Surrogate Models for Hysteresis Response Prediction of Steel Braces under Seismic Loading

by

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Abstract

Numerical simulation is extensively used in advanced analysis of structures under seismic loading. Even though computational power and solution algorithms have advanced over the years, response evaluation of complex structures using numerical methods can still be challenging due to high computational cost, uncertainties associated with material properties, boundary conditions and numerical elements, access to advanced commercial software packages, and lack of scalability. The development of advanced techniques, including machine learning (ML) methods, along with abundant extensive laboratory test data linked to diverse structural elements, has opened new avenues for structural analysis. These methods offer potential solutions to the problems encountered in numerical simulation.

This M.Sc. thesis aims to develop data-driven surrogate models for the prediction of nonlinear hysteresis response of braces in steel concentrically braced frames and steel buckling-restrained braced frames under seismic loading using artificial neural networks powered by the long short-term memory (LSTM) algorithm. These surrogate models are intended to be used in nonlinear seismic analysis of steel braced frame structures. The data-driven models are designed using two approaches: 1) the first approach estimates the hysteresis response parameters of the brace using LSTM architecture trained on laboratory test data and synthetic numerical data of steel braces, namely tensile yielding force capacity, compressive buckling and post-buckling capacities are estimated using the surrogate models. 2) the second approach expands the application of the proposed LSTM model to predict the complete axial load time history of steel braces using transfer learning methodology leveraging the knowledge learned by the initially trained LSTM model. The surrogate models developed using these approaches are validated using laboratory and synthetic data. Particularly, static analysis of isolated braces and pseudo-dynamic hybrid simulation of a complete steel braced frame structure subjected to earthquake accelerations are performed.

The findings suggest that the proposed surrogate models offer a computationally efficient technique with sufficient accuracy to conduct both nonlinear static and nonlinear dynamic analyses of steel braced frame structures under seismic loading. Moreover, the application of transfer learning, as an innovative approach for nonlinear hysteresis prediction in steel structures, is demonstrated to bypass the complexity associated with constructing response prediction surrogate models.

Preface

This thesis is an original work of Sepehr Pessiyan. A preliminary version of Chapter 3 has been accepted as Pessiyan, S., Mokhtari, F., and Imanpour, A. “Artificial Neural Network-Based Hysteresis Model for Steel Braces in Concentrically Braced Frames” to be published in *Proceedings of the 2023 CSCE annual conference,* Moncton, NB Canada, May 2023.

Chapters 3 and 4 will be submitted to a journal as Pessiyan, S., Mokhtari, F., and Imanpour, A. “Prediction of Hysteresis Response of Steel Braces Using Long Short-Term Memory Artificial Neural Networks,’’ and “Transfer Learning-based Neural Networks for Hysteresis Response Prediction of Steel Braces,” respectively.

Sepehr Pessiyan as the main author was responsible for developing the methodology, collecting data, performing computations, analyzing the results, and drafting the manuscripts. Ali Imanpour and Fardad Mokhtari supervised the findings of this work and provided critical feedback. Ali Imanpour reviewed the manuscripts.

All data, models, or codes supporting the findings of this study, which were developed by the author of this thesis, are available from the author and the supervisor upon reasonable request after the publication of the mentioned journal papers.

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Abbreviations

1D-CNN: One-Dimensional Convolutional Neural Network.

AI: Artificial Intelligence.

ANN: Artificial Neural Network.

BRB: Buckling-Restrained Brace.

BRBF: Buckling-Restrained Braced Frame.

CBF: Concentrically Braced Frame.

CNN: Convolutional Neural Network.

Conv-LSTM: Convolutional Long Short-Term Memory.

DNN: Deep Neural Network.

FEM: Finite Element Method.

GMP: Giuffrè-Menegotto-Pinto.

HSS: Hollow Structural Section.

LSTM: Long Short-Term Memory.

ML: Machine Learning.

MLP: Multilayer Perceptron.

MSE: Mean Square Error.

PhyCNN: Physics-Guided Convolutional Neural Network.

PsDA: Pseudo-Dynamic Analysis.

RNN: Recurrent Neural Network.

SVM: Support Vector Machine.

Chapter 1
Introduction

1.1 Background

In recent years there has been a notable increase in the demand for complex structures characterized by unique designs and intricate systems, particularly in response to the imperatives of architectural aesthetics and the growth of the population [1]. Structures must be analyzed properly to ensure the safety of occupants and minimize potential economic losses associated with natural hazards such as earthquake damage [2]. Among the analysis methods, dynamic analysis stands out, especially in regions with a higher probability of earthquakes. Various methodologies are used to address dynamic analysis: numerical simulation, laboratory experiments, and the recently developed data-driven approaches.

Numerical simulation is a vital and powerful tool, facilitating a virtual platform for the analysis of structures. This technique involves the application of computer-based methods and mathematical modelling to calculate the response of structures. The finite element method (FEM) is one of the powerful numerical techniques that has been extensively utilized in structural engineering for the analysis of structures [3]. The core principle involves employing a meshing system to dissect the study's subject into smaller, more manageable elements, thereby simplifying the analysis. Although FEM analysis is known for its accuracy and reliability, there are certain scenarios where it may face some challenges. These could include convergence problems when modelling structures with extremely nonlinear materials or mesh distortion during substantial deformations, as well as an overall rise in computational expenses.

When the results of numerical simulations are unreliable, an alternative approach is to conduct experimental tests in the laboratory. During tests for lateral loadings, a quasi-static cyclic loading can be applied to assess the behaviour of seismic-resistant elements. Shake tables can also be used to simulate random lateral loads, which helps in measuring the response of various structural elements to earthquake forces. Compared to numerical simulations that are virtually modelled with lower cost and time investment, experimental testing demands extensive preparation and significant financial resources to yield precise results. Therefore, while valuable, laboratory testing is not always the optimal solution especially when the nonlinear response of multiple elements is required in complex structures.

For decades, laboratory testing and numerical simulations have been the main tools in structural engineering, allowing researchers to analyze elements under diverse loading conditions and geometry. The vast amounts of data generated by these methods in past decades have been underutilized. However, due to the development of data processing techniques and powerful computing capabilities, the emergence of data-driven approaches has been made possible [4]. With the help of previous findings, researchers can develop data-driven models to predict future scenarios that the structure can experience. Furthermore, with the advancement of machine learning (ML) and artificial intelligence (AI), data-driven models have been widely used in applications such as structural health monitoring [5], design optimization [6], and response prediction of structures under seismic loads [7]. A novel advancement in this area is the concept of hybrid simulation, which merges data-driven models with traditional experimental tests and numerical simulations. Structural engineering hybrid simulation includes real-time and pseudo-dynamic methods [8]. In this setup, one or multiple components of the model, such as a brace, are represented by a data-driven model, while the remaining elements are either tested experimentally or simulated using FEM software. The flexibility and versatile application of data-driven models offer significant advantages, notably the acceleration of experimental or simulation processes and substantial reductions in time and costs. This capability allows researchers to study more complex structural scenarios, including those involving extreme loading conditions that might be impractical or cost-prohibitive through traditional testing or simulation. While some researchers are skeptical about trusting the results when applying data-driven approaches, the undeniable progress and contributions of these methods in recent years suggest a growing shift away from relying exclusively on traditional methodologies.

In the analysis of structural elements, it is crucial to assess the hysteresis response. Simulation of the hysteresis response of structural elements allows researchers to comprehend their nonlinear characteristics, such as stiffness and strength degradation, residual deformations, and energy dissipation. The hysteresis response of steel braces, part of steel concentrically braced frames, is of interest in seismic engineering as these elements are expected to yield and buckle under seismic loading and develop hysteresis energy.

1.2 Problem Statement

Three features, including 1) reliability of structural response, 2) financial constraints, and 3) time efficiency should be considered when selecting an analysis method for hysteresis response assessment of steel braces. Each of the traditional analysis methods (laboratory testing and numerical simulation) possess advantages and disadvantages. Laboratory testing offers valuable insights into material behaviour and real-world structural interactions. However, it can be expensive, time-consuming, and limited in its ability to replicate complex loading scenarios or large-scale structures. Numerical simulation provides a versatile tool for analyzing diverse loading conditions and complex geometries. The accuracy of results depends heavily on material models, element types, and assumptions regarding boundary conditions. Additionally, complex simulations can be computationally expensive. Recent advancements have brought forth data-driven modelling as a potential alternative [9]. The data-driven model leverages existing laboratory datasets or corroborated numerical simulation results. This approach offers advantages in terms of cost and time efficiency. The accuracy of data-driven models is inherently tied to the quality and quantity of the training data. Furthermore, data-driven models may struggle to generalize to scenarios not encountered during training, potentially leading to unreliable predictions for novel loading conditions or structural configurations. A relative comparison between these three response assessment alternatives is presented in Fig. 1.1.

This M.Sc. thesis investigates the potential for a more comprehensive approach to the nonlinear structural response assessment of steel braces. By combining the accuracy and reliability of traditional methods with the efficiency of data-driven modelling, this research aims to develop steel brace data-driven models that can address the challenges of the current structural analysis methods. This thesis identifies and addresses two main challenges.

The first challenge lies in developing robust data-driven models for steel braces under cyclic loading. Available datasets on steel braces are limited, and most are not publicly accessible, making it a challenge for data-driven surrogate modelling of steel braces, which require diverse datasets. Furthermore, experimental testing, while reliable, is not always feasible. The data-driven solutions are designed to learn the governing physical phenomena of the structural response to ensure accurate prediction of a response without the need for constant refinement.

The second challenge concerns the adaptability and scalability of data-driven models to new scenarios. A data-driven model of steel braces is constructed on a predefined distribution of data, meaning the geometry, and load type of the datasets used in the process of training and validating the model are consistent. This feature makes it burdensome for the proposed model to be applied to other types of braces or loading conditions. Also, building new models often requires significant re-training or re-modelling for each new case study, leading to an increase in costs, and modelling time. Hence, a framework should be developed to create the possibility of adjusting an existing steel brace model by transferring its knowledge of hysteresis response prediction to the new data-driven model that is developed for the new scenario, thereby solving the burden of the re-modelling process.

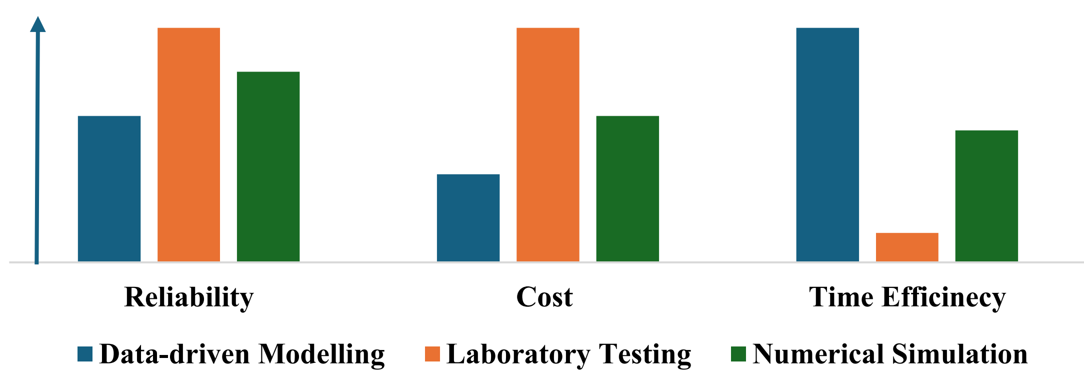

Fig. 1.1. Relative comparison of the three structural response assessment methods.

1.3 Research Objectives

This M.Sc. project aims to develop data-driven models for response prediction of steel braces of concentrically braced frames (CBFs) to enhance the nonlinear analysis of CBF systems. The specific objectives of this project are as follows:

1) Develop data-driven models using machine learning techniques to predict the hysteresis response of steel braces under cyclic loading (Chapter 3).
2) Develop a method to expand the input data for better feature extraction when limited brace data is available for training and validation of the model (Chapter 3).
3) Propose a machine learning framework to transfer the knowledge of a steel brace hysteresis response from one model to another with similar but different characteristics, without undergoing a complete reconstruction of the data-driven model (Chapter 4).
4) Perform static and pseudo-dynamic analyses under earthquake vibrations using the proposed models to demonstrate the application of brace data-driven models (Chapter 4).

1.4 Research Methodology

To achieve the objectives of this project, two main phases are studied:

Phase 1: Artificial neural network (ANN)-based models that utilize the long short-term memory (LSTM) algorithm are employed to extract the hysteresis response of steel braces when subjected to cyclic loading. The primary challenge is to overcome the scarcity of laboratory datasets for steel braces and to propose an optimal LSTM network that can identify the temporal dependencies of the nonlinear response. To validate the proposed data-driven model, experimental tests and numerically simulated data are used. The data-driven model extracts key design information about the steel brace, including tensile yield strength, buckling strength, and post-buckling capacity.

Phase 2: The proposed LSTM model is implemented in the framework of pseudo-dynamic analysis (PsDA) of a steel braced frame. The LSTM model of Phase 1 is used to construct the foundation of the model in Phase 2 using the transfer learning (TL) approach. This phase is intended to demonstrate the adaptability of the model, inherited from Phase 1, to alternative scenarios with minimal adjustments and reduced time investment.

1.5 Organization

This M.Sc. thesis is organized as follows:

Chapter 1 provides information on the background, problem statement, research objectives, and research methodology.

Chapter 2 reviews past literature on simulation methods for the hysteresis response of structural elements, and machine learning techniques used for structural response prediction.

Chapter 3 proposes and verifies the LSTM approach for data-driven modelling of steel braces under cyclic loading. This chapter, under the title "Prediction of Hysteresis Response of Steel Braces Using Long Short-Term Memory Artificial Neural Networks'' will be submitted to a journal.

Chapter 4 develops a framework using TL to predict the hysteresis response of steel braces under earthquake ground motions. This chapter, under the title "Transfer Learning-based Neural Networks for Hysteresis Response Prediction of Steel Braces" will be submitted to a journal.

Chapter 5 presents a summary, research contributions and conclusions, limitations, and recommendations for future studies.

A summary of the LSTM model developed in Chapter 3 is presented in Chapter 4 to help readers navigate the enhanced data-driven model in Chapter 4.

Chapter 2

Literature Review

2.1 Introduction

This chapter provides a review of past literature that focuses on the simulation of hysteresis responses of structural elements. The chapter explains the different models used for deriving the hysteresis response of structural elements, including mathematical and data-driven models. It also introduces the latest research trends in each of these methods. As this thesis mainly focuses on the data-driven approach, the chapter summarizes the history and past research of machine learning (ML) with a focus on time series forecasting and its applications in structural response assessment. Lastly, the chapter reviews recent research on the transfer learning (TL) approach in time series data and its application in the field of structural dynamics.

2.2 Hysteresis Response Simulation Methods

Hysteresis, a concept that permeates various scientific disciplines, is broadly characterized by the phenomenon where the state of a system depends on its history or previous states. Hysteresis forms when characteristic looping behaviour governs the graph of the questioned dataset [10]. In 1885, Ewing first defined hysteresis in the context of magnetism [11]. There are many hysteresis functions based on their application in mathematical literature [12] that can be used in electronics, material properties and smart alloys [13], and even economics [14].

In this research, hysteresis is defined as the relationship between the applied load (force or moment) and the resulting deformation (displacement or rotation) during a cyclic loading and unloading process in a graphical representation. In steel braces, the looping graph of the brace responses, such as its axial force plotted against its deformation, is defined as its hysteresis where the graph can be captured in a laboratory test subjected to repetitive cyclic inelastic axial displacements [15]. A representation of the concentrically braced frames (CBFs), and the hysteresis of a single steel brace is shown in Fig. 2.1 and if it is a buckling-restrained brace (BRB), the configuration of the frame in the form of buckling-restrained braced frames (BRBFs), and the hysteresis will be as Fig. 2.2.

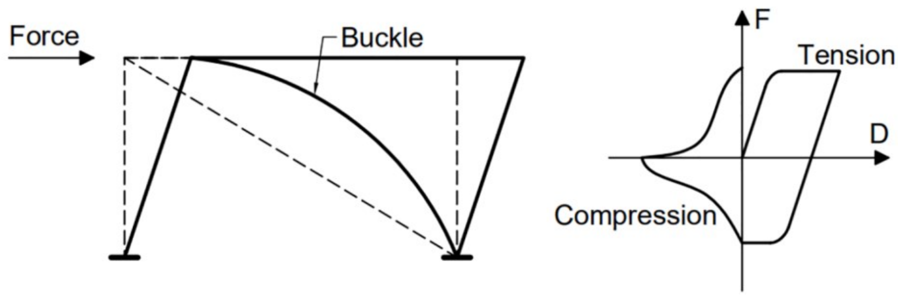

Fig. 2.1. Representation of the CBF and an ideal hysteresis response of a steel brace (Figure adapted from [16]).

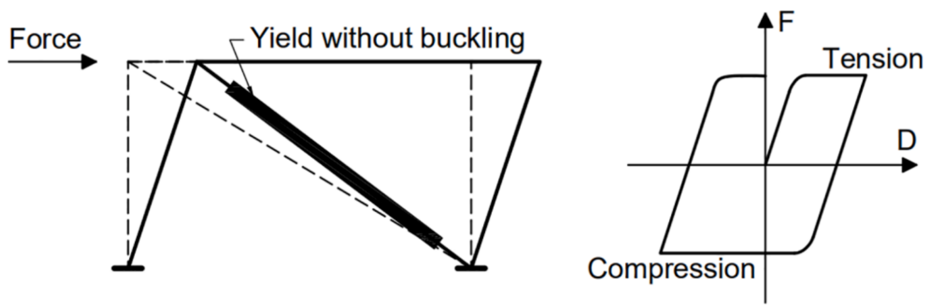

Fig. 2.2. Representation of the BRBF and an ideal hysteresis response of a BRB (Figure adapted from [16]).

Each hysteresis represents how a structural element behaves under specific loading conditions. In the hysteresis of the single steel brace in Fig. 2.1, the resistance of the steel brace in CBF can be observed as it showcases its capacity in cyclic lateral loading such as earthquake ground motions, and information about the brace's tensile yield force, buckling force, and post-buckling capacity can be achieved [17, 18]. The BRBF in Fig. 2.2 is usually constructed from a steel element confined by concrete to avoid buckling in the brace. As depicted in the hysteresis of Fig. 2.2, the BRB can dissipate more energy by undergoing more plasticity without forming a plastic hinge, whereas the normal steel brace in Fig. 2.1 dissipates less energy due to buckling [19]. Hence, understanding the hysteresis response of the steel brace is crucial to engineers and researchers to assess the performance of such braces in the process of designing or retrofitting the structures in severe lateral loading such as earthquake vibrations. Several models have been proposed to extract the nonlinear hysteresis response of structural elements, each with varying levels of runtime, accuracy, and complexity. The two approaches that are used in this research are mathematical and data-driven models, which are explained in the following sections.

2.3 Mathematical Models

Mathematical models can be classified into parametric and non-parametric models. In statistics, a parametric mathematical model is a finite-dimensional model that is based on a true physical or mathematical concept that governs the case study. These models are derived from experimental data or mathematical formulations, utilizing a limited set of parameters to characterize the system [20]. In structural dynamics, multiple parametric models are used in the analysis of structures. A well-known example is the dynamic equilibrium of single or multiple degrees of freedom to explain the general behaviour of a lumped mass under lateral movement [21]. However, in nonlinear structural analysis, challenges arise due to interactions between structural elements, material nonlinearities, and the stochastic nature of structural behaviour. In such cases, parametric mathematical modelling often relies on laboratory testing to inform the model parameters. When modelling the hysteresis response of structures under dynamic loads, parametric models are employed to simplify the analysis and enable modelling within software platforms. One of the commonly used parametric mathematical models is Giuffrè-Menegotto-Pinto (GMP) [22]. GMP was first developed by Giuffrè and is widely used for modelling the nonlinear response of reinforcing steel under cyclic loading. This model is based on the coupon test of rebar with a diameter of 10 mm, and its parameters were improved later by Menegotto and Pinto. To be able to use this model in steel designs which undergo higher strain amplitudes, Filippou et al. [23] introduced isotropic hardening into the constitutive law, resulting in the widely adopted Steel02 model. Steel02 finds extensive application in modelling various steel structural elements, including steel braces. Another hysteresis model that is used for modelling the BRBs is Steel4 [24, 25].

A fundamental challenge in structural analysis lies in accurately representing complex data using parametric mathematical models. In complex structural analysis, many simplification factors are made in the materials, boundary conditions, and geometry of the structure to allow the derivation of constitutive equations suitable for parametric mathematical models. While such simplifications enhance the tractability of the models by allowing for the derivation of constitutive equations, they inherently compromise accuracy. An example of the mathematical models in the form of finite elements methods (FEM) can be seen in Fig 2.3 where Yoo et al. [26] compared the detailed FEM model of a CBF to experimental test results. As shown, the model made accurate brace hysteresis results while the accuracy was reduced during the tensile yield excursions and the last few cycles. Although such models are created with a detailed meshing system and take a lot of time, the results are not as perfect as their experimental test results.

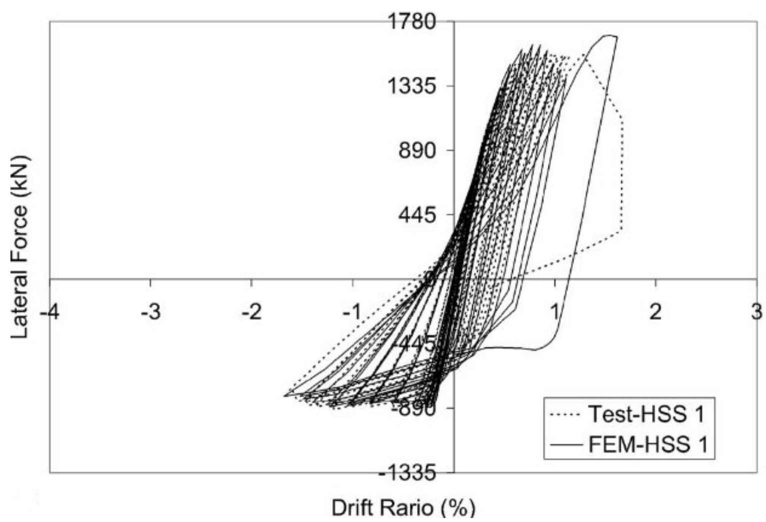

Fig. 2.3. Comparison of a numerically simulated steel brace to its laboratory test results (Figure adapted from [26]).

By avoiding such simplifications, data will exhibit high nonlinearity and cannot be adequately captured by a limited number of parameters. Thus, such data is modelled by a non-parametric mathematical model. Recent research has explored the incorporation of data uncertainties into structural analysis. Examples include stochastic finite element models for material properties [27] or a general non-parametric probabilistic approach to model uncertainties for dynamic systems using the random matrix theory [28]. While these techniques improve model accuracy by accounting for uncertainties, modelling each structural element with perfect detail is still computationally impractical. Therefore, most approaches for simulating complex phenomena like hysteresis response still rely on parametric mathematical models. As a complementary approach, data-driven modelling accurately predicts the hysteresis response of structural elements using experimental test data without the need to extract the mathematical governing equations. This M.Sc. project focuses on developing a data-driven model that utilizes a parametric mathematical approach for predicting the hysteresis response of steel braces.

2.4 Data-Driven Models

2.4.1 Artificial Intelligence-based Response Prediction in Structural Engineering

Artificial Intelligence (AI) has been widely used in many fields due to its effective performance in industrial applications [29]. AI-based models are mainly developed using ML algorithms, and the improvement of deep learning has led to enhanced analytical and data processing capabilities with models exhibiting remarkable performance [30]. ML algorithms can be broadly categorized into four primary groups based on the nature of the learning process: supervised, semi-supervised, unsupervised, and reinforcement learning. Supervised learning involves training the model on a labelled dataset, where each input data possesses a corresponding known output or target value. The model can predict unseen data by learning the inherent mapping between inputs and outputs. Regression and some classification such as image recognition can be a part of supervised ML applications. Unsupervised learning algorithms work on unlabeled data to identify inherent patterns or structures without human intervention. Finding hidden links or groups in the data is usually the main objective. Applications of unsupervised ML can be found in semantic clustering [31] and anomaly, aka outlier, detection [32]. Most of the applications of unsupervised learning in structural engineering are focused on structural health monitoring techniques and damage detection techniques [33]. Semi-supervised learning is a combination of supervised and unsupervised ML. The model is trained using a combination of labelled and unlabelled data, taking advantage of the strengths of both approaches. This approach is utilized in tasks such as classification and clustering, especially when there is a shortage of labelled data [34]. Reinforcement learning takes place in a simulated environment, where an agent learns through a trial-and-error process based on a reward and penalty system. Reinforcement learning has made significant advancements in robotics and can be applied in structural engineering research, such as characterizing the hysteresis behaviour of shape memory alloys [35]. Selecting the most suitable

ML approach depends on the data characteristics, its behaviour, and the intended application. In structural engineering, AI-based models mostly benefit from supervised ML since the involved parameters are known and labelled. Furthermore, the AI-based models showed promising results in structural response prediction as well [36 – 44]. One of the earliest applications can be found in the work of Adeli and Yeh on beam design optimization [45]. However, the task of extracting the nonlinear hysteresis response in structural dynamics presents a greater challenge due to its time series nature. To capture the hysteresis dynamic response of a structural element, a specific category of AI-based approaches, namely time series forecasting, will generally be utilized.

Time series forecasting involves predicting future values based on a sequence of past observations. This method uses ML algorithms to reveal important patterns and relationships in chronological data. Since many real-world phenomena display temporal patterns, time series forecasting is vital for comprehending and foreseeing trends in the datasets. Applications of time series forecasting are widely used in finance [46] and climate forecasting [47]. When dealing with the time parameter, using the right ML algorithm that can understand the temporal dependency and the hysteresis response is crucial [48]. A data-driven model based on time series forecasting can benefit hysteresis response predictions in structural dynamic analysis.

2.4.2 Data-Driven Modelling in Structural Response Prediction

Traditionally, structural engineering and research relied on scarce data often obtained from laboratory experiments designed to validate specific hypotheses. The digital era has brought about an unparalleled surge in data generation across several industries, resulting in the creation of enormous information banks [4]. ML methods have significantly facilitated the use of available data for decision-making and new case studies. The emergence of AI-based models has encouraged researchers to seek alternatives to traditional approaches such as expensive laboratory tests and numerical simulations that require substantial processing power. These AI-based models are called "surrogate models," and they encompass a variety of techniques. By using the old data at hand, and facilitating the correct ML approach, a surrogate model trained on data (aka a data-driven model) can be produced. The general steps to design a data-driven model are explained in Fig. 2.4.

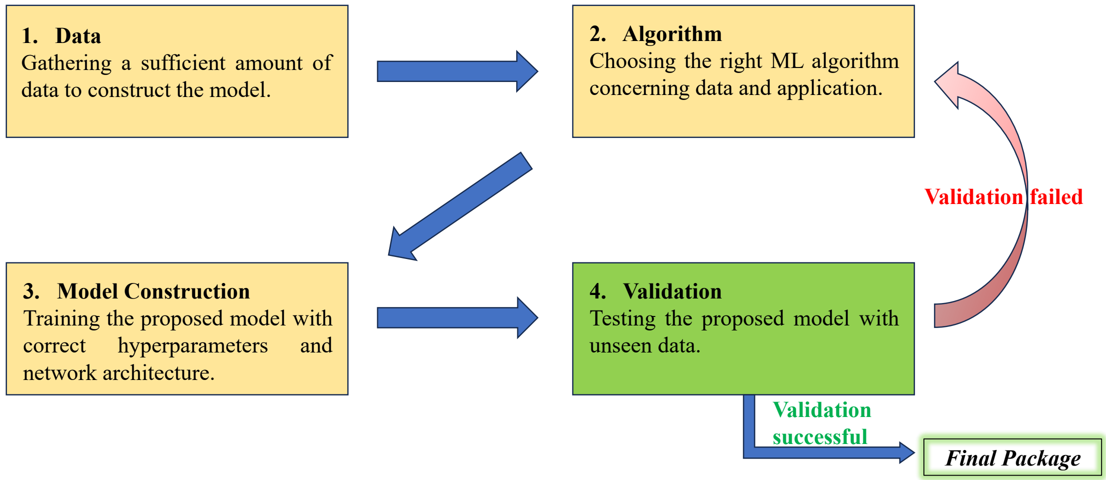

Fig. 2.4. Flowchart of the steps of data-driven modelling.

As explained in the previous section, when the temporal nature of the data plays a critical role, time series forecasting can be utilized and offers a compelling approach for constructing data-driven models for the hysteresis response of structural elements. Two of the famous time series forecasting algorithms that showed promising results in response prediction of structural elements are convolutional neural networks (CNN), and recurrent neural networks (RNN). CNNs are a class of deep learning models created especially for computer vision, image recognition, and visual processing applications [49]. By adding specialized filters that can automatically and adaptively learn hierarchical representations of visual data, CNNs have entirely revolutionized the field [50]. One-dimensional CNNs, also known as 1D-CNN, were proposed by Waibel et al. [51] in the format of a time-delay neural network for speech recognition; these can be beneficial in constructing models for time series or sequences such as dynamic responses of structures. By strategically restructuring the data and employing a controlled mapping function, normal CNNs can be adapted for dynamic response prediction of structures as well. Wu et al. [52] applied the CNN network to a single-degree-of-freedom system to capture both its linear and nonlinear responses under random excitations. To predict the building response under seismic loads, Kwan Oh et al. [53] used CNN to create a surrogate model for a four-story building and used the earthquake acceleration, and displacement recorded for the structure, to extract its dynamic response model. Wang et al. [54] modelled a three-dimensional building to achieve the Probabilistic Seismic Response Prediction using Bayesian CNN, which combines variational inference with the backpropagation algorithm used in conventional deep learning model training. CNNs can even be infused with other ML approaches such as physics-guided modelling where physical phenomena are implemented as catalysts in the data-driven model. Zhang et al. [55] implemented a physics-guided convolutional neural network (PhyCNN) for data-driven seismic response modelling.

Recurrent neural networks (RNN) are a class of artificial neural networks designed for processing sequential data and addressing the challenges posed by the temporal dependencies inherent in such data [56, 57]. Because RNNs can remember and use information from earlier time steps, unlike standard feedforward neural networks, they are ideally suited for applications like time series analysis, speech recognition, and natural language processing. A subclass of RNNs, long short-term memory (LSTM) [58] showed promising results in structural response prediction in dynamic analysis. One of the first studies to use LSTM for nonlinear structural seismic response prediction was done by Zhang et al. [7] in 2019, using an LSTM network to capture a nonlinear hysteretic system of a real-world building with field sensing data, and a steel moment resisting frame responses. Xu et al. [59] solved the issue of sampling rate in the ground motion response using the Recursive LSTM network. LSTM can also be infused with a physics-guided neural network which Zhang et al. [60] used for metamodeling of the nonlinear response of structures. Liao et al. [61] used LSTM in the attention-based method [62] to model the seismic response of bridges, demonstrating its applicability to other ML methods.

While CNNs and RNNs have been extensively studied for system-level structural response prediction, there is a gap in the existing research specifically focused on hysteresis response as the primary topic. Mokhtari and Imanpour [63, 64] proposed a new substructuring technique using Corroborating numerical data, referred to as PI-SINDy, for hybrid simulation of BRBFs under seismic loading. Other ML approaches have been applied to extract the BRBs hysteresis responses [65 – 67]; however, there has been limited investigation of the complexities associated with stiffness and strength degradation in CBF braces regarding data-driven modelling for these elements.

Previous research shows the positive evolution of data-driven modelling for nonlinear response predictions, but the increasing complexity of these models is a growing concern among researchers. This complexity hinders interpretability, making it challenging to understand the underlying mechanisms within the AI-based framework. In many of the data-driven approaches, the model is tailored and specific to a type of data that loses its generalizability. Techniques like transfer learning (TL) offer potential solutions by allowing the transfer of knowledge acquired from one model to another.

2.5 Transfer Learning

Transfer learning (TL) is a technique in ML where the knowledge gained in the process of solving a specific problem is reused and applied to a different but related problem. Many conventional ML techniques make the basic assumption that training and future data must have the same distribution and be in the same feature space. However, TL has shown itself to be a potent strategy for enhancing model performance in deep learning by addressing the data distribution issue. This approach is particularly valuable in situations where there is limited data available in the target domain. By leveraging existing knowledge and adapting it to new problems, transfer learning enables models to achieve improved performance. The different approaches to using TL are classified as follows: inductive, transductive, and unsupervised [68]. Inductive TL refers to the process where the source and target tasks are different, but it is assumed that the underlying data distributions are similar. This is the most commonly used approach in ML applications. On the other hand, transductive TL involves identical source and target tasks, but with different data distributions. In this approach, the model relies on the labelled source data to make predictions on the unlabelled target data. Finally, unsupervised TL focuses on transferring knowledge between tasks where neither the source nor the target data are labelled.

TL has not been directly used for dynamic response prediction of structural elements; it has mainly been utilized for damage detection and structural health monitoring research [69 – 71]. Liao et al. [72] used a TL approach to propose an identification method for structural seismic responses. Although research topics that focus on structural seismic responses using TL are limited, TL can be useful in the domains of time series data [73, 74]. In the hysteresis response prediction of structural elements, especially steel braces, the data-driven models are constructed on a set of limited datasets. When the domain of the data used for training and validating the data-driven model is small, the proposed model can struggle in facing the future target such as a new geometry or loading conditions. As the hysteresis response is also a time series and by drawing inspiration from past studies, this research aims to leverage TL to extend the capabilities of the proposed data-driven model. This will involve adapting a pre-trained model, potentially from a different time series prediction task to the domain of complex response prediction in structural dynamics.

Chapter 3

Prediction of Hysteresis Response of Steel Braces Using Long Short-Term Memory Artificial Neural Networks

3.1 Abstract

This article proposes Artificial Neural Network approaches that utilize the long short-term memory (LSTM) algorithm to approximate the nonlinear hysteresis response of steel buckling-restrained and conventional hollow structural section braces. The proposed models overcome the two main challenges, including the complexity of hysteresis response and limited training data using an LSTM network and auxiliary parameters. The proposed models are validated, which confirmed their capability to predict axial force – axial deformation response of BRBs and steel braces. The development of a suitable training dataset is first presented. The architecture of the proposed models is then described followed by the validation of the model against unseen brace hysteresis responses. The validation results demonstrate that the proposed LSTM model is both accurate and computationally efficient in predicting the response of steel braces to random lateral loads.

3.2 Introduction

The finite element method (FEM) has widely been used as an important tool to evaluate the response of structures under various loading conditions considering their geometrical properties, material characteristics, and boundary conditions. While the FEM offers an efficient performance evaluation technique, in particular when analyzing complex structures under time-dependent loading conditions, such as earthquakes, it often involves simplified and idealized assumptions associated with materials, geometry, and boundary conditions [75]. Furthermore, a FEM-based model may involve high computational expenses, which could be exacerbated in complex structural systems and under dynamic loading.

Given the advancement in machine learning (ML) algorithms and availability of data, physical and synthetic, the development of data-driven, aka surrogate [76, 77], models using ML algorithms can be a viable alternative for FEM-based simulation for the prediction of structural response [78], in particular, when a complex structural phenomenon such as stability is of concern. In the framework of structural response prediction, a surrogate model is defined as a special case of a supervised ML model trained on labelled data [79], which can approximate the behaviour of complex physical phenomena with sufficient accuracy and reduced computational costs compared to numerical simulations. As a subclass of ML approaches, artificial neural networks (ANN) have become the most widely used method in structural engineering because of their popularity and ease of use [45, 80]. A multilayer perceptron (MLP) [81], a branch of ANN is often used when a static analysis problem is concerned; however, more complex ANN models with multiple hidden layers called deep neural networks (DNN), have been shown as a suitable approach for dynamic problems. Among DNNs, recurrent neural networks (RNN) [57] have been designed to interpret sequential information, such as time histories or time-dependent phenomena such as structural response to earthquakes. While RNNs can comprehend temporal dependencies, in long sequences, the error signal can become vanishingly small or exponentially large as it backpropagates through many layers which is called the vanishing and exploding gradient, respectively [82, 83]. These issues make it difficult for the RNNs to learn from past information and adjust weights effectively, hindering the ability of the network to converge to an accurate solution. RNNs are therefore improved by long short-term memory (LSTM), a subclass of RNNs, to train models that can predict complex time- or history-dependent responses. LSTM network can be used for developing surrogate models to derive the nonlinear response of structures, especially in the dynamic analysis as presented in [7, 59].

This paper proposes LSTM-based surrogate models to predict the nonlinear response parameters of steel braces. Two steel bracing systems are studied: steel hollow structural sections (HSS) braces of concentrically braced frames (CBFs) and steel buckling-restrained braces (BRBs) of buckling-restrained braced frames (BRBFs). The proposed models of steel braces are trained using available experimental data and synthetic data generated using corroborated numerical models. An overview of the nonlinear response of the steel braces and LSTM algorithm is first presented. The architectures of the steel brace surrogate models are then described. The adequacy and generalizability of proposed models are then validated using available brace data.

3.3 Background

3.3.1 Nonlinear Response Parameters of Steel Braces

Steel concentrically braced frames (CBFs) and buckling-restrained braced frames (BRBFs) are widely used as the lateral load-resisting system of building structures. CBFs dissipate seismic-induced energy through axial yielding and buckling, the latter involves significant out-of-plane deformation in the brace. Steel BRBFs offer higher ductility compared to their conventional counterparts through yielding in both tension and compression [15, 84]. Under lateral seismic loading, steel BRBs and braces develop the hysteresis (axial force – axial deformation) responses as shown in Figs. 3.1a and 3.1b, respectively.

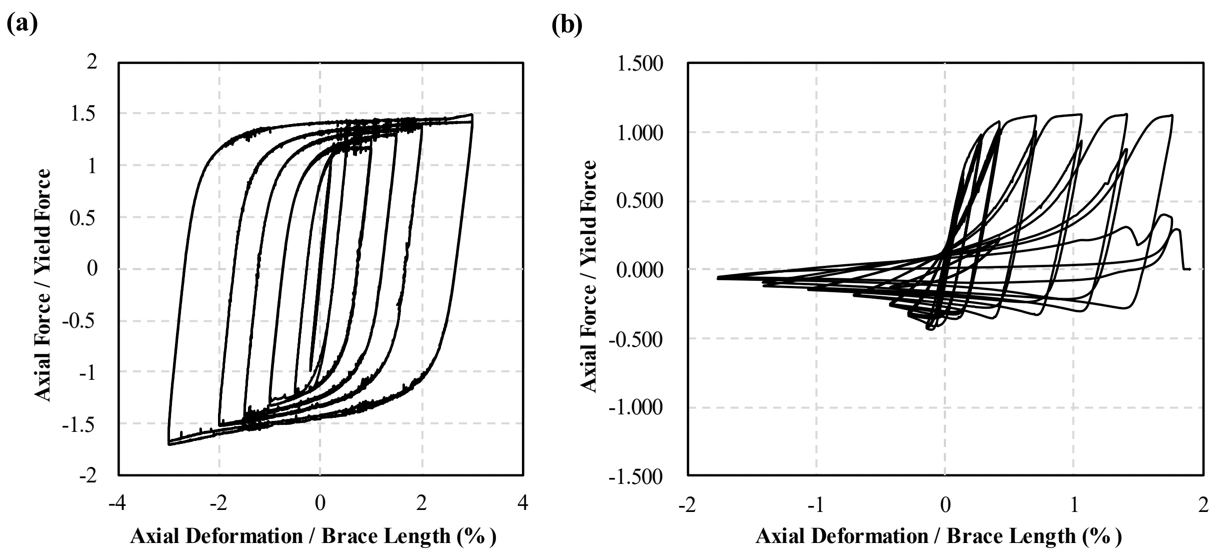

Fig. 3.1. Brace hysteresis response: (a) BRB (data from [85]); (b) CBF brace (data from [86]).

BRB hysteresis response in Fig. 3.1a represents an almost symmetric behaviour in compression and tension. Referring to Fig. 3.1b, the hysteresis response of conventional braces involves strain hardening in tension and stiffness and strength degradation in compression due to global and local instabilities. Instability under a compression load is associated with a sudden loss of load-carrying capacity plus significant lateral deflection, and it depends on the effective length factor of the brace, which is defined as the ratio between the brace's effective length and the radius of gyration of the cross-section. In design, the peak force features, such as tensile, compressive, and post-buckling capacities extracted from the hysteresis response are required. Such response parameters can be obtained from experiments and FEM-based models. However, experimental testing is often expensive and limited in scope due to laboratory constraints. Numerical simulations, such as FEM-based simulations, involve several limitations as described earlier. Many ANN-based models were developed in the past to estimate key cyclic response parameters of steel columns and braces experiencing buckling [87 – 96]. Mokhtari et al. [63, 64] proposed a data-driven model based on lasso regression to predict the cyclic response of steel BRBs. While their model demonstrated high accuracy, as the proposed model cannot be applied to CBF braces. Steel BRBs were the subject of other data-driven models [65 – 67] where researchers used laboratory tests to train and predict the response of BRBs in cyclic loading.

3.3.2 Artificial Neural Network

A summary of the ANN framework, which will be used to develop the surrogate model, is given here. ANN mimics the structure and behaviour of neurons in the human brain [97] involving an input layer that feeds the data to the hidden layers, which consist of neurons (nodes) where the main mathematical computations are performed on the input data $\boldsymbol{x}$ using an activation function $f(\boldsymbol{y})$, where $\boldsymbol{y}$ is the weighted sum. The activation function introduces nonlinearity to the network, allowing it to capture complex, nonlinear relationships. The output $\boldsymbol{Z} = f(\boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b})$ located at the end of the loop represents the predicted results, where $\boldsymbol{W}$ is the weight matrix and $\boldsymbol{b}$ is the bias vector. During training, weights are updated through backpropagation operation, in a repetitive process, using the optimization algorithm gradient descent to minimize the final loss function, mean square error (MSE) here [98].

RNNs designed to interpret sequential information can be applied to time-dependent problems in seismic engineering, such as the response history of structural elements and systems. Long short-term memory (LSTM) allows RNN to interpret more complex time series. Each LSTM unit consists of cells with a forget gate, an input gate, and an output gate, as shown in Fig. 3.2.

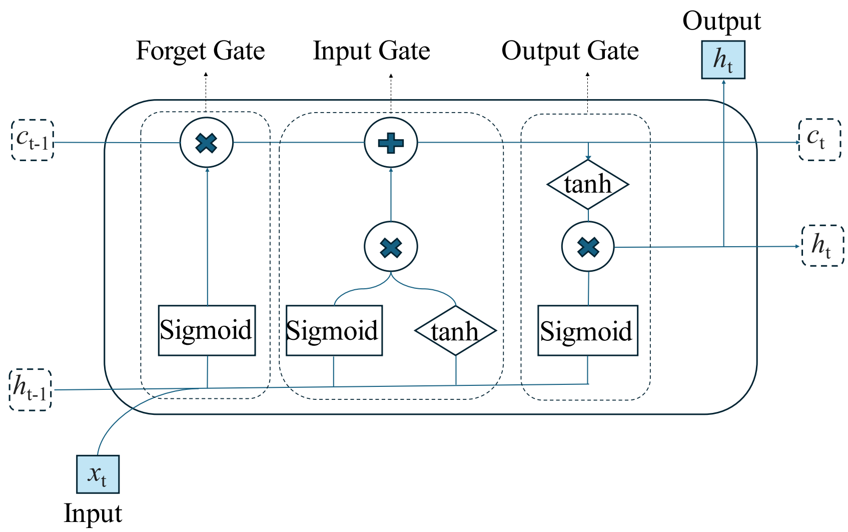

Fig. 3.2. Architecture of the LSTM cell.

Following the LSTM cell in Fig. 3.2, the input data associated with the time step t, x_t, and the output associated with the previous time step t-1, h_{t-1}, pass a logistic sigmoid function in the forget gate to determine which portions of the previous cell state, c_{t-1}, should be retained (value close to 1) or discarded (value close to 0) in the current cell state. This selective forgetting allows the LSTM to focus on the most relevant long-term dependencies, considering both the current input and the previous understanding of the network. Then, the input gate receives the two inputs of the LSTM cell, x_t and h_{t-1}, to create a new proposed long-term memory. It employs the tanh function to generate a vector of candidate values, $\tilde{c}_t$, for the new cell state, c_t, and another sigmoid function to decide how much of this candidate information should be incorporated into the new cell state. To generate a new cell state, two outputs of the input gate and the forget gate are combined. The first output from the forget gate determines which information from the previous cell state to retain. The second output from the input gate introduces the new information to include in the updated cell state. This ensures the LSTM cell can effectively learn and retain relevant information over long sequences. The current output of the LSTM cell, h_t, aka hidden state of the LSTM cell, which represents the short-term memory of the cell is created using the cell state, c_t, and the two inputs, x_t and h_{t-1}. This gate utilizes a sigmoid function to determine what information from the current cell state should be exposed as the current hidden state. In the LSTM cell, all the trainable weights will be allocated to x_t and h_{t-1}, with cell states controlled by the input values. More detailed information regarding the mathematical operations involved in LSTM can be found in [99]. LSTM algorithm is a promising choice for predicting the hysteresis response of steel braces. Unlike the traditional RNN algorithm, LSTM can effectively handle long data sequences. It can retain important information about the nonlinear response of the brace as it undergoes stiffness degradation in each cycle.

3.4 Architecture of the Proposed Surrogate Model

An LSTM network architecture is proposed for the hysteresis prediction of steel BRBs, and CBF braces made of HSS. The surrogate modelling of BRBs is first studied due to their simpler hysteresis response compared to CBF braces, making it easier to investigate the capability of the LSTM approach in hysteresis simulation. First, an architecture of the LSTM model, referred to as standard LSTM, is shown in Fig. 3.3. As shown, the standard LSTM model consists of two LSTM layers, each with 100 cells, and one fully connected dense layer, with 100 neurons, and the *ReLU* activation function is used between layers to introduce nonlinearity to the output. This model was designed and implemented using the Keras library in Python. The model was then trained using BRB hysteresis data to predict BRB axial force as a function of BRB axial displacement.

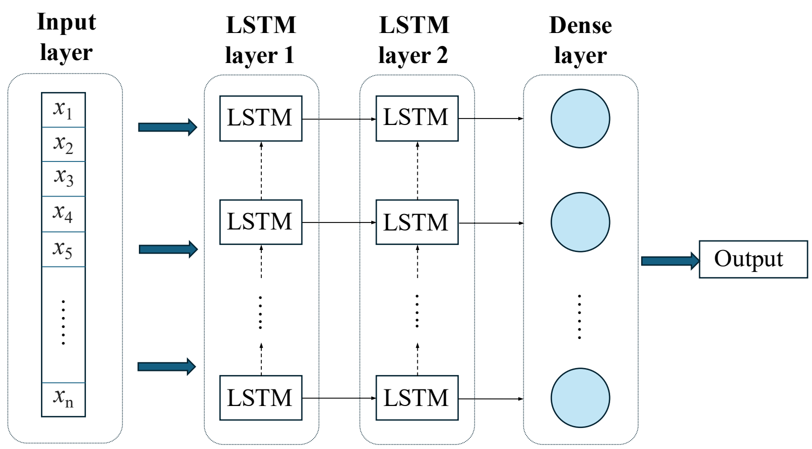

Fig. 3.3. Architecture of the proposed model for steel BRBs.

One of the challenges of developing ANN-based hysteresis prediction models in seismic engineering is that deformation is the only time history data acting as the input feature of the model to achieve a signal-to-signal, i.e., axial deformation to axial force, prediction. Fortunately, BRB hysteresis involves almost identical repetitive cycles due to the absence of buckling, suggesting that the dataset represents a recurring pattern. As such, for the LSTM network to learn the pattern of the BRB response, the hysteresis loop corresponding to one of the cycles would be sufficient to train the model.

The training data, involving BRB axial force and displacement, were normalized by the yield capacity of the BRB in tension and compression, and axial deformation at yield, respectively, to enhance the distribution of the training data. Normalization allows for the utilization of datasets from different test programs having different BRB geometries and mechanical properties. The standard LSTM model is trained on three BRB hysteresis responses.

Evaluation of the BRB standard LSTM model is done using a random monotonic axial deformation protocol presented in Fig. 3.4a [85]. The predicted BRB force is compared in Fig. 3.4b against the target force. As shown, the standard LSTM model can grasp the axial force – axial deformation response of BRB with acceptable accuracy if the BRB dataset does not experience a long loading period. The limited discrepancy in BRB force observed during the last cycles is associated with concept shift that may occur in LSTM when the underlying statistical properties of the data change over time, or when the behaviour of the data is not the same at the end of the loading process as it was at the beginning.

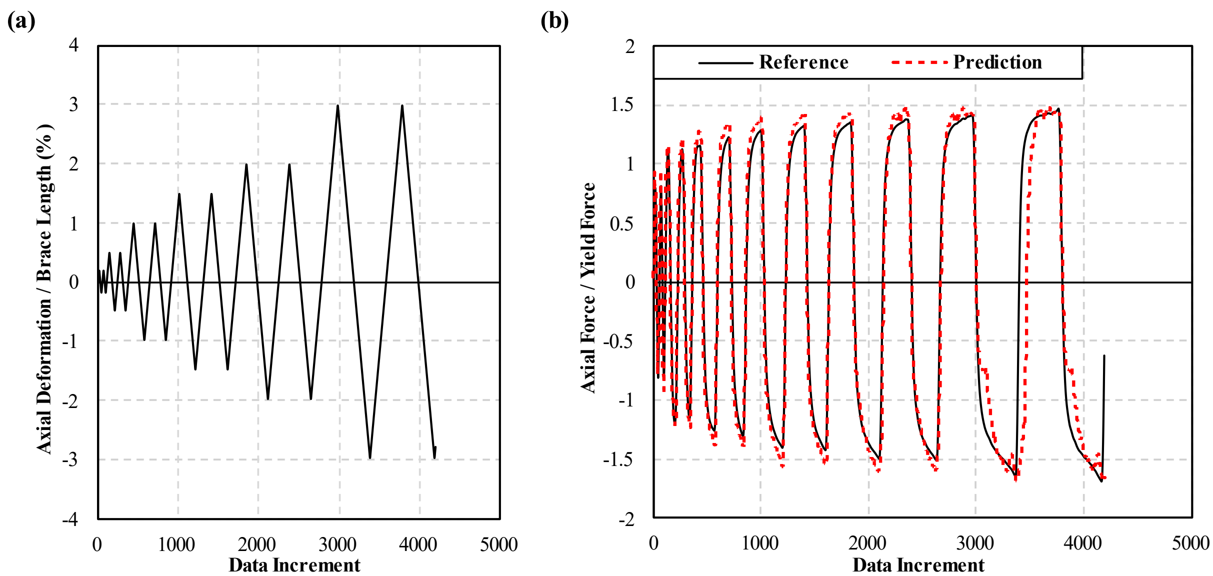

Fig. 3.4. BRB response prediction: (a) BRB axial deformation protocol, and (b) BRB axial force prediction vs. reference.

The prediction of the axial force-axial deformation response in steel CBF braces may require more effort due to asymmetry in their hysteresis response, primarily caused by the loss of strength and stiffness in compression, caused by the buckling. Another challenge when developing an ANN model for steel CBF braces is the direct influence of brace geometry, such as length and cross-section, on its hysteresis response, which prevents the direct normalization of the force as was performed in BRBs, suggesting that the training data for the steel CBF model should preferably come from the same experimental test program with braces having almost the same geometry, material properties and loading conditions.

To create a surrogate model that can predict the hysteresis response of steel CBF braces using the available experimental training data, a deeper LSTM network was developed. The architecture of the proposed ANN model is presented in Fig. 3.5. Since the force – deformation response of steel braces is not an injective function (see Fig. 3.1b), the hysteresis prediction is highly sensitive to the time or history of the response. Furthermore, the peak buckling load and tensile hardening are two distinct phenomena, corresponding to compression and tension branches of loading, respectively. The input, x_i, where i refers to the increment of input data, is therefore separated into two branches, tension branch T_i, representing the ascending phase of loading, and compression branch C_i, involving the descending phase of loading. This strategy also helps better interpret the relationship between different data points at different time increments. The differentiator matrix, D_i consisting of {-1, 0, 1} is stacked with T_i in inputs. The stacked matrix of D_i and T_i, and matrix C_i then enter LSTM layers with 50 cells to enrich input data and expand the input features. The outputs of both layers are concatenated together for the integrity of axial deformation and pass through two layers of LSTM with 100 cells and a fully connected dense layer with 100 neurons. The activation function *ReLU* is used in each layer of the proposed LSTM architecture. The final output, i.e., predicted force, is made of the predictions associated with T_i, and C_i matrices are added together to form the final force prediction.

Fig. 3.6a shows how the input dataset is decoupled into two independent subsets where the compression branch is associated with the value of zero when loading advances in the tension branch and vice versa.

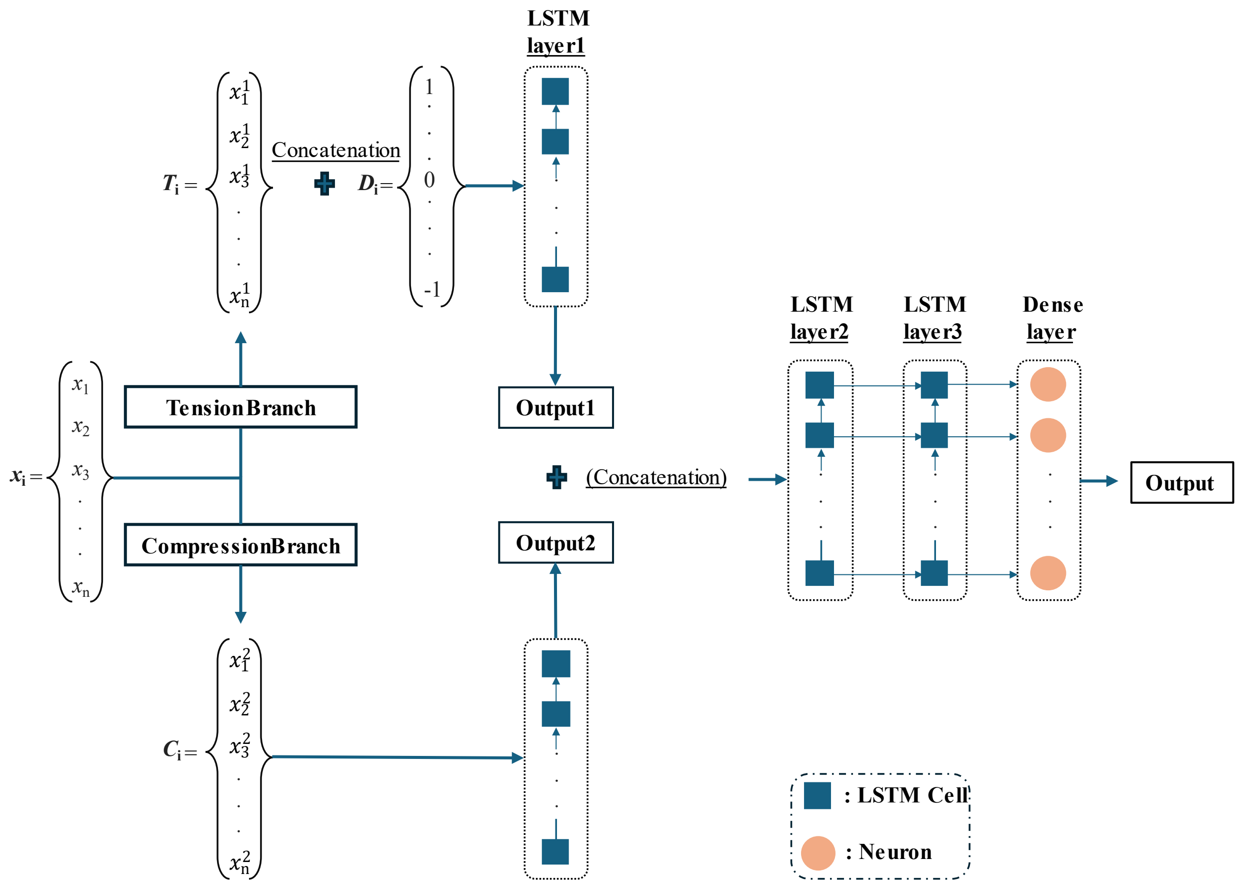

Fig. 3.5. Architecture of the proposed model for steel CBF braces.

Given that the cyclic response of steel braces involves multiple force outputs for a given axial deformation input, extra guidance should be provided to the ANN model for distinguishing between repeated cycles, particularly in the presence of stiffness and strength degradation. An array of -1, 0, and 1 is proposed to differentiate between the segments of the same cycle and two adjacent cycles where a data point in the tension branch receives the value of 1 and the data point in the compression phase is assigned zero. As shown in Fig. 3.6b, the value -1 is taken during the second cycle of the same deformation amplitude to account for the lower tensile capacity due to elongation in the first cycle and strength degradation in compression resulting from severe post-buckling. The matrix {-1, 0, 1}, called the differentiator, D_i acts the same as the dummy variables generally used in separating data features and is stacked up with one of the two decoupled subsets described earlier. This strategy also facilitates setting up the boundaries between different cycles so that the predicted force remains within the target hysteresis response.

(a)

(b)

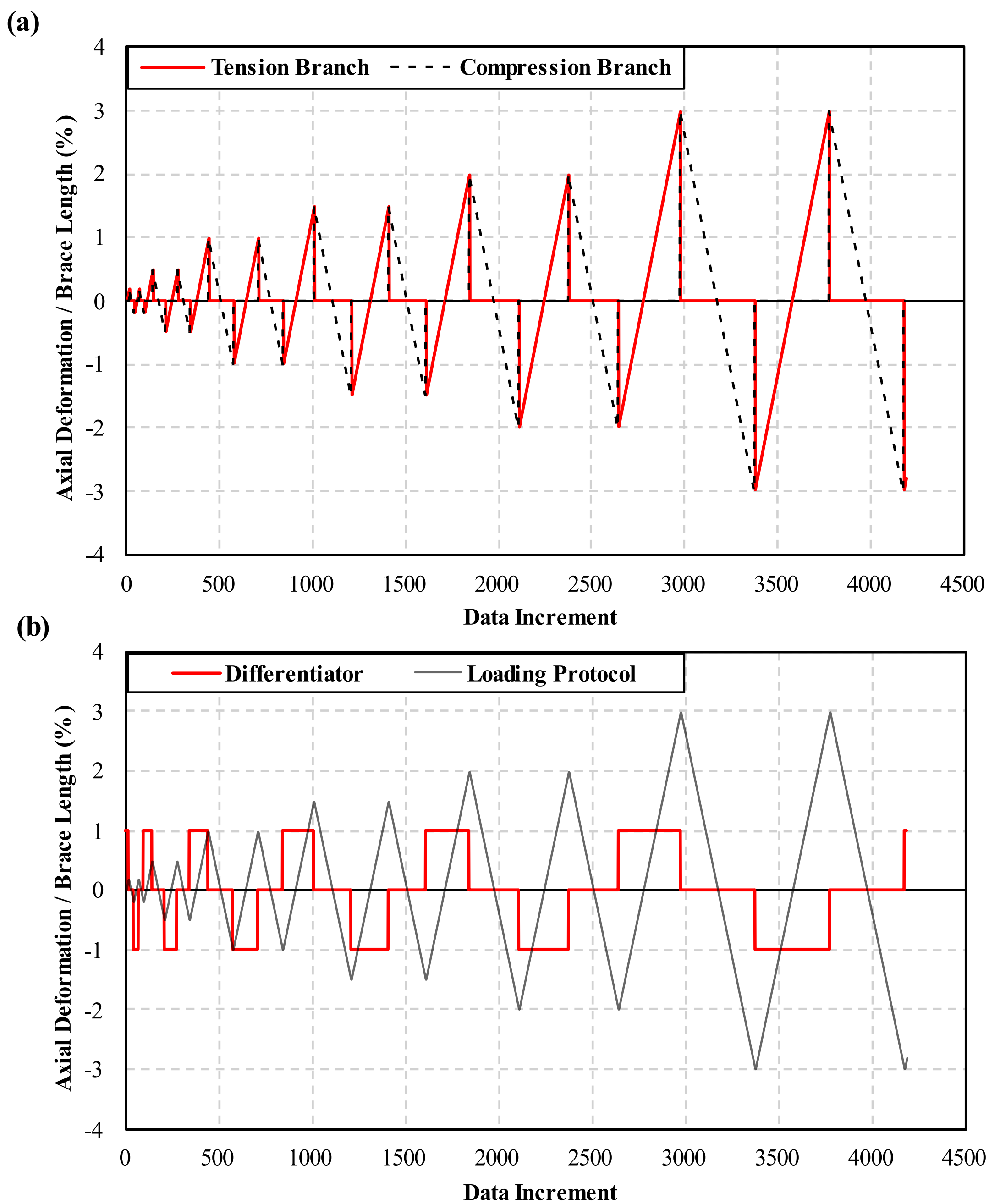

Fig. 3.6. (a) Decoupled axial deformation history into tension and compression branches; (b) Differentiator parameter in the axial loading protocol.

3.5 Input data preparation

Laboratory test datasets often cover a limited domain of response and are accompanied by noises. A supplementary dataset generated using a corroborated numerical model was used to enrich the diversity of the training dataset. To investigate the influence of adding simulated data to the input dataset, the BRB forces were predicted by the trained ANN model of the standard LSTM model of Fig. 3.3, once using pure experimental data from [100] and then using a combination of experimental data and two sets of synthetic data using a numerical model of the same experimental braces constructed in *OpenSees* [101] under BRB testing protocols from [102] and [103]. The *OpenSees* model is a simple one-element corotational truss with Steel4 material [25], using Young's modulus (E) of 200 GPa where the equation of motion is solved using the Newton method with Line Search algorithm [104]. The experimental test used to calibrate the *OpenSees* model is a two-tier diagonal BRBF with alternating orientation in each tier, and pinned ends that consist of a BRB constructed with a steel plate having a cross-sectional area of 2510 mm^2, and an effective brace length of 6165 mm. The yield strength of the steel material, F_y is 270 MPa. Additional information on the test setup and specimen can be found in [100]. BRB force and deformation can be normalized to achieve stress and strain, respectively, without affecting its hysteresis response and nonlinear properties. The standard LSTM model was used for this validation to avoid the effects of other parameters in the comparison, such as the differentiator, and then the main LSTM model of Fig. 3.5 was used for the final validation. The history of predicted BRB forces is compared in Fig. 3.7 against the reference BRB force. A Savitzky-Golay Smoothing function [105] and moving average filtering technique were used to fit a polynomial of degree five function to minimize the noises in the experimental data. A significant improvement is observed as a more diverse dataset is used to train the ANN model. Note that a smaller learning rate was used to train the model with pure experimental data to achieve more accurate results and avoid any convergence issues. Table 3.1 shows the number of epochs, number of learning rates, and MSE for the two strategies used to train the BRB model. As shown, the MSE was reduced by a factor of nearly four when supplementary numerical data was used in training. After demonstrating the positive influence of adding synthetic datasets to the training set, the final training for the proposed LSTM model of Fig. 3.5 was done using the three BRB datasets mentioned earlier. Two Keras callbacks, including Early Stopping and Model Checkpoint, were used to bypass models with the best fitting and minimum MSE possible in the epochs. A total of 5000 epochs were used in training. Adam optimizer with a learning rate of 0.001 was also used to achieve better convergence through the training. The MSE of the training phase of the proposed LSTM model of Fig. 3.5 is found to be

2.1587×10^{-5} for BRB braces, which is significantly improved compared to the previous prediction of the standard LSTM model presented in Table 3.1.

Table. 3.1. Number of epochs, learning rates and prediction Errors for the BRB model.

Training Data	epochs	Learning Rate	MSE
Laboratory test	5000	0.0001	0.4275
Laboratory test and numerical data	5000	0.001	0.1127

Following the same approach of using synthetic datasets as the BRB model, the laboratory test data of HSS 127×127×7.9 braces from [86] was used along with four numerically generated steel HSS braces developed in *OpenSees* under the loading protocols adapted from [106] to develop CBF brace training dataset [107]. The steel brace was simulated using a nonlinear beam-column element with the Giuffré-Menegotto-Pinto material model [23] using Young's modulus (E) of 200 GPa where the equation of motion is solved using the Newton method with Line Search algorithm. The experimental test [86] used for calibrating the *OpenSees* model consists of a single HSS 127×127×7.9 brace, with a cross-sectional area of 3400 mm^2, and an effective length of 4160 mm. The measured yield strength of the steel material, $F_y = 389$ MPa. CBF brace data, axial deformation and axial force were normalized by dividing the axial deformation by the brace length and the axial force by the yielding capacity of the brace network. Given a low quantity of datasets, overfitting may arise if training is not performed with caution as the model may only memorize the training data and fail to learn the inherent behaviour of the brace under cyclic loading, resulting in poor predictions when new data is fed to the model.

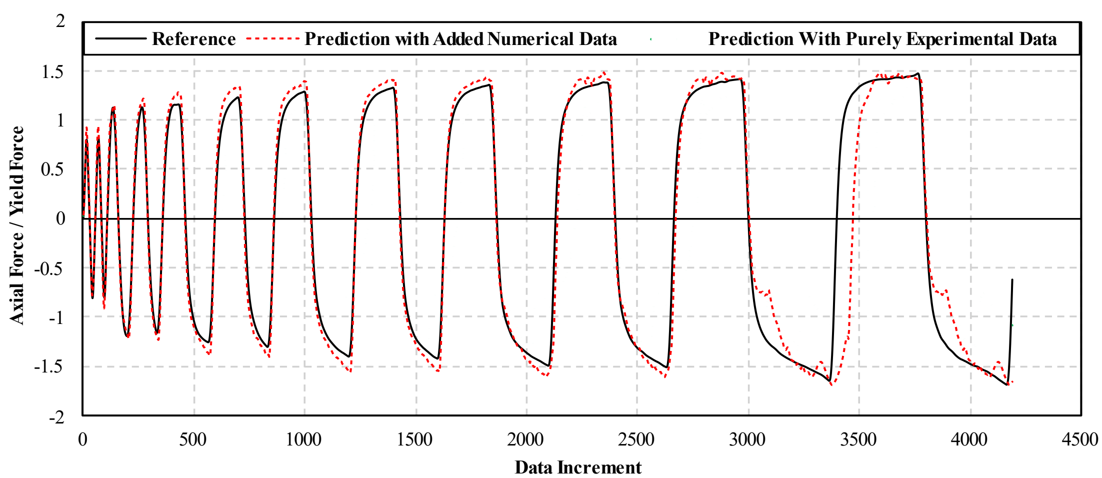

Fig. 3.7. BRB axial force history: predicted by the ANN models vs. the reference data.

The same Keras callbacks, optimizer, and learning rate as the BRB training were used. A total of 10000 epochs, two times higher than the BRB model, were used in training due to the complexity of the CBF brace hysteresis response. The MSE of the training phase is found to be 6.4765×10^{-6} for CBF braces, which is deemed acceptable.

3.6 Model Validation

The BRB and CBF brace models trained in the previous section were validated using unseen axial force – axial deformation responses. Two sets of input deformation histories were considered for each brace type. For the BRB model, the loading histories in Fig. 3.4a and Fig. 3.9a (data from [85]) were selected, while the deformation histories of Fig. 3.10a and Fig. 3.11a (data from [106]) were utilized for the CBF brace model. The prediction of BRB axial force under the cyclic loading protocol of Fig. 3.4a is shown in Fig. 3.8. Referring to this figure, an excellent correlation was observed between the predicted and target forces. The accuracy of the prediction dropped when a random BRB deformation history (Fig. 3.9a) is used as shown in Figs. 3.9b, and 3.9c. The numeric errors associated with each loading scenario are given in Table 3.2 for the BRB model. As shown, the proposed model, although trained on only three sets of hysteresis responses, can properly predict the axial force of the BRB and its peak forces, which are often used in the design of steel BRBFs.

Table. 3.2. MSE of testing and peak force values for BRB and CBF brace models.

Brace Type	Deformation History	MSE of Testing Phase	MSE of Peak Forces (Tension)	MSE of Peak Forces (Compression)
BRB (Cyclic)	Fig. 3.4a	1.257×10^{-2}	9.299×10^{-3}	6.591×10^{-3}
CBF (Cyclic)	Fig. 3.10a	6.472×10^{-3}	2.716×10^{-2}	2.044×10^{-4}
BRB (Random)	Fig. 3.9a	1.767×10^{-1}	1.481×10^{-1}	6.874×10^{-2}
CBF (Random)	Fig. 3.11a	4.001×10^{-3}	5.837×10^{-3}	5.068×10^{-3}

The prediction of CBF brace forces using the proposed LSTM model under the cyclic deformation history of Fig. 3.10a is shown in Figs. 3.10b and 3.10c, which confirms the capability of the proposed model in predicting the brace force. The MSE values given in Table 3.2 reaffirmed this finding. A similar prediction is observed in Figs. 3.11b and 3.11c under a more complex random deformation history of Fig. 3.11a. After analyzing the results of the two tests of the CBF brace shown in Table 3.2, it was observed that the random deformation test produced fewer errors compared to the cyclic loading protocol. One possible reason for this is that in cyclic loading, the LSTM model receives identical axial deformation that needs to be linked to different axial forces. While this was advantageous in the BRB model, it seems to be confusing the model in the CBF brace due to the stiffness and strength degradation. The better performance of the CBF brace model compared to the BRB model in predicting a random response is likely attributed to a larger training dataset available for the LSTM model of the CBF brace (five vs. three), suggesting that enriching the diversity and quantity of the training data can significantly influence the prediction capability of the proposed LSTM-based models. Furthermore, the remaining minor noises implicit in the training data, which were more pronounced in the BRB training data, can influence the accuracy of the prediction.

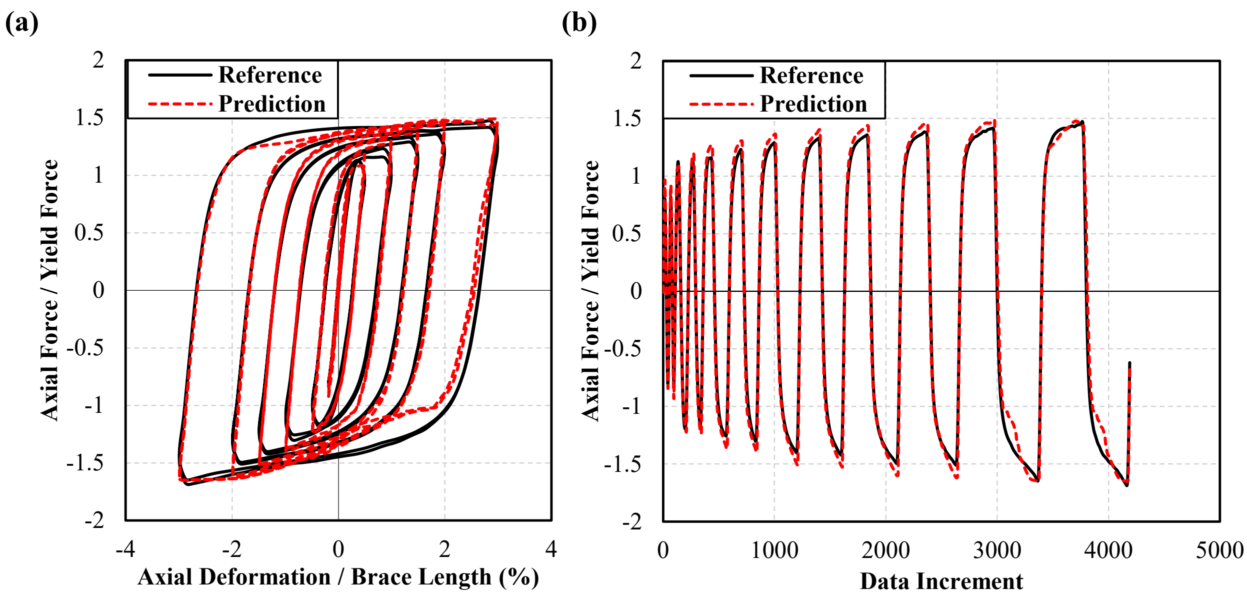

Fig. 3.8. Predicted vs. reference data for steel BRB under cyclic loading protocol of Fig. 3.4a: (a) hysteresis response, (b) axial force history.

The peak brace force capacities, including the maximum brace tensile and compressive forces, as predicted by the proposed LSTM models are evaluated as the peak values are typically used in the design of steel braced frames to compute seismic-induced forces on adjacent members of a braced frame. Table 3.2 provides the MSE values of the predicted peak brace forces in tension and compression. As shown, the average MSE values associated with the peak forces are relatively low (7.945×10^{-3} and 1.368×10^{-2} for the BRB and CBF brace, respectively) when a gradually increasing cyclic loading protocol is used. The prediction of peak forces becomes challenging by the proposed model when the model is subjected to a random deformation history (1.084×10^{-1} vs. 5.068×10^{-3} for the BRB and CBF brace, respectively) in the BRB model due to the same reasons mentioned earlier for the MSE of testing for the complete hysteresis response. The MSE of the peak tension forces is higher than that of compression peaks, particularly in the case of CBF braces, which is mainly due to the limited diversity of the training dataset for potential tension scenarios, as illustrated in Table 3.2. Since compression mainly governs the steel brace capacity over tension, it can be safely concluded that the proposed LSTM approach can be advantageous in the design process.

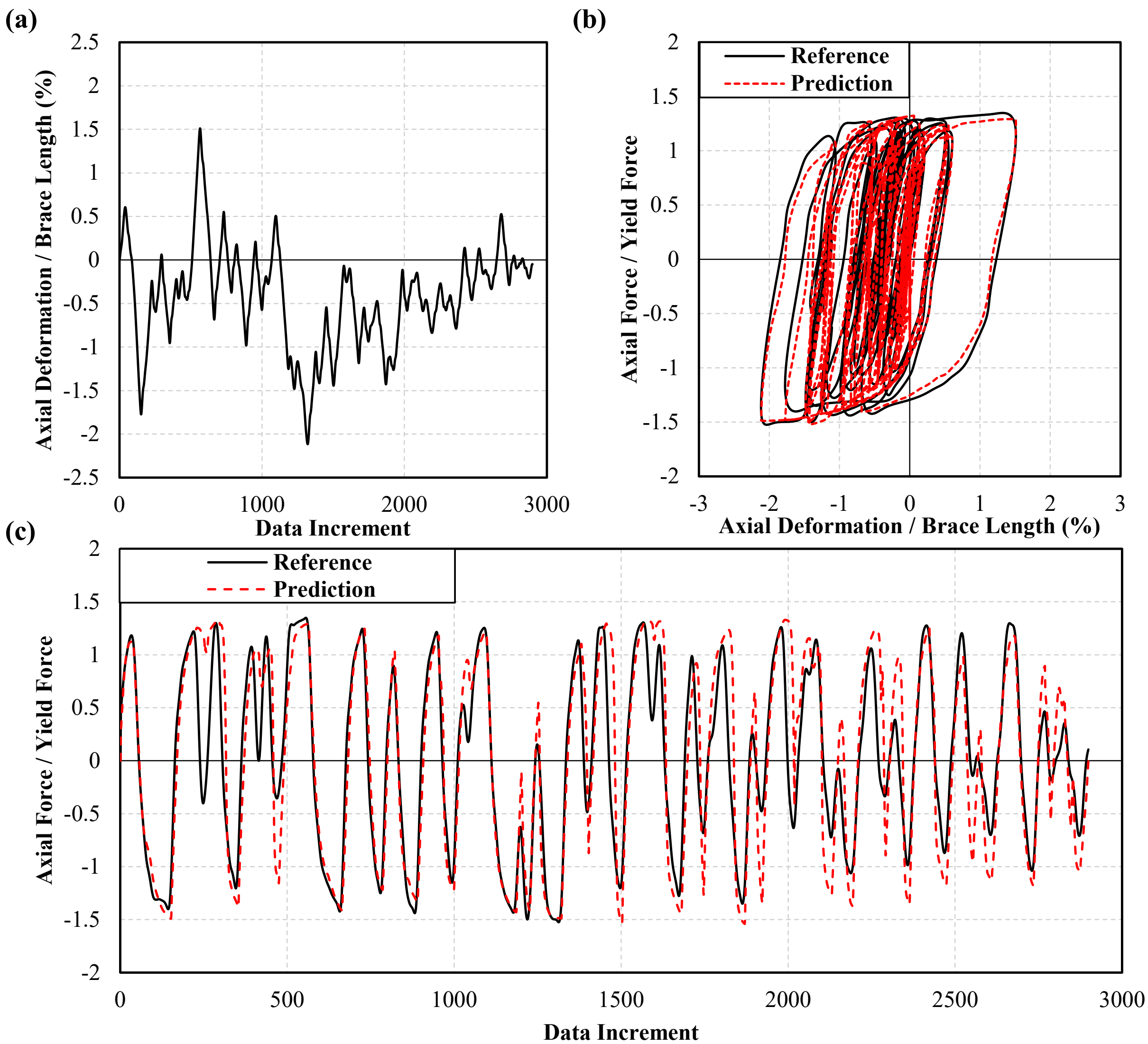

Fig. 3.9. Predicted vs. reference data for steel BRB under (a) random loading protocol: (b) hysteresis response, (c) axial force history.

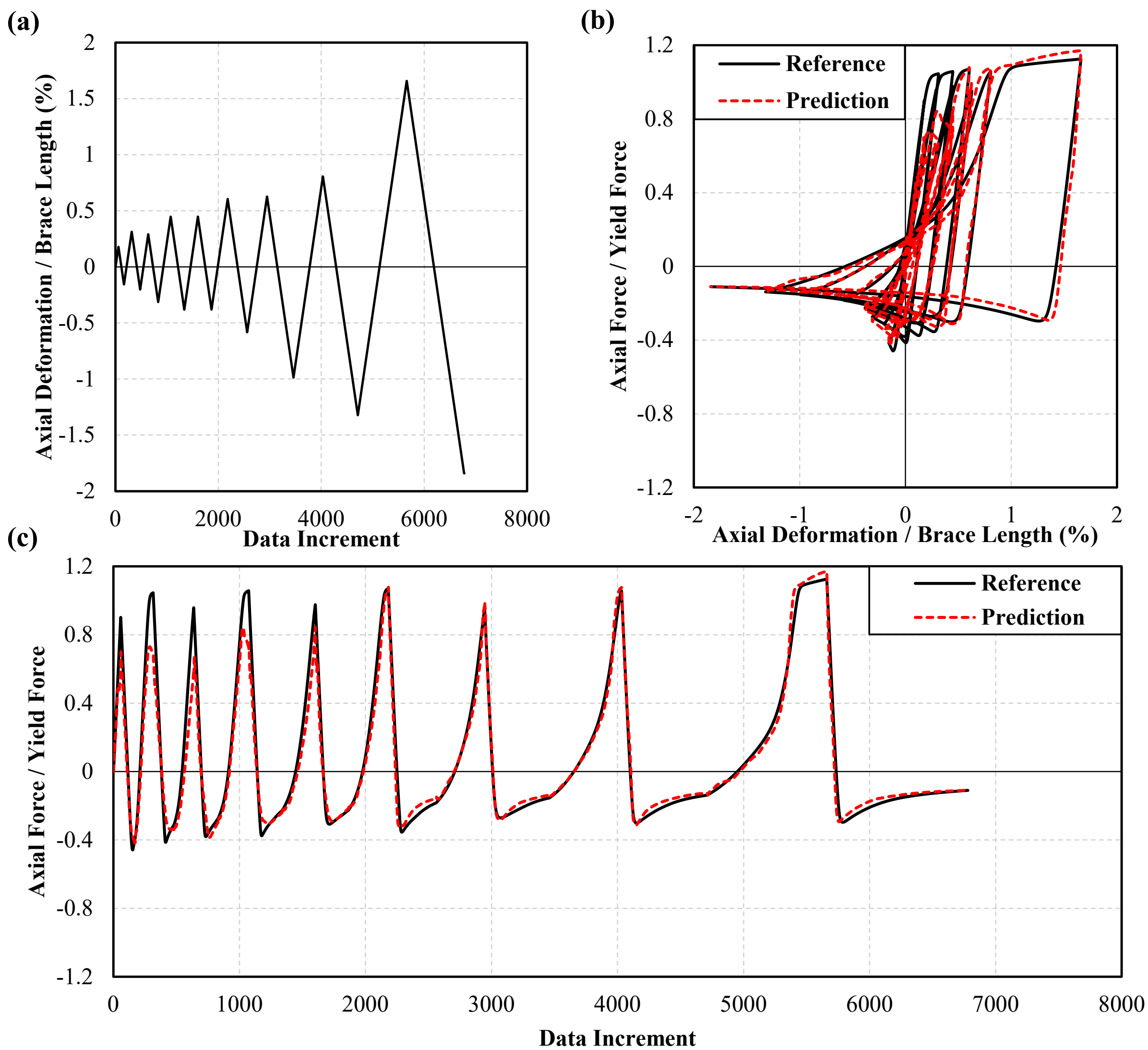

Fig. 3.10. Predicted vs. reference data for steel CBF brace under (a) cyclic loading protocol: (b) hysteresis response, (c) axial force history.

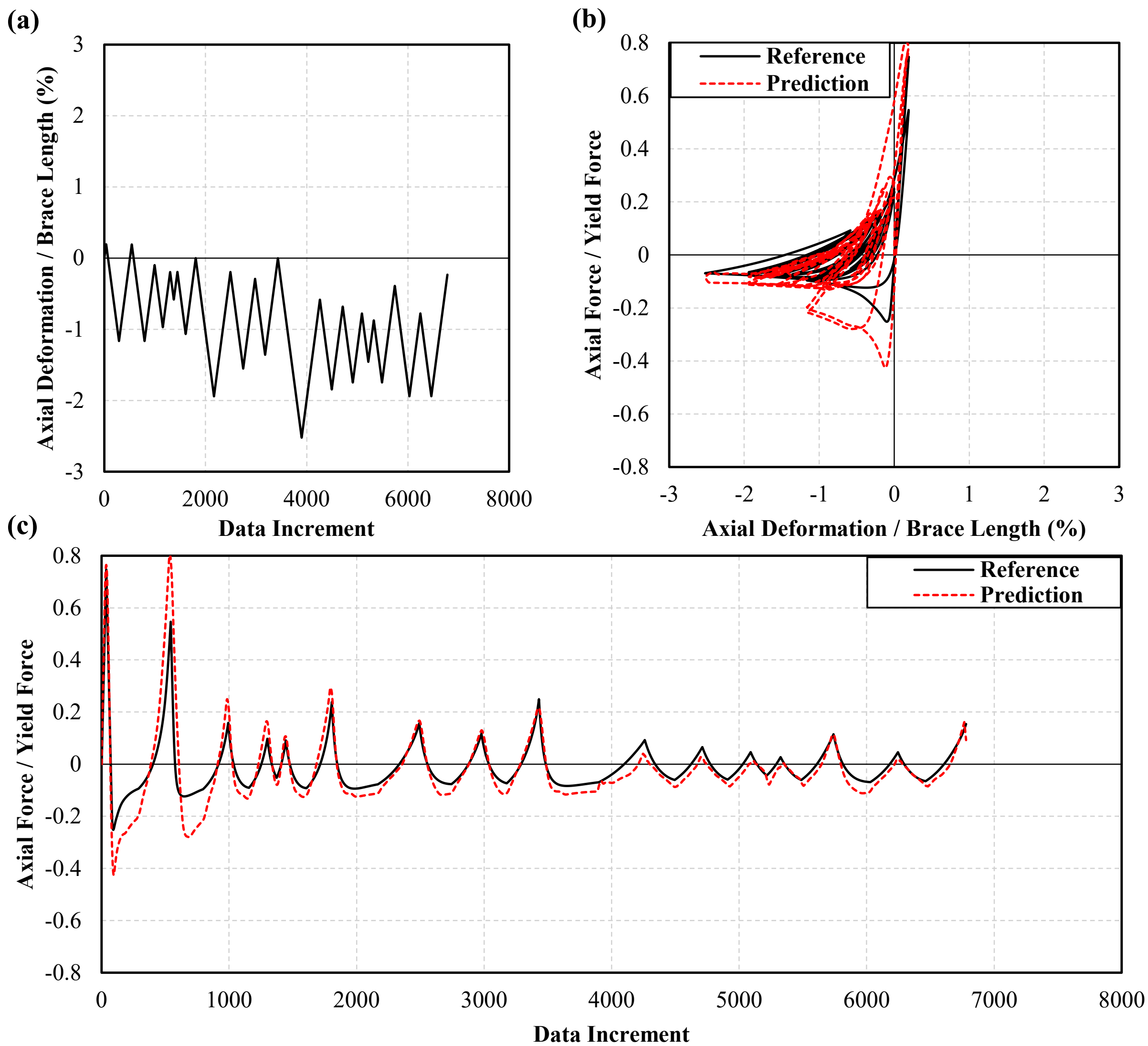

Fig. 3.11. Predicted vs. reference data for steel CBF brace under (a) random loading protocol: (b) hysteresis response, (c) axial force history.

The effectiveness of the proposed differentiator shown in Fig. 3.6b is verified here. A CBF model similar to the one shown in Fig. 3.5 is developed with the exception that the differentiator is disabled. The history of brace forces predicted by this model is compared in Fig. 3.12 to the reference data and the prediction by the model in Fig. 3.5. Referring to this figure, one can confirm that the proposed differentiator, which meant to set the boundaries between different loading cycles and determine appropriate outputs for a given input feature at a given cycle, is required to achieve an accurate prediction. Without the differentiator, the model struggles to find the appropriate peak values of the force in tension and compression.

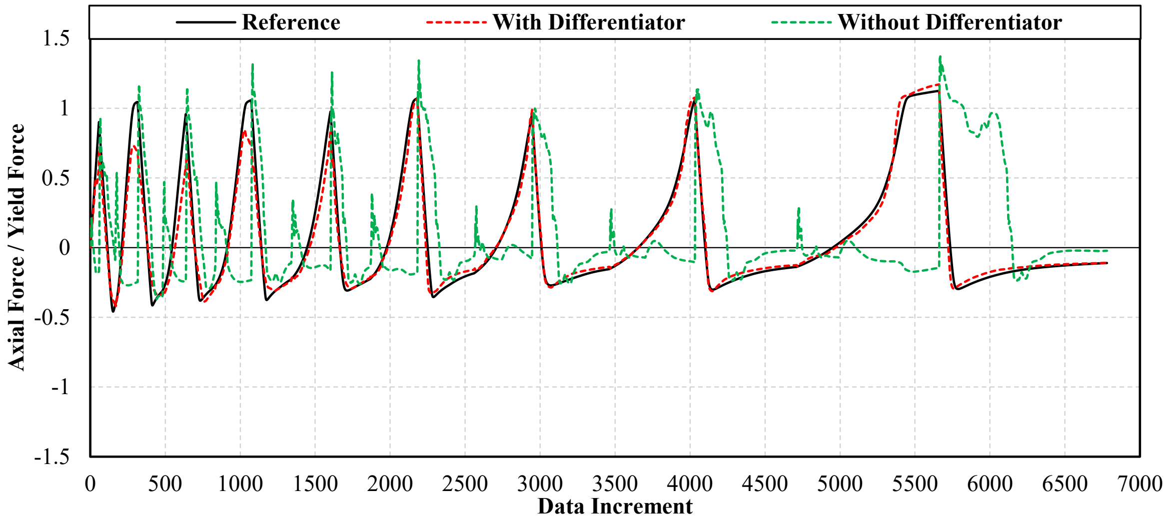

Fig. 3.12. CBF brace axial force history from the model with and without differentiator vs. reference data.

3.7 Conclusion

This paper proposes two data-driven surrogate models to extract the nonlinear hysteresis response of steel BRBs and steel CBF braces under random seismic loading. The proposed models consist of a functional ANN architecture with multiple layers of LSTM and a fully connected dense layer. The methodology to develop the training input data is first presented followed by the architecture of the models. The proposed models were validated using two sets of deformation histories as the input for each of the proposed models. The key features of the proposed ANN-based models are summarized below:

- A functional LSTM architecture is proposed instead of a sequential model as a proposal to solve the limited training data challenge.
- The input deformation protocol is decoupled into tension and compression branches to expand the input features and help the LSTM model to better interpret the incoming data.
- An auxiliary variable named differentiator is proposed to help the model identify the boundaries of each hysteresis loop and return appropriate force feedback for a given repetitive axial deformation feature.

The proposed LSTM approach achieved promising results in predicting the axial force – axial deformation response of steel BRBs and CBF braces with limited experimental training data enriched by synthetic data. While the proposed LSTM model demonstrated encouraging results in validation, it does have certain limitations. The proposed model employs an LSTM algorithm which may encounter concept shift, owing to stiffness and strength degradation, resulting in error accumulation towards the end cycles of the hysteresis response. Although the BRB model delivers more precise outcomes in cyclic axial deformation, its accuracy diminishes in random deformation history. Conversely, the CBF braces exhibit the opposite trend. Future studies should refine the proposed models based on training data solely obtained from laboratory test programs specifically planned to develop surrogate models with consistent boundary conditions and geometrical properties. The proposed methodology in this study can be applied to other structural components with similar hysteresis responses under seismic loading, e.g., steel eccentrically braced frame links.

Chapter 4

Transfer Learning-based Artificial Neural Networks for Hysteresis Response Prediction of Steel Braces

4.1 Abstract

This paper proposes a novel data-driven approach for predicting the hysteresis response (i.e., axial force – axial deformation response) of steel braces under seismic loading in concentrically braced frames using transfer learning (TL)-based artificial neural networks. The model leverages a pre-trained long short-term memory (LSTM) network and transfers its existing knowledge to the new proposed data-driven hysteresis model for steel braces. The proposed model is validated using four case studies with different approaches in utilizing input data from laboratory tests and data generated using random earthquake-induced vibration, featuring a wide range of frequency contents, amplitudes, and durations. A pseudo-dynamic analysis is then performed on a steel braced frame system to demonstrate the application of the proposed data-driven model in the system-level response evaluation while verifying the capability of the model in real-time simulations. The results obtained from the validation study confirm the proposed brace hysteresis model can properly estimate the underlying physical relationship between the input displacement and output force using the TL approach. The proposed model can be exploited as an efficient method to evaluate the dynamic response of steel braced frames.

4.2 Introduction

The application of artificial neural networks (ANN), a subclass of machine learning (ML), in structural engineering has witnessed significant advancements over the past decade with access to big data, the development of data-driven surrogate models, and increased computational power [108, 109]. However, most recent endeavours have predominantly focused on structural analysis and optimization problems [110 – 112], structural health monitoring [5, 113], damage detection [114, 115], and strength and resistance of structural elements [116, 117]. In seismic engineering, structural response, which depends on constitutive response, geometrical properties and loading conditions, is defined as time series data. The development of data-driven models that define time-dependent mechanical phenomena requires advanced algorithms and feature extraction techniques, particularly, given that time history data requires signal-to-signal mapping in training and response prediction. This aspect is even more important when the model is intended to predict based on random data, such as earthquake ground motion with long temporal dependency [118]. While data generated under earthquake ground motions is beneficial to obtain critical information about the structural response of elements, feeding such data into a data-driven model can be challenging due to the random nature of the ground motions and variabilities in their characteristics, such as predominant frequency, duration, and amplitude. Several efforts have been made in the past to develop data-driven models to replicate the inherent hysteresis response of structural elements under seismic loading as an alternative to the finite element method for solving nonlinear systems. Among those, support vector machine (SVM) has been widely used [38]. Kim et al. [39] used a convolutional neural network (CNN) to create a data-driven model for a hysteresis response prediction of a single-degree-of-freedom system under dynamic loads. Physics-based CNN was employed in more complex systems, e.g., to estimate building deformation under earthquake ground motions [55]. long short-term memory (LSTM) [99], which is a type of recurrent neural network (RNN) [56, 57], has been widely utilized in dynamic systems due to its capability to learn long-term dependencies in sequential data. LSTMs, as opposed to traditional procedures like vanilla RNNs [82], enable the flow of gradients over long sequences using memory cells and gating mechanisms. LSTM networks were used by Zhang et al. [7] to estimate the inner-story drift ratio of a building using ground motion acceleration data gathered through field-sensing. To optimize the accuracy of seismic response predictions, Torky and Ohno [37] developed a surrogate convolutional-LSTM (ConvLSTM) network where the measurements from ground sensors were used to predict the response of superstructure. Similar research can be found in the past literature on the seismic response of structures where a surrogate model was utilized to predict the structural response [40, 41, 43, 44, 53, 60, 61, 119 – 121]. Data-driven models are often intended to predict system-level responses, such as the overall deformation of the structure under lateral loads, which also bounds their application to the boundary of the system and datasets used for training. For example, the buckling-restrained braces (BRBs) surrogate model developed by Assaleh et al. [67] is trained on a limited number of BRBs under cyclic loading and its performance outside of this range, for example, when subjected to monotonic or random seismic loading may not be as good as training. Mokhtari et al. [64] developed a data-driven model for steel seismic fuses using the Prandtl-Ishlinskii hysteresis model and Lasso regression to reproduce non-degrading hysteresis response of steel BRBs, and degrading hysteresis response of steel moment-resisting frame connections. Furthermore, there are many loadings and geometry scenarios in the process of response prediction of structures, and creating a data-driven model for each can be burdensome and time-consuming. Thus, another method should be employed to generalize the existing data-driven model for similar case studies without the need for a newly generated surrogate model.

To achieve more robust data-driven models, transfer learning (TL) can diversify the pattern and behaviour of the training dataset for potential new data that may be encountered in future. Specifically, TL is used to transfer the knowledge of a pre-trained model to the new data-driven model to avoid reconstruction of the model from the first step for new datasets [122]. In most TL applications, the source and target tasks are not identical, but a fundamental assumption is that the underlying data distributions are similar [68]. One of the common methods to develop TL-based models is to adapt a pre-trained model and implement the whole or part of that model into the new model. In structural engineering, TL has been used successfully in various areas, including structural health monitoring [123] and damage detection [69]. Additionally, this approach can be used to develop data-driven models for problems where the training data is insufficient [124]. Limited applications of TL in predicting the dynamic response of structural elements exist in the literature. Pak and Paal [125] proposed a TL approach to investigate the transferability of the knowledge in the pre-trained models for lateral strength of reinforced concrete columns with limited data.

Taking advantage of the TL approach, this paper proposes a new ANN data-driven model for the prediction of the dynamic response of steel concentrically braced frame (CBF) braces under earthquake loading. Following an introduction to the cyclic behaviour of steel CBF braces, a LSTM model based on laboratory test data is presented. Four different case studies are presented for training to verify the capability of the proposed method in predicting brace hysteresis response. The model is then used to transfer the knowledge of brace hysteresis behaviour to a new model to perform dynamic responses. The model is finally validated in two phases, static and pseudo-dynamic analyses (PsDA) for steel braced frames.

4.2.1 Cyclic Response of Steel Braces

CBFs are commonly used in building structures to resist lateral loads [84]. Under lateral seismic loads, braces of CBF structures may undergo large inelastic deformation due to yielding in tension and buckling (global member instability) in compression, developing asymmetric hysteresis loops as shown in Fig. 4.1. The buckling load for commonly used braces is appreciably lower than the brace yield force.

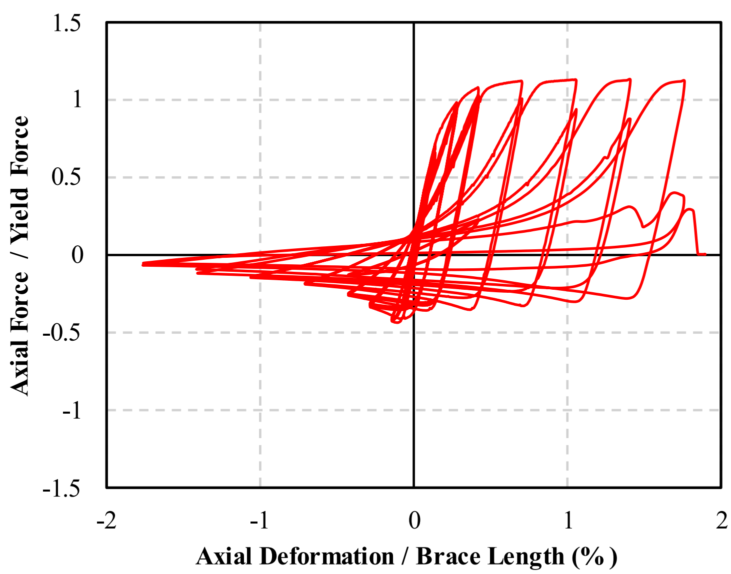

Fig. 4.1. Axial force – axial deformation response of a steel brace (data from [86]).

As shown in Fig. 4.1, after the first buckling point, noticeable stiffness and strength degradation occur, which reduce brace strength in subsequent lateral cycles, which is further exacerbated due to the formation and accumulation of plastic deformations in the plastic hinge location, e.g., mid-length of the brace unsupported length.

4.2.2 Brace Hysteresis Simulation using LSTM-based Surrogate Modelling

The architecture of the proposed LSTM-based model developed to predict the hysteresis response of steel CBF braces is shown in Fig. 4.2. As shown, the input is first decoupled into two sets, one describing the tension-dominated phase of the brace response and the second focusing on the compression-dominated phase. This aims to help the model better interpret the correlations and relationships inherent in data. The tension-dominated phase input is then stacked with the auxiliary parameter, the differentiator, and the two separated inputs are each sent to a LSTM layer of 50 cells. After preprocessing the input in LSTM Layer1, the output matrices will concatenate, and the result enters the main body of the proposed model comprising two layers of LSTM with 100 cells each and a dense layer with 100 neurons. The activation function used in the hidden layers is *ReLU*. In this model, the normalized axial deformation of the brace is used as input and the output consists of the normalized axial force. Five different laboratory test responses were used for training the model [86, 106]. To evaluate the model, a new laboratory test example was used where Fig. 4.3a is the axial deformation of the brace, and its result in the format of axial force – axial deformation hysteresis is plotted in Fig. 4.3b with a Mean Square Error (MSE) of 6.472×10^{-3}.

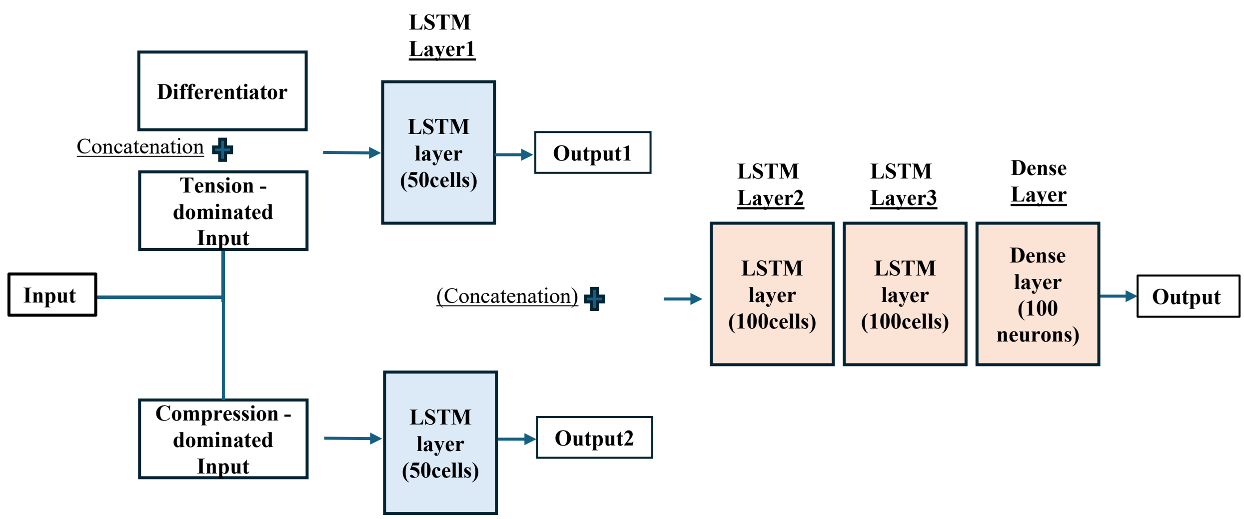

Fig. 4.2. Architecture of the LSTM network.

The model is trained using an axial deformation signal as the only input signal in time and the geometric properties of the brace are scalar, which cannot be used as new features. To infuse the geometry of the brace, the axial deformation is normalized by the length of the brace. Similarly, the output signal is normalized by the brace yield strength to create output data independent of the brace material. The test data should preferably belong to the same test program and same steel brace size, but be subjected to different loading protocols, to avoid inconsistency in the dataset. Given the limited access to experimental data of this nature, synthetic data was produced in this study using a corroborated numerical model of the brace to fill the data gap and achieve diverse and rich training data. A new variable, called the differentiator, consisting of a matrix of {-1, 0, 1} was added to the model to avoid prediction confusion, given that the cyclic response of CBF braces involves multiple force outputs for the same axial deformation. The value of 1 is fed to the model when the axial deformation signal increases until it reaches its peak, while when the loading is reversed and advances in compression, the value of 0 is selected. The value of 1 is replaced by -1 every two cycles to provide extra guidance for distinguishing between two unequal outputs when facing identical axial deformation, as the brace force often reduces in the second cycle of the same axial deformation due to plastic hinging in the brace.

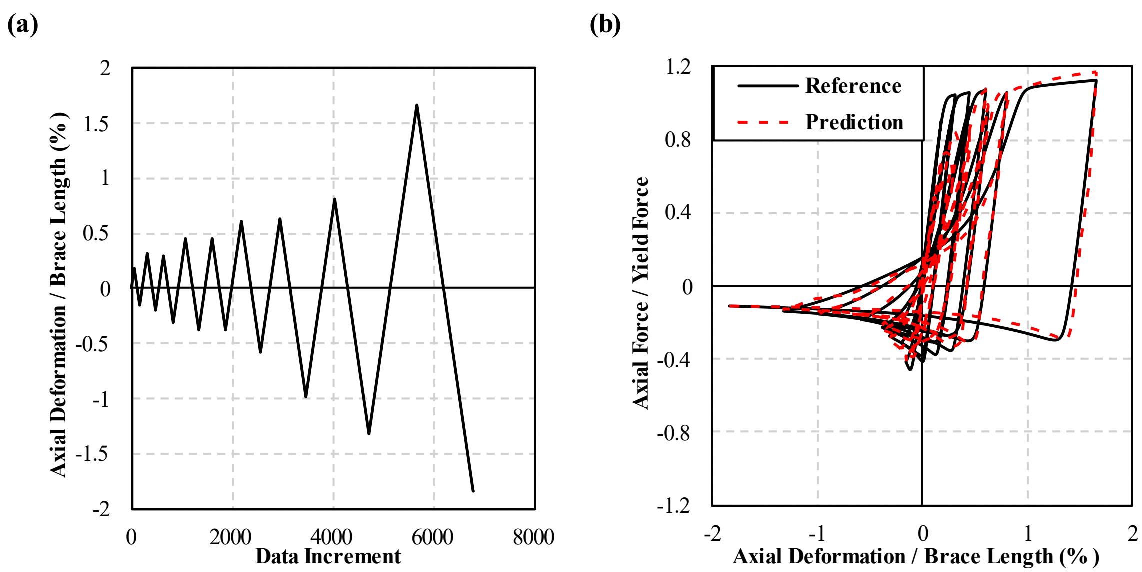

Fig. 4.3. Validation of LSTM-based brace hysteresis model (a) input axial deformation; (b) brace hysteresis prediction.

Despite the acceptable performance of the model under cyclic displacement protocol (see Fig. 4.3), hysteresis response prediction can be quite challenging when the brace is subjected to random deformation due to actual earthquake accelerations. One potential approach to tackle this problem is to exploit the knowledge built by the baseline LSTM-based model in more enhanced machine learning, e.g., designed by benefiting from the TL technique, a model customized for earthquake histories.

4.3 Brace Hysteresis Simulation Using Transfer Learning

TL was used here as a model designing technique to leverage the hysteresis response knowledge gained in the previous step by the LSTM-based model to achieve a better prediction under random displacement history generated by earthquake ground motions. TL definition by [68] is as follows: *Given a source domain* $\mathcal{D}_S$ *and learning task* $\mathcal{T}_S$, *a target domain* $\mathcal{D}_T$ *and learning task* $\mathcal{T}_T$, *Transfer Learning aims to help improve the learning of the target predictive function* $f_T(\cdot)$ *in* $\mathcal{D}_T$ *using the knowledge in* $\mathcal{D}_S$ *and* $\mathcal{T}_S$, *where* $\mathcal{D}_S \neq \mathcal{D}_T$, or $\mathcal{T}_S \neq \mathcal{T}_T$.

In other words, the domain and target task inputs can have identical distribution of data but different marginal distribution of the output data or vice versa. It is noteworthy that both the inputs and outputs of domain and target task can contain different distributions which is not the focus of this research. Fig. 4.4a demonstrates traditional machine learning approaches that can be used to develop a data-driven model (Model A or B). Fig. 4.4b highlights how TL can be used to transfer the knowledge created for Task A to build the model that performs Task B.

Fig. 4.5 details the steps involved when designing a data-driven model using TL with *n* number of layers. Let us assume the original model is created for Task A with its specific input dataset. The layers approaching the output layer are heavily involved in learning more task-specific information compared to earlier layers. Therefore, *m* number of layers that focus on learning the features of input data in Task A are frozen, meaning that all the trained weights maintain their values, and the rest of the network is modified. Then, *x* new layers are added to the model to retrain the new customized model using the Task B dataset. Finally, the frozen parts of the model are activated to retrain the model with the Task B dataset which is called fine-tuning of the model.

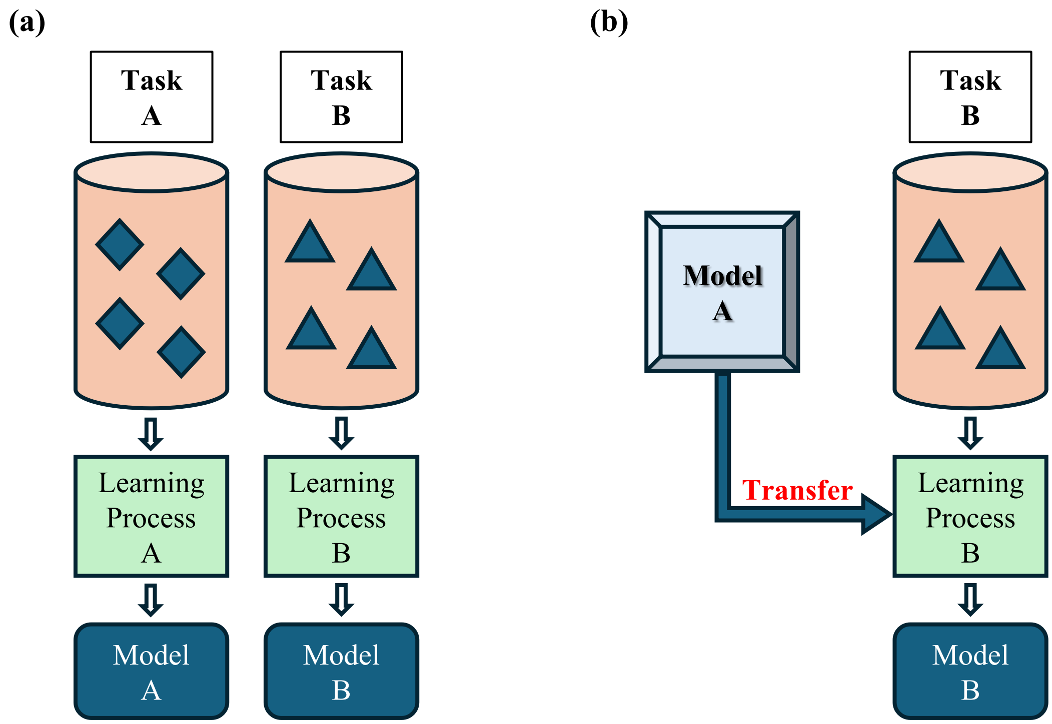

Fig. 4.4. Data-driven model development: (a) Traditional ML method; (b) TL approach.

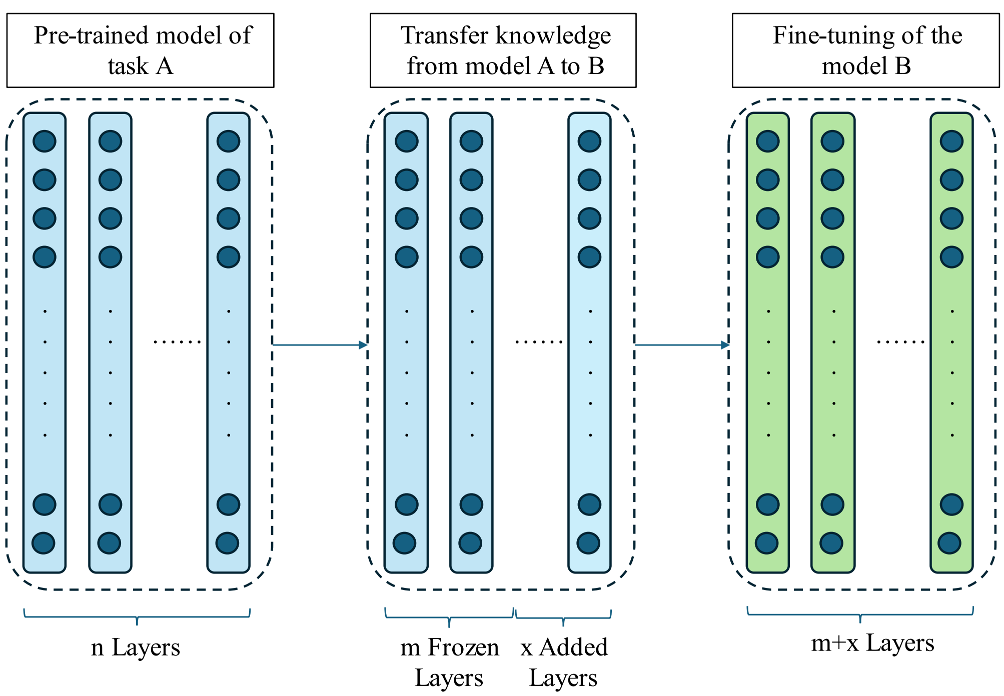

Fig. 4.5. Steps of the transfer learning approach.

One of the drawbacks of TL-based models is that the final model fails to predict the response associated with the original dataset. In other words, the model is custom-made for the new target data and to a certain degree overfitted over the new dataset.

The LSTM model developed and validated in Fig. 4.2 serves as the foundation for the proposed TL framework. While the original model (Fig. 4.2) is not directly applicable to PsDA due to its inability to access the complete brace deformation upfront during the simulation, the core architecture consisting of LSTM Layers 2 and 3 with 100 cells forms the basis for the TL-based model. This approach leverages the knowledge acquired by the original model to predict random deformations induced by real earthquake accelerations. To adapt the baseline model for PsDA, the final dense layer in Fig. 4.2 is removed and replaced with a new dense layer with 100 neurons specifically trained for the new data distribution. The final architecture of the proposed model is illustrated in Fig. 4.6. The training process utilizes a dataset comprising brace axial force-axial deformation responses generated under random vibrations mimicking real earthquake ground motions. During the training of the TL model, the LSTM layers are initially frozen. This implies that their weights remain unchanged, while only the weights associated with the newly introduced dense layer are trainable. After this initial training stage, the entire network is unfrozen for fine-tuning. The Keras library in Python was employed to facilitate the training process. The model was trained for 5000 epochs, and the Adam optimizer was used with a learning rate of 0.001 with the last 100 epochs being used for fine-tuning with a learning rate of 0.00001.

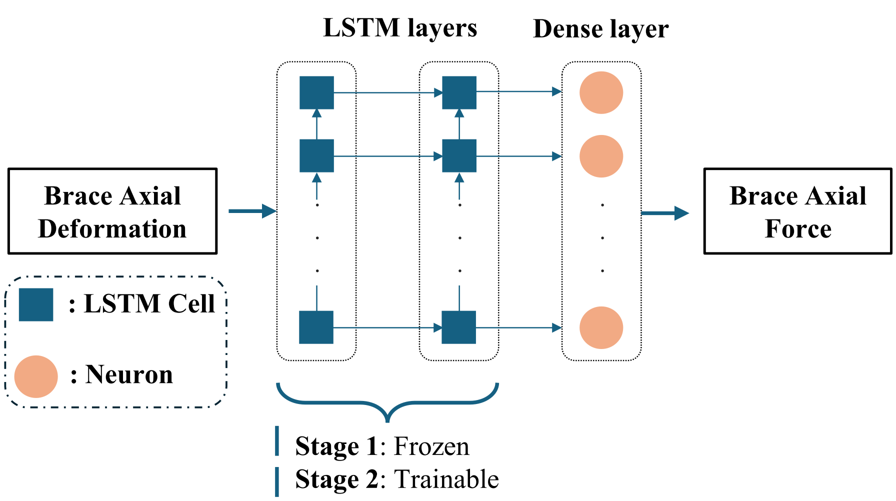

Fig. 4.6. Architecture of the proposed TL-based model.

4.4 Validation of Proposed Models

Static and pseudo-dynamic analyses (PsDA) were used to validate the applicability of the proposed TL model in Fig. 4.6. In static analysis, the model predicts the hysteresis response of CBF braces while having access to the full history of the brace axial deformation signal. In PsDA, the substructuring technique is used to create two modules, the data-driven model simulating the response of the brace and the computational model numerically simulating the response of the rest of the structure and solving the equation of motion under a ground motion acceleration. The predictive response from PsDA was compared against the response obtained from a pure numerical model of the braced frame developed in the *OpenSees* program [101]. The validation study using static analysis comprises four cases: *i*) the model trained on laboratory tests without utilizing TL; *ii*) the model trained on the synthetic data generated under earthquake ground motions given in Table 4.1 (labelled as training); *iii*) the model trained on both datasets associated with *i* and *ii*; *iv*) the model employing TL trained on the simulated ground motion data while taking advantage of the main body of the original model described in case *i*. These four cases were studied to find the best solution for performing the final training and prediction in the PsDA. The models were trained using the full-time history of the response in these cases. The most effective case was then used in the PsDA simulation. The evaluation criteria for static analysis and PsDA validations include prediction error, adaptability, and applicability to other potential loading scenarios with minimal effort required.

4.4.1 Static Analysis

Static analysis is conducted to evaluate the prediction capability of the Fig. 4.2 model in reproducing the cyclic response of steel braces under seismic loads. As described earlier, in the model of Fig. 4.2, LSTM Layer 1 was used to preprocess the axial deformation signal. After modification of the LSTM model in Fig. 4.2, the architecture of Fig. 4.7a remains. The architecture presented in Fig. 4.7a was first tested to evaluate its capability in learning brace hysteresis response. The model was then tested to predict brace axial force – axial deformation response using Fig. 4.3a deformation as illustrated in Fig. 4.7b. The MSE of the prediction shown in this figure is 1.15×10^{-2}, which confirms the capability of the model in estimating hysteresis simulation; however, the accuracy of the prediction is still inferior compared to the one presented in Fig. 4.2, primarily due to the concept shift. Despite this fact, to be able to perform the PsDA in the next step, The model of Fig. 4.7a was utilized to predict cases *i*, *ii*, and *iii*, while the model of Fig. 4.6, which has the same layers as Fig. 4.7a, was used in case *iv.* All models have the same layer property and were trained for 5000 epochs to achieve a consistent comparison.

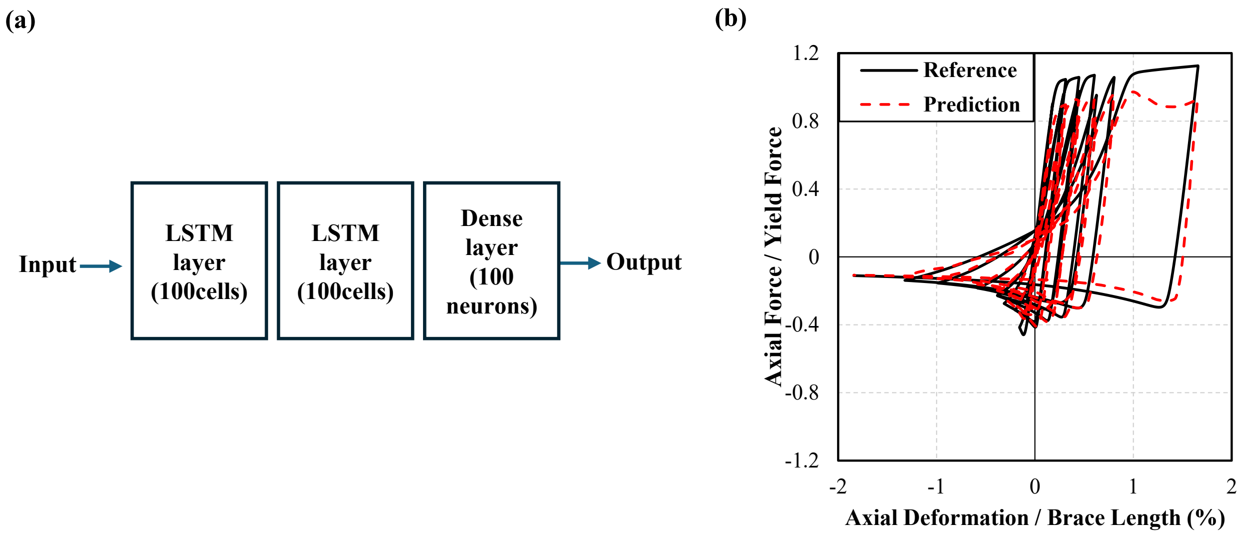

Fig. 4.7. LSTM architecture for (a) training cases *i*, *ii*, and *iii*; and (b) hysteresis prediction based on loading protocol of Fig. 4.3a as the test data.

The training data used to perform static analysis consists of 10 steel brace hysteresis datasets, five sets from experimental testing performed on isolated HSS 127×127×7.9 brace from [86, 106], and the other five involving synthetic brace cyclic data generated using the numerical model of a steel braced frame structure in *OpenSees* under earthquake accelerations shown in Table 4.1. The braced frame comprises the same cross-section for the brace as the one used in training and was simulated using a nonlinear beam-column element with the Giuffré-Menegotto-Pinto material model [23] using Young's modulus (E) of 200 GPa where the equation of motion is solved using Newton method with Line Search algorithm [104]. The numerical model was initially calibrated against experimental test data reported in [86] involving a single HSS 127×127×7.9 steel brace, having a cross-sectional area of 3400 mm^2, an effective length of 4160 mm, and a material yield strength of 389 MPa.

To test the performance of the model, a set of two synthetic datasets produced using the numerical model under the ground motion accelerations shown in Table 4.1, with different characteristics, namely, dominant frequency, duration, and amplitude, was used. Figs. 4.8a and 4.8b show the axial force – axial deformation responses of the braces used to test the model obtained from the braced frame subjected to accelerations shown in Figs. 4.8c and 4.8d, respectively. In these figures, brace axial force is normalized by the yielding capacity of the brace and axial deformation is normalized by the length of the brace. The validation of the proposed data-driven models for the four cases described earlier is presented in the following section. The force predictions of all cases are shown in Figs. 4.9 and 4.10 for the 1978 Tabas-Dayhook and the 1979 Imperial Valley-Cerro Prieto earthquake, respectively against the reference axial force shown in Figs. 4.8a and 4.8b.

Table. 4.1. Details of crustal ground motion records used for training and testing of the models of Figs. 4.6 and 4.7a.

Training	Testing	Event	Magnitude (M_W)	Depth (km)	Year	Recorded Station	Scale Factor
●		San Fernando	6.61	8.4	1971	Castaic-Old Ridge Route	2.68
●		Friuli, Italy-01	6.5	10	1976	Tolmezzo	2.27
●		Loma Prieta	6.93	19	1989	San Jose-Santa Teresa	2.54
●		Loma Prieta	6.93	19	1989	Anderson Dam	2.59
●		Nortridge-01	6.69	18.2	1994	Santa Susana Ground	2.57
	●	Tabas, Iran	7.35	10	1978	Dayhook	2.19
	●	Imperial Valley-06	6.35	11.6	1979	Cerro Prieto	3.53

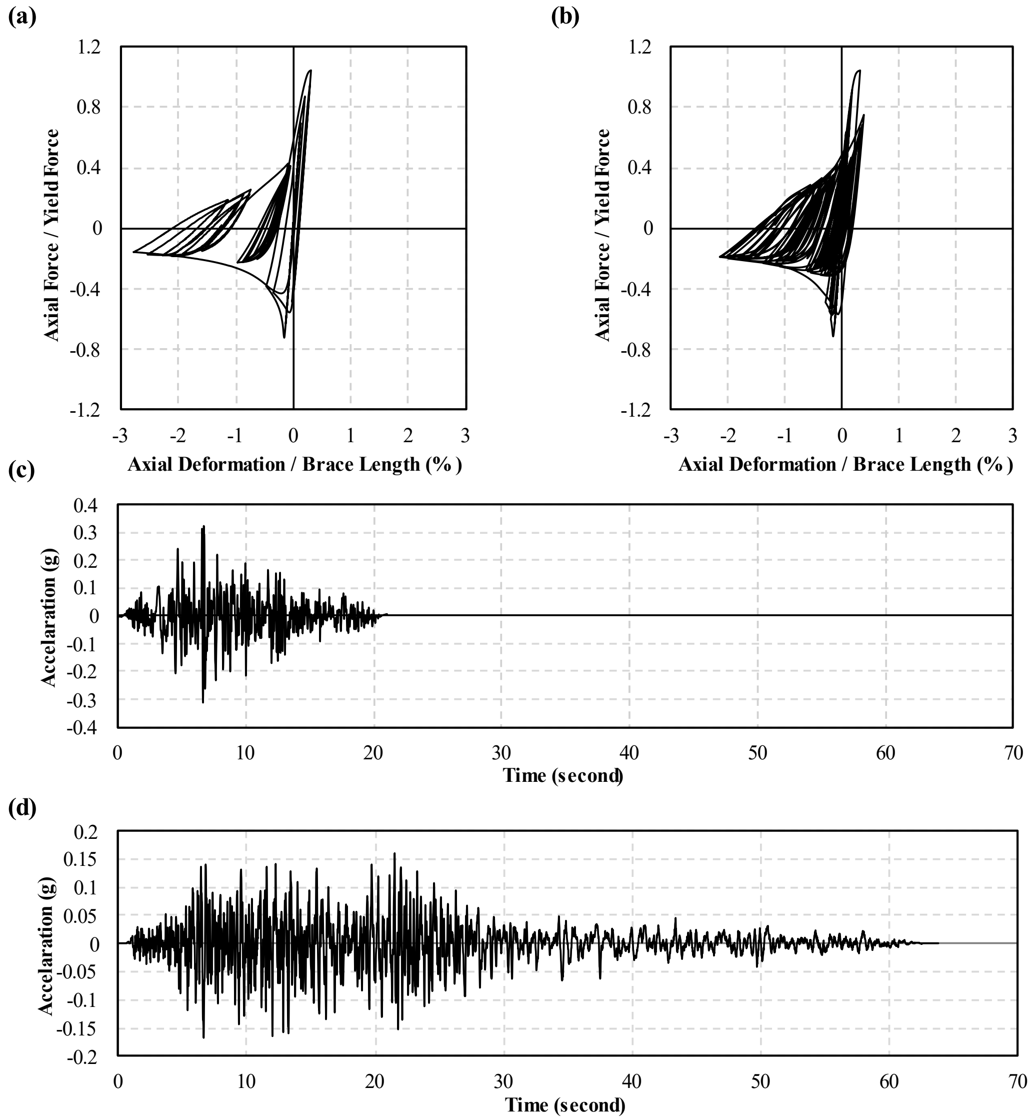

Fig. 4.8. Axial force – axial deformation of HSS 127×127×7.9 brace when the braced frame is subjected to (a) 1978 Tabas-Dayhook earthquake; (b) 1979 Imperial Valley - Cerro Prieto earthquake; (c) acceleration history of the 1978 Tabas-Dayhook earthquake; (d) acceleration history of the 1979 Imperial Valley - Cerro Prieto earthquake.

Case I: The normalized axial deformation of the brace is used as input to predict the axial force of the steel brace. The MSE of the prediction, as shown in Figs. 4.9 and 4.10, are 1.55×10^{-2} and 9.47×10^{-3}, respectively. Referring to Figs. 4.9 and 4.10, the peak forces in tension and compression are not adequately captured using the proposed data-driven model. This could be attributed to the cyclic nature of the training data used to train the model, which may not well interpret the randomness implicit in the brace forces generated using ground motion time histories. On a bigger scale, these results suggest that the traditional machine learning techniques, e.g., the one used in the model Figs. 4.2 and 4.7a in this study, are often tailored to a specific distribution of data and fail to achieve a generalized response prediction machine within the scope of seismic engineering.

Case II: The prediction capability of the model significantly improved when the model was trained based on the data generated using random vibration of earthquake ground motions. In particular, peak brace forces are predicted relatively better compared to Case I. However, the accuracy of the force prediction degraded mainly in the second half of the simulation, specifically under the 1979 Imperial Valley-Cerro Prieto earthquake shown in Fig. 4.10. This is also confirmed by the MSE values for the two simulations shown in Figs. 4.9 and 4.10, 2.73×10^{-3} and 9.05×10^{-3}, respectively. One potential reason for this observed inaccuracy is that the model trained using data from earthquake ground motions may be overfitted. To address this shortcoming, the training data can potentially be enriched in future studies.

Case III: all the data from both Case I and Case II was used to train the model in this case. Compared to the two previous cases, the overall results of the axial force prediction of the model improved, which is also confirmed by the MSE values for the two simulations shown in Figs. 4.9 and 4.10, 3.78×10^{-3} and 3.83×10^{-3}, respectively. Using all the training datasets for this case allowed the model to learn two different distributions of data in one training process. However, since the distribution of the laboratory data and the data generated using random vibration of earthquake ground motions are not the same but similar, the model did not achieve the lowest MSE in each of the two tests. The result suggests that more training epochs are needed to reach a lower error function which takes a longer training time.

Case IV: The LSTM-based model in Fig. 4.6 using the TL method was employed in this case. The training and fine-tuning conditions are explained in the previous section. The axial force prediction shown in Figs. 4.9 and 4.10 acquired the MSE values of 4.51×10^{-3} and 1.95×10^{-3}, respectively. Case IV showed the lowest MSE among others in the test of the 1979 Imperial Valley-Cerro Prieto earthquake shown in Fig. 4.10. The overall error of the prediction is lower compared to the previous cases as well. However, the result of the 1978 Tabas-Dayhook earthquake test as shown in Fig. 4.9 is worse than Case II. A possible explanation can be that the foundation LSTM model needs further improvement to accurately transfer hysteresis response knowledge.

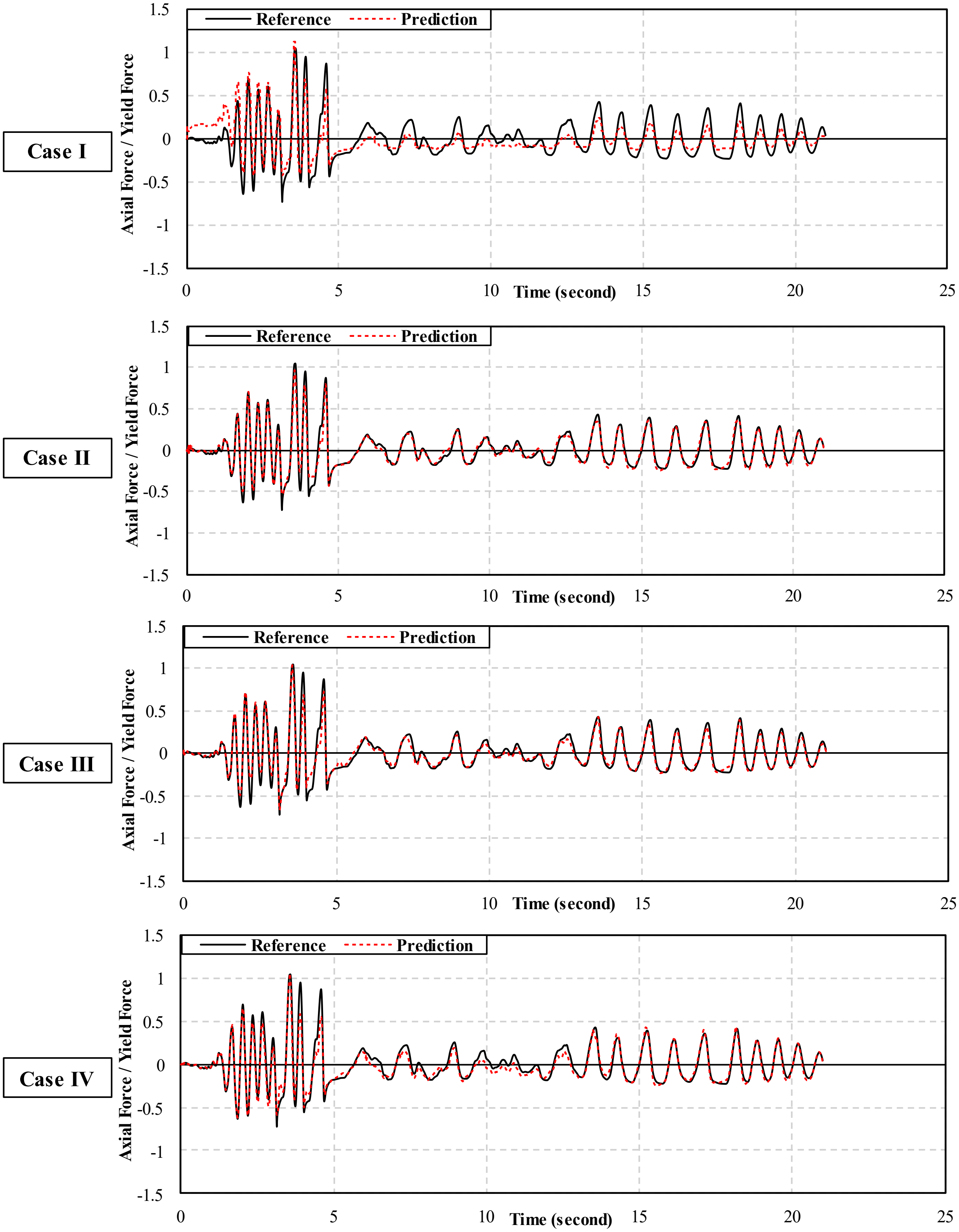

Fig. 4.9. Axial force response predictions for the 1978 Tabas-Dayhook earthquake.

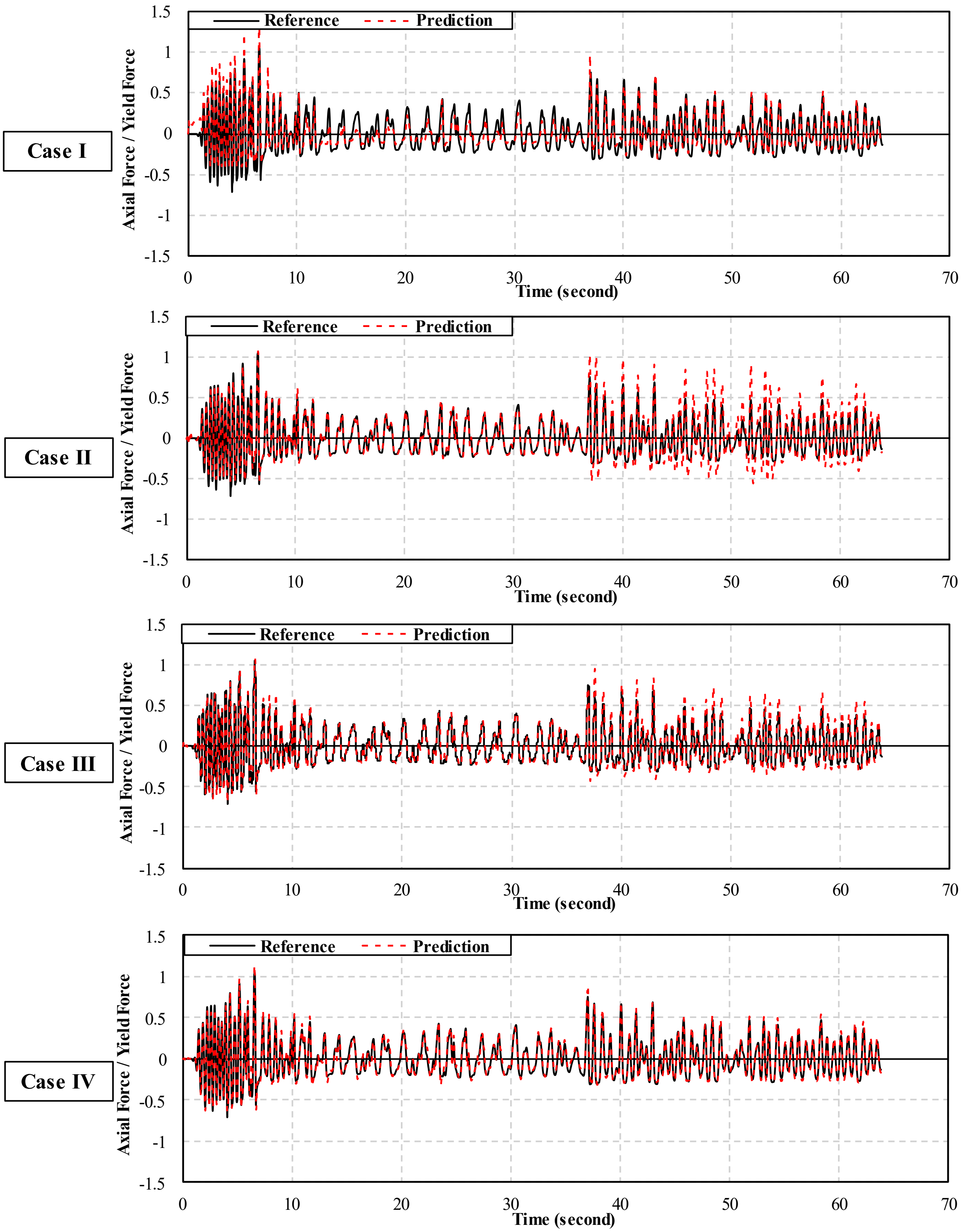

Fig. 4.10. Axial force response predictions for the 1979 Imperial Valley - Cerro Prieto earthquake.

The results of the four cases investigated here confirmed the effect of source data used for training the model and the influence of the technique used to develop the data-driven model for brace hysteresis prediction. Overall, Case IV, taking advantage of the TL technique, yielded the lowest average MSE (3.23×10^{-3}) compared to the other cases. In terms of efficiency of training, Case IV performed superior compared to the other cases. To compare the relative training time, Case IV was twice as fast as Case I and Case II, while Case III was four times slower than Case IV. The absolute training time is not presented as it is affected by the user's computational power in training the model.

The TL model trained based on the brace hysteresis obtained from earthquake displacement histories was found to be the most efficient and accurate data-driven hysteresis model for the steel braces. Brace hysteresis obtained from earthquake displacement histories is currently not widely available from laboratory testing as the majority of the past brace experiments were performed using cyclic loading protocols. Therefore, this study benefited from laboratory test data in its LSTM layers to develop the foundation for brace hysteresis prediction. This model was then enhanced by transferring the knowledge developed in the initial model to a more enhanced hysteresis model created using the TL approach. This methodology can be employed for other braces geometries and loading conditions.

4.4.2 Pseudo-dynamic Analysis

PsDA was conducted on a single-storey steel braced frame in which the response of the brace is reproduced using the proposed data-driven model of Fig. 4.6 in a Python environment. The remaining elements of the braced frame are simulated in the *OpenSees* environment, where an elastic beam-column element and a corotational truss element were employed to represent columns and the beam, respectively, to experience minimal or no inelastic deformations. To account for the lateral out-of-plane support provided by the perpendicular framing systems, the out-of-plane translation at the top of the columns was restrained. A lumped mass of 102 kN s^2/m was assigned to the top of each column to represent the seismic weight of the CBF system and material properties for the steel were defined with the Giuffré-Menegotto-Pinto material model using Young's modulus (E) of 200 GPa. Rayleigh damping with a critical damping ratio of 2% was implemented to simulate the classical viscous damping in the first vibration mode of the structure. The equation of motion is solved using the Generalized-Alpha method (integration module) [126]. The geometry of the braced frame, the integration module, and the data-driven model are presented in Fig. 4.11. The communication between two substructures is facilitated using a middleware, UT-SIM framework, which sends every time increment displacement signal from the integration module to the data-driven model and receives force feedback from this model [127, 128].

PsDA is initiated by feeding the braced frame model the elastic displacement of the brace using a simple mass-spring system, instead of the actual signal from the brace data-driven model. The reason is that incoming data is not rich enough at the beginning of the simulation. As more data becomes available after small elastic oscillations, the data-driven model is activated to predict the force response for a given deformation signal received from the integration module. At every time increment during the response prediction by the data-driven model, all available data from the beginning of the analysis is exploited to enrich the diversity of data for force prediction.

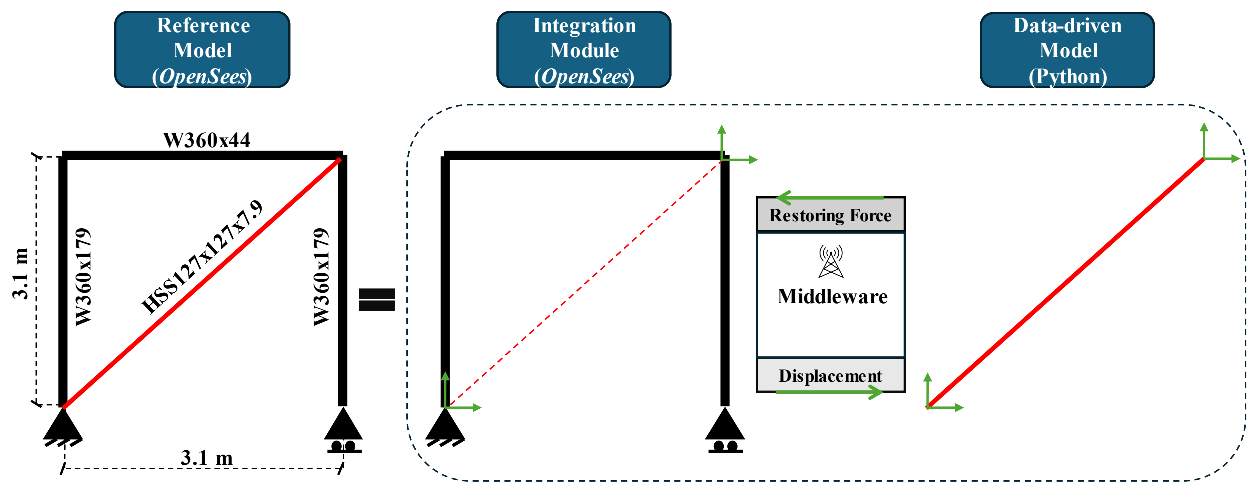

Fig. 4.11. Schematic of pseudo-dynamic analysis of the steel CBF.

Figs. 4.12a and 4.12b show the histories of axial force from the braced frame as compared to the brace forces obtained from a pure numerical model constructed in *OpenSees* following the technique described earlier for the 1978 Tabas-Dayhook earthquake and the first 21 seconds of the 1979 Imperial Valley - Cerro Prieto earthquake, respectively. Overall, a good agreement is found between PsDA results and those of the dynamic analysis from the pure numerical model, suggesting that the proposed data-driven model can estimate brace axial force with sufficient accuracy using the data generated and fed during the analysis. However, higher discrepancies are observed between prediction and target brace forces when the results of PsDA are compared to those from static analyses presented earlier. This can be attributed to the fact that the LSTM data-driven model in PsDA receives data gradually, which limits its ability to make accurate predictions due to less access to response history. The values of MSE between the predicted and target brace forces are 1.30×10^{-2} and 3.31×10^{-2} for the 1978 Tabas-Dayhook earthquake and the first 21 seconds of the 1979 Imperial Valley - Cerro Prieto earthquake, respectively.

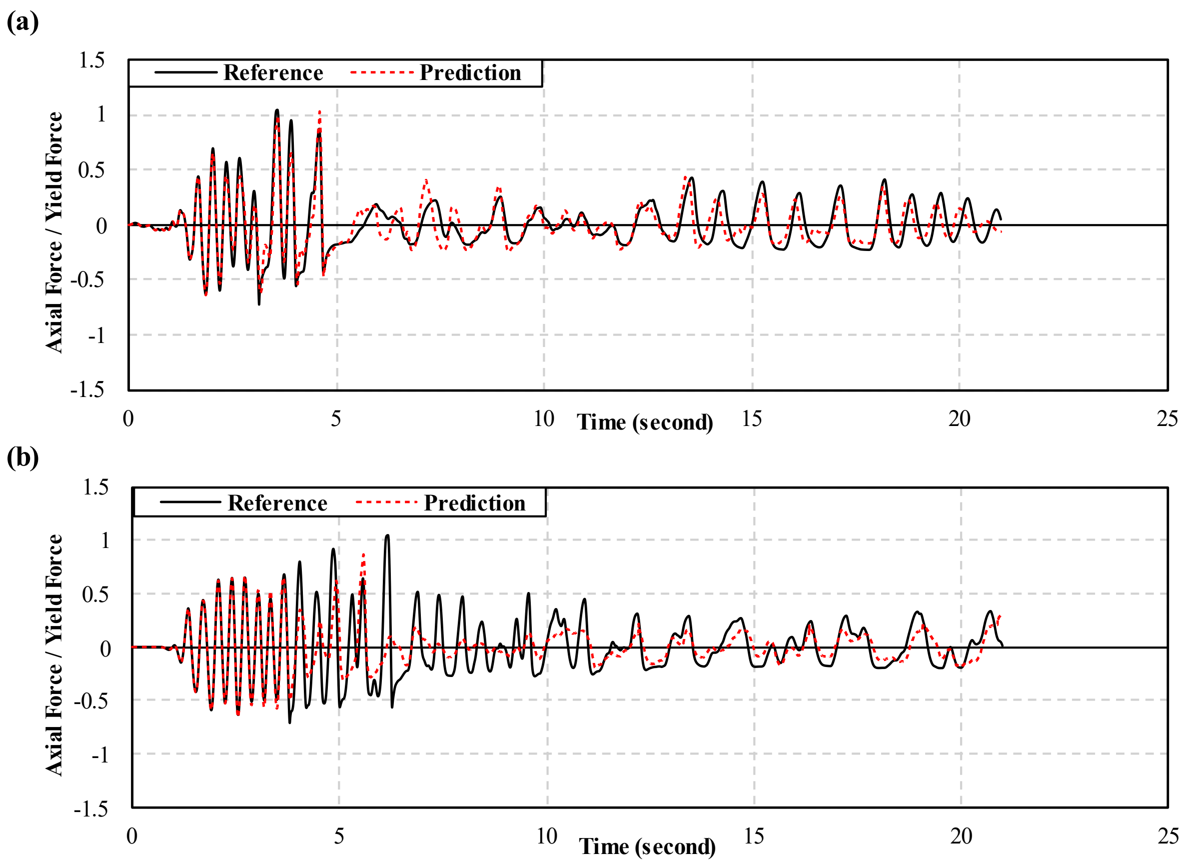

Fig. 4.12. Brace axial force histories from pseudo-dynamic analysis (a) the 1978 Tabas-Dayhook, (b) the 1979 Imperial Valley - Cerro Prieto earthquake (only the first 21 seconds is shown).

4.5 Conclusions

This article developed a new data-driven approach for the hysteresis response simulation of steel braces in concentrically braced frames (CBFs) utilizing transfer learning (TL). A long short-term memory (LSTM) neural network designed to estimate the nonlinear cyclic response of steel braces was used to implement the TL method, which was intended to transfer the brace hysteresis knowledge developed using an initial machine learning-based model to a more enhanced data-driven model. The proposed brace data-driven model has the following key features:

- The architecture of the TL model consists of two layers of LSTM adapted from a pre-trained data-driven model on the cyclic response of steel braces and a dense layer added to tailor the new proposed model to seismic loads.
- The proposed TL model is first trained with the LSTM layers frozen and then fine-tuned with all the weights set as trainable to better fit the new earthquake ground motion data.
- By freezing the LSTM layers, the model can converge faster and train fewer weights, leading to a faster training process. This advantage is particularly evident when compared to traditional machine learning methods, where the training process is often prolonged due to the need to compute an exhaustive search over the entire parameter space.

The proposed data-driven model was validated in two phases: static analysis of an isolated steel brace and pseudo-dynamic analysis (PsDA) of a steel braced frame using the substructuring technique. Synthetic earthquake acceleration-generated signals were used in the validation studies with average MSE of 3.23×10^{-3} and 2.31×10^{-2} for static and dynamic analyses, respectively. Validation results exhibit accurate predictions with a place for improvement, especially in PsDA. Given that developing data-driven models requires rich data that can replicate physical phenomena with high accuracy, future studies should include experimental testing of steel braces under various earthquake histories to enrich the dataset and enhance the brace data-driven model proposed here. Additionally, ensemble learning can be used alongside transfer learning in the future. This will assign any given time window of simulation to a model that can better predict the target response. Overall, TL-based brace hysteresis simulation presents a promising approach for dynamic response evaluation of steel-braced frame structures, which can also be applied to other structural applications in future.

Chapter 5

Conclusions and Recommendations for Future Studies

5.1 Summary

Earthquake engineering traditionally relies on two primary methods for evaluating structural response under seismic loads: numerical simulation and laboratory testing. Despite significant progress in computational capabilities and integration algorithms, numerical simulations are still hindered by high computational costs, uncertainties arising from constitutive material models, boundary conditions, mesh density, and geometry simplifications. Furthermore, Numerical simulations of complex and highly nonlinear structures can be challenging and computationally expensive. Laboratory testing, although highly reliable, its application is bounded by the available laboratory equipment and space, which often involves high preparation costs and time.

In response to these challenges, due to the advancement of data processing techniques and the recent strides in machine learning (ML) applications, data-driven modelling has proven to be an asset across diverse engineering disciplines, with structural engineering prominently among them. The motivation to harness ML algorithms emanates from their vast application, fast execution, and their capacity to utilize previously available experimental and numerical data. Consequently, data-driven models can function as surrogate models, offering a faster, cheaper, and more user-friendly alternative to traditional techniques. Additionally, these models can be combined with other techniques in a hybrid simulation format, serving as specific components or systems within a numerical simulation or laboratory test to reduce overall structural complexity and expedite computation. In this M.Sc. thesis, the nonlinear hysteresis response of concentrically braced frames (CBFs) braces and buckling-restrained braces (BRBs) were studied under cyclic loading to construct data-driven surrogate models that can understand the underlying relationship between axial deformation signal and axial force signal to produce respective hysteresis response. A deep artificial neural network based on the long short-term memory (LSTM) algorithm was utilized to develop surrogate models for steel brace, which facilitated leveraging limited laboratory test data available in the literature for hysteresis simulation. The performance of the model was tested using both laboratory tests and synthetic data. The model for the CBF brace was verified using static and pseudo-dynamic analyses (PsDA) under earthquake vibration. To enhance the versatility of the proposed hysteresis model for predicting the nonlinear response of steel braces under dynamic loading, a state-of-the-art transfer learning (TL) technique that utilizes the proposed LSTM model was devised in the second phase of the study. The accuracy and efficiency of the TL method were evaluated using data generated with earthquake accelerations.

5.2 Research Contribution and Conclusions

The academic contributions and conclusions of the data-driven surrogate models developed in this study are summarized in the following sections.

5.2.1 LSTM Data-Driven Model

The features of the proposed LSTM data-driven model for steel braces are summarized below:

- The proposed model demonstrated the effectiveness of LSTM in capturing the temporal dependencies inherent in the hysteretic response of steel braces under cyclic loading. This solution addressed limitations in traditional ML algorithms associated with learning complex nonlinear behaviour of structural elements.
- The proposed data-driven model deviates from the standard sequential LSTM architecture by decoupling the primary input (axial deformation) into two separate streams. One stream focuses on capturing tensile yielding, while the other targets stiffness and strength degradation due to buckling. This approach enhanced the learnability of the LSTM model and reduced the challenges associated with missing input features by expanding them through multiple LSTM layers to allow accurate predictions using limited brace datasets.

- The introduction of an auxiliary parameter, the differentiator, assisted the LSTM model in recognizing the boundaries of the hysteresis response cycles. This feature improved the ability of the model to generalize across datasets with varying data lengths.
- Using Synthetic brace data is a key strategy to enhance the LSTM model's prediction. Performance evaluation confirmed the positive impact of this approach by comparing the model with and without synthetic data.

5.2.2 Transfer Learning-based Data-driven Model

The key features of the proposed transfer learning (TL) framework to develop the data-driven surrogate model of steel braces are as follows:

- The TL method was utilized to transfer the knowledge of a pre-trained LSTM model of CBF braces to a more enhanced surrogate model tailored for dynamic response evaluation of steel CBFs. This approach significantly reduces processing time by four times, required for training, and eliminates the need to create a new data-driven model for the specific loading condition.
- The TL approach achieved superior accuracy in handling the shift in data distribution when compared to alternative approaches such as increasing the training dataset size or customizing the training data specifically for the original LSTM model in static analysis and PsDA.
- TL is a viable approach for creating models in which training datasets are limited. By leveraging pre-existing knowledge, TL enables the development of robust data-driven models within a shorter timeframe.
- The application of transfer learning allows the use of pre-trained models with new geometry or loading conditions. This approach has the potential to pave the way for greater automation in data-driven model development, allowing for faster and more efficient construction of accurate models for various structural response prediction tasks.

5.3 Limitations and Recommendations for Future Studies

- The proposed LSTM model demonstrated promising results in capturing key aspects of the nonlinear response in steel braces, including strain hardening in tension and stiffness and strength degradation under compression. However, a phenomenon known as "concept shift," characterized by accumulating error over extended loading periods, was observed in some results.

- One of the primary limitations of this research involved finding a balance between the available training data and the complexity of the proposed model. Achieving superior performance potentially necessitates a larger collection of training datasets. However, the accessibility of laboratory test data on steel braces to the public audience remains limited. Additionally, this research prioritized training the model to mimic the most accurate form of hysteresis response, which is only achievable through real-world laboratory testing rather than synthetically generated data. This rationale explains why a large dataset of numerically simulated data was not employed to address the data limitation. Given the limited data, increasing the model's depth and complexity could negatively impact its trainability.
- The proposed LSTM model achieved accurate results for both BRBs and CBF braces. However, the CBF brace model was developed using only one type of steel brace, due to the dependency of input and output signals of steel braces, axial deformation and force, to brace geometry. In the future, development efforts should focus on generalizing the proposed brace model presented here.
- While the proposed LSTM model effectively predicted results in static analysis, its performance in PsDA was affected. This challenge demands the application of TL to enhance its capabilities. For optimal knowledge transfer in TL, a well-trained foundational model with a substantial dataset is essential. Despite limitations in the training data for the initial LSTM data-driven model, the TL approach delivered accurate results. However, the evolved model was only tested on a single-story diagonal steel braced frame in PsDA. Further investigations are required to apply the methodology to larger-scale models to assess its generalizability and performance.
- The PsDA employed the communication tool UT-SIM to communicate signals with the data-driven model. Alternative communication tools that can provide greater access to the sources of errors should be explored in future.
- Integrating well-established physical principles into the data-driven model through physics-guided neural networks represents a promising direction [129]. This approach can

help incorporate fundamental hysteretic response characteristics, potentially accelerating the learning process of the data-driven model.

- Steel brace response parameters involving high uncertainties, such as low-cycle fatigue fracture, should be incorporated in data-driven surrogate models in future studies.
- Enhancing the TL method can be accomplished by leveraging a series of well-trained data-driven models from previous hysteresis models via ensemble learning [130, 131]. An effective strategy is to explore the suitability of alternative machine learning algorithms beyond LSTM for distinct scenarios, to incorporate other algorithms into the ensembled model and to address scenarios where LSTM may fall short in providing accurate predictions.

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