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A COST BASED METHODOLOGY FOR DESIGN OPTIMIZATION

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ABSTRACT

Design optimization algorithms have traditionally focused on lowering weight and improving structural performance. Although cost is a vital factor in every emerging design, existing tools lack key features and capabilities in optimizing designs for minimum product cost at acceptable performance levels. This paper presents a novel methodology for developing a decision support tool for designers based on manufacturing cost. The approach focuses on exploiting the advantages offered by combining parametric CAD, Finite element analysis, feature based cost estimation and optimization techniques within a single automated system. This methodology is then applied in optimizing the geometry for minimum manufacturing cost of an engine mounting link from a Rolls-Royce civil aircraft engine.

INTRODUCTION

Cost is often one of the biggest considerations in product design and development. Over the entire lifecycle, it is generally accepted that the design process typically represents only 5% of the total development cost but it can fix up to 75-85% of the total product costs [1, 2]. Life cycle cost is emerging as one of the key issues in aerospace manufacturing as business models change from selling products to providing a service, for example; the concept of *"Power by the hour"* and the *"Total Care"* agreements by Rolls-Royce plc [3]. This requires reliable and accurate cost predictions to be made as early as possible within the design cycle and traded with other product attributes, as it becomes progressively more difficult and expensive to make modifications later on. This is a paradoxical situation as making an accurate cost estimate requires detailed product and process information, which is usually unavailable during early design stages [4].

Advances in Computational Solid Mechanics (CSM), Computational Fluid Dynamics (CFD) and optimization algorithms have provided designers with sophisticated tools to rapidly assess and modify designs to optimize performance. However, designers working on new part designs find it extremely difficult to estimate the cost effects of critical decisions made by them, as there is a dearth of reasonably accurate cost estimation and reduction techniques integrated within the design process. Though various guidelines to simplify design complexity and lower production costs are used in the concept design stage, collectively known as Design for Excellence (DFX) [5], it can be argued that many of these guidelines are merely rules of thumb as they do not provide an explicit metric for product cost to be used for comparison between different designs [6]. Methods broadly classified as Design for Manufacture and Assembly (DFMA) are quite popular in industry to identify design problems at an overall product structure level, but they cannot provide redesign solutions or be employed to modify existing design geometry and dimensions for achieving minimum manufacturing cost [7]. Although parametric relationships between weight, volume and cost have been used in Multi disciplinary optimization (MDO) processes, there are disadvantages to this cost estimation approach [8] as it is designed to work at a higher layer of design abstraction and cannot capture the detail necessary to provide an effective comparison between differing design geometries. A high performance design may be expensive to manufacture causing a reduction in unit profit to the company or an oversimplified design might unnecessarily increase material volumes and cost. It is important to model these conflicting interactions between cost and performance and to simultaneously optimize designs for low cost at acceptable performance levels.

This paper describes the construction of a system which overcomes the above issues by presenting a quantitative methodology for seeking trade-offs between performance measures and production costs, using feature based cost estimation, a parametric CAD model, a finite element analysis (FEA) tool and an optimizer concurrently to evaluate various designs. The remainder of the paper is organized as follows.

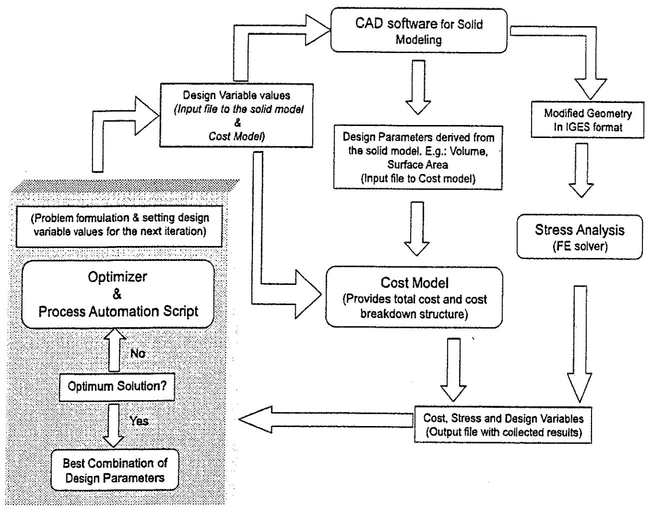

Figure 1. An overview of the proposed cost optimization methodology

First we present an overview of the process followed by an explanation on the role of geometry parameterization, stress analysis and the cost modeling method used. This section also briefly describes the various software tools used for the functions listed above. Finally, in the last two sections, we discuss two different strategies of optimization applied to this problem with the results and conclusions drawn from this entire study.

OVERVIEW OF THE PROCESS SEQUENCE

The four elements essential to the process used here are: (1) a parameterized solid model of the component (2) a suitable FEA tool for structural analysis of the component (3) a feature based cost model for computing manufacturing costs and (4) a robust optimizer to provide the inputs to the solid model while simultaneously validating the output stresses, and cost values against the formulated problem. Figure 1 shows the frame-work and flow of data in this process. The optimizer drives the entire process by feeding a set of input parameters to the parametric solid model within a CAD tool. The modified geometry is then passed on to the Finite Element solver for analysis by converting it to the IGES format. The cost is computed from the inputs given to the CAD tool and a few derived parameters from the modified geometry such as volume and the area of the surfaces generated. The calculated stress and cost are then passed back to the optimizer. The optimizer uses a specified algorithm to calculate the input parameters for the subsequent iteration by comparing the stress and cost output against the objective and constraint functions. This process is continued iteratively evaluating numerous candidate geometries until the optimum design solution is found.

Generating a Parametric Solid Model

The three dimensional geometry of a Rear Mount link from one of the Rolls-Royce civil aircraft engines is used to demonstrate the proposed methodology. Component geometry can be parameterized in many different ways. For example, Samareh [9] reviewed seven different methods of geometry

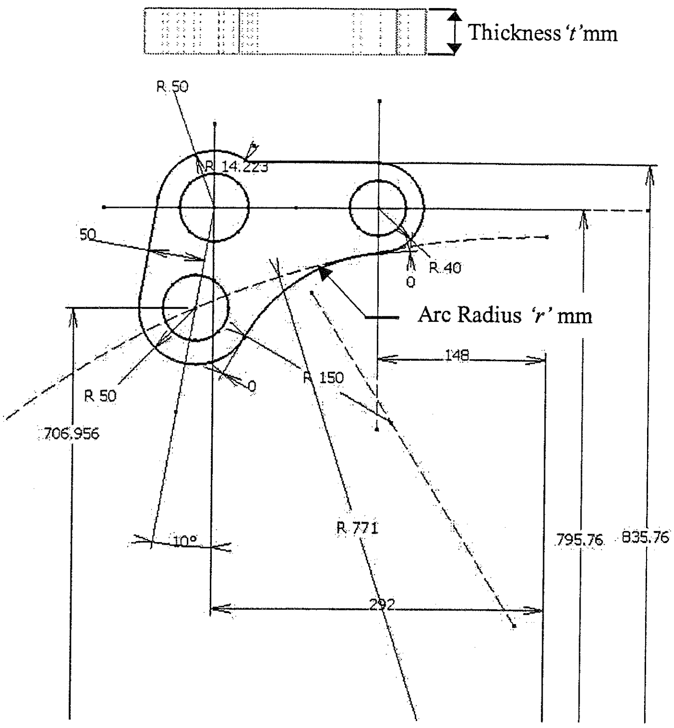

Figure 2. Parametric master model of the Rear Mount link with the design variables *r* & *t*

parameterization. Component specific codes written in C and FORTRAN have been used to parameterize 2D aerofoil shapes in many cases [10]. A solid modeling approach within a CAD tool (CATIA V5™) is adopted here as it gives adequate control for creating and modifying dimension driven objects [9]. Parameterization is achieved by a combination of geometric constraints and Boolean expressions*. The parametric model is shown in Fig. 2. Most modern CAD tools, including CATIA V5™, permit external control of dimensions from a source outside the software. In our study, the parametric master model is loaded into the CAD tool and a function known as the 'Design Table' is used wherein a list of values pertaining to the various dimensions on the part is acquired from a text file written by the optimizer for every iteration. These dimensions are the design variables for the optimization process. The number of design variables in optimization can be controlled by choosing the number of dimensions to be modified in the solid model.

The parameters (inputs) to the CAD model varied for the design search described in this paper are the Thickness (*t*) and the Arc Radius (*r*), See Fig. 2. These two parameters were selected from a list of modifiable parameters to study their influence on stress and cost. Each combination of *r* and *t* represents a unique design concept. Figure A in the appendix shows a range of geometries developed in this manner. The CAD model is also programmed to generate as outputs a few derived parameters from the modified geometry such as the weight, volume, and the surface area, to provide inputs to the cost model.

*A detailed description of solid model construction using geometry and Boolean expressions is omitted to maintain the logical structure of the paper.

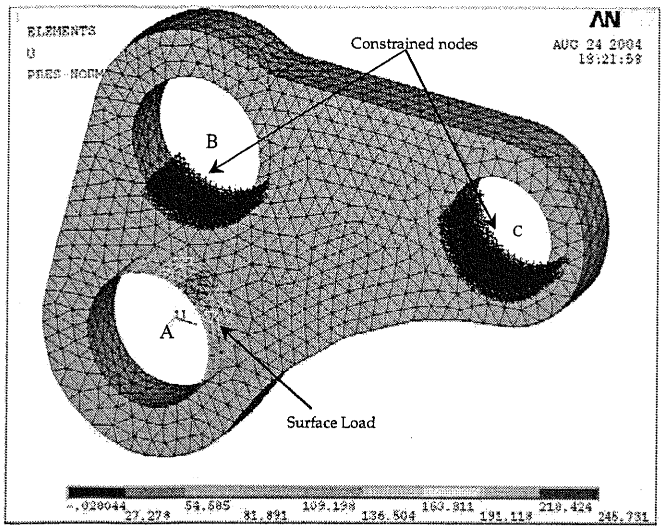

Figure 3. The Applied Boundary Conditions for Finite Element Analysis

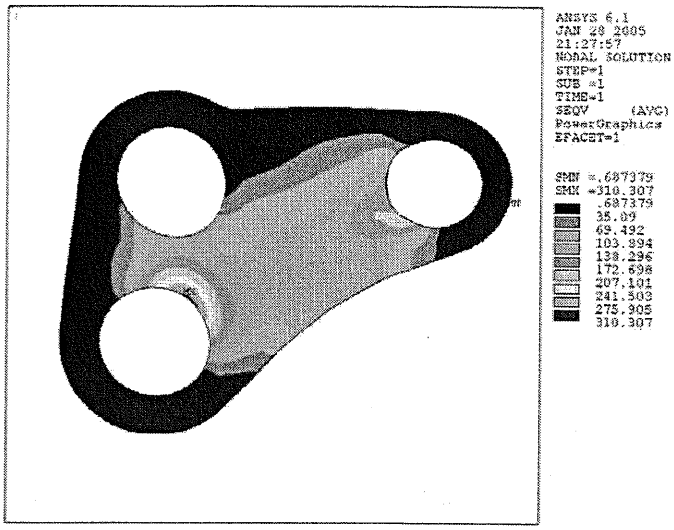

Figure 4. Analysis Results showing the contours in the stressed part

Stress Analysis

Structural analysis is performed in ANSYS 6.1™. The CAD geometry is transferred using the IGES format. The component is meshed with higher order tetrahedral solid elements (Element Number 187). Uniformly varying surface loads are applied on the inside edges of *hole-A*, whereas specific areas on *holes-B & C* are fixed, see Fig. 3. These boundary conditions were adopted after studying the published Rolls-Royce data and load bearing function of the mount link within the engine [11]. Post-processing is carried out to extract the maximum *Von-Mises* stress induced in the component, after considering stress concentration effects arising from the FE solution process, and this is written to the output file. The results from one of the analyses are shown in Fig 4. All stresses are in MPa.

Cost model structure and costing method

For the purpose of evaluating alternative designs and subsequently optimize for low cost, it is necessary to identify and isolate those constituents of product cost that vary with changes in the design parameters such as geometry and component dimensions. The selected method of estimation must also be robust enough to provide a reasonably accurate cost estimate with the limited amount of information available in early design. Extensive research in machining economics has produced quantitative models for evaluating times and costs related to machining operations [12]. Boothroyd & Radovanovic [13] published a report on cost estimation of machined components during early design. The methods of cost estimation also vary depending upon the amount of design information needed as input to these systems. Here we contrast parametric and feature based cost models.

Parametric costing

Parametric costing is typically based on the use of Cost Estimating Relationships (CERs) which are quite popular as they require sparse knowledge of the final design. Cost is defined as a function of one or more parameters such as weight or volume and this relationship is determined by studying a number of similar designs or model variants [8, 14]. The demerits of such an approach are as follows;

A large amount of historical data is required in order to identify parametric relationships in a statistically meaningful manner which is generally hard to find in a low volume production setup typical of aerospace manufacturing. New manufacturing processes and significant changes to production and assembly methods can invalidate these parametric relationships and may misguide the optimization process in which they are used. In some cases the initial condition of supply for a product remains fixed. Therefore if a weight-based parametric is used as a cost estimator, reducing weight may seem to make the design cheaper when in fact it may become costlier as further material has to be removed by additional machining.

Feature based Costing (FBC)

The growth of CAD/CAM technology and 3D modeling tools has brought into focus feature-based design. Feature based costing follows from the basic concept of defining a finished part as a collection of features such as slots, holes and surfaces. Researchers have published a number of studies on cost estimation through breaking the product into constituent features [15-18]. Each feature has a cost associated with production, material removal and labor. These costs, when added, represent the cost of the entire product. Since this method of costing relies on final component geometry and is not an approximation, it is more accurate as compared to parametric cost relationships. It also aids better decision making by providing the designer with the incremental cost of each geometric feature incorporated in the component. Unfortunately, there have been many differing opinions on how features should be classified and standardized [18-20].

The approach used here is based on calculating the cost of a '*manufacturing feature*'. A manufacturing feature is defined as a change in the state of a component. This state change is often a change in geometry caused by a machining process.

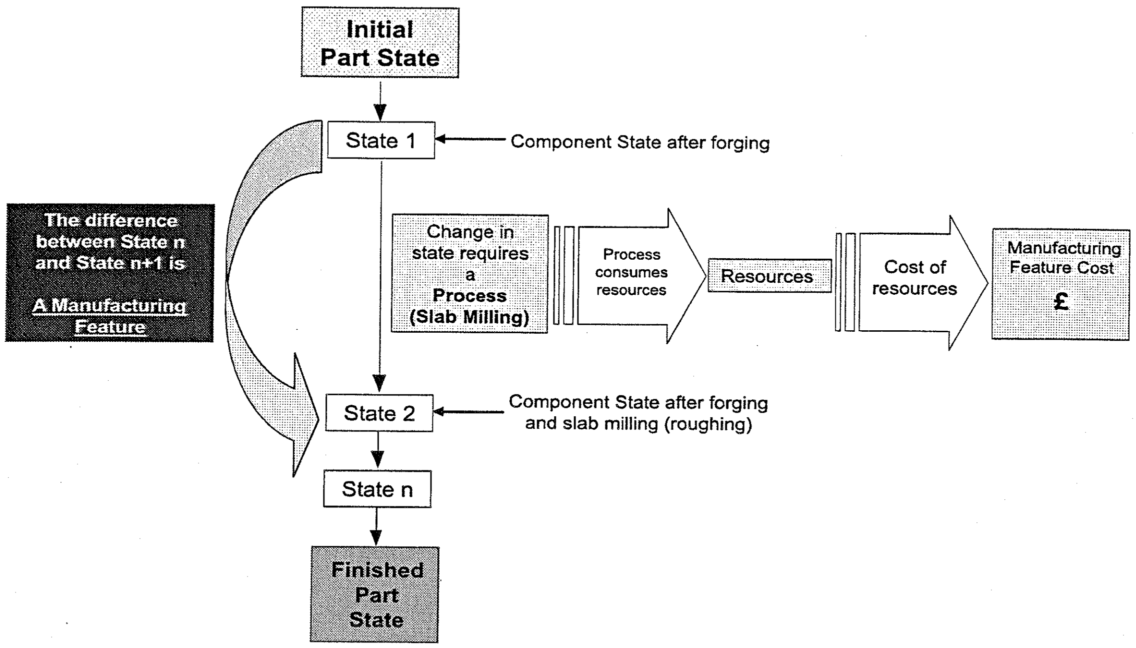

Figure 5. State Transition and Manufacturing Feature Costs

Some processes however do not cause any obvious change in the geometry such as surface treatment but these also cause a change in component state. The final component geometry is achieved after a set of manufacturing features are applied to the raw material. The cost of a manufacturing feature is the cost of resources expended in making the transition from state *n-1* to *n* as shown in Fig. 5. Manufacturing features can be further sub-divided into classes depending on material removal process involved in each of them. For example; rotational (turned), prismatic (face-milled), Slab (end-milled) and revolving (drilled, reamed, bored) features. Every component can be broken down into features which may belong to the above four classes. The total manufacturing cost is a summation of the costs incurred in making the constituent features. Machining features costs are evaluated separately using the formulations published by Jung [20].

Feature classification in this study is used to calculate the manufacturing cost only and there is no attempt made to automate the process of feature extraction or generating a process plan based on them.

Here the component undergoes the processes listed in table 1 that are directly affected by the design variables Arc radius (r) and Thickness (t). The processes required for drilling and grinding the holes A, B and C (See Fig. 3) and shot-peening are neglected as the design variables r and t do not affect the cost of these operations. This simplification was done to reduce the time taken for computations. It is also possible to extend this costing methodology to include company specific overheads.

The total cost is expressed as a summation of processing and material cost. The material cost is expressed as a function of the volume whereas processing cost is a product of the utilized resources and a unit cost rate. We have expressed the utilized resources in form of time (seconds) taken to complete the entire operation (summation of all processes) which includes both man and machine time with corrections for allowances and setup. The operation cost rate per unit time includes direct labor and cost of running the machine.

Table 1. Manufacturing Sequence

State	Process	Surfaces Affected	Resources utilized	Cost (derived from used resources)	Machining Feature
1	Condition of supply, State when material bought			Bought Price / Material cost	
2	Face Milling (Roughing)	Top and Bottom	Quantity of material removed, Man-hours with correction for allowances, Machine-hours with correction for setup, tool setup, tool wear and engaging time.	Roughing Cost	Prismatic
3	End Milling (Roughing)	Periphery		Roughing Cost	Slab
4	Face Milling (Finishing)	Top and Bottom		Finishing Cost	Prismatic
5	End Milling (Finishing)	Periphery		Finishing Cost	Slab

Therefore the total cost can be expressed as

Total Cost = Forging Cost + Operation cost.

Operation cost is expressed as

$$Cost_{op}=\left(R_o+R_m\right)\left(\frac{T_{su}}{Q}+T_{ot}+T_{no}\right) \quad (1)$$

where

$Cost_{op}$ is the Operation cost

R_o & R_m are the unit cost rates of the operator and machine respectively,

Q is the Batch quantity,

T_{su} is the setup time for tooling and machines over the entire batch,

T_{ot} is the operation time required to carry out the various processes to achieve final shape and

T_{no} is the non-operation time involves loading, unloading and fatigue allowances.

The formulations for calculating the operation time depend on a) whether it is a roughing or finishing operation b) type of feature generated from the operation (prismatic, slab....etc), c) The material removal rate (M.R.R) for roughing and d) the surface generation rate for finishing operations.* The M.R.R and surface generation rate were obtained from Rolls-Royce machining database. The costing method explained above has been encapsulated within DecisionPro™, a decision support software tool [21]. DecisionPro, unlike commercial costing tools is a modeling tool that was not overtly designed for engineering cost analysis. Its attraction lies primarily in its hierarchical structure allowing users to decompose a problem into a logical series of steps. Consequently the resulting model is more likely to have a clear and easy to comprehend structure. A page from the model is shown in Fig. B of the appendix. The hierarchical tree structure used for capturing cost computations offers easy readability to end users (designers), and simplified audit procedures for developers unlike spreadsheets where the logic is often difficult to follow as calculations assume greater complexity. The different nodes in the trees can be instantiated as objects from a populated library. This allows for modularity and reuse of costing knowledge and data on frequently used manufacturing processes can be stored in the libraries. The complete cost model can be uploaded to a server and queried remotely which allows better integration capability in an existing MDO environment. Few other functions include;

A. presentation of equations and logic in formal mathematical notation,
B. sensitivity and Monte-Carlo analyses capabilities and
C. ability to link to data-bases.

These functions offer significant advantages over spreadsheets or similar software which could be considered as an alternative for building models and are instrumental in helping build detailed cost models for complex products.

The resources utilized (see column 4, table 1) for each manufacturing feature are computed within the model and finally expressed in terms of the cost in GBP. Figure C in the appendix shows the time computed for the prismatic features, *'Top & bottom face milling (Roughing cut)'* and *'Top & bottom face milling (finishing cut)'*. The input *'tbsurfacearea'* is given from the CAD tool (CATIA V5). Only the process stages mentioned in table 1 are modeled in this study, but this could be scaled up to represent downstream assembly and surface coating processes by adding more features at the end of the existing tree structure in this cost model. The inputs for the cost model are three derived parameters from the CAD model: part volume, the area of the surfaces generated by end-milling and face-milling. This allows for flexibility in optimizing the design as the variables can be changed or their number increased. The part volume is used to calculate materials cost which is a substitute for weight. In this manner, we need not minimize weight separately. This is based on the assumption that the initial product state can be modified. If this is not the case, then lowering weight/volume has to be modeled conversely as a machining process for removing material from the initial state.

* Formulations used are omitted here due to space limit. Details can be found in Jung [20].

DESIGN OPTIMIZATION AND AUTOMATION

Design optimization in the aerospace community has generally focused on weight, aerodynamics, structural performance or all three [22]. Cost of manufacture has rarely been used in optimization as it is difficult to model cost in terms of the design variables. However, Mitchell et. al [23] have reported using a automated costing model to drive the design of composite frames. Researchers at NASA published work on custom built software tool for life-cycle cost optimization called COSTADE [24]. An integrated data management and optimization package called OPTIONS has been used in this study [25]. OPTIONS provides a flexible framework for incorporating user codes ranging from very simple scripts to complete external software packages as well as more than forty search algorithms that can be used interactively or in batch mode. MatLab™ is used to provide the scripting and automation required for running the optimization process iteratively until the search strategy converges. The bound constraints for the design variables are selected after testing the behavior of the system on a range of values applied to both variables, and omitting those combinations which cause the CAD tool to produce infeasible geometries. Two different optimization strategies have been adopted for this problem:

1. meta-model based optimization, and
2. multiobjective optimization and construction of a Pareto front for stress and cost.

Meta-model based optimization

The presence of multiple software and computationally intensive tools such as FE solvers in this integrated system prohibit search using the full problem code over a very large design space. Meta-model based optimization is a technique designed to circumvent this problem. Meta-modeling uses the basic idea of analyzing an initial set of candidate designs to generate data which can be used to construct approximations of the original system. The entire process can be represented by a functional relationship $y=f(x)$, where x is the vector of inputs to the system code and y is the output. The objective is to construct an approximate model (the meta-model) $\hat{y}=\hat{f}(x)\approx f(x)$ that is computationally cheaper to evaluate and which approximates the outputs (objective function, constraints) from the input parameters (design variables) with reasonable accuracy [10]. The meta-model is then searched by the optimizer over a very large number of design points for the optimal values. When a good design is found, the corresponding inputs are given to the original system code to evaluate just this design. If there are significant differences in the results given by the full code and the meta-model at this point the new data is added to that used to construct the meta-model and the search process carried out again. This sequence can then be repeated as many times as desired, gradually improving the meta-model. Consequently, this gives better approximations and a better design at the end of the search. The present problem is formulated as follows;

$$\begin{aligned}&\text{Minimize Cost,}\\&\text{subject to } 120 \le r \le 1200,\ 10 \le t \le 50,\ r, t \in \mathrm{R} \qquad (2)\\&\text{and } \textit{Von Mises} \text{ Stress} \le 200 \text{ MPa}.\end{aligned}$$

In our case, the design variables (r and t) form x (the input vector) whereas cost and *Von Mises* stress form the $\hat{y}$ (the output vector) of the meta-model which is constructed using the following procedure; the initial set of candidate designs is generated by one of the three following methods; a) Random sampling, b) Latin hyper cube sampling c) $LP\tau$ sampling. Random sampling is equivalent to a Monte Carlo Simulation (MCS) technique, wherein the basic idea is to employ a random number generator to sample the design space. Mckay et al [26] proposed the Latin hypercube sampling (LHS) technique, which is a computationally more efficient alternative to MCS for designing computer experiments. The underlying idea is to divide the design space into regions of equal probability and generate pseudo random points, such that no two points lie in the same bin. $LP\tau$ sampling [10] is based on distributed sequences in space and gives a mechanism for generating points in n-dimensional space which are reasonably uniformly distributed. After generating an initial set with a suitable technique, we have approximated the actual relationship between r, t, Cost and *Von Mises* stress using a cubic spline radial basis function (RBF) of the form

$$\hat{y}_{n+1} = \sum_{i=1}^{n} a_i \phi\left(\left|X_{n+1} - X_i\right|\right), \qquad (3)$$

where $\phi(x) = x^3$.

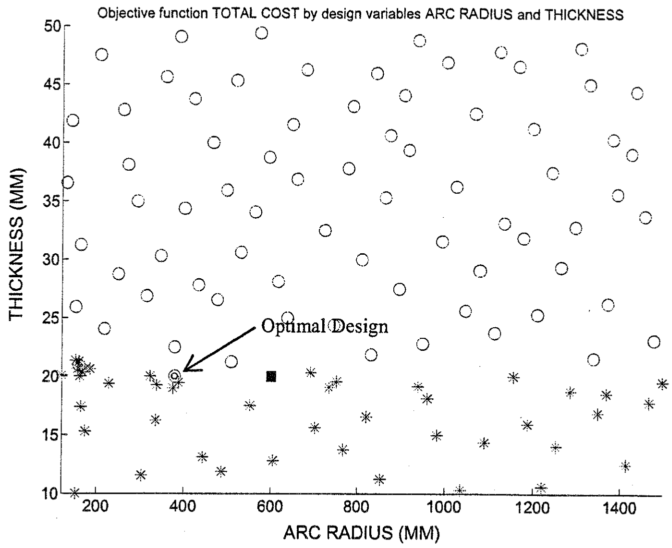

Figure 6. The design concepts evaluated by the optimizer.

A simulated annealing [27, 28] algorithm is used to search the meta-model over 5,000 design points before every update point is provided to the data set. The update loop is carried out a fixed number of turns before the optimal design is predicted. The meta-model structure, number of updates and results for three different evaluations is given in table 2. Figures 6 and 7 depict the results obtained from model no.3 listed in table 2. Figure 6 shows the search space with the feasible designs shown in blue circles and the designs that violate the imposed constraints are denoted by red asterisks. Figure 7 shows the values of the objective function obtained during generation of initial candidate designs and meta-model refinement over 50 updates.

The meta-model when searched returns the same optimal value of the objective function (total cost) when it cannot be refined anymore as may be seen from iteration numbers 126 onwards. A solid model representation of the optimal geometry achieved at the end of this search is shown by Fig. D in the appendix. Figures 8 and 9 show the variations of cost and *Von Mises* stress with respect to r and t as depicted by the refined meta-model generated after all the updates. The Meta models were validated by using multiple starting points for a few trial searches prior to generating the results shown in table 2.

Table 2. Results from meta-model based optimization

Model No.	Initial Design Set Size	Technique	Type of Approximation	No. of updates	Optimized Value of Design Variables (r, t) mm	Total Cost (£)
1	10	Random	Cubic Spline Radial Basis Function	30	281, 20	339.04
2	5	Latin Hyper Cube	Cubic Spline Radial Basis Function	20	508, 20	338.57
3	100	$LP\tau$	Cubic Spline Radial Basis Function	50	378, 20	337.92

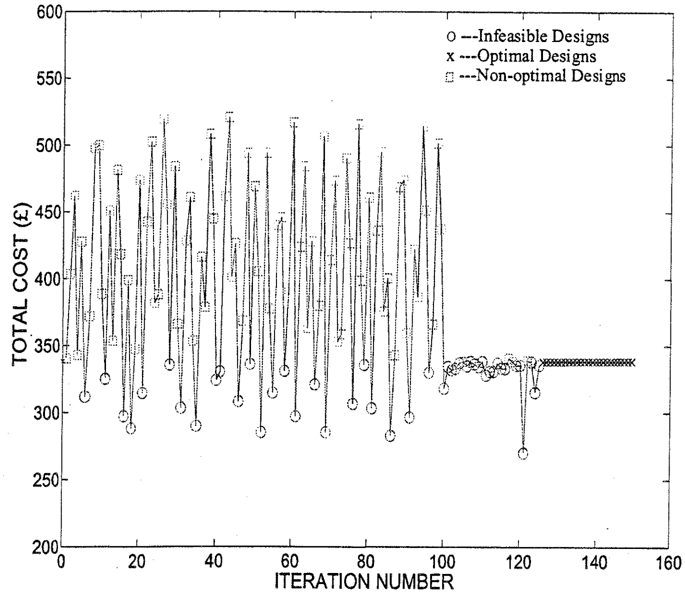

Figure 7. Optimization history

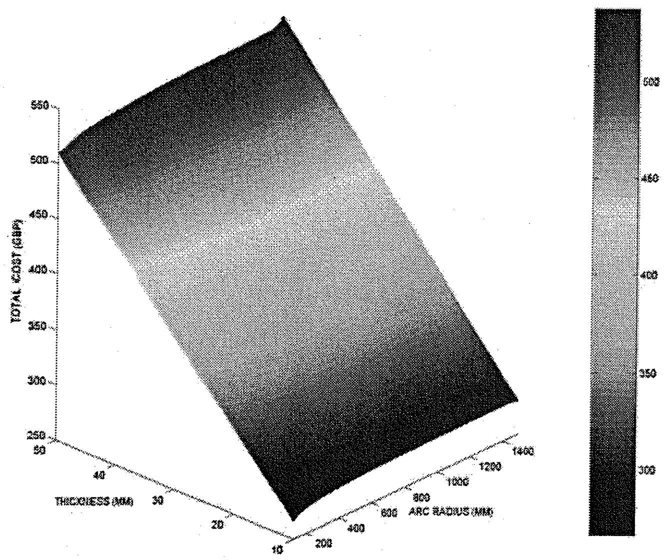

Figure 8. The Response Surface of Cost against the Design Variables

From table 2, Fig.8 and Fig.9, it can be seen that the thickness (t) dominates the cost value and the optimizer can quite easily search for the best value of thickness to satisfy the constraints for a minimum value of cost. The relation between thickness and output parameters are relatively simple, however the arc radius (r) has a more complex non linear interaction with the stress throughout and very little effect on total cost once r is greater than 200 mm. it can also be deduced that a relatively small initial dataset can approximate the cost and thickness values with reasonable ease whereas searching for the optimum r value needs more data and meta-model refinement. These results suggest that the final design with minimum cost must have a thickness of 20mm and an arc radius in the interval $280 \leq r \leq 510$ mm.

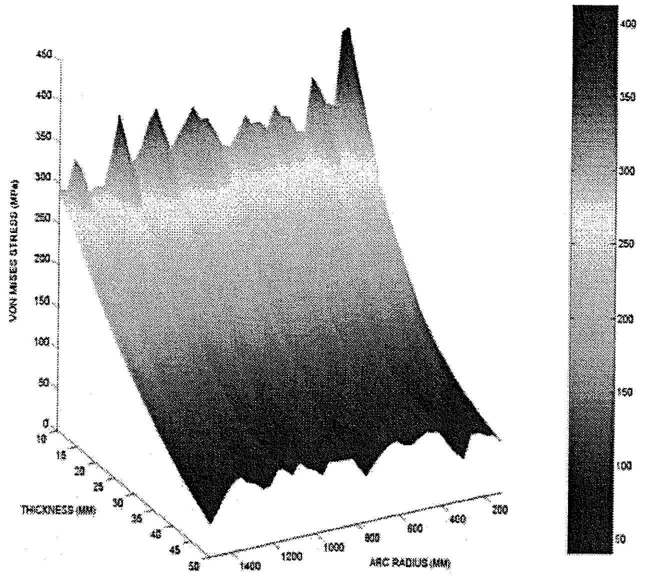

Figure 9. Response Surfaces of Cost and Von-Mises Stress against the Design Variables

A further optimization routine with minimum stress as the sole objective could be run to determine the optimum arc radius value. It can also be seen from the computed cost values that a meta-model search is very accurate and allows a search for the minimum cost design within an error of $\approx 1\%$.

Multiobjective Optimization of Stress and Cost

Conventional optimization algorithms are based on well defined objective and constraint functions. Often design problems cannot be formulated into explicit expressions. There is also a possibility that there may be more than one objective and that they are conflicting in nature. If a problem has multiple, conflicting, objectives and these cannot be combined by assigning relative importance to each of the goals, then the problem leads to the construction of a Pareto front or surface and the idea of Pareto Optimization [25]. A Pareto front is formed from a set of design solutions to a single design problem where each member of the set is an optimal solution for an aggregate goal. This aggregate goal can be formulated by assigning weights to each objective and taking the weighted sum. The present problem can be formulated in such a manner by simultaneously trying to minimize both stress and cost. This means that in moving from any single design in the set to any other, although one objective in the problem may be improved, the other is made worse. In this case, there are two objectives and the problem is formulated as follows;

$$\text{Minimize } c = a(cost) + b(stress)$$
$$\text{subject to, } 120 \leq r \leq 1200, \text{ and } 10 \leq t \leq 50, \; r, t \in \mathrm{R} \quad (4)$$
$$\text{where } a \in (0, 0.2, 0.5, 0.8, 1) \text{ and } b \in (1, 0.8, 0.5, 0.2, 0)$$

In this problem there would be a set of five optimal solutions for the aggregate objective function each of them computed by assigning a unique combination of a and b values. For example; (0, 1), (0.2, 0.8) ….. (1, 0). To construct an appropriate aggregate function, the units of measure used to define cost and stress must also be considered. Therefore Eq.4 can be rewritten as

$$c = a(w_1.cost) + b(w_2.stress) \quad (5)$$

where w_1 and w_2 are weight parameters.

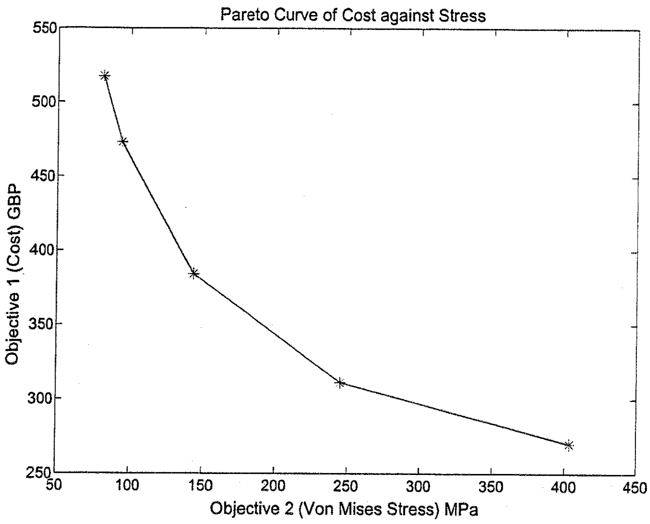

Figure 10. The Pareto curve plotted through five points of evaluation.

In this study we have set both weight parameters to unity as the cost values in GBP and *Von Mises* stress values in MPa have similar magnitudes. The results from this analysis are shown in Fig.10.

Figure 10 shows a range of designs, all of them optimal combinations of the parameters arc radius and thickness for different values of weighting between stress and cost. A designer can now easily move along this surface to choose the best trade-off that fits into the specific requirements of his product and company. We have evaluated only five different combinations of the aggregate function in this study as these evaluations were carried out by running the full problem code. In practice, many more combinations would have to be evaluated to form a dense Pareto curve to provide numerous alternatives for the designer to choose from, which may make this strategy computationally prohibitive. Moreover, for modeling deceptive relationships between objectives (for example; a convex Pareto curve), a more sophisticated strategy would have to be applied.

CONCLUSION

This study aims to provide a realistic and effective tool in generating cost driven designs aiding better decision making in the product development process. Many organizations have a traditional cost estimating department whose role has been to provide specific estimates in response to requests from a designer. This has often been a source of significant delay and frustration to the design function. The methodology proposed here is intended to shorten the lead time in acquiring the cost estimates for most if not all candidate geometries. The results obtained from the two different optimization strategies tested on the engine rear mount link prove that the search for a low cost, better performing design even for a simple mechanical component involves modeling complex relationships between geometry, stress, cost and manufacturability. This methodology would be applied in the near future to design more sophisticated parts than the present component to appreciate the efficacy of this tool.

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APPENDIX

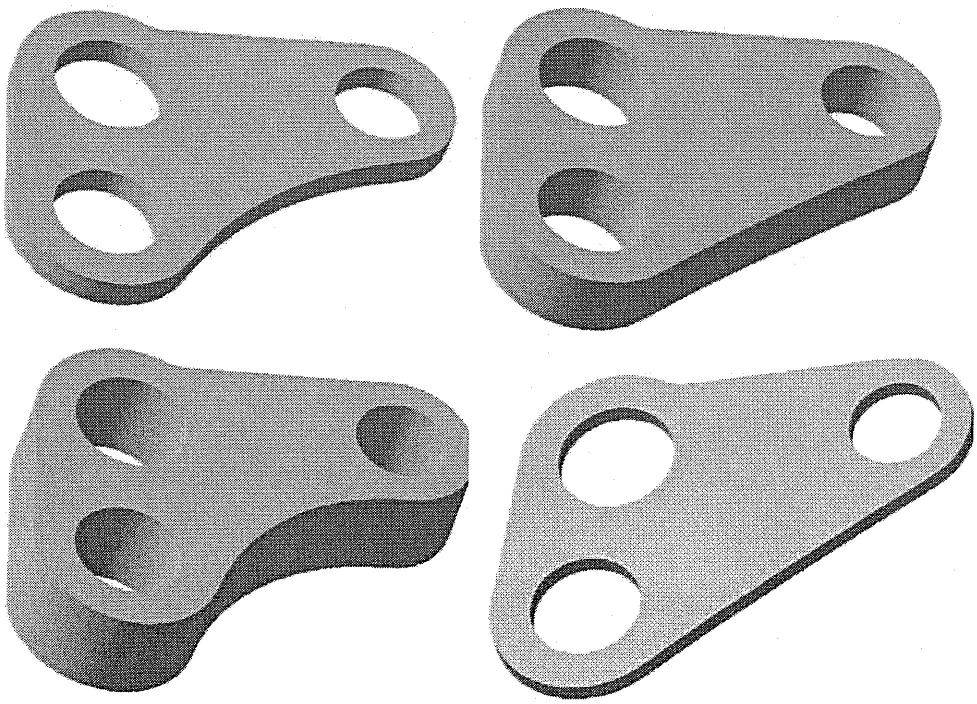

Figure A. Range of Geometries generated by varying the inputs of a Parametric CAD Model

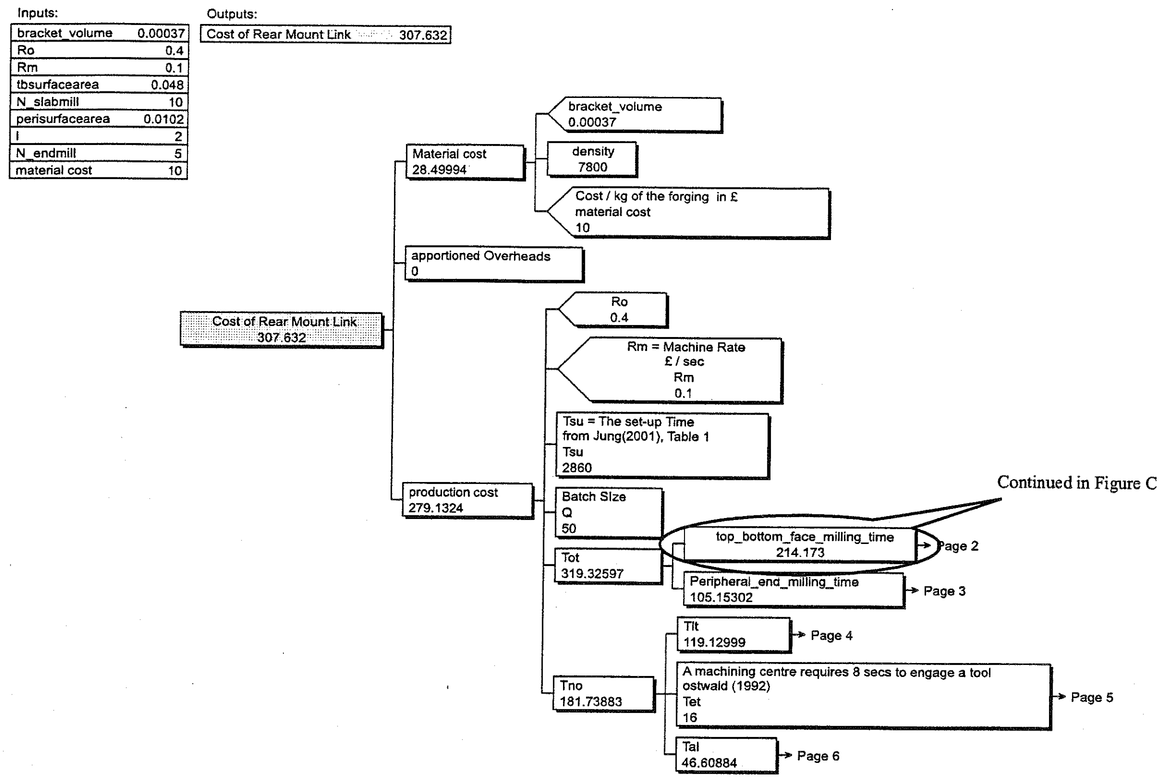

Figure B. Snapshot of the Cost Model within DecisionPro™

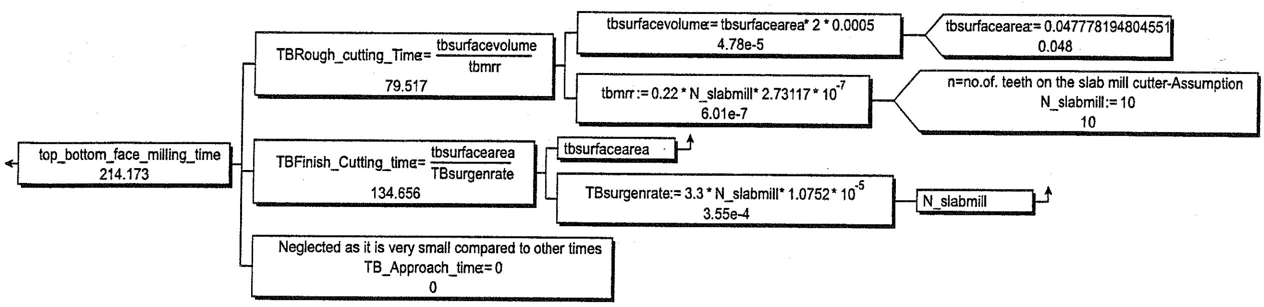

Figure C. Detail from cost model

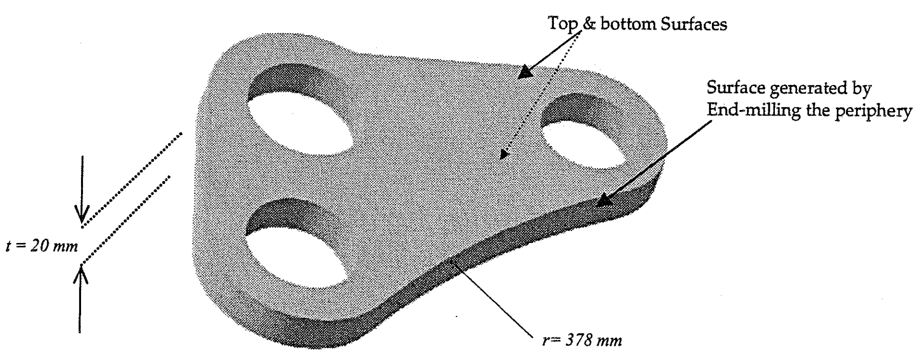

Figure D. Minimum Cost Geometry for Result No. 3 in Table 2