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# Evolutionary design optimization of MEMS: a review of its history and state-of-the-art

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**Abstract**

As an important part of the internet of things (IoTs) and cyber-physical systems (CPS), Micro-Electro-Mechanical-Systems (MEMS) is playing more and more irreplaceable role in current industrial community and the forthcoming era of the Industry 4.0. The limitations of some frequently used design methods for MEMS design optimization are analyzed in this review. In order to overcome these difficulties, a recent trend in design optimization of MEMS is inspired by the natural evolution mechanism. Many powerful techniques, especially the evolutionary computation (EC), have been used for the design optimization of MEMS. This paper presents a review of the achievements in this promising research area which utilizes EC methods for the design optimization of MEMS and also proposes three open issues that it is facing.

**Keywords** Micro-Electro-Mechanical-Systems (MEMS) · Design optimization · Evolutionary design · Evolutionary computation · Enterprise systems

## 1 Introduction

In enterprise systems, effective, flexible and excellent design is a foundation to realize intelligent production. How to create powerful design methods becomes one of the key issues of the enterprise systems.

Micro-Electro-Mechanical System(MEMS)is a kind of important high technological devices. The MEMS devices comprise both mechanical and electronic components which are manufactured on a common silicon substrate by micromachining techniques adopted from integrated circuits (ICs). MEMS have very small scales which can usually be measured in micrometers. As an important part of the internet of things (IoTs) and cyber-physical systems (CPS), MEMS is playing more and more irreplaceable role in current industrial community and the forthcoming era of the Industry 4.0 (Uhlmann et al. [1]).

The next sections are arranged as follows: in the Sect. 2, the limitations of traditional MEMS optimal design is introduced; in the Sect. 3, multiple evolutionary design optimization methods of MEMS are reviewed; in the Sect. 4, three open issues on the evolutionary design optimization methods of MEMS are listed and discussed; and in the Sect. 4, conclusions are given.

In the field of MEMS design, researchers are faced with some special challenges. One of these is analyzing the interrelated physical phenomena between MEMS devices operating in tiny geometries. Micro-electromechanical Systems involve many subjects such as mechanics, electrical science, electronics, fluid mechanics, optics, chemistry, etc. Moreover, this is still a young field that is far from perfect. Many physical phenomena are unknown or not sufficiently explained in scientific way. Accordingly, some methods that are widely used in mature fields, such as differential equations, are often more difficult to apply in the field of MEMS design. Another conundrum is that the search space of design is so huge and complex that traditional optimization methods, which are often stuck in local optimum, is extremely difficult to seek the global optimal design solution in the search space [1].

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## 2 Evolutionary design of MEMS

A central part of the design process can often be formulated as an optimization problem. However, in the complex design space of MEMS, traditional optimization algorithms are difficult to find the globally optimal solution set. Therefore heuristic search method, especially evolutionary computation (EC), is widely considered as an alternative and promising approach. EC has been successful applied in many engineering optimization applications. It has the ability to deal with complex multi-modal search regions and discontinuous design variables. It will bring meaningful thoughts to the reasonable and rapid optimization design in the field of MEMS automatic design.

Compared to the large number of groups utilizing traditional MEMS design methods, only a small number of research groups are involved in the MEMS evolutionary design, which include UC Berkeley [2–9], California Institute of Technology [5, 7, 9], NASA, Michigan State University [10, 11], Technical University of Denmark [10, 12], and Cambridge University [13, 14]. Some important conferences have also put a focus on this area, such as GECCO [6], SPIE [7], ASME [2, 4, 15, 16].

Since H. Li and E. K. Antonsson started the pioneering work of applying Genetic Algorithm (GA) for mask design synthesis [15], many evolutionary techniques have been developed to deal with MEMS design at different levels. A brief account is as follows.

### 2.1 Hierarchical evolutionary synthesis of MEMS

Senturia first proposed to divide the MEMS model into four parts: the system layer, the device layer, the physical layer and the process layer [17], as shown in Fig. 1. For the system layer model, Fan has implemented a BGGP strategy that combines genetic programming and bond graphs [18]. Genetic Programming (GP) [19] is an effective evolutionary computation method based on tree structure. As a modeling tool, Bond Graphs (BG) [20] provides a unified approach for modeling and analysis of dynamic systems (especially for hybrid multi-domain systems). At the system level, Genetic Programming and Bond Graph are combined to realize interactive modeling and simulation of MEMS components as well as electronic devices. In the work of Fan, Z. [18], functions are loaded into each node of the tree. Experimental data show that, after defining the feasible function set, the topology structure and parameters of bandpass filters (RF MEM devices) can be evolved and optimized, to fulfill the predefined design specifications.

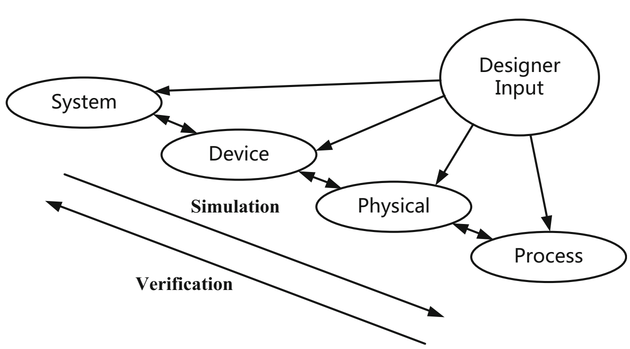


**Fig. 1** Model classification proposed by Senturia [17]

Fan et al. further studied the physical layout synthesis involving both system layer and device layer [11]. the geometric dimension parameters of the basic components are optimized [17]. In most cases, these basic components are selected from micro electromechanical devices with fixed topologies. As a result, the design problem can be formulated as a constrained optimization problem, and GA is usually used to solve it.

The overall performance optimization of MEMS gyroscope is considered from the system level [21]. The authors have systematically optimized the thermostability and high frequency oscillation of the gyroscope. Through the practical test, it has shown better environment adaptability than results obtained by other methods.

### 2.2 Mask design synthesis of MEMS

The device layer requires a layout with a basic two-dimensional structure, including components such as beams. In some cases, if a MEMS is based on a surface micromachining process and does not exhibit significant three-dimensional (3-D) characteristics, design of this layer will complete with a single cycle. However, more generally, it is necessary to perform an efficient 3D modeling and analysis of MEMS. From the point of view of manufacturing details and functional design of devices and systems, automatic mask design and related industrial process synthesis are very helpful in alleviating design difficulties [22].

Evolutionary methods are applied to mask design and process synthesis in Li and Antonsson's study [15]. GA was applied in a geometrically efficient mask design population to iteratively search for the global optimum. A 3-D corrosion simulator called Segs simulates the production of each layout by the same team. This research is further improved by utilizing object-oriented structures, and whichever forward process simulation can be evaluated [23].

Evolutionary algorithms are applied to mask design [24, 25]. The testing and coordination of design rules between the schematic and the layout are also considered in the design of mask [24]. Compared to single mask design, better performance of MEMS is achieved.

## 2.3 Multi-objective optimization strategy

Due to the complex characteristics of MEMS design, more than one target is often considered in many cases. The optimal design of MEMS can often be considered as a multi-objective optimization problem. For example, the design objectives of designing a meander resonator include: minimize the difference to the target value of the resonance frequency and the stiffness of the foot in each direction, and to minimize surface area at the same time [4]. As another example, for the ADXL150 accelerometer, the design objectives include: to minimize the difference between the angular frequency and the target angular frequency, to minimize the design area, and to maximize sensing capacitance [26]. Zhou et al. were among the first group of automatic synthesis designers to apply the multiple objective genetic algorithm (MOGA) (New developments in MOGA research are documented in literature [27] to MEMS (meander resonators) [2, 4]. In their experiments, the topology and size of the devices were optimized using MOGA. The geometric (graphical) validity of each design is verified through a MEMS simulation toolbox SUGAR [28]. In the multi-objective genetic algorithm, the Pareto optimization (in Fig. 2) is used to find a variety of non-dominated optimal solutions, and fitness value sharing is used to keep the diversity of the solution set. Based on the work of Zhou, Kamalian analyzed the influence of geometric constraints on resonator case studies, and extended the approach to the design of more advanced MEMS devices, such as accelerometers and gyroscopes [29]. Zhang continued the research of Zhou and Kamalian, and proposed a hierarchical MEMS design and optimization structure [30]. The effectiveness [3] of MOGA is demonstrated by comparing the performance of MOGA and other methods [Simulated annealing (SA) [31] and single-object genetic algorithm (SOGA)] in MEMS optimization design. The results of optimizing a meander resonator by using the above method show that, SOGA is faster than MOGA, but easier to fall into the local optimum. In some cases, SA is more efficient than genetic algorithms, but can only treat one single goal and have the difficulty of finding the optimal solution. It is shown to have low robustness in performance on many MEMS synthesis problems. A similar experiment has been conducted using a simple and extensible genetic programming language by Lohn et al. [32]. In literature [33], the size and power of micro resonator are optimized simultaneously by combining NSGA-II algorithm and sequence planning. In the optimization process, to minimize the size is taken as the main objective, and two feasible schemes are obtained according to the actual manufacturing principle. In literature [34], the multi-objective evolutionary design of piezoelectric energy harvesting MEMS is carried out. The design results are also evaluated and discussed, which shows that MOGA-II is superior to NSGA-II in some cases.

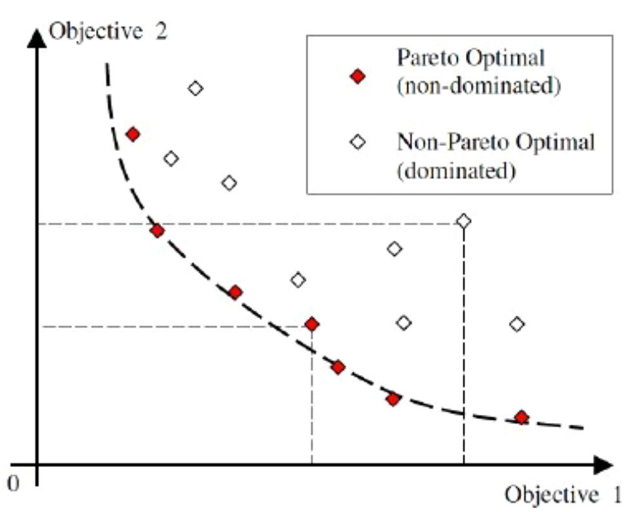


**Fig. 2** Pareto optimization for minimization problems of two-dimensional objects

After 2010, Zhang and Agogino have published two new works: A hierarchical multi-objective genetic algorithm with proper genotype expression of components is developed, which integrates the engineering knowledge of specific fields into the design optimization process, and applied in the optimization design of MEMS [5]. An interactive hybrid evolutionary computation method is proposed to solve the problem of subjectivity and inconsistency incurred in expert evaluation [9]. In the process of integrating expert experience into MEMS evolutionary design, their research results are in the leading position in this field.

To demonstrate the advantages of multi-objective genetic algorithm, a comprehensive design optimization is carried out for three manipulators with 3 degrees of freedom in literature [35]. According to the optimization results, it is proven that the genetic algorithm can obtain global optimal solutions, which cannot be obtained by human design before. Similarly, a micro accelerometer is optimized by using multi-objective genetic algorithm in literature [36]. The robustness, stability, sensitivity and other indexes of a gyroscope are also optimized by using multi-objective genetic algorithm in literature [37]. The experimental results show that the proposed algorithm has obtained designs with better performance than those of human designs obtained mainly by empirical studies.

## 2.4 Robustness design

With the current micro mechanical technology conditions, the variation caused by the MEMS manufacturing process is inevitable. It therefore has become a very important issue on how to design MEMS insensitive to the variation caused by the manufacturing process. The concept of robustness is thus introduced to help study how to improve the quality of the product when there are significant uncertainties in the process. Some research groups have tried robustness design in the MEMS optimization design. On the basis of previous researches on mask design and process synthesis [22], Ma proposed a robust design technique called Genetic Algorithm with Robust Solution Search Technique [38]. In their approach, interference factors are first loaded into the design process, and then a design solution is obtained by using GA. Hornby proposed two modification strategies to obtain better robustness for generating a design solution by GA cyclic evolution [39]. One strategy is loading local interferences, and the other is applying pre-stressing to the design.

Fan formulated the robustness design problem as a constrained multi-objective optimization problem in which the two design objectives were minimized in the MEMS layout design. Then an efficient algorithm, NSGA-II, was used to find the optimized solutions [16]. In this approach, only a modification of the objective function is required without modifying any algorithmic process. In Fan's more recent studies, an improved differential evolution (DE) algorithm based on stochastic sorting is developed, which has better performance [41] in the robustness design of MEMS than the NSGA-II [40].

In the literature [42], to address the uncertainty of etching process in MEMS machining, all types of possible uncertainties are considered as unknown and bounded. An etching process uncertainty set is designed according to different conditions, which is combined with topology optimization to adapt to the uncertainty in the etching process. In the literature [43], various uncertain factors that affect the performance of MEMS are analyzed, with the strength, reliability and performance index of MEMS machining process modeled. Then, genetic algorithm is used to optimize the indicators in order to obtain an optimal scheme considering various possible uncertainties.

### 2.5 Efficiency improvement

The large evolutionary population of each generation makes the computational cost of the simulation process very high. As a result, the evolutionary optimization design process of MEMS is usually complex and time-consuming. It is a very important research to improve the efficiency of finding the global optimal design solutions in the real world applications.

A hybrid evolutionary computation method with two layer optimization techniques, global random search and local optimization based on gradient, is proposed by Zhang et al. [30], which is an extension of Zhou's work [4]. The method utilizes a geometric model of a fixed design by the end of the global search, thus effectively integrates local optimization technology based on gradient to further optimize and finetune a promising design solution.

Kamalian et al. carried out the work of embedding sight control of the designer and interactive evolution computation (IEC) of the domain knowledge in the MEMS computer aided design process [6]. The example of meander resonators shows the effectiveness of the IEC method. Zhang developed an interactive hybrid algorithm (IHC) [29] to avoid the heavy workload on the IEC and to compensate for the lack of recognition of good patterns for hybrid GAs. IEC and IHC both treat preference problems in a forthright way.

Since the initial population of MOGA is set up by the user or randomly generated, the case-based reasoning (CBR) method proposed by Cobb et al. can be integrated into the MEMS design process to speed up the synthesis process [7]. A case index library of previously successful MEMS designs and semi-finished products is created. The CBR provides a repository of approximate designs for current goals, which can store current best designs for future use. Their experimental results show that combining CBR and MOGA tools helps to increase the number of viable conceptual designs. Their more recent work in this field can be seen in literature [8].

In order to improve the speed of evolutionary computation in parameter optimization of MEMS relay, a parallel evolutionary computation method is designed in literature [44]. In order to improve the efficiency and load balancing of computer resources, the fitness calculation process of evolutionary algorithm is processed in parallel. Multiple machines connected in a LAN communicate with each other in a master–slave mode. The individuals of the population are distributed to the client by the server for evaluations, and finally the individuals are collected, to reduce the running time of the algorithm. Experimental results show that the parallel evolutionary algorithm has high computational efficiency and can obtain better solutions in a short period of time.

## 3 The main problems of MEMS evolutionary design

Although many progresses have been made in MEMS evolutionary design, as an emerging field, three major open issues still exist:

(1) As Chaudhuri and Deb pointed out on a broader level, the evolutionary optimization community rarely considers the preferences of traditional decision makers systematically and comprehensively

[45]. However, for design issues, preferences are not to be ignored, and sometimes even crucial [46–49]. Therefore, it is an important research topic to integrate preference into MEMS evolutionary design.

(2) The complexity and complex systems have drawn wide attention from academia. The journal Science has published a series of complexity and complex systems in nearly 10 years. Some MEMS (such as distributed MEMS, distributed intelligent MEMS [58, 59]) are undoubtedly complex systems. The current MEMS evolutionary design research has not yet fully exploited methods for complex systems, and utilized existing research results of complex systems, such as in literature [50–59].

(3) After the design has been completed, the system augmented performance evaluation of multiple schemes will be conducted, which integrates program selection design, performance evaluation, and selection of interdisciplinary research ideas and technical route. This research has not been reported elsewhere.

Research on these issues has important scientific and practical value for the development of new methods for MEMS evolutionary design. In summary, the following research directions are suggested.

(1) Apply the idea of preferences before, during, and after the design process and combine human intelligence with machine intelligence. It is beneficial to realize man–machine combination reasonably and effectively, to construct a scientific, feasible and even innovative design scheme of MEMS. In this regard, there are many research opportunities with great scientific significance.

(2) Integrate preference based evolutionary design method into computer decision support system for MEMS. It is the development of the current MEMS design tool, which has wide application prospect, and can be expected to obtain high economic value.

## 4 Conclusions

As an important part of the internet of things (IoTs) and cyber-physical systems (CPS), Micro-Electro-Mechanical-Systems (MEMS) is playing more and more irreplaceable role in current industrial community and the forthcoming era of the Industry 4.0.

Design is the foundation of manufacturing. This paper reviews the related research on the evolutionary approaches applied for optimizing MEMS design. These approaches are applied in different aspects of the MEMS design process, from the system level, device level, to the physical level and the process level. In this review, we find that to a large extent, these evolutionary approaches are more capable of solving multi-objective problems and gain better performance for searching global optimum solutions.

Although with great potential, this field is facing some difficulties, including e.g., how to consider the preferences in the multi-objective optimization process, and how to adopt the fruit achievements of the complex science. These open issues are important and interesting, and are worthwhile to be investigated and explored in depth.

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