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Framework for Online Model Updating in Earthquake Hybrid Simulations

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Hybrid simulation has been effectively utilized to assess structural response subjected to intense dynamic loads. The process comprises dividing the structure into experimental and numerical modules. The experimental modules represent the critical components responses, which cannot be idealized reliably through analytical approaches. The responses of the different modules are combined through a stepwise integration scheme. In conventional hybrid simulations, the number of experimental components is restricted by the capacity of the test facility; usually 1–3 components, and the numerical simulation does not benefit from the information acquired from the tested component during the analysis. In this article, a framework is proposed to identify the material constitutive relationship from the tested component(s) and to update the corresponding numerical parts that share close characteristics with the physical tests. Optimization tools and neural networks are presented as alternatives for the identification procedure; the framework is however extendable and scalable. The communication protocol between the different structural components is also discussed within the proposed framework. Several analytical examples are presented to prove the feasibility of the presented framework, while experiments are used to verify the process in a companion article.

Keywords Model Updating; Hybrid Simulation; Constitutive Model; Optimization Tools; Neural Networks; Nonlinear Analysis

1. Introduction

Hybrid simulation has been widely used for structural assessment under earthquake loads. This approach provides accuracy as the critical components that show complex behavior are tested in the laboratory; meanwhile, cost efficiency is preserved where the majority of the structural components are simulated numerically [Mahin and Shing, 1985]. Hybrid simulation approach was proposed in the early 1970s [Hakuno *et al.*, 1969; Takanshi *et al.*, 1975]. Since then, it has been verified analytically and experimentally for different applications [Elnashai *et al.*, 1990; Shing *et al.*, 1984]. Due to the limited capacity of the testing facilities, the value of hybrid simulations is restricted for structures that include few critical components [Kwon and Kammula, 2013]. For such structures, it is inevitable to address the reliability of numerical model. The numerical modules idealize the actual member's response mathematically based on either theoretical understanding or empirical formulations [Kwon *et al.*, 2008]. However, this idealization is not usually sufficient to characterize the response of structures experiencing cases of intense plastic deformations or in representing crack propagations in the analyzed member [Elnashai *et al.*, 1990].

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In hybrid simulations, the accuracy of both experimental and numerical components is crucial to achieve reliable structural assessment.

Model updating approach was introduced to evaluate the response of structures that include several critical components [Yang *et al*., 2012]. During the hybrid simulation procedure, the physical specimen provides a valuable amount of information, which is traditionally analyzed after finishing the experiment. Model updating aims to utilize this information during the test through identifying some action-deformation properties from the physical component, in order to modify the behavior of the corresponding numerical parts [Hashemi *et al*., 2014]. The success of this approach requires that the source and the modified components share close characteristics [Elanwar and Elnashai, 2014]. Hybrid simulations provide some features that are suitable for the development of the model updating approach. For instance, the integration scheme is performed in a stepwise manner, which implies that incremental modifications can be performed to the numerical module. In addition, hybrid simulation experiments can be conducted at slow rates. Hence, it allows the time required to investigate the behavior of the tested specimen and to identify the parameters needed for model updating.

In this article, a framework for model updating in hybrid simulations is presented. This framework addresses the action-deformation characteristics to be updated, the identification procedure adopted for updating the model, and the communication protocols between the different components of hybrid simulation analysis. Optimization tools and neural networks are proposed as possible alternatives to identify the required model characteristics during the experiment. The scope of this work also includes verifying the proposed concept through several analytical examples. A companion article titled "Application of In-test Model Updating to Earthquake Structural Assessment" verifies the applicability of the proposed framework for actual experimental models.

2. Review of Previous Research

Model updating aims to enhance the response of the analytical platforms to approach the actual structural results. Therefore, the expression of model updating applies also for cases of calibrating the numerical model parameters based on the actual structure records [Jang *et al*., 2013]. However, this research focuses on identifying the model parameters dynamically during hybrid simulations to update the numerical modules accordingly. The review below is restricted to the specific aspect of model updating that is pertinent to the work presented in this article, and not to model updating as related to "system identification".

In 2012, Yang *et al*. introduced the concept of model updating in hybrid simulations. Whereby, Nelder-Mead Simplex Method was utilized as an optimization tool to determine the parameters governing a lumped spring model connected to the boundaries of a rigid bar. These parameters were determined such that the global restoring forces of the lumped spring match as close as possible a more complicated fiber analysis model. The results of an analytical example showed the potential of model updating to improve the accuracy of the spring model response [Yang *et al*., 2012]. In 2013, two researches utilized a similar model updating framework to modify the parameters governing Bouc-Wen hysteretic model from experimental components [Hashemi *et al*., 2013; Kwon and Kammula, 2013].

For all these studies, the results showed that model updating is an intuitive tool that can improve the response of conventional hybrid simulation applications. Nevertheless, modifying Bouc-Wen hysteretic model or updating a spring model parameters addresses the structural behavior on the global level, which impose some limitations. For instance, the source or the modified modules must be assessed as a one entity. However, if there are regions of abrupt changes in the characteristics of the analyzed module, the identified parameters will not be representative to the global behavior of the other modules. In addition, this approach does not allow for inter-element investigations, where it smears the different sources of uncertainties of the tested member. On the other hand, the constitutive relationship provides a deeper level of understating and more flexibility when selecting the appropriate source and modified modules [Elanwar and Elnashai, 2014]. The analytical constitutive models usually fail to represent actual structural response, especially in the inelastic stage [Lowes, 1999]. Moreover, the reliability of the manufacturing procedure of the analyzed specimen might impact the behavior of the constitutive relationship [Elnashai and Chryssanthopoulos, 1991]. The numerical and experimental modules in hybrid simulations are subjected to similar test environment; therefore, it is convenient to identify the constitutive relationship from the tested specimen to update the other numerical components.

3. Analytical Platform

In this section, some of the hybrid simulation features are presented. These features are integrated with the proposed model updating framework as will be shown in subsequent discussions. There are few software programs that can coordinate between the different structural modules during hybrid simulation analysis. Among others, UI-SIMCOR program is used in this research [Kwon *et al.*, 2007]. UI-SIMCOR can communicate with a number of analytical platforms. In addition, it can coordinate with multiple tested modules even if they exist in different facilities [Kwon *et al.*, 2008]. The responses of the discrete structural components are combined at the interface degrees of freedom through the stepwise integration scheme.

UI-SIMCOR offers several alternatives for user in terms of the finite element platform and the utilized time integration scheme. However, for model updating purposes some features are highlighted, which are as follows.

1. UI-SIMCOR is an open source program and hence, its subroutines are modified to dynamically exchange the constitutive relationship data required for updating the model.
2. ZeusNL is used as a nonlinear finite element platform [Elnashai *et al.*, 2002]. ZeusNL provides a robust dynamic analysis algorithm, especially for models subjected to cases of extreme loading. Moreover, its library includes various constitutive relationships for steel and concrete materials, which makes ZeusNL suitable to support various model updating applications.
3. A predictor corrector α–operator splitting technique is used as a stepwise integration scheme. This technique is a non-iterative implicit method, with unconditional stability feature [Combescure and Pegon, 1997].

ZeusNL built-in library includes different constitutive relationship alternatives. Among those, the subroutines of three steel and one concrete models are modified to support the proposed updating procedure. These models are: (1) a bilinear steel model (STL1); (2) Ramberg-Osgood steel model (STL2) [Ramberg and Osgood, 1943]; (3) Menegotto-Pinto model (STL3); and (4) a modified version of the nonlinear concrete model developed by Mander *et al.* (CON2) [Mander *et al.*, 1988; Martinez-Rueda and Elnashai, 1997]. Figure 1 shows the illustrations for the four models and the parameters that govern the behavior of each of them. These parameters are the main component that are used to update the model response during the analysis. For more details about the constitutive relationship characteristics, ZeusNL program manuals can be consulted [Elnashai *et al.*, 2002].

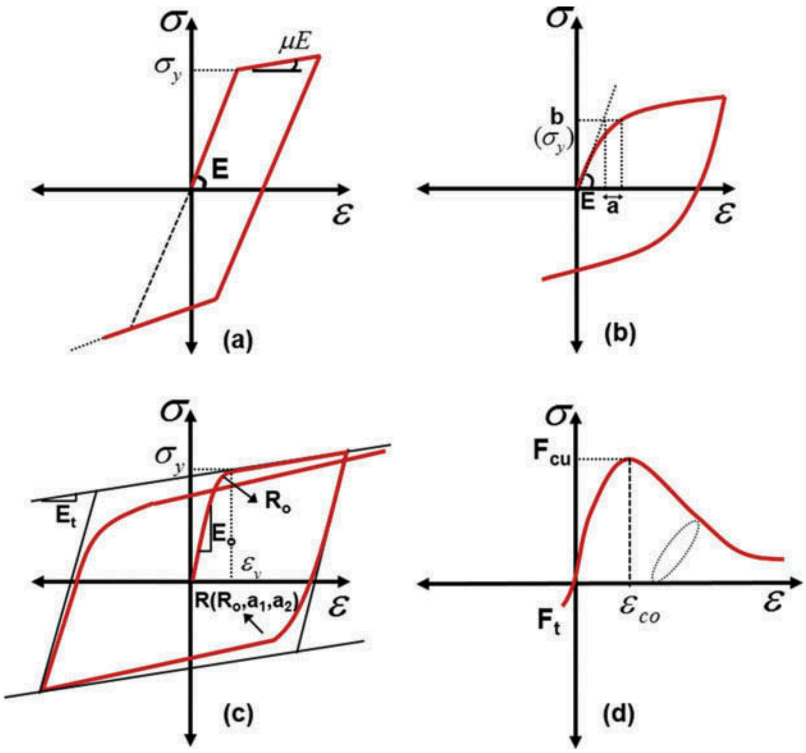

FIGURE 1 ZeusNL constitutive relationships: (a) bilinear steel model, (b) Ramberg-Osgood steel model, (c) Menegotto-Pinto steel model, and (d) modified Mander concrete model [Elnashai *et al*., 2002].

4. Methodology

Model updating requires several modifications to the conventional hybrid simulation procedure. This section will discuss the general framework of model updating, followed by two alternatives used for identifying the model characteristics. Finally, the communication protocols between the different components will be presented.

4.1. Model Updating Approach

In hybrid simulations, stepwise integration schemes are used to combine the response of experimental and numerical components. This feature provides a suitable framework to update the numerical model characteristics incrementally. Figure 2 shows a schematic diagram for the model updating procedure, which can be summarized as follows.

- The structure is divided into three modules based on their level of complexity, where a representative sample of the critical members that exerts large levels of deformations is tested in the laboratory (i.e., accurate module). Meanwhile, the modules that share close characteristics to the accurate one are simulated numerically, yet their constitutive relationships are updated incrementally during the analysis according to the information obtained from the accurate module. The rest of the structure, which is expected to behave in the elastic range, are numerically simulated without applying any updating procedure.

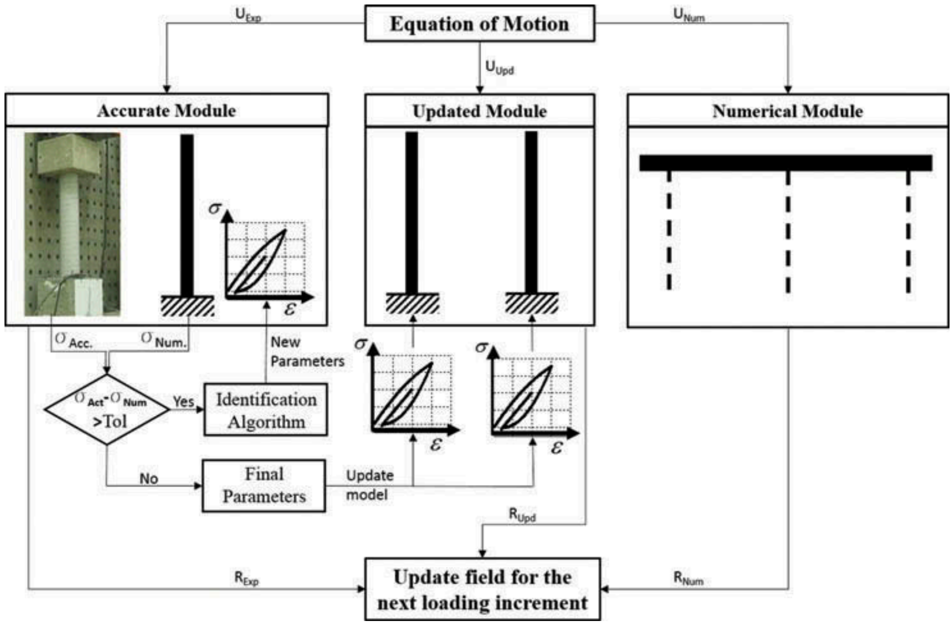

FIGURE 2 The framework of model updating approach.

- The equation of motion (stepwise integration scheme) analyzes the model properties and the restoring forces acquired from the previous loading step to determine the deformation applied in the future step. As shown in the figure, the deformations are discretized based on the modules subdivisions such that U_{Exp}, U_{Upt}, and U_{Num} are applied to the accurate, updated and numerical modules, respectively.
- For the accurate module, an auxiliary finite element model is developed. This model is used to evaluate the error in response between the accurate and the finite element model. If the error exceeds a certain tolerance, an identification algorithm is processed to determine a new set of constitutive relationship parameters. Accordingly, the constitutive relationships in the updated modules are modified based on the identified parameters. On the other hand, if the error is within the acceptable tolerance, the analysis proceeds conventionally without updating the model.
- Finally, the restoring forces evaluated from the accurate (R_{Exp}), updated (R_{Upt}), and numerical modules (R_{Num}) are recorded to be used by the equation of motion for the future loading step. The same analysis procedure is repeated at each loading increment.

As shown from the model updating procedure, the development of an auxiliary model and the identification algorithm are the main modification to the conventional hybrid simulation process. The next section will discuss the different alternatives for the identification algorithms.

4.2. Identification Algorithms

There are several identification algorithms that can be used to determine the constitutive relationship response from the accurate module. Whereby, optimization tools and neural network are adequate for model updating purposes. First, optimization can be defined as a tool that searches for the values of the decision variables (unknown parameters) that minimize a certain objective function, which is subjected to some constraints [Haftka and Gurdal, 1992]. The main components of optimization can be described within the context of the constitutive model problem such that: (1) the decision variables are the values of the parameters governing the behavior of the stress-strain model (i.e., Young's modulus, yield strength, concrete strength, etc.); (2) the constraint functions are the conditions that the identified procedure must always satisfy such as the lower and upper bound values; and (3) the objective function is the difference between the accurate and the analytically determined stress values. Minimizing this difference implies that the analytical model is behaving as close as possible to the accurate module. Equation (1) shows an example for the objective function:

$$\sum_{i=1}^{n} |\sigma_{Exp}(\mathrm{t}_i) - \sigma_{Num}(\mathrm{t}_i)|^2, \tag{1}$$

where (σ) is the stress value, (t) is the time step, and (n) is the total increments of the input load. Optimization can be classified into gradient and non-gradient (random) based optimization approaches; each of them has its own advantages and drawbacks. Gradient-based optimization requires the objective function to be continuous and differentiable. It utilizes the gradient vector and the Hessian matrix to identify search direction for the optimum solution, which makes it computationally efficient. However, the output solution of the gradient based methods depends significantly on the initial guess of the decision variables and, hence, the solution might be trapped in a local minimum. On the other hand, non-gradient based optimization searches randomly through the solution domain to determine the unknown parameters. This randomness helps in avoiding local minimum results. Yet, it requires much longer computational time compared to gradient based ones. Consequently, in large-scale problems it might not be feasible to use random based methods [Haftka and Gurdal, 1992]. In this article, interior point methods (IPM) and genetic algorithms (GA) are utilized as gradient and non-gradient based approaches, respectively. IPM is applied to convex problems and it reconstructs the objective function to include self-concordant barriers [Nemirovski and Todd, 2008]. IPM can handle sparse problem and always satisfies the constraints; also, it can recover from infeasible solutions such as complex numbers [Byrd *et al*., 1999]. GA is a random based approach motivated by nature. It depends on the fitness of the possible candidates to determine the solution rather than depending on the gradient vector [Sastry *et al*., 2005]. Therefore, this approach can be suitable for cases where the objective function is not accessible. For example, if the objective function calculations are performed in an external program, GA can be utilized as an optimization tool. Due to the long computational time requirement, GA might not be feasible for large-scale problems. However, for the considered constitutive relationships it can find the solution in reasonable time, because of limited number of the unknown parameters.

In MATLAB there is a built-in toolbox for both IPM and GA. Hence, this toolbox was utilized to confirm that the proposed approach is suitable to identify the constitutive relationship parameters. Figure 3 shows four examples for STL1, STL2, STL3, and CON2 models, where IPM was utilized to determine the analytical solution. The exact stress-strain values were generated using ZeusNL, where a single degree of freedom model was subjected to an earthquake loading.The results shows that optimization was able to identify the behavior of the four considered models. It is worth noting that the same examples were solved once more using GA and the output was almost the same as in the IPM case. The main difference is that GA required more time to determine the solution.

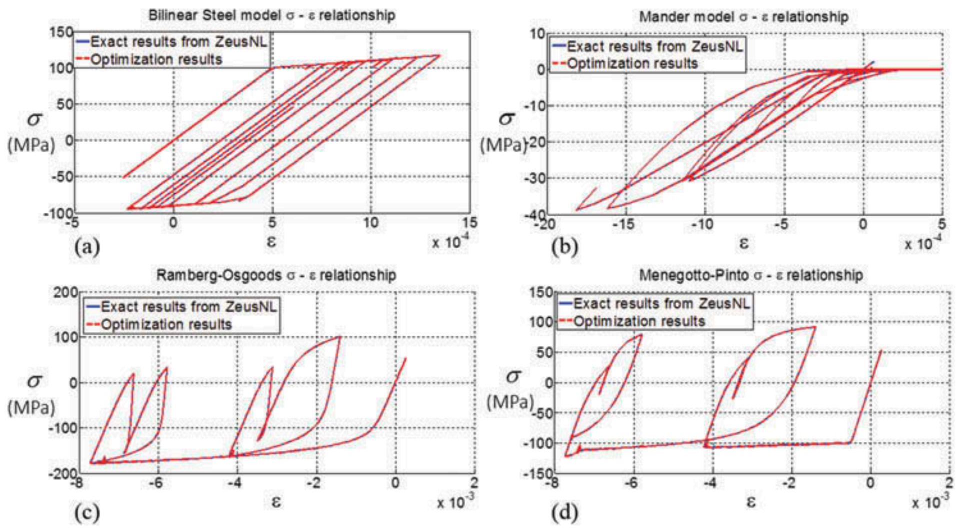

FIGURE 3 A comparison between the exact and optimization constitutive model results for: (a) STL1, (b) CON2, (c) STL2, and (d) STL3.

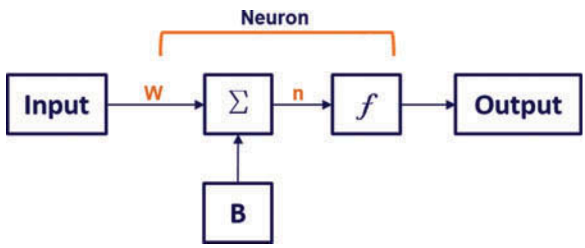

FIGURE 4 Fundamental components of a single neuron.

Therefore, IPM is used as the default algorithm for the following problems. However, GA is provided within the model updating framework, which can be utilized for future applications.

Neural network (NN) is another alternative for identifying the constitutive relationship behavior. Unlike optimization tools, NN does not require an analytical model to start from and to update its parameters. Instead, NN generates a set of mathematical formulas that connect the input data to the output results. The neural network concept was first inspired by human brain architecture, which is composed of neurons that interconnect to provide the required knowledge and skills for humans [Ghaboussi *et al.*, 1991]. The fundamental component of NN is the neuron, which can be discretized into three main elements: (1) weight factors (W); (2) biases (B); and (3) transfer functions (f), as shown in Fig. 4. The input value is multiplied by a certain weight factor, and then a bias is added to the outcome before it is activated by a transfer function [Yun *et al.*, 2007]. In general, this basic formulation of the neuron is not sufficient to handle actual engineering problems. Instead, several neurons are generated in the same layer in addition to creating a number of hidden layers. There are different techniques used to train the network. In the forward and backward propagation approach, the network is activated through providing the input parameters. The input parameters propagate forward in the network and their values are modified based on the initially assigned neuron parameters (i.e., weight factors and biases). The output is then compared to the reference solution and the error is evaluated. Gradient descent method is used to find the share of each connection of the error. The connections that are responsible for the larger portion of error are given smaller weight factors in the next iteration. Finally, these steps are applied iteratively until the stoppage criterion is satisfied [Ghaboussi *et al.*, 1991].

The capacity of the NN is determined by the number of hidden layers, the number of neurons in each layer, and the connection between them. On the other hand, the number of input and output layers is governed by the physical understanding of the problem [Kim, 2010]. In 1991, Ghaboussi *et al.* introduced a NN configuration that can evaluate the uniaxial constitutive model problem. Later, several researchers updated this approach to identify the hysteretic model behavior for different applications such as material models, moment-rotation response, etc. [Yun *et al.*, 2008a; Kim, 2010; Hashash *et al.*, 2006]. The main challenge in identifying the hysteretic behavior of a material is the one-to-many mapping problem, where for each value of strain there are several corresponding stress values and hence, the network cannot determine the correct loading or unloading path [Ghaboussi *et al.*, 1991; Yun *et al.*, 2008b]. This issue has been addressed through defining the appropriate set of input parameters. Figure 5 shows an example of a NN configuration with the input includes five parameters, which are: (1) the strain in the previous step (ε_{i-1}); (2) the stress in the previous step (σ_{i-1}); (3) the strain in the current step (ε_i); (4) hysteretic energy in the previous step ($\xi = \varepsilon_{i-1} \times \sigma_{i-1}$); and (5) hysteretic energy of the current step ($\eta = (\varepsilon_i\text{-}\varepsilon_{i-1}) \times \sigma_{i-1}$) [Kim, 2010]. The sign conventions of the described input parameters provides a distinct definition for each of the six loading/unloading paths. Therefore, the problem of one-to-many mapping is solved and the NN can be used to handle the hysteretic model problem. The network configuration shown in Fig. 5 will be utilized to identify the bilinear steel model behavior in subsequent examples. The neural network toolbox available in MATLAB is used to train the network according to the discussed procedure.

4.3. Communication Protocols

For model updating purposes, the subroutines of the simulation coordinator platform UI-SIMCOR and the finite element program ZeusNL are modified to be able to exchange the stress-strain information during the hybrid simulation analysis, as shown in Fig. 6. Although the subroutines of both programs are open source and can be directly modified. Yet, the Network Interface for Console Applications (NICA), which transfers the deformations and the restoring forces between the two programs, is inaccessible. Therefore, updating the constitutive model in ZeusNL was a challenging task. To overcome this issue

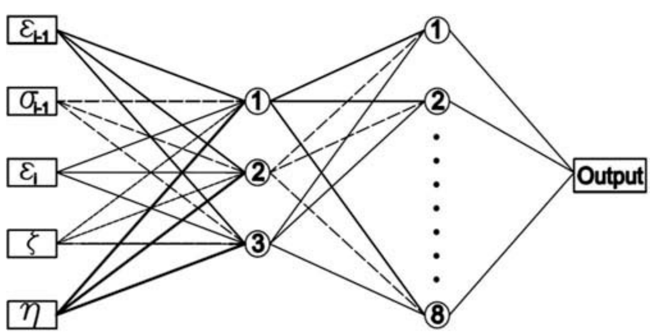

FIGURE 5 Neural network configuration used for the constitutive model problem.

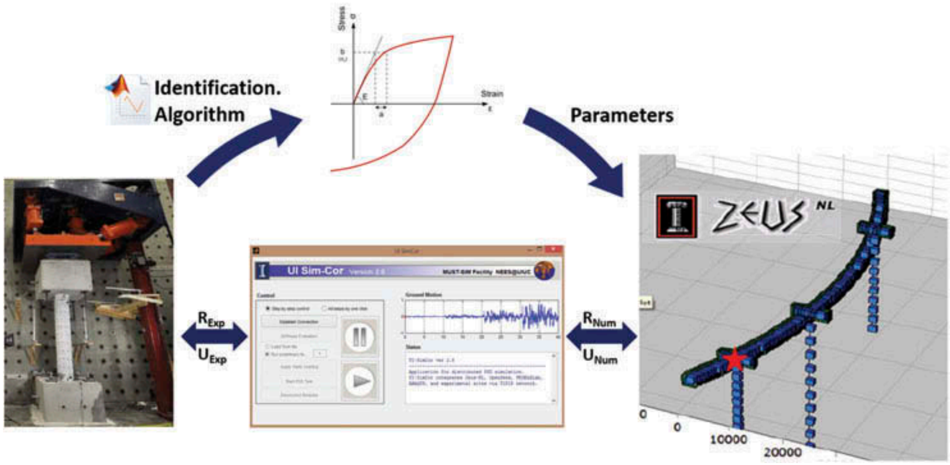

FIGURE 6 Communication protocols between the different model components in hybrid simulation analysis.

an external path was developed to identify the constitutive relationship parameters and impose them incrementally to ZeusNL. The procedure followed by this approach can be summarized as follows.

- At the beginning of the analysis UI-SIMCOR and ZeusNL run in parallel to initialize the different model components. At this stage, NICA pauses ZeusNL until the deformations applied to each module are evaluated by UI-SIMCOR.
- While ZeusNL is pending for the deformations, the identification algorithms is processed to determine the new constitutive model parameters, which are saved in the memory waiting for the next loading increment.
- UI-SIMCOR evaluates the deformations and NICA sends them to ZeusNL. Accordingly, ZeusNL reads the model parameters recoded in the memory and utilize them in the required calculations.
- The same steps are repeated at each loading increments to update the numerical model.

Inducing external algorithm to the hybrid simulation process increased the computational time slightly. This approach is adopted because NICA subroutines are not accessible. For future applications, it would be more convenient to transfer the constitutive model parameters through NICA, provided that the program subroutines are available.

4.4. Developed Program

Model updating requires several components to be modified in the conventional hybrid simulation procedure. These components include: the communication protocols to exchange stress-strain information during the analysis, modifying the subroutine of the constitutive models in ZeusNL to be compatible with the model updating procedure, and the identification algorithms used to determine the model parameters (i.e., optimization and neural networks). Therefore, a graphical user interface (GUI) program was developed to integrate the different components required for model updating. This program is user-friendly in terms of defining the input parameters. In addition, the output and feedback allows the user to evaluate the response of the analyzed modules in a stepwise manner. The input requirements includes dividing the structure into accurate, updated, and numerical modules based on the categories described in the model updating framework. Next, the user selects the constitutive relationship that is suitable for the analyzed problem. Finally, either optimization or neural network must be defined as the identification approach used to determine the constitutive model behavior. On the other hand, the output allows the user to track the identified parameters instantaneously. Hence, the updating procedure can be controlled in case illogic responses are observed. The following sections will explore several analytical problems to verify the efficiency of the proposed model updating approach.

5. Verification Examples

In this section, three numerical examples are analyzed to verify the proposed model updating framework. The objective of these examples is to evaluate the ability of model updating to improve the numerical module response. In addition, they confirm the efficiency of the communication protocols used to exchange the stress-strain information during the analysis. The first example assesses the response of a structure with irregular geometric configuration. Next, an example is analyzed to explore the ability of model updating to modify the behavior of the simple bilinear steel relationship to match a more complicated model. The last example aims to verify the neural network ability to represent the constitutive relationship behavior.

5.1. Irregular Frame

Updating the structural components on a fundamental level such as the stress-strain relationship provides flexibility in the analysis procedure. This example aims to show that the approach of updating the stress-strain relationship can be used to analyze structures even if the source and the modified modules represent different geometric and cross-sectional properties. The model designed for this problem is a two-bay one story steel frame, as shown in Fig. 7. All the members are defined through a single cubic elasto-plastic frame element, which is integrated at two Gauss points. The section of each Gauss point is sub-divided into 196 filaments. The beam is defined to be rigid, while the columns are represented by the bilinear steel model. The bilinear model is governed by three parameters, namely; Young's modulus (E), yield strength (F_y), and strain hardening factor (F). The geometric dimensions of the left column are different compared to the middle and right columns. However, the length and the cross-sectional moment of inertia are selected to yield approximately equal stiffness for the member. The figure shows the cross-sectional properties of the three columns also it shows that the middle column supports twice the mass when compared to the external columns. The frame is subjected to the North-South component of the Imperial Valley earthquake, which occurred in May 19, 1940 [Chopra, 1995]. In order to develop a model analogous to an actual hybrid simulation problem, this frame is analyzed for three different cases such as follows.

- The exact case: The bilinear model parameters (i.e., E, F_y, and F) are defined using certain values, which are assumed to represent the exact solution. The results of this case are recorded as a reference solution and they are used to evaluate the accuracy of the other two analysis cases.
- Hybrid simulation case: The left column parameters are defined using the same values assigned for the exact case. However, the parameters of the middle and right column are distorted with an error of 10%. This case resembles an actual hybrid

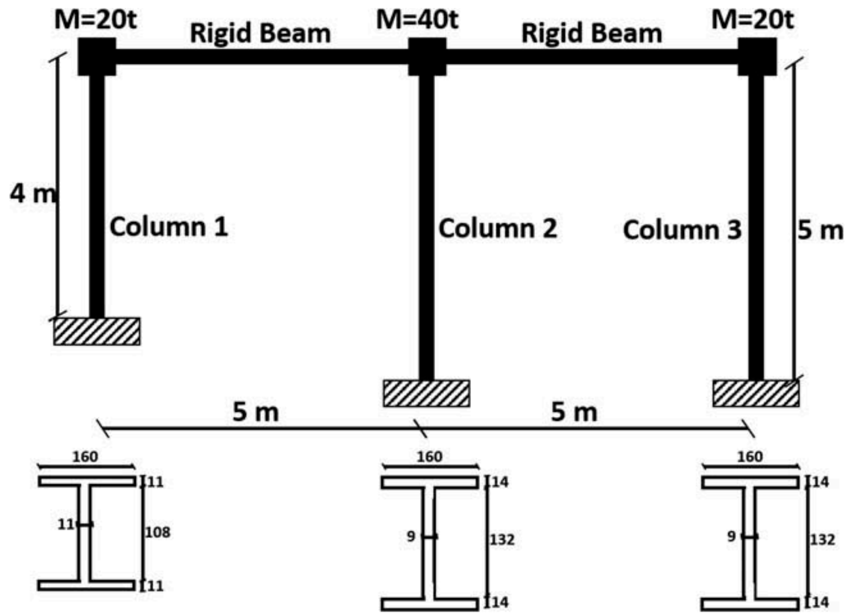

FIGURE 7 Geometric configuration and cross-sectional dimensions for the irregular steel frame.

simulation problem, where the tested column represents the accurate response (i.e., left column in this example), while the numerical components show uncertainty in their behavior. Therefore, 10% error is induced to the middle and right column to demonstrate this uncertainty.

- Model updating case: It shares the same characteristics as in the hybrid simulation case. However, the constitutive model parameters of the right and middle columns are updated instantaneously during the analysis based on the information learned from the left (accurate) component. Interior point methods is adopted as the optimization tool used identify the model parameters.

The parameters values assigned for the three analysis cases are listed in Table 1. The left column is defined in the three cases using the assumed exact parameters. For the middle and right columns, a distortion is applied to the model parameters in the hybrid simulation and updated cases. There are several criteria that can be used to evaluate the performance of the three analysis cases such as the column deformations, restoring forces, frequency response, etc. However, the response of any of these criteria reflects the accuracy of the constitutive model. Hence, in this example the deformation of the top node of the left column are used as a representative criterion to evaluate the accuracy of the different cases. It is worth noting that the top nodal displacements for the three columns are the same as the beam is defined to be rigid. Figure 8 shows the top nodal displacements of the left column against time for the three analysis cases. It can be observed that the results of the exact and the model updating case nearly coincide. Meanwhile, the response of the hybrid simulation case deviates from the exact values.

Figure 9 focuses on the error of the hybrid simulation and updated cases, where it illustrates the difference in the nodal displacements with respect to the exact case response. From this figure, a number of observations can be noted.First, model updating approach was able to reduce the error significantly even when the source and modified components

TABLE 1 Irregular frame constitutive model parameters for the different analysis cases

Module	Left Column			Middle Column			Right Column		
Parameter	E (Mpa)	F_y (Mpa)	F	E (Mpa)	F_y (Mpa)	F	E (Mpa)	F_y (Mpa)	F
Exact	200,000	140	0.10	200,000	140	0.10	200,000	140	0.10
Updated	200,000	140	0.10	210,000	160	0.12	210,000	160	0.12
Hybrid Simulation	200,000	140	0.10	210,000	160	0.12	210,000	160	0.12

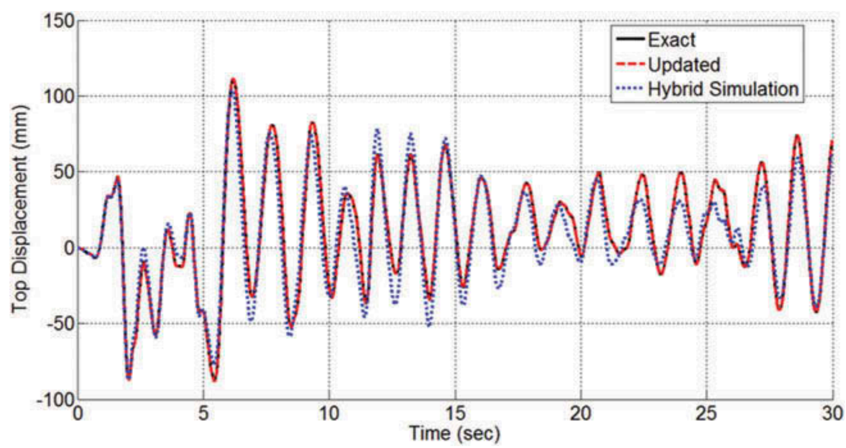

FIGURE 8 Irregular frame left column top nodal displacements for the different analysis cases.

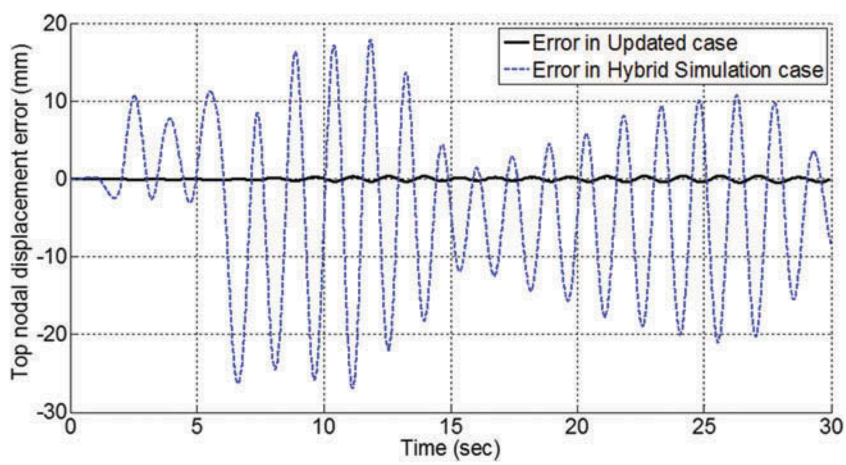

FIGURE 9 Error in the top nodal displacement of the irregular frame for the updated and hybrid simulation cases.

had different geometric properties. Quantitatively, this improvement can be expressed as the average absolute error was reduced from 8.54 mm in the hybrid simulation case to 0.17 mm when model updating was applied. In addition, the error in the model updating case kept accumulating toward the end, which is expected because any error that takes place in the model is preserved during the analysis and cannot be recovered afterwards. Consequently, updating the model at the early stages provide more reliable structural response. Moreover, it is observed that the error in the model updating case was relatively negligible. Through further investigations, it was noted that the source column (left column) was subjected to slightly higher levels of loading compared to the other columns. Hence, optimization algorithm had the precedence to identify the model parameters from the source components few steps before the modified columns approaches the same level of loading. Therefore, it is important to select the source component to be ahead of the modified ones in terms of loading.

This example highlighted two important conclusions: (1) updating the model on the constitutive level can significantly improve the structural response, even if the source and modified components have different geometric characteristics; and (2) it is important to select the source component to be ahead of the modified members in terms of loading, which allows optimization to determine the new model parameters before applying the same level of loading to the updated members.

5.2. Updating the Bilinear Steel Model

This example aims to update the bilinear steel model (STL1) parameters based on the response of the more complicated Ramberg-Osgood steel model (STL2). STL2 model is characterized by four parameters, which are Young's modulus and three other parameters that represent the best fit of experimental data. On the other hand, STL1 is characterized by three parameters as described in the previous example. In addition, STL1 function is of lower order for the elastic and nonlinear behavior compared to STL2. The objective of this example is to provide a simplified analogy to an actual model updating experiment, such that the idealized constitutive relationship in the numerical module is modified to resemble the behavior of the complicated physical specimen. Figure 10 shows the configuration of the analyzed frame. The input excitation and the procedure followed in the previous example is adopted also in this problem. However, the definition of the three analysis cases is modified, where in the exact case the three columns are represented using STL2 model. Meanwhile, in the hybrid simulation and model updating cases, the left column is defined using STL2, but the middle and right columns are represented using the STL1, as shown in Fig. 10. In the model updating case, optimization is used to modify the behavior of STL1 in a stepwise manner to approach STL2 response.

The frame was subjected to Elcentro earthquake and the results were recorded. Figure 11 shows the top nodal displacement of the left column for the three analysis cases. There is an obvious inconsistency between the hybrid simulation and exact cases. This result is expected because STL1 could not develop the same behavior as STL2. On the other hand, when model updating was applied the error was reduced considerably, especially at the peak response. The value of the peak response is of important significance in the structure engineering assessment as it might trigger a serviceability or failure limit state for the model. These results confirms that the optimization algorithm was able to identify the constitutive relationship parameters for STL1 to approach STL2 behavior.

Figure 12 shows the displacement errors in the left column top nodal displacements. The errors in the hybrid simulation case is more significant when compared to the model updating results. The average absolute displacement errors in the hybrid simulation and

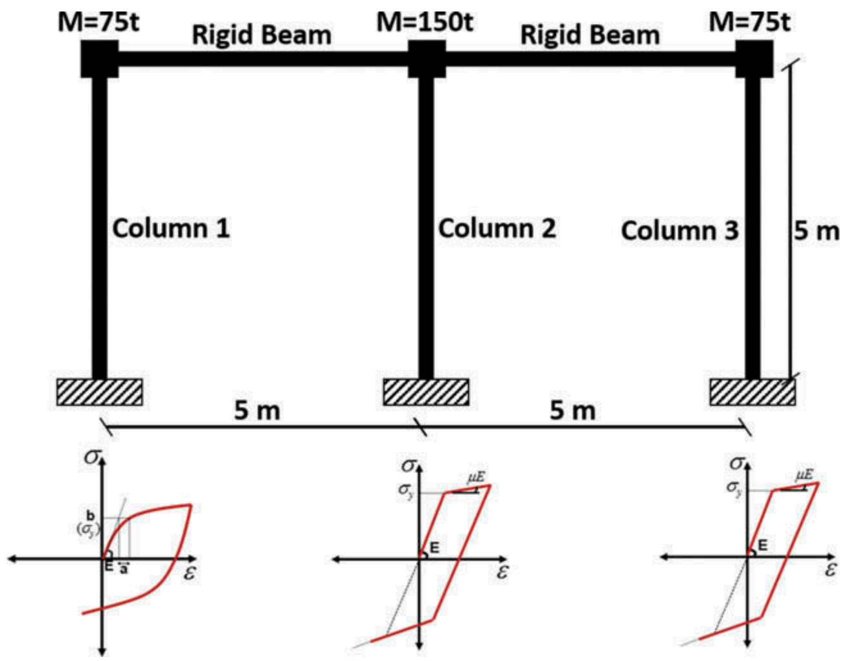

FIGURE 10 Geometric configuration of a two-bay, one-story steel frame.

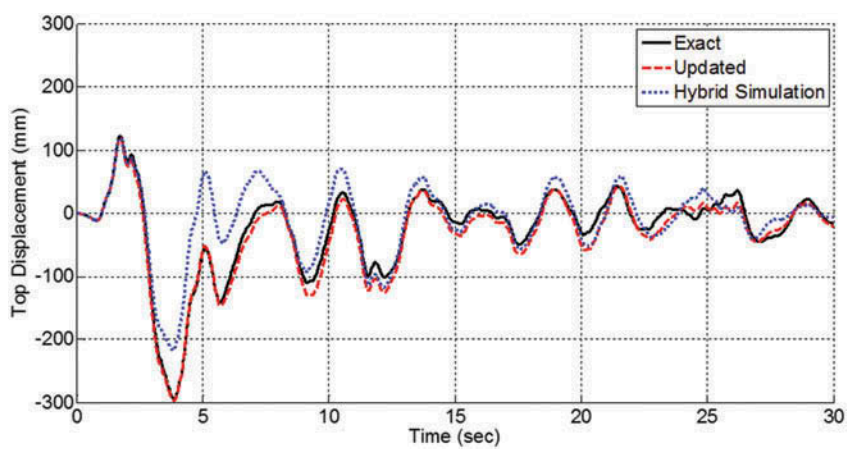

FIGURE 11 Two-bay steel frame left column top nodal displacements for the different analysis cases.

model updating cases were 12 mm and 5.1 mm, respectively. In addition, the maximum displacement error was reduced from 122.1 mm in the hybrid simulation to 24.5 mm when model updating was applied.

Figures 11 and 12 highlighted the improvement in the response on the global level of the structure when model updating procedure was utilized. However, it is important to investigate the constitutive model behavior before and after applying optimization algorithms for the different cases. Figure 13 compares the constitutive relationship for the exact and hybrid simulation cases. Figure 13b shows the results of the most stressed fiber in the

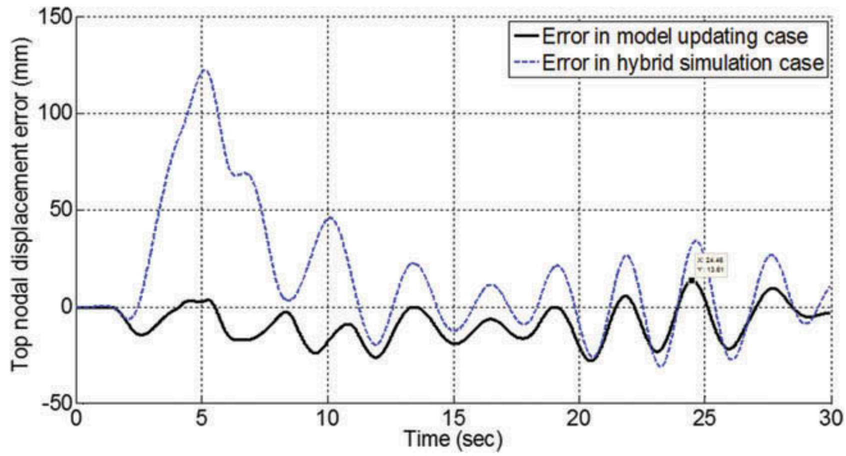

FIGURE 12 Left column top nodal displacement errors for the two-bay, one-story steel frame.

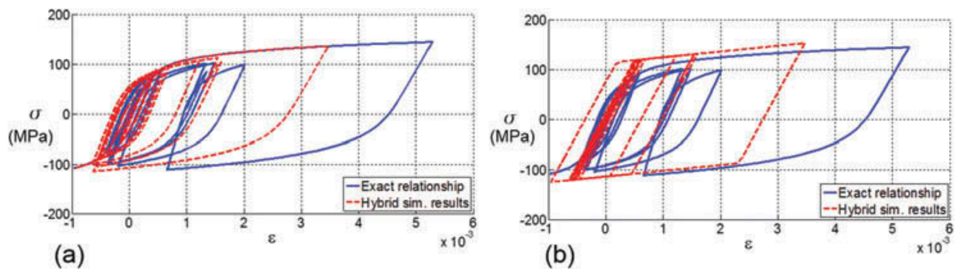

FIGURE 13 Constitutive relationship behavior for the exact and hybrid simulation cases: (a) left column and (b) right column.

right column. It is obvious that STL1 could not develop the same response as STL2 model. Meanwhile, Fig. 13a shows the response of the left column, where STL2 results were negatively impacted in the hybrid simulation analysis by the inaccurate response of the middle and right columns. This behavior is expected because the problem is inter-dependent, where the inaccuracy in any structural component affects the response of the other components.

On the other hand, Fig. 14b shows the impact of updating STL1 model parameters during the analysis. It can be observed that optimization modified the value of Young's modulus to smear the behavior of STL2 backbone curve as close as possible. Additionally, the yield strength and the strain hardening factors in STL1 were incrementally updated to approach STL2 inelastic behavior. Updating STL1 parameters in the middle and right columns had a positive effect on the response of the left column, as shown in Fig. 14a.

The analysis of this example confirmed the effectiveness of model updating to improve the numerical component response. It was also shown that the proposed identification procedure was able to reduce the gap between the behavior of STL1 and STL2 models, which was achieved through incrementally updating the constitutive relationship parameters of STL1. Finally, the results of this example confirmed that the reliability of the numerical modules cannot be overlooked during the analysis, where they have indirect impact on the response on the accurate component.

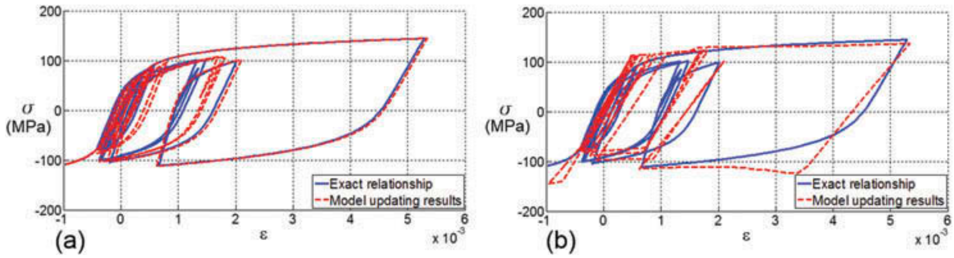

FIGURE 14 Constitutive relationship behavior for the exact and model updating cases; (a) left column and (b) right column.

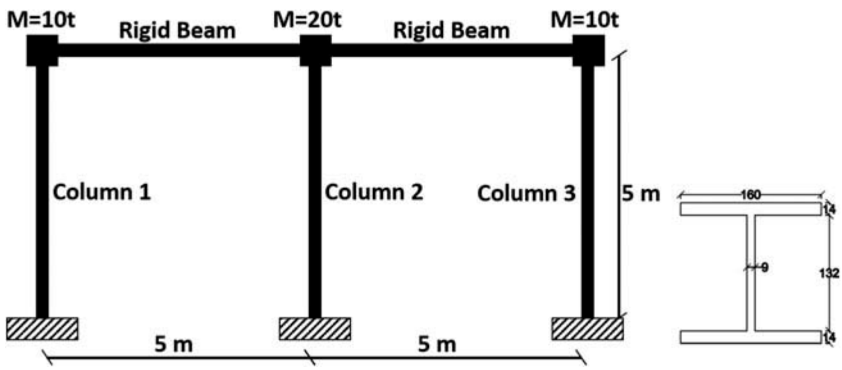

FIGURE 15 Geometric configuration of a two-bay frame analyzed using neural networks.

5.3. Neural Networks

The previous two examples applied optimization algorithms to modify the behavior of predefined constitutive relationships. On the other hand, the neural network (NN) is advantageous as it can be utilized for applications where the initial constitutive relationship is not defined. However, the NN in this example is not trained in an incremental manner as presented in the optimization approach. Instead, the network is trained according to the structural response of an entire loading history. Afterwards, the NN can be assigned to the numerical model in case the structure is subjected to a different input excitation. The procedure adopted in this example can be summarized as follows.

- The two-bay steel frame shown in Fig. 15 is subjected to an artificially generated earthquake record based on 475 years return period (ACC-475).
- At this stage, the three columns are defined using STL1 model. Then, the stress-strain data are recorded from two different fibers, which are (1) the most stressed fiber and (2) a representative fiber subjected to elastic deformations.
- The network configuration shown in Fig. 5 is utilized to train the network based on the stress-strain data recorded for the two fibers. The backward propagation approach is used to train the NN.
- In order to verify the ability of the NN to develop the constitutive model behavior, the trained network replaces STL1 model in ZeusNL. Then, the analyzed frame is subjected to a different ground motion, which is the horizontal component of Big Bear earthquake (Civic center station 6/28/1992).

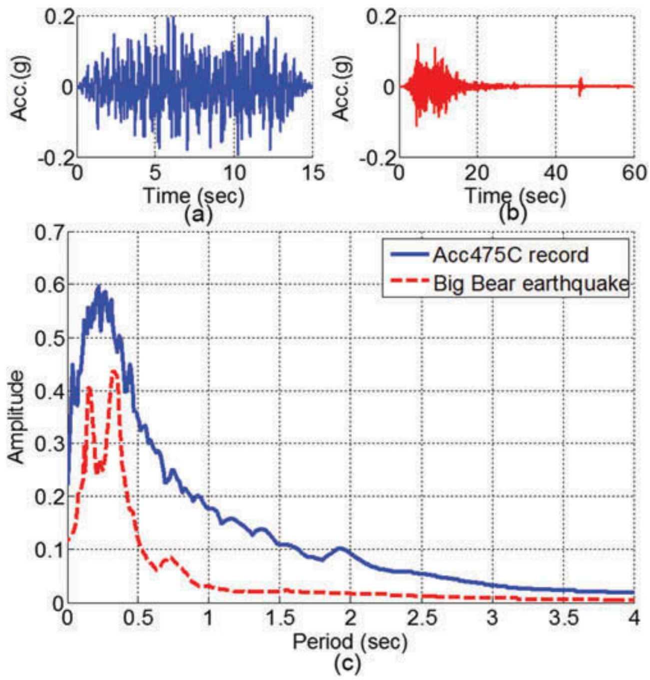

FIGURE 16 Input excitation used in the model analysis: (a) the time history for the artificially generated record, (b) the time history record for the Big Bear earthquake, and (c) the response spectrum for the two records.

The input ground motions were selected such that the artificially generated earthquake (ACC-475), which is used to train the network, includes a wide range of frequencies. Figure 16 shows the response spectrum of ACC-475 against the response spectrum of the Big Bear earthquake. Big Bear records were scaled down to confirm that its amplitude is within the envelope of ACC-475. This approach is adopted to guarantee that the input records explore the different characteristics of the analyzed frame and hence, they provide a general representation of the NN. It is important to mention that when the NN was trained based on the stress-strain data of the most stressed fiber only, it tended to curve fit the model response instead of capturing the its behavior. Therefore, another fiber subjected to elastic stresses was included to achieve a robust training process.

The network used for this example is shown in Fig. 5, which is composed of input, two hidden, and output layers including 5, 3, 8, and 1 neurons, respectively. The two intermediate layers applied a log-sigmoid transfer function, while the output layer used linear function. In actual structural engineering problems, the constitutive relationships do not strictly follow the proposed theoretical idealization. In order to have a more realistic representation for the NN model, the stress-strain data recorded from the most stressed fiber was distorted by a random noise in the order of 5% from the yield strength value. Therefore, the network was trained based on the distorted data, which added complexity to the training process. The identified network parameters were assigned to ZeusNL using the communication protocol developed for model updating. Figure 17 illustrates the results of the NN against the reference analytical solution for STL1 when the frame was subjected to the Big Bear records. It can be observed that the NN was able to capture the main features of the bilinear model. Yet, there are inconsistencies at some regions.

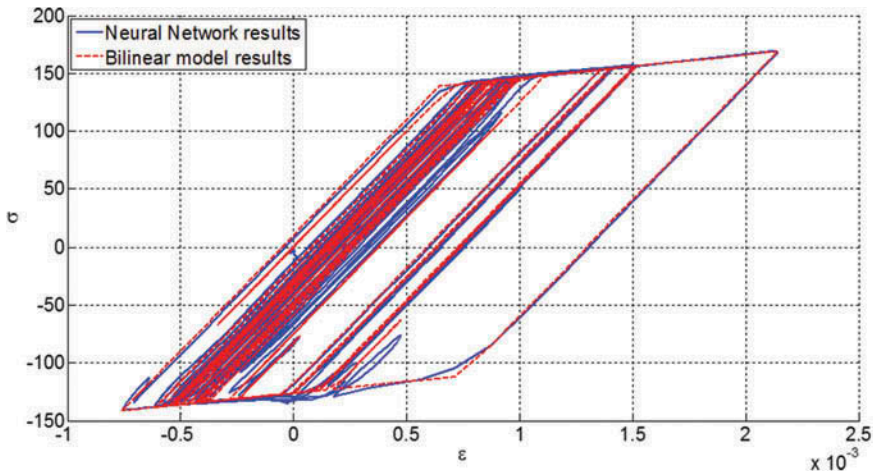

FIGURE 17 Constitutive relationship behavior for the neural network case and the reference analytical solution.

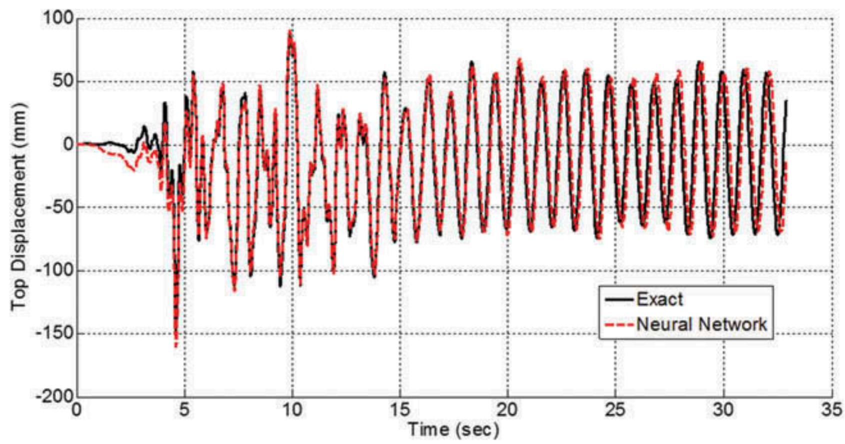

FIGURE 18 Top nodal displacement of the left column for the exact and neural network cases.

In order to evaluate the NN response on the global level, Fig. 18 shows the top nodal displacements of the left column when the frame was subjected to Big Bear earthquake record. The figure compares the displacements using the identified NN against the reference STL1 response. It can be noticed that the pattern and the amplitude of the NN results are consistent with the accurate structural response. There is a phase shift in the displacement values, especially near the end of the time history record. This behavior can be justified as the NN constitutive model did not match exactly with STL1 relationship, which affected the modal characteristics of the structural response.

This example showed that NN can be used to determine the constitutive relationship behavior for cases where the initial analytical model is not provided. The NN was able to capture the main features of the constitutive model, even after distorting the raw stress-strain data with noise. It is worth noting that the errors were almost negligible when the raw stress-strain data was used to train the network. However, noise was added to represent a more realistic case, where the actual records do not strictly follow the analytical idealizations. Finally, it is important to mention that the network was trained based on the full history of a different input loading. For actual applications, the NN can be trained based on the response of the components of auxiliary experiments that share close configuration to the considered hybrid simulation test. However, in future work it would be more convenient to modify the neural network framework to update its characteristics in a stepwise manner during the analysis.

6. Summary and Conclusions

In this article, a framework for updating the numerical model during hybrid simulations was presented. This framework provided several alternatives for the user to select the appropriate constitutive relationship and identification procedure to fit the case being considered. In addition, the communication protocols between the different structural components during the analysis were presented. Model updating aims to identify the constitutive model parameters from the accurate structural component to update the corresponding numerical parts. Hence, the scope of the work included verifying the proposed model updating concept through analyzing several numerical problems. The main conclusions from the presented work are summarized as follows.

- In earthquake assessment using hybrid simulation, the structural response is characterized by the behavior of both experimental and numerical modules. If the number and influence of the analytical components is much larger than the physically tested parts, hybrid simulation loses its claim to better accuracy.
- A procedure for model updating of the numerical components using instantaneous information obtained from the physical tests has been developed and verified as an approach that has the potential to considerably improve the accuracy of the overall hybrid simulation results.
- Updating the constitutive relationship of the model provides flexibility in the analysis framework, where the source and the modified components do not need to share all geometric and loading conditions.
- Optimization tools have the capacity to modify the behavior of parametric constitutive relationships to closely match complex structural behavior.
- Neural networks has the ability to represent the accurate constitutive models. However, in this research the network was not trained in a stepwise manner. For future applications, more advanced neural network techniques can be utilized to update the model incrementally.

Model updating has been introduced as an approach that can greatly improve the accuracy of analytical components in the conventional hybrid simulations. In this article, the feasibility of the framework has been confirmed through analyzing several numerical examples. In a companion article, the framework is verified by re-assessing complex conventional hybrid simulation results and showing the accuracy payoff of its deployment.

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