Creating Recommender Systems for Industrial Engineering Problems Using a Mixed Categorical-Continuous Data-Driven Method

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Surrogate models are an essential engineering tool, and their popularity is constantly increasing due to the high computational cost of evaluating real-world simulations. However, most of these functions are described by mixed variables (continuous and categorical), which makes it harder to create accurate interpolation functions. This work builds a surrogate model from a given mixed data set, in order to quickly and accurately calculate the mechanical performance of hybrid discontinuous composites materials, see Figure 1. Then, in order to find the optimal hybridization, three different approaches are performed: mono-objective, inversion and multi-objective. Starting from an experimental database, the mixed categorical-continuous optimization process is performed by coupling a multi-armed bandit strategy and a continuous Bayesian optimization algorithm. The efficiency of our proposed approach is tested, and two main results are achieved. Firstly, the obtained surrogate models are shown to be sufficiently accurate, having an R^2 score greater than 90% on average. Secondly, our proposed optimization process is able to identify correctly optimal fibres with respect to desirable targets provided by the industrial partner. While demonstrated for composite material optimisation in this work, the approach is applicable and has been proven to work on many other industrial problems that are characterised by both categorical and continuous variables including packaging design optimisation, steam engine optimisation and medical diagnostic tools.

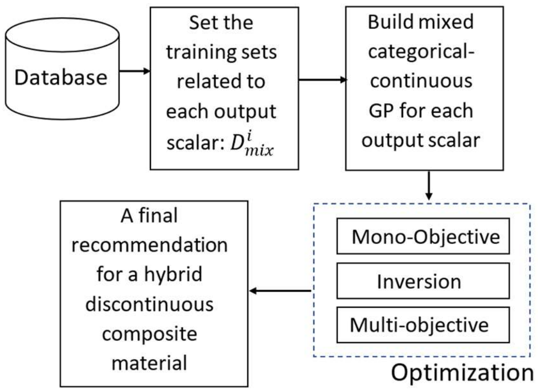

Figure 1 An overview of the data-driven optimization

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