

STRATEGIES TO ENHANCE DESIGN ANALYSIS REUSE: A CASE STUDY IN UNCERTAINTY

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ABSTRACT

The uncertainties prevailing in design evaluation activities often have a great impact on the success of the end product performance. Because of these uncertainties, the capabilities of analytical and simulation tools are not yet adequate to allow for the wholesale replacement of physical testing. At present, theories and techniques for characterising uncertainty are not widely used mainly due to inefficient data and information management. Despite the maturity of information technology, engineering companies still fail to exploit the data and information collected throughout the product lifecycle mainly because of the limited structure in the information representation and the lack of reuse strategies in place. This paper describes a knowledge-based approach to capture and represent information that could facilitate the effective management of uncertainty in design evaluations. A case study and a number of scenarios are presented to illustrate the framework. The framework for capturing the design evaluation process knowledge is envisaged to facilitate reuse, improved uncertainty management and accumulation of engineering knowledge and understanding. The knowledge and insights can be used to evaluate confidence and risks in modelling capability at an earlier stage in the design process, to support selection of design tools and techniques and to optimise resource allocation in simulation-based design.

Keywords: Uncertainty, design analysis, reuse, case study, parametric design

1 INTRODUCTION

The uncertainties prevailing in design evaluation activities often have a great impact on the success of the performance of the end product. Because of these uncertainties, the capabilities of analytical and simulation tools are not yet adequate to allow for the wholesale replacement of physical testing. Traditionally, risk management employs a proactive methodological process to identify, assess, plan and mitigate risks caused by uncertainties. In design, conservative safety factors are applied in performance calculations to accommodate for the unknowns in model and data representation. Probabilistic design approaches facilitate improved understanding of uncertainty through the incorporation of stochastic data. Recent research developments focus on methods for characterising imprecise uncertainty using subjective judgement [1]. However, although such methods may be plausible in some situations (e.g. when data collection is not feasible), ultimate confidence in design evaluation can only be achieved by accounting for uncertainty in an objective manner.

Due to incomplete understanding and continuously evolving knowledge, design evaluation processes are characteristically iterative, *ad hoc* and usually emergent with each step aiming to increment the knowledge state. As a result, the data used and generated during the design evaluation process is always changing state (uncertainty, confidence etc.) as it is continuously being validated. In simulation-based design, critical decisions are often based on predictive models supported by complex and sophisticated computer-aided tools and techniques. A major concern in such complex simulation processes is the lack of confidence in information that the simulation is dependent upon, for instance, due to lack of knowledge or assumptions made during the simulation processes.

At present, documentation of the outcome of design evaluations is often anecdotal, greatly simplified and retrospective. Such practice has contributed to the significant lack of structure and consistency and omission of detail leading to the inability to reuse the models and data, potentially causing errors and inefficiencies in design. As a result, knowledge becomes implicit and the effectiveness of design

evaluations relies greatly on individuals' competency and experience. Despite technological capability in continually and automatically collecting large volumes of data, engineering companies still fail to exploit the data and information collected mainly because of the limited structure in the information representation and organisation as well as the lack of reuse strategies in place. Poor data sharing in current documentation practice means that more advanced and data-intensive approaches like probabilistic methods have not been widely adopted in mainstream engineering. This is in spite of the maturity of tools and techniques for many years. As a result, complex simulation processes generally still assume deterministic and conservative values, enormously reducing the realism and opportunities in simulation processes [2]. Therefore, improvement in uncertainty characterisation has to be supported by documentation practice that increases traceability and sharing of objective data across design iterations and variants.

This paper describes strategies to enhance design analysis reuse based on a process modelling framework to capture and structure information that could facilitate the effective management of uncertainty in design analyses. The main hypothesis proposed in this paper is that data and information related to the design evaluations for predicting performance of engineering artefacts can be managed to improve understanding of uncertainty and to exploit the representation of the information associated with these for reuse in future design activities. The framework proposed previously will be reviewed and discussed in the context of a case study and a number of scenarios applied to the case study.

2 MANAGING UNCERTAINTY IN DESIGN EVALUATIONS

2.1 Background and related work

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 for modelling design processes has been reported elsewhere [3]. Recent developments in process representations for Business Process Management (BPM) and Work Flow Management (WFM) have focused on information representation that supports sharing and exchange across a broader range of processes in the product lifecycles.

In this respect, developments based on the eXtensible Mark-up Language (XML) are complementary [4]. For example, MathML, Mathcad XML, Finite Element Modelling Markup Language (femML), Predictive Model Markup Language (PMML) and UnitsML are useful technology for interoperability enhancement in engineering applications. The availability of such interoperable technologies avoids the processing of information in proprietary formats, thus enabling each element in the process model to be plugged-and-played in a neutral environment.

In order to adopt the process modelling approach for the documentation of the design evaluation process, suitable notations and nomenclatures need to be derived. In addition, a number of research developments in terms of taxonomy and ontology have been observed. One of the first developments of taxonomy in mechanical design problems was proposed in 1988 [5]. Recent work in this subject includes, for example, an ontology for generic engineering design activities and a product development process ontology [6, 7]. Developments include the identification of constructs such as design activities and their classes, resources and information/knowledge etc. as well as defining the relationships between these constructs. In order to reduce efforts in applying these ontology and taxonomy, methods for automatically capturing of design activities in an electronic environment may be useful. For example, an automated mechanism for inferring meaningful design procedure sequences by capturing events in the Computer-Aided Design (CAD) environment has been developed [8]. A tool for capturing information about the user's interactions with computer has been demonstrated to provide activity profiles about the tasks being carried out [9].

More specifically, a taxonomy for ignorance in simulation processes that includes error and uncertainty has also been developed [10]. Such a classification may be a useful basis for developing a schema for documenting design evaluations to indicate the maturity of the information contained therein. Additionally, a method for dealing with uncertain information such as fusion rules has been demonstrated and is promising for automatic processing of uncertain information [11].

2.2 Capturing design evaluation knowledge

We have proposed a framework for structured and formal documentation of design evaluation activities based on a process modelling approach. The framework development and its substantiation has been established in greater depth elsewhere [12]. The approach assumes that a modular process model for the design evaluation activities can be identified and represented at different levels of granularity. Activities are linked to one another (through formalised relationships) to form a network of activities that are performed to satisfy specific objectives, along with information flows and interdependencies. The idea is most suited to recording transactional processes, where clear objectives can be identified and the activities required to achieve them are known. An example of a transactional process is the stress analysis of a crankshaft using a validated finite element model (FEM) to assess its performance against a material failure condition. In this analysis, data is typically drawn from various sources to describe the present understanding of the geometrical dimensions, material properties, load cases etc.

Discussion on the level of abstraction in this context has been reported in [12] where an *activity level* and *transfer function level* are introduced. An activity is defined as 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. The *transfer function level* representation includes a set of activities that are characterised by transfer functions. 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. They can be derived from physics and science, including analytical equations and numerical models. The *transfer function level* processes are bespoke, modular and *ad hoc*.

For the *activity level* process, it was argued that the transactional processes can be developed using a taxonomy of design evaluation activities and templates for them can be provided. The objectives in these processes are to evaluate the performance of a design against the specified values of the performance indicators such as function, safety, cost, reliability and quality. The *activity level* representation encompasses activities that are not described by the transfer functions. The activities may include pre- and post-processing such as statistical distribution fitting and heuristic functions and rules, compare-evaluate-verify-assess etc. A number of common design evaluation processes and their objectives are suggested:

- Sensitivity analysis – To determine the percentage contribution of each design parameter to the variation in performance parameters.
- Performance modelling – To determine the performance parameters from the mapping of a set of design parameters.
- Reliability analysis – To determine the probability of failure or reliability of components and systems.
- Verification and Validation – To determine modelling system meets specifications and fulfils its intended purpose.
- Error evaluation – To determine errors between estimated and actual performance.
- Optimisation – To determine optimum design parameters that meet some objectives, e.g. minimum cost, weight or probability of failure.

For our purpose, the process modelling notations and nomenclatures have been adapted for describing design evaluation activities, the information entities and relationships between them. This requires formalising extensions that are relevant to a range of analysis processes, including applications where uncertainty prevails in the data and model. The underlying premise in such transactional analytical processes is that they are guided by one or more objectives that can be characterised by performance parameters at the *transfer function level*. In related work [13], a classification has been presented based on three dimensions considered critical to making judgement about uncertainty in design analysis process: *performance parameter*, *evidence* and *design space*. Each of the dimensions is measured according to the quantity of data available to characterise them, where a classification of confidence levels has been derived (see confidence scale in Figure 2). The confidence scale allows us to interpret the level of precision associated with a design correlation that is consistent with uncertainty theories applied in the analysis. The *design space* is a discrete or continuous region where parametric variants can be realised through parameterisation of design variables. The more instances explored in the design space, the higher confidence we have in the capability and performance of our

analytical techniques. Based on the comparison between performance parameter and evidence, the error functions are obtained. The mathematical formulation of error functions has been studied previously [13] and included in Figure 1 (a) for reference. The method adopted separates the first and second moment of error, providing the normalised error functions for each component.

In this paper, the framework concepts will be demonstrated through a case study application with particular emphasis on the complex information interdependencies, iterative characteristics and aspects of uncertainty and decision-making based on the outcome of design evaluations. At this level, Table 1 summarises some meta information that are useful to capture about the data and transfer function in the framework. Those attributes present in the case study described in the following section are also indicated in the same table.

Table 1. Examples of meta information to be captured in the framework

| Data | Transfer Function |
|--|---|
| <p>Type</p> <ul style="list-style-type: none"> – Design parameter (controllable/uncontrollable as in Robust Design)* – Performance parameter* <p>Characteristics</p> <ul style="list-style-type: none"> – Discrete/continuous (scalar*, vector, field*) – Dependency (time, other variable) – Nonlinearity – Statistical correlation* <p>Uncertainty</p> <ul style="list-style-type: none"> – Absolute minimum/maximum – Interval/range – Fuzzy set – Probability distribution (normal, others)* <p>Error function</p> <ul style="list-style-type: none"> – First moment* – Second moment* <p>Source</p> <ul style="list-style-type: none"> – Test (test program, conditions, sample size)* – Validated data (Product Data Management) – Assumed data (published, approximated)* | <p>Type</p> <ul style="list-style-type: none"> – Closed-form* – Finite element* – Empirical model/response surface – Heuristics/rules – Neural network <p>Source</p> <ul style="list-style-type: none"> – Benchmark (e.g. NAFEMS) – Validated model – Standards & best practices – Knowledge/theory* <p>Constraint</p> <ul style="list-style-type: none"> – Assumptions* – Boundary & initial conditions <p>Resources</p> <ul style="list-style-type: none"> – Tools & techniques* – Software (spreadsheet, package)* – Person (name)* – Computer, calculator* – Time |

Note: Attributes marked with * are present for the case study described in later section.

3 CASE STUDY – FAILURE IN SHRINK-FIT UNDER TORSION

3.1 Introduction to shrink-fit design

A shrink-fit is a semi-permanent assembly method commonly used in industry to locate one or more components on a shaft or to transmit torque from the shaft. Usually, expansion of the external part by heating or reduction in size of the shaft by cooling is employed, the parts located and then the whole assembly returned to the room temperature. This establishes a pressure at the radial interface through interference in dimensions. The design of a shrink-fit often refers to the ISO Limits and Fits [14] that provides a selection of fit conditions to suit a range of engineering applications.

In order that shrink-fits are properly designed and produced to achieve the required functionality in a consistent manner, a number of considerations are important [15]:

- For the required fit condition and a given nominal dimension, optimum interference between the shaft and inner diameter of the hub and resultant radial pressure at the interface are determined by referencing standards and/or design guidelines [16].
- Very low dimensional variation or precise dimensional control through inspection of the component parts is required. For example in Six-Sigma methodology [17], the manufacturing process capability data is referred for estimating the dimensional variability of a shrink-fit design for the given manufacturing processes (usually by turning or grinding).
- Surface roughness values should range from 0.4 to 1.6µmRa to provide adequate frictional

adhesion between the shaft and hub bore.

- The working stresses and stress concentrations due to the shrink-fit pressure and additional stresses during operation must not exceed strength of the parts. Common failure modes such as material failure and fretting fatigue should be fully evaluated to ensure that the designed shrink-fits would fulfil its function (torque transmission) without encountering failures. Material properties for evaluation such as the Young's Modulus and strength data can be obtained from supplier databases or published sources.
- The method of achieving interference through thermal expansion and contraction by the heating and/or cooling must be feasible as well as economical for materials chosen. The assembly requirements must be considered, e.g. components must be cleaned thoroughly and rapid assembly achieved after component heating/cooling avoiding misalignment.
- Holding torque needs to be established from calculations to ensure torque requirement will be satisfied. Allowance for uncertainty may be necessary, for example, by applying a safety factor.
- Alternative manufacturing processes or materials may be considered in iteration in order to satisfy all design requirements.

3.2 Application of framework to shrink-fit design evaluation

Although the shrink-fit design process is a relatively simple one, the design evaluations involved are sufficiently complex and require much richer representations in order to improve ability to reuse in the future. This case study is selected because it is a typical design problem and the modelling aspects are familiar to most engineers but not trivial in its complexity. This section discusses the application of the framework to the modelling of shrink-fits performance under torsion.

Modelling the failure mechanism of a shrink-fit consists of two serial stages involving two performance parameters: contact pressure, P and holding torque, T_H – the contact pressure is an input parameter used in the holding torque model. At the *transfer function level*, the alternative models (shown by links labelled <source_model>), the design and performance parameters (inward and outward arrows labelled <input> and <output> respectively) are shown in Figure 1 (c). The contact pressure in shrink-fits can be modelled using a classic closed-form Lamé's thick cylinder formula [16]. The analytical equation relates radial (or contact) pressure, P at the interference of a solid shaft and hub of the same material to basic variables of a shrink-fit. Alternatively, finite element modelling can also be used to establish the contact pressure between shaft and hub interface in a shrink-fit assembly. A design formula can be derived based on the assumption that failure of a shrink-fits occurs when the radial pressure is insufficient to carry the applied torque and slipping occurs simultaneously along the contact surface. The holding torque at point of failure is therefore a function of friction, area of contact and radial pressure. Similarly, alternative more detailed modelling of the slipping mechanism to predict the holding torque can be achieved through a micro-mechanical [15] or finite element model. Experimentally, both contact pressure and holding torque can be measured using a photoelastic method [18] or a mechanical approach [15] to provide validation to the modelling approaches. The photoelastic illustration in Figure 1 (a) is adapted from [19].

At the *activity level*, there are three processes where Sensitivity Analysis (SA), Verification and Validation (V&V) and Error Function evaluation (EF) are performed in this case study as shown in Figure 1 (a). The *activity level* processes are typically encountered in design evaluations and may be performed in different order or combination. These processes are considered to be transactional processes where the constituent activities for achieving the objectives are consistent and known. The SA process aims to determine the percentage contribution of the variation in each design parameter to the variation in the performance parameters, i.e. P and T_H . The V&V process aims to establish that modelling was performed correctly and that models are a valid representation of the real systems/mechanisms. The EF process aims to characterise the discrepancies between results from various modelling and experimental approaches. Tables and graphs for the results are shown in Figure 1 (b). Reliability analysis could have been performed in this case study to evaluate the probability of failure from the performance distributions but is not elaborated for conciseness.

Several important characteristics of this case study are noted:

- Specific to this case study, although undesirable for economic reasons, a selective assembly procedure was needed due to a manufacturing process that resulted in large variation in the tolerances of the shaft and hub diameters. Statistically, the selective assembly process introduces some correlation between d_s and d_H , which reduces the variability in $\gamma(d_s - d_H)$. This

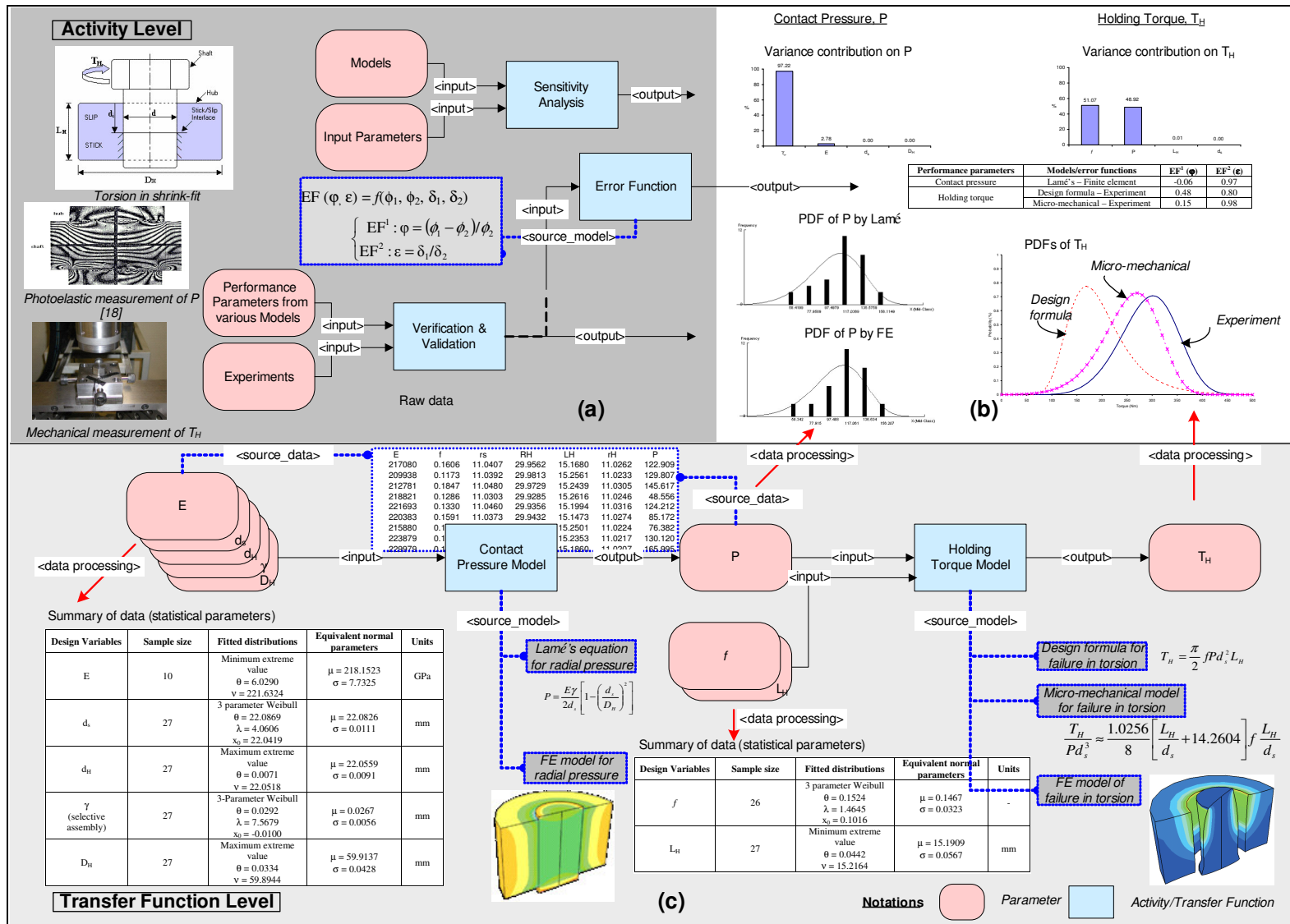


Figure 1. Application of framework to shrink-fit case study

information needs to be carefully documented in the analysis as it has significant effect on the variations in P and T_H .

- Large variation in T_H is observed from the Probability Density Functions (PDFs), which vary considerably from 0 to 500 N.m despite selective assembly being carried out. The variation can be described by Coefficient of Variation (C_v) obtained from dividing standard deviation, σ with mean, μ of a normal PDF. The C_v values for the PDFs for T_H are found to be between 20 to 30%. This criterion may prompt the designer to consider ways of quality control (e.g. additional grinding process) for reducing the performance variation in shrink-fits produced. The modelling predictions from micro-mechanical and design formula models also show systematic errors of varying magnitudes (refer to Table 2 in section 4).
- As observed in the Pareto plots of variance contribution, the sensitivity results indicate both P and f as the main source of variation in T_H , and the variation in P is mainly due to the variation in γ , (and in turn diameters, d_s and d_H). This observation may prompt the engineers to carry out further measurements of f and investigate its dependency on other variables such as contact pressure and diameters when conditions at the interface change. When new data becomes available in the second iteration, data used for deriving the statistical information needs to be updated to reflect present understanding.
- There is a significant reuse of data and models in the case study. This practice is not atypical in design evaluations as observed from other case studies in literature [12]. In this case study, in verifying the contact pressure and holding torque models, the same set of data for the design variables and parameters are used. In addition, the same geometrical model for the shaft and hub are used in calculation of both the contact pressure and holding torque using finite element modelling. The initial and boundary conditions as well as the element types used in these models however were different.
- The relationship between derived and original data is not immediately identifiable. For example, error functions are derived from data generated in the V&V process upstream but the links to the original data is not apparent.
- During the design of shrink-fits, data and information for dimensional tolerances and variations can be drawn from external sources like the ISO Standards for Limits and Fits and the Process Capability (C_p) [17]. Such data may be contained within standard documentation or proprietary databases. The reference to these data sources are often lost, in many cases are difficult to locate.

Due to space constraints, the issues and observations have been elaborated for only one case study in this paper. The above observations are generic to a range of design evaluations collated in [12]. For transactional processes where a number of activities and the objectives are known and identifiable, the next section discusses the potential benefits that might accrue from the development of an environment based on the proposed framework.

4 DISCUSSION

The framework has been applied to a case study with respect to managing knowledge of uncertainty in design evaluations. A number of scenarios are now discussed to project how such an approach can manage uncertainty in design evaluation more effectively.

1. The case study presented in this paper is atypical, in that the performance parameter is described probabilistically, and statistical evidence is also available. This correlation allows designers to infer the error functions with highest confidence, i.e. first and second moment errors can be characterised precisely. However, the classification also allows for less precise description of uncertainty to be incorporated through deterministic and interval values. These cases can be associated with one of the six confidence scales defined in the classification scheme. From the definition of error functions in Figure 1 (a), where EF^1 denotes the error function accounting for first moment error (or systematic component) and EF^2 denotes the error function accounting for second moment error (or random component), we can see that the errors are minimum when:

$$\varphi \rightarrow 0 \text{ and } \varepsilon \rightarrow 1 \quad (1)$$

The error functions for both contact pressure and holding torque are summarised in Table 2.

Table 2. Error functions for contact pressure and holding torque

| Performance parameters | Models/error functions | EF ¹ (ϕ) | EF ² (ϵ) |
|------------------------|--------------------------------------|----------------------------|--------------------------------|
| Contact pressure | Lamé's – Finite element [†] | -0.06 | 0.97 |
| Holding torque | Design formula – Experiment | 0.48 | 0.80 |
| | Micro-mechanical – Experiment | 0.15 | 0.98 |

Knowledge of these errors can inform the designer to be more or less conservative in making decisions during concessions. In practice, if large numbers of instances of simulation and observation data can be recorded in a structured manner and attributed to specific elements/parts of the process model, a machine learning approach might be employed for updating error more realistically. The error model can then be incorporated into future design activities to reflect an updated understanding of the problem (modelling capability, concept etc.).

- When the performance of the design (outcome of a process) is observed, evidence of the error for that process becomes available. The network of activities can be used to infer unknown uncertainties, sensitivities and errors from indirect evidence by allowing a visualisation of the process. In the case study, the prediction of the holding capacity of shrink-fits consists of a two-stage analysis process (at transfer function level). The contact pressure is first established, then this information feeds into a holding torque model for final performance evaluation. From Figure 2, we can deduce that the confidence in the estimation of errors in P and T_H are both high since the knowledge of uncertainty is precise in this case study (i.e. all the performance parameters can be described probabilistically). This is indicated by the highest level of confidence from the six graduated gray scale in Figure 2.

From Table 2, the contact pressure models from the closed formula and finite element modelling have been verified satisfactorily (relatively small errors) but there are moderate errors in the estimation of holding torque even in the case of micro-mechanical modelling (a more detailed model). From the network of activities, we can infer the source of error in the prediction of holding torque to either come from the uncertainty in the holding torque models or the design variable f and L_H. This allows for visualisation of the uncertainties and errors (Figure 2), particularly if this is only part of a more complex process. The error functions and confidence can be marked-up on the results to allow for more transparent and objective consideration of risks during decision-making.

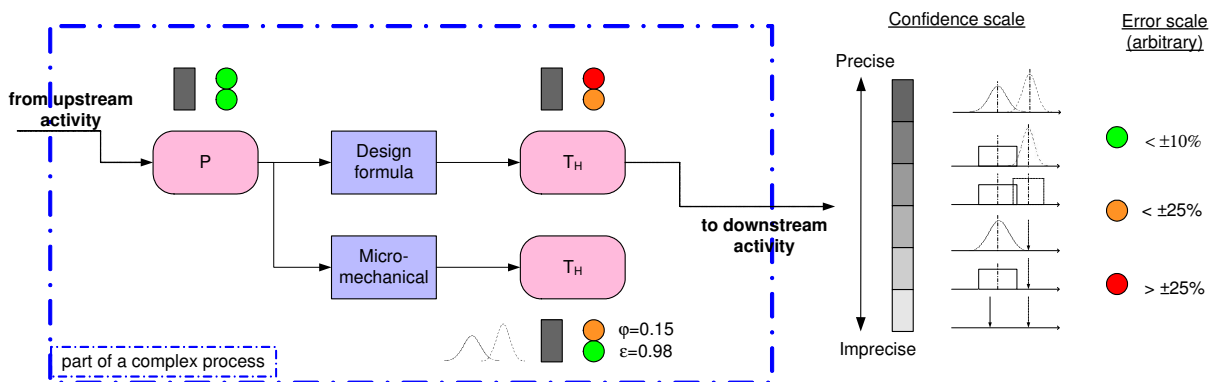


Figure 2. Visualisation of errors in shrink-fit modelling[‡]

- The case study presents a single realisation in the *design space*, where potentially a large number of parametric design solutions may exist. If the framework is adopted consistently over many variants (e.g. in parametric design), response surfaces for the performance can be built. The functions can be used for interpolating between design cases especially in early phases of

[†] For discussion purposes, we assume finite element provides a more accurate estimation of contact pressure than Lamé's equation.

[‡] Error scales based on deviation from $\phi = 0$ and $\epsilon = 1$.

design. For instance, shrink-fits of various sizes can be obtained through the parameterization of diameters of the shaft and hub. In a similar manner, a parametric error model can be developed if evidence for many parameterisation is systematically collected. This way, we can start to build up knowledge of *epistemic uncertainty* (especially in model uncertainty which is usually difficult to characterise). In cases where large numbers of parametric design instances are observed, the parametric error models can be built and used in early phases to adjust the predictions using relatively simpler and inexpensive models. Reducing modelling errors in early design process (where highest level of uncertainty in models and data is present) can avoid costly iterations downstream and reduce the risks of selecting sub-optimal design concepts.

4. As observed in the case study, automatic data extraction and processing modules can be developed in accordance with the schema that allows for each entity in the framework to be computer-identifiable. For example, the data points for each performance parameter may need to be processed by a statistical processor to fit and display PDFs. Conversely, from the tabulated statistical parameters, a sampling script can be invoked to feed pseudo-random numbers for probabilistic designing (i.e. Monte Carlo approach). If for example, new data may be added to the initial sample set after SA is performed as well as in the case when the data becomes obsolete and replaced, the process can be executed to dynamically reflect the changes (updating knowledge). This capability requires that the data can be stored in a non-proprietary format and processed separately by tools/programs for specific purposes. Further to this, the data processing module can be inferred from the *activity level* process. In the case of SA, a numerical differentiation algorithm can be invoked to obtain the sensitivity coefficient (from gradient of the function).

A framework for managing uncertainty to enhance reuse of design analysis has been discussed through a case study in shrink-fit design. It is envisaged that such structured approach can allow for uncertainties and errors in a complex analytical process to be made more explicit to the benefits of decision-makers. In particular, the framework may provide a common reference to exchange uncertain data with more confidence within a collaborative environment. This way, potential risks associated with uncertainties can be taken into account in an informed manner. Furthermore, the modular process model representation also enhances our ability to reuse the data, models and processes, if the rich contexts surrounding the analytical processes can be captured effectively through a unified framework.

5 CONCLUSIONS

Uncertainty in engineering design is inevitable because of its very nature – seeking to find a solution to an abstract and incompletely understood problem. However, uncertainty in design evaluation can be managed to improve confidence through a more robust strategy for capturing, sharing and reusing information. This paper has presented a structured approach to managing uncertainties in engineering design using a systematic and formal representation based on a process model. The process model framework is used to describe activities and information flows, so that an initially incomplete understanding can be updated when new evidence becomes available. The benefits that can accrue from the theoretical framework proposed in terms of managing uncertainty in design evaluations also include the population of error functions, inference of uncertainty and errors in complex simulation processes and parametric modelling.

Ultimately the improvement to design documentation may aid revision of design episodes for identification of decision rationale and assessment of decision impacts more quickly. The knowledge and insights can be used to evaluate confidence and risks in modelling capability more upfront in the design process and to support selection of design tools and techniques and optimisation of resource allocation in simulation-based design. Further work involves the development of an activity taxonomy for the framework to be used effectively and development of approaches for integrated product, process and rationale representations in the framework under the Immortal Information and Through-life Knowledge Management project [20].

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