PINN or SPINN for the topology optimization?

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Physics Informed Neural Networks (PINNs) [1] are a successful approach to approximate solving of differential equations. Yet, in case of topology optimization, they are barely competitive to traditional methods, like SIMP, in terms of computational effort. Therefore, the search for improvement in efficiency is an active area of scientific research. One of such promising approaches is a so-called Separable PINN. The idea is to use separate artificial neural nets for each coordinate (for instance, in case of 3-dimensional domain – 3 distinct networks are utilized). According to original paper [2], substantial improvement in performance was obtained. It is additionally increased by forward differentiation and reducing differentiation time by calculating only one derivative per net.

The aim of the research is to determine the performance of SPINN w. r .t. its predecessor, i.e. PINN, used as a core for displacements determination in structural topology optimization algorithm. Both methods were also compared to the ground truth, which was taken to be the traditional approach (i.e. SIMP). The topology optimization algorithm used linear elasticity formulation. The aim of the optimization was a structure compliance minimization, with given *a priori* volume constraint condition.

The author examined a 3-dimensional example of beam, fixed at both ends (left and right), loaded with concentrated force, applied at the center of the top surface of the beam, just like shown on the left in Fig. 1.

The preliminary simulations did not confirm the jump in performance for the topology optimization problem, as it was shown by the authors of the idea, based on the several examples of solving 3-dimensional differential equations. Nevertheless, obtaining better results is still potentially possible through hyperparameters optimization, which will be the next step of the author's research.

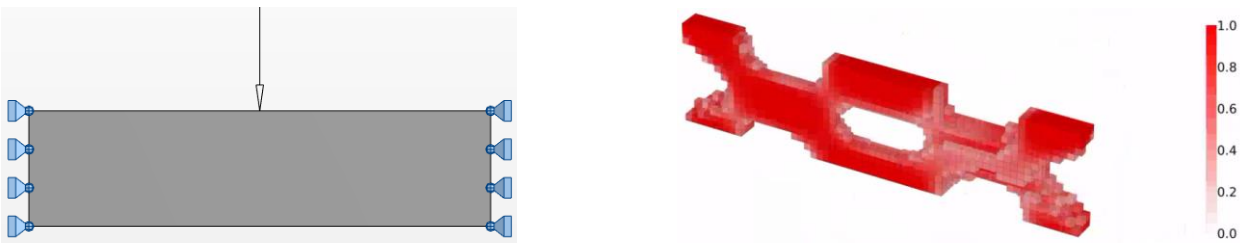

Figure 1. Analysed example and the example PINN solution.

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