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A data-driven approach using Neural Network for real-time modeling of spot welded patches under impact

A. Pulikkathodi ^a, E. Lacazedieu^{a,b}, L. Chamoin^{a,c}, J.P. Berro Ramirez ^d, L. Rota ^e, M. Zarroug ^e

a. Université Paris-Saclay, CentraleSupélec, ENS Paris-Saclay, CNRS, LMPS - Laboratoire de Mécanique Paris-Saclay, 91190, Gif-sur-Yvette, France.

b. EPF, Ecole d'Ingénieurs, Cachan, France

c. Institut Universitaire de France (IUF), Paris, 94230, France

d. Altair Engineering France, Antony, 92160, France

e. Stellantis, Route de Gisy, Vélizy-Villacoublay, 78140, France

email : afsal.pulikkathodi@ens-paris-saclay.fr

Abstract :

Solving large structural problems with complex localized behaviour is extremely challenging. To address this difficulty, both intrusive as well as non-intrusive multiscale methods have been developed in the past. To reduce the computational time further, we propose the use of Model Order Reduction (MOR) of local scale. This paper presents the MOR technique based on a novel physics-guided architecture (PGA) of neural networks, incorporating physical variables into the architecture. The proposed approach is illustrated in the case of spot-welded plates undergoing large deformation.

Keywords : Artificial Neural Networks, Data-driven mechanics, Local-glocal coupling approach, Explicit dynamics, Spot-Welds.

1 Introduction

The automotive structure's body-in-white (BIW) comprises plate and shell assemblies. The components are joined together with numerous tiny spotwelds. These spotwelds might have complex properties due to the heat treatment during the welding process. Spotwelds in the full vehicle crash simulation are modelled using simplified 1D elements. However, in order to capture the localized complex nonlinear behaviour, fine 3D elements are required. Due to the length and time scale discrepancies between the global response of the structure and the localized phenomena, such mesh refinements drastically increase the computational cost.

Numerous numerical methods devoted to multiscale computing have emerged over the last three decades to address this issue. They are often based on domain decomposition techniques such as the dual FETI method [1] or the mixed Latin scheme. They are well suited to problems in which the refinement zones

are fixed. In the case of rapidly evolving problems, non-intrusive domain decomposition techniques based on local-global approaches have proven to be effective [2]. This method enables the global mesh to remain unchanged while the local problem is refined in space and time. This technique was applied successfully for coupling a 2D model and 3D model in thin composite panels with local stress concentration and debonding [5]. The same approach was extended in the context of explicit dynamics in [4]. Sub-modelling techniques are another non-intrusive option widely available in commercial FEM software. However, they are referred to as "one-way coupling" because the data exchange is from global to local, and the global solution is not updated after the local solution has been modified.

Modelling the local scale problem is computationally demanding because of its refined space and time scales. Model Order Reduction (MOR) seems an appealing choice to overcome this issue. Projection-based MOR methods, which rely on linear transformations with some additional constraints, such as the Proper Orthogonal Decomposition (POD), the Reduced-Basis technique, and Galerkin projection, are widely used. However, these linear mappings are only locally accurate; they cannot be used to model more complex nonlinear phenomena and often require prior knowledge of the governing equations of the problem physics. Artificial Neural Networks (ANNs) based on a machine learning framework have proven to be highly effective at learning nonlinear manifolds, which often outperform traditional meta-modeling techniques in terms of prediction accuracy and capability to capture the underlying nonlinear input-output relationship for complex systems. The main advantage of this method is that once trained (referred to as the offline phase), the response in the online phase is real-time. The main limitation of this technique is the correct selection of the tuning parameters of the network, also called hyperparameters.

Training an ANNs demands vast amounts of data that must contain a rich input-output relationship, which is not available for the vast majority of engineering problems. We develop an innovative physics-guided deep learning paradigm to address this fundamental challenge. The key idea is to incorporate high fidelity simulation data into ANNs, which will enhance learning within a solution space. It can also take into account unmodeled physics with fewer experimental data by imposing some basic solid mechanics principles [6, 7].

2 Physics-guided deep neural networks for metamodeling

For illustration purpose, we consider the reference problem shown in Figure 1a (left). It shows the partitioning of the overall domain Ω_G into two regions, a coarse mesh Ω_C where a simple linear elastic constitutive law is adopted, and a fine mesh Ω_L in the region in which localized features exist, and where an elastoplastic constitutive law is considered. The two regions are tied together at the interface Γ . Two different time steps $\Delta t_g = t^{n+1} - t^n$ and $\Delta t_l = t^{m+1} - t^m$ are then applied in the two partitions Ω_C and Ω_L (Figure 1b). In a non-intrusive local-global coupling framework, the global model extends over the whole structure with a coarse mesh and never changes, while the local analysis is carried out with a more refined mesh where the boundary conditions are derived from the global problem. Separate explicit dynamics analyses of the two meshes are concurrently performed, allowing the models to run with their own time increment. The substitution of the local model within the global one is achieved through iteratively exchanging the velocities and forces at the interface Γ , as displayed in Figure 1a (right).

In this context, our interest is to develop an effective metamodel based on ANNs for the local problem that could establish an efficient and accurate mapping from interface velocities to interface forces. In addition to the mapping, the metamodel should be capable of predicting the time evolution so that both

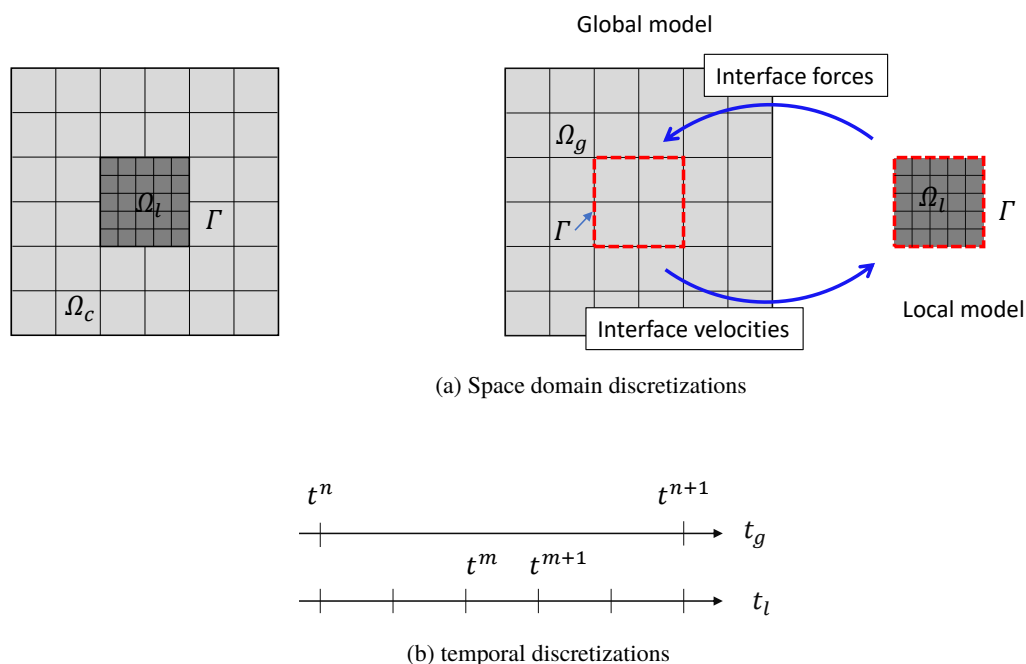


FIGURE 1 – Heterogeneous discretization in space and time of reference problem. (left) Domain with locally detailed mesh. (right) Initial global and local model domains

the global and local problems have the same time step. The following subsections introduce the basic concept and algorithm architectures of the proposed new paradigm.

2.1 Artificial neural networks (ANNs)

Neural networks are made up of layers of neurons (called Perceptron), and consist of an input layer, one or more hidden layers, and an output layer, which are connected by weighted synapses (Figure 2 (left)). These weights control the quantity of forward-propagation through the neural network, which is mathematically defined as follows :

$$x^{[l]} = \sigma(w^{[l]}x^{[l-1]} + b^{[l]}) \quad (1)$$

where l is the index of current layer, w and b are the weight matrix and bias vector respectively. The activation function σ is a nonlinear function. Neural networks work by propagating forward inputs, weights and biases.

The NN is learned by minimizing the difference between the actual result and the correct result, performed using a backpropagation algorithm that determines the exact changes to make to weights and biases to produce an accurate result. The hyperparameters to be learned are the number of hidden layers and the number of neurons in a single hidden layer. The higher the number of hidden layers, the greater the ability to capture the underlying non-linearity.

2.2 Proposed physics-guided ANN architecture

Training the neural network just using the data coming from interface velocity and interface force is challenging because this mapping is dependent on numerous other parameters, such as material pa-

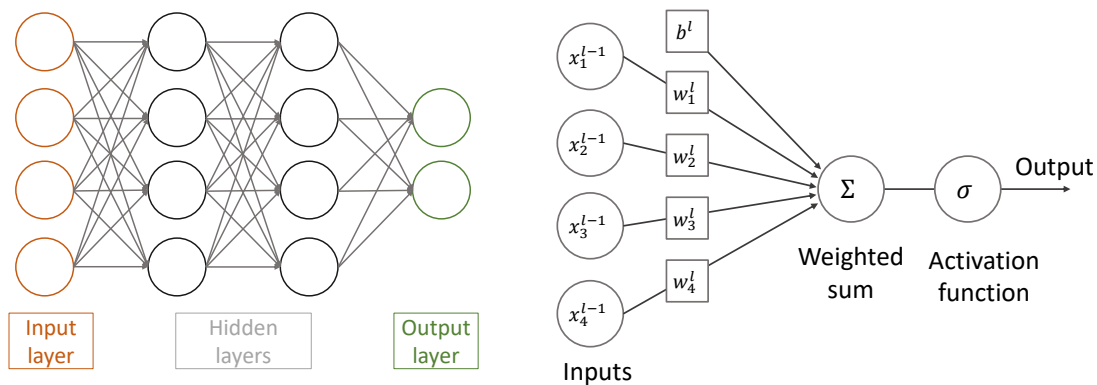


FIGURE 2 – (left) Representation of neural network architecture, (right) nonlinear model of a single neuron.

rameters, geometric parameters, etc. To address this issue, a new layer containing information about full-order displacement is added between the input and output layers. The full-order displacement could be considered as structured data similar to images (treated as 3D images for 3D domains) making use of convolutional architectures. The proposed algorithm consists of four main steps, as shown in Figure 3.

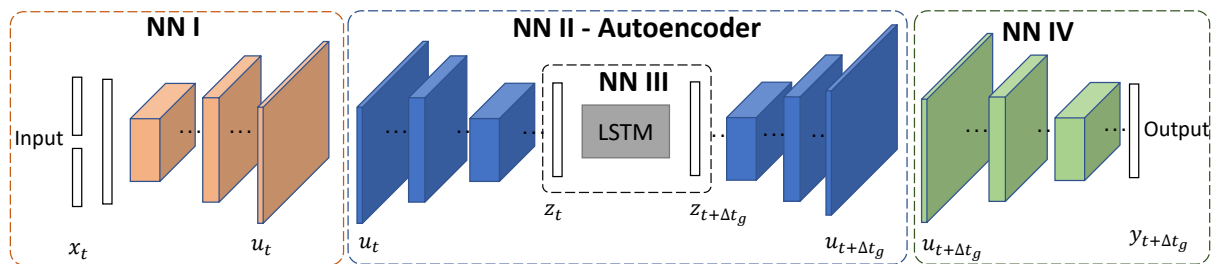


FIGURE 3 – Proposed neural network architecture

First, the nonlinear relationship at time t between the inputs (x_t) and corresponding deformation of full order model (u_t) is learned using $NN1$. The velocities and relative displacements of the interface nodes are fed into the model as input vectors and combined together to form an intermediate layer. Few 3D convolutional layers (Conv3D) are added in between the combined layer and the output of $NN1$. The number of these added layers and their properties, such as the number of filters used and filter size, are the main hyperparameters to learn in this model.

Secondly, the full order model is encoded to a reduced manifold called latent vector, with a nonlinear mapping using an autoencoder. An autoencoder neural network is trained by setting the target values to be equal to the inputs, where the size of the middle layer, the latent vector, is much smaller than that of the input layer. The convolutional layers between input/output and latent vector allow a smooth transition. The main objective is to optimize the size of the latent vector. Such a reduced manifold increases the training performance of the proceeding model, which predicts the time evolution of the system. The autoencoder can filter the noise generated due to the explicit dynamics simulation while keeping the most dominant features of the system.

The objective of the third network is to predict the latent vector at time $t + \Delta t_G$ using an LSTM network. This network's input is a series of latent vectors from a few past global timesteps, and its output is a series of latent vectors in future timesteps. We employ an encoder-decoder LSTM Model. This indicates that

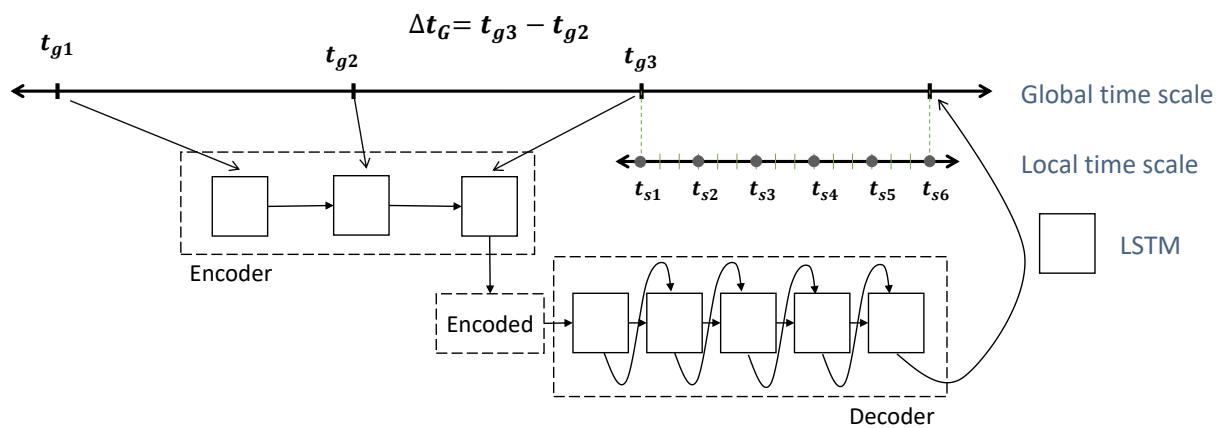


FIGURE 4 – Proposed recurrent neural network architecture used. The network is trained by taking the latent vectors from the past three global time steps and the following five latent vectors of local scale as output.

the model will not output a vector sequence directly. The model will instead consist of two sub-models : the encoder, which will read and encode the input sequence, and the decoder, which will read the encoded input sequence and make a one-step prediction for each element of the output sequence (Figure 4).

The final network is used to map from the predicted displacement $u_{t+\Delta t_G}$ to interface force $y_{t+\Delta t_G}$. The architecture used is similar to the encoder part of the autoencoder. In the following section, the proposed method is implemented on a spot-welded plate assembly. The non-intrusive local-global coupling strategy is not employed in the present study.

3 Numerical example : spot-welded plates

The proposed physics-guided ANNs is tested and validated for metamodeling of a highly nonlinear local problem. We consider the 3D model of spot-welded plate assembly with elastoplastic material shown in Figure 5. The spot-weld is joined to both the top and bottom plate. The top and bottom plates have a size of 12.5 mm and thickness of 1.53 mm and 1.17 mm , respectively. The diameter of the spot-weld is taken as 5.5 mm .

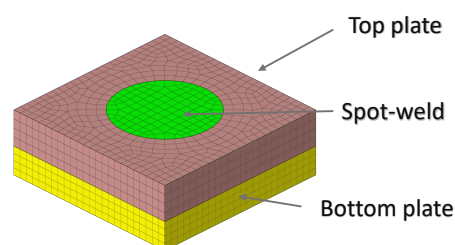


FIGURE 5 – Model of spotwelded plate assembly

The isotropic elastoplastic material is described using the Johnson-Cook material model. Neglecting the effect of temperature or strain rate, the expression for stress reads as :

$$\sigma = a + b\epsilon_p^n \quad (2)$$

where ϵ_p is the plastic strain. Following values are taken for defining the elasto plastic material, the Young's modulus $E = 210 \text{ GPa}$, the Poisson ratio $\nu = 0.3$, the material density $\rho = 7800 \text{ Kg/m}^3$, the yield stress $a = 0.792 \text{ GPa}$, the hardening modulus $b = 0.51 \text{ GPa}$ and the hardening exponent $n = 0.26$.

The dataset required to train the neural network is generated using a RADIOSS explicit dynamic solver. Velocity boundary conditions are applied monotonically for 10 *ms* on nodes of side faces top and bottom plate. For the sake of simplicity, only six principal loading cases are selected. 170 test cases are generated with several types of principal loading and their magnitude. 1000 snapshots of internal force at the boundary and full order displacement are collected from each test case, making up 170000 pairs of input/output datasets. In order to improve training performance, all data are standardized to a scale of [0,1] using a MinMax scale. The full order displacement is interpolated to a cartesian grid of size $31 \times 31 \times 8$ to treat it like images. 15 % of the dataset is used for validation to avoid overfitting. The mean square error used to evaluate the quantitative performance of each NN architecture measures the deviation between the actual and predicted data for each pass. Throughout this work Rectified Linear Unit (ReLU) function is used as an activation function. The network training has been performed in the Python environment using TensorFlow using NVIDIA RTX Quadro RTX 4000 GPU cards.

The input layer of *NN1* consists of two vectors representing velocity boundary conditions and the relative position of nodes where the boundary conditions are applied. These two vectors are appended to form a combined size layer (2892,1). Then a dense layer is added to help reshape to a 4D layer of shape (4,4,2,64). Three hidden Conv3DTranspose layers with 64,32 and 16 filters are added to achieve an output shape of (31,31,8,3). Each filter of the convolutional layer has a kernel size of (2,2,2). We employ an Adam optimizer with a 0.001 learning rate and a 0.001 decay rate. We set the training batch size to 64 to ensure better generalization of each batch. It is important to note that in our method, memory and computation cost depend primarily on image size, not the size of the full order solution. The trained model is evaluated on a load case, combination of principal loading, that is not present in the training set. Figure 6 shows that the proposed architecture is able to reconstruct the full order displacement with reasonable accuracy.

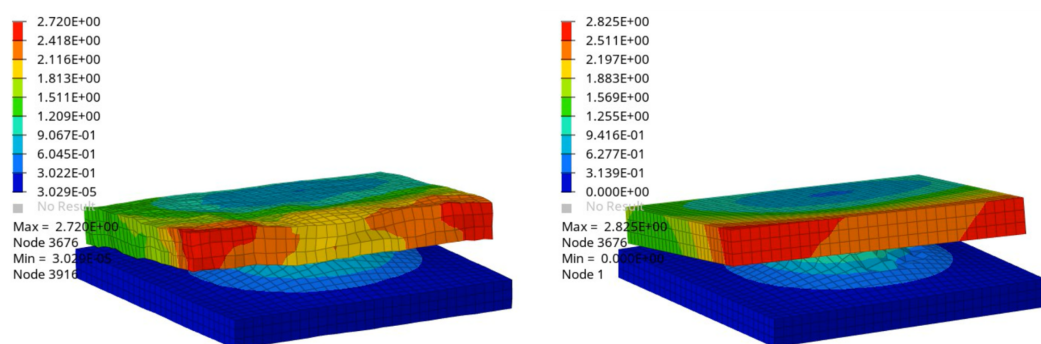


FIGURE 6 – (left) Full order displacement reconstructed using Neural Network (right) reference solution from RADIOSS

4 Conclusion

This paper presents a novel physics-guided neural network paradigm for metamodeling of local nonlinear structural system, exemplified by explicit dynamic spot-welded structure. We compared the results

obtained from PGNN architecture to traditional FEM methods to demonstrate its capacity to generate physically consistent and generalizable solutions ; the network yields promising results. Future research will investigate applications of the proposed architecture on more realistic examples with boundary conditions coming from the global problem. Future research will also investigate a coupling strategy for non-intrusive integration of the metamodel with commercial FEM solvers. Some preliminary results on these aspects will be shown at the conference.

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