Surrogate Models of Optimised Topologies for Parameterised Channel Flows with Deep Reinforcement Learning

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ABSTRACT

The increasing demand for electric vehicles necessitates of innovative solutions to tackle the multi-physics and multi-objective topology optimisation problem inherent in efficient Battery Thermal Management Systems (BTMS) [1]. Traditionally, the design of BTMS relies on manual trial-and-error methods using gradient-based approaches, leading to a time-consuming and inefficient process. Additionally, each new design iteration featuring different battery distributions or power specifications requires the topology optimisation process to be recomputed. Thus, there is a pressing need to address the parametric topology optimisation problem arising in BTMS to accommodate new design configurations seamlessly.

In response to this challenge, a novel extension of the surrogate concept is introduced: a surrogate model of quasi-optimal solutions. Instead of merely accelerating the optimisation loop by replacing full-order computations. The proposed model directly captures the relationship between design parameters and optimised solutions, eliminating the need for an optimisation algorithm on top of it. This new surrogate model aims to provide quasi-optimal designs suitable for the early stages of the design process rather than high-fidelity solutions.

To achieve this, Deep Reinforcement Learning (DRL) techniques are employed as a gradient-free optimisation algorithm to train a data-driven surrogate model. Thus, following the work by Brown on structural topology optimisation [2], a Deep Neural Network is trained to produce quasi-optimal topologies for channel flow problems with parameterised inlet and outlet boundaries.

[1] Zhong, Qixuan, et al. "A comprehensive numerical study based on topology optimization for cooling plates thermal design of battery packs." Applied Thermal Engineering 236 (2024): 121918.

[2] Brown, Nathan K., et al. "Deep reinforcement learning for engineering design through topology optimization of elementally discretized design domains." Materials & Design 218 (2022): 110672.

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