

TOPOLOGY OPTIMIZATION OF MICRO-FLOWS UNDER UNCERTAINTY USING A STOCHASTIC GRADIENT APPROACH

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Abstract

Micro-fluidic systems are highly sensitive to uncertainties such as fluctuating inflow conditions, geometric variability arising from manufacturing processes, and random blockages within the flow domain. Such uncertainties can severely degrade performance and deterministic topology-optimized designs often fail when deployed in real-world applications. This work presents a stochastic-gradient based topology optimization framework for robust micro-flow design, enabling uncertain operating scenarios to be incorporated directly and efficiently into the optimization loop.

The proposed method of stochastic gradients extends the standard topology optimization formulation by introducing an objective function that depends not only on the design field but also on sampled uncertainty parameters. Instead of evaluating all uncertainty scenarios at each iteration, an approach that becomes computationally expensive even for modest uncertainty spaces, we simulate one uncertainty realization per iteration and store its corresponding objective and gradient. These historical samples are combined through a nearest-neighbor weighting model that determines the relevance of each past sample, allowing the method to emphasize poorly performing scenarios while naturally reducing the influence of outdated samples as the design evolves.

This workflow results in an update rule that maintains computational costs close to a deterministic topology optimization run, despite effectively exploring a high-dimensional uncertainty space. Preliminary performance comparisons with multi-scenario brute-force optimization show that the stochastic approach reaches comparable design quality while requiring fewer state and adjoint solves, highlighting its suitability for large-scale and high-uncertainty applications.

The approach is applied to micro-fluidic Stokes-flow problems. Under uncertain inflow conditions, the optimized structures reproduce behavior similar to viscous-loss minimization: multiple inflows naturally merge into a trunk channel before redistributing evenly to all outlets, yielding robust performance despite fluctuating inlet activation. When uncertainties such as random blockage locations are introduced, the resulting designs diverge meaningfully from deterministic solutions,

forming multiple flow paths to preserve equal outlet distribution even in the presence of partial occlusions.

The framework provides a scalable and computationally efficient pathway for incorporating uncertainty into micro-flow topology optimization. The demonstrated robustness to uncertain operating conditions has direct relevance to the design of microfluidic components such as lab-on-a-chip platforms, micro-mixers, and compact thermal management systems. Ongoing work includes extending the method to enforce local geometric constraints, combining multiple uncertainty types simultaneously, and evaluating robustness on more complex, application-specific micro-flow configurations.