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Abstract

Optimization of Micro-Electromechanical Lorentz Actuator Using a Surrogate Model Accelerated Genetic Algorithm †

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Abstract: A surrogate model (SM)-assisted multi-objective genetic algorithm (GA) is presented that is used to accelerate the performance optimization of a MEMS actuator. The GA employs both finite element method (FEM) simulations and the SM together to undertake the multi-objective optimization. The algorithm evolves the actuator geometry to meet a required 1 µm displacement while seeking to achieve the objectives of minimal temperature rise and resonant frequency over 5 kHz. The result is a continuous surface of Pareto optimal designs for the decision maker to choose from. The SM was found to compute similar solutions as the FEM with a 100,000× faster computation speed.

Keywords: MEMS; Lorentz actuator; design optimization; surrogate model; genetic algorithm

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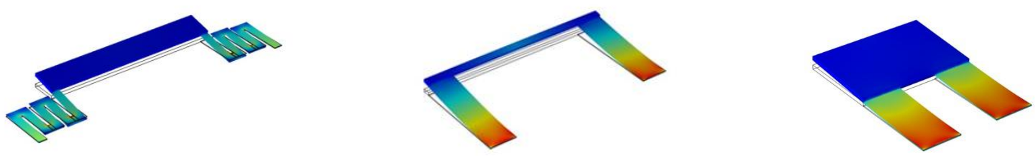
1. Introduction

Genetic algorithms (GAs) have been used to find optimal MEMS designs by several research groups [1]. GAs are used because of their ability to evolve the design of MEMS towards multi-objective performance needs. The device to be optimized in this paper is a MEMS Lorentz actuator (Figure 1a). This Lorentz actuator is to be used in an array to control the topology of a deformable mirror's (DM) reflective surface. The Lorentz force controlling the actuator motion is proportional to the strength of an external magnetic field, in this case B = 0.3 T, and the actuation current [2]. The GA is assisted by an SM, which means that after a certain number of generations, a machine learning model is trained to map the device's design inputs to its performance outputs to within a certain tolerance. The much faster SM is used to replace most of the time-consuming FEM evaluations of device performance. Furthermore, the SM allows for the decision maker to rapidly estimate and explore the performance of devices in the solution space's continuous hyper-surface that were not explicitly calculated by the population evolved during the GA optimization.



(a) (b) (c)

Figure 1. (**a**) Original starting device that the GA undertakes to improve. (**b**) The design with the lowest mechanical stress and highest first resonance frequency, f_0. (**c**) The design with the smallest temperature increase.

2. Method

The "U-shaped" Lorentz actuator consists of a central crossbar supported by micro-springs on either side. The substrate material is silicon, with an aluminum coating to enable current flow across the actuator. The GA optimizes the design by first parameterizing the design into nine geometric design variables, each of which is given a range of possible values. The GA explores this nine-dimensional design space by iteratively combining and altering the best performing designs, with the goal of seeking the objectives of the following: 1 μm vertical displacement of the central crossbar; minimal temperature change; and a resonance frequency that is over 5 kHz. The conclusion of the GA's evolutionary process results in a Pareto optimal set of device designs that can no longer be improved within the parameter ranges.

The algorithm implemented is the second version of the non-dominated sorting genetic algorithm (NSGA-II) [2]. This NSGA-II implementation initializes 256 randomly chosen device designs. The end goal of the algorithm's device evolutions is to produce 256 non-dominated designs, which means no single objective can be improved without a simultaneous decrease in performance to at least one other objective. The GA algorithm is setup so that each iteration produces 256 new designs, with 80% produced using simulated binary crossover (SBX) with binary tournament selection, and the remaining 20% being produced using single-point polynomial mutation (PM) and random selection. Both SBX and PM use a distribution index of 16. At the end of each generation, an SM is trained using the FEM data of each device performance to enable the SM to predict performance parameters to under 5% mean absolute error. Then, the SM is employed to undertake 90% of the time-costly FEM evaluations, with the remaining 10% still being solved using FEM to continually validate the model's performance. For this generalized device, an FEM evaluation requires 5.1 s of computer time, whereas the SM evaluation takes only 50 μs, representing a computational acceleration of about 100,000 times.

3. Results and Discussion

Table 1 shows the performance of the original unoptimized design and four feasible optimized designs after 55 iterations of the NSGA-II algorithm. Figure 1 shows the designs for each of the devices considered. The algorithmic optimization results show improvements, in simulation, in all objectives except actuation current compared to the initial design. The designer can then decide which optimized design best meets their objectives given the trade-offs from the other optimized designs.

Table 1. Selected results from the optimization, each operating at required 1 μm displacement.

Actuation Current (mA)	Temperature Increase (°C)	Mechanical Stress (MPa)	Resonance Frequency, f_0 (kHz)	Comments
4.68	7.35	2.89	2.58	Original design (a)
14.0	2.25	2.22	5.96	Best stress and f_0 (b)
36.0	0.99	2.33	4.61	Best temp. increase (c)

Supplementary Materials: The data Supplementary Material of this work is available online at https://www.mdpi.com/article/10.3390/proceedings2024097191/s1.

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