# Graph Neural Networks to predict quasi-optimal designs in parametric topology optimisation

**Giorgio Zamberlan*, Matteo Giacomini and Antonio Huerta**

Laboratori de Càlcul Numèric (LaCàN), E.T.S. de Ingeniería de Caminos, Canales y Puertos, Universitat Politècnica de Catalunya, Barcelona, Spain
Centre Internacional de Mètodes Numèrics en Enginyeria (CIMNE), Barcelona, Spain

## ABSTRACT

Additive manufacturing has opened unexplored possibilities in the fabrication of elastic structures not manufacturable via traditional moulding and machining processes.

Topology optimisation methods are commonly used to determine the optimal material distribution by minimising a cost functional - e.g., the compliance of the structure - pending that the displacement field satisfies the linear elasticity equation and a constraint over the volume or the perimeter of the structure is fulfilled. [1]

Whilst existing numerical methods have been proved suitable to effectively solve single instances of topology optimisation problems, the computational cost associated with multiple queries of such problems becomes quickly unmanageable. This is, for instance, the case of parametric topology optimisation problems, where the material coefficients of the structure, or the location and angle of the applied loads are uncertain or modified by the user.

In this context, surrogate models can significantly enhance existing topology optimisation pipelines by predicting *quasi-optimal* topologies to be used as initial guess in classic iterative strategies. To achieve this goal, topology optimisation algorithms based on the finite element method (FEM) are coupled with graph neural networks (GNN), to identify spatial correlations among data leveraging the information of the FEM connectivity matrix. [2]

Numerical results of a surrogate-based topology optimisation algorithm for linear elastic structures will be presented, exploring the suitability of the proposed methodology to devise *quasi-optimal* topologies, as well as, *quasi-adapted* computational meshes. Special attention will be devoted to the assessment of the robustness and accuracy of the GNN surrogate models, including its extrapolation and interpolation capabilities.

[1] Sigmund, O., Maute, K. Topology optimization approaches. Struct Multidisc Optim 48, 1031–1055 (2013).

[2] Thomas N. Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. CoRR, abs/1609.02907, 2016.

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* Presenting author