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A Multi-Objective and Multidisciplinary Optimisation Algorithm for Microelectromechanical Systems

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Abstract Microelectromechanical systems (MEMS) are a highly multidisciplinary field and this has large implications on their applications and design. Designers are often faced with the task of balancing the modeling, simulation and optimisation that each discipline brings in order to bring about a complete whole system. In order to aid designers, strategies for navigating this multidisciplinary environment are essential, particularly when it comes to automating design synthesis and optimisation. This paper outlines a new multi-objective and multidisciplinary strategy for the application of engineering design problems. Two case studies are presented, the first focusing on a common speed reducer design problem found throughout the literature used to validate the methodology and a more complex example of design optimisation, that of a MEMS bandpass filter. Results show good agreement in terms of performance with past multi-objective multidisciplinary design optimisation methods with respect to the first speed reducer case study, and improved performance for the design of the MEMS bandpass filter case study.

Keywords Microelectromechanical systems · MEMS · Multidisciplinary · Multi-objective Optimisation

1 Introduction

The growth of the application of microelectromechanical systems (MEMS) into an increasing number of disciplines means there is a need to balance the objectives, constraints and functionality of the whole system across these disciplines during the design stage. The design of complex systems found in large engineering environments such as aerospace are often decomposed into a number of disciplines or components and are tackled by specific design teams or departments within an organization (Tribes et al (2005)). However this concurrent design approach can lead to sub-optimal trade-offs, as compromises will have to be made when each discipline or component is integrated together to form a whole system. A number of automated methods have been developed and applied over the decades to overcome some of the problems associated with this class of multidisciplinary design optimisation (MDO) problem. The field of MEMS design optimisation mirrors this particular class of design problem due to the nature of the large numbers of interacting components and disciplines in which they act through. Therefore a design

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strategy that can aid designers overcome some of the problems associated with this particular problem would be of great benefit. This paper looks to address this by developing and validating a multi-objective and multidisciplinary design optimisation algorithm that allows designers to decompose their multidisciplinary systems and optimise them individually before recombining to the whole system. This is validated using a common speed reducer problem and also a more complex MEMS design problem.

The rest of this paper is organized as follows. Section 2 provides an overview of multidisciplinary optimisation strategies in the literature and the different architectures that are employed. Section 3 presents a novel MDO problem formulation that can handle multi-objective design problems. Section 4 details the case studies and experimental setup used to validate this new MDO approach with results presented in section 5 and finally conclusions follow in sections 6.

2 Multidisciplinary Optimisation Strategies

2.1 Multidisciplinary optimisation

Complex large scale systems found in many engineering problems today can consist of many components and disciplines coordinating together to form some function or behaviour. In a real design engineering problem, each discipline typically represents a design team concerned with the design of one aspect or component of this complete system. This makes perfect sense as it allows many more people to work upon a particular problem while also allowing specialized designers to focus upon their respective disciplines (Balling and Rawlings (2000)). There are however drawbacks, with the possibility of each discipline having to interact with others the chances of infeasible / non-viable designs occurring due to conflicts with other engineering teams and their separate disciplines is possible (Tribes et al (2005)). This is often solved with a post-optimisation trade-off where in order to solve such inconsistencies and obtain a feasible design; changes need to be made which often lead to a sub-optimal solution (Tribes et al (2005)). Therefore there is a need to both optimise the individual disciplines and their constituent parts or components all the while maintaining some level of global design optimisation for the system as a whole. MDO is one such class of algorithm which looks to coordinate these individual disciplines and components towards a system design that is optimal as a whole and satisfies all constraints, while maintaining some level of design autonomy (Tosserams et al (2010)). This often involves the decomposition of the original design problem into a set of hierarchical coupled elements often based upon the analysis techniques which are used to analyze the physical or behavioural characteristics of the system, or the possible different physical scales, components within the system. As such the total structural performance of the whole system can be a combination of responses that are evaluated from each level within the hierarchy (de Wit and van Keulen (2010)).

Once a hierarchy of decomposed elements is present their coordination and level of autonomy need to be assigned within the optimisation routine. The lowest level of control may be called analysis autonomy where the role of each disciplinary group is limited to the selection and analysis of models (Balling and Rawlings (2000)). The simplest examples are the single-level methods such as multi-disciplinary feasible (MDF), individual disciplinary feasible (IDF) or an all-at-once approach (AAO) (Cramer et al (1994)) which generally focus upon a centralized decision making process at one level, where analysis can also be undertaken at each discipline or element as shown in figure 1a. It is possible to improve these single level methods by utilizing multiple computers or grid systems for distributed analysis, and database management to give improved efficiency and maintainability. However the reliance on a single optimizer to act as a central decision maker and control all aspects of design for what is often a large scale and complex design problem is still a drawback (Kroo and Manning (2000)). The natural progression and next level of autonomy

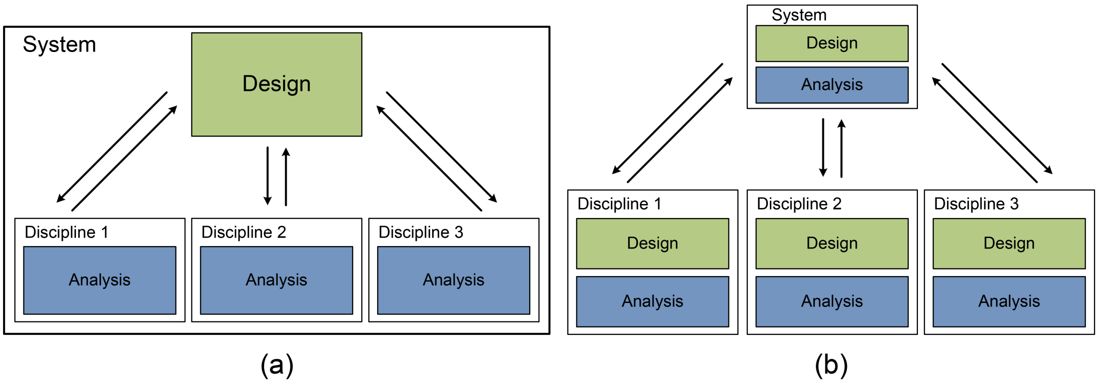

Fig. 1: Disciplinary autonomy with (a) single-level analysis autonomy and (b) multi-level design autonomy

is the inclusion of both analysis models and optimisation algorithms in a distributed multi-level optimisation structure in what can be coined optimisation autonomy. Here each level can contain its own set of analysis and optimisation routines and maintains some element of control over them as shown in figure 1b. The coordination of a decomposed problem solution such that the overall global solution is found is a challenging task (Schoeffler (1971)) however over the last thirty years a large body of work has been conducted towards this goal (Sobieszczanski-Sobieski (1990)) (Kodiyalam and Sobieszczanski-Sobieski (2001)). In the literature there are 6 main approaches to MDO which stand out from the rest; these are Optimisation by Linear Decomposition (OLD) (Sobieszczanski-Sobieski et al (1985)), Collaborative Optimisation (CO) (Braun et al (1996)), Concurrent SubSpace Optimisation (CSSO) (Sobieszczanski-Sobieski (1988)), Bi-Level Integrated System Synthesis (BLISS) (Sobieszczanski-Sobieski et al (1998)), Analytical Target Cascading (ATC) (Kim et al (2003)) and the method of Quasi-separable Subsystem Decomposition (QSD) (Haftka and Watson (2005)). Each method differs in the way it coordinates the solution of a decoupled multilevel optimisation problem. Newer methods include the inexact penalty decomposition method (DeMiguel and Murray (2006)) and augmented Lagrangian coordination (Tosserams et al (2008)). An overview of the current main approaches to MDO can be found in (de Wit and van Keulen (2010)) and (de Wit et al (2006)). A list of the major MDO methods within the literature is shown in table 1.

2.2 Multi-objective multidisciplinary optimisation

The approaches outlined previously that include optimisation routines within all levels of the design optimisation framework generally utilize traditional gradient-based optimisation methods using a single solution only and focusing on a single objective. A number of authors have adapted these traditional methods to create multi-objective MDO formulations using a single weighted sum or aggregated objective (Tapetta and Renaud (1997) McAllister et al (2005)). However the majority of design engineering problems are highly complex with non-linear responses, discontinuous and multi-modal search spaces and contain both discrete and continuous decision variables. All these factor in a number of pathologies to the search efficiency of the more traditional optimizers, while single solution strategies only provide a single Pareto solution from each run for a designer to choose from. Therefore looking to incorporate more robust population-based algorithms such as those found within the field of evolutionary computation that focus upon

Table 1: Chronological review of developments in multidisciplinary optimisation

Contributors	Date	Description
Sobieszczanski-Sobieski et al (1985)	1985	OLD, optimisation by linear decomposition
Sobieszczanski-Sobieski (1988)	1988	CSSO, concurrent subspace optimisation,
Cramer et al (1994)	1994	IDF, individual discipline feasible method, each discipline is solved independently outside of system level
Cramer et al (1994)	1994	MDF, multidisciplinary feasible method, each discipline is directly coupled in some way through input and output analysis, system level controls global / local design variables
Balling and Sobieszczanski-Sobieski (1996)	1996	SAND, simultaneous analysis and design
Braun et al (1996)	1996	CO, collaborative optimisation,
Sobieszczanski-Sobieski et al (1998)	1998	BLISS, bi-level integrated system synthesis,
Kim et al (2003)	2003	ATC, analytical targeting cascade,
Haftka and Watson (2005)	2005	QSD, quasi-separable subsystem decomposition,
DeMiguel and Murray (2006)	2006	IPD, inexact penalty decomposition,
Tosserams et al (2008)	2008	ALC, augmented lagrangian coordination,

multi-objective design problems could be beneficial. An early example created by (Kurapati and Azarm (2000)) featured an immune network system multi-objective genetic algorithm approach (MOGA-INS) for MDO designed to solve hierarchically decomposed multi-objective problems. Each decomposed unit or subsystem contained a MOGA which focused on a specific set of design variables held within the subsystem population representation. Limitations with this approach involved the need for each subsystem to contain the same objectives as all others and being limited to a hierarchical structure. In order to overcome limitations from this previous work (Kurapati and Azarm (2000)), the authors in (Gunawan et al (2003)) created a multi-objective multidisciplinary optimisation algorithm for hierarchically decomposed problems which allowed for differing objectives within each subsystem. This particular approach used quality metrics as a basis for objective function measurement for individual solutions at the system level. Other multi-objective population based algorithms have been implemented within MDO over the years with varying degrees of implementation and success (Giassi et al (2004) Aute and Azarm (2006) Rabeau et al (2007) Huang and Wang (2009) Zadeh et al (2010)). A list of multi-objective MDO algorithms found within the literature is shown in table 2.

2.3 Decomposition methods

One important part of the MDO process is in how the designers go about decomposing the original problem into a set of sub-problems. Decomposition can be seen as identifying weak links between elements that are coupled, and therefore allowing the elements to represent individual though coupled optimisation problems (de Wit and van Keulen (2010)). In general decomposition methodologies can be done in several ways such as object, aspect, sequential and model-based (Wagner (1993)). Model decomposition is a partitioning method based upon functional dependencies between design variables and functions included in the problem (Choudhary et al (2005)). The main approaches to decomposition are the aspect-based and object-based methods, and are discussed further below along with examples of MDO application to design optimisation based upon these decompositions in tables 3 and 4. Aspect-based decomposition focuses on breaking up the particular problem based upon the actual discipline analysis associated with it. This can be aerodynamics, structural, thermal in the case of aircraft design, or electrical, mechanical, fluidic and structural in the case of a MEMS device. In large-scale design environments the system as a whole can be structured according to the individual components of the system such as turbine

Table 2: Chronological review of developments in multi-objective multidisciplinary optimisation

Contributors	Date	Applications	Description
Tapetta and Renaud (1997)	1997	Numerous	Multi-objective collaborative MDO, system level contains a weighted sum of subsystem level objectives, subsystems aim to minimize interdisciplinary inconsistencies
Kurapati and Azarm (2000)	2000	Speed reducer	MOGA-INS, immune network simulation method integrated with MOGA to give hierarchically decomposed MDO
Gunawan et al (2003)	2003	Speed reducer, UAV payload	Hierarchically structured MOGA MDO, requires separable or additively separable objectives
Gunawan et al (2004)	2004	Speed reducer	Hierarchical structured MOGA MDO, system level optimizer focuses upon shared design variables / objective while subsystem focus on local variables and objectives
Giassi et al (2004)	2004	Roll stabilizer fin	MORDACE, a MOGA MDO that incorporates robust design with each discipline design solutions able to handle variation from shared data during a compromise at end of routine
McAllister et al (2005)	2005	Race car design	Integrated linear physical programming with collaborative MDO
Aute and Azarm (2006)	2006	Speed reducer, numerical test problem	Multi-objective collaborative MDO, system level optimizer focuses upon shared design variables / objective while subsystem focus on local variables and objectives
Rabeau et al (2007)	2007	Speed reducer, dock design problem	COSMOS, collaborative optimisation strategy for multi-objective systems, optimizer focuses upon shared design variables / objective while subsystem focus on local variables and objectives
Huang and Wang (2009)	2009	Container ship	Mixed weighted and multi-objective collaborative MDO utilizing multi-island genetic algorithms on all levels of design
Zadeh et al (2010)	2010	Race car design	Particle swarm multi-objective collaborative MDO, a fuzzy decision maker is used to select best design along Pareto front

engines or wing structures. These often correspond to engineering departments within a company and an object-based decomposition approach mimics this. Decomposing the problem into individual components brings with it a natural mirror to real-world design optimisation along with a simplification and grouping of design variables associated with these components.

2.4 MDO Architectures

Microelectromechanical systems often contain a large number of coupled devices or components that provide some form of desired behaviour or function through their collective actions. The system as a whole or the individual components that make it up also often covers a number of disciplinary domains, be they mechanical (Fedder and Mukherjee (1996)), electrical (Farnsworth et al (2010)), or more recently fluidic (Isoda and Ishida (2006)) and biological (Hostis et al (2006)). The increased complexities from designing such multidisciplinary systems can make it harder for designers to build such devices as they often require explicit knowledge in more than one discipline. The application of automated design synthesis and optimisation techniques towards multidisciplinary design problems such as those found in MEMS could greatly speed up the design process and ease the burden of design placed upon the designer. The relationships between the disciplines or components within a design problem often form the basis for the structure the multidisciplinary optimisation routine will take when looking to apply a MDO algorithm. The current state of the art in multi-objective population based MDO employs a multi-

Table 3: Chronological review of developments in aspect-based decomposition

Contributors	Date	Applications	Description
Kroo and Manning (2000)	2000	Supersonic aircraft design	Decomposition of supersonic aircraft into three major disciplines (aerodynamics, structures and mission analysis)
Giassi et al (2004)	2004	Roll stabilizer fin	Sequential optimisation with hydrodynamic optimisation solutions fed into structural subsystem optimizer compared against MORDACE which provided superior performance
Tribes et al (2005)	2005	Structural wing	Decomposition into a system level performance objective and subsystem aerodynamics / structural disciplines
McAllister et al (2005)	2005	Race car design	Consisted of two system level objectives, minimize lap time and maximize normalized weight, with subsystem decomposition into aerodynamic and force disciplines
Huang and Wang (2009)	2009	Container ship	Decomposition into static, mode and dynamic disciplinary analysis
Zadeh et al (2010)	2010	Race car design	Similar decomposition to McAllister et al (2005) with aerodynamic and force disciplinary analysis

Table 4: Chronological review of developments in object-based decomposition

Contributors	Date	Applications	Description
Balling and Rawlings (2000)	2000	Structural bridge	Decomposition of the main components of bridge structure, the superstructure and deck in a conceptual MDO approach
Kurapati and Azarm (2000)	2000	Speed reducer	The design problem objectives and variables are decomposed up into separate subsystems and solved independently before recombining
Gunawan et al (2003)	2003	Speed reducer, UAV payload	Payload design with the goal to maximize probability of success, UAV design variables decomposed between subsystem levels
Aute and Azarm (2006)	2006	Speed reducer, numerical test problem	Decomposition of design problem objectives and variables, similar to Gunawan et al (2003)
Rabeau et al (2007)	2007	Speed reducer, dock design problem	Decomposition of dock structure into separate subsystems containing individual cantilevered beams attached to vertical wall

level hierarchical structure with an upper and lower level relationship that can be structured to contain the decomposed design problem into a set of discipline or component subsystems.

These two approaches mimic the aspect and object decomposition methodologies described previously and both can be equally applied to the MDO of MEMS. Figure 2 provides an example of how a real world MEMS device, the ADXL150 accelerometer, can be broken up using an aspect based (a) and an object based (b) methodology. Here the aspect based decomposition contains lower level subsystems which undertake specific disciplinary analysis required for design optimisation with design variable, objective and constraints often linked to the individual discipline. The object based decomposition concerns its self with the major constituents of the device or system, with design variables heavily linked to these constituent parts and objectives and constraints often tailored so as to optimise these individual components in such a way as to benefit the global design goals situated at the system level.

The integrated and coupled nature of MEMS and the devices and components within them can mean that it is not always possible to fully decompose a design problem and that there still requires some level of communication between each of the lower level subsystems. In the ADXL150 accelerometer example outlined above, it is conceivable that analysis and design variable information altered within one subsystem is needed by another. The calculation of the

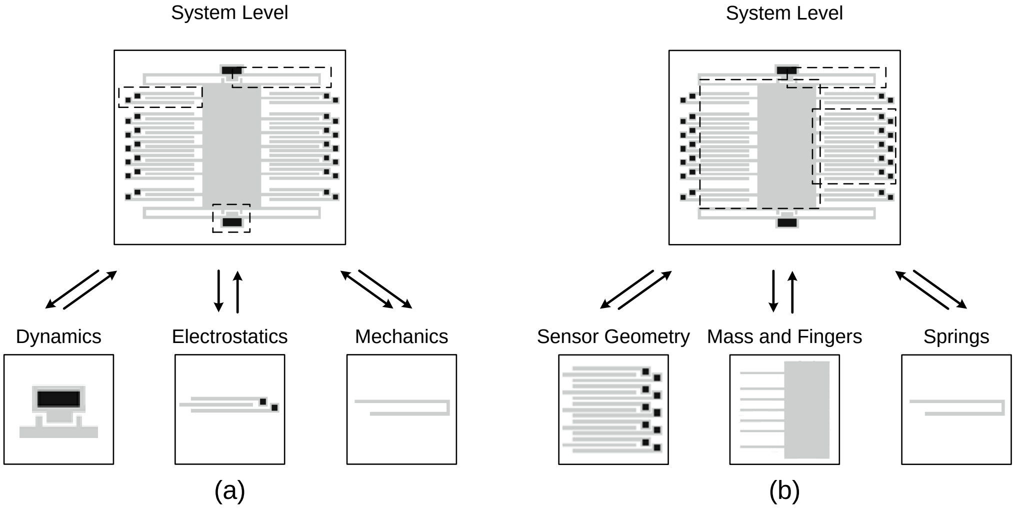

Fig. 2: Decomposition of ADXL150 accelerometer for MDO using an aspect based (a) or object based (b) methodology (Tosserams et al (2010))

electrostatic force is required for the calculation of the mechanics of the device in particular the displacement and stiffness of the suspended springs (Tosserams et al (2010)). The current state of the art in multi-objective population based MDO employs a hierarchical structure with each individual lower level subsystem isolated from all others in a fully decomposed design problem. Such hierarchical structures often require the design problem itself to be hierarchically decomposable with its objectives separable or additively separable which may not always be possible (Gunawan et al (2003)). A non-hierarchical structure however allows communication between the individual subsystems therefore allowing solutions within each subsystem to be provided with the correct disciplinary analyses or subsystem design variables. A number of ways have been presented on how to transfer coupled variables in order to reconcile each of the subsystems into the formation of a complete solution. The cooperative co-evolutionary algorithm set out in (Potter and De Jong (1994)) looks to choose the current best solution from each sub species and recombine them with the chosen solution in the current subsystem to be evaluated. In (Rabeau et al (2007)) a different approach looks to pass approximations of coupled variables from the system level to each subsystem. The difference between the real, but inaccessible, value and the approximate values decreases during the optimisation process. Updated coupling values from each subsystem are sent at every system level invocation and then passed on to all other subsystem levels later on, however they soon become approximations again as each subsystems optimisation routine evolves. The next section outlines the multi-objective and multidisciplinary optimisation algorithm designed to handle non-hierarchical communication between subsystems and used throughout this paper.

3 Methodology

3.1 MDO problem formulation

In applying the MDO algorithm we first begin with the decomposition of the design problem into a number of subsystems each with their own decision variables, local objectives and constraints. The decision on how this decomposition is undertaken is up to the user and within the MDO literature

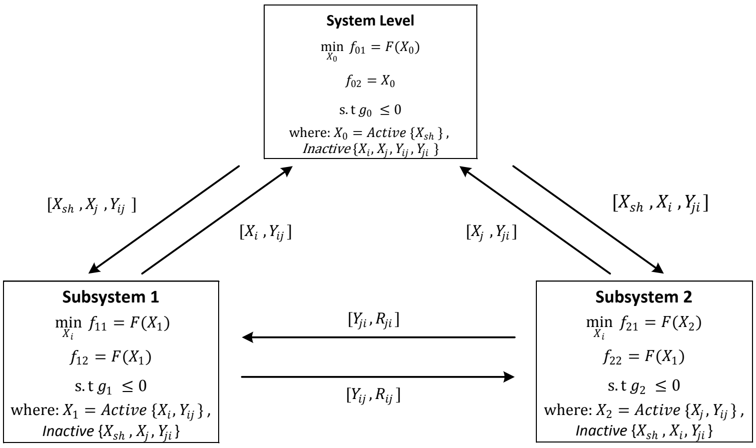

Fig. 3: Multidisciplinary optimisation non-hierarchical structures for decomposed problem

there are a number of methodologies two of which, aspect and object have been discussed. There are also similar methods for identifying the important functions, analysis and objectives in a design problem for example axiomatic design (Conceicao Antonio (1999)) which can also lend their support. The decomposition of a multi-objective problem into a number of subsystems is shown in figure 3. Here the default design problem is held and optimised within the system level with the original objectives f_{01}/f_{02} and constraints g_0 active and a chosen set of decision variables X_{sh} open for variation. The decision on what variables are included within the X_{sh} set are up to the designer however they are often decision variables that are common to more than one subsystem (Gunawan et al (2004)) and often hard to separate so are shared throughout all subsystems. All other decision variables are closed to the system level and remain fixed.

The subsystems are constructed as a non-hierarchical design with communication both from the system to subsystem or parent to child level and from subsystem to subsystem occurring. Each of the subsystems contains its own local objectives f_{11}/f_{12} and these can be unique, additively separable from one of the system level objectives or one of the system level objectives in its own right as shown in figure 3. In a similar vein the constraints g_1/g_2 held within each subsystem can also be unique or taken from the system level design problem. The active decision variables within each subsystem consist of local disciplinary design variables X_i/X_j and the coupled disciplinary design variables Y_i/Y_j. Where the local disciplinary design variables are fixed to each subsystem the coupled design variables are not and as a result they are transferred from their local subsystem to all other subsystems within the structure every cycle. Finally not all problems can be fully decomposable in respect of their disciplinary analysis and as a result more than one system may rely on information garnered from another. Therefore when applicable coupled analysis response variables can also be passed between the child subsystems, with the origin of the subsystem analysis passing on these variables to any other subsystem that requires them. A default chromosomal representation of the various design and response variable sets for a single solution is shown in figure 4.

The overall process of the multidisciplinary optimisation algorithm can be broken down into a number of key steps, in this instance linked to a multi-objective population based optimizer and they are described below.

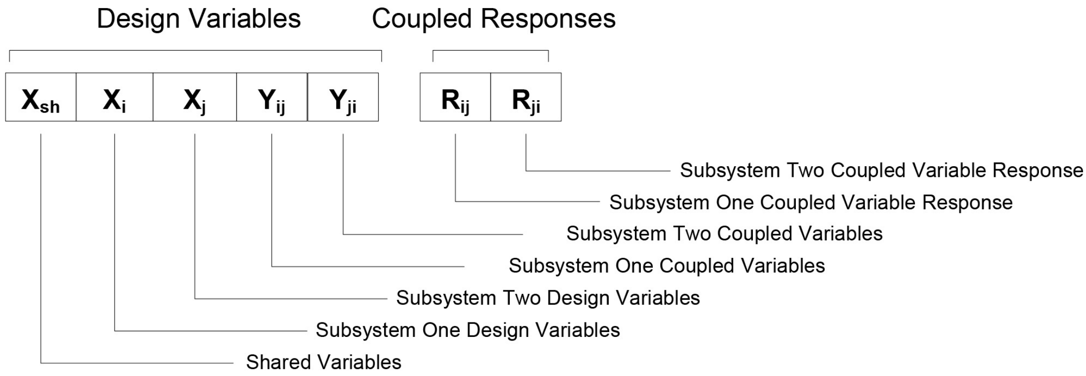

Fig. 4: Multidisciplinary optimisation design and response variable sets for a chromosomal representation

First

The first step begins with the initialisation of the system level population; in particular the various variable sets as shown in figure 5. Any coupled variable response values are set to null to be filled later after functional evaluation. The filled system level population set popCurrent is than ready for variation. Functional evaluation of each individual is based upon system level objectives f_{01}, f_{02}

Second

A selection set is chosen from the current system level population ready for variation and the creation of an offspring population set. Only the system levels shared variables X_{sh} are varied based upon the chosen optimizers operators. At the system level this offspring set is then used depending upon the chosen the optimizers replacement operators as the basis for the next popCurrent set. However as shown in figure 6 the newly created system level offspring population set is also passed on to the each of the subsystems within the multidisciplinary optimisation structure.

Third

The next step shown in figure 5 moves on to the subsystem level of the design process, upon receiving the offspring sets the individual solutions are used to fill the local subsystem populations. Subsystem populations with a lower number of solutions than the supplied offspring set are filled using a truncation operator. For each subsystem the local population sets now need to be evaluated using local objectives $f_{11}, f_{12}/f_{21}, f_{22}$ and constraints before then undertaking a standard routine of selection, variation and replacement. Each of the subsystems variation operators are restrained to only alter their local disciplinary design variables X_i/X_j and the local coupled disciplinary design variables Y_i/Y_j. After variation has occurred, any coupled variable within each subsystem offspring solution is passed on to all other subsystems, as a result all subsystem offspring set sizes are fixed to the same size. Finally functional and constraint evaluation of each subsystem offspring population set is undertaken and where necessary coupled disciplinary analysis variable values are also transferred to any subsystem solutions that may require them for functional or constraint evaluation. The local subsystem offspring sets are then combined with their local population sets before replacement operators update each subsystem with a new population set. This iterative process then continues for a fixed number of cycles before ending and moving on to the next step.

Fig. 5: Multi-objective multidisciplinary optimisation process

Fourth

The final step in figure 5 looks to take the evolved subsystem population sets and combine them into a Total Population set for evaluation of objectives and constraints at the system level f_{01}, f_{02}. The size of the total population set is fixed to the total sum of all subsystem population sets. This total population set is then combined with the system level popCurrent set to form a unified Grand Pareto set which is then used to create a new popCurrent set using the optimizers replacement operators. Upon completion of this step the process begins again at step two and the whole process is repeated until a chosen criterion is used to determine whether it should be stopped.

4 Case Studies and Experimental Setup

Two case studies have been chosen to validate the multi-objective multidisciplinary optimisation method outlined in this paper. The first is a more traditional design-engineering problem designed by Golinski for the optimisation of a speed reducer used to test a number of multi-objective and multidisciplinary optimisation algorithms within the literature (Kurapati and Azarm (2000)Gunawan et al (2003)Aute and Azarm (2006)Rabeau et al (2007)Gunawan et al (2004)). The second case study concerns the design optimisation of a MEMS bandpass filter. Both of these case studies are outlined in further detail below.

4.1 Speed reducer problem

The Golinski problem looks to optimize the sizing of a speed reducer component and originally formulated as a single objective problem (Golinski (1970)) it has also been expanded into a two (Kurapati and Azarm (2000)) and three objective (Gunawan et al (2003)) design problem with formulations for multidisciplinary optimisation also constructed within (Gunawan et al (2004)). The speed reducer consists of 7 design variables all tied to the component with the objectives set out to minimize the volume while simultaneously reducing the stress placed upon the shafts. The objectives for the design problem are shown in equations 1 to 3 for both the two and three objective problem and 4 and 5 for the decomposed objectives. In the case of the two objective design problem only objectives f_1 and f_2 are used, while for the multidisciplinary optimisation approach two subsystems are used, the first focusing on objectives $f_{1,1}$ and f_2 and the other $f_{1,2}$ and f_2 for the two objective design problem and $f_{1,2}$ and f_3 for subsystem two in the three objective problem. . Also associated with the speed reducer problem are 11 inequality constraints outlined in equations 6 to 16. Finally table 5 holds the decision variables for the speed reducer problem along with their type and upper / lower bounds.

$$f_1 = 0.7854x_1x_2^2\left(\frac{10x_3^2}{3}14.933x_3 - 43.0934\right) - 1.508x_1(x_6^2+x_7^2) + 7.477(x_6^3+x_7^3) + 0.7854(x_4x_6^2+x_5x_7^2) \tag{1}$$

$$f_2 = \frac{\sqrt{\left(\frac{745x_4}{x_2x_3}\right)^2 + 1.69\times 10^7}}{0.1x_6^3} \tag{2}$$

$$f_3 = \frac{\sqrt{\left(\frac{745x_5}{x_2x_3}\right)^2 + 1.575\times 10^7}}{0.1x_7^3} \tag{3}$$

$$f_{1,1} = 0.7854x_1x_2^2\left(\frac{10x_3^2}{3}14.933x_3 - 43.0934\right) - 1.508x_1x_6^2 + 7.477x_6^3 + 0.7854x_4x_6^2 \tag{4}$$

$$f_{1,2} = -1.508x_1x_7^2 + 7.477x_7^3 + 0.7854x_5x_7^2 \tag{5}$$

$$g_1 \equiv \frac{1}{x_1x_2^2x_3} - \frac{1}{27} \leq 0 \tag{6}$$

$$g_2 \equiv \frac{1}{x_1x_2^2x_3^2} - \frac{1}{397.5} \leq 0 \tag{7}$$

$$g_3 \equiv \frac{x_4^3}{x_2x_3x_6^4} - \frac{1}{1.93} \leq 0 \tag{8}$$

$$g_4 \equiv \frac{x_5^3}{x_2x_3x_7^4} - \frac{1}{1.93} \leq 0 \tag{9}$$

$$g_5 \equiv x_2x_3 - 40 \leq 0 \tag{10}$$

$$g_6 \equiv \frac{x_1}{x_2} - 12 \leq 0 \tag{11}$$

$$g_7 \equiv 5 - \frac{x_1}{x_2} \leq 0 \tag{12}$$

$$g_8 \equiv 1.9 - x_4 + 1.5x_6 \leq 0 \tag{13}$$

$$g_9 \equiv 1.9 - x_5 + 1.1x_7 \leq 0 \tag{14}$$

$$g_10 \equiv f_2 - 1300 \leq 0 \tag{15}$$

$$g_10 \equiv f_3 - 1100 \leq 0 \tag{16}$$

4.2 MEMS bandpass filter

Large engineering design problems for example those found within the aeroplane industry can be difficult or impossible to undertake as a whole due to the large number of design variables, constraints and disciplinary analyses of the problem. In reality the design problem is often decomposed and each individual component solved or optimized separately by a design team, often

Table 5: Speed Reducer Variable Information

Variable Tag	Sub Tree Type	Lower Bound	Upper Bound
Variable 1	Real-Valued	2.6	3.6
Variable 2	Real-Valued	0.7	0.8
Variable 3	Integer	17	28
Variable 4	Real-Valued	7.3	8.3
Variable 5	Real-Valued	7.3	8.3
Variable 6	Real-Valued	2.9	3.9
Variable 7	Real-Valued	5.0	5.5

focusing on specific variables, constraints and objectives. MEMS are inherently multidisciplinary through the interaction of the mechanical and electronic components of the device. The application of MEMS into fields such as biology or chemistry through lab on-chip devices increases the number of disciplines a designer or design team must understand and integrate into the design process. A MEMS bandpass filter forms the basis of the second case study. It consists of an array of coupled folded flexure resonator tanks that collectively function as the filter itself, examples can be found in (Wang and Nguyen (1999)Lin et al (1992)).

The design of a bandpass filter in this instance consists of a single discipline in the form of electrical circuit simulation. Modelled as an electrical equivalent circuit, it contains equivalent elements for the mechanical resonator tanks and coupling springs that make up the bandpass device. Each of these components plays an important role in how the frequency transmission of the bandpass filter is shaped. A detailed breakdown of the modelling, simulation and optimisation approach can be found in (Farnsworth et al (2010)). The aim of this design problem is to create a solution whose bandpass characteristics match the targets outlined by the designer.

A number of design objectives have been created to solve this particular problem and are outlined in figure 6. A frequency transmission from a single micromechanical resonator consists of a number of frequency data points plotted against the magnitude in units of dB as seen top left of figure 6. The quality and performance of the filter transmission can be measured by simply calculating where each data point lies within the pass band and stop band ranges outlined and measured against their target magnitude, in this case 0dB for points within the passband and -20dB within the stop band regions. The overall frequency performance can then be quantified as a sum of the total deviation from each of these ranges for the data points within the frequency transmission. Ideally all data points that lie within the pass band will have 0 insertion loss and no gain giving a magnitude of 0dB, while all points within the stop band will be -20dB or less and therefore have a deviation of 0 for both regions.

Central frequency of the bandpass filter is important when wanting to design a frequency transmission for a targeted portion of the spectrum. The central frequency of a transmission is simply calculated as the distance of the peak frequency data point to the desired central frequency outlined by the designer. The objective shown on the top right in figure 6 is both a targeted design goal and a guide to the optimizer, allowing individual or coupled resonator transmission responses to move closer to the targeted region of interest. The design variables for this problem are shown in table 6 and represent the values attributed to each resonator tank of the electrical circuit equivalent model. The representation is a varied length chromosome dependent on the number of tanks present. The bandpass filter characteristics are shown in table 7 for this particular design target.

The object based decomposition of the bandpass filter begins with classifying the customer requirements at the highest level, in this instance the characteristics of a bandpass filter with low insertion loss and high bandwidth over a target frequency range. The global objectives to try and meet these targets have already been outlined previously in the filter response and central

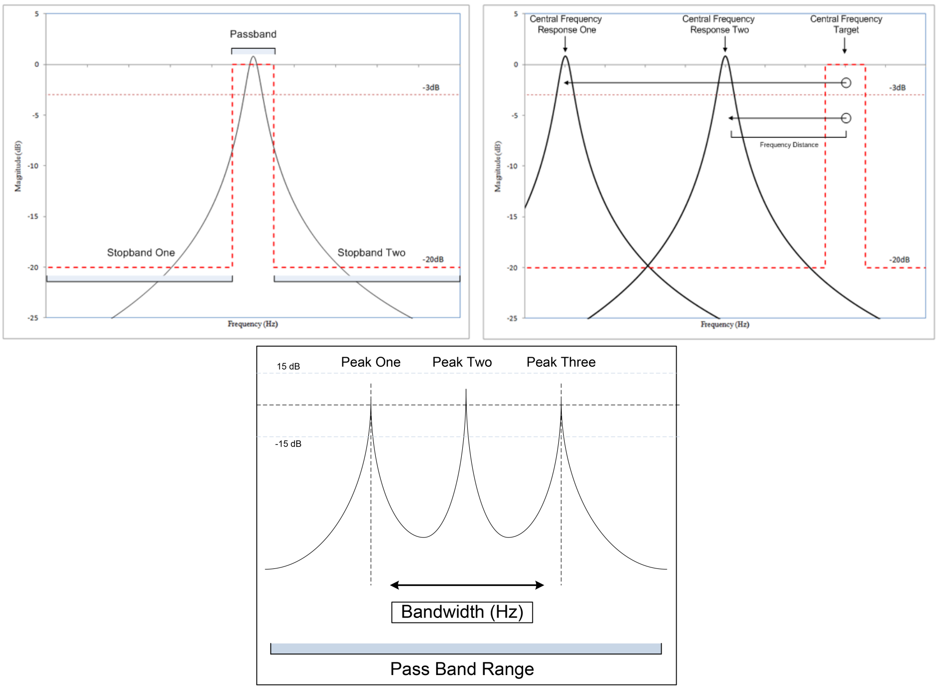

Fig. 6: MEMS bandpass filter synthesis breakdown for filter objective

Table 6: Bandpass Filter Problem Information

Variable Tag	Sub Tree Type	Lower Bound	Upper Bound
Voltage	Real Valued	1	200
Tank Number	Integer	1	9
Finger Number	Integer	1	200
Thickness (m)	Real Valued	2	30
Capacitance (F)	Real Valued	3E-15	8E-15
Inductance (H)	Real Valued	40000	80000
Coupling Spring Capacitance (F)	Real Valued	3E-15	8E-15
Tank	Branch	N/A	N/A
Objectives		Constraints	
Bandpass Filter Response Error	Minimize	N/A	
Bandpass Central Frequency Error	Minimize		

Table 7: Bandpass Filter Parameter Ranges

	Bandpass Filter Characteristics
Passband	9.5kHz 10.5kHz
Stopband 1	1Hz 9.5kHz
Stopband 2	10.5kHz 15kHz
Central Frequency	10kHz

Table 8: Bandpass Multidisciplinary Optimisation Objectives

	System Level		Subsystem 1		Subsystem 2	
	Objective 1	Objective 2	Objective 1	Objective 2	Objective 1	Objective 2
Objective Type	Minimize	Minimize	Minimize	Minimize	Minimize	Maximize
Objective Description	Filter Response	Central Frequency	Pass Band Error	Central Frequency	Stop Band Error	Bandwidth
Constraint Type	N/A		Inequality		N/A	
Constraint Description	N/A		Stop Band Error $\leq$ 1000		N/A	

frequency objectives and in order to undertake a MDO approach new objectives are required as the system is decomposed. The decomposition of these objectives and the bandpass filter device into separate system and subsystem elements can then occur to try and aid the overall design process. The literature (Wang and Nguyen (1999) Bannon. F. D Clark and Nguyen (2000)) points to the effect each individual resonator has on central frequency of the bandpass filter, both individual and coupled resonators and their mass, stiffness and damping values reflect their central frequency peak within the whole transmission shape. The pass band ripple and insertion loss are also heavily influenced by the constituent resonators that make up the bandpass filter (Wang and Nguyen (1999)). Subsystem one is tasked with solving this particular functional requirement, with specific objectives and constraints as shown in table 8. The design of a filter which has a flat pass band characteristic within the target frequency range means the addition of a pass band error objective. This new objective is calculated exactly as in the filter response however, only the pass band is taken into consideration.

The bandwidth of the filter device should be sufficient enough to cover the target pass band range, however the frequency transmission than needs to possess a sufficient roll off either side of the pass band into the stop band region to be effective. Both the bandwidth and stop band functional requirements are heavily influenced by the number of resonator tanks within the filter and the coupling spring stiffness that couple them (Wang and Nguyen (1999) Lin et al (1992)). Subsystem two contains objectives designed to focus on these particular functional requirements, the construction of a bandwidth objective, the goal of which is to maximum the bandwidth of the first and last peaks of the filter transmission as shown at the bottom of figure 6 is included. The bandwidth is calculated as the distance in Hz between the first and last peaks of the bandpass filter divided by the average gain of the two peaks. Each peak is calculated simply as a point where either side shows a decline in the magnitude dB, and it must lie within the pass band range and have a magnitude between 15 dB and -15 dB. In the case where only one peak is present, then the bandwidth is set to a value of 1. The final objective for subsystem two is for stop band error and like the pass band error objective is calculated from the filter response.

In addition to the objectives a new constraint is added to the overall design process. Subsystem one contains a constraint to the total stop band error of the frequency transmission; this is to stop certain frequency transmissions from dominating at a detriment to the overall design optimisation, these transmissions characteristically have a frequency response of 0 dB from start to finish of the bandpass target range giving them 0 pass band error, but large stop band error.

4.3 Experimental setup

The improved design synthesis and optimization of MEMS devices is the targeted outcome of this approach through the application of automated optimization heuristics in conjunction with available MEMS modeling and simulation tools.

From the field of evolutionary computation two of the current state-of-the-art multi-objective algorithms have been chosen to undertake design synthesis, firstly NSGAII (Deb et al (2000)) and finally SPEA2 (Zitzler et al (2001)). Both algorithms have been explored in terms of performance and applied successfully over a number of areas and problems outside and within MEMS design synthesis. These multi-objective algorithms are used as the base optimisation to compare the outlined MDO method for both case studies outlined. The default parameters for both algorithms across both case studies are shown in table 9.

Table 9: Default Algorithm Parameters NSGAII and SPEA2

Algorithm Parameter	Default Value
Population Size	100
Offspring Size	100
Selection Size	100
Replacement Size	200
SBX Distribution Index	20
Polynomial Mutation Distribution Index	20
Probability of SBX Crossover	0.8
Probability of Mutation	0.142857
Generations	100
Tests	5

The speed reducer case study uses a mixed integer and real-valued tree-based chromosome structure, while the bandpass filter case study uses a varied length tree-based structure to account for the decrease or increase in resonator tank numbers. In order to account for this varied length approach new crossover and mutation operators have been introduced or adapted from those present within both NSGAII and SPEA2. The details of these can be found in (Farnsworth et al (2010)) but they essentially allow for the insertion and removal of resonator tanks and there associated variables within the chromosome during variation. The standard single level representation of the bandpass filter design problem is shown in figure 7. This also includes an overview of related structural tags and node markers. Structural tags relate to specific branch nodes within the representation and the nodes that control the count or number present. Node markers are used to provide additional information for a particular operator such as SBX crossover within NSGAII, marking certain nodes that can have crossover performed or not.

As discussed in order to undertake the MDO approach each case study has been decomposed into a number of subsystems. The speed reducer follows past examples (Gunawan et al (2003)Gunawan et al (2004)) and the representation used throughout this experiment is shown in figure 8 for both the two and three objective problems. The MEMS bandpass filter case study is detailed in figure 9 and contains the system, subsystem and coupled variables created from the decomposition of the original design problem. This decomposition is based upon the relation certain variables have with the particular objectives set out in each system or subsystem. At the system level the objectives naturally remain the same as the original conception, but only the voltage, finger number and thickness variables are evolved. These values influence the comb transducer of the bandpass filter device and in the circuit model its effect on resistance values of each individual LCR tank. Subsystem one focuses upon passband ripple and insertion loss that is directly affected by the capacitance and inductance of each individual resonator tank. Subsystem two variables focus upon the bandwidth of the device, which is heavily influenced by the coupling spring capacitance and tank number of the device. At the end of each subsystem cycle coupled variables are swapped between subsystem solutions.

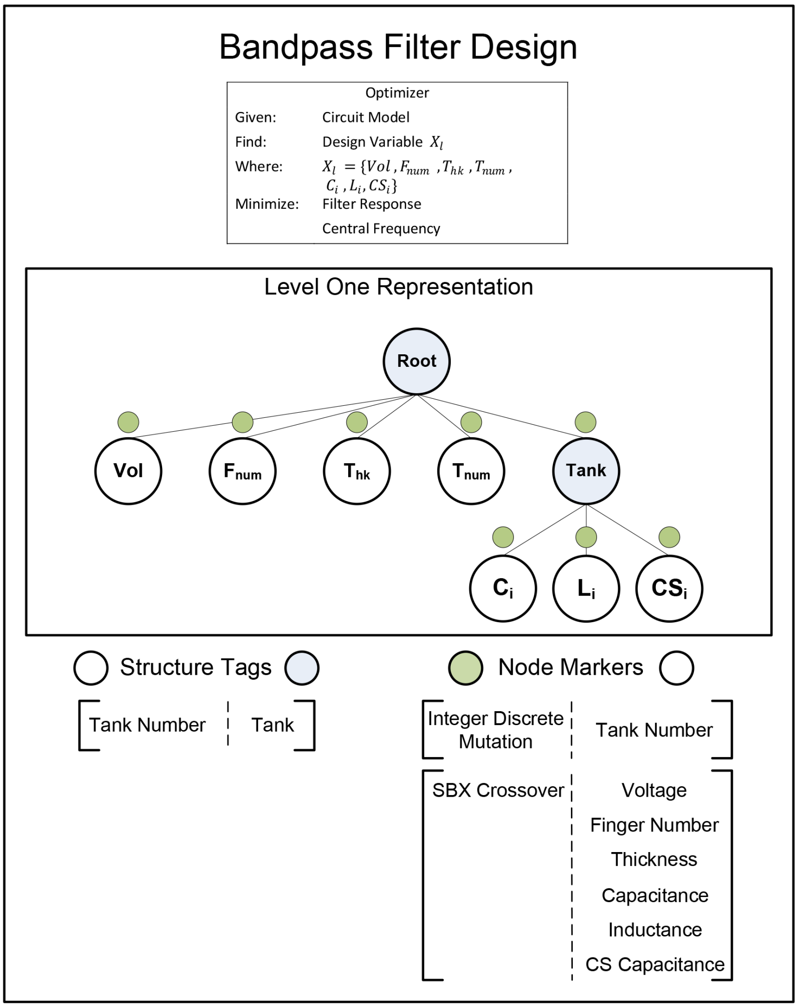

Fig. 7: Bandpass filter design template, with overview of problem, default representation, associated structure tags, node markers and global variables

The design process of the multidisciplinary strategy is essentially split between system and subsystem calls, and the cycle between them. Both the system and subsystem levels have the same default algorithmic parameters and population levels and therefore there is a choice into how many cycles each level is run in order to allow successful design optimisation within a budget of 10,000 functional evaluations. In the system level multidisciplinary optimisation design process the system level is run every 10 cycles, while each subsystem is run concurrently every cycle, this allows each subsystem to evolve its local population for 10 generations before the solutions are passed up to the system level. The population parameters for both algorithms and case studies are shown in table 10.

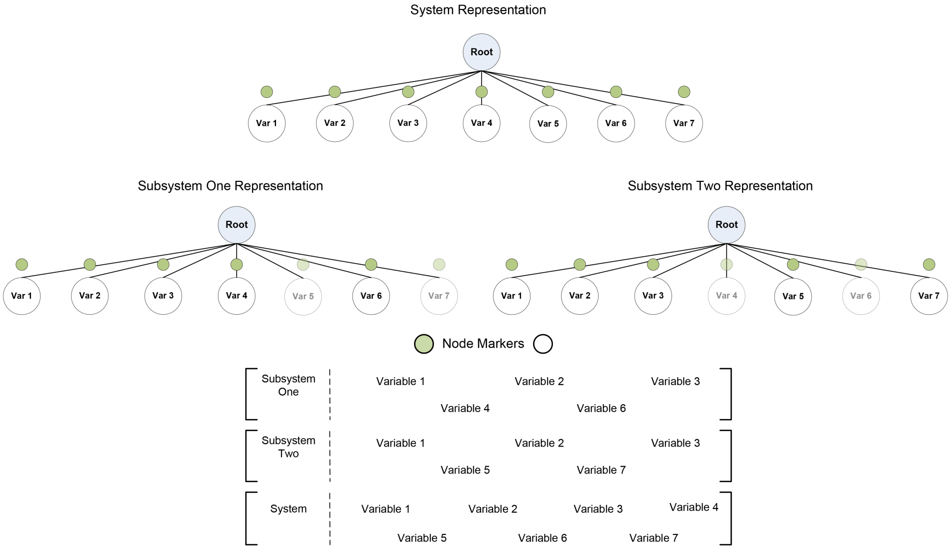

Fig. 8: Speed reducer multidisciplinary optimisation representation

Table 10: Population Parameters Multidisciplinary Optimisation

Algorithm Parameter	Default Value
System Population Size	100
System Offspring Size	100
System Selection Size	100
System Replacement Size	200
Grand Pareto Size	300
Subsystem Population Size	100
Subsystem Offspring Size	100
Subsystem Selection Size	100
Subsystem Replacement Size	100
Subsystem Total Size	200

5 Results

The results for both case studies are presented below and consist of a number of final population sets, hypervolume values, solution characteristics and additional analyses. In order to assess the performance of each of the algorithms on the two case studies the hypervolume metric is used to both evaluate the Pareto spread and dominance of the objective space each of the tests final populations has produced. The mean and bound hypervolume results for each algorithm are shown for each example, with the chosen nadir point for the objectives indicated below the specific table.

5.1 Speed reducer problem

Looking at the results in the two and three objective speed reducer problems there is similar performance in terms of population spread across both algorithms and strategies as shown in figure 10. The hypervolume results shown in table 11 indicate some difference in performance across the five runs with the single level NSGAII outperforming all others on the two objective

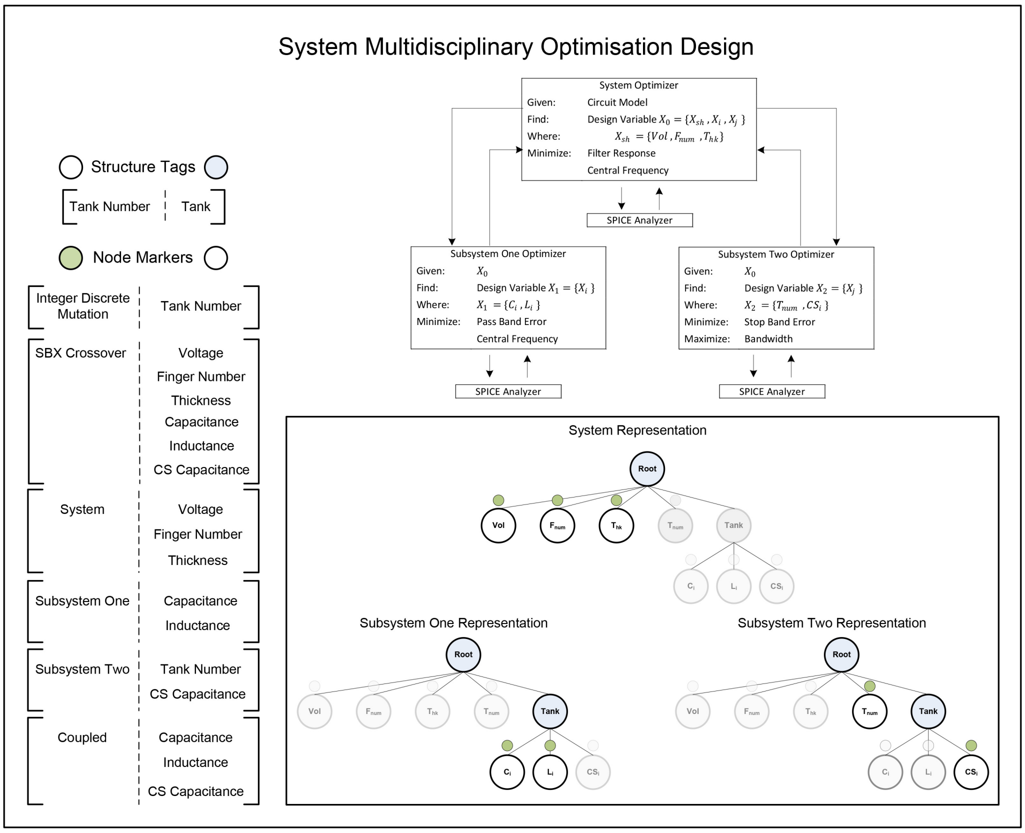

Fig. 9: Bandpass filter multidisciplinary optimisation design template, with overview of problem, default representation, associated structure tags, node markers and global variables

problem and the MDO algorithm outperforming the others on the three objective problem. If we are to compare these results with past examples found in (Kurapati and Azarm (2000)) for the two objective and (Gunawan et al (2003)) for the three objective problem we see similar performance, with less functional evaluations required and more solutions generated. As a validation of the outlined MDO algorithm the speed reducer case study has proven a successful demonstration of its capabilities.

5.2 MEMS bandpass filter

The results presented are the individual final population sets for each of the five tests performed by each algorithm of the MDO strategy, shown in figures 11. Also shown are the best frequency transmissions found by the MDO strategy for each algorithm, ranked by the filter frequency objective in figure 12. The objective values of the best result ranked by the filter frequency objective for every run are held in table 12. Finally the hypervolume values for both algorithms are shown in table 13, with the best results shaded.

Undertaken by both NSGAII and SPEA2 the characteristic performance of both shows the single level SPEA2 outperforming the single level NSGAII in this example. Though the SPEA2 MDO implementation performed similar to the single level strategy its results seem to indicate that this is possibly not due to convergence to a suboptimal front as was prevalent in the single level strategy. Instead the Pareto population sets for the SPEA2 MDO results are more fragmented, with both poor and good fitness response fronts in the objective space. The structured nature of the MDO strategy, with separate subsystems and objectives can result in an inefficient use of resources or in this case functional evaluation cost as populations migrating from the system to subsystem levels need to be re-evaluated. This cost equates to about 1600 functional evaluations of lost search, a significant amount, which could have lead to the algorithm refining those transmissions from a 1400 filter response error to a lower one. NSGAII MDO on the other hand shows a robust performance over the 5 runs, significantly performing better than its single level counterpart as shown in table 12. An interesting characteristic of this approach is that a number of population fronts are continuous over a large range of the frequency fitness error objective. Whether the internal workings of the NSGAII algorithm and its crowding operator has had a positive effect on the solution spread which is filtered through to the MDO strategy in some way is a possibility though not certain and for brevity is left unexplored. The overall performance of both algorithms when compared against the single level strategies is shown in figure 13, with NSGAII outperforming the single level significantly and SPEA2 showing similar performance.

Two examples of a generational system population set for SPEA2 MDO are shown in figure 14 showing each population set progressively moving towards the optimal in separated fronts indicating how each cycle contributes to Pareto objective fitness. A major component of the MDO strategy is its structured system and subsystem hierarchy and the exchange of genetic material between each subsystem every generation. The partitioning of the design process into system and subsystem cycle events breaks up the design process as population sets are transferred from system to subsystem and vice versa. Figure 15 highlights the generational change to each subsystems population set through the individual hypervolume values of each run. The effect on subsystem one is negligible with steady improvement throughout the design process and typical of the system MDO level hypervolume results. However subsystem two shows a marked decrease in hypervolume or performance of the Pareto front after every system level update, where a new offspring population set is passed to each subsystem. This is in part due to the possible loss of good solutions through the passing of the offspring set, or the disparity of the genotype / phenotype of these solutions from the system level objective space, which uses the standard central frequency and filter response objectives, to subsystem two objectives of stop band and bandwidth. There is a slight exaggeration of the hypervolume dip because solutions with a stop band of 0 are not found at the system level, these are evolved afterwards. The loss in the hypervolume performance of the population set is often linked to the bandwidth objective of

Table 11: Speed Reducer Two and Three Objective Design Problem Hypervolume Metric Values

Speed Reducer 2 Objectives			
	NSGAII	SPEA2	MDO NSGAII
S^U	1927425.898	1926371.720	1926094.169
S^M	1927096.298	1925150.499	1925560.005
S^L	1926533.553	1921631.936	1924012.468
Speed Reducer 3 Objectives			
	NSGAII	SPEA2	MDO NSGAII
S^U	669348872.86	674722574.432	672953351.4
S^M	667099790.88	667656079.534	670425237.7
S^L	664741675.34	660545560.310	666497637.0

*$(S^U S^M S^L)^1$ [5800, 1350] *$(S^U S^M S^L)^2$ [6000, 1350, 1100]

Table 12: Bandpass Filter Results

NSGAII					
Test	Index	Filter Objective	Central Frequency Objective	Voltage	Tank Number
1	0	1750.493	101	61.34	3
2	0	1680.625	235	105.75	3
3	31	1248.642	32	190.34	3
4	0	3315.054	910	30.64	2
5	0	2148.439	206	144.01	3
Multidisciplinary Optimization NSGAII					
Test	Index	Filter Objective	Central Frequency Objective	Voltage	Tank Number
1	25	1103.233	310	183.27	3
2	28	1323.016	711	105.25	3
3	2	1268.895	370	133.04	3
4	9	1128.922	308	111.34	3
5	8	832.363	23	56.044	3
SPEA2					
Test	Index	Filter Objective	Central Frequency Objective	Voltage	Tank Number
1	29	984.904	430	11.785	3
2	15	1936.521	160	199.10	3
3	1	1925.665	180	139.56	3
4	8	1012.157	40	85.27	3
5	80	1643.993	175	48.73	3
Multidisciplinary Optimization SPEA2					
Test	Index	Filter Objective	Central Frequency Objective	Voltage	Tank Number
1	4	1117.323	350	147.73	3
2	15	1493.894	490	177.23	3
3	4	1789.087	82	134.85	3
4	60	1489.723	212	13.81	3
5	15	1412.127	147	70.87	3

Table 13: Hypervolume Results for NSGAII and SPEA2

NSGAII		
Hypervolume	Single Level	Multidisciplinary Optimisation
S^U	43755994.223	45837863.064
S^M	39634066.167	44060899.260
S^L	32507262.763	43035839.206
SPEA2		
Hypervolume	Single Level	Multidisciplinary Optimisation
S^U	44945558.089	44084774.987
S^M	42433896.104	42559736.279
S^L	40276362.685	41041427.413

* (S^U S^M S^L) [10000, 5000]

subsystem two, where solutions at the system level often have smoother pass bands with peaks within the pass band range giving smaller bandwidths then those evolved locally before. The subsystem then has to search and evolve past solutions with an equivocal bandwidth.

Exploring the effect of each subsystem and the decision variables under their control and how the genes and their alleles evolve over the design process are presented next. Shown in figures 16 and 17 are a series of generational filter frequency transmissions for the best solution found in the system, subsystem one and two population sets for NSGAII MDO run 1 and SPEA2 run 1 respectively. Each solution chosen was ranked by the filter frequency error, passband error and bandwidth objective respectively and the objective values and tank values for each filter are shown below the response.

The frequency transmissions for both examples NSGAII run 1 and SPEA2 run 1 show an incremental improvement over the three separate partitions, cycle 1, 11 and 21, and are followed with phenotypes that show minimal change over the following examples in cycles 31 and 41. The only deviation from this is in figure 17 and subsystem two results that switch to a phenotype that is locally better than that of the best global system level solution. Looking at the specific subsystems, each one begins with the evolution of tailored frequency transmission characteristics, with subsystem one containing solutions focusing on the pass band region predominately with little regard for the stop band if only to remain unconstrained. The overall characteristic of the subsystem one solution in figures 16 and 17 takes on the shape of a typical bandpass filter, though with an unrefined pass band, at cycle 11 until convergence to the final phenotype at cycle 21. Subsystem two focuses upon both bandwidth and the stopband region of the frequency transmission. The bandwidth of the frequency transmission between two or more peaks is established around cycle 11 in both NSGAII and SPEA2 examples and this is evolved to give wider bandwidths further on in the design process. The next question is to what effect each subsystem and the solutions they evolve have on the global system level where the designer wishes to evolve the solutions they want to match the target filter characteristics. Interestingly in both examples the phenotypes of one subsystem match more closely the phenotype of the system level solution, here NSGAII subsystem two and SPEA2 subsystem one show closer affinity. The genotypic values in figures 16 and 17 of each of these solutions also show a close correlation, with individual capacitance and inductance values for each resonator tank closely resembling their system level counterparts, in particular SPEA2 subsystem one being identical. The frequency transmission of the system level solution begins to match more closely with the best subsystem one solution from cycle 21 onwards, probably in part due to the pass band objective playing a more dominant part in the system level frequency error objective at this stage of the design process. However subsystem two frequency transmission results on a number of examples do not mirror the example found or retained at the system level. The bandwidth of the subsystem two best solutions are often associated with the 2nd and 3rd peaks with the 1st outside the target passband range and therefore ignored.

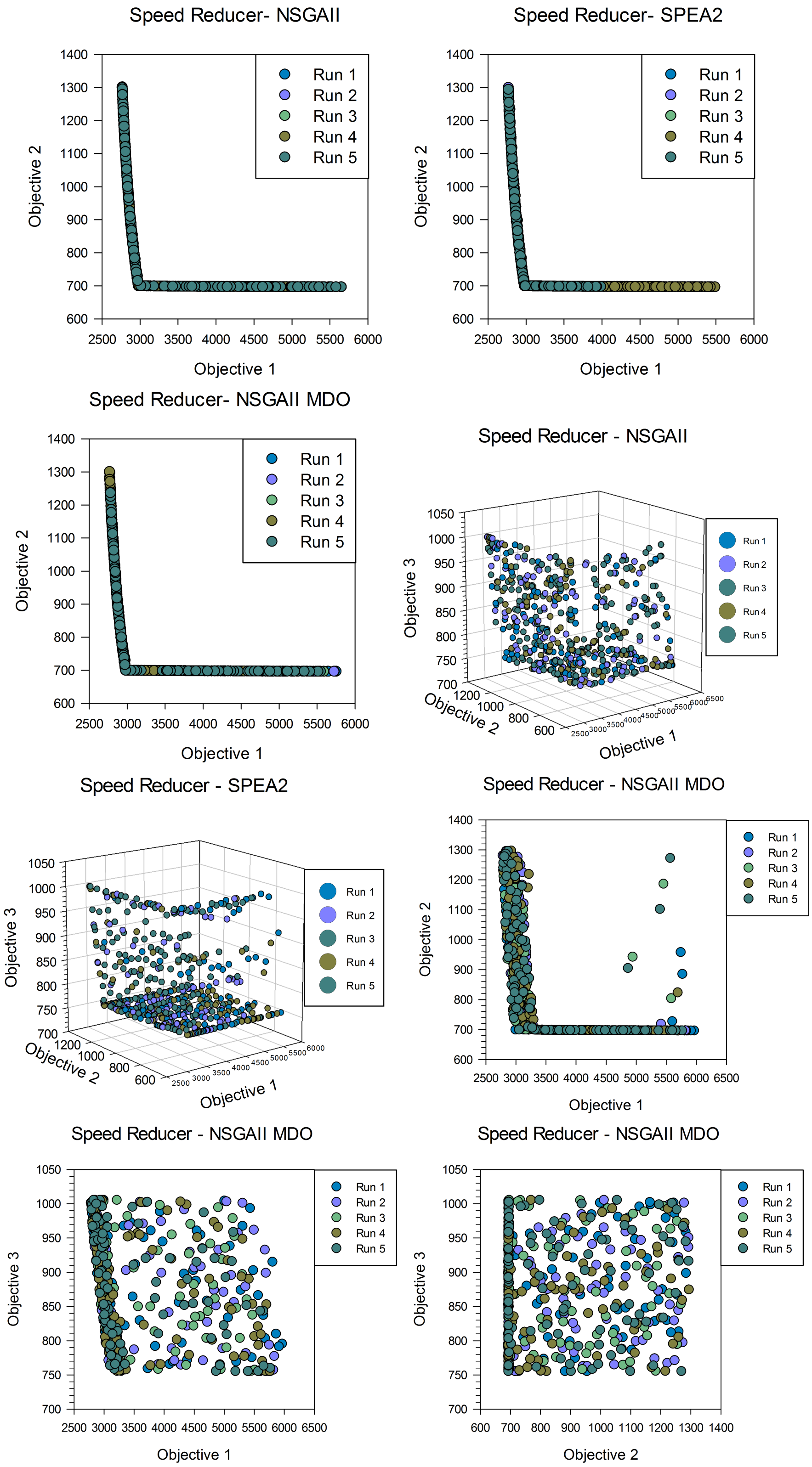

Fig. 10: Final population sets two and three objective speed reducer problem

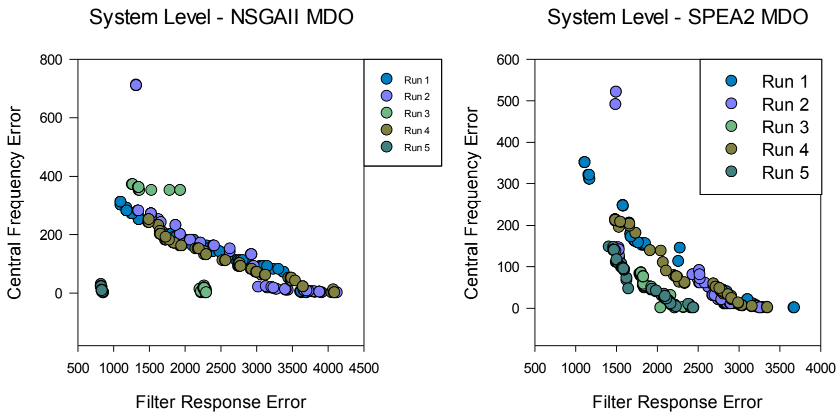

Fig. 11: MEMS bandpass filter run 1 - 5 final population sets for (left) NSGAII multidisciplinary optimisation and (right) SPEA2 multidisciplinary optimisation

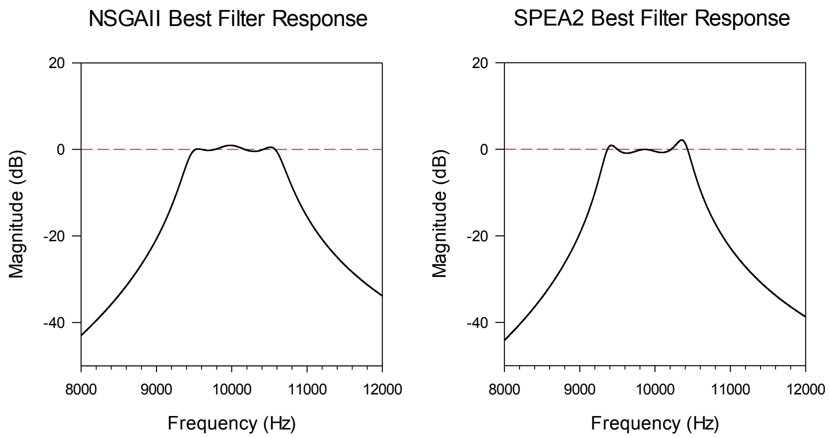

Fig. 12: System level best filter response ranked by filter frequency objective for (left) NSGAII multidisciplinary optimisation and (right) SPEA2 multidisciplinary optimisation

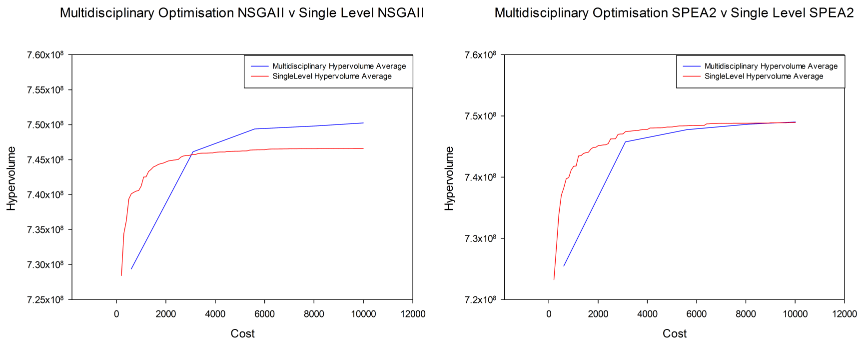

Fig. 13: Bandpass average hypervolume results for the 5 runs of the multidisciplinary optimisation and single level NSGAII and SPEA2 strategies * (S^U S^M S^L) [182000, 4150]

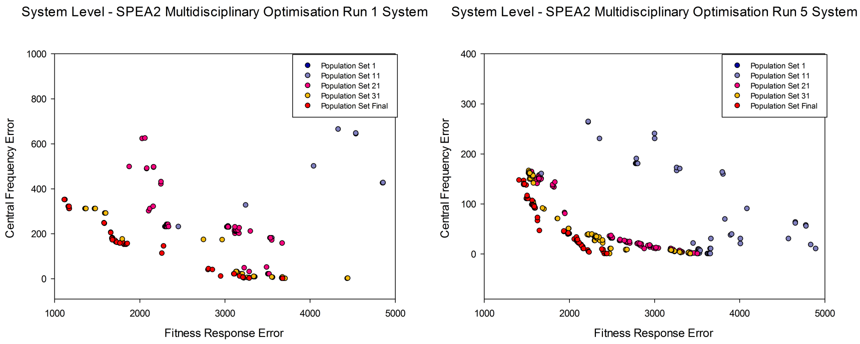

Fig. 14: Generational system population plots for SPEA2 multidisciplinary optimisation runs 1 (left) and 5 (right) - each plot contains 5 equally distant generational plots

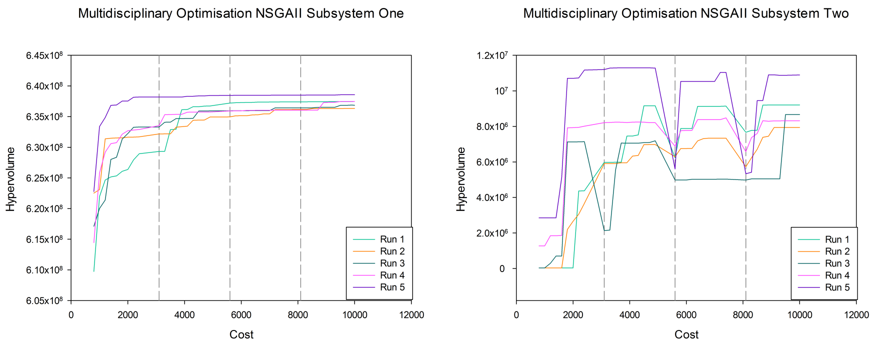

Fig. 15: hypervolume results for the 5 runs of the NSGAII multidisciplinary optimisation strategy for subsystem one (Left) * (S^U S^M S^L) [4000, 160000] and subsystem two (right) * (S^U S^M S^L) [12000, 2.0]

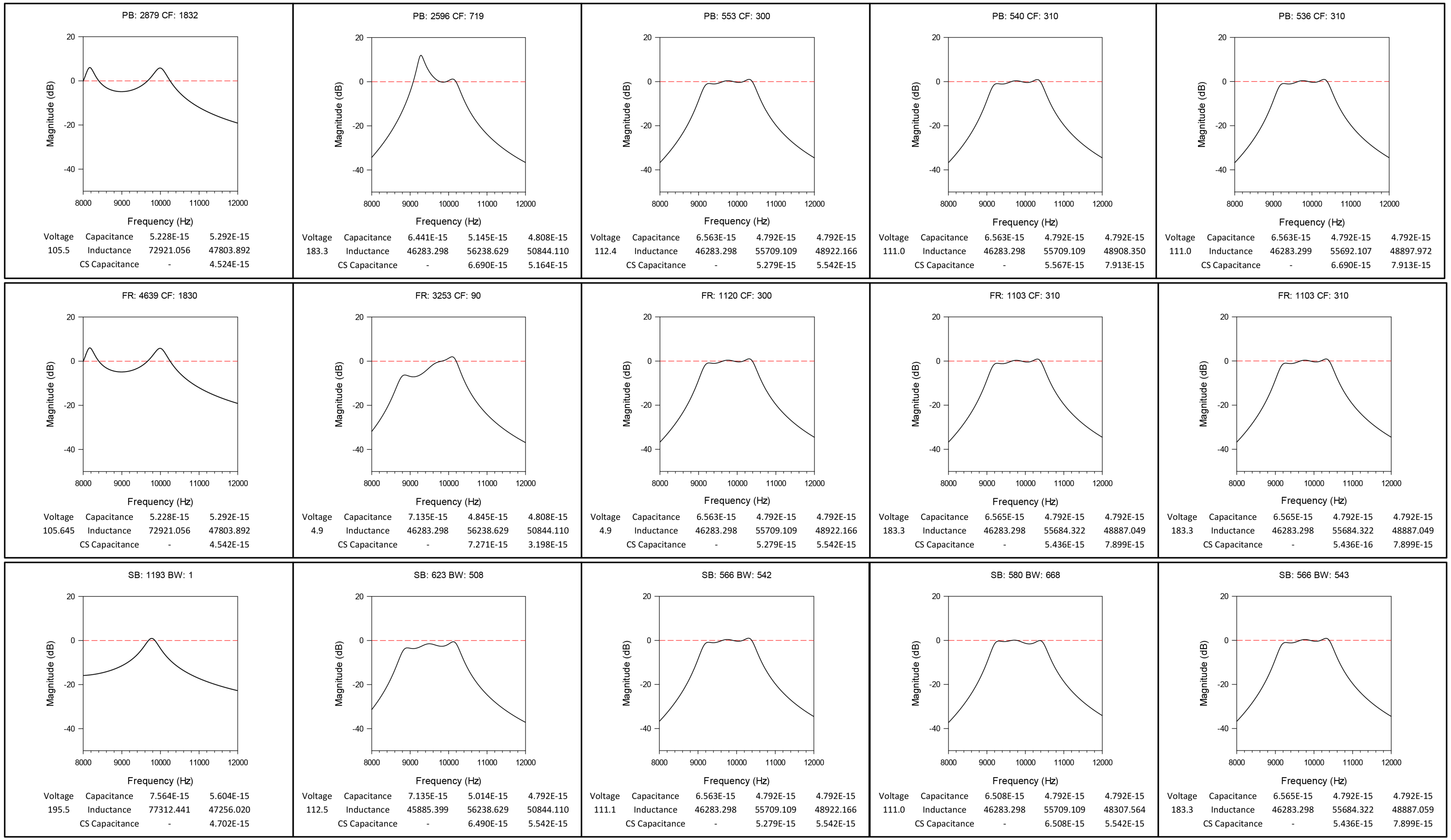

Fig. 16: Best filter transmission plots for population (ranked by filter response objective), subsystem one (ranked by passband objective) and two best (ranked by bandwidth objective) over 5 generations (1, 11, 21, 31, 41) for NSGAII run 1. Each plot includes objective values and genotype values for each solution

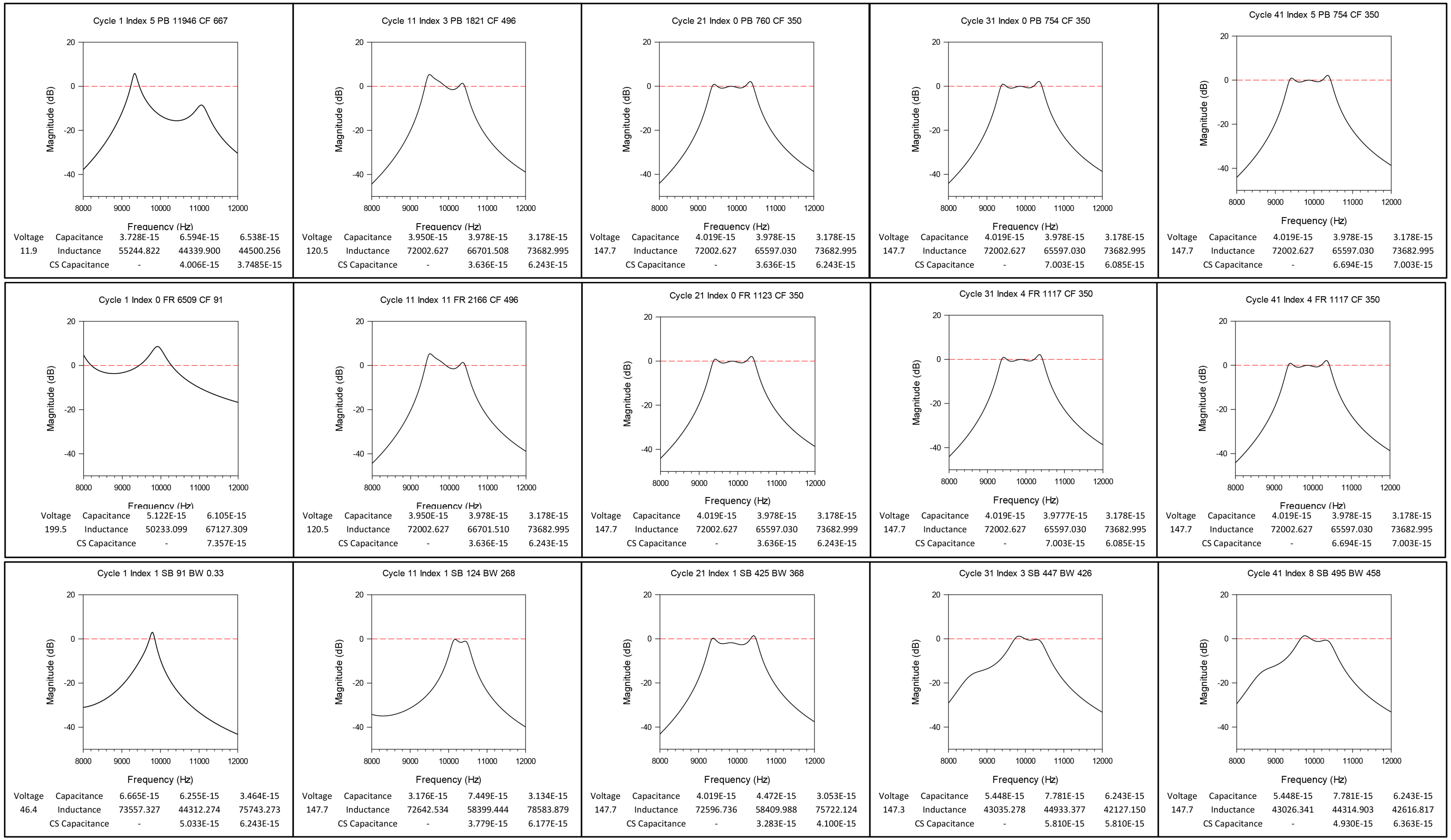

Fig. 17: Best filter transmission plots for system population (ranked by filter response objective), subsystem one (ranked by passband objective) and two (ranked by bandwidth objective) over 5 generations (1, 11, 21, 31, 41) for SPEA2 run 1. Each plot includes objective values and genotype values for each solution

6 Conclusions and Future Work

The integration of MEMS into more complex commercial devices is only going to grow in the coming decades as new fields such as biology and chemistry are opened up with lab-on-chip devices. The function and utility of MEMS is also only going to increase further, often resulting in devices that contain many components and covering a number of multidisciplinary behaviour. The automated design synthesis and optimisation of these new MEMS devices will require the ability to handle the multiple disciplines present and the large number of components that make up the system. This paper has outlined a new multidisciplinary and multi-objective design optimisation algorithm, validated and evaluated over two case studies. The last of which involved the design optimisation of a MEMS bandpass filter comparing standard single level and multidisciplinary optimisation methods through the use of both NSGAII and SPEA2 algorithms. Results show good agreement in terms of performance with past multi-objective MDO methods with respect to the first speed reducer case study, and superior performance for the design of the MEMS bandpass filter case study. The MDO approach offers designers the ability to decompose design problems, and their associated objectives, constraints and variables into specific subsystems. These subsystems can then be evolved separately as a means to focus on a particular discipline or design objective and then later recombined into a whole, providing the final design solution. The next step in this work is to experiment on more MEMS design case studies across other disciplines and modelling methods, for example finite element analysis.

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