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Machine Learning in Topology Optimisation - Challenges and Prospects

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Topology optimisation (TO) is a mathematical approach to mechanical and multiphysics design aimed at maximising the structural performance by spatial optimisation of the distribution of material within a defined reference domain. This research field has undergone a tremendous development, culminating in recent applications to where the design domain is discretised by more than two billion elements [1]. This TO procedure is based on efficient adjoint sensitivity analysis and deterministic gradient descend methods but is nevertheless timeconsuming and requires access to expensive super-computing facilities. As alternatives to gradient-descend algorithms, many works have considered non-gradient approaches like genetic algorithms for TO. However, due to large number of design variables and expensive function evaluations, such approaches have been found inapplicable [4]. Lately, applications of neural networks (NNs) and other machine learning (ML) methods for topology optimisation and inverse problems have become extremely popular and new papers are appearing weekly within the traditional topology optimisation community as well as in computational physics and nano-photonics in particular. So far, however, most applications suffer from weaknesses similar to those of non-gradient approaches: training of networks becomes extremely expensive and obtained results are non-convincing. A thorough review of the current research within this field has identified an overall lack of understanding of ML capabilities and ability to appropriately asses the performance of new solution frameworks incorporating such models. Efforts are made towards clarifying why current trends are problematic as well as formulating recommendations for future progress. Among other, it is postulated that bruteforce training based on ground truths obtained by regular topology optimisation runs are not the way to proceed. Instead, learning based methods should be applied to sub-problems like mapping of homogenisation-based multiscale results [2], more efficient iterative solution methods [3] or yet to be seen local design acceleration approaches.

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