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A FRAMEWORK FOR CAPTURING DESIGN ANALYSIS KNOWLEDGE FOR REUSE USING DESIGN PROCESS MODELS

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1. Introduction

The design process can be viewed as a series of decision-making processes that starts with an abstract, often vague and uncertain description of the new product to be developed and leads onto specification of the final product attributes. Design analysis is conducted to aid these decision-making processes using various forms of computational and mathematical models. Hence, the output from the design process is a representation of the designed artefact as well as a collection of evaluations of the artefact supported by a variety of models [Ohsuga, 1989]. A key focus is on the design analysis conducted in the embodiment stage of the design process where a range of simulation tools and techniques such as Finite Element Analysis (FEA) are applied. At this stage design concepts are embodied and transformed into detailed designs and key decisions regarding the form and attributes of the product need to be made. During this work, reduction of uncertainty and imprecision in the representations of the data, model or process is crucial to enable effectiveness in decision-making. To achieve this, information has to be drawn from various stages of the product development process such as feasibility study, production planning, manufacturing process capability and testing.

In adaptive and variant design the application of product domain-specific knowledge and experience is most pertinent. In such design, the product attributes and the appropriate design methods and strategies are well known to the design team, and the notions of conceptually static design, product family, modular design platform and parametric design are applicable concepts. Even in this mode of design, product evaluation has traditionally relied heavily on tests and experiments that are expensive and time-consuming in modern lean product development processes. For this reason, design practice in industry is characterised by the move towards simulation-based evaluation using modular analysis tools. The trend is especially evident in the automotive and aerospace industry. However, an important prerequisite to the success of this ‘virtual’ engineering is the need to rigorously understand and manage risks and uncertainties in the embodiment and evaluation processes. In light of this, there is a need to capture the steps of design analysis processes and reusing knowledge from past design cases to enhance decision-making performance and minimise uncertainty and risk.

This paper presents a framework for capturing knowledge and understanding of uncertainty to support the reuse of design information and knowledge in the context of adaptive and variant design. It is hypothesised that a process modelling approach can be used for recording instances of the design analyses in a structured and consistent manner such that information and knowledge can later be traced, revisited and reused. The framework developed in this paper will provide a basis for the development of strategies and tools for capturing design analysis knowledge towards and ultimately to provide a complete “extended product model” to support through-life knowledge management. The extended product model will incorporate information about the product, process and rationale.

2. Review of related methods

Design analysis processes typically involve information that is uncertain and activities are characteristically *ad hoc*, intuitive, iterative and disparate. For example, a simple design analysis may be characterised by deterministic data, closed-form equations with a discrete performance parameter whereas a complex design analysis process may be characterised by probabilistic data, numerically modelled with a field performance parameter. Increasingly, design analyses are becoming more complex as customers demand products of high quality and reliability, delivered rapidly and cost efficiently. Probabilistic methods are applied in computational models to allow for the effect of stochastic uncertainty on design performance to be fully investigated [Riha, 2002]. Probabilistic analysis offers the opportunities for more holistic understanding of product performance thus improving design confidence. However, the availability and management of information to support such resource-intensive analyses has proven significant challenges to engineering companies to date.

In order to support reuse, there is a need to dictate structure and formalism in modelling of these complex analysis processes such that information sources, quality and uncertainty can be traced. A process model can be used as a basis for a structured representation and organization of information and knowledge over a range of design analyses. Process modelling is typically used to describe interrelated or sequential activities in a process to understand systems operation and to facilitate the visualisation of information flow in the systems. It allows for the decomposition of complex processes into suitable levels of abstraction, and the separation of information and activity provides a suitable basis for the accumulation of knowledge about the uncertainty and imprecision associated with each.

A review of process modelling approaches that are typically available to designers for modelling design processes, including Data Flow Diagram (DFD), Structured Systems Analysis and Design Method (SSADM), Integrated Definition (IDEF), Petri nets, Unified Modelling Language (UML), Design Structure Matrix (DSM) and Signposting has been reported elsewhere [Goh, 2003]. Developments in process representations for Business Process Reengineering (BPR), Work Flow Management (WFM) and manufacturing process planning have focused on information representation that supports sharing and exchange across a broader range of processes in the product lifecycles.

Process models are used in various applications for modelling information and activity dependencies and flows. For instance, in modelling the generic engineering design process, [Vajna, 2001] introduced definitions and concepts for a knowledge-based engineering process model, and suggested some 50 common *process elements* (termed activities in this paper). The application emphasis in this paper is in design analysis. This requires nomenclatures relevant to a range of analysis processes, including applications where uncertainty prevails. It was concluded in the previous study that a single process modelling language that contains sufficiently rich nomenclatures for representing the design analysis process is not yet available [Goh, 2003]. A relevant work in the representation of analysis information is the Engineering Analysis Core Model (EACM) [Leal, 1999]. The EACM defines relationships between information about the process and about the product, including analysis and test, thereby integrating the functions of Product Data Management (PDM) and WFM. Such development in standard terminology, definitions and classification towards providing an ontology will contribute to enhancing the capability for process modelling of design analysis.

3. Framework development

This section proposes a foundational framework for capturing design analysis knowledge using a process modelling approach. The framework was developed based on the authors' past experience in simulation-based design, uncertainty management, process modelling and knowledge management. Case studies were modelled using the framework without reference to any specific modelling language. The motivation for this exercise is to test the ideas and to emphasize issues associated with modelling of design analysis processes. The practicalities of the hypothesis are then reflected.

3.1 Definitions

For clarity, several terms are now defined in the context of this paper.

- An **activity** is an act that consumes some inputs to produce some outputs. A **process** consists of inter-related activities performed to achieve specific goals. A process is composed of other activities, and may itself be an activity within a larger process [Arkin, 2002].

- **Transfer functions** are the mathematical representation of a relationship over a defined range of conditions that relate the input variables to the output variables with the purpose of evaluating the characteristics of interest of a physical system.
- **Design parameters** are key input variables in the physical domain that characterise a design. The **design space** is a feasible region for realisation of several product variants through parameterisations of the design parameters (as in parametric design).
- **Performance parameters** are the output variables from transfer functions that are determined from the mapping of a set of design parameters. The **performance space** is the region where performance parameters are described to give a meaningful exploration of the analysis results. The performance parameters can be described as a discrete variable, a function of another variable or a field variable.
- **Evidence** concerns data collected relating to elements, products or systems of identical or similar attributes to a design case. For example, evidence regarding the actual performance of the modelled artefact can be gathered from product behaviour in service, failure data, prototype tests and correlation with similar products.

3.2 Activity levels of abstraction

Often in process modelling the level of modelling abstraction needs to be determined depending on the scope and details required and the viewpoints being represented. Some modelling languages allow for multiple levels of abstraction to resolve this issue, using a hierarchical structure (e.g. IDEF0, UML). The level of abstraction is a trade-off between simplicity and usefulness – too broad results in insufficient detail and too detailed requires extensive resources in building and storing the model. For the purpose of this paper, two levels of abstraction were adopted for describing the analysis processes. The low level of abstraction is a set of activities that are characterised by transfer functions. They can be derived from physics and science, including analytical equations and numerical models.

High level abstraction – providing a coarse view of the analysis process – encompasses activities that are not described by the transfer functions. This abstraction shows the overall framework to be populated in a domain, including the key activities and principal information flow. The activities may include pre- and post-processing such as statistical distribution fitting and heuristic functions and rules, compare-evaluate-verify-assess etc. A potential source for defining a set of activities in design analysis is the Process Handbook published by the Massasuchettes Institute of Technology (MIT) [Malone, 2003]. The handbook consists of knowledge repositories about business and software processes organised in classification systems, available at http://process.mit.edu/.

Design analysis processes that are typically carried out in the embodiment stage are listed in Table 1. These processes typically consist of a series of common high-level activities and share characteristic activity patterns. For instance, in validation processes, typical activities involved are "assess performance", "compare with evidence", "evaluate against acceptance criterion", and "decide to accept or reject the model". In these processes, a number of performance indicators are established against some success criteria for the product where performance is assessed using these indicators. They may be either economical or technical parameters. For example, an economical performance indicator is the sales volume exceeding the break-even thresholds; a technical performance indicator for the same product is the number of hours of service before the first failure is encountered. The objectives are to qualify the performance of a design against the specified values of the performance indicators such as function, safety, cost, reliability and quality.

It is proposed that standard process templates such as that illustrated in Figure 1 can be developed for each of these processes, while allowing some customisable properties for variation between process instances. It should be noted that although the IDEF0 notation [IDEF, 1993] is adopted to illustrate the discussion, it is not suggested that the same language be used for describing the extended product model. Contextual information about the activity such as a brief summary, execution time, analyst, constraints and their rationale, resources and how they are used in the activity should also be recorded. Similarly, additional information about the data such as number of specimens, test condition and machine identification should be documented. This metadata can be stored and used in organising and retrieving process instances for reuse purposes.

Table 1. Proposed classification of design analysis processes and objectives

Design analysis process	Design analysis objective	Description
Sensitivity Analysis	Pareto ranking of variables	To determine the percentage contribution of each design parameter to the variation in performance parameters
Performance evaluation	Performance parameters	To determine the performance parameters from the mapping of a set of design parameters
Reliability analysis	Probability of success or failure	To determine the probability of failure or reliability of components and systems
Optimisation	Recommended variables	To determine optimum design parameters that meet some objectives, e.g. minimum cost, weight or probability of failure
Validation	Evaluation against acceptance criteria	To determine the validity of modelling results
Error evaluation	Error functions	To determine errors between estimated and actual performance

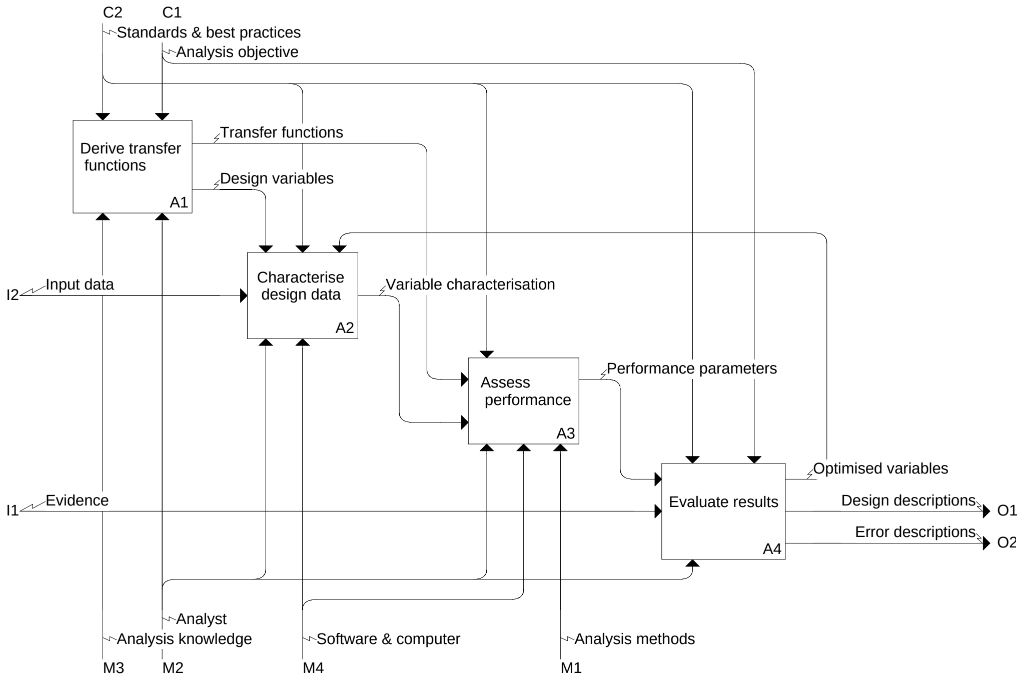

Figure 1. A high level template-based process model

For the low-level abstraction, the activities are transfer functions that consume input data to produce output data. In broad terms the input data comprise the “design parameters” and the output data comprise the “performance parameters” with transfer functions acting as the transformation relationships between them. From observation, the constructs of processes at this level of abstraction are much more bespoke, modular and *ad hoc* compared to the high-level processes. We have adopted notation similar to the Design Roadmap [Park, 1999], without commitment, to illustrate in Figure 2 an example of an analysis process described at this level of granularity. For our purpose, the transfer functions may be modelled online or offline depending on the existing level of tool integration. This means the tools used for solving transfer functions A1 – “Buckling Analysis Using Donnell Type Equations” and A4 – “Nonlinear Static FEA” do not need to be compatible, but the data format for D4

– “Buckling Load of Perfect Shell” and D5 – “Buckling Load of Imperfect Shell” must be interchangeable after some processing. Sharing of some process entities may occur in a multi-objective analysis scenario where transfer functions and data may be used repeatedly in various stages. As evident in the same diagram, both shell dimension and material property data appear as input data to transfer functions A1 and A4. The modelling approach adopted at this level of abstraction is to allow for processes to be modularly built and to incorporate alternative transfer functions to assess their utility. The purpose of the low-level abstraction is to model the analysis data and transfer functions in greater detail, and to associate uncertainty with each of the process entities to allow aggregation and accumulation of errors as discussed next.

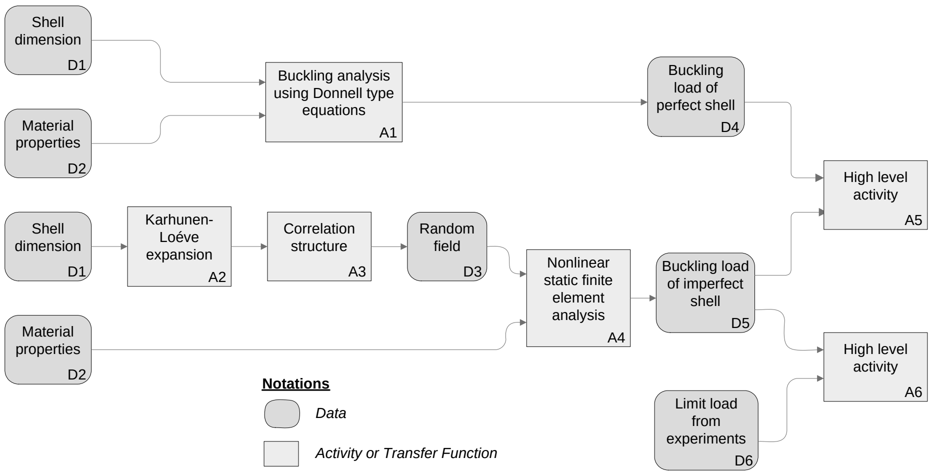

Figure 2. A low level modular bespoke process model [Goh, 2005]

3.3 Incorporating uncertainty modelling in design analyses

Conventionally, success in design under uncertainty is ensured by over-designing through conservative design formulae using ‘safety factors’. In design analyses, uncertainty may be associated either with the representations of the data or the transformation activities. In mechanical engineering, the classes of design parameters typically described in a transfer function are physical or property data describing the geometry, material or load. For the representation of numerical information, a number of properties need to be recorded along with the original data. The properties include dependency, correlation and behaviour such as nonlinearity, discontinuity, validity region etc. As noted previously, description of uncertainty in these parameters can vary from deterministic values to probabilistic distribution functions. For instance, dimensional parameters usually assume nominal or mean values in Computer-Aided Design (CAD) models. Then, tolerances are specified on the dimensions considering assembly criteria, manufacturing processes and economy. Process capability charts or databases can be consulted for information on stochastic uncertainty.

Uncertainty in the transfer functions can be caused by deficiencies in knowledge of the physical behaviour, e.g. stress analysis often requires simplifying assumptions on the material property and behaviour, as well as deliberate simplifications for economy and convenience. For instance, an approximation model (e.g. response surface) introduces errors by simplifying the actual functions with low-order polynomials. In solving the transfer functions, numerical approximation used in FEA introduces discretisation errors. In general, the accuracy of models is known to decrease when the complexity in the physical problems rises. The complexity in modelling may be caused *inter alia* by implicity, non-linearity, discontinuity, time-dependency in the parameters and relationships.

The presence of uncertainty in the evaluation of performance will undoubtedly affect the quality and accuracy of decision-making. In advanced analytical processes, much more complete information about the data and transfer functions is required than in deterministic evaluation drawing information from various stages of the product development process including experience with past products. A process model approach allows for uncertainty to be explicitly associated with each of the interdependent information entities and activities, for example, by maintaining links with the information source. This association can then be used to trace and manage uncertainty, errors and deficiencies in a complex analytical process.

Typically in design analysis, evidence is collected to validate the predicted performance of a product. The source of information for evidence may come from prototype testing, benchmarking, past experience etc. and may be subjective and qualitative. When objective and quantitative evidence is available, error functions can be derived representing the discrepancy between predicted and actual performance [Goh, 2005]. The characterisation of evidence is a subject of ongoing research, where its values in terms of provenance and relevance are being considered. Referring to Figure 2 as an example, the comparison between D5 – "Buckling Load of Imperfect Shell" and D6 – "Limit Load from Experiments" yields an error representation of the discrepancy between the predicted and experimentally measured limit load of thin shell in buckling (refer to the first case study in Table 2). If uncertainty in both the shell dimension and material properties can be characterised, the uncertainty due to the transfer function (nonlinear static FEA) can be estimated. This way, the process model can aid the visualisation of information dependencies in complex processes.

4. Case studies

Twenty cases from a wide range of design analysis applications of varying complexities were studied to test and validate the framework [Goh, 2005]. The analysis processes were modelled as closely as possible to the descriptions given in the original literature. Besides observing the common content of the case studies, some distinguishing features are also highlighted to facilitate detail specification of the extended product model. For conciseness, only six of these cases are summarised in Table 2. A process model for the buckling of imperfect shell case study is shown in Figure 2.

5. Discussions

A framework for capturing and handling design analysis knowledge has been developed based on the consolidation of our understanding of typical design analyses, previous knowledge in disparate disciplines and a review of process modelling approaches. The proposed framework requires changes in the way information and analytical processes are recorded. Currently, they are recorded in reports summarising aspects of the analysis with references to key sources of information. Such format does not allow for automatic trace of information dependencies and dynamic updating when new information becomes available. Often, in a complex multi-objective analysis process, the data and transfer functions may be shared. In process models, relationships can be defined such that data and model dependencies can be traced easily.

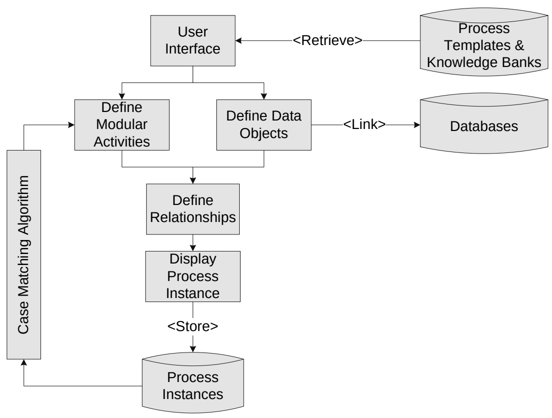

Figure 3. Software architecture of the knowledge capture framework

In order to support knowledge utilisation and reuse, the engineering community needs to continue its effort in defining standards, neutral formats and ontologies. The proposed framework requires an ontology to be defined for the high-level activities, and process templates written in a suitable language. Data items should be stored in computer-interpretable formats to allow for automatic processing. Then, for example, a statistical module can be invoked on this data to calculate the mean and standard deviation of the set of data. Knowledge banks can be constructed to store theory, best practices, standards and design rules that can be updated dynamically. Figure 3 shows a potential software architecture of the framework for capturing design analysis knowledge. The user interface can be used to collect contextual knowledge about processes. The information provided at the high-level abstraction can be assessed against economy, suitability and utility metrics thus providing best-practice advice to novice engineers regarding optimum analysis routes, methods and models.

Table 2. Summary of analysis processes reported in case studies

Case study	Design analysis process	Design analysis objective	Observations
1. Buckling of imperfect thin shell	Performance evaluation	Statistical distribution of the limit load	• Activities that are typically performed in numerical analysis (mesh size, adaptive meshing, boundary conditions etc.) • Validation using solutions from simplified problem • Small sample size for experiments used in validation
	Validation	Percentage error between estimated limit load and analytical solution	
2. Thermal performance of heat sinks	Validation	Percentage error between estimated thermal resistance and another design and experiments	• Multi-objectives analysis requiring data and activity sharing • Performance space characterised by a function of another variable
	Optimisation	Geometrical variables that maximise thermal resistance	
3. Fracture of steering knuckle	Validation	Percentage error between estimated and experimental rupture velocities	• Multi-objectives analysis with activity sharing (transfer function used in various instances) • Field performance space • Evidence of model performance in another application
	Optimisation	Shape that maximises critical energy and minimises weight	
4. Sheet metal flanging	Validation	Acceptable error between estimated springback angle and experiments	• Multiple validation cases in design space giving more confidence • Alternative routes allowing for use of alternative models
5. Life of roller bearing	Performance evaluation	Statistical distribution of bearing life	• Evidence inferred from early life data • Data sharing between processes of different abstraction
	Reliability analysis	Probability of failure at corresponding life	
6. Shrink-fit failure in torsion	Sensitivity analysis	Pareto chart ranking for variance contribution	• Evidence available to suggest confidence in part of the process and overall process • Combination of recorded instances to suggest best route/alternative models

6. Conclusions

In order to capitalise on the knowledge economy, companies need to be able to record their knowledge and experience such that they can revisit, update and reuse information and knowledge. Many industries today are moving from supplying products to owning, maintaining and upgrading them on behalf of their customers over many decades. This move to a product-service business model means there are greater opportunities to capture and reuse information and knowledge in the design process, because the designing company is also in control of the through-life service element. To justify the use of advanced resource-intensive simulation tools and methods to deliver improved performance and reliability, systems and mechanisms to support information requirements need to be in place. This paper has reported on a conceptual framework for capturing design analysis knowledge towards providing such information and knowledge-support systems for timely access to information to aid effective decision-making in virtual engineering. The framework allows for representing understanding of the state of data, information and analytical relationships in engineering domains as well as the uncertainty and imprecision associated with them. It is not the intention of this paper to deliver a tool or a modelling language but to discuss a framework towards defining a complete extended product model to support through-life knowledge management. This approach presents a new opportunity to systematically and automatically record for error in each analysis instance that might be used to correct simulation predictions. It is speculated the framework might allow for data mining or Case-Based Reasoning (CBR) to improve confidence in the next product variant.

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