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COMBINING EVIDENCE TO JUSTIFY THE APPROPRIATE USE OF MODELS IN ENGINEERING DESIGN

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Abstract

Computer models in engineering design are representations of products or processes that may be prone to uncertainty, variability and error. Indeed, although a model may give accurate results it cannot be absolutely validated and verified for most practical applications due to our incomplete understanding of the world. Typically, certifying that a model is appropriate for a specific use is an informal, ad hoc procedure although several methodologies to provide some structure to this certification have previously been proposed. These methodologies are briefly described along with one recently developed by the authors of this paper that uses Bayesian Belief Nets to capture the reasoning associated with justifying model trustworthiness. As the application of the methodology to engineered models in an industrial setting is still in progress, a hypothetical case study is presented to illustrate the expected benefits. A significant section in this paper concerns features or attributes of modelling and simulation that could be used to make any assessment of trustworthiness more rigorous and objective. The research reported here contributes to the development of a decision support system that is required to advance the effective modelling of increasingly complex engineered products.

Keywords: Systems modelling, product modelling, expert systems

1 Introduction

In engineering design, properties of products and processes such as function and cost may be described or predicted using computer models. It is widely acknowledged that any model is unavoidably a simplification of reality and, although it might give accurate results, it can never be completely exact [1], [2]. The authors of this paper contend that to comprehensively assess the quantitative influence of all model uncertainties, variabilities and errors requires exhaustive sensitivity analysis and validation, which is highly impractical if not impossible in almost all realistic engineering applications. Furthermore, certifying that a model is suitable for a specific purpose is, in practice, conducted in an unstructured, subjective manner at an engineer's discretion. The purpose of the research described in this paper is to capture the engineer's decision-making process in a formal and systematic manner so that as engineered systems grow in complexity, the most appropriate and effective use of modelling can be ensured.

An important part of this paper presents means to make the assessment of model trustworthiness more objective. Hence, in Section 6, metrics or indicators associated with features or attributes of modelling are proposed to help quantify such an assessment. The preceding four sections cover topics that provide the context to the proposed metrics or indicators. Section 2 expands on reasons why selecting and using models is difficult. In

Section 3, existing methodologies to help in decision-making concerning models are briefly reviewed. This is followed in Section 4 by a synopsis of a methodology proposed by the authors of this paper aimed at reasoning about the trustworthiness of models. Then, in Section 5, a hypothetical case study of the methodology application is presented.

2 Key tasks in model selection

Typically, in engineering design, there may be more than one model available for a given purpose. For instance, in designing engineered products where fluid mechanics are relevant, one could use a Direct Numerical Simulation (DNS) of the Navier-Stokes equations or a Computational Fluid Dynamics (CFD) model. In order to justify the use of a particular model, one must first understand the factors that influence its selection in preference to competing models. Such factors include model functionality, model fidelity and the availability of input data along with the cost, requirements and duration of execution. It is a paramount requirement that the functionality of a model fulfills the purpose for which it will be used. Satisfying this requirement may be aided by a structured analysis of the system under consideration, followed by a detailed problem description and, finally, the formalisation of model requirements.

Having matched a model to a purpose, demonstrating model fidelity, accuracy or truthfulness is typically performed by conducting the tasks of validation and verification. One interpretation of these tasks is that the former is establishing whether the “right” model is being built with respect to modelling objectives whilst the latter is establishing if the model is being built “right” [3]. Various techniques exist for these tasks ranging from informal model “eye-balling” by appropriate engineers to thorough statistical analysis and comparison of model results with field tests [3]. However, it is widely acknowledged that absolute fidelity can never be demonstrated and due to our incomplete understanding of the real world, a model of a system that is true in all respects would be the system itself [4]. There may be a number of reasons why model validation is always incomplete [2]. For instance, a model is only validated with respect to its purpose and there is no such thing as general validity. As such, there may be no real world to compare against (e.g. for models of purely conceptual engineered products). Also, there may be different interpretations of the real world and its data can often be inaccurate.

Model accreditation is the official certification that a model is acceptable for use for a specific purpose [5]. Another term used in modelling and simulation is credibility, which is a measure of confidence in the correctness of a model and its appropriateness to the application of interest [6]. In the United States, the defence community invested significant resources during the 1990s to improve validation, verification and accreditation of computer models. However, there remains no widely accepted methods available to quantify or measure fidelity [7]. Given the inability to demonstrate absolute model validity and the importance of the specifics for the application domain, it is left to subject-matter experts to evaluate, select and use models appropriately based upon their experience and expertise.

3 Existing methodologies for model credibility assessment

A number of methodologies have been developed that are intended to capture the subjective decision-making processes concerning model selection and use. It has been suggested that with a well-developed hierarchical structure of claims, arguments and evidence, credibility becomes easier to demonstrate [8]. Furthermore, a hierarchy of credibility assessment stages for evaluating the acceptability of simulation results has been proposed [9]. It has also been claimed that the quality of model validation and verification activities can be represented by credibility indicator networks or trees [6], and a template of such a tree has been developed [10]. The indicators, that are measures of different model aspects, may be propagated using Fuzzy logic, Bayesian logic, Dempster logic and Multi-valued logic. However, only the latter has been actively pursued, which involves combining linguistic assessments of adjacent indicators using the conjunctive operator of three-valued pessimistic logic [10].

When concerned with the credibility of modelling and simulation, qualitative assessments can often be decomposed into a collection of quantitative assessments [11]. Fossett et al. (1991) propose a framework of qualitative factors for assessing military model credibility and apply this to three competing models [12]. Balci (2001) suggests that quantitative and qualitative concepts may be evaluated using hierarchies of indicators that are direct or indirect measures [13]. Those indicators that cannot be directly measured must be decomposed into those that can and, following evaluation, these may then be combined using the Analytical Hierarchy Process. The "Evaluation Environment™" software tool developed by Orca Computer, Inc. and employed since 1999 in the United States National Missile Defence Program, uses such indicators for model certification [13]. However, Gass (1993) raises the important observation that a quantitative credibility assessment referred to as an "accreditation score" has no meaning by itself and must be combined with a written report and sensitivity studies so that model users can make better decisions [14]. Consequently, Gass (1993) proposes a model accreditation rating system also using the Analytical Hierarchy Process that has been implemented in the software, "EXPERT CHOICE".

4 A Bayesian Belief Net based methodology

The authors of this paper have recently developed a methodology that utilises Bayesian Belief Nets (BBNs) for reasoning about user confidence in models [15], [16]. A BBN is a directed acyclic graph that can be used for reasoning under uncertainty. Software tools exist in which sensitivity analysis can be automatically performed for BBNs both from cause to effect and vice versa. Such automated sensitivity analysis, which is not provided by software tools associated with the methodologies mentioned previously, enables the identification of the most significant sources of model concern such as uncertainties, variabilities and errors. While this may be intuitive when dealing with individual models, it is less so if dealing with complex networks of inter-operating models. Thus, our methodology facilitates more cost-effective employment of those available resources, which are used to improve complex models of engineered products.

Our BBN based methodology has been implemented as a prototype software tool to support the appropriate use of models by BAE SYSTEMS in developing increasingly complex and integrated military aircraft systems. A case study concerning the application of the methodology is in progress, which is intended to demonstrate the capture of the reasoning process used in modelling and simulation. The software elicits assessments on various model aspects, using several means, via a graphical user interface. For instance, probability wheels and number lines [17] are provided that enable assessments to be graphically visualised. Additionally, linguistic descriptors [18] within the software tool may be used to express these assessments instead of numerical values. Furthermore, three mathematical means of belief consensus have been implemented that allow the combination of multiple engineer assessments. These means employ probability pools [19], Fuzzy logic [20] and Dempster Shafer theory [21] to provide flexibility by allowing for assessments that range in their vagueness.

5 A hypothetical case study

As the application of the BBN based methodology within BAE SYSTEMS is still in progress and in order to preserve company confidentiality, the benefits expected are now presented using a fictitious case study. Depicted below (Fig. 1) is part of a feasible breakdown of an air-vehicle into mass components. It is proposed that this breakdown could represent a network of inter-operating models with varied purposes. The fictitious circumstances supposed are that a performance model exists for the “Air Vehicle”, which requires data from a fatigue tolerance model for the “Airframe Structure” and a financial cost model for the “Systems Equipment”. It is further supposed that the model for the “Airframe Structure” in turn requires data from an aerodynamic characteristics model for the “Wing” while the model for the “Systems Equipment” in turn requires data from a frequency response model for the “Flight Controls”.

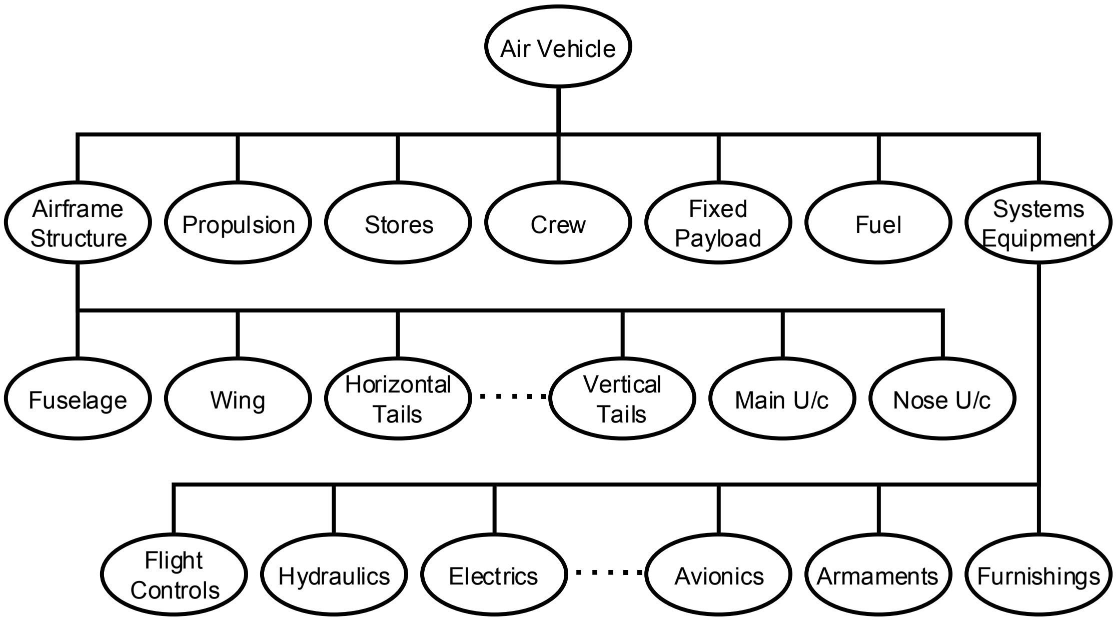

Figure 1. Air vehicle mass breakdown / hypothetical network of inter-operating models

The key objective of our methodology is to help indicate preferred modelling routes through the breakdown structure for a complex engineered product and this objective is facilitated in three ways. Firstly, one may “plug and play” with alternative models in a given network to determine which selections provide the most credible desired result. In this case study, the result could be the outcome from the fatigue tolerance model for the “Airframe Structure”. As an example of “plugging and playing”, one may want to compare using a vortex lattice method versus using a panel method as the aerodynamic characteristics model for the “Wing”. Secondly, it may be feasible to experiment with the network itself in order to achieve the most credible desired result. Assuming appropriate model compatibility, one may observe an improvement from, for example, bypassing certain models in the network (i.e. Why use N models when less than N models will suffice or even perform better?). In the case study, it may be appropriate to neglect the financial cost model for the "Systems Equipment" and instead take cost data directly from models for the components at the bottom of the depicted breakdown. Finally, sensitivity analysis can be performed using some existing BBN tools on assessments concerning the credibility of modelling and simulation. This enables the identification of those aspects of modelling, which have most influence upon a result of interest. Hence resources that are used to improve modelling and simulation, may then be better employed. For the case study, in order to obtain a more credible result from the performance model for the "Air Vehicle", it may be found that resources are best transferred from developing the frequency response model for the "Flight Controls" to developing the aerodynamic characteristics model for the "Wing". Sensitivity analysis with some existing BBN tools can be performed at varying levels of granularity from the fine details of individual models to clusters of models in a network.

6 Indicators for a model credibility assessment methodology

The BBN based methodology developed for model credibility assessment [15], [16], as well as existing methodologies presented in Section 3, require subjective judgements by expert engineers on various aspects of modelling. The following subsections (6.1 to 6.8) concern means to add rigour to the process of credibility assessment. Indicators or metrics are proposed, which pertain to the various phases of modelling and simulation, and could assist in making credibility assessments more objective. Ultimately however, modelling can be considered an art and subjectivity cannot be totally eliminated from credibility assessments because these assessments are dependent on the specific circumstances [3].

6.1 Indicators for non-specific phases of modelling

Many model validation techniques exist and Balci (1998) attributes a wide selection of these to phases in the modelling life-cycle [3]. It is proposed that if such techniques are configured as checklists then a tally of those conducted with successful results could provide a metric for model credibility assessment. However, the specific choice of technique is an important factor affecting the extent of validation [22]. For instance, Muessig (2000) claims validation against field test data to be superior to validation against expert opinion (i.e. face validation), which in turn is superior to validation against other simulations (i.e. benchmarking) [23]. Hence, when evaluating the validation effort to provide a metric for credibility assessment, one could weight the techniques used according to their relative effectiveness. The metric should also consider the extent to which a validation technique has been applied with successful results, and one means of providing for this is now demonstrated for an example model (Table 1). Here, the validation techniques listed in the second column are a selection compiled from a number of sources [3], [24-29]. The relative effectiveness of each technique is described in the third column using a suggested weight, a_i that ranges from 1 (low) to 5 (high). The extent to which the validation technique has been applied to the model of interest with successful results is described by a proportion, b_i in the fourth column. The proposed metric, m for the example model (Table 1) is calculated using the following expression:

$$m = \frac{\sum_{i=1}^{i=n}(a_i \times b_i)}{\sum_{i=1}^{i=n} a_i} \tag{1}$$

where "n" is the number of validation techniques available and "m" will vary from 0 (no validation) to 1 (total validation). Hence, for the example model (Table 1) m equals 0.47.

Table 1. Evaluating the validation of an example model

i	Validation technique	Effectiveness weight, a_i	Proportion applied, b_i	$(a_i \times b_i)$
1	Animation	2	0.30	0.60
2	Assumption validation	5	0.50	2.50
3	Audit	4	0.90	3.60
4	Documentation checking	1	0.95	0.95
5	Event validation	5	0.00	0.00
6	Extreme condition testing	5	0.75	3.75
7	Face validation / Eyeballing	4	0.15	0.60
8	Inspection	3	0.80	2.40
9	Review	4	0.80	3.20
10	Sensitivity analysis	5	0.40	2.00
11	Spectral analysis	5	0.00	0.00
12	Statistical analysis	5	0.55	2.75
13	Tracing	4	0.60	2.40
14	Turing testing	5	0.00	0.00
15	Walkthrough	4	0.95	3.80
	$\sum_{i=1}^{i=n} a_i =$	61	$\sum_{i=1}^{i=n} (a_i \times b_i) =$	28.55

6.2 Indicators for the conceptualisation phase

Conceptualisation is the initial phase in modelling and simulation that involves developing a specification of the physical system of interest and its environment [30]. Assessing the quality of this phase is often reduced to logical and structured reasoning [31]. In a military model for instance, when analysing the impact of aspect dependence signature on airborne target detection, a 6-Degree of Freedom (DoF) model would automatically be chosen over a 3-DoF model [31]. One must specifically question whether the modelled physical entities and their functions, as well as the modelled environment and interactions within it, meet requirements sufficiently [23]. To help in making an informed judgement about the quality of model conceptualisation, one should both query the existence of, and inspect, relevant information. This includes the description and specification of the problem, formalisation of model requirements, and documented analysis that links the two [22]. Activity cycle diagrams [32] and cause-effect graphing [3] may be useful for validating conceptual models and the existence of these may be used as an indicator of credibility. Direct metrics for the quality of model conceptualisation are proposed by Pace (1998) as follows [11]:

- number of “entities” modelled expressed as a fraction of those possible,
- depth with which “entities” are represented expressed as a fraction of the number of possible “levels” (e.g. system of systems, system, sub-system, component),
- “influences” upon entities expressed as a fraction of those possible, and
- “relationships” between entities expressed as a fraction of those possible.

6.3 Indicators for the mathematical modelling phase

Mathematical modelling involves converting a conceptual model of a problem into precise analytical statements [30]. Assumptions must frequently be made during this phase (e.g. modelling fluid dynamics using Bernoulli’s equation assumes steady, inviscid and incompressible flow). In order to assess the appropriateness of a model assumption, one should question whether the effect of a counter-assumption will have any bearing on the use of model results [28]. As for conceptual modelling, cause-effect graphing [3] may be used as an indicator in evaluating the quality of mathematical modelling. In addition, Pace (1998) suggests "order" to be an appropriate indicator of simulation fidelity [11]. Applied to expressions of motion for example, 1st order relates to assuming fixed velocity, 2nd order relates to assuming variable velocity but fixed acceleration, 3rd order relates to assuming variable acceleration but a fixed rate of change of acceleration and so on.

6.4 Indicators for the discretisation phase

Discretisation involves converting the mathematical model from a calculus problem to an arithmetic problem [30]. Suitable metrics to characterise this phase are values associated with attributes of model precision. Such metrics include interpolation intervals and both temporal and spatial step lengths [11].

6.5 Indicators for the computerisation phase

Rules of thumb have been suggested for evaluating the quality of model computerisation. For instance, structured programming that is modular or object oriented has been proposed as an indicator of high quality [26], [27]. Also, Sargent (1999) states that models developed in a "special-purpose simulation language" typically have fewer errors than those developed in a "general-purpose simulation language", which in turn typically have fewer than those developed in a "general-purpose higher level language" [29]. A range of techniques exist for the verification of model computerisation [3], [26], [27] and one might enumerate techniques as a metric to assess the quality of this phase of modelling. With respect to executable computer-based models, Whitner and Balci (1989) present a detailed taxonomy of verification techniques based on effectiveness [33]. Such a taxonomy could be developed to provide a metric for the quality of model computerisation in a manner similar to that shown previously in Table 1.

6.6 Indicators for the parameter data selection phase

In assessing the quality of model parameter data, one must consider the appropriateness and error-freeness of both embedded data (e.g. Boltzmann's constant) and run-time or scenario-specific data [23]. The use of high quality parameter data may be claimed if taken from reliable and authoritative data sources [23], [32]. The "Confidence Levels in Model Behavior" (CLIMB) process was developed to categorise data for missile models according to accuracy [22]. Such categories could be developed to provide metrics for the quality of parameter data. If the error or variability in model parameter data is known, for example by statistical distribution, then there is a range of techniques for assessing their aggregated influence on model output [16]. The effect of data transformations such as unit conversions, co-ordinate transformations and pre/post processing algorithms [23] may be similarly assessed. The metrics that these assessments provide can help in quantifying model fidelity [11], [31].

6.7 Indicators for the numerical solution phase

The adequacy of the numerical solution of a computer model can be confirmed by manual calculation and by verification against a known analytical solution [27]. In the absence of an analytical solution, one could utilise suitable metrics of model precision such as round-off procedures [11] and convergence tolerance settings.

6.8 Indicators for the results representation and interpretation phase

The effectiveness with which model output is interpreted is largely influenced by the skill of the model user. However, features of output display can be of significance particularly for visual models such as flight simulators. Possible metrics concerning the phase of results representation include brightness, contrast, resolution of detail, pictorial cues, frame update rate, atmospheric effects, visual dynamic effects and depth compression [4], [11].

7 Conclusions

As engineered products increase in complexity, it becomes an onerous task to certify models of their behaviour as being credible. The need arises for the formal capture of the reasoning process employed by the modeller using diverse factors such as the opinions of subject-matter experts and relevant indicators or metrics. Existing methodologies to help capture this process were briefly described as well as a BBN based methodology and supporting software recently developed by the authors of this paper. Indicators or metrics associated with the various stages of modelling and simulation were then suggested to provide more rigour to the assessment of model credibility. Other considerations in modelling, such as the financial cost of simulations, make model selection a difficult task. Indeed a compromise must frequently be made between the often-competing criteria of the fidelity of a model and the cost of executing it. These considerations contribute to "total quality" [3] or "acceptability" [13] of models. The management of information concerning these aspects has been claimed by some to be a task that can be eased by computer support [3], [34], [35]. Hence the authors of this paper are developing a decision support system to enable the continued effective use of modelling and simulation in engineering design as more complex models arise.

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