Automatic Synthesis of MEMS Devices Using Self-Adaptive Hybrid Metaheuristics

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ABSTRACT

This paper introduces a multi-objective optimization approach for layout synthesis of MEMS components. A case study of layout synthesis of a comb-driven micro-resonator shows that the approach proposed in this paper can lead to design results accommodating two design objectives, i.e. simultaneous minimization of size and power input of a MEMS device, while investigating optimum geometrical configuration as the main concern. The major contribution of this paper is the application of self-adaptive memetic computing in MEMS design. An evolutionary multi-objective optimization (EMO) technique, in particular non-dominated sorting genetic algorithm (NSGA-II), has been applied together with a pattern recognition statistical tool, i.e. Principal Component Analysis (PCA), to find multiple trade-off solutions in an efficient manner. Following this, a gradient-based local search, i.e. sequential quadratic programming (SQP), is applied to improve and speed up the convergence of the obtained Pareto-optimal front. In order to reduce the number of function evaluations in the local search procedure, the obtained non-dominated solutions are clustered in the objective space and consequently, a post-optimality study is manually performed to find out some common design principles among those solutions.

Categories and Subject Descriptors

B.5.2 [**Register-Transfer-Level Implementation**]: Design Aids – *automatic synthesis, optimization, control structures;*
G.1.6 [**Numerical Analysis**]: Optimization – *constrained optimization, global optimization, gradient methods*;
I.5.1 [**Pattern Recognition**]: Models – *statistical*.

General Terms

Design.

Keywords

Evolutionary multi-objective optimization, local search, principal component analysis, MEMS design.

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1. INTRODUCTION

MEMS are tiny mechanical devices that are built upon semiconductor chips and are measured in micrometers. They usually integrate across different physical domains a number of functions, including fluidics, optics, mechanics and electronics, and are used to make numerous devices such as pressure sensors, gyroscopes, engines, and accelerometers etc. Many designs of MEMS are made through engineering experience and back of the envelop calculations, and are highly dependent on designers knowledge and experience. One reason for this is the complexity involved in the modeling, design and fabrication of MEMS. There are many constraints in designing and fabricating MEMS devices due to the limitations of current fabrication techniques [1, 3]. However, as process technologies become more stable, research emphasis can be shifted from developing specific process technologies towards the design of systems with a large number of reusable components, such as resonators, accelerometers, gyroscopes, and micro-mirrors. It greatly benefits the MEMS designers if the routine design of frequently used components can be optimized automatically by computer programs, while the designers can take more time in contemplating the more creative conceptual designs [1].

Although traditional mathematical programming oriented numerical optimization techniques have been widely used in the design optimization of MEMS, current challenging areas of optimization in general engineering design applications look for means to overcome some of the limitations within local gradient-based search by incorporating a more stochastic approach which provides essential explorative and robust search capabilities. Evolutionary Algorithms (EA) are a class of algorithms which are designed to handle complex multi-modal or multi-funnel design landscapes and moreover have already been incorporated into MEMS design in which the emphasis was put mainly on planar designs.

This paper presents a methodology for investigation of optimum layout synthesis of a MEMS device, i.e. a comb-driven micro-resonator, aiming at having minimum size (i.e. smallest device area), and simultaneously having minimum power (i.e. voltage), subjected to several design constraints. More specifically, the choices of different sets of geometrical design parameters for comb drive, folded flexure beam and shuttle mass (see Fig. 1) have been investigated in order to achieve the goals mentioned above which are in essence conflicting. An evolutionary multi-objective optimization (EMO) algorithm, i.e. non-dominated sorting genetic algorithm (NSGA-II [2]) is initially performed for a fixed number of generations, and following this, PCA is applied progressively in a way to provide self-adaptive search capability to EMO algorithm. PCA is mainly used to reduce relatively large design parameter set into few variables by recognizing higher variation in the large data set, which corresponds to population set after different number of generations, by utilizing the covariance matrix information. This methodology enables EMO algorithm to handle less but more sensitive design variables, eventually leading to faster convergence towards Pareto-optimal front (as compared to the performance of the EMO algorithm alone). The non-dominated solutions found so far have been clustered based on their Euclidean distances (in the objective space) in a prefixed grid structure to reduce the number of the solutions, which will in turn be served as initial starting points for the gradient-based local search technique, i.e. sequential quadratic programming (SQP). The ε-constraint method is applied by fixing the first objective (i.e. voltage) as a constraint for each clustered non-dominated solutions independently to obtain the modified optimized front. Further improvement in accuracy and confidence in the convergence of the Pareto-optimal front is achieved, and following this, a brief post-optimality study is performed to unveil some common design principles among members of the clustered Pareto-optimal set.

2. MEMS MODEL

A case study in the area of MEMS design (originally taken from [3,4]) was carried out to verify the effectiveness of the design optimization methodology given above following a memetic computational approach which involves evolutionary multi-objective optimization coupled with a simple clustering algorithm as well as a gradient based local search technique. The design problem is a comb-drive micro-resonator (see the layout in Fig. 1), with fourteen mixed-type design variables (Lb, w_b, L_t, w_t, L_{sy}, w_{sy}, L_{sa}, w_{sa}, w_{cy}, L_c, w_c, x_0, V, N_c), and twenty four design constraints, both linear and nonlinear. More detailed description of the design problem in terms of analytical equations will be provided later (they are not included due to limited space).

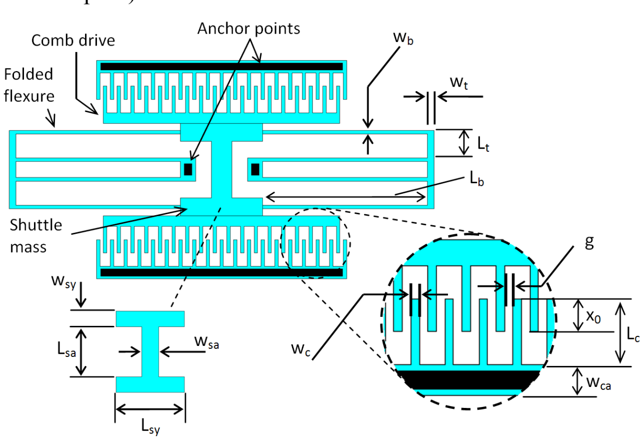

Figure 1: MEMS model (adapted from [3, 4].

3. OPTIMIZATION PROBLEM

In this section, the multi-objective optimization problem (MOP), briefly described in the previous section that is related to the layout synthesis of MEMS components with respect to dynamics response (i.e. voltage) and the size of the device, is formulated. Optimum design parameters, i.e. geometrical features of the flexure beams, comb drives and the shuttle mass, are investigated to simultaneously minimize the power consumption or in other words the voltage and the area of the MEMS device. The formulation of constrained multi-objective optimization problem is given below,

$$\begin{aligned}
&\textit{Minimize}: f_1(\mathbf{x}) = V,\\
&\textit{Minimize}: f_2(\mathbf{x}) = A_{total} = (A_s + A_t + A_b + A_c),\\
&\textit{subject to}: g_i(\mathbf{x}), \text{ for } i = 1, 2, \ldots, 24 \qquad (1)\\
&\qquad \mathbf{x} = \{Lb, w_b, L_t, w_t, L_{sy}, w_{sy}, L_{sa}, w_{sa}, w_{cy}, L_c, w_c, x_0, V, N_c\}
\end{aligned}$$

where $g_i(\mathbf{x})$ are the design constraints and $\mathbf{x}$ is the vector of design variables.

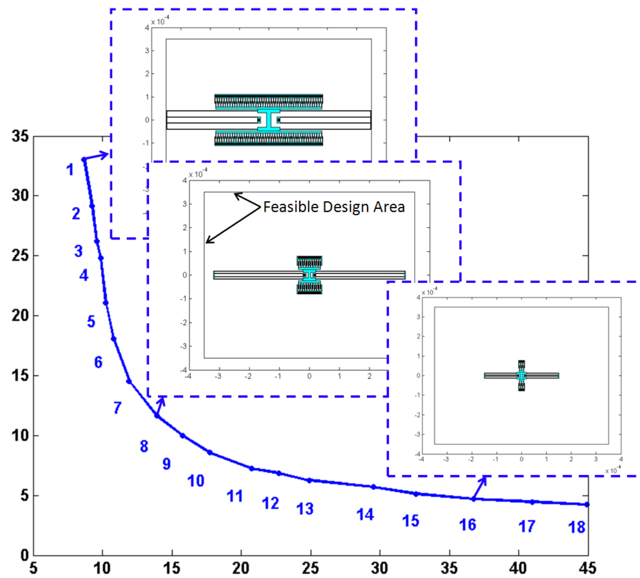

Figure 2: Different layouts on the Pareto-optimal front.

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