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DATUM Project: Cost Estimating Environment for Support of Aerospace Design Decision Making

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The results of a Rolls–Royce sponsored program of design to cost research are outlined. The role of cost modeling within the design process for the development of a civil gas turbine engine is outlined. The novel application of a generic financial modeling tool to an engineering cost estimating problem is demonstrated. This use of this tool to capture and disseminate costing knowledge is described and the use of modular library elements to develop cost models is shown. A prototype systems for the creation of an elegant cost model structure to enable direct integration with a CAD representation of a part and the integration of the costing capability within an automated design search and optimization environment is described.

I. Introduction

IN 1982 the Rolls–Royce Tay family of engines (Fig. 1) was born when Ralph Robins, then managing director of Rolls–Royce and Allen Paulson, founder of Gulfstream Aerospace met at a company Christmas dinner at New York's Waldorf Astoria [1]. The basic performance, price, quantity, and payment terms for the deal were agreed in the space of a 10 min conversation and scribbled on a napkin.

This is, perhaps, an extreme example of parametric cost estimating and product design. Ralph Robins was able to commit the company to this ultimately successful venture knowing that the proposed engine would draw heavily on the existing product base whose costs and performance he understood. In fact the RB 183 Mk 555 Spey design provided the basic core and gearbox and the RB211-535E4 provided a low pressure system and fan design for the new engine.

Clearly this undertaking did entail a significant calculated risk. However, the business model prevalent within the aeroengine industry at that time allowed for a margin of error in purchase price. The bulk of the income from an engine project was derived from spares and aftermarket support. The deal was not, therefore, wholly sensitive to the purchase price agreed, and hence Ralph Robins was perhaps entitled to be adventurous in his negotiations.

The current business model between airlines and aeroengine suppliers is not so tolerant of early estimating errors. In the past decade the civil aircraft industry has witnessed deregulation and privatization of national airlines. There has been an emergence of low-cost carriers and intense competition based on "no frills," low-cost flights. The change in the airline business has stimulated the demand by operators for "power by the hour" for aircraft engines and "total care" contracts.

The impact of these agreements on the aeroengine business model is significant and the design process has had to adapt accordingly. Recently there has been a particularly strong emphasis on understanding the relationship between cost and product design within the aviation industry in general.

II. Cost in the Design Process

Many aerospace companies now follow a standardized product development process with clearly identified review procedures and decision points as illustrated in Fig. 2. This process seeks to minimize the risk to the company by ensuring that uncertainties are systematically identified and minimized.

Aerospace companies are developing increasingly sophisticated tools with which they are able predict the performance of their products with considerable accuracy. Static strength tests frequently validate computational predictions to within a few percent. Similarly, drag and fuel consumption predictions are often accurate to within fractions of a percent.

Cost predictions are rarely as accurate at the early design stage and have, until recently, depended upon simplistic parametric estimates. This is a major source of risk within the product development process.

Figure 3 gives an overview of the product development process. In the early design phase exploration takes place largely using analogous reasoning based on implicit design parameters such as performance, life and reliability. Hence, for example, the designer would predict performance at this level by scaling from known designs. This entails a relatively high risk of error because it makes the assumption that the emerging design is sufficiently similar to

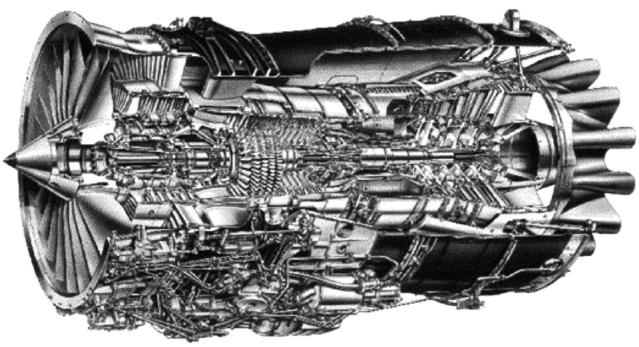

Fig. 1 Rolls–Royce Tay.

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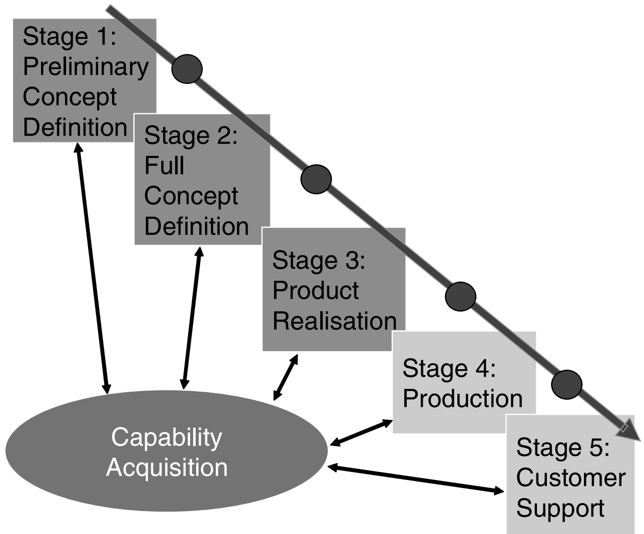

Fig. 2 The Rolls–Royce product development process.

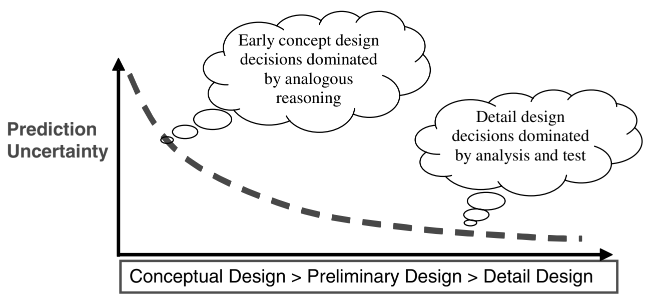

Fig. 3 Design methods and phases.

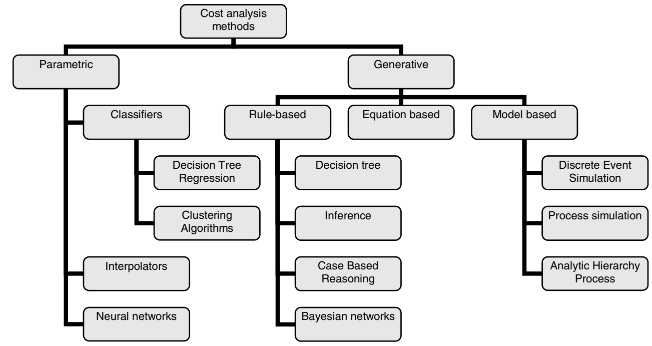

Fig. 4 Cost tool classification hierarchy.

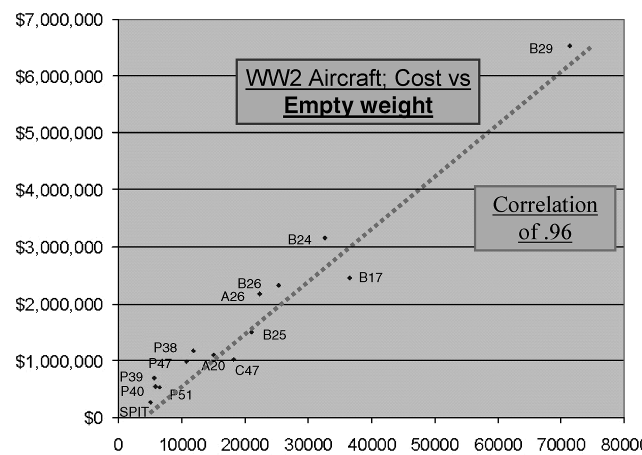

Fig. 5 Example weight/cost correlation.

historical designs and that an appropriate linear or nonlinear scaling parameter can be applied.

Modern computer aided design (CAD) and product life-cycle management (PLM) tools attempt to introduce higher fidelity models and design by analysis techniques as early as possible in the design process with a consequent reduction in risk of error. However, this is computationally expensive and may not be possible or desirable at the concept design stage. A key goal for cost researchers and one that is central to the DATUM project is to achieve an earlier adoption of costing by analysis rather than costing by analogy (parametrics).

III. DATUM (Design Analysis Tool for Unit-Cost Modeling) Project

Rolls–Royce launched the DATUM project in 2002 with the aim of establishing a costing capability to better support design decision making throughout the product development cycle.

The early priority within this program was to gain a deep understanding of current and emerging costing tools and methods worldwide. A thorough survey was therefore undertaken and this concluded that tools essentially fall into two distinct classifications; parametric and generative (Fig. 4). It is interesting to note that there is a complete absence of commercial costing tools that transcend these two classes. Marx et al. [2] suggest that within the research community there are high-level cost models based on parametrics and low level models based on manufacturing knowledge and that few models exist between the two ends of this spectrum. Worse still they state that "no suitable method has been demonstrated which accepts multifidelity data from multiple levels of product definition."

It is clear that this issue remains unsolved and there still exists a compelling need for a costing capability that can seamlessly transcend multiple levels of design abstraction.

Essentially parametric tools use historical data to discover patterns and relationships, whereas generative tools seek to rationalize and generate a cost prediction from first principles and fundamental manufacturing knowledge.

IV. Parametric Estimating

There has been a long history of parametric cost estimating within defence and aerospace industries. It was employed extensively in WWII when the U.S. government needed a quick and simple method of agreeing unit prices with manufacturers. Initially, very simple parameters were used such as aircraft weight. Figure 5, for example, shows excellent correlation between cost and empty aircraft weight for a wide range of WWII military aircraft [3].

To construct this parametric analysis the underlying data have been normalized, corrected for inflation and a learning curve correction factor applied. Such data preparation requires a significant amount of effort. This is often neglected by analysts and can lead to very misleading parametric predictions.

A similar analysis has been conducted for a range of post WWII military jet aircraft (Fig. 6).

This shows that the simple parametric approach gives a much poorer correlation partly because of the technological diversity represented by this sample. It is of note that the budgeted cost of the Joint Strike Fighter (JSF) is significantly below the correlation line in Fig. 6 and represents a very aggressive cost challenge for such a complex product [4]. Nevertheless, in the absence of an alternative, a high-level parametric analysis provides some useful capability and guidance at the conceptual stage of design.

In the early 1950s, the Rand Corporation further refined the parametric cost estimating method. Rand used parametric cost estimating for first and second-generation intercontinental ballistic missiles, jet fighters, jet bombers, and cargo aircraft using cost estimating relationships (CERs) based on speed, range, altitude, and complexity [5].

A number of commercial parametric tools are available and the market in this category is dominated by tools such as Price H [6] and Cost Advantage [7].

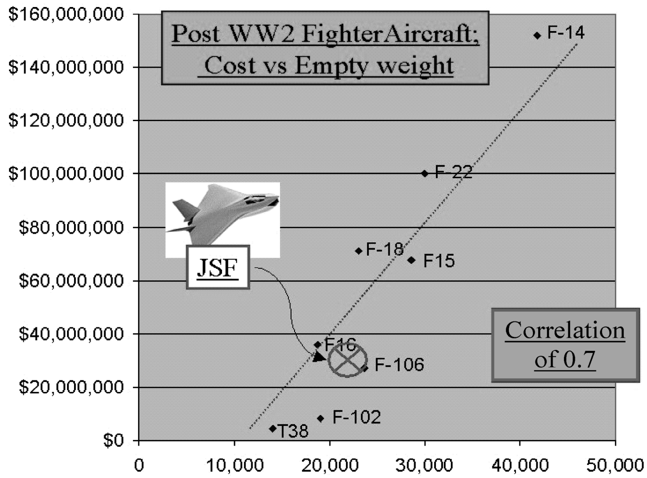

Fig. 6 Weight/cost correlation military jet aircraft.

V. Generative Costing

This class of cost analysis is also widely referred to as “bottom-up” costing. The objective is to calculate the cost of an object by using fundamental engineering knowledge. In the limit a generative model will be based on laws of physics, process capabilities and materials data.

Generative costing is very closely associated with generative process planning (GPP) which has been the subject of considerable research effort over the years. Generative process planning tools seek to automate the creation of a detailed production plan by capturing the cognitive thinking employed by a manufacturing engineer.

One avenue of research concerns the use of feature recognition which analyses part geometry in order to decompose the shape into elements for which there is an associated manufacturing process [8]. It is generally agreed that this work faces many difficulties and a widely adopted general solution has yet to emerge. In particular, the effort required to capture, test, deploy, and maintain the knowledge base associated with a practical generative process planning system is seen as prohibitive.

An alternative is to use a feature-based design approach which requires the design and manufacturing communities to agree a common feature library. The designer then uses this feature library to construct geometry which is readily associated with a manufacturing process thus circumventing the need for a feature recognition algorithm.

There are, nevertheless, a number of widely acknowledged difficulties associated with feature-based design [9]:

1) A feature library restricts the freedom of the design function and may stifle innovation and the exploration of radically new design solutions.

2) The rigorous definition of and strict adherence to a feature taxonomy is arduous. There are many examples of features that do not fit particularly well into a strict hierarchy. Many features exhibit anomalous behavior.

3) It is not obvious what level of granularity is appropriate for a feature library. If the library is too coarse it limits design flexibility. If it is too fine it does not map well to manufacturing processes.

4) Features cannot be regarded merely as geometric constructs. To have any manufacturing significance a feature needs a coherent context including such information as material type and production volume for example.

5) Features cannot be treated as isolated objects. The effect of feature combinations is difficult to predict and may lead to dramatically different manufacturing solutions.

While well aware of the above issues Rolls–Royce is cautiously implementing a pragmatic feature-based design approach for key components and a specific feature set. This facilitates the integration of design and manufacturing product viewpoints.

VI. DATUM Requirements

The objective within the DATUM project is to develop a costing capability that will support design decision making for all phases of the product development process. Therefore a key imperative is to try to bridge the gulf between the parametric and generative domains.

As a first step the DATUM team put considerable effort into gaining a deep understanding of the information requirements of the Rolls–Royce design team. Based on this consultation the following critical success factors were identified for the DATUM project:

1) The costing tool must be capable of dealing with uncertainty in terms of both design uncertainty and process knowledge uncertainty.

2) The cost estimate must be easy to audit and rationalize. The design team must be able to quickly and easily navigate the model and be able to “drill down” into the detail.

3) The tool should facilitate dissemination and deployment across a large number of geographically dispersed users.

4) The tool should integrate with company data sources, design tools, and optimization tools.

5) DATUM should provide support for costing at multiple levels of design abstraction.

VII. Knowledge Management

Probably the most important aspect of the DATUM project concerns the way knowledge is captured, represented, and deployed. A recent review of expert systems development and long term use was carried out by Nurminen et al. [10]. This important study, which was based on a large number of industrial case studies, identified the defining characteristics of successful expert systems. The key findings are that

1) Expert systems should seek to complement rather than replace human experts.

2) Users prefer usability over automation.

3 Early benefits to experts themselves are important.

4) “If-then” rules fail to represent engineering knowledge adequately and are prohibitively expensive to maintain.

5) Technical knowledge deals with artefacts and their relationships, formulae, and numeric values that are more easily expressed as classes and objects.

6) Fast and agile development is important.

The DATUM project has sought to embrace such principles in its development program to ensure that it leads to a long term, sustainable system.

A further consideration that has shaped the work is an awareness that organizations cannot afford to use proprietary or closed standards for data. Systems should be designed with the assumption that data, which represents the primary system asset, may eventually need to be migrated to another software tool or environment.

Furthermore the need for specialist skills for capturing, representing, and manipulating knowledge limits the rate at which models can be created. There was, therefore, a strong incentive to employ software tools that avoid the need for specialist software skills.

VIII. Spreadsheet Crisis

Many large companies such as Rolls–Royce have outsourced the management and support of their IT systems to third parties. Very strict management processes and procedures for the acquisition and implementation of new systems have been introduced. A side-effect of this policy is a tendency for employees to make extensive use of spreadsheets and macro programming languages for data storage, analysis, and manipulation. These applications establish themselves as a legitimate part of the business processes of the organization despite the essentially uncontrolled nature of their development. This is a worrying trend as these applications are frequently undocumented, rarely fully tested or validated, and are produced by people who often have little or no formal training in good systems development practice.

By their very nature, large spreadsheets are very difficult for a third party to comprehend as their very flexibility allows users to generate

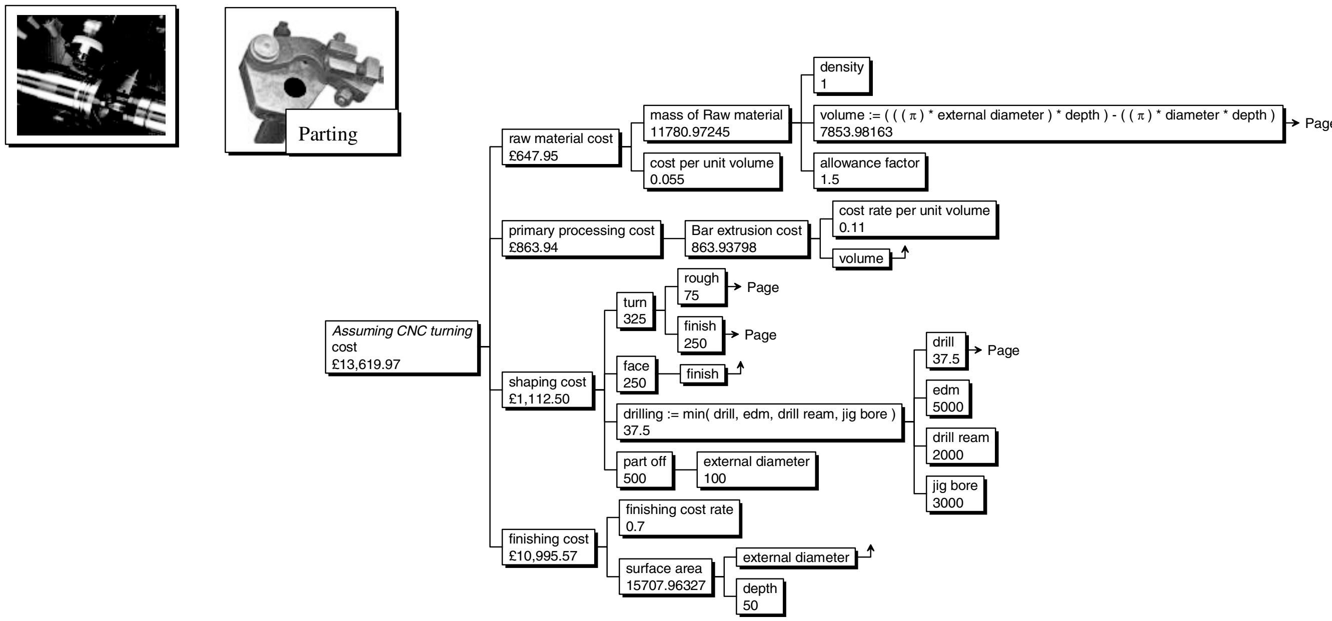

Fig. 7 Example hierarchical model.

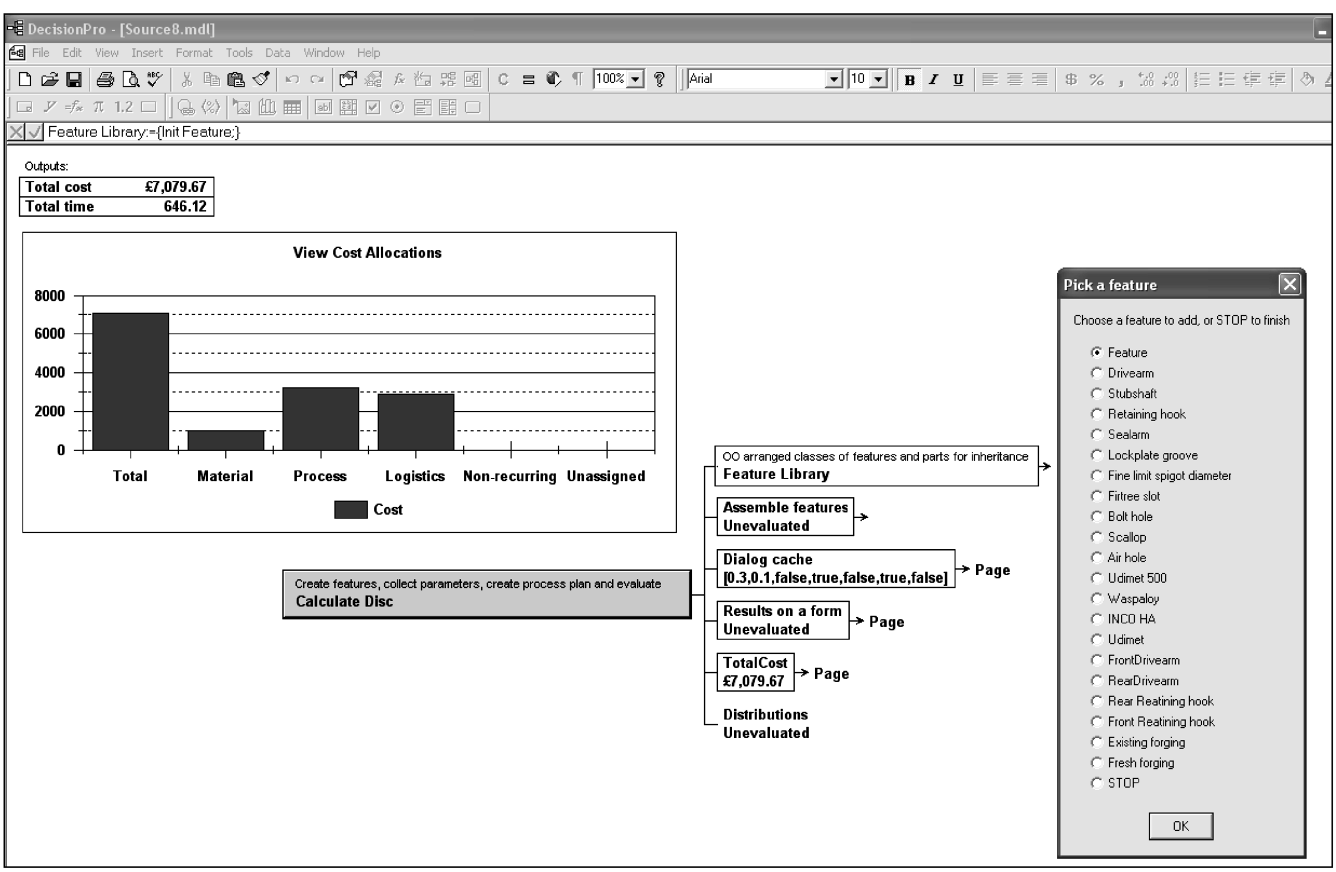

Fig. 8 Object library prototype.

a complex web of cell references which are arduous to audit [11]. Worse still, there is a tendency for the spreadsheet author to misguidedly compound the problem by expending a considerable amount of effort into hiding the detail behind an elaborate and visually attractive "front end." Should the author of such an application leave the organization, it is commonly abandoned as colleagues are reluctant to master its complexity and often refuse to take ownership of it.

Paine [11] states that spreadsheets have almost no features for building applications out of parts that can be developed and tested independently. Panko [12] suggests that "Given data from recent field audits, most large spreadsheets probably contain significant errors."

The most recent audit he cites found errors in at least 86% of spreadsheets audited. In 1997 Panko [12] reported that 90% of the spreadsheets audited in a study carried out by Coopers and Lybrand

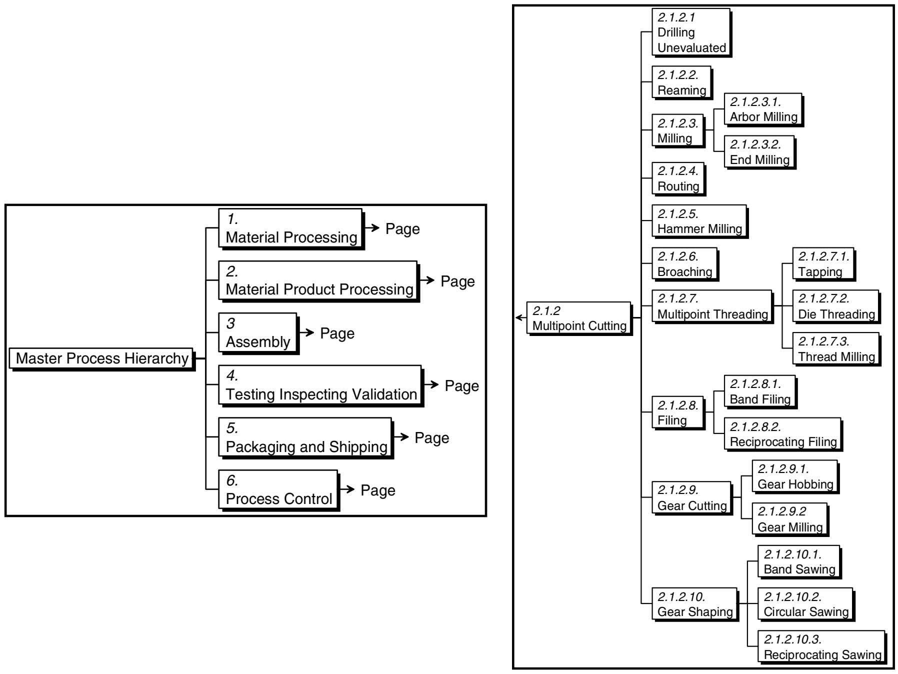

Fig. 9 Process taxonomy.

were found to have errors. Given the billions of spreadsheets in use, this leaves the worlds of business and finance horribly vulnerable to programming mistakes. These studies show that the chances of any given spreadsheet cell containing an error are somewhere between 0.3 and 3%, so that a spreadsheet of only 100 cells has about a 30% chance of having one error or more.

IX. Software Tool Selection

The challenge facing the team was to select a software environment that is as easy to use and as flexible as a spreadsheet but which avoids all the cited pitfalls of spreadsheet based systems.

An exhaustive tool selection exercise was undertaken and this resulted in a detailed evaluation of the DecisionPro suite of tools produced by Vanguard Software Corporation [13]. DecisionPro, unlike commercial costing tools, is a generic modeling tool that was not overtly designed for engineering cost analysis.

The attraction of DecisionPro lies primarily in its hierarchical structure. This structure forces 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. An example DecisionPro model is shown in Fig. 7

Trials of this software were undertaken which established

1) Ease of use.
2) Powerful stochastic and analytical capabilities.
3) Ease of deployment through standard Web browsers.
4) Neutral, text based storage of models which facilitates integration and "future proofing."

Nevertheless a number of additional enhancements were identified to meet the needs of the DATUM project. These were prototyped as part of the DATUM research activities. A particularly important enhancement concerned the use of the sophisticated library function which would provide an object-oriented capability to allow classes and instances to be defined.

X. Object-Oriented Cost Models

The advantages of an object-oriented approach for representing systems has long been recognized. The particular advantages in the context of the DATUM project are

1) Reuse of data, equations and logic.
2) Simplified maintenance.
3) Consistency of model structure and standards.

The DATUM team undertook some initial prototype work whereby libraries of materials, processes and features were created and could be instantiated within a cost model. The goal was to allow a library of cost objects to be defined which

1) Have been validated and tested.
2) Can easily be instantiated within a cost model.
3) Can easily be created without the need for specialist software skills.
4) Have controlled access.

An example of this work is shown in Fig. 8 based on a hypothetical HP turbine disc. Various user interaction metaphors were experimented with and agreed Object functionality is now being built into a set of DecisionPro library models by the vendors.

The cost objects are stored in a series of hierarchical library files which are based on the IMTI taxonomy of manufacturing[¶] [14]. The structure for the process library, for example, is shown in Fig. 9.

XI. System Architecture

The architecture for the DATUM tool is illustrated in Fig. 10. This shows the DecisionPro tool being used in a relatively unstructured manner to capture knowledge. This knowledge is then tested, validated and deconstructed into a series of library objects which are stored in a controlled hierarchical file structure. All reference data is stored outside each object in the Enterprise relational database.

The design users are able to access this cost object hierarchy either directly through a standard Web browser or via an interface to a CAD tool. For design optimization a scripting environment is used to drive a geometry tool, performance analysis tools, and the relevant cost objects. This is described in more detail later in the paper.

XII. Structure of Models

A standardized model structure has been adopted so that a uniform approach is maintained throughout the object library. This structure (illustrated in Fig. 11) facilitates integration and automation.

The structure embraces a number of key principles:

1) All expressions within the cost model should be defined exclusively in terms of the product definition. This ensures that any changes to the product definition (design) will be reflected in the cost model.

2) The model differentiates between resources and costs. The model is primarily concerned with calculating the resources required

[¶]Electronic address: http://www.IMTI21.org/ [cited March 2004].

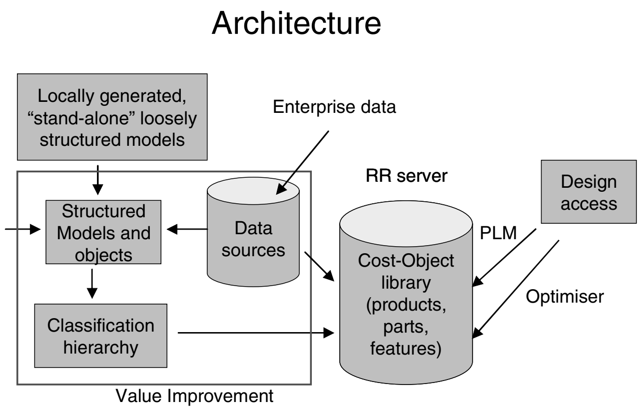

Fig. 10 Illustration of system architecture.

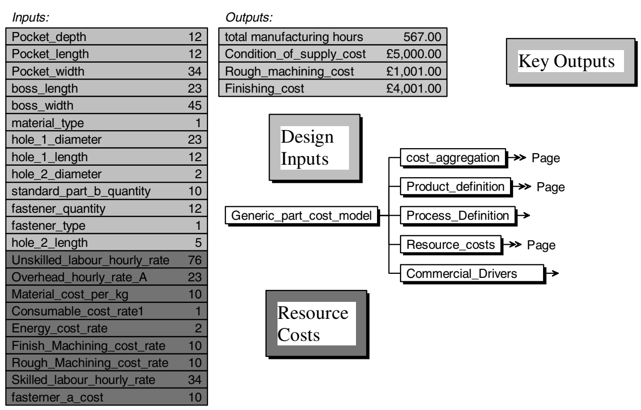

Fig. 11 Detail part cost model structure.

to realize a product definition. The cost of each resource is held explicitly as a separate structure to partition the effect of fluctuations in resource prices.

3) All parameter values are entered in relevant engineering units as DecisionPro is able to undertake unit conversion. So, for example, if a parameter expressed in meters per second is multiplied by a parameter expressed in Newtons of force DecisionPro will convert the unit to power expressed as Watts. Trials have shown that this is extremely useful as it flags up inconsistent units and potential errors in the logic of the cost model.

4) All base data should be held as SQL statements referencing data sources held outside the cost model. This facilitates maintenance of information.

The structure illustrated in Fig. 11 also shows that nodes within the cost tree can be declared as either input or output nodes. The significance of this is that it allows any of the variables that the designer may want to manipulate to be shown on the same sheet as the root node thus permitting easy navigation. Similarly key output metrics can be shown on the same sheet.

XIII. Using DATUM Cost Models in Design Optimization

Design optimization in the aerospace community has generally focused on weight, aerodynamics, structural performance, or all three [15]. Cost of manufacture has rarely been used in optimization as it is difficult to model cost in terms of the design variables. The inaccuracy of cost predictions in the early design phase have been a major reason for not using cost alongside hi-fidelity finite element (FE) and CFD tools to optimize design geometry.

However, the object-oriented models developed in DATUM add another dimension to the design optimization process by unearthing critical trade-offs to be made between high performance and high cost. Preliminary work in this area was carried out on a rear mounting link from a Rolls–Royce civil aircraft engine [16]. A scripting environment was set up using a parametric CAD model of the mounting link, an FE solver, a structured cost model developed in DATUM for the component. An optimizer was then used to search for the geometry which costs the least while satisfying the structural constraints. The process model is shown in Fig. 12 below.

This process is repeated for a certain number of iterations until optimum values are obtained for all design variables. Figure 13 shows the results of an optimization problem formulated as follows:

$$\text{Minimize cost,}$$
$$\text{subject to } 120 \le r \le 1200, \qquad 10 \le t \le 50, \qquad r, t \epsilon \mathrm{R} \tag{1}$$
$$\text{and Von Mises stress} \le 200 \text{ Mpa}$$

r, t are geometry parameters being optimized from the CAD model.

Figure 13 depicts the design space searched by the optimizer. Both infeasible and nonoptimal candidate designs are evaluated before converging on the minimum cost design within the constraints. The optimizer returns the same combination of output values for cost and the design variables successively, if they cannot be improved any further. This study emphasizes the need for a more structured approach towards cost estimation. It can be seen from the above results that cost influences can change the optimal design solution. A

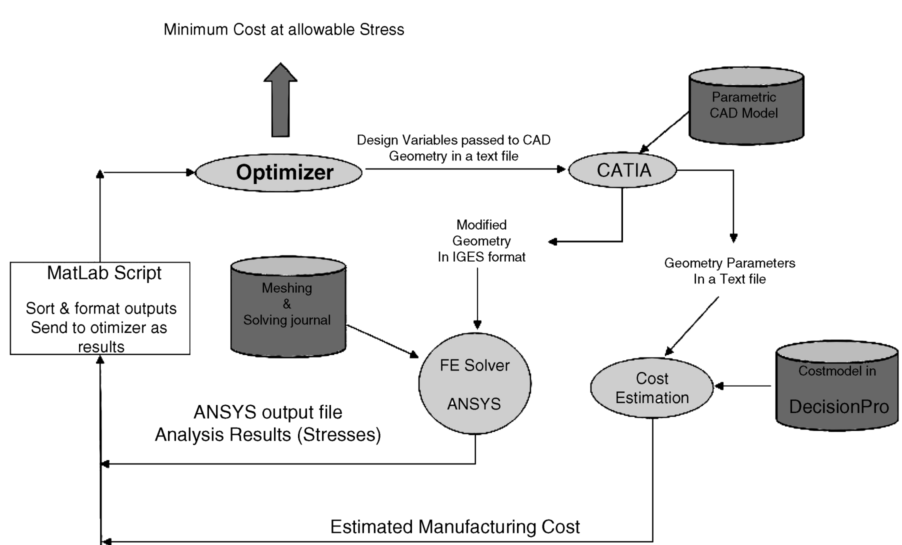

Fig. 12 The cost optimization process model.

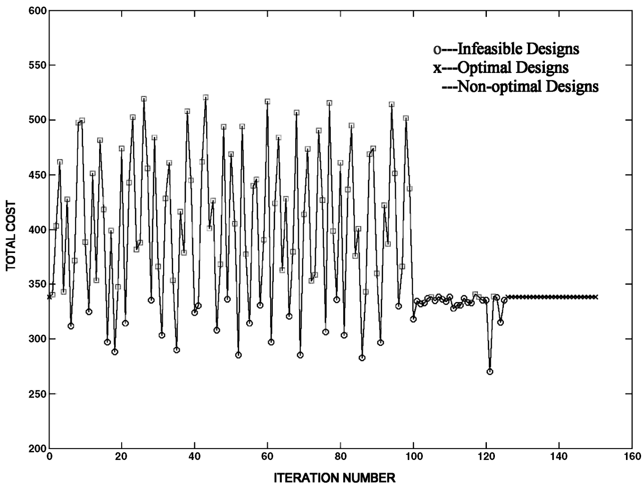

Fig. 13 Optimization output.

low stress design may not always be a low-cost design and hence prohibitive to manufacture. Simplification of a part may increase the structural performance and reduce processing cost but increase material cost and weight. Reduction in weight may not reduce material costs but increase processing costs and scrap rate. Clearly the search for an economically feasible design depends on accurately modeling complex relationships between these mutually interacting phenomena and the various design parameters.

XIV. Conclusions and Future Work

A number of important conclusions have been drawn from this work.

First, the need for a multidisciplinary approach to the development and dissemination of cost models is essential. It is important to develop cost models in partnership with designers in order to anticipate the scope of design exploration needed and hence determine the flexibility of model required. It is vital that a designated part of the organization take responsibility for developing, publishing, and maintaining cost knowledge. 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. It is clear that in the context of increasing design automation this role needs to change. In the future the estimating function needs to be concerned with providing cost tools rather than specific estimates to the design community.

The initial cost of a software tool is dwarfed by the investment an organization makes in populating it with data. It is important to try to protect this investment by storing the data in a neutral text or XML (eXtensible Markup Language) format. It is surprising how many commercial costing tools fail to provide this basic capability.

To be effective, the DATUM tools need to be adopted widely and therefore the cost per software license needs to be relatively competitive compared with the benchmark alternative of spreadsheet tools. Costing tools with license costs measured in thousands of dollars are unlikely to be widely deployed even within "blue chip" organizations such as Rolls–Royce.

For internal deployment of cost models a Web capability using standard browsers is important. Nonstandard browsers or plug-ins often require complex and lengthy testing and approval within large organizations before acceptance. The alternative of limited licenses deployed throughout the organization is not desirable for reasons of cost and narrow deployment.

The collection of cost knowledge and creation of cost objects represents a major bottleneck. One of the critical factors concerning the speed with which this happens is the complexity of software required to code the knowledge. If specialist knowledge or deep software skills are required this will have a severe impact on the rate at which cost knowledge is formalized and deployed. The use of Lisp, Java, or other similar programming languages requires a significant level of training. Competence in such languages typically takes years of experience. The DecisionPro tool requires levels of computing skill commensurate with spreadsheet authoring and hence an engineer can reach an adequate level of competence in weeks given a small amount of training.

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References

[1] Norris, G., "Power-Shift," *Flight International*, 5 Oct. 2004, pp. 60–63.
[2] Marx, W., Mavris, D., and Schrage, D., "A Hierarchical Aircraft Life Cycle Cost Analysis Model," *AIAA Aircraft Engineering, Technology, and Operations Congress*, 1995.
[3] Craven W., and Cate, J., *The Army Air Forces in World War II: Men and Planes*, Vol. VI, 1st ed., University of Chicago Press, Chicago, 1955, pp. 311–312.
[4] Khalilzad, Z., and Shapiro, J., *Strategic Appraisal: United States Air and Space Power in the 21st Century*, Rand Corp., Santa Monica, CA, 2002.
[5] Younossi, O., Arena, M., and Moore, R., *Military Jet Engine Acquisition Technology Basics and Cost-Estimating Methodology*, Rand Corporation, Santa Monica, CA, 2002.
[6] Price H, Price Systems, L.L.C., 17000 Commerce Parkway, Suite A, Mount Laurel, NJ, 08054.
[7] Cost Advantage, Cognition, 209 Burlington Road, Bedford, MA 01730.
[8] Thien, T., "Lamina-Based Feature Recognition and Applications in Manufacturing," Ph.D. Thesis, Department of Mechanical and Chemical Engineering, Heriot–Watt University, Edinburgh, U.K., July 2000.
[9] Lee, Kwang Hoon, McMahon, C., and Lee, Kwan H., "Design of a Feature-Based Multi-Viewpoint Design Automation System," *International Journal of CAD/CAM*, Vol. 3, No. 2, 2003, pp. 67–75.
[10] Nurminen, K., and Karonen, O., "What Makes Expert Systems Survive over 10 Years: Empirical Evaluation of Several Engineering Applications," *Expert Systems with Applications*, Elsevier, New York, 2003, Vol, 24, pp. 199–211.
[11] Paine, J., "Spreadsheet Structure Discovery with Logic Programming," *Proceedings of EuSpRIG 2003*, pp. 16–17.
[12] Panko, R. P., "Spreadsheet Errors: What We Know, What We Think We Can Do," *Proceedings of EuSpRIG 2000*, pp. 7–17.
[13] DecisionPro Developer, Vanguard Software Corp., 1100 Crescent Green, Cary, NC 27511.
[14] IMTI: The Integrated Manufacturing Technology Initiative, P.O. Box 5296, Oak Ridge, TN 37830.
[15] Sobieszczanski-Sobieski, J., and Haftka, R. T., "Multidisciplinary Aerospace Design Optimization: Survey of Recent Developments," *34th AIAA Aerospace Sciences Meeting and Exhibit*, AIAA Paper 96-0711, 1996.
[16] Rao, A. R., Keane, A. J., and Scanlan, J. P., "A Cost Based Methodology for Design Optimization," *ASME 2005 International Design Engineering Technical Conference* (to be published).