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Towards producing innovative engineering design concepts using AI

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Introduction

The discovery of innovative engineering design concepts is difficult and costly. Typically, a design is created, modelled and simulated by skilled engineers who make design decisions based on simulation results. Experience and subject knowledge play a major role in interpreting these results and making the decisions, and consequently, as the same knowledge, experience and tools are used to develop new designs, each new generation is similar to the last, and so stagnates innovation. Artificial intelligence (AI) is beginning to inform engineering design processes [1-3]. A promising technology is generative design (GD) which allows engineers to explore and select more innovative designs through the use of processes such as topology optimisation. Evolutionary algorithms (EAs) are a form of AI that can produce innovative design concepts by creating a population of possible designs and updating these over many generations through permutations of the design's parameters, mimicking nature's processes of evolution such as selection and mutation. Alongside EAs, neural networks (NN) are layers of connected neurons, each with different weights and biases relating inputs to outputs, where the mapping from inputs to outputs are refined through learning processes. The NN can be seen as a decision process where inputs (results of engineering simulations) are intepreted to create an output (design changes), and thus have the potential to control design.

This paper examines the application of a novel Evolutionary-Development (Evo-Devo) system that integrates AI tools within the conceptual design process to produce populations of innovative design options. The aim is to allow the behaviours of designs to be learned and then exploited later in the design process. Here a design concept (referred to as an organism) is constructed from cells, which have an evolving NN architecture controlling each cells'parameterisation. The following work demonstrates the application of the Evo-Devo process on a volume-to-point heat transfer problem, returning design concepts with a network of heat channels that direct heat built up in the plate to a point at ambient temperature.

Evolutionary-Development Design System

The Evo-Devo system consists of a development cycle embedded within an evolutionary loop. The evolutionary loop uses NSGA II [4], a multi-objective EA, creating populations of genomes which encode rules and policies and are evolved using typical evolutionary processes, including selection, crossover, and mutation. These rules describe the design behaviours given a set of input values or cell state. Specifically, an extended version of NEAT [5] represents the genome as real value encoded networks, as well as supporting both model complexity and being computationally efficient. The genome acts on the parameters of a cell it is associated with, the

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topology and geometry of which represents the physical form of the design and hence are used to build a simulation model for performance evaluation. Simulation results are inputs to the network, the outputs of which are directly applied to the cell's parameters, creating geometric or topological changes. An instance of these changes is a development step, of which multiple become the development cycle of the Evo-Devo system.

In the following example, the organism is a volume, modelled as a flat plate, discretized into triangles. The volume is modelled using 2D shell elements (cell) with thickness (parameter), and the channels as 1D beam elements (cell) with a circular cross-section and area (parameter). The two are connected via the shared nodes of the beams and shells. The environment includes two distributed heat fluxes of different magnitude applied to different zones of the plate, with the sink temperature at a point, P on one outer edge, shown with the resulting temperature distribution in Figure 1(a). The design goal was to create design options with minimal average temperature across the plate and minimal channel volume within the plate, i.e., maximize cooling with minimal intrusive conductive volume. Figure 1(b) shows two organisms produced by the system. It can be seen that; 1) the organisms have developed to include a connected channel network; 2) the thickness of the channels increases towards the sink point, reflecting the accumulation of thermal load and 3) the channel volume is directed toward the hottest area of the plate. It should be noted that the neural network has learned to direct the design in this way, i.e., develop channels towards areas of higher temperature whilst distributing volume across the network from high to low, away from the heat sink.

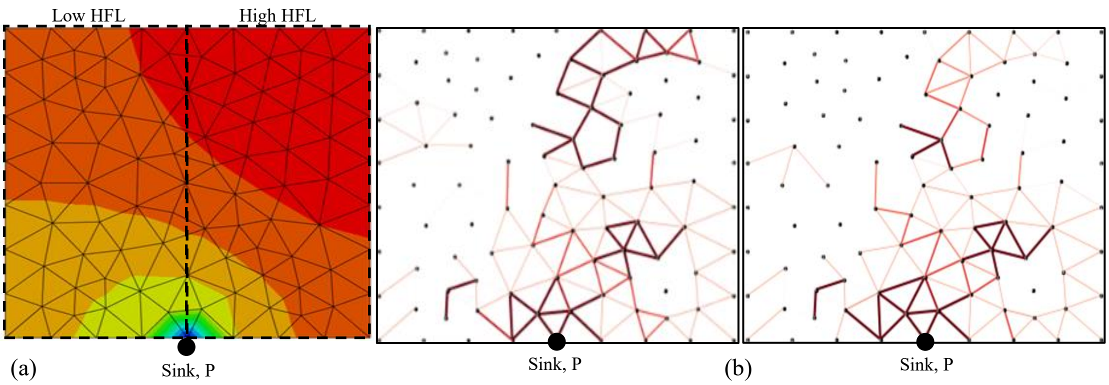

Figure 1 (a) Organism without channels, showing heat flux application, sink point and temperature distribution. (b) Channel network in evolved organisms, showing sink point. (Darker colour represent thicker cross-section)

For the system to perform in this way, there are numerous considerations to be made when setting up the GRN, defining the evolutionary criteria and selecting the modelling parameters and simulation variables. The success of the genome, the rules and knowledge of the organism's behavior within the environment, which this work intends to capture, are beholden to the definition of these parameters and variables. This work successfully demonstrates the Evo-Devo system in a volume-to-point thermal conduction problem as a step towards capturing innovation during the conceptual design phase.

Keywords: Evolutionary Development, Engineering Design

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