



HAL
open science

A multi-scale computational strategy for fast transient problems with a physics-guided neural-network local modeling

Elisabeth Lacazedieu, Ludovic Chamoin, Afsal Pulikkathodi, Juan Pedro Berro Ramirez, Laurent Rota, Malek Zarroug

► To cite this version:

Elisabeth Lacazedieu, Ludovic Chamoin, Afsal Pulikkathodi, Juan Pedro Berro Ramirez, Laurent Rota, et al.. A multi-scale computational strategy for fast transient problems with a physics-guided neural-network local modeling. 26e Congrès Français de Mécanique, Laboratoire d'Etude des Microstructures et de Mécanique des Matériaux (LEM3 - UMR CNRS 7239), Aug 2025, Metz, France. <hal-05312873>

HAL Id: hal-05312873

<https://hal.science/hal-05312873v1>

Submitted on 14 Oct 2025

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



HAL Authorization

A multi-scale computational strategy for fast transient problems with a physics-guided neural-network local modeling

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

a. LMPS, ENS Paris Paris Saclay

b. IUF, Institut Universitaire de France

c. LAMIH, UPHF, INSA HDF

d. ALTAIR Engineering

e. STELLANTIS

Résumé

On s'intéresse ici à une modélisation multi-échelle de phénomènes physiques transitoires rapides. La formulation proposée est basée sur un couplage global local avec une stratégie d'apprentissage profond pour décrire l'échelle locale. Elle assure une modélisation précise du comportement complexe local tout en maintenant une efficacité de calcul pour la prédiction des modèles physiques à grande échelle et en taille réelle. Un couplage non intrusif est mis en œuvre grâce à une procédure itérative préservant les propriétés de stabilité et de convergence de la solution, tandis que la précision locale est assurée par une modélisation par réseaux de neurones incluant un contrôle des effets mémoire, afin de prédire le comportement dynamique de solides soumis à des charges externes. Une configuration élémentaire est considérée comme une application et les premiers résultats tendent à confirmer la robustesse de la méthode.

Abstract

One considers here a multi-scale approach for modeling fast transient physical problems. The proposed formulation involves a local global coupling with a deep learning enhanced strategy for describing the local scale. It ensures an accurate modeling of local complex behavior while maintaining a computational efficiency for predicting large scale real size physical patterns. A non-intrusive coupling is involved through an iterative procedure preserving stability and convergence properties of the solution whereas the local accuracy is ensured thanks to a neural-network based modeling including a control of memory effects since one wants to deal with prediction of dynamical behaviors of material solids submitted to external loads. An elementary configuration is considered as an application and the first results tend to confirm the robustness of the method.

Mots clefs : Mots clefs

Local global coupling, physics-guided neural network architecture

1 Introduction

The goal of this work is to develop a practical, non-intrusive coupling strategy for explicit dynamic simulations, enabling the use of a cost-effective reduced model for localized features, like spot welds, while maintaining a coarse model for the rest of the structure. Numerous numerical methods devoted to multiscale computing have emerged in the past three decades to address the simulation of local entities. They are mostly based on Domain Decomposition techniques such as the primal BDD method, dual FETI method, and the mixed Latin scheme (Ladevèze et al. 2001). The basic idea is to simultaneously solve both the global problem involving a large structure with a coarse mesh on one hand and the local problem (focusing on a localized feature with a fine mesh) on the other hand. They are solved separately and on their respective time scales. Interface quantities are exchanged between global and local problems. While these methods are well-suited for problems with fixed refinement zones, they become complicated for rapidly evolving problems, which requires remeshing for the global mesh. As a result, these methods are intrusive in nature.

A non-intrusive approach for local-global methods was introduced in Whitcom (1991). It uses a local/global iterative solver that connects a coarse global model with a detailed local model. One key advantage of this method is that it eliminates the need for remeshing the global model by fictively prolongating the global region into the local domain, although this comes with the added cost of iterations.

In an explicit dynamic local/global coupling framework, the input and output of the local problem are the interface velocities and interface reaction forces, respectively. However, these quantities are highly noisy in nature, making it difficult to obtain direct input-output relationships. To address this, a Physics-Guided Neural Network (PGANN) introduced in our previous work (Pulikkathodi et al. 2023) is employed as the reduced model for the local problem. The key idea behind this approach is to inject high-fidelity simulation quantities, such as displacement, stress and strain of the local problem, between the input and output layers of the ANNs to improve learning within the solution space.

Firstly the basic formulation of non-intrusive local/global couplings is presented. Then the strategy used to implement the non-intrusive local/global coupling with the use of a local neural network model is developed. Then results are discussed with an elementary example. The article concludes with final remarks and outlooks.

2 Physical problem

Let us consider an elastic rectangular heterogeneous structure referred to as the reference two-dimensional configuration, as depicted in Figure 1a. The structure is clamped on its left boundary. A quadratic, monotonically increasing tensile load, which varies with time, is applied to its right edge. The left half of the domain has a Young modulus E_L , while the right half has a Young modulus E_G . Both halves are discretized using a uniform mesh composed of 4-node quadrilateral elements. This arrangement ensures that the interface Γ aligns with the edges of the elements, with coincident nodes at the interface. The mesh of the global and local problems are presented in Figures 1b and 1c, respectively. The global model represents a homogeneous structure with a uniform Young modulus E_G across the entire domain, while the local model covers only the left half of the domain and has a Young modulus E_L .

The fixed parameters of the reference problem are as follows: density $\rho = 7800 \text{ kg/m}^3$; Poisson's ratio $\nu = 0.3$; length of the domain $L = 20 \text{ m}$; height of the domain $H = 10 \text{ m}$. The simulation spans from an initial time $t_0 = 0 \text{ s}$ to a final time $t_{\text{end}} = 0.01 \text{ s}$. The time step Δt is determined based on the estimation of the critical time step using the CFL condition. For simplicity, a constant time stepping approach is employed, so that the time interval $[t_0, t_{\text{end}}]$ is divided into N time steps Δt . Parameter values are given in Table 1.

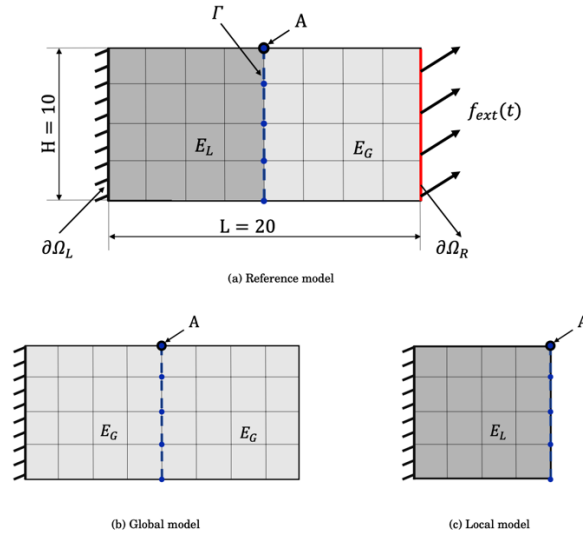


Figure 1 : Coupling configuration of problem: (a) reference model, (b) global model, (c) local model.

Parameter	Range	Increment
E_L	[200 500] GPa	25
E_G	[200 500] GPa	25
f_{ext}^{max}	{10, 30, 60, 90} GN	-

Table 1 : Parameter values for Young modulus and load.

3 Computational strategy

The schematic representation of the proposed NN architecture of the local problem is shown in Figure 2. The principle is recalled below. It uses the NN-based formulation described in Pulikkathodi et al. 2023. Notations u , v , a , r designate respectively displacement, velocity, acceleration and corrected force fields. The inputs of proposed NN are the solutions at the interface Γ (u_Γ , v_Γ , a_Γ) and values of problem parameter Young moduli E_L and E_G ; the outputs are $r_{l,\Gamma}$ and $r_{c,\Gamma}$. The displacement u_l in the local domain is introduced as additional information layer. Introducing such additional layer of information does not have significant effect in this example, but it is significant in case of complex problems.

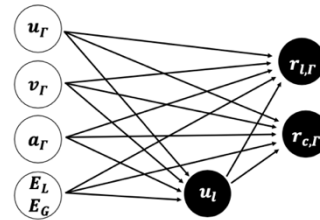


Figure 2 : Local neural-network based-model

The proposed architecture comprises two subnetworks. The first subnetwork addresses a forward problem by taking inputs ($u_\Gamma, v_\Gamma, a_\Gamma, E_L, E_G$) to predict the corresponding displacement in the local domain u_l . The second subnetwork uses this predicted displacement and the inputs from the first subnetwork to predict $r_{l,\Gamma}$ and $r_{c,\Gamma}$. The main hyperparameters of the NN that require tuning include the number of layers, the number of neurons per layer and the choice of

activation functions for both subnetworks. Other general parameters to optimize are the type of loss function, the learning rate and the batch size. The complete dataset is then partitioned into a training set, comprising 80% of the total data, and a validation set, making up the remaining 20%.

The trained NN consists of four dense layers in each subnetwork, each layer containing between 40 and 100 neurons. After training for 10,000 epochs, the NMAE for the validation dataset is recorded at 8.5×10^{-5} . To evaluate the NN's predictive accuracy on unseen parameters, two additional simulations were generated using new parameter sets, not available in the training set. The results, including the parameters and their corresponding NMAE values, are presented in Table 2. These outcomes demonstrate the NN's robust performance in predicting for unseen parameters.

Case	E_g (MPa)	E_l (MPa)	f_{ext} (N)	NMAE
I	480	390	5×10^{10}	9.1×10^{-5}
II	385	265	2×10^{10}	8.2×10^{-5}

Table 2 : NMAE on NN training for various test cases.

The next step involves replacing the local problem into the coupling algorithm so as to , the solve the global problem, followed by an evaluation of the trained NN model using boundaries derived from the global problem. Subsequently, the reaction forces computed by the NN are used to update the accelerations at the global interface nodes. These updates are then incorporated in the subsequent time step of the global problem.

3 Computational results

The accuracy of the method is validated using test cases presented in Figure 3. displays the velocity at point A (marked in Figure 1) using the NN-coupled model and the reference model for the two test cases mentioned in Table 2. The velocity at point A for the NN-coupled model closely matches its corresponding reference solution.

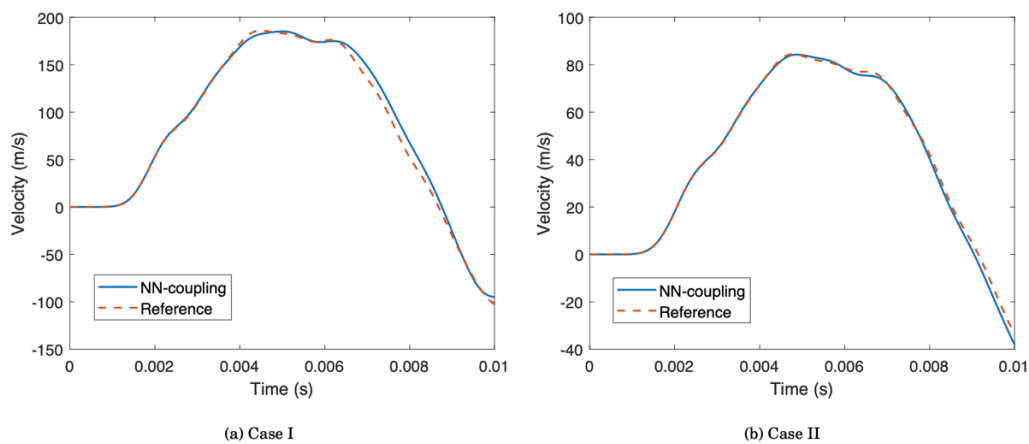


Figure 3 : Comparison of velocity at point A in Figure 1 between the NN-coupled model and the reference model for two test cases from Table 2.

Figure 4 provides a comparison of the displacement in the x and y directions between the NN-coupled solution and the reference solution for case I, further affirming the model's accuracy.

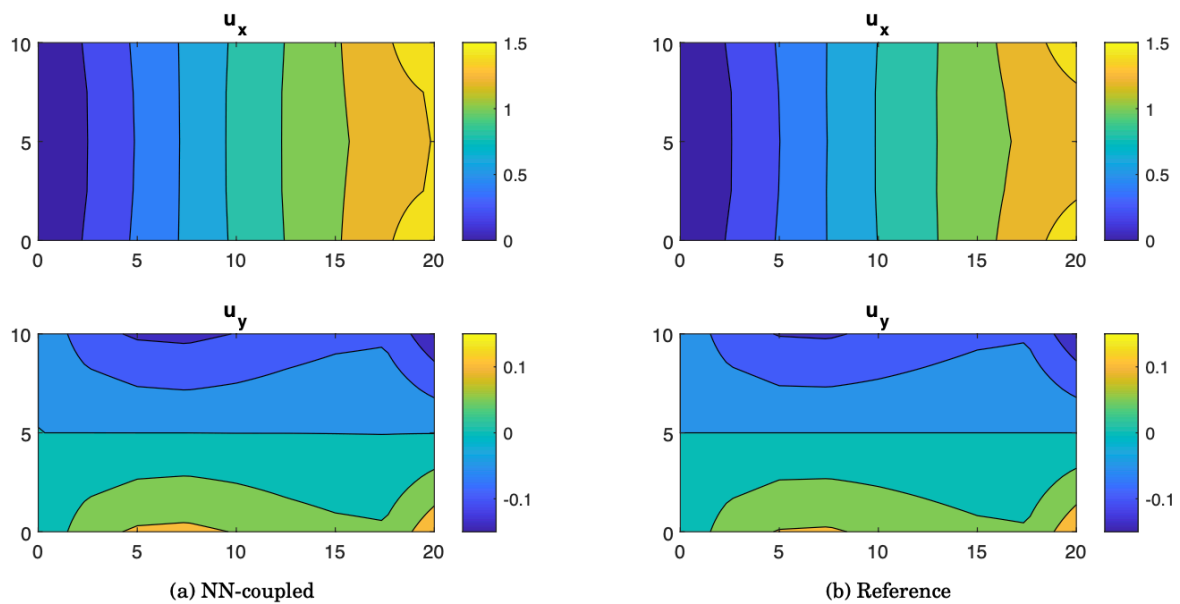


Figure 4 : Comparison of displacement between the NN-coupled model and the reference solution for case I.

Conclusion

The performance of the method during the online phase, in terms of computation time, is not presented for this example due to the significant cost associated with loading the trained NN models from the disk in each cycle. This is primarily due to the computational cost of loading the TensorFlow library. This issue has been addressed in further works where the computational time performance is demonstrated.

References

- Ladevèze P, Loiseau O, Dureisseix D. A micro–macro and parallel computational strategy for highly heterogeneous structures. *International Journal for Numerical Methods in Engineering*. 2001, 52, 121-138.
- Whitcomb JD. Iterative global/local finite element analysis. *Computers & structures*. 1991, 40(4), 1027-1031.
- Pulikkathodi, A. , Lacazedieu, E. , Chamoin, L. , Ramirez, J P B. , Rota, L. , Zarroug, M. A neural network-based data-driven local modeling of spotwelded plates under impact. *Mechanics & Industry*. 2023, 24:34.