the physical response based on the information contained in the observed data. In the informational approach, the information about the behavior based on the underlying mechanics is extracted directly from available analytical and/or experimental data and stored in neural networks. This implies that the neural network model does not need a pre-defined mathematical expression, in contrast to the mechanical approach. Moreover, if the modeling complexity is of concern, the neural network model is an attractive alternative approach because the primary benefit of neural networks lies in the fact 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 complex hysteretic behavior of bolted connections motivated the development of informational models with neural networks. In chapter 4, neural network modeling was examined and applied successfully to the two examples based on the mathematically-generated data and experimental data. It was not necessary to employ any mathematical expression and to make any assumptions to simplify the problem. However, the neural network model of the top-and-seat angle connection was limited to predicting only the overall response of the whole connection. It could not represent the contribution of individual components and hence does not provide an insight into the underlying
mechanics of the components. This poses problems in extended applications to other configurations and material properties.

In conclusion, 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 general use by changing the configuration and material properties. However, there are components of the deformation that are not suited to mechanical representations. This may be due to (i) the underlying theory is not available or not sufficiently developed, or (ii) the existing theory is too complex and it therefore not suitable for modeling within building frame analysis. An example of such a component of deformation is slippage at and ovalization of bolt holes. These two specific components are shown to be exceptionally challenging to model within an efficient representation for beam-column connections in frames. They are more suitable for informational models. The corollary of the above treatment is that a hybrid formation that includes the most effective mechanical and informational aspects of the complex connection behavior would be a clear option worthy of investigation.
6.2 CLASSIFICATION OF COMPONENTS IN HYBRID MODELING

In the hybrid modeling formulation, a component-based approach is enhanced by using informational components. The key stage of the hybrid modeling is the classification of the identified deformable components; be they mechanics-based or information-based components.

6.2.1 Top-and-seat angle connection

Angle connections have the most diverse deformation components among bolted beam-to-column connections. Table 6.1 and Figure 6.1 illustrate important deformation sources of a top-and-seat angle connection.

<table>
<thead>
<tr>
<th></th>
<th>Description of deformation sources in a top-and-seat angle connection</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>The top or seat angles yield first and become the main energy dissipative component, provided that the shear strength of bolts is sufficient.</td>
</tr>
<tr>
<td>2</td>
<td>The column panel zone is the other major source of deformation as well as a source of energy dissipation, if it is not excessively stiffened by continuity or doubler plates.</td>
</tr>
<tr>
<td>3</td>
<td>The contact and separation between the face of the column flange and connecting angles introduces stiffening and pinching effects into the comprehensive joint behavior.</td>
</tr>
<tr>
<td>4</td>
<td>The slippage between angles and beam flanges causes reduced moment transferring through the connection (pinching).</td>
</tr>
<tr>
<td>5</td>
<td>The bolt hole becomes ovalized if excessive stresses are concentrated on it and therefore the slip deformation increases.</td>
</tr>
<tr>
<td>6</td>
<td>The clamping force should be considered to describe contact problems including slippage and friction.</td>
</tr>
<tr>
<td>7</td>
<td>The prying effects are activated on the boundary condition of the outstanding legs of angles.</td>
</tr>
<tr>
<td>8</td>
<td>Hot-rolling process develops residual stresses of angles as well as beams and columns. In addition, geometrical imperfection is produced from fabrication processes and influences buckling strength.</td>
</tr>
</tbody>
</table>
Figure 6.1 Deformation sources in a top-and-seat angle connection

6.2.2 Classification of components of bolted connections

The identified components of bolted connections are placed on the two-dimensional chart in Figure 6.2. The connecting elements including angles and plates and column panel zone are classified as mechanics-based components, as their constitutive relationships are formulated from simple elastic and inelastic analysis using only their material and geometric properties. On the other hand, the prying action is classified as an information-based component. Although the effects can be evaluated by using a detailed mechanical approach, it requires detailed finite element models that are not suitable for a frame analysis. Since the geometric imperfection and the residual stresses are generated from the fabrication process, they have inherently large uncertainty. Pre-assumed mathematical formulations are necessary to implement these effects into a numerical analysis and they induce diverse simplifications. This feature brings the informational approach as an alternative. The contact/detachment components are effectively idealized by using simple mechanisms although they represent interaction between a column and angles. The
behavior of the modeled components sufficiently matches the reality and therefore the contact/detachment may be considered a mechanics-based component.

![Figure 6.2 Classification of components of bolted connections](image)

The slip is the most critical component that influences hysteretic behavior of bolted connections and excessive slip is directly involved with bolt hole ovalization. The components of slip and ovalization are very challenging from a mechanical viewpoint. This may be due to the complexity of approximating (i) continuously-varying slip stiffness (ii) slip load sensitivity to several parameters, and (iii) slip displacement due to ovalization. First, the derivation of the comprehensive slip stiffness is neither straightforward nor practical in building frames. The overall slip response of a connection may result from the combination of local slippage at each bolt hole. The local slip movement varies in its slip load, direction, and amount of displacement. The clamping forces at each bolt hole are different. The local slip directions may not be parallel to the
comprehensive slip direction because bolts slip at different instances. The varying directions and bolt placement results in different local slip displacements. Moreover, the slip load is computed by a slip coefficient and clamping force, which are influenced much more by factors other than fundamental material and geometric properties. A slip coefficient is indeed categorized as a system property. Unlike true material properties such as yield strength, the slip coefficient depends on velocity and interface conditions between the materials. In addition the clamping force tends to experience considerable relaxation after only a few cycles, which cannot be obtained from material properties. Another complicating consideration is that high-strength bolts are usually placed in holes that are nominally 1/16 inch larger than the bolt diameter. As a result, the theoretical maximum slip displacement that may occur prior to ovalization is 1/8 inch. However, in practical terms, the observed slip is generally less than 1/8 in, provided that more than 2 bolts are used in more than 2 bolt-lines. This might be due to misalignments inherent in the fabrication processes. In addition, accurate evaluation of the ovalized bolt hole requires detailed finite element analysis. This is not suitable for incorporation into building frame analysis. Therefore, the informational slip model could be an attractive substitute for an excessively simplified mathematical model, an empirically-fitted numerical model, or an extremely complex detailed three dimensional finite element model.
6.3 MATHEMATICAL MODELING

The hybrid modeling method employs the concept of a component-based approach. A group of mechanics-based components comprises a mathematical model within the hybrid model. In bolted connections, the connecting elements including angles, plates, and shear panel zone are possible parts of the mathematical model and their constitutive relationships are presented in this section. After constitutive relationships of the mechanics-based components are formulated as one-dimensional springs, a mathematical model using rigid bars and springs as components is assembled.

6.3.1 Shear panel zone

Shear deformation in the column panel zone contributes significantly to connection rotational behavior. The tri-linear model developed by Krawinkler et al. (1971; 1975) is employed as a shear force versus shear deformation relationship, which consists of the three performance divisions of elastic range, after column web yielding, and after column flange yielding. For further details, refer to chapter 3.4.2.

6.3.2 Angles

Angles are the most flexible components among connecting elements due to the L-shape geometry, provided that the thickness of an angle is relatively small. The constitutive relationship of angles is formulated as a tri-linear curve and kinematic hardening rule. The parameters including the stiffness and the yield strength are computed on the basis of the theory of elasticity and plastic mechanism analysis. For further details, refer to chapter 3.4.1.
6.3.3 Flange-plates

In flange-plate connections, a beam is connected to a column by using top and seat plates. Those plates are connected to the column by welding, while they are connected to the beam by bolting. The welds produce no contact issues, but the bolting brings about slip actions. Therefore, the pinching effects are developed mostly by slip behavior. This matches well with the observation of the experimental tests.

![A flange-plate connection](image)

**Figure 6.3** A flange-plate connection

The constitutive relationship of the flange-plates is derived into a tri-linear curve by using the theory of elasticity as can be seen in Figure 6.4. The net area resists tension or compression forces until one of bolt lines yields. The yielding point \((P_y, \delta_y)\) is calculated by the following equations,

\[
P_y = \text{NetArea} \times f_y \\
\delta_y = l \times \varepsilon^e
\]

(6.1)
where $f_y$ is nominal yielding strength of steel and $\varepsilon^E$ is the strain (0.0012) at yielding of steel as can be seen in Figure 6.4 (a). The initial stiffness ($K_0$) is simply computed by $P_y/\delta_y$. A hinge line develops near to the column flange and the flange then continues to deform until the strain reaches the hardening point. The transition point $(P_t, \delta_t)$ is calculated by the following equations,

$$
P_t = Area \times f_y
$$
$$
\delta_t = \delta_y + h \times \varepsilon^h
$$

where $h$ is the length of hinge on the flange-plate, which is assumed to be the distance between the column flange and the first line of bolt holes, as can be seen in Figure 6.3. $\varepsilon^h$ is the strain (0.014) at steel hardening as can be seen in Figure 6.4 (a). After this point, the ultimate stiffness is simply estimated by using the hardening ratio ($\mu$) of steel.

$$
k_u = k_0 \times \mu
$$

(a) Stress-strain curve of steel  (b) Tri-linear curve

Figure 6.4 Constitutive curve of a flange-plate
6.4 HYBRID MODELING BY USING SELF-LEARNING SIMULATION

6.4.1 Informational neural network component model

A neural network component model in beam-to-column connections represents some aspects that are not amenable to the mathematical modeling. All information-based components are candidates for the neural network component model. Additionally, if the interactions between components are significant, the combination of the identified components (regardless of which are mechanics-based or information-based components) may be developed as a neural network component model. For example, Figure 6.5 presents a top-and-seat angle connection (a) and two hybrid models (b) and (c) including different neural network component models. In the first hybrid model (b), the mechanics-based components including shear panel zone, angles, and contact/detachment form a mathematical model and the other information-based components compose a neural network component model. In the other hybrid model (c), all components related
to the connection on either the top or bottom parts are combined to form a neural network component model, which includes both mechanics-based and information-based components. This implies that the neural network is expected to learn interactions among the components as well as the superposition of all contribution of the components. In this study, the hybrid model (c) will be first used for self-learning simulation. The extracted data would contain the information based on the underlying mechanics for the entire top or bottom part. The information would be based on inherent features of bolted connections, including the highly inelastic response as well as instantaneous variability in stiffness, strength and ductility. The extracted data sets are easily extended to the application of a new sub-hybrid modeling. For example, the extracted data sets themselves are able to become reference sets for a sub-hybrid modeling, as can be seen in Figure 6.6. This process is equivalent to the hybrid model (b) in Figure 6.5.

The autoprogressive algorithm and self-learning simulation have been used to develop the neural network material model (Ghaboussi et al., 1998; Shin and Pande, 2000; Hashash et al., 2003; Hashash et al., 2006) and are extended to develop the neural

![Figure 6.6 Sub-hybrid systems](image-url)
network component model in this study. In similar fashion to the neural network material modeling, the data for the neural network component model is extracted directly from overall connection responses. The basic premise is that an underlying mechanics exists to explain the difference between the behavior of a mathematical model and the measured response of an overall connection; hence the information contained in the data is based on the underlying mechanics to describe the difference. As mentioned in the previous chapter, the difference may contain significant aspects that the mathematical model leaves out; for example, interactions between the components and highly inelastic behavior after yielding of the components.

The architecture of the neural network in force-displacement domain used in the self-learning simulation is similar to the one used in chapter 4. The examples of symbolic notation are written in the following equations,

\[ f_n = \hat{F}_{NN}\{d_n, d_{n-1}, f_{n-1}, \xi_n, \Delta \eta_n\} : \{\text{NN architecture}\} \] \hspace{1cm} (6.4)

\[ f_n = \hat{F}_{NN}\{d_n, d_{n-1}, f_{n-1}, \xi_n, \Delta \eta_n, E_{n-1}\} : \{\text{NN architecture}\} \] \hspace{1cm} (6.5)

where \( n \) and \( n-1 \) denotes the current and the previous load step.

6.4.2 Self-learning simulation framework

A self-learning simulation is adjusted to extract the component behavior, such as connecting parts, from the overall connection behavior. The self-learning simulation consists of several modules including pre-training, autoprogressive training, forward analysis, and training control techniques. The flowchart of the self-learning simulation is illustrated in Figure 6.7. The control modules of the self-learning simulation are
developed using MATLAB. The neural network training module, which is associated with pre-training and autoprogressive training, is done with NANN (Ghaboussi, et al. 1997).

The key part of the self-learning simulation is autoprogressive training, which is associated with four kinds of iterative loops: solution loop, autoprogressive cycle, load step loop, and pass loop. Pre-training and autoprogressive training are outlined for the application to beam-to-column connections and details of the self-learning simulation will be demonstrated with a simple example in the following section.

Figure 6.7 Numerical architecture of self-learning simulation
6.4.2.1 Pre-training

In self-learning simulation using the hybrid model (c) in Figure 6.5, the neural network component model is pre-trained by approximating elastic stiffness of the angle component. The pre-training sets are generated by using a mathematical model of the angle. The mathematical model may exhibit some discrepancy to the target elastic behavior, but it is usually acceptable as the initial behavior by the pre-trained neural network component model does not have to be exact. In this study, the neural network component model is initialized with the pre-training data sets covering a comparatively large elastic range as can be seen in Figure 6.8 (a). However during the autoprogessive training, only reduced elastic range is effective as can be seen in Figure 6.8 (b) because the inelastic behavior of the updated neural network model may be incompatible with the fully linearized pre-training data sets.

![Figure 6.8 Range of pre-training data sets](image)

(a) Before training phase  
(b) During training phase
6.4.2.2 Autoprogressive training

Figure 6.9 illustrates an autoprogressive cycle. In the autoprogressive cycle, two forward analyses—force controlled analysis (FCA) and displacement controlled analysis (DCA)—are conducted to generate training cases as force and displacement pairs. In FCA, a measured moment (reference moment) is applied at the control point A. The computed local force vector at each cycle is considered to be an acceptable approximation when equilibrium is considered and the correct boundary force is used. This is represented by a thin horizontal shaded line on the force domain y-axis in Figure 6.10 (a). The local displacement vectors at early cycles are considered to be poor approximations due to the discrepancy between computed and measured rotations at the control point A and are then converged. In DCA, a measured rotation (reference rotation) is enforced at the control point A. The computed local displacement vector at each cycle is considered to be an acceptable approximation when compatibility is considered and the correct boundary displacement is used. This is represented by the thin vertical shaded line on the displacement domain x-axis in Figure 6.10 (b). The local force vectors are estimated poorly at early cycles due to the discrepancy between computed and measured moments at the control point A and are then converged. The forces from the FCA and the displacements from the DCA comprise a set of complementary pairs to train the neural network component model. The newly collected training cases are temporarily added to the training database. The neural network is trained and updated with the training database. Several autoprogressive cycles repeat to gradually update the neural network component model and to achieve satisfactory agreement between deformation quantities from both the FCA and DCA. The same process is repeated at the next load increment.
until all loading history is covered. The maximum number of the autoprogressive cycles is usually given and it is denoted as NoCycle.

Figure 6.9 Autoprogressive cycles

Figure 6.10 Collection of training cases

(a) Analysis A: FCA

(b) Analysis B: DCA
Training data collection

The purpose of autoprogressive training is to find the most appropriate training cases and then to train the neural network with the collected training database. Each load step requires a certain number of autoprogressive cycles to minimize the displacement error between computed displacement from FCA and the measured displacement. The neural network is updated during the cycles but the latest training cases are saved in the training database when the cycles for the present load step are finished. The training database at load step \( n \) always contains data sets from all of the previous load steps. The process of collecting training cases is illustrated in Figure 6.11, where the independent solution loops are described by using notation of nodal force and displacement. The criterion to stop autoprogressive cycles is to check the displacement error. It is difficult to quantify the direct relationship between the displacement error and the accuracy of the neural network component model, especially when there are some measurement errors. Therefore, it is similarly effective to perform a smaller number of cycles for a step, rather than repeating many cycles with tight displacement error criteria (Hashash et al. 2003; Marulanda et al. 2004). This increases the number of passes, but also increases the chance of obtaining a realistic component model.
Solution loops

In the autoprogressive training, the equilibrium iteration of two solution loops, FCA and DCA, are performed with the Newton-Raphson scheme. Similar to conventional nonlinear solvers, at every iteration both the tangent stiffness matrices are constructed and out-of-balance force vectors are computed. The neural network component model functions like a conventional constitutive mathematical equation.

At the load step n, the tangent stiffness matrix can be formed by assembling the component tangent stiffness. The tangent stiffness ($k_{NN}$) of the neural network component is approximated by the following equations:

Figure 6.11 Collection of training cases
\[ k_{NN} = \frac{NN[d_n + \varepsilon] - f_n}{\varepsilon} \]

where, \( \varepsilon = \alpha(d_n - d_{n-1}) \)

\[ NN[d_n + \varepsilon] = \hat{F}_{NN}\{d_n + \varepsilon, d_{n-1}, f_{n-1}, \xi_n, \Delta \eta_n\} \quad (6.6) \]

\( NN[] \) is a simple form of a feed-forward calculation of the neural network and \( \varepsilon \) is a small displacement increment with the range of \( 0 < \alpha << 1 \). The force \( f_i \) at \( i \)-th iteration is computed through the neural network component model, where only the current displacement is updated and other inputs are kept constant throughout the iteration.

\[ f_i = NN[d_i] = \hat{F}_{NN}\{d_i, d_{n-1}, f_{n-1}, \xi_n, \Delta \eta_n\} \quad (6.7) \]

Table 6.2 shows how inputs of the neural network are formulated. Common input vectors are formed from the training database to calculate the tangent stiffness, while independent and different input vectors are used to calculate the out-of-balance forces.

### Table 6.2  Formulation of neural network inputs in solution loops

<table>
<thead>
<tr>
<th>Stiffness Residual</th>
<th>Residual</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>a_FCA</strong></td>
<td>[ f_n = \hat{F}<em>{NN}{d_n^a, d</em>{n-1}^b, f_{n-1}^a, \xi_n^a, \Delta \eta_n^a} ]</td>
</tr>
<tr>
<td><strong>b_DCA</strong></td>
<td>[ f_n = \hat{F}<em>{NN}{d_n^b, d</em>{n-1}^b, f_{n-1}^b, \xi_n^b, \Delta \eta_n^b} ]</td>
</tr>
</tbody>
</table>

**Pass and load step loop**

The autoprogressive cycles repeat several times before moving to the next load step. If the full range of loading history is covered—that is, one pass is finished—the saved database plays the role of pre-training data sets for the next pass. Usually, satisfactory
training requires several passes. The maximum number of passes is usually given and denoted as NoPass. In the application to model a hysteretic constitutive relationship, more than three hysteretic loops are used as reference data and each loop has at least 40 load steps. In the case of complicated hysteretic loops like pinched loops, a larger number of loops and load steps are required to obtain acceptable training data sets. The number of load steps is denoted as NoStep.

6.4.3 Details of self-learning simulation

6.4.3.1 Mathematically generated example

In order to demonstrate that the hybrid modeling is effectively characterized in beam-to-column connections and to describe the training control techniques, a hypothetical example is considered in order to replace a real experimental test. The hypothetical example is simulated with a mathematically based model. As seen in Figure 6.12 (a), a component-based model consists of two nonlinear springs for connecting elements, a linear spring for the shear panel zone, and rigid bars. The nonlinear spring is formulated with a Ramberg-Osgood type function in the hypothetical model and this will be the target component behavior to be modeled by neural networks in a hybrid model. Figure 6.12 (b) shows the simulated moment-rotation curve of the whole connection. This will be the reference data in hybrid modeling. Therefore, the self-learning simulation will extract the force-displacement relationship for the connecting component from moment-rotation reference data of the whole connection. In the next chapter, a more realistic
example is presented in which a neural network component model is trained to represent
the real complex hysteretic behavior of bolted beam-to-column connections.

![Diagram](image)

(a) Mathematically based model  (b) Simulated overall response

Figure 6.12 A hypothetical connection

In order to create the hypothetical structural response data, an analytical Ramberg-
Osgood model was used to represent the 1-D force-displacement behavior of the
connecting members:

\[
f = \frac{K_0 d}{\left(1 + \left(\frac{K_0 d}{f_0}\right)^n\right)^{\frac{1}{2}}}
\]  

(6.8)

where \(K_0\) is the initial stiffness, \(f_0\) is the asymptotic force level, and \(n\) is a shape
parameter for the curve. For computational considerations, the tangent stiffness is defined
as a continuous function of displacement. Taking the derivative of the above equation
with respect to the displacement, the following equation is obtained:
where \( K_t \) is the tangent stiffness modulus expressed explicitly in terms of displacement and the three Ramberg-Osgood parameters. The following parameter values were selected: \( K_0 = 6.65 \times 10^5 \) N/mm; \( f_0 = 2.96 \times 10^5 \) N; \( n = 2 \). This analytical model was used in a conventional non-linear analysis to compute the moment-rotation response shown in Figure 6.12 (b).

### 6.4.3.2 Neural network component model

For this example, a neural network is supposed to represent a smooth but not-pinched inelastic hysteretic behavior for the connecting components. The input layer has 5 nodes including the current axial displacement, the previous axial displacement and force, and two hysteretic parameters, and the output layer has 1 node of the current axial force. Two hidden layers are used and 15 nodes are assigned to each hidden layer. The compact description of the architecture of a neural network component model is as follows:

\[
f_n = \hat{F}_N \{ d_n, d_{n-1}, f_{n-1}, \xi_n, \Delta \eta_n \} : \{ 5-15-15-1 \}
\]

### 6.4.3.3 Elastic pre-training

Before starting the self-learning simulation, the neural network component model should be initialized. The neural network is pre-trained on a data set generated from a linear
elastic constitutive model, rather than assigning random initial connection weights. In this example, 160 pairs of pre-training cases are generated randomly by using linear stiffness (665072 N/mm), with axial displacement lying in the range of (-0.6, 0.6mm). The pre-training data set consists of 4 consecutive subsets, constructing a four-cycled response data. Each subset contains 40 training cases and is bounded by the gradually increased range as shown in Figure 6.13 (a)–(d). The overall pre-training data set is illustrated in Figure 6.13 (e) and is also illustrated as a cyclic response representation in Figure 6.13 (f). The neural network is trained through the full range of the cyclic response data until a selected error tolerance is satisfied. The connection weights are initialized randomly at the beginning and then updated during the training. Figure 6.14 shows how well the neural network has learned the linear elastic force-displacement behavior of the component, where 1000 epochs are carried out. Figure 6.15 depicts the rotation-moment curve of the connection when the pre-trained neural network component model is utilized in the analytical analysis. The inelastic behavior will then be captured through the next steps of the self-learning simulation.
Figure 6.13 Training cases of the simple example connection
Figure 6.14  Performance of pre-trained NN component model

Figure 6.15  Forward analysis of example connection using pre-trained neural network component model
### 6.4.3.4 Training mode and window size

In the originally proposed autoprogessive algorithm, all of the given number of load steps NoStep is repeated on the given number of passes NoPass. For certain types of problems, especially modeling complex behaviors where there are distinctive changes in inelastic behavior, convergence failure frequently occurs in either solution loop. If no solution is obtained within the given autoprogressive cycles NoCycle, the self-learning simulation immediately stops and cannot cover a full range of load steps.

![Figure 6.16 New training mode](image)

Table 6.3 Number of training cases in the training database

<table>
<thead>
<tr>
<th>Pass</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of training data</td>
<td>4(pre)</td>
<td>4+6</td>
<td>4+7</td>
<td>10</td>
</tr>
<tr>
<td>Step No. at failure</td>
<td>7</td>
<td>8</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>
A modified training mode is introduced here. Since the self-learning simulation is designed to evolve the neural network model and not to make it deterministic, the failure of convergence does not mean the failure of modeling. Therefore, when no solution is obtained at step k in pass 1, a new pass starts back at the first step, where the training database contains newly-collected training cases until step k-1, as well as pre-training subsets. The new pass is expected to run until step m and then the next pass restarts, replacing the training database with the latest collected sets (until step m-1) as well as the pre-training subsets. At a certain pass, the full range of load steps is covered. Several passes usually follow, where the training database excludes the pre-training subsets to avoid incompatibility with the updated neural network. The new training mode is illustrated with a simple inelastic behavior in Figure 6.16. The global reference response is described with 10 measurements. The first pass starts with 4 pre-training cases and collects 6 new training cases to update the neural network for a local component. The self-learning simulation stops at step 7 due to convergence failure in either solution loops. The forward analysis with the updated neural network does not show a good agreement with the target. Newly-collected training cases are added into the training database and the second pass runs through more load steps. In the third pass, the full range of load steps is covered and the forward analysis approaches the target. The training database now contains the latest-collected 10 training cases, but the pre-training sets are excluded. One more pass is completed to obtain more accurate results. The number of training cases stored in the training database is presented in Table 6.3. This new training mode will be used for the following applications.
6.4.3.5 Collecting techniques

Stiffness control

The bolted beam-to-column connections exhibit sudden change in hysteretic behavior due to component yielding, slip, and other geometric inelastic issues. These sudden changes frequently cause the self-learning simulation to stop because the solution loops do not converge with the partially trained neural network, which is not capable of capturing the sudden change. Two pre-defined stiffness are used to avoid unexpected non-convergence in the solution loops. They are denoted as StiffMax and StiffMin.

![Figure 6.17 Stiffness control](image)

The stiffness of the neural network component model is basically computed by Equation 6.6. However in certain cases an inappropriate stiffness may be calculated and this causes failure in solution loops. Those cases are illustrated in Figure 6.17. At early passes, the training cases may be collected with considerable error and the computed inappropriate stiffness with these data prevents the solution loop from reaching convergence. For
example, in Figure 6.17 (a), when the very gentle slope is expected in the target response curve, the training case collected at step n may produce slightly negative stiffness and then the solution cannot be obtained. In this case, StiffMin is applied instead. On the other hand, even if the training data is acceptably collected, the estimated stiffness may cause too much iteration and may therefore increase the possibility of failure in the solution loops. When sharp change is expected in the target as can be seen in Figure 6.17 (b), StiffMax is applicable instead of the estimated stiffness. In addition, StiffMax is necessary at the unloading point in Figure 6.17 (c). In the example of the simple connection, they are set as StiffMax = 665072 N/mm and StiffMin = 150000 N/mm.

Additional guide data

In order to find training cases effectively, additional guide data are introduced to train the neural network component model. The additional guide data are generated by using the estimated stiffness of the neural network model. These data are temporarily added to the training database at the present load step and newly-estimated data replace the old ones on the next load step. A small number, or none, of the guide data (≤3) are added when the target response changes smoothly, as can be seen in Figure 6.18 (a). On the other hand, a comparatively larger number of guide data are added when above stiffness control is required, as can be seen in Figure 6.18. If the additional guide data are properly used together with the stiffness control technique, they would allow the self-learning simulation to perform more effectively.
6.4.3.6 Updating type at load steps

For highly nonlinear problems, the solution loops of FCA or DCA might not converge at certain load steps. If either FCA or DCA fails at all given numbers of the autoprogressive cycles in a certain load step, the present pass of the self-learning simulation stops. This is referred to as updating type I. In this example, the Ramberg-Osgood type function creates the plateau at a largely deformed range. This may often cause the failure of FCA during autoprogressive cycles. The updating type II is proposed when dealing with this type of problem. In the updating type I each solution loop runs entirely independently, whereas the updating type II allows the two solution loops to communicate when one of them fails at all autoprogressive cycles (4 cycles in this example). For instance, when the FCA does not yield \((U^a_n, P^a_n)\) at \(n\)-th load step, FCA and DCA share \((U^b_n, P^b_n)\) from DCA for the next load step (refer Figure 6.11). This algorithmic technique is reasonable because the self-learning simulation aims for coincidence between \((U^a_n, P^a_n)\) and \((U^b_n, P^b_n)\) at an extreme pass.
Figure 6.19 Evolution in updating type I

Table 6.4 Collection of training cases in updating type I

<table>
<thead>
<tr>
<th>Pass</th>
<th>Number of converged load steps</th>
<th>Number of existing training cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>134</td>
<td>50</td>
</tr>
<tr>
<td>2</td>
<td>66</td>
<td>134</td>
</tr>
<tr>
<td>3</td>
<td>114</td>
<td>134</td>
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<td>4</td>
<td>57</td>
<td>134</td>
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<td>5</td>
<td>205</td>
<td>134</td>
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<td>6</td>
<td>59</td>
<td>205</td>
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<td>7</td>
<td>59</td>
<td>205</td>
</tr>
<tr>
<td>8</td>
<td>179</td>
<td>205</td>
</tr>
<tr>
<td>9</td>
<td>99</td>
<td>205</td>
</tr>
</tbody>
</table>
Table 6.4 presents the process of data collecting in the updating type I. The second column shows the number of load steps, where both solutions loops of FCA and DCA converge. The third column shows the number of training cases in the training database, which is taken over from one of the previous passes. Before pass 1 starts, the training database contains 50 pre-training cases. Throughout the pass, new training cases are added to the training database at each converged load step. Before pass 2 begins, the training database contains 134 newly-collected training cases through pass 1. The last column of the table represents this pass number. Until pass 5, the number of converged load steps is less than that of pass 1. This may imply that the solution loops cannot converge with the newly updated neural network model and therefore the newly-collected training cases may not be good candidates. At pass 5 the training database still keeps the data cases from pass 1. Although 205 training cases are collected and the training database is updated by being replaced with the newly-collected training cases at pass 5, the self-learning simulation does not complete the end of the final cycle within pass 9, which can be seen in Figure 6.19 (d). Figure 6.19 shows the evolution of moment-rotation curves by using the updating type I.

Similarly, Table 6.5 presents the process of data collecting in the updating type II. At pass 1, training cases are collected at all 210 load steps. The last column is often updated because the newest-collected data cases are considered more reliable. Figure 6.20 shows the evolution of moment-rotation curves by using the updating type II. The updating type II shows a relatively more effective evolution than the updating type I. Therefore, the updating type II will be used for the following applications.
Figure 6.20 Evolution in updating type II

Table 6.5 Collection of training cases in updating type II

<table>
<thead>
<tr>
<th>Pass</th>
<th>Number of converged load steps</th>
<th>Number of existing training cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>220</td>
<td>50</td>
</tr>
<tr>
<td>2</td>
<td>212</td>
<td>220</td>
</tr>
<tr>
<td>3</td>
<td>220</td>
<td>220</td>
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<td>4</td>
<td>220</td>
<td>220</td>
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<td>5</td>
<td>66</td>
<td>220</td>
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<tr>
<td>6</td>
<td>98</td>
<td>220</td>
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<tr>
<td>7</td>
<td>220</td>
<td>220</td>
</tr>
<tr>
<td>8</td>
<td>65</td>
<td>220</td>
</tr>
<tr>
<td>9</td>
<td>220</td>
<td>220</td>
</tr>
</tbody>
</table>
6.5 SUMMARY

The challenge of modeling the behavior of beam-to-column connections in steel frames lies in the inelastic responses of individual components and their interactions. Some deformation components such as angles and flange-plates can be modeled with acceptable satisfaction by using only mechanical properties, while others such as slip and ovalization are more suitable for informational modeling. In this chapter, the hybrid modeling framework is fitted for modeling the complex hysteretic behavior of beam-to-column connections.

In bolted beam-to-column connections, the mechanics-based components including angles, flange-plates, and panel zone, are modeled in a mathematical model. Through self-learning simulation, the information that the mathematical model leaves out is collected to train the informational components. A self-learning simulation framework is developed to extract the component behavior from the overall connection behavior. The collected information is stored in the neural network for the informational components. Finally, a hybrid model is ready to predict the complex behavior of beam-to-column connections.

To the end, the control modules of the self-learning simulation are developed using MATLAB. The performance of the self-learning simulation is improved by introducing several techniques; an effective formulation of the input vectors; a new training mode; stiffness control schemes; additional guide data; and an effective algorithmic updating formulation (type I). In the next chapter, series of examples will be presented to verify the hybrid models of beam-to-column connections.
CHAPTER 7 : APPLICATION EXAMPLES OF BOLTED CONNECTIONS

The hybrid modeling framework is demonstrated through a series of example applications to bolted beam-to-column connections. A simple example has already been introduced in chapter 6. In that example, an analytically-simulated test was performed with a mathematical component by using a Ramberg-Osgood-type function. The analytical results from the simulation were considered as reference data (moment-rotation pairs) by replacing a real experimental test. The mathematical components exhibit smooth non-pinched hysteretic loops and this smooth behavior is successfully modeled by using the hybrid formulation. In this chapter, three real experimental tests of bolted connections will be used for reference data and validation purposes. The behavior of informational components in the force-displacement domain will be extracted from the reference data in the moment-rotation domain. The formulated hybrid models of bolted connections will be compared to the experimental tests. Finally, the obtained hybrid model will be used to predict a newly-designed connection for which no response information exists.
7.1 HYBRID MODELS OF BOLTED FLANGE-PLATE CONNECTIONS

In past experimental research of bolted flange-plate connections, they exhibit complex hysteretic behavior. It has been observed that the slip behavior between the flange-plates and beam flanges greatly influences the hysteretic behavior. Such a connection is therefore suitable for hybrid modeling. In this section, a bolted flange-plate connection will be modeled through the developed hybrid modeling framework.

7.1.1 Bolted flange-plate connection

7.1.1.1 Experimental tests

Eight full-scale bolted flange-plate connections were tested in the Newmark Structural Engineering Laboratory at the University of Illinois at Urbana-Champaign (Schneider and Teeraparbwong, 2002). A bolted flange-plate connection labeled as BFP06 is chosen for the purpose of hybrid modeling and its validation. The specimen was designed assuming a plastic hinge forming in the flange-plates. The design process was consistent with the design process of the 1994 AISC/LRFD Specification (1994). The column (W14x145) and the beam (W24x68) were used in the specimen. Two flange-plates (25.4x254x495.3 mm) and shear tap (9.525x114.3x482.6 mm) were welded on the column flange. A490 bolts and oversized holes were used in both the beam flange and the flange-plates for the specimen. The predetermined cyclic deformation loading history was specified by the SAC Joint Venture (1997) test protocol. The yield strength and the ultimate strength are 410 (N/mm2) and 534 (N/mm2) for the column; 386 (N/mm2) and 510 (N/mm2) for the beam; 248 (N/mm2) and 400 (N/mm2) for the flange-plate. It was
observed that the slip and yielding of the flange-plates were major sources of inelastic deformation and also the panel zone distortion contributed to the inelastic behavior after the slip.

7.1.1.2 Mathematical modeling

The first step of hybrid modeling is to identify deformation sources in the bolted flange-plate connection, and to model the mechanics-based components as a mathematical model. The flange-plates and column panel zone are classified as mechanics-based components since their constitutive relationship is formulated from simple elastic and inelastic analysis using only their material and geometric properties. They are idealized by using the methods presented in sections 6.3.3 and 3.4.2, and assembled into a mathematical model as seen in Figure 7.1.

![Figure 7.1 A bolted flange-plate connection (BFP06) and the mathematical model](image)

The moment-rotation curve simulated by using the mathematical model is presented for comparison with the observation of the experimental test in Figure 7.2. There is remarkable discrepancy between them. In the moment-rotation curve of the mathematical
model, the pinching effects are not described at all. This is because the mathematical model does not include the deformation source of slip. In addition, the initial and unloading stiffness are overestimated. In this type of connection, the slip is the most critical source that exhibits the pinching effects, and in order to describe these effects the slip component will complement the mathematical model as informational components. It is noted that the shear tab is ignored because it has negligible influence on the moment-rotation behavior of the whole connection.

![Graphs showing moment-rotation curves for experimental test and mathematical model](image)

(a) Experimental test  (b) Mathematical model

Figure 7.2 Moment-rotation curves of the bolted flange-plate connection (BFP06)

7.1.1.3 Hybrid modeling by using self-learning simulation

As mentioned in the previous section, the slip contributes the most to pinching effects. Since the slip behavior cannot be described by the material and geometric properties, it is suitable to be modeled with the informational approach. In this hybrid modeling, the slip component is the target component to be modeled with neural networks. The training data

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for the neural network component model is extracted by using the self-learning simulation. The hybrid model in the self-learning simulation is presented in Figure 7.3. The hybrid model contains sub-hybrid models illustrated by shaded boxes. There are two stages of the self-learning simulation. In the first stage, the entire top or bottom parts are considered as informational components, called NN1. The self-learning simulation extracts the data for NN1. The collected data for the NN1 then become the reference data for the sub-hybrid models. The data for the NN2 can be extracted by using another self-learning simulation. In this example, the linear decomposition technique may be used for the sub-hybrid models instead of the self-learning simulation. Finally, force-displacement pairs are collected for the training data of the target component.

![Figure 7.3 Hybrid model for the bolted flange-plate connection (BFP06)](image)

Table 7.1 summarizes the details of the parameters for the self-learning simulation. NoCycle, NoStep, NoPass, StiffMax, and StiffMin are explained in chapter 6. The number of epoch at each autoprogressive cycle is denoted as NoEpochCycle; the number of epoch between passes is denoted as NoEpochPass; and the number of additional guide data is denoted as NoAGD.
Table 7.1 Parameters for self-learning simulation of the bolted flange-plate connection (BFP06)

<table>
<thead>
<tr>
<th></th>
<th>NoCycle</th>
<th>NoEpochCycle</th>
<th>NoStep</th>
<th>NoEpochPass</th>
<th>NoPass</th>
<th>StiffMax</th>
<th>StiffMin</th>
</tr>
</thead>
<tbody>
<tr>
<td>NoCycle</td>
<td>4</td>
<td>50</td>
<td>180</td>
<td>1000</td>
<td>9</td>
<td>1000000</td>
<td>100000</td>
</tr>
<tr>
<td>NoStep</td>
<td>180</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NoPass</td>
<td>9</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NoAGD</td>
<td>0–5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Structure of neural network

\[ f_n = \hat{F}_{NN}[\{d_n, d_{n-1}, f_{n-1}, \xi_n, \Delta \eta_n\} : \{5 - 20 - 20 - 1\}] \]

Scale factors of [inputs]:[output]

\[ [15\ 15\ 2700000\ 35000000\ 2300000] : [2700000] \]

First, the force-displacement data for the top and bottom parts which include both mechanical components and an informational component (NN1 in Figure 7.3) are extracted from the moment-rotation reference data of the whole connection. Before starting the training phases, the neural network is initialized by pre-training. The pre-training data are generated assuming linear elastic behavior (stiffness=1000000 N/mm) as shown in Figure 7.4 (a). The pre-training database consists of 4 consecutive cycles and each cycle has 10 randomly selected training cases, as shown in Figure 7.4 (b).
Although the neural network is initialized with a total of 40 pre-training cases, only 20 of the 40 pre-training cases are contained in the training database when pass 1 begins. After pass 2, the newly-collected training cases in the previous pass replace the pre-training cases. The process of collecting the training cases is summarized in Table 7.2. A total of 9 passes were carried out. The evolution of the moment-rotation curves of the whole connection is shown in Figure 7.5. The forward analysis of the hybrid model was performed in recurrent mode. During the 9 passes, dramatic improvements of the moment-rotation behavior are achieved even though the evolutionary rate gradually decreases. The most important behavior, including the highly pinched behavior, was successfully captured. However, there are some mismatches even in pass 9. This might be because the training cases at certain load steps are not properly collected. This can be improved by changing the control parameters of the self-learning simulation or by adding more moment-rotation data from experiments with reliability.

Table 7.2  Collection of training cases in the bolted flange-plate connection (BFP06)

<table>
<thead>
<tr>
<th>Pass</th>
<th>Number of converged load steps</th>
<th>Number of existing training cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>165</td>
<td>20 N/A</td>
</tr>
<tr>
<td>2</td>
<td>145</td>
<td>165 1</td>
</tr>
<tr>
<td>3</td>
<td>164</td>
<td>165 1</td>
</tr>
<tr>
<td>4</td>
<td>171</td>
<td>165 1</td>
</tr>
<tr>
<td>5</td>
<td>157</td>
<td>171 4</td>
</tr>
<tr>
<td>6</td>
<td>149</td>
<td>171 4</td>
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<tr>
<td>7</td>
<td>153</td>
<td>171 4</td>
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<tr>
<td>8</td>
<td>159</td>
<td>171 4</td>
</tr>
<tr>
<td>9</td>
<td>158</td>
<td>171 4</td>
</tr>
</tbody>
</table>
Figure 7.5 Evolution of moment-rotation curves in the bolted flange-plate connection (BFP06)
The training data for the target component NN2 is easily computed by using simple linear elasticity from the reference data for sub-system NN1. The training database is constructed with the training cases in the opposite loading direction from the top (a) and bottom (b) parts in Figure 7.6, respectively. Since this training data exhibits highly complicated behavior, the neural network component model is trained with the 6-input structure:

\[
f_n = \hat{F}_{NN}[\{d_n, d_{n-1}, f_{n-1}, \xi_n, \Delta \eta_n, E_{n-1}\} : \{6 - 20 - 20 - 1\}] \tag{7.1}
\]

Parametric studies about the neural network architecture are performed to obtain satisfactory accuracy and stability of the neural network. The selected neural network has 20 neurons in each hidden layer.

Figure 7.6  Training data for the target neural network component model in the bolted flange-plate connection (BFP06)
To validate the developed hybrid model, the analytically-predicted moment-rotation curves are compared with the experimental test results. In Figure 7.7, the hybrid model is capable of predicting the pinching effects with satisfaction while the mathematical model is not. The mathematical model is improved by combining the informational components, and the hybrid model is then capable of representing the aspects that the mathematical model leaves out. The neural network component model is mainly associated with representing the slip between the flange-plates and the beam flanges.
7.2 HYBRID MODELS OF ANGLE CONNECTIONS

As mentioned in the previous chapters, bolted beam-to-column connections with angles exhibit complex hysteretic behavior. They have diverse deformation components, which introduce highly pinched hysteretic loops. This is suitable for hybrid modeling. In this section, two bolted angle connections will be modeled through the developed hybrid modeling framework.

7.2.1 Top-and-seat angle connection I

7.2.1.1 Experimental tests

The reference data for the hybrid modeling is obtained from the moment-rotation response of a real experimental test. A top-and-seat angle connection of 12 test cases performed by Kukreti and Abolmaali (1999) is selected to demonstrate the hybrid modeling. These details are presented in the section 3.6.2.2.

7.2.1.2 Mathematical modeling

As previously described, the first step of the hybrid modeling is to identify deformation sources in the top-and-seat angle connection, and the mechanics-based components are modeled as a mathematical model. The angles and column panel zone are classified as mechanics-based components since their constitutive relationships are formulated from simple elastic and inelastic analysis by using only their material and geometric properties. These components are modeled mechanically in the same way as presented in chapter 3.
The stiffness enhancement as it comes into contact between the column flange and the angles is added to the mathematical model because this effect can be easily described by the resistance of column web compression. The loss of stiffness at the separation between them will be represented by the following informational model. Figure 7.8 illustrates the configuration of the top-and-seat angle connection and its mathematical model.

![Figure 7.8 A top-and-seat angle connection I and the mathematical model](image)

The moment-rotation curve simulated by using the mathematical model is presented for comparison with the observation of the experimental test in Figure 7.9. Although the mathematical model displays reasonable agreement in terms of initial and unloading stiffness, there is remarkable discrepancy from the moment-rotation curve of the experimental test. This may be due to the analytical hysteretic loops not including the pinching effects and mild deterioration of stiffness and strength. In order to describe these effects, informational components will complement the mathematical model in the following section.
7.2.1.3 Hybrid modeling by using self-learning simulation

The slippage is a key component that affects the pinched response, and slip deformation is considered to be an information-based component. In this section, the slip component is targeted for modeling by the neural networks. The training data for the neural network are collected by using the self-learning simulation. As the data from real experiments are extremely limited, the self-learning simulation is ideal for collecting the training data because it is capable of producing the comprehensive data that affects the pinched hysteretic loops. The data collected by using the self-learning simulation may contain the information about not only the slip, but also about other minor effects—including bolt hole ovalization, nonlinear contact/detachment, prying effects, residual stresses, and geometric imperfection—as the information contained in the training data are based on the underlying mechanics representing the difference between the mathematical model and the experiment.
The hybrid model in this self-learning simulation is presented in Figure 7.10. The force-displacement pairs are collected for the training of the target component NN2. Table 7.3 summarizes the details of the parameters for the self-learning simulation.

![Figure 7.10 Hybrid model for the top-and-seat angle connection I](image)

**Table 7.3 Parameters for self-learning simulation of the top-and-seat angle connection I**

<table>
<thead>
<tr>
<th>NoCycle</th>
<th>4</th>
<th>NoEpochCycle</th>
<th>120</th>
</tr>
</thead>
<tbody>
<tr>
<td>NoStep</td>
<td>168</td>
<td>NoEpochPass</td>
<td>1000</td>
</tr>
<tr>
<td>NoPass</td>
<td>8</td>
<td>StiffMax</td>
<td>1000000</td>
</tr>
<tr>
<td>NoAGD</td>
<td>0–5</td>
<td>StiffMin</td>
<td>100000</td>
</tr>
</tbody>
</table>

Structure of neural network

\[ f_n = \hat{F}_{NN}\{\{d_n, d_{n-1}, f_{n-1}, \xi_n, \Delta \eta_n\} : \{5 - 20 - 20 - 1\}\} \]

Scale factors of [inputs]:[output]

\[ [10 10 600000 4000000 450000] : [600000] \]

The pre-training data are generated assuming linear elastic behavior (stiffness = 1000000 N/mm) as shown in Figure 7.11 (a). The pre-training database consists of 4 consecutive cycles and each cycle has 14 randomly selected training cases as shown in Figure 7.11 (b).
A total of 6 passes were done in the self-learning simulation and the process of collecting the training cases are summarized in Table 7.4. At pass 1, only 20 pre-training cases were contained in the training database. After pass 2, the newly-collected training cases in the previous pass replaced the pre-training cases. As the number of passes increased, more training cases were extracted and the quality of training cases improved. In pass 5, the full range of reference loading history was covered with the updated neural network. Figure 7.12 shows the evolution of moment-rotation curves of the entire connection during the training in self-learning simulation. The forward analysis of the hybrid model was performed in recurrent mode. There are significant improvements of moment-rotation behavior through the passes. The highly pinched behavior was successfully captured in the pass 6.
Figure 7.12  Evolution of moment-rotation curves in the top-and-seat angle connection I
Table 7.4 Collection of training cases in the top-and-seat angle connection I

<table>
<thead>
<tr>
<th>Pass</th>
<th>Number of converged load steps</th>
<th>Number of existing training cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>113</td>
<td>20</td>
</tr>
<tr>
<td>2</td>
<td>80</td>
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<td>167</td>
</tr>
<tr>
<td>6</td>
<td>168</td>
<td>168</td>
</tr>
</tbody>
</table>

The training data for the target component NN2 is presented in Figure 7.13. They may contain information that is mainly about slippage and other minor inelastic effects. The neural network component model is trained with the 6-input structure and 20 hidden neurons in each hidden layer.

Figure 7.13 Training data for the target neural network component model in the top-and-seat angle connection I
To validate the developed hybrid model, the analytically-predicted moment-rotation curves are compared with the experimental test results. In Figure 7.14, the hybrid model is capable of predicting the pinching effects with satisfaction while the mathematical model is not. The mathematical model is improved by combining the informational components, and the hybrid model is then capable of representing the aspects that the mathematical model leaves out. The mentioned aspects are mainly associated with the slip between the angle and the beam flange, and other minor inelastic effects including bolt hole ovalization and separation between angle and column flange.
7.2.2 Top-and-seat angle connection II

7.2.2.1 Experimental tests

Full scale experimental tests of bolted connections were carried out by Bernuzzi et al. (1996). A top-and-seat angle connection labeled as TSC/D is chosen for the purpose of hybrid modeling and its validation. The specimen consists of a long beam stub of an IPE 300 section and a rigid counter-beam, which is regarded as a column but the deformation of column flanges and panel zone is disregarded. The loads are applied to the free end of the specimen by means of a device that transfers horizontal forces only. The loading history refers the recommendations approved by the European Convention for Constructional Steelwork (ECCS, 1986) but it allows only one cycle at the same level of displacement ratio. All bolts were grade 8.8 bolts fully preloaded according to the Italian code 4. Tension coupon tests for angles were conducted to determine the yield (313 N/mm²) and ultimate (459 N/mm²) strength.

7.2.2.2 Mathematical modelling

Similar to example I, a mathematical model was built by using only material and geometric properties. The angles are idealized to a one-dimensional and tri-linear spring. The panel zone is idealized as a linear spring with greater stiffness \( K_p \approx 1.16 \times 10^{11} N mm/\text{rad} \), as the deformability may be negligible. The component describing the contact between the angles and the column flange is idealized to a one-dimensional linear spring with stiffness \( K_{cwc} \approx 5.29 \times 10^6 N/mm \), which is
approximately 15 times greater than the initial stiffness \((K_a \approx 3.59 \times 10^5 N/ \text{mm})\) of the angle component in order to achieve negligible column deformation. A mathematical model assembling the above three components is compared to the experiment of the top-and-seat angle connection.

The moment-rotation curves of the experimental test and the mathematical model are presented in Figure 7.15. Although they display reasonable agreement in terms of initial and unloading stiffness, the hysteretic loops of the mathematical model do not include the pinching effects.

![Graphs showing moment-rotation curves](image)

(a) Experimental test  
(b) Mathematical model

Figure 7.15 Moment-rotation curves of the experimental test and the mathematical model in the top-and-seat angle connection II

### 7.2.2.3 Hybrid modeling by using self-learning simulation

In order to represent the pinching effects, a hybrid model is adopted in a similar way as in example I. Figure 7.16 is the hybrid model, where NN is the target component to be modeled by neural networks. The training data of the target component are extracted
from the moment-rotation response of the connection. Table 7.5 summarizes the details of the parameters for the self-learning simulation.

![Figure 7.16 Hybrid model of a top-and-seat angle connection II](image)

**Table 7.5 Parameters for self-learning simulation of the top-and-seat angle connection II**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>NoCycle</td>
<td>4</td>
</tr>
<tr>
<td>NoStep</td>
<td>210</td>
</tr>
<tr>
<td>NoPass</td>
<td>7</td>
</tr>
<tr>
<td>NoAGD</td>
<td>0~6</td>
</tr>
<tr>
<td>NoEpochCycle</td>
<td>100</td>
</tr>
<tr>
<td>NoEpochPass</td>
<td>1000</td>
</tr>
<tr>
<td>StiffMax</td>
<td>500000</td>
</tr>
<tr>
<td>StiffMin</td>
<td>100000</td>
</tr>
</tbody>
</table>

Structure of neural network: \[ f_n = \hat{F}_{NN}[\{d_n, d_{n-1}, f_{n-1}, \xi_n, \Delta \eta_n\} : \{5 - 20 - 20 - 1\}] \]

Scale factors of [inputs]:[output]: [8 8 200000 1350000 1530000] : [200000]

First, the force-displacement data for the top part, which includes both mechanical components and an informational component, are extracted from the moment-rotation reference data. Table 7.6 and Figure 7.17 show the progress of collecting the training cases and the evolution of moment-rotation curves of the entire connection during the training, respectively. In the first pass, 202 force-displacement pairs are already extracted as the two solution loops of FCA and DCA successfully converge at 202 out of 210 load applications.
steps. The forward analysis at pass 1, as can be seen in Figure 7.17 (a), shows an acceptable agreement with the curve of the experimental test. There is localized discrepancy at the final cyclic loop at pass 1 and 2. This might be because the neural network is not yet fully trained. The moment-rotation curves with the trained neural network for the top part do not change too much after pass 3. They are capable of exhibiting the pinching effects with excellent agreement.

Table 7.6 Collection of training cases in the top-and-seat angle connection II

<table>
<thead>
<tr>
<th>Pass</th>
<th>Number of converged load steps</th>
<th>Number of existing training cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>202</td>
<td>20</td>
</tr>
<tr>
<td>2</td>
<td>209</td>
<td>202</td>
</tr>
<tr>
<td>3</td>
<td>208</td>
<td>209</td>
</tr>
<tr>
<td>4</td>
<td>210</td>
<td>209</td>
</tr>
<tr>
<td>5</td>
<td>210</td>
<td>210</td>
</tr>
</tbody>
</table>
Figure 7.17 Evolution of moment-rotation curves in a top-and-seat angle connection II
At pass 5, all the force-displacement data for the top part are successfully extracted at all of the 210 load steps. The training data for the target component is easily computed by using simple linear elasticity. Finally, the training data obtained for the target neural network component model is illustrated in Figure 7.18, which would contain the information mainly about slippage and other minor inelastic effects.

(a)

(b)

Figure 7.18 Collected training data in a top-and-seat angle connection II

To validate the developed hybrid model, the analytically-predicted moment-rotation curves are compared to the experimental results, as can be seen in Figure 7.19. It is observed that the results of the hybrid model satisfactorily match the experimental results. In particular, the overall behaviors of both cases are characterized by the pinched shape, which are shown after the second cycle. Although the mathematical model cannot predict the pinching effects, the hybrid model combined with the information-based component is capable of representing those. However, the curve of the hybrid model is not very smooth at the points corresponding to radians -0.02 and -0.03, when the slip reaches the
face of the bolt hole and the overall responses are stiffened. This may be remedied through obtaining more reliable training data for the information-based component.

Figure 7.19  Hybrid model of top-and-seat angle connection II
7.3 NEWLY-DESIGN BOLTED FLANGE-PLATE CONNECTION

A developed hybrid connection model can be used to predict the behavior of newly designed connections that have similar yielding or failure modes. For verification purpose, another experimental test of a bolted flange-plate connection (labeled as BFP03) is selected, as seen in Figure 7.20. The hybrid model developed for the bolted flange-plate in section 7.1 is applied to predict the moment-rotational hysteretic curve of the BFP03 connection.

![Figure 7.20 A bolted flange-plate connection (BFP03)](image)

The BFP03 connection was tested in the same experimental program as the BFP06, but it was designed with the different flange-plates, column, and beam. The geometrical and material properties of both connections are presented for comparison in Table 7.7. Figure 7.21 shows the moment-rotation curve obtained from the experimental test of the BFP03. If it is compared with the moment-rotation curve of the BFP06 connection in Figure 7.2 (a), it is observed that the BFP03 connection has less flexibility in terms of the initial stiffness, but much more moment capacity in terms of the yielding strength of the flange-plates. However, they have similar inelastic deformation sources, for example: flange-plate yielding, shear panel zone yielding, and slip between the flange-plates and beam.
Figure 7.22 shows the moment-rotation curve simulated by the hybrid model of the BFP03. In this hybrid model, the different mechanical properties from the BFP06 are reflected in the change of the response of the BFP03, just like other mechanics-based models. They change the envelope curve of the hysteretic loops, which is described by the initial stiffness and yielding strength. In addition, the neural network component model for the slip contributes to the exhibition of the pinching effects. It is known that the slip force is related to the clamping force, and the clamping forces increase proportionally with the number of bolts. When applying the hybrid model to the BFP03, the force quantities of input variables in the neural network component model is scaled down by 5/8. Finally, it is proven by the comparison with the experimental results in Figure 7.21 that the hybrid model can predict the complex hysteretic behavior of the
BFP03 with acceptable agreement. It is noted that the hybrid model overestimates the pinching effects at the 5th and 6th cycles because the model is developed based on the connection using oversized bolt holes, and this example is designed with a standard bolt hole. Further self-learning simulations for the connections using standard bolt holes can improve the application of the hybrid model.
Figure 7.21  Moment-rotation curve from the experimental test of BFP03

Figure 7.22  Moment-rotation curve simulated with the hybrid model of BFP03
7.4 SUMMARY AND DISCUSSION

A hybrid modeling framework is developed for the purpose of realistic simulation. The basic premise of the developed methodology is that not all features of system response are amenable to mathematical modeling; hence considering informational alternatives. In this chapter, the potential of hybrid modeling is demonstrated in three application examples. Three actual experimental tests including one bolted flange-plate connection and two top-and-seat angle connections are used for reference data in self-learning simulations. Herein, application process and subsequent findings are summarized.

In two top-and-seat angle connections, the overall behaviors of both connections are characterized by the highly pinched shape. It is observed that the pinching is caused by the separation between angles and column flanges as well as the slip. These are suitable for informational modeling. In hybrid modeling, angles, column panel zone, and contact between column flange and angles, are idealized to a mathematical model. A hybrid model is developed by being complemented with the neural network component models, which are trained with the information that the mathematical model leaves out. The fitted self-learning simulation makes this possible. As a result, the mathematical model exhibits only smooth hysteretic behavior without pinching effects, while the hybrid model is capable of representing all important aspects including pinching effects and mild degradation in stiffness.

In a bolted flange-plate connection, the entire connection also exhibit highly pinched hysteretic behavior. It is observed that the pinching is mainly caused by bolt hole slip. In hybrid modeling, flange-plates and column panel zone are idealized to a mathematical model. Likewise, a hybrid model is developed by being complemented
with the neural network component models, which are trained with the information that the mathematical model leaves out. The comparison shows that the hybrid model is capable of representing the highly pinched hysteretic behavior. In addition, the developed hybrid connection model is used to predict the behavior of a newly-designed connection. In the hybrid model of the newly-designed connection, the physical part is remodeled with the new inputs of geometric and material properties, and the informational part is simply scaled down by $5/8$ in force quantities. It is known that the slip force is strongly correlated to the clamping force in bolting. The connection for training has flange-plates fastened with 10 bolts but the new connection has 16 bolts. Finally, the moment-rotation curve of the hybrid model is validated with that of the experimental test. The comparison shows acceptable agreement, although the slip behavior is slightly overestimated. This would improve if the hybrid model is trained with more reliable data.
CHAPTER 8: CONCLUDING REMARKS

8.1 SUMMARY OF RESEARCH

The objective of this thesis is to develop mathematical and informational models as well as hybrid mathematical-informational models that can predict the complex hysteretic behavior of beam-to-column connections. Conclusions have been given in the appropriate chapters of the thesis. Hereafter, an overview of the conclusions and their significance is given. First, two distinct approaches, namely mathematical models and informational models, are investigated and their merits and drawbacks are discussed. Next, a new approach, a hybrid modeling framework, is introduced in order to capitalize on the merits of both mathematical and informational representations. Finally, the hybrid framework is applied to modeling several beam-to-column connections to demonstrate its potential use.

8.1.1 Mathematical and informational models of beam-to-column connections

Traditionally, the analysis of steel and composite frames has been carried out by idealizing beam-to-column connections as being either rigid or pinned. Although some advanced analysis methods have been proposed to account for semi-rigid connection behavior, the performance of these methods strongly depends on proper modeling of connection behavior. In order to take advantage of semi-rigid connections in analytical assessment and in analysis for seismic design, it is necessary to accurately represent the hysteretic behavior of connections.
Two approaches are proposed in order to incorporate the complex behavior of semi-rigid connections into the frame analysis and design process. A mathematical model and an informational model are developed to represent the behavior of steel bolted beam-to-column connections. The modeling focuses on top-and-seat angle connections as they have diverse components of deformation and exhibit the most complex hysteretic behavior—including the pinching effects.

**Mathematical modeling: component-based mechanical model**

- In a component-based mechanical model, components of deformation are identified and formulated with individual force-displacement relationships. The constitutive relationships of components are derived by using only material/geometrical properties and theoretical mechanics consideration. The capability of predicting the moment-rotation relationship under cyclic loads is investigated through comparison with the experimental test results. Although the mathematical model predicts quite well envelope curves in terms of initial stiffness and yielding strength, it is not capable of capturing the pinching effects. It is observed that the pinching behavior is closely related to slip, which is not amenable to mathematical modeling.

**Informational modeling: neural network model**

- Neural networks are used to learn behavior based on the underlying mechanics directly from analytically-generated or experimental data. The informational neural network models show acceptable agreement when compared to the actual response. Adding the degradation parameter improves the neural network model, especially when modeling complex behavior. The results emphasize that neural network model
may be a good alternative to mathematical model for predicting hysteretic behavior, even where considerable pinching is observed. However, the neural network model is limited to predicting only overall response of the whole connection. It could not represent the contribution of individual components and hence does not provide an insight into the underlying mechanics of the components. This also poses problems for extended applications to connections with different configuration or material properties.

The mathematical expressions utilized in mathematical model are easy to extend to general use by changing the geometrical and material properties. However, there are components of deformation that are not suitable for mechanical representations. This may be due to (i) the underlying theory is not available or not sufficiently developed, or (ii) the existing theory is too complex and it therefore not suitable for modeling within a building frame analysis. Examples of this type of deformation component are slip and ovalization of bolt holes. They are most suitable for informational modeling. The corollary of the above treatment is that a hybrid formulation that includes the most effective physical and informational aspects of the complex connection behavior would clearly be an option worthy of investigation.

8.1.2 Development of a hybrid modeling framework

The response of a natural or engineered system is traditionally expressed in terms of mathematical equations. This mathematically based approach is referred to as mathematical modeling. The mathematical modeling involves idealization when
deducing mathematical representations from the information about the system response. Idealization may often result in mathematical equations that exclude some aspects of the system behavior that may be significant. An alternative approach is informational modeling, which constitutes a fundamental shift from mathematical equations to data that contain the required information about the system behavior. Computational intelligence methods have made this possible and effective. The informational approach also has limitations. In this study, a new hybrid modeling framework is proposed to achieve the realistic simulation of a system. The formulation of the hybrid framework is summarized as follows.

- Two distinct approaches—mathematical modeling and informational modeling—are outlined by referring to the problem solving strategies in engineering fields.
- The concept of component-based modeling is adopted in the hybrid framework. The components are classified as either mechanics-based or information-based, which are suitable for mathematical modeling or informational modeling, respectively.
- A mathematical model can be idealized using known physical laws and mathematics; for example, the strength of materials, elasticity theory, and the finite element method.
- The self-learning simulation reveals the information that is missing from the mathematical model, and the information is stored in neural networks.
- The developed hybrid model is therefore capable of representing the complex behavior of the system.

In a hybrid model, the conventional mathematical model is complemented by informational methods. The role of informational methods is to model the aspects of the
system behavior that the mathematical model leaves out. Finally, a hybrid model of the system is more effective in realistic simulations and prediction of similar future events.

8.1.3 Hybrid models of beam-to-column connections

The challenge of modeling behavior of beam-to-column connections in steel frames lies in inelastic responses of individual components and their interactions. The potential of the hybrid framework is illustrated through modeling complex hysteretic behavior of beam-to-column connections. The description of the hybrid modeling framework as applied to beam-to-column connections and the subsequent findings of application examples are summarized as follows.

- After identifying the deformation sources, mechanics-based components are modeled in a mathematical model. All of the mechanics-based components are idealized by using only material/geometrical properties and theoretical mechanics considerations.
- A self-learning simulation framework is developed to extract the component behavior, such as connecting parts, from the overall connection behavior. The data for the target component are collected through autopgressive training, which consists of two analysis sub-modules and the supervised-learning neural network. The control modules of the self-learning simulation are developed using MATLAB. Through self-learning simulation, neural network component models in the hybrid modeling framework learns the aspects that the mathematical model leaves out. The information contained in the missing aspects is represented by the difference between the mathematical model and the experiment.
• In order to improve the performance of the self-learning simulation, several techniques are introduced. First, an effective formulation of the input vectors is suggested for the feed-forward calculation of stiffness and out-of-balance forces in neural network components. Second, a new training mode is introduced along with controlling the training database from past passes. The database does not only include the newly collected training cases at the present pass but is also updated with the training cases at the pass where the maximum number of training cases are obtained among the past passes. The effectiveness of this mode is verified with application examples. Third, to improve the training performance, stiffness control schemes and additional guide data are implemented, especially when a flat region or sudden changes are expected in the target behavior. The effectiveness of these techniques is also verified through application examples. Lastly, an algorithmic updating formulation is investigated to determine a more efficient formulation of the self-learning simulation. Throughout the mathematically generated example, type II is recommended because it shows a more effective evolution than type I.

• The hybrid modeling formulation is demonstrated through a bolted flange-plate connection and two angle connections. All of them exhibit substantial pinching effects in their hysteretic behavior. In hybrid modeling, the flange-plates/angles and panel zone are idealized to mathematical models. The experimental test data are used as the reference data for self-learning simulations, which extract data for information-based components. In the case of a flange-plate connection, it is observed that slip is a major source of the pinching effects. In the case of angle connections, separation between angles and column flanges as well as slip is main source. These components of
deformation are suitable for informational modeling. Finally, the moment-rotation curves of the hybrid models are validated with those of experimental tests. The comparison shows that the hybrid models are capable of representing the highly pinched hysteretic behavior of beam-to-column connections.

- The developed hybrid connection model is used to predict the behavior of a newly-designed connection. In the hybrid model of the newly-designed connection, the mechanics-based components are remodeled with new inputs of geometric and material properties, and the information-based components are simply scaled down by 5/8. Finally, the moment-rotation curve of the hybrid model is validated with that of the experimental test. The comparison shows acceptable agreement although the slip behavior is slightly overestimated. This would be improved if the hybrid model is trained with more reliable data.

8.1.4 Summary

In this study, two modeling approaches—mathematical modeling and informational modeling—are rigorously investigated. A new method, the hybrid modeling framework is developed to achieve realistic simulation. The basic premise of the developed methodology is that not all features of system response are amenable to mathematical modeling; hence considering informational alternatives. The potential of the hybrid framework is demonstrated through modeling the highly pinched hysteretic behavior of beam-to-column connections. The hybrid methodology will be great interest to those related to the realistic modeling and simulation of complex systems.
8.2 RECOMMENDATION FOR FUTURE RESEARCH

The recommendations for future study fall into two categories. The first is related to the beam-to-column connections, and the other is related to hybrid modeling. As some issues are interrelated, they are discussed in the most appropriate place.

*Beam-to-column connections*

- Design method for frames is strongly related to the behavior of beam-to-column connections. If a beam is designed stronger than a connection, the connecting elements such as angles, flange-plates, and other elements in the connections exhibit inelastic behavior before the beam does. The behavior of connecting elements therefore governs the overall inelastic behavior of the connections. The connections employed in this study are categorized in this case. On the other hand, if the beam is designed similar to or weaker than the connections, hinge is formed on the beam beyond the end of the connecting elements and therefore the inelastic behavior of the hinge should be accounted for in the behavior of connections.

- This hybrid model can be extended to concrete-filled tube (CFT) as well as reinforced concrete (RC) connections. The configuration of CFT connections is very similar to one of the pure steel connections, but the interaction between steel tube and filled-in concrete needs to be considered. This interaction is suitable for hybrid modeling. In addition, the reinforced concrete connections exhibit highly pinched hysteretic behavior with significant degradation of strength and stiffness. Hybrid modeling may also provide a good option.
• The connection models can be improved by adding some components, such as slab. The slab normally provides a certain level of constraints to the deformability of connections, but this effect is difficult to model mechanically. This effect is also very suitable for the informational method in hybrid modeling, provided that reliable experimental tests are available.

• Shear-Flexure interaction may be an excellent fit for a hybrid modeling application. Flexure may be easily estimated with mechanics-based approach like section analysis, while shear effects can be evaluated with informational approach.

• This study focuses on the pinched behavior of connections because the pinching effects obviously reduce the energy absorbing capacity. However, this study does not fully investigate how pinched behavior of connections influences the behavior of frames. There should be an investigation as to how the pinched behavior of connections—including beam-to-column, base-plates, beam-to-beam, and column-to-column—affects the structural behavior of steel frames, especially when subjected to severe earthquakes.

**Hybrid modeling framework**

The hybrid modeling framework is developed to achieve realistic simulations of complex systems, thus enable better understanding of behavior in structures, components, and materials. The developed methodology can be extended to a broad spectrum of engineering applications. Some future studies are suggested as follows.

• In the last ten to fifteen years, Structural Health Monitoring (SHM) technologies have emerged creating an exciting new field within various branches of engineering. Although SHM technologies become increasingly common, they are worth exploring.
Measuring devices have been improving at dramatic rates and consequently the measurement has become more reliable. In order to capture the specific response of the structure, exact models are essential in addition to reliable measurement. As measured data are integrated into hybrid modeling, the model can be realistic (and therefore accurate) so that the hybrid modeling framework is an excellent fit for damage detection or updating structural properties in real-time monitoring structures.

- The hybrid modeling framework has inherent features for solving inverse problems because it is complemented by informational methods. The hybrid framework takes advantage of the difference between a mathematical model and measured data of a system. The difference would be knowledge base to identify unknown properties of the system. This demonstrates that one of the potential uses of the hybrid modeling framework is in its ability in the area of system identification.

- In general, composite materials show complex nonlinear and inelastic behaviors. As informational methods have the unique capability of learning the complex nonlinear relationships, constitutive modeling of the composite materials is suitable for hybrid or informational modeling. In addition, composite materials like fiber-reinforced plastic (FRP) have been widely used to reinforce existing structures or to retrofit damaged structures. It is worthwhile to develop a tool for estimating the change of behavior in reinforced or retrofitted structures.

The potential applications of the proposed hybrid modeling and simulation can reach far beyond the field of structural mechanics/engineering and into the fields of bio-medicine, business, and social science. Proper future development could produce a realistic
simulation of the target system in a variety of fields. As realistic (and therefore accurate) results might be a knowledge base on a more effective assessment of the system, this assessment could lead to a more economical and sustainable design of the system.
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