A Novel Approach to Multi-level Evolutionary Design Optimization of a MEMS Device

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Abstract. This paper introduces a novel approach to the evolutionary design optimisation of an MEMS bandpass filter, incorporating areas of multi-disciplinary, multi-level and multi-objective design optimisation in the process. In order to demonstrate this approach a comparison is made to previous attempts to design similar bandpass filters, providing comparable results at a significant reduction in functional evaluations. In this endeavour, a circuit equivalent of the MEMS bandpass filter is evolved extrinsically using the SPICE Simulator.

Keywords: Multi-Disciplinary Optimisation; Multi-Objective Evolutionary Algorithm; Multi-Level Optimisation; MEMS; Micro-Electro-Mechanical Systems; Extrinsic Evolution.

1 Introduction

Micro-electro-mechanical systems (MEMS) or micro-machines [1,2] are a field grown out of the integrated circuit (IC) industry, utilizing fabrication techniques from the technology of Very-Large-Scale-Integration (VLSI). The goal is to develop smart micro devices which can interact with their environment in some form. The paradigm of MEMS is well established within both the commercial and academic fields. At present encompassing more than just the mechanical and electrical [3], MEMS devices now cover a broad range of domains, including the fluidic, thermal, chemical, biological and magnetic systems. This has resulted in a host of applications to arise, from micro-resonators and actuators, gyroscopes, micro-fluidic, and biological lab on chip devices, to name but a few. Normally, designs of such devices are produced in a trial and error approach dependant on user experience and naturally an antithesis to the goal of allowing designers the ability to focus on device and system design. This approach, nominally coined a ‘Build and Break’ iterative, is both time-consuming and expensive [2]. Therefore the development of a design optimisation environment [15,16], which can allow MEMS designers to automate the process of modelling, simulation and optimisation at all levels of the MEMS design process, is fundamental to the eventual progress in MEMS Industry [2]. Work in MEMS design automation and optimisation can be seen to fall into two distinct areas; firstly the more traditional approaches found within numerical methods such as gradient-based search [7]; and

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secondly the use of more powerful stochastic methods such as simulated annealing and/or Evolutionary Algorithms (EAs) [4-6]. There has been a recent shift towards the use of EAs, and more specifically the use of Multi-Objective Genetic Algorithms (MOGA) [17] as these stochastic algorithms allow for a more robust approach to tackling the issues of a complex multi-modal landscape. The bulk of the work utilising Genetic Algorithms (GAs) and MOGA has been undertaken by researchers from the University of California, Berkeley, focusing solely on planar MEMS devices [4-6]. The paper highlights and builds upon past approaches introducing a novel multi-objective approach to the multi-level and multi-disciplinary design optimisation of a MEMS. A bandpass filter is chosen as a MEMS case study for this paper in order to demonstrate comparable results to the state of the art in the field. This MEMS device is evolved extrinsically in its equivalent analog circuit form using the SPICE simulator and then physically envisioned using the SUGAR Nodal simulator. Results are compared with those within the literature.

This paper begins with a brief overview of the hierarchical design environment of MEMS in section 2, followed with a definition of the bandpass filter problem used in this study in section 3. The next section focuses on a novel evolutionary design optimisation approach to solving this problem in section 4 followed by results in section 5 and ending with conclusions.

2 Hierarchical MEMS Design

The hierarchical nature of MEMS design process provides designers with the problem of how best to approach the possible decomposition of the device at the various levels of modelling and analysis abstractions presented to them. Outlined by Senturia [14] the four levels (System, Device, Physical, and Process) each harbour its own set of tools and modelling approaches. The system level focuses upon the use of lumped element circuit models or block diagrams to model device performance, utilising powerful circuit simulators. They provide the possibility to interface with the mechanical elements of the device, either through analytical models, HDL models, reduced order models or alternatively electrical equivalent representations of the mechanical component. Both the device and physical level provide models of varying granularity. At a device level, a designer can look to build accurate 2D layout models through the use of NODAL simulators and various atomic MEMS elements, or by building mathematical analytical representations. The physical level generally utilises more expensive finite element and boundary element methods to simulate and analyse 3D models of the device. The process level looks towards the creation of appropriate mask layouts and process information needed for the batch process generally employed to fabricate the device. Therefore, by utilising system level tools it is possible to derive the function of the whole coupled electromechanical device, while the device or physical levels allow the device to be envisioned and thus allow fabrication to follow function.

3 Problem Definition

Analog circuit design for Hi, Low and Bandpass filters have been successfully undertaken using evolutionary methods in the past [8] [9], mainly through the use of genetic programming and a circuit or bond graph representation [10]. These approaches looked to use components associated with circuit design and connect them in various topologies in order to match the target filter response. Recently MEMS have become a focus upon which to build devices that can provide superior performance to traditional mechanical tank components such as crystal and SAW resonators [11], widely used in bandpass filters within the radio frequency range. A feature of certain MEMS devices is the ability to represent the device as a whole in both mechanical and electrical equivalents. Taking for example a simple folded flexure resonator [11], the device can be represented as a simple spring-mass damping system, and equally this system has a similar equivalent within the electrical domain. Here the values for Mass (m_{rs}), Stiffness (K_{rs}), and Damping (C_{rs}) of the resonator can be mirrored as Inductance (L), Capacitance (C), and Resistance (R) in the electrical domain. Therefore a mechanical folded flexure resonator can be represented and therefore analysed at a system level by building a simple RLC circuit. The coupling of such resonator units or 'tanks' through the use of mechanical bridges or springs allows the development of devices, which can provide certain filter responses. This can also be achieved in the circuit equivalent. The approach on relating the physical parameters of the folded flexure resonator to that of the equivalent circuit values has been outlined by Nguyen [11] and the subsequent equations are shown below.

$$R_{xn} = \frac{c_{rs}}{\eta_{en}^2} = \frac{\sqrt{k_{rs}m_{rs}}}{Q\eta_{en}^2} \tag{1}$$

$$L_{xn} = \frac{m_{rs}}{\eta_{en}^2} \tag{2}$$

$$C_{xn} = \frac{\eta_{en}^2}{k_{rs}} \tag{3}$$

$$\eta_{en} = V_{pn}\frac{\vartheta C_n}{\vartheta x} \tag{4}$$

$$\frac{\vartheta C_n}{\vartheta x} = \frac{2\xi N_{fin}\varepsilon_o h}{d} \tag{5}$$

Where V_{pn} is the dc bias voltage, ξ is a constant that models additional capacitance due to fringe field electrics, ε_o is the permittivity of air, h is the structural layer thickness, N_{fin} is the number of comb drive fingers and d is the comb finger gap spacing. Using these equations it is possible to derive resistor, capacitor and inductance values from the damping, stiffness and mass values of the resonator and equivocally vice versa. This allows a direct link between the system and device levels and as a result allows designer to derive both function and fabrication to one particular instance of the MEMS filter design. Figure 1 outlines an approach to decompose a MEMS bandpass filter into separate modelling levels, extract the chosen design variables and construct suitable genotype representations in the case of EAs. In order to assess these two levels, objective functions for evaluation need to be introduced. In the case of filter design, a target response based upon chosen design targets of 'passband', stopband' and 'central frequency' can be constructed. Figure 2 shows how to break the filter response into sections of 'stopband' and 'passband' with ideal target values of '-20dB or less' and '0dB'. A sampling of the frequency response can then be undertaken over a specified range with the goal to have a filter response in the stopband range equal to or below the target value and in the passband range the goal

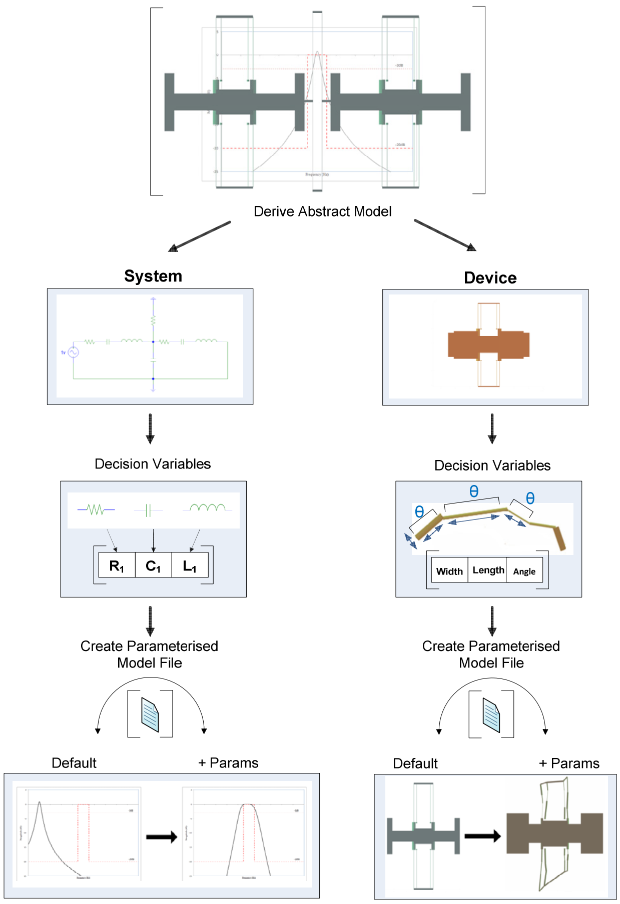


Fig. 1. Filter Design Synthesis Breakdown

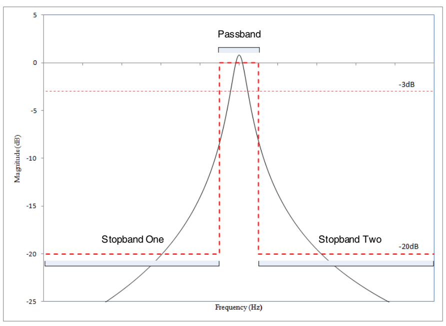


Fig. 2. Filter Objective Breakdown

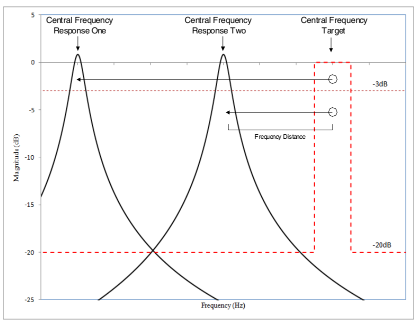


Fig. 3. Central Frequency Objective Breakdown

is to simply match the target value. In both cases the objective function is simply the sum of the absolute error for the two ranges however considering the stopband is considerably larger a weighting factor is used to reduce this value. A second objective as shown in figure 3 looks to evaluate the distance of the peak filter response of the individual from the target central frequency. The goal being to differentiate between similar filter shapes which however may lie farther away from the target required. Once a suitable filter response has been found, the circuit model can then be converted to the equivalent mechanical values and then used as targets for 2D resonator layout design.

4 Multi-objective Evolutionary Algorithm Filter Design Synthesis

The design and optimisation of a MEMS bandpass filter forms the basis of our multi level problem. The approach used in this paper looks to couple a multi-objective genetic algorithm NSGAII [17] with an electrical circuit model representation, coined (GAECM). Utilising a varied length, real-valued and integer representation, the goal is to allow the GAECM approach to evolve the topology and parameters of the circuit in order to match the frequency response of a bandpass filter. Once a suitable filter design has been found, its values can then be converted into the equivalent mechanical values for mass and stiffness using the calculated η_{em}, and then used as objective targets for the evolution of a 2D layout folded flexure resonator device. Past attempts [12][13] towards MEMS filter design optimisation have looked to couple the powerful approach of genetic programming with a bond graph representation, coined (GPBG). Though successful a large number of functional evaluations were required (2.6 million) and no respective circuit values were given and therefore it is not possible to derive whether the actual designs were physically feasible. Even so an approach was outlined to allow the automatic synthesis of a physical device in this case utilising an analytical model of a folded flexure resonator and linking it with the powerful approach of GAs [12-13]. The approach proved successful for the set of targets outlined, in this instance to match certain values for both mass, stiffness and damping of a single resonator device. However it was not a true multi-objective algorithm, nor did the actual values come from the previously designed filter. In order to solve each design problem alterations were made to the NSGAII algorithm in order to improve the overall search ability of the optimizer. The 'SBX' crossover for the GAECM algorithm has been adapted to be restricted to only occur between the length of the shortest individual as shown in figure 4. Included in the mutation operator is the ability to 'clone' or remove tanks from the individual in an attempt to aid topological search, as shown in figures 5 and 6.

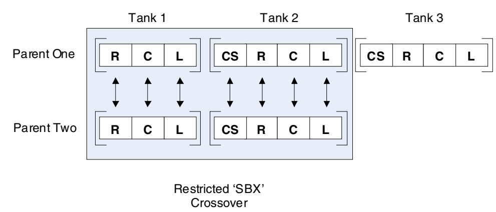


Fig. 4. Restricted Crossover for System Level Representation

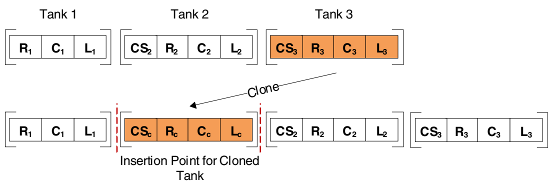


Fig. 5. Cloning Mutation Operator

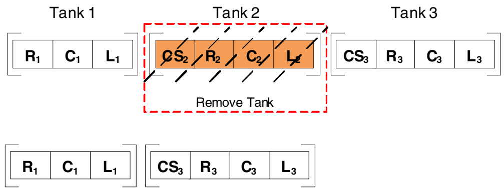


Fig. 6. Removal Mutation Opreator

The design optimisation of the resonator looks to utilises the model representation and simulation of the NODAL analysis tool named ‘SUGAR’. This particular approach follows that of previous work [8-10] in design optimisation of MEMS using the SUGAR platform, however in this instance a completely new folded flexure resonator as shown in figure 7 is evolved in place of previous simpler meandering resonator devices. Utilising a similar hierarchical representation, the whole device consisting of both components of the central mass and supporting springs of the folded flexure are evolvable. The central mass is made up of ten beam elements, four of which can be designed and then simply mirrored to the other half of the mass. The folded flexure springs are made up of eight individual springs, four at the top and bottom, each connected by three truss beams. Each spring is made up of a number of beam elements each with their own set of design variables, in this case ‘width, length and angle’. In this particular design problem constraints are placed upon the resonator so as to adhere to a more ‘classical’ design, with fixed angles for the central mass and folded

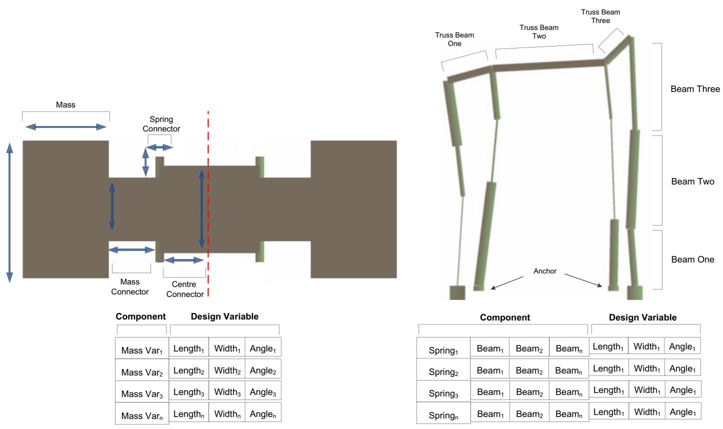


Fig. 7. Device Level Representation

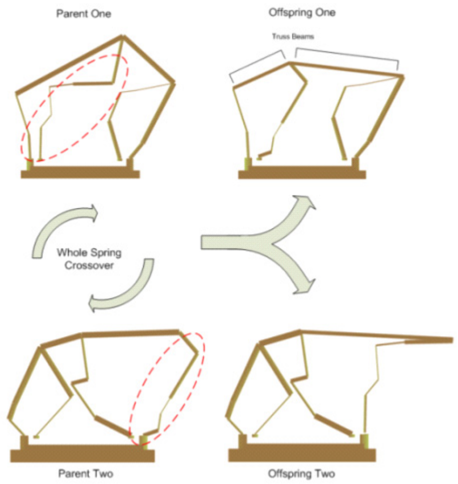


Fig. 8. Whole Spring Crossover

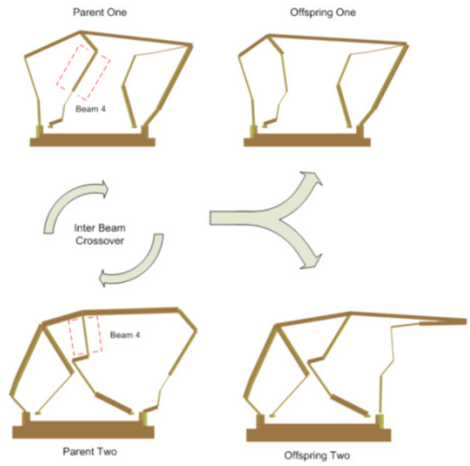


Fig. 9. Inter Beam Crossover

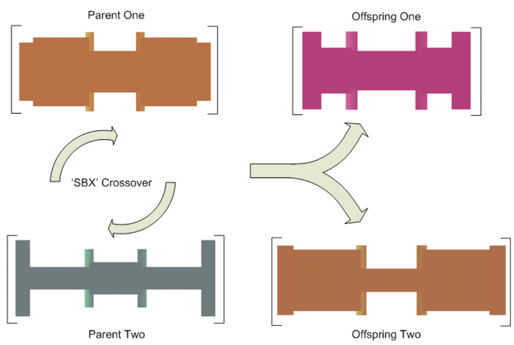


Fig. 10. Central Mass Crossover

flexure springs and a simple mirroring along the x and y axis. Adaptations to the crossover operator were introduced to mimic that of previous work [4] and replace the classic 'SBX' operator, with a 'whole spring' crossover and 'inter beam' crossover, shown in figures 8 and 9 respectively when evolving spring design. Central mass crossover in figure 10 however uses the original 'SBX' crossover operator. The use of SUGAR provides advantages over a single use analytical model, as it allows more complex devices to be evolved and in the future allows for more novel devices to be incorporated.

Three case studies as shown in table 3 form the basis of testing this new approach to filter design, beginning with a relatively low frequency filter taken from [12,13], two more filter design problems are introduced to test the robustness of the algorithm at higher frequencies. The parameters used by NSGAII to solve both the system and device level design problems are shown in table 1, in this instance the system level contains a higher mutation rate to facilitate the chance of adding or removing 'RCL' tanks. Also two population and offspring sets were run for each case study at the system level. Table 2 holds the various parameters for the circuit design problem, resistance is worked out from capacitance, inductance and equation (1) and therefore left blank. Each case study was fixed to a specific range where points were sampled at specific frequencies and then used to evaluate the two objectives outlined previously for the system level design. These were a range of [0Hz-10kHz] for case study 1 resulting in 10,000 sampling points, and [0Hz-25kHz] and [85kHz-110kHz] for case studies 2 and 3 respectively, resulting in 25,000 sampling points. As a result weighting factors for the sum of the stopbands were set to 'divide' the value by 9 and 25 in order for the algorithm to not focus to heavily on optimising the stopband.

Table 1. NSGAII Parameters

NSGAII	System	Device
Probability of SBX Crossover	0.8	0.8
Probability of Mutation	0.35	0.10
Distribution Index for crossover	20	20
Distribution Index for mutation	20	20
Population Size	100 / 20	100
Offspring Size	100 / 10	100
Selection Size	100 / 10	100
Generations	100	100
Tests	5	-

Table 2. Circuit Design Variable Parameters

	Case Study One		Case Study Two		Case Study Three	
Variable Type	Lower Values	Upper Values	Lower Values	Upper Values	Lower Values	Upper Values
Tank No	1	9	1	9	1	9
Voltage	1	200	1	200	1	200
Resistance (Ω)	-	-	-	-	-	-
Capacitance (F)	1e-15	1e-11	1e-17	1e-14	1e-18	1e-15
Inductance (H)	10	100000	10	100000	10	100000
Finger Number	1	200	1	200	1	200
Thickness (μm)	2e-6	3e-5	2e-6	3e-5	2e-6	3e-5

Table 3. Case Study Parameter Ranges

	Case Study One	Case Study Two	Case Study Three
Passband	312Hz – 1000Hz	19.5kHz – 20.5kHz	99.5kHz – 100.5kHz
Stopband 1	1Hz – 312Hz	1Hz – 19.5kHz	85kHz – 99.5kHZ
Stopband 2	1000Hz – 10kHz	20.5kHz – 25kHz	100.5kHz – 110kHz
Central Frequency	656Hz	20kHz	100kHz

5 Results and Comparison

Results for each case study, and each population set for the system level filter design problem are found in table 4, with the best result ranked by filter objective listed for each test. The circuit models for test 4 of case study one for population 100 set, test 1 of case study two and test 5 of case study 3, both population 20 sets were converted to their mechanical equivalents as shown in table 5 and for each resonator 'tank' used as objective functions for the design synthesis of a 2D layout resonator device. The filter responses for each of these are shown in figure 11, and the evolved 2D layout designs for these filters are shown in figure 12. In the case of the 2D layout design optimisation, results which had an error of less than 0.1% for each objective were extracted. In comparison with earlier work [12,13] the results presented here show this particular approach to be robust over a set of different case studies where previous attempts focused only on one. In the course of solving each case study the GAECM method provided comparable bandpass filter shapes at a relatively small number of functional evaluations given the state of the art [12,13]. Finally the coupling of NSGAII with the NODAL platform SUGAR provided effective and fast design optimisation of the required 2D resonator layouts.

Table 4. Best results for each case study ranked by filter objective

Best Result Case Study 1: Population 100				
Test	Filter Objective	Central Frequency Objective	Voltage	Tank Number
1	941.76	110	112.5	2
2	953.40	86	161.7	2
3	565.25	293	66.4	3
4	478.65	24	43.9	3
5	942.03	256	159.7	2
Best Result Case Study 1: Population 20				
Test	Filter Objective	Central Frequency Objective	Voltage	Tank Number
1	940.47	112	1	2
2	1974.60	97	32.70	2
3	476.76	240	7.28	3
4	2130.29	0	109.85	2
5	2130.30	1	108.75	2
Best Result Case Study 2: Population 100				
Test	Filter Objective	Central Frequency Objective	Voltage	Tank Number
1	1798.99	230	84.3	3
2	2259.23	1250	54.99	5
3	1990.79	30	16.98	3
4	3085.71	50	102.68	2
5	2422.73	190	2.43	3
Best Result Case Study 2: Population 20				
Test	Filter Objective	Central Frequency Objective	Voltage	Tank Number
1	988.58	100	44.16	5
2	1293.24	260	78.03	5
3	2998.03	10	45.62	2
4	2095.91	150	115.56	3
5	1048.50	210	26.65	3
Best Result Case Study 3: Population 100				
Test	Filter Objective	Central Frequency Objective	Voltage	Tank Number
1	1632.81	170	86.87	6
2	2405.76	40	31.78	2
3	2712.51	110	169.61	2
4	1561.27	50	152.39	2
5	2289.03	30	197.81	5
Best Result Case Study 3: Population 20				
Test	Filter Objective	Central Frequency Objective	Voltage	Tank Number
1	2319.79	40	127.72	2
2	2181.26	30	40.30	2
3	1672.20	10	66.03	3
4	1628.61	20	27.54	3
5	1304.11	190	22.17	9

Table 5. Equivalent mass and stiffness (Kx) values for the best results of each case study

Individual Folded Flexure Resonator Values		Best Result Case Study		
		1	2	3
Tank 1	Equivalent Mass (kg)	5.92e-9	2.34e-10	3.92e-10
	Equivalent Stiffness (N/m)	0.083	3.91	160.52
Tank 2	Equivalent Mass (kg)	4.78e-8	2.50e-10	4.15e-10
	Equivalent Stiffness (N/m)	0.073	3.24	159.72
Tank 3	Equivalent Mass (kg)	3.03e-8	2.67e-10	4.03e-10
	Equivalent Stiffness (N/m)	0.281	3.99	159.74
Tank 4	Equivalent Mass (kg)	-	2.77e-10	3.92e-10
	Equivalent Stiffness (N/m)	-	3.99	160.52
Tank 5	Equivalent Mass (kg)	-	2.26e-10	2.95e-10
	Equivalent Stiffness (N/m)	-	3.92	159.74
Tank 6	Equivalent Mass (kg)	-	-	3.90e-10
	Equivalent Stiffness (N/m)	-	-	159.74
Tank 7	Equivalent Mass (kg)	-	-	4.18e-10
	Equivalent Stiffness (N/m)	-	-	158.80
Tank 8	Equivalent Mass (kg)	-	-	4.11e-10
	Equivalent Stiffness (N/m)	-	-	160.52
Tank 9	Equivalent Mass (kg)	-	-	4.07e-10
	Equivalent Stiffness (N/m)	-	-	159.74

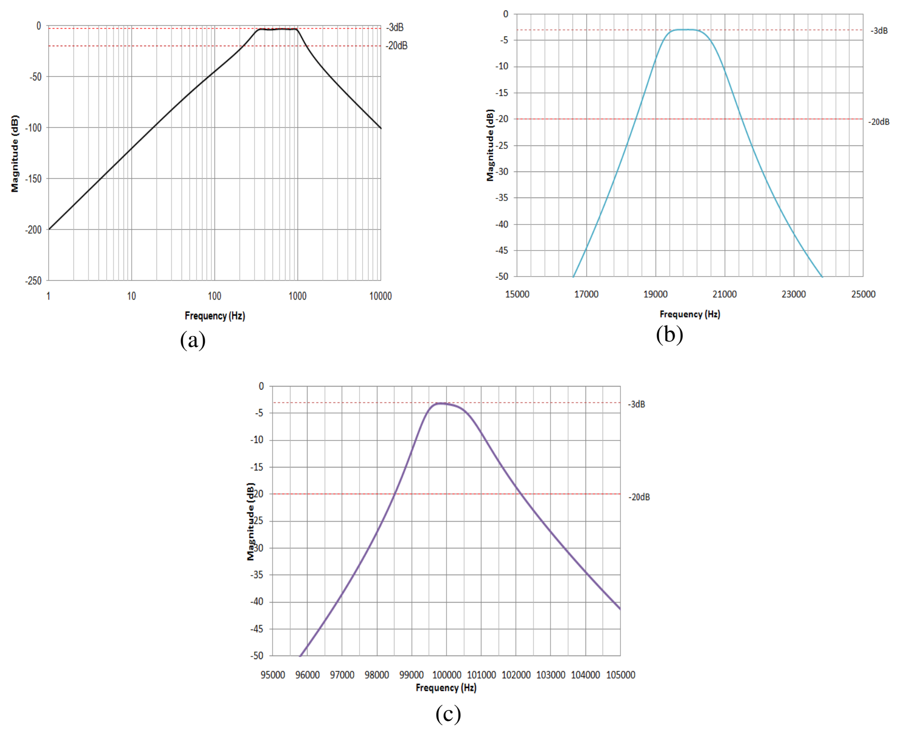
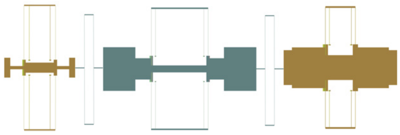
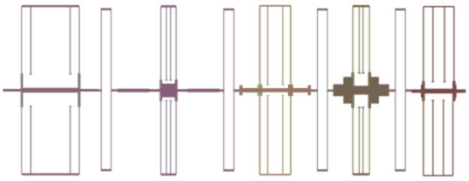


Fig. 11. Filter frequency response for the best result for case study one (a), case study two (b) and case study three (c), ranked by filter response objective



(a)



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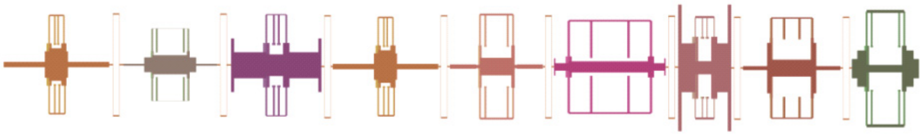

(c)

Fig. 12. Folded flexure resonator layout designs for best results from case studies one (a), two (b) and three (c)

6 Conclusions and Future Work

Moving towards a more multi-level approach to design optimisation of MEMS will prove to be a challenging task. Presented here was a simple approach to the coupling of both system and device level tools in the hope of designing and optimising a MEMS bandpass filter. This involved combining multiple disciplines from the electrical and mechanical domain, utilising separate circuit level modelling and analysis tools such as 'SPICE' with a mechanical NODAL simulator 'SUGAR. The new GAECM approach proved successful in evolving designs which gave comparable results to earlier work [12][13], but at a fraction of the cost, needing only 10,000 functional evaluations in comparison to 2.6 million with the GPBG approach. Also our designs were restricted to bounds which gave rise to feasible and realisable physical targets unlike previous attempts, by using the required electrical equivalent to mechanical equivalent conversion method presented in [11]. This allowed for the creation of filter designs which could be feasible and realisable in terms of fabrication of the resulting 2D layout designs. The design synthesis of the specific 2D folded flexure resonator devices was undertaken through the SUGAR platform and then using the multi-objective genetic algorithm NSGAII designs were evolved to match the required targets optimally found at the system level. By using NSGAII it is possible to undertake true multi-objective optimisation and the integration of it at both system and device level make the job of coupling the two levels together at a later date far easier than a separate genetic programming and GA approach. The use of a NODAL simulator proved successful in evolving designs that could match the target values required proving 100% successful in solving all designs with 0.1% target error for each objective set. Also the functional evaluations for each design stood only at 10,000, significantly less than the 137,500 of the current state of the art approach [12,13]. The approach presented proved to be robust enough to handle bandpass filter design problems over a wide range, topological search was facilitated by the introduced changes in the GAECM approach, as can be seen in table 5 with 'cloning' of RCL tanks proving essential to both case studies 2 and 3. Overall the novel approach proved to be around 260x faster in terms of required functional evaluations for the filter design problem at the system level, and around 14x as effective at the device level when compared with the state of the art currently [12,13].

Future work looks to expand this approach to include more levels of the MEMS design process, specifically that of the physical level. Here designers utilize finite element and boundary element models to accurately analyse and design MEMS devices at a significant computational cost. Therefore any approach which can look to automate and hasten the design optimisation at this level will be of great benefit.

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