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A FRAMEWORK FOR THE HANDLING OF UNCERTAINTY IN ENGINEERING KNOWLEDGE MANAGEMENT TO AID PRODUCT DEVELOPMENT

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1. Introduction

Simulation-based design is becoming essential in an integrated product development process due to pressures to reduce cost and time for product evaluation. For simulation-based design to be successful, we need much greater understanding of the uncertainties and imprecisions in the simulation processes than was formerly necessary in product development processes based primarily on testing. Knowledge management, with emphasis on these uncertainties, is needed to gain insights into accuracy, limitations and confidence in simulation techniques and in design data used in design analyses. Many companies could potentially benefit from better utilisation of knowledge and lessons learnt from in-service experience and in particular past failures to aid decision-making especially in variant designs [1]. This paper proposes a framework for the handling of uncertainty in engineering knowledge management to improve confidence in simulation-based design. A method for representing disparity between simulation results and experimental observations via error functions will be presented.

2. Background and motivation

The term "simulation-based design" is used to refer to the extensive use in the design process of simulation and analysis tools, especially computer-based, for the evaluation and verification of the product performance. Simulation-based design is becoming an essential part of a modern Product Development Process (PDP), as engineers need to deliver high quality products to their customers under increasing cost and time constraints [2]. The move of product evaluations from physical to virtual testing has, however, increased the scope for error [3]. Even if best modelling practice is followed and simulations are carried out correctly using the most advanced tools, predictions may be in error owing to a number of factors. There may be a lack of knowledge about how best to construct models and on the consequences of modelling approximations. There may be uncertainty or incomplete information concerning loading, geometry, material properties or time-dependent behaviours [4]. In some situations there are limitations in the capabilities of even the best models e.g. in residual stresses or material inhomogeneity. All these factors lead to substantial risks associated with the reliance on simulation predictions [5, 6].

In order that reliable virtual product evaluation is achieved, uncertainties associated with simulation parameters and models need to be actively managed to increase confidence in the results obtained. A method of assessing the adequacy of simulation methods in a given situation, given the current understanding of the state of data and modelling techniques, is required to inform where simulations are appropriate and where not, and where resources need to be expended to reduce the risk of error. The focus of the work is on improving confidence in design analysis at the embodiment stage of a typical PDP [7]. To this end, there is a need for more formal organisation of knowledge [8] to provide insights into the level of confidence that may be placed in an analysis or simulation approach and to estimate the risks and uncertainties inherent in its application. In the research, we are interested to record evidence of model discrepancy or inadequacy and use this information firstly to suggest analysis strategy and secondly to predict an error function for the analysis case, based on knowledge of comparisons between analysis and prototype tests or in-service experience of the product performance. The organisation of knowledge is based on a framework, for engineering knowledge management that seeks to characterise both systematic and stochastic uncertainty arising from the simulation process and to use this characterisation to aid decision-making in design simulation.

3. A framework for uncertainty characterisation

The simulation of the performance of an engineering product will typically involve multiple design targets, each associated with different load cases and failure modes. The analysis of each load case will be based on design parameters, and will involve one or more transfer functions[1] for the computation of the performance parameters of interest. These transfer functions may take different forms depending on the mechanism for the physical process. For instance, the thermal fatigue, mechanical fatigue and wear of an engine will be modelled differently. In design simulation, virtual prototypes built on various theories and computational models will be tested against the performance targets that the product is designed to achieve, and the performance parameters identified from these virtual prototypes may be compared to physical evidence to verify the accuracy of the virtual evaluation.

A systematic organisation of the knowledge accumulated from such simulation activities, in particular concerning the comparisons of model and physical evidence, is needed to give insights into the level of confidence in model estimates. These insights will indicate where data collation, experimental work and research and development are needed in a simulation-based design environment. The framework proposed in this paper allows the design correlations to be characterised in terms of the extent and nature of the evidence concerning uncertainties in design data and in the simulation models. A classification developed in the framework organises knowledge of simulation results and experimental observations through a 3 dimensional Cartesian system in Figure 1.

The axes of this figure are: *i*-axis - performance parameter, *j*-axis – physical evidence and *k*-axis - design space. The *i*- and *j*-axes are scaled according to the quality and quantity of data characterising the variables. The design space (*k*-axis) is organised according the number of variants of the design concept for which data are available. The origin (0,0,0) represents cases with no prior evidence of similar system and analysis model available, e.g. design of a state-of-the-art structure or a novel technology space vehicle. In this situation, indirect and subjective evidence are sought to accumulate more understanding about the system to be designed. When sufficient confidence is attained in a concept, further examples may be produced and experience with them will validate initial findings. For an established design

[1] Transfer functions are the relationships that relate the input variables (design parameters) to the output variables (performance parameters) with the purpose of evaluating the characteristics of interest for a physical system, often represented by mathematical and computational models developed from first principles, empirical relationships and heuristics.

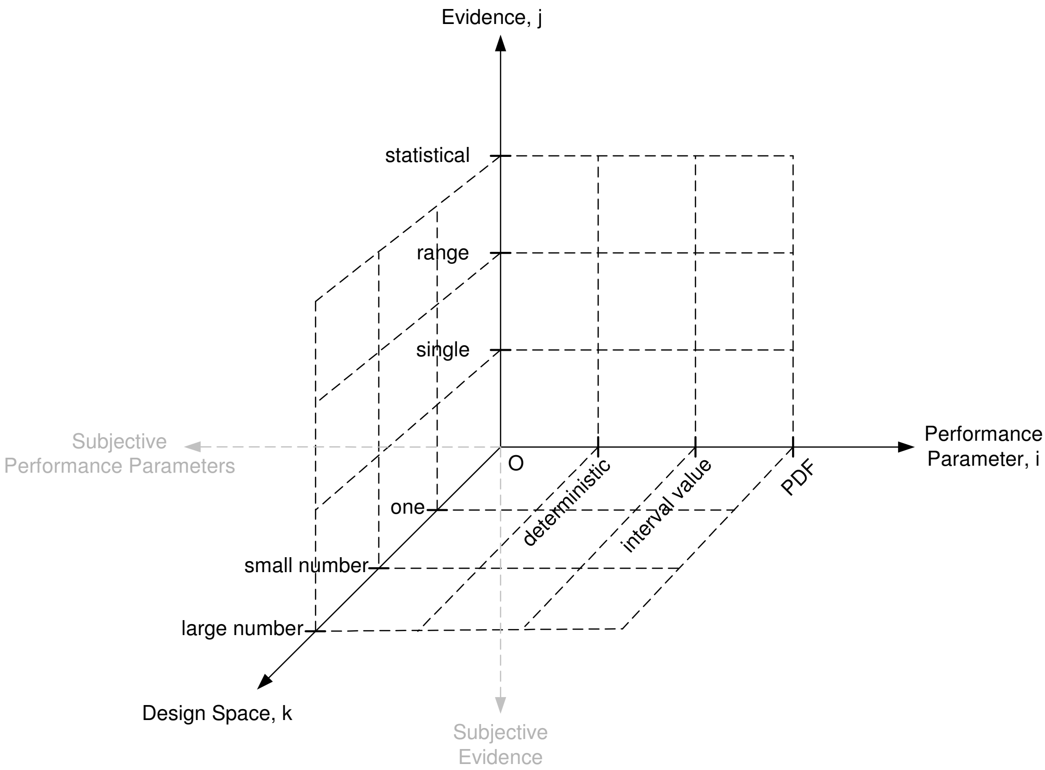


Figure 1 Classification of correlations, (*i, j, k*) = (performance parameter, evidence, design space)

there may be many exemplars, and as more similar systems are designed and validated, the knowledge accumulated in this manner enhances the knowledge base for adaptations of the design, signifying the progression of design *know-how*, i.e. knowledge for each axis improves away from the origin. The definitions for scales in each axis are detailed in subsequent sub-sections.

3.1 Performance parameter (*i*-axis)

Design parameters are defined by Nam Suh [9] as the key physical variables in the physical domain that characterise the design that satisfies the specified functional requirements. The performance of the design is characterised by performance parameters, derived from the design parameters by considering the design subject to some operating regime. The relationship between design parameters and performance parameters may be considered to be modelled by some form of transfer function(s). Variability and uncertainties in this relationship can be found in the design parameters (e.g. dimensional or material properties), in the characterisation of the operating regime (the load cases) and in the transfer function itself [10]. Models used in the mapping are approximations to real world systems, in which there are conditional assumptions, limited available data or incomplete knowledge [11]. Therefore, uncertainty in both design parameters and transfer functions is reflected in the performance parameters, which are used to qualify performance of a design against the specified values of the design targets or functional requirements in the design process [12]. The presence of uncertainty in virtual performance parameters reduces confidence in simulation predictions, and introduces risks in decisions based upon them.

A classification of performance parameters according to the completeness of the data used to describe them has been devised. The scale progresses from the limited data contained in a single deterministic value to the increasing completeness or precision of a Probability

Distribution Function (PDF), as shown in Figure 1. The definition for each scale position in the *i*-axis is:

1. **'Deterministic'** means the output of a transfer function is only available for a single value (or set of values), obtained by propagating a nominal set of design parameters through the function.
2. **'Interval value'** means the output of a transfer function is available as intervals with no information of the likelihood of occurrence except for the absolute lower and upper bounds.
3. **'PDF'** means the output of a transfer function is described probabilistically. The normal distribution is supposed here due to its wide use in engineering.

3.2 Evidence (*j*-axis)

Evidence regarding the performance and uncertainty in analytical models is typically gathered from in-service product behaviour, failure records, prototype tests and correlation analyses for similar but not necessary identical products. The sources of evidence available in correlation can be distinguished as primary and the secondary sources according to their correspondence with the analysis [13]. In general, the **primary evidence** provides a direct correlation between modelling results and experimental measurements for an engineering product leading to the highest confidence for validation purposes. Where primary evidence is not available, the **secondary evidence** or indirect evidence may have to be sourced from experience with the performance of similar products in similar service conditions. Using this type of evidence involves some decision-making in justifying its confidence and reliability. Some examples of secondary evidence are:

- Evidence of performance of similar techniques for similar models – e.g. generic confidence in Computational Fluid Dynamics models or the NAFEMS technical benchmark [14] used to draw conclusions about the current numerical model.
- Evidence of satisfactory/unsatisfactory performance of similar but not identical artefacts – e.g. in-service or historical evidence of satisfactory or unsatisfactory performance of artefacts.
- Evidence of performance of parts of the more complex process – e.g. stress analysis as part of a fatigue model.
- Results from other validated models – e.g. verification of results from a new method with conventional solutions.

Correlations and validation of simulation results against experimental test data can be complicated by the lack of evidence due to resource constraints and difficulty in obtaining real life data, but in some cases there may be abundance of evidence for engineers to draw correlations against. Therefore, evidence of varying degrees may exist for correlations and used in validation to justify the confidence in design analysis [15]. A scale for classifying the availability of validation evidence has been defined as follows:

1. **'Single'** observation – validation evidence is available for a single observation only, for example from a prototype test.
2. **'Range'** of observations – validation evidence is available for a small number of observations, but no inference on likelihood could be drawn from these observations except for the absolute bounds.

3. **‘Statistical’** set of observations – most likely to be collected from a large batch of artefacts in service providing a reliable source of evidence.

3.3 Design space (*k*-axis)

The design space is a feasible region for several parameterisations of the design parameters for a product (as in parametric or variant design). For example bearings of various sizes, and load capabilities may be produced for a single design principle. Both analysis and evidence about product performance may exist for a single set of product parameters (e.g. fatigue life of a particular bearing geometry), or more extensively for a wide range of parameters in the feasible design space (e.g. fatigue life for many similar bearings of different sizes). For state-of-the-art systems, analyses and tests for each performance parameter may have been conducted only for a specific product. In more common engineering products, however, several variants often exist and the same type of analytical procedures and tests may have been conducted for verifying the behaviour of a family of product variants. The latter enables the comparisons of predicted results with experimental data for more parametric cases to evaluate the model performance in the design space. The classification proposed categorises the design space into three main groups:

1. **‘One’** means the correlation of performance parameter and evidence is only available for a single parameterisation of a product.
2. **‘Small number’** means the correlation of performance parameter and evidence is available for a few parameterisations of a product/variants to suggest the correlation within a limited range of parameters in the feasible design space.
3. **‘Large number’** means the correlation of performance parameter and evidence exists for a relatively large number of parameterisations of a product to suggest the general confidence of analytical methods in the feasible design space.

This definition of design space allows for new and variant or adaptive designs to be distinguished – the scales correspond to the extent of knowledge available for product evaluation as determined by the number of prior variants designed.

The method of classification proposed intends to cover diverse situations in engineering validation. For example, in cases where the collection of experimental evidence on the behaviour of the whole artefact is prohibited by cost or difficulty in obtaining real data (e.g. reliability of nuclear plant), engineers typically resort to extensive use of secondary evidence combined with highly conservative design strategies. In complex analysis cases, deterministic analysis may be carried out but a large amount of physical evidence may be collected to qualify the design targets and reliability. For well-established design principles and extensive field experience it may be possible to undertake fully probabilistic analysis. To substantiate and populate the classification in the framework, various cases from different design domains have been collected and are presented next.

4. Supporting cases

Twenty cases from the literature have been collected and two more extensive case studies have been conducted by the authors [16, 17] to substantiate and populate the (i, j, k) coordinate system shown in Figure 1. Although the number of cases represents a substantial population size, it only represents a partial population of the 48 coordinates (4 x 4 x 3) in the classification. Summaries of the literature cases and references to them are documented in [18] with relevant information to this paper given briefly in Table 1. These cases are used to

Table 1 Illustration of case studies and literature cases

Case No.	**Case description**	**Performance parameter**	**Transfer function**	**Analysis**				**Evidence**				**Design Space**		
				0	1	2	3	0	1	2	3	1	2	3
[16]	Suspension dynamics	Average and range vertical top mount force	Equations of motion Multi-body dynamics				✓		✓			✓		
[17]	Shrink-fit subject to torsion	Contact pressure Holding torque	Stress analysis Contact mechanics				✓				✓	✓		
1	Failure of bonded joint	Fracture strength Material strength	Fracture mechanism Material behaviour				✓	✓				✓		
2	Solenoid torque	Stress rupture torque Torque at loosening	Material failure Loosening criterion				✓	✓				✓		
3 (a)	Reliability handbook data	Failure rates	Failure mechanisms	✓					✓			✓		
3 (b)				✓						✓		✓		
3 (c)				✓							✓	✓		
4	Heat sinks performance	Thermal resistance Pressure drop	Fluids mechanics Heat transfer		✓				✓			✓		
5	Die surface press.distribution	Pressure	Upsetting process		✓				✓				✓	
6	Static failure theories	Combined stress	Static material failure		✓				✓					✓
7 (a)	Fatigue life of steering knuckle	Fatigue life cycle	Fatigue failure		✓				✓			✓		
7 (b)					✓					✓		✓		
8	Brake design	Torque due to friction	Force and moment balance			✓			✓			✓		
9 (a)	Safety factor	Structural strengths	Failure limits		✓				✓				✓	✓
9 (b)					✓					✓			✓	✓
10	Pitting of gear	Number of cycle to pitting	Fracture mechanics (contact)		✓						✓	✓		
11 (a)	Sheet metal flanging	Springback angle	Flanging process				✓		✓				✓	
11 (b)							✓			✓		✓		
12	Structural analysis	Displacement	Structural reliability			✓				✓		✓		
13	Rupture of steering knuckle	Rupture velocity	Brittle rupture			✓				✓		✓		
14	Shot peening life increase	Fatigue life	Residual stress in shot peening process			✓					✓	✓		
15	Residual stress in quenching	Surface axial residual stress	Quenching process			✓					✓	✓		
16 (a)	Tolerance stack analysis	Assembly tolerance	Geometry			✓					✓			✓
16 (b)							✓				✓			✓
17	Buckling of cyl. shells	Buckling limit load	Structural buckling				✓				✓	✓		
18	Bearing failures	Bearing life	Failure mechanisms				✓				✓	✓		
19	Fatigue crack growth	Fatigue life	Fatigue crack growth				✓				✓	✓		
20	Residual stress and fracture toughness	Fracture toughness	Residual stress influence on fracture toughness				✓				✓		✓	

illustrate the rationale for the development of suitable error function for each of the categories they represent. The cases collected however, do not intend to provide the current state-of-the-art in each branch of the study involved, although some sectors of industry do tend to collect more statistical data and perform probabilistic design more than others.

5. Error functions

From the evaluation of the requirements for uncertainty characterisation, a method for representing the disparity between simulation results and experimental observations via error functions is developed next. The requirement for the error function is to record uncertainty information from existing systems and to propagate the error characterisation for use in future design applications to assist decision-making and to improve simulation results. From the various combinations of model, data and the extent of available evidence, it is proposed that it may be possible to identify an error function for each load case, design target or failure mode using:

$$\text{Evidence} = \text{Transfer function } \Theta \text{ Error function} \tag{1}$$

where Θ = addition and/or multiplication.

The addition or multiplication operations allow for correction of the predicted response from the transfer function to better reflect the reality. Similar formulations have been mentioned by [19] in what was termed an 'adjustment factor approach'. According to the authors, the adjustment factor may assume a hypothetical PDF reflecting the model prediction uncertainty. The approach however, seemed to have been adopted in an *ad hoc* manner in risk analysis.

5.1 Formulation of error functions

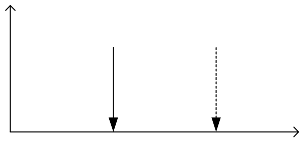
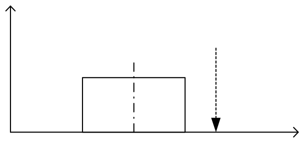
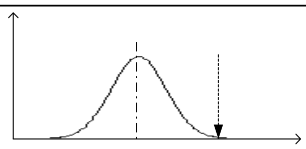
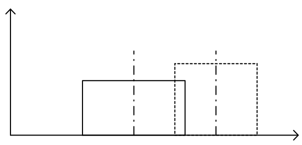
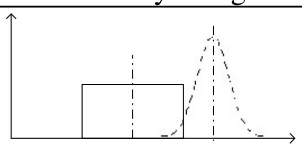
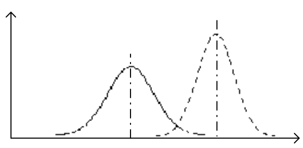
The classification in the framework leads to several categories of correlation cases as summarised in Table 2. This classification may be used to identify the most appropriate method for handling uncertainty in the design simulation including Fuzzy set theory, interval analysis and probabilistic methods. Suitable error functions may be formulated for each category using purely conventional uncertainty theories, or a combination of these. Figure 2 illustrates two distinct classes, unhatched (A, D, F) – correlations between parameters characterised by pure uncertainty theories (probabilistic method, interval analysis, Fuzzy set) and hatched (B, C, E) – correlations that require a combination of uncertainty theories to formulate an error function. Even though the mathematics within a pure uncertainty theory is well established, research in dealing with a combination of different uncertainty theories is less mature [20]. In this paper the consistency principle, a generally accepted relationship between the probability and the possibility axioms, is adopted for the transformation of data of varying precision for the development of error functions in the combination categories (B, C, E). This principle states that the degree of possibility of an event is greater or equal to its degree of probability [21], which is given by an inequality relationship:

$$\int_A p(x)dx \le \max_{x \in A}\left(\frac{\mu(x)}{\max \mu(x)}\right) \tag{2}$$

where $p(x)$ = probability distribution

$\mu(x)$ = Fuzzy membership function.

Table 2 Categories of correlation between analysis and experiment results (*i* - performance parameter, *j* - physical evidence and *k* - design space)

Cate-gory	**Graphical representation**	**Cate-gory**	**Graphical representation**
A	 (1, 1, *k*) – The performance parameter is characterised by deterministic data and the experimental evidence by a single value.	**B**	 i. (1, 2, *k*) – The performance parameter is characterised by deterministic data and the experimental evidence by a range of values. ii. (2, 1, *k*) – The performance parameter is characterised by interval value and the experimental evidence by a single value.
C	 i. (1, 3, *k*) – The performance parameter is characterised by deterministic data and the experimental evidence by statistical data. ii. (3, 1, *k*) – The performance parameter is characterised by distribution function and the experimental evidence by a single value.	**D**	 (2, 2, *k*) – The performance parameter is characterised by interval value and the experimental evidence by a range of values.
E	 i. (2, 3, *k*) – The performance parameter is characterised by interval value and the experimental evidence by statistical data. ii. (3, 2, *k*) – The performance parameter is characterised by distribution function and the experimental evidence by a range of values.	**F**	 (3, 3, *k*) – The performance parameter is characterised by a distribution function and the experimental evidence by statistical data.

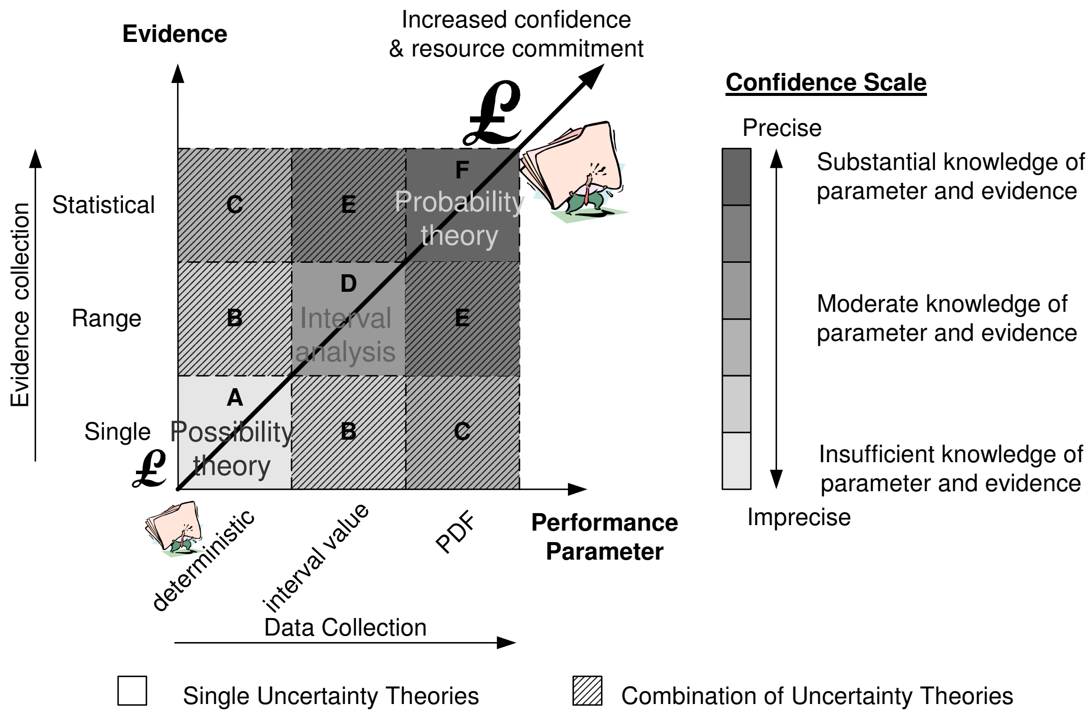


Figure 2 Precision of error functions and the progression of confidence

The possibility distribution, $\prod(x)$ that optimises the information content [22] obtained from this transformation encodes the family of confidence intervals around the mode of the probability distribution, p(x), i.e. the α-cut of $\prod(x)$ is the $(1 - \alpha)$ confidence interval of p(x) [23].

A pragmatic method for recording uncertainty information is proposed by separating the first and second moments of data to capture the systematic and random aspects of uncertainties for existing systems in correlation with evidence. In statistical terms, the first moment of a sample of data is the central tendency (or mean), and the difference between the means of the actual and predicted performance parameters is the systematic or bias uncertainty measure, φ. The second moment of data is the measure of dispersion (or variance), and the difference between the variances of the actual and predicted performance parameters is the random uncertainty measure, ε. The error functions can be defined as:

$$\mathrm{EF}\,(\varphi, \varepsilon) = f(\phi_{real}, \phi_{TF}, \delta_{real}, \delta_{TF}) \begin{cases} \mathrm{EF}^1 : \varphi = \left(\phi_{real} - \phi_{TF}\right)/\phi_{TF} \\ \mathrm{EF}^2 : \varepsilon = \delta_{real}/\delta_{TF} \end{cases} \tag{3}$$

where EF^1 denotes the error function accounting for systematic discrepancy

EF^2 denotes the error function accounting for random discrepancy

ϕ_{real} = first moment of the observed performance parameter

ϕ_{TF} = first moment of the predicted performance parameter

δ_{real} = second moment of the observed performance parameter

δ_{TF} = second moment of the predicted performance parameter.

The development of error functions presently is based on the assumption of symmetric data and that, for a deterministic parameter, a suitable Fuzzy number may be elicited from experts. This definition of systematic and random uncertainty measures can be extended to cases described by Fuzzy and interval numbers, by denoting the first and second moments of data with their equivalent parameters, e.g. ϕ = average and δ = range of an interval number.

Separation of aleatory and epistemic uncertainty has been widely recognised [24, 25] but little work is seen in mitigating both types of uncertainties in simulation-based design environments [26]. It is envisaged that the isolation of systematic and random uncertainties will better represent epistemic uncertainty and stochastic variability arising from simulation processes. This characterisation is also to be found more suitable to allow incorporation of uncertainty characterisation into the modelling of future engineering processes [18]. Although the error functions will not correct for uncertainty with absolute accuracy, they are potentially useful to give insights to the accuracy of the data and models used in simulation procedures for variant design applications. The uncertainty measures in error functions can be applied in the next variant via:

$$\phi_{real} = \phi_{TF} (1+ \varphi) \tag{4}$$

$$\delta_{real} = \delta_{TF} * \varepsilon \tag{5}$$

where φ = systematic uncertainty measure

ε = random uncertainty measure.

The error functions support uncertainty characterisation by indicating the discrepancies in modelling and observed results, aiding the assessment of confidence in data and model representations for an analysis procedure. For example, the systematic uncertainty measure, φ, may be used to judge if a modelling approach is consistently over ($\varphi<0$) or under-estimating ($\varphi>0$) the actual behaviour or performance parameter of interest. Accuracy in alternative models may be compared and over-conservatism resulting in uneconomic designs can be avoided. A value close to zero for φ indicates less bias uncertainty, therefore the model correctly predicts the actual performance parameter. The random uncertainty measure, ε, may have significant influence on the accuracy of results, especially for performance criteria that are sensitive to dispersion, e.g. probability of failure. Under-estimation of variability ($\varepsilon>1$) in this case will cause higher than expected number of product failures, whereas over-estimation of variability ($\varepsilon<1$) may cause designers to specify tighter specifications, e.g. manufacturing tolerances or material strength that results in extra cost and weight. A value close to unity for ε indicates less random uncertainty.

5.2 Suitability to design applications

Uncertainty characterisation using error functions is most suited to the third scale in the design space classification in the framework (k = 3) – i.e. design with a large number of variants in the design space where products are adapted from existing ones over many iterations. This is because the quality and quantity of data required for accurate modelling is acquired through several iterations and including at least one model or prototype test. This type of information is typically available in variant and adaptive design [5, 27]. Since these design types constitute about 80 % of engineering products [7], many companies can benefit from better utilisation of information and knowledge through prototype tests or lessons learnt from past failures. The extensive experience and knowledge accumulated from a large number of design variants could allow for very useful inference of the accuracy of modelling or simulation techniques to build up a reliable knowledge-based system. The error functions can be stored along with the data, model and load cases, and could be retrieved for reuse in a similar design case. The feasibility of such a system using a knowledge repository for an engineering model has been investigated by other researchers [8].

5.3 Improving confidence in design simulations

The precision in error functions developed according to the classification in the framework can be used to judge confidence in correlations between analysis performance parameter and evidence. For instance, a scale (graduated shades) for confidence related to the precision in error functions is indicated in Figure 2. The density of shading is an indication of the completeness of data describing the analysis performance parameters and evidence. The precision (and confidence) in an error function does not however, imply that the actual response is accurately predicted. For instance, the error functions obtained from correlation between probabilistic parameters (Category F) are precise but accuracy in the modelling may be low due to large systematic errors between the modelling results and evidence. The error functions may be used to identify critical areas and to optimise allocation of resources to reduce errors – to select more suitable design representations, to focus effort in data collation, and to select suitable design techniques by indicating relative measures of uncertainty and confidence among the available alternatives. For instance, in situations where the bias uncertainty is significantly larger than the random uncertainty, i.e. $\varphi >> \varepsilon$, a deterministic analysis and a scalar valued error function may suffice until more detailed model with higher accuracy can be justified. In this manner, error functions provide a mechanism to estimate the risks and uncertainties inherent in an application of analysis/simulation and to assess the adequacy of simulations in replacement of prototype tests in order to focus engineering effort to progress confidence in simulation-based design.

The probabilistic method is by far the most appropriate to represent uncertainty in engineering simulations due to its suitability to propagate numerical and objective uncertainty information [28]. Ideally, the design process should progress diagonally upwards through design iterations as design data becomes more complete, i.e. from deterministic to probabilistic values as more information is gathered. Similarly, the error representation through error functions will also evolve from imprecise possibility to precise probability but there is an increasing intensity of resource and effort needed to achieve improved precision as shown in Figure 2. The collection of data and evidence will be inevitably limited by design constraints and business pressures in reality. The framework provides a roadmap to identify a progression from current state of data and model representations to achieve the most desired state (Category F) in order to attain confidence in design simulations. The framework and error functions will be illustrated next for a case study conducted in collaboration with an automotive company.

6. Case study

A case study on the suspension dynamics of a sports utility vehicle [16] was conducted to compare analytical and experimental value of loads transferred onto the chassis to gain an understanding of the systematic and variance errors arising from various data and model representations. The collaborating company was interested to establish the influence of statistical variability in component dimensions, properties and assembly factors onto the estimated loads from simulations, as well as the confidence in these predictions. In particular, if the company can establish sufficient confidence in simulation-based design, intermediate prototypes can be reduced (especially in non-critical areas) thus saving product development time and cost. The correlation assessed from the current system is then used to judge the potential accuracy of modelling predictions for the estimation of load transfer in early design stage of a variant vehicle where experimentally measured response is not available. The characteristics relating to the framework and error functions for this case study are now established.

Classification

Performance parameters – the average and range of vertical top mount force were predicted from two models, where:

- Design parameters were suspension component properties, with their statistical variations first assumed from published data and specifications, then improved with data measured from tests conducted.
- Transfer functions were available to provide an analytical relationship between the design parameters and performance parameter of the function:
    a. Computational model – ADAMS model (37 degree of freedom)
    b. Analytical model – simplified model (1 degree of freedom).

Performance parameters from various data sets and models were described by normal PDFs, providing a probabilistic description of its variability. This corresponds to $i = 3$ in the scale for performance parameter.

Evidence for the top mount force was derived from a load history measured from a laboratory test on a prototype vehicle. Experimental or test evidence exists for the performance parameters from a single vehicle, but the actual properties (design parameters) of this test system is unknown. Testing requires very expensive hardware and data acquisition systems that typically cost automotive companies millions of dollars of investment per car tested and take months to set up. Evidence for this case study was only available from a single vehicle, corresponding to $j = 1$ in the scale for evidence.

The **design space** for this case study contains only one correlation case for a specific suspension system design, but the collaborating company will have collected vast experience from designing variants of the vehicle type. However, the design space considered in this case study involved only one suspension variant, therefore implying $k = 1$ in the scale for design space.

Error functions

The mathematical formulation of error functions for category C from Table 2 has been applied to this case study. The error functions required a combination of a Fuzzy number (fitted to the singly available evidence) and a normal PDF, and were developed based on the consistency principle (Eq. 2). Error functions formulated for various models and data sets for the prediction of top mount force indicated varying degree of systematic and random uncertainties associated with them. The route for the development of confidence in simulation is to follow the path from C-E-F, which requires the company to collect more evidence regarding the performance of more similar systems to enable more precise characterisation of error. A systematic documentation of evidence collected over many design variants such as that proposed in the framework is suggested to assist the company to build a more robust and reliable simulation-based design environment.

7. Conclusions

A framework for the systematic organisation of understanding of uncertainties in product development and in simulation procedures has been presented and substantiated with 22 case studies from different design domains, involving varying degrees of uncertainty in the simulation data and varying quantities of evidence from test or service performance. A classification is devised based on the organisation of knowledge regarding the disparity between analytical and experimental evidence, and this classification is used to identify the most appropriate method for the representations of error. The incorporation of error functions into the modelling of variant design processes is suggested to aid analysis strategy and to identify the progression of confidence to achieve reliable virtual product evaluations. The improvement of confidence in simulation-based design environments through management of knowledge gained from previous design activities and from in-service experience with products will aid decision-making in future design applications.

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