Novel design and additive layer manufacture for function

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1 Track record

1.1 ALM and RP in Exeter

1.2 Personnel

2 Proposed work and its context

The overall aim of this work is to utilise evolutionary multi-objective optimisation coupled with finite element modelling to achieve designs optimised over competing objectives for additive layer manufacturing.

Recent advances – metal deposition, mixed material deposition and process reliability – in additive layer technology mean that it is feasible to manufacture rather than simply prototype engineering artifacts†. Additive layered manufacturing (ALM), however, has vast potential beyond conventional manufacturing processes, for example: fine control over micro-structure permits precisely graded materials to be made; mixed material deposition allows additional control over material properties; artifacts can be constructed with interior voids or complex internal structures, such as honeycombs, that are difficult or even impossible to make with conventional manufacturing techniques such as machining. ALM carries the huge advantage that almost any shape can be manufactured: it is not confined to Euclidean shapes and, importantly, artifacts may have interior, and the micro-structure of the artifact may be varied across the artifact to produce inhomogeneous and graded material properties – for example an artifact with an interior void encased in a rigid protective cage at one end, but smoothly passing to a foam-like micro-structure at the other end can be manufactured in a single pass. This extreme flexibility of shape and material properties possible allows us to envisage additive layer manufacture of massive artifacts, such as an aircraft wing with rigorous structural properties and incorporating fuel tanks, ducts for wiring and supports for ancillary equipment, all in a single manufacturing pass. Although ALM is beginning to find a place in small production runs † it is not yet widely used: this proposal aims to enable optimised design of complex artifacts for additive layer manufacture.

† Refs

† Statistics to back this up?

Design of such complex structures is, however, very challenging. Current CAD tools employ the paradigm of assembling a complex artifact from simple, usually Euclidean, components – such as cylinders, prisms, etc – that can be simply manufactured, but to which ALM is not confined. Furthermore, manual specification of micro and macro-structure of components to achieve the desired structural properties of the whole is an extremely complex task; one which is unsupported by current CAD tools. Topological optimisation has been used with some success in the design of artifacts for conventional manufacture †. However, its use has generally been limited to conventional manufacturing methods and to optimising a single characteristic, for example compliance for a given weight.† In this proposal we aim to bring the power of evolutionary algorithms, capable of optimising problems with a large number of design parameters, to bear on design for ALM. Furthermore, we recognise that most engineering design involves a trade-off between several objectives: for example, in wing shape design, the drag under cruising conditions, the divergence between cruising drag and non-cruising drag, the pitching moment and the weight of the wing are all to be optimised [Obayashi, 2006]. Adoption of optimised multi-objective design by industry will require intuitive and easy to use design tools and we therefore aim to work closely with industrial partners † to develop CAD tools for ALM using multi-objective optimisation.

† Refs

† Refs

† Say who!

2.1 Aims and objectives

Under the overall aim of using evolutionary multi-objective optimisation to locate optimal designs for additive layer manufacture, we identify the following principal objectives.

- **Development of an evolutionary optimiser capable of optimising external topology and internal micro-structure.** In this proposal we recognise that usually the design engineer will want to optimise at least one objective, for example: strength, weight and porosity. Clearly, it will not usually be possible to simultaneously optimise all of these competing objectives in a single design. The optimal trade-off curve (for two objectives) or surface (for three or more objectives) is known as the *Pareto front*, and we therefore propose to use and develop evolutionary multi-objective algorithms to locate designs close to the Pareto front. Crucially, the designer will not know the trade-offs before optimisation, but with these Pareto-optimal designs on hand the designer may make a reasoned choice between the possible optimal trade-offs.
- **Manufacture and materials characterisation.** A variety of ALM methods are available in Exeter: metal deposition using XXX, YYY † and polyamide in a sinter station. An important aspect of this work will be to ensure the veracity of the finite element simulations of additive layer constructions, which are used in the multi-objective optimisation. The laminated nature of the construction and the possibility of occasional imperfections in layer-to-layer bonding means that there will inevitably be anisotropies in the material characteristics that must be modelled. † Details

  We shall also manufacture Pareto-optimal designs to verify that they have the required characteristics.
- **Tools for design with optimisation.** Current CAD tools force the designer to assemble an artifact from primitives, whereas a design to be optimised must be specified in terms of the desired properties and constraints (for example, points of contact with other components, bounding volumes). An primary objective of this work will therefore be to develop interactive design tools to allow designers to specify and manipulate and visualise designs to be optimised.

[**FIXME** *Something about industrial involvement underpinning the work*]

2.2 Multi-objective optimisation

Computational optimisation of engineering design has been enabled by the recent availability of computing resources. Most straightforwardly, the dimensions (for example, strut diameters) of a manually constructed design may be optimised without altering the topological design†. Usually the objective being optimised is evaluated for each new set of parameter values by finite element analysis. More generally, topological optimisation methods parameterise the shape of an artifact, which is then adjusted to optimise the required objective. Although characterisation of the shape in a Hilbert space may be used †, a more general method, which does not constrain the optimised design to have the same topological form as an initial design, is to divide the design space into finite elements and allow an optimisation algorithm to distribute material between the elements; see Bendsoe [1995] and Sigmund [2000] for reviews. The flexibility of this approach also allows the design of

† Refs

† French refs

micro-structures to produce material with required properties, such as thermal expansion coefficients [Sigmund and Torquato, 1997] or auxetic materials [] or compliant mechanisms [Larsen et al., 1997].

Although topological optimisation is quite well developed for the optimisation of a single objective, such as compliance for a given weight, multi-objective optimisation has not been used for structural optimisation. Designers who wish to optimise more than once aspect of the design have thus far optimised a weighted sum of the objectives; for example, Chiandussi et al. [2004] optimise a weighted sum of three static loading conditions and a single dynamic load when designing a McPherson rear suspension subframe. In contrast to the weighted sum approach, which reduces a multi-objective optimisation problem to a single objective problem, it is possible to directly seek the Pareto front or optimal trade-off curve between the different objectives. Knowledge of the trade-off curve or surface then allows the designer to choose the best design with an understanding of how the objectives affect one another, rather than in ignorance as must be done when assigning values to the weights in a weighted-sum formulation before the optimisation is carried out and the relative importance of the objectives is unknown. Furthermore, Das and Dennis [1997] have shown that sections of the Pareto front are inaccessible to a optimisation using a weighted-sum formulation.

We propose to employ multi-objective evolutionary algorithms to locate Pareto optimal structures. Such algorithms (see Coello Coello [1999] for a review), rely on the notion of *dominance* to compare two structures. If the configuration is described by a vector $\mathbf{a}$ and the configuration of an alternative by $\mathbf{b}$, then $\mathbf{a}$ dominates $\mathbf{b}$ ($\mathbf{a} \prec \mathbf{b}$) if all of the objectives for $\mathbf{a}$ objectives are better than those of $\mathbf{b}$. If neither $\mathbf{a} \prec \mathbf{b}$ nor $\mathbf{b} \prec \mathbf{a}$ then the structures are mutually non-dominating and the set of all mutually non-dominating solutions that are not dominated by any other feasible solution comprise the Pareto front. In essence evolutionary algorithms operate by maintaining an elite set E of mutually non-dominating solutions which form a (possibly poor) approximation to the Pareto front. Solutions in the approximation are selected, copied and perturbed (mutated), and the objectives for the perturbed solution are evaluated by finite elements analysis (FEA). If the perturbed solution is not dominated by any of the solutions in E the perturbed solution is added to E and any solutions in E which it dominates are removed. In this way E can only get closer to the Pareto front. There are a number of variations to this straightforward algorithm, including genetic algorithms [Deb et al., 2002] and multi-objective simulated annealing, developed by us [Smith et al., 2007, 2008], have been found to be efficient on a wide range of problems. While multi-objective optimisation has been used in the design of aircraft aerodynamics [Obayashi, 2006] and bicycle frames [Suppapitnarm et al., 2000], to our knowledge it has not been employed in ALM except by us for choosing the placement of artifacts in a sinter-station where the warping due to thermal stresses is traded-off against the volume of material consumed in the build [Leitao et al., 2007].

Evolutionary search procedures for a single objective has been used for topological optimisation for a number of years †, since they offer the advantages of being universal, derivative free and simple to use: any objective that can be evaluated can be optimised. The most straightforward representation of the problem is to divide the design domain into a large number of elements, each one of which may be either filled with material (set to 1) or is void (set to 0) during the optimisation. However, it is found that optimal solutions are often those in which filled element is surrounded by void elements, yielding a *checkerboard* pattern †, which reflects the fact that a minimum weight structure is composed of very fine

† refs 4-7 in Bureerat

† Picture needed? ref?

elements: subdividing the design domain further merely results in a checkerboard pattern on the finer scale. To counteract this effect the solution is regularised by adding to the objective a penalty function penalising checkerboard patterns, which amounts to a lowpass filter. A further difficulty is that discretisation of the design domain results in a very large number of elements ($> 5 \times 10^5$) and thus design variables that to be optimised. Such large spaces are clearly difficult to search for optimum solutions, requiring the repeated, expensive FEA of candidate configurations[1]; furthermore the solutions located by evolutionary methods may thus show poor consistency over repeated optimisations †.

† Bureerat refs 8, 9

We propose to address the both checkerboard and the large search space dimension problems by representing a structure by the superposition of a number of basis functions, such as non-uniform rational B-splines (NURBS), or wavelets or radial basis functions, over the design domain. For example the density $\rho(\mathbf{x})$ of the structure at location $\mathbf{x}$ might represented by:

$$\rho(\mathbf{x}) = \sum_{i=1}^{N} a_i \psi_i(\mathbf{x}; \theta_i) \tag{1}$$

Here $\psi_i(\mathbf{x}; \theta_i)$ is a basis function which may also depend upon some parameters θ_i. Using radial basis functions, for example, if $\psi(\mathbf{x}; \boldsymbol{\mu}, \sigma) \propto \exp\{-\|\mathbf{x} - \boldsymbol{\mu}\|^2/\sigma^2\}$, then the parameters $\boldsymbol{\mu}$ and σ^2 determine the location and width of the basis function. A candidate structure is then represented by the collection of coefficients a_i together with the basis function parameters $\theta_i = \{\boldsymbol{\mu}_i, \sigma_i\}$. The optimiser may then adjust the relatively small numbers of coefficients, basis function locations and widths in order to model the optimum density across the design domain. At the end of the optimisation and during the FEA of each candidate structure densities below a threshold are set to zero, representing a void. Although we have used the example of radial basis functions here, NURBS are also attractive basis functions due to their extreme flexibility, smoothness control (including discontinuities) parameterised by knot locations, and part of our work programme will be to evaluate alternative basis function representations.

In contrast to a binary representation, which allows only for the presence or absence of material, the representation (1) allows the density of the material to vary across the artifact. ALM, unlike subtractive machining methods, is able to build regions with graduated material properties by adjusting the micro-structure. This enables us to optimise the large scale (e.g., millimetre) structural properties. Following this macroscopic optimisation unit cells of with the appropriate micro-structures may either be selected from a pre-computed library or may be themselves computed by evolutionary optimisation of the unit cell.

The freedom conferred by ALM to manipulate micro-structure may be further utilised for MOO. In addition to representing the density as a superposition (1), we propose to also represent in the same way other material properties, for example, local elastic moduli. During evolutionary optimisation, these too are optimised to provide a complete specification for, say, the density and elastic moduli at every location in the design domain. Unit cells with the correct properties are then selected from a library or computed in separate small-scale, fast optimisations. It may be expected that these optimisations will be rapid because the optimised configuration for one unit cell is very likely to be a good initialisation for the neighbouring cells which have similar properties.

[1] As a benchmark, a straightforward FEA of 3×10^5 elements requires approx 4 minutes on a 1.8GHz quad processor.

The main components of the proposed work, which are organised into a series of work packages (WPs) resulting in measurable objectives (MOs), are as follows.

The workprogramme divides into a set of discrete but complementary workpackages. We will develop the ability to optimise macrostructure, beginning with two dimensions and developing into three dimensions (WP1). By optimising microstructures we will seek to develop a library of unit cells (WP2) from which we can select and integrate those appropriate to any given macrostructure optimisation (WP3), thereby reducing computational demand. In parallel with, and in support of, the optimiser development we will run finite element validations and 'what-if' studies of the ALM process (WP4). The theoretical work will be iteratively validated by ALM delivery of real artefacts, which will be characterised and compared against the predictions (WP5). End-user open-source plug-in software will be developed for at least one of the leading 3D CAD software packages and linked into the optimiser and at least one of the existing ALM systems at Exeter (WP6). Something about aiming to produce a modest part for the MotoGP partner???

Workpackage 1: Macrostructure optimisation. Beginning, for computational expedience, with two-dimensional models, the optimisation techniques outlined above will be developed and tested. The work will then be extended to three-dimensional models, to incorporate functional grading by variation of topology.

Milestones: working 2D optimiser; working 3D optimiser

Deliverables: weight & compliance optimised 2D structure; published paper on 2D and 3D; optimised designs with voids / for 3 & 4 objectives, such as honeycomb interior or truss-like structure; optimised designs with & without specified exterior shapes (e.g. connectivity rules or mechanical constraints)

Workpackage 2: Microstructure optimisation. A set (library) of unit cell structures will be developed to provide a wide range of known properties, for example, unit cells on the Pareto front between porosity and tensile strength.

Milestones: method of specifying microstructure (by parameterisation); software optimiser

Deliverables: library of (at least dozens of) validated microstructures (unit cells) with known properties; published paper on multi-objective microstructure optimisation

Workpackage 3: Full-scale optimisation. The outputs from WP1 and WP2 will be integrated to provide a functional MOO tool allowing optimisation of desired artefacts with reference to library components and/or local micro- optimisation across the structure, leading ALM artefact production.

Milestones: technique for auto-selection of microstructures from the library

Deliverables: full-scale optimiser capable of optimising real 3D engineering artefacts (such as *** something for partner); published papers and case studies; examples of artefacts ready for manufacture

Workpackage 4: Finite Element Analysis. iterative support for and validation of the MOO activity rewrite this. It will be necessary to evaluate the time penalty of simulating every layer in the structure and whether it is acceptable to provide lumped-parameter or coarse-mesh approximations. ***talk about parallelisation***

Milestones: commissioning of FEA hardware and software

Deliverables: bidirectional connectivity between optimiser and FEA software to allow full-scale optimiser to 'call' FE solver

Workpackage 5: Material characterisation. Experimental validation by means of additive-layer construction of unit cells on at least 2 machines, leading to 'characterisation' of the ALM machines, to include evaluation of structural properties and topology by SEM and static (tensile) and dynamic(??) testing. FEA simulation of real-world imperfections or inconsistencies in the ALM process, such as intra- and inter-layer bonding.

Milestones: identification of appropriate characterisation techniques for ALM; sample structures manufactured; definition of table of ALM 'Feature Set' fed to optimiser; definition of layer connectivity in FEA model

Deliverables: report on ALM characterisation; evaluation of Feature Set for at least 2 ALM machines

Workpackage 6: Design for optimisation. We will design and implement a system which allows:

- users to open CAD files and visualise parts described (fig 1)
- them to express constraints they wish to place on parts (fig 2)
- definition of information relating to the output ALM system.
- Delivery of candidate solutions to the operator
- Optimises the geometry given the constraints described (fig 3)
- Produces appropriate control information to drive the selected ALM system

The system will be a GUI which allows a user to open a particular geometry or geometries, place constraints on the geometry (such as where fixing points must be, extents of shell of part, expected loads to be supported, desired mass etc). These constraints will ultimately be delivered to the multi-objective optimiser to generate possible candidates for new modified geometry suitable for ALM manufacture. This process will be iterative. The final chosen part will be processed so that it is suitable for manufacture on the chosen piece of ALM equipment.

Milestones: visual method for model interaction and [ALM] system-controlled and user-controlled constraint definition; connectivity to full-scale optimiser

Deliverables: GUI functionality for user control of full-scale optimiser; at least one concept-to-delivery finished part

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- Overview and summary of entire proposal
- Describe the current engineering design process; optimisation of structures by thinning struts etc. Refs to the state of the art in this – what is it?
- ALM – rapid prototyping, now possible to manufacture with ALM, Exeter has the machines and expertise. ALM allows novel structures, e.g., with internal cavities and interesting microstructure
- Number of competing objectives, therefore MO; Pareto front, allows the engineer to select the optimal trade-off. Refs to MOO for engineering design.
- Proposal to couple the two together to design for function; therefore MOO, FEA for material properties; ALM.
- Ramifications: micro-structures and large scale design; FEA; verification of material properties. Programme of work (packages)
- Model the structure by:
  - variable density and other material properties function over the whole domain, modelled by splines, wavelets or radial basis functions.

    This will prevent the checkerboard effect.
  - Either a library of micro-structure unit cells or separate optimisations to produce unit cells with the required properties. Texture mapping.
- How to produce solutions that have, for example, a solid surface on the outside and a light-weight truss structure on the inside or something like a bone-structure on the inside.
- Not merely topology optimisation, but also the optimisation of material properties and performance.

2.3 Principal components

- Multi-objective optimisation of structures
- Testing and building of the artifacts.
- Address the design process, with plug-in or tool for this sort of design. How much should the designer be able to specify? Eg: internal bone structure.

3 Strengths and risks

3.1 Strengths

- Lots of kit
- MOO expertise
- FEA expertise
- Materials testing expertise

3.2 Weaknesses

- Have to show sufficient academic expertise in Engineering as well as CS.
- Collaborative partner?