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MATURITY OF MODELS IN A MULTI-MODEL DECISION SUPPORT SYSTEM

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Abstract

To reduce uncertainty in decisions, engineers experiment with models, such as, exploring what-if scenarios, and thus increase knowledge. Still, because modelling is an idealisation of reality, there is often substantial uncertainty involved, and this decision makers less confident to lean onto models alone when making decisions. The aim of this paper is to conceptualize a design support for improving confidence and validity in models, by communicating uncertainties from modelling and simulation to relevant stakeholders. The paper reports on empirical data from a research profile workshop. The findings illustrate the importance of communicating uncertainties from models between relevant stakeholders in order to drive action. The paper then presents an approach to visualize model maturity levels as well as impact levels in relation to one or several aggregated models. With this approach, focus can move to discuss the knowledge about the knowledge that is created from modelling, and to facilitate discussions on a meta-level about the modelling and simulation. This is exemplified by a test scenario where a multi-disciplinary modelling and simulation of an asphalt roller is presented.

Keywords: Decision making, Simulation, Uncertainty, Visualisation, Modelling

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1 INTRODUCTION

Product development is an iterative decision process (Ullman, 2001), which is characterised by uncertainty and ambiguity (Stacey and Eckert, 2003), and thus with associated risks due to imperfect knowledge. This is even more pronounced early in the process as well as when dealing with multi-disciplinary products, which combines knowledge bases from multiple domains (e.g., mechatronic products), where information is scarce and even conflicting. Often modelling and simulation (M&S) is used to build on the knowledge base. M&S is used to analyse and test ideas long before building the first prototype (Walter et al., 2014). It allows testing many more ideas and concepts at a lower cost. This way of supporting design decisions throughout the product development process with M&S is referred to as simulation-driven design (SDD) (Wall, 2007). As models are abstractions of reality, modellers make simplifications, assumptions, and idealisations. This is essential in modelling and, as a consequence, models are uncertain (Walter et al., 2014). This is further accentuated with recent trends in modelling, where intangible aspects such as, value (Isaksson et al., 2013) and sustainability (Bertoni et al., 2015), are included, which increases uncertainty. Still, firms want to base more decisions on M&S, allowing them to perform fewer physical experiments. There is a need (Simpson and Martins, 2011) to deal with uncertainties when modelling; How can decision makers improve confidence in their models?
The aim of this paper is to explore ideas how trust and confidence in models can be supported in the early design phases. The paper first reviews previous works on uncertainty, modelling validation, and model maturity constructs. Thereafter, empirical information from a workshop with industrial practitioners is presented to investigate the need of integrating support for simulation in the development process. Next a decision support for how uncertainty of models could be communicated within a cross-functional team is presented. The preliminary support, with main functionalities and appearance, is exemplified by an application on an industrial case. Finally, the discussion as well as conclusions and future work centres on needs for development and further research to arrive at a design and decision support tool in use with the simulation models.

2 RESEARCH APPROACH

The approach for this work has been centred around a case study approach (Yin, 2003). Empirical data has been collected via a workshop in a research project on model-driven development and decision-making. Participants to the workshop were industrial experts who are working in roles that relate to management of model-driven efforts in their respective firms, including collaboration with academia to strengthen their capabilities in the area of SDD. They are therefore driving development and introduction of modelling capabilities in their firms. The main aspect of interest during the workshop was on how to enable the industrial adoption of the models developed in research, where trust and model fidelity are commonly expressed barriers. Problems in the current situations as well as wishes for the future was discussed. The data has been collected using field notes and reflections, which was then distributed to the participants of the workshop discussion for verification and their opportunity to change statements. From this, the researchers have elaborated on a decision support by ways of various ideations, focusing on conceptual constructs as well as visualisations.

3 THEORETICAL BASIS: TRUST IN MODELS AND KNOWLEDGE LEVELS

To reduce uncertainty in decisions, engineers experiment with models, exploring what-if scenarios, to increase knowledge. Neelamkavil (1987) defines a model as *"... a simplified representation of a system intended to enhance our ability to understand, predict and possibly control the behaviour of the system."* In engineering science, two broad categories of models are identified; physical models (e.g., scale models) and virtual (symbolic) models (e.g., mathematical models). With increasing computational power, and developments of algorithms and software, more and more engineering problems is studied using mathematical models (hereafter referred to simply as *models*).
The same system may be represented with sufficient accuracy by models of different fidelity (i.e., detailed representation of what is modelled), where the investigation objectives decide which fidelity is suitable (Clay et al., 2008). The investigation objectives should therefore be specified unambiguously. Thereafter, a suitable experimental frame can be developed, with a specification of the conditions to study (Zeigler et al., 2000). The modelling process aims at developing a model that mimics the studied

system with sufficient accuracy in the specified experimental frame. However, the experimental frame and required model fidelity naturally looks different depending on the current status of the development process. Early on, models of low fidelity are typically deployed while models of higher fidelity are used in later stages.

3.1 Uncertainties and unknowns

Uncertainty is absence of certainty, or knowledge – meaning it is about unknowns. Here it is possible to distinguish between known-unknowns and unknown-unknowns, between uncertainty and ambiguity, respectively (Carleton et al., 2008), distinguishing between whether we know or do not know which parameters to find. Uncertainty can also be described as aleatory or epistemic (Hofer, 1996). Aleatory uncertainty (Walter et al., 2014) is the variance of having a certain information value, although the exact value is mathematically described and statistically estimated with a probability distribution, originating from randomisation. Epistemic uncertainty comes from incomplete, insufficient, and non-existing information and knowledge, depicting lack of knowledge. It can be reduced and turned into aleatory uncertainty by doing research activities. These can also be related to stochastic uncertainty (quantified according to probability theory), estimated uncertainty (with known effects, but difficult to quantify fully), and unknown uncertainty (not possible to quantify) (Engelhardt et al., 2011). A major source of uncertainty are users and their perceptions, which means that simplifications, idealisations, and abstractions, which are central to modelling, will drive uncertainty (Walter et al., 2014). There are four types of uncertainties in M&S, relating to both aleatory and epistemic uncertainty concepts, in simulation (Walter et al., 2014); data uncertainty (i.e., variance and vagueness), M&S uncertainty (i.e., idealisation, modelling as well as human errors), phenomenological uncertainty (i.e., unknown-unknowns), and uncertainty in human behaviour (i.e., interpretation, decision maker, and ambiguity in declarations). Funtowitz and Ravetz (1990) introduce the concept of pedigree to assess uncertainty in the knowledge by use of qualitative expert judgment in their NUSAP method. Reducing uncertainty, involves gathering information about variables that are known to the problem solvers, whereas reducing ambiguity is about model building, negotiation, problem framing, evaluating and reframing, and model testing (Schrader et al., 1993). Previous research (Wall et al., 2011) shows that an all-at-once approach to simulating multi-disciplinary systems, simultaneously considering all relevant disciplines and aspects, is superior to sequential approaches. In such interlinked multi-level model hierarchy, the problem will be more pronounced as uncertainties and associated risks propagate through the model hierarchy.

3.2 Simulation validation and verification

Model validation is important, because used as decision support, models must be perceived as trustworthy (Walter et al., 2014). Definitions of the terms ‘verification’ and ‘validation’ are by no means consistent, neither in practice nor in literature. Verification, as used here, is the process of determining if the model works as intended, that is, that model coding and implementation is done correctly. Validation, as used here, is a measure of usefulness in relation to the investigation objectives. These processes are vital for models to be trusted as support for design decisions (Sargent, 2011).

The model maturity constructs (i.e., (Clay et al., 2008; Oberkampf et al., 2007; Anon, 2008)) reviewed in this paper explicitly advocate validation and verification *as a part* of improving the model maturity levels, thus also indicating that the problem is complex and dependent on more factors.

Harmon and Youngblood have suggested a simulation validation process (Harmon and Youngblood, 2005), which is based on levels, similar to CMMI (Anon, 2011). These process levels range from initial/subjective validation through objective activities to automated validation.

3.3 Model maturity

In literature, most maturity constructs stem from two main streams; either the product-/systems-focused Technology Readiness Levels, TRLs (Mankins, 1995), which was developed by NASA and the US Department of Defense, or the process-focused Capability Maturity Model, CMM (later developed into Capability Maturity Model Integration, CMMI) (Anon, 2011), developed by the Software Engineering Institute (SEI) at Carnegie Mellon University. From these two, many adaptions have then been developed for specific areas, effectively to adapt to the specifics of these contexts, because straight adaptation is either impossible or non-intuitive for the developers.

For many of the maturity constructs, maturity denotes the compromise, or distance, between actual uncertainty and ideal/target uncertainty (Grebici et al., 2007), and is assessed by use of a level-scale, with definitions ranging from an initial level to an optimising level. NASA has developed a Standard on Modelling and Simulation (Anon, 2008), to provide decision makers with information about the credibility of M&S. They suggest a Credibility Assessment Scale with a scale with five levels (0-4) over eight factors that contribute to the credibility of M&S results. US agency Sandia National Laboratories have developed a few approaches to assess the quality of M&S efforts. The Predictive Capability Maturity Model (PCMM) (Oberkampf et al., 2007) is a structured method to assess the level of maturity of computational M&S efforts. In an investigation to apply TRLs for M&S applications, Sandia created a TRL for M&S (Clay et al., 2008), which found that the basic NASA TRLs are too static for application in M&S, and thus needed to be developed and take in specific modelling context. They suggest a framework and methodology that merges with the PCMM approach, which is expanded over relevant areas for physics-based M&S of geometrical components, to represent both the modelling process and the TRLs, thus integrating with standard TRL measures.
Apart from having one, or a set of scalars, an effect from assessing maturity of M&S efforts that has been identified is that the assessment in itself engenders discussion and communication (Oberkampf et al., 2007) about these issues, which would not happen otherwise.

4 MODEL MATURITY IN THE DECISION ARENA

In the research project described in Chapter 2, all results are packaged – in addition to the research production of papers – as models, which then can be used in concert for SDD, with multi-disciplinary optimisation. To facilitate this and to drive their usefulness as decision support, an integrated decision environment, called the "Decision Arena", is created. Diverse models are used together to arrive at a holistic understanding of the decision. In this view, the role of trust and uncertainty is important to deal with, because of the cross-disciplinary models and stakeholders, with different conventions for presenting information.

4.1 The need for model-meta-knowledge

In the workshop discussion, the challenge of promoting increased use of models (especially models from research) in decision making in firms were addressed. All decisions must be motivated. For engineers, this means either developing models, and relying on their results, or performing physical testing and measurements. A major challenge in decision making in the firms is *if* they feel confident to make a certain decision. Information is needed, but *sometimes* expectations for what the information should be, what question should be answered, and how, are undefined or poorly communicated beforehand, which means that the information produced *might not* motivate the decision. Then it might end up being *no* decision made, and they revert to try and find the '*right*' information by other means than M&S (e.g., physical measurements). Participants expressed frustration with this, where they often would like to see that *a* decision is made – even if it is the "*wrong*" decision – because that keeps momentum. A wrong decision can be changed, but with no decision there is also no action.
A challenge is to know in which contexts a simulation model is valid to base a decision upon. It is both down to the models, and also the context for which the model should provide an answer. It is important to understand the applicability of the model, and as much when *not* to use a certain model. When models are not trusted, firms do physical testing and measuring – just to be sure. One participant rhetorically wondered "*if they were doing too much physical measuring*" for this reason. They wished for a framework to describe the models' fitness for purpose and assumed uncertainty, so that they know if a model is valid for a certain decision. They want to understand which parameters would describe the model from a meta-perspective so that they can assess and question the model's usefulness and effect on the decision in a constructive manner.

4.2 Visualization of maturity and impact for models

This part of the paper presents ideas for how to support the representation of models' uncertainty contributions and usefulness in projects. The idea is to support communication by proposing a visualisation approach that presents meta-information about the models (Figure 1). The suggested visualisation displays two main dimensions relating to confidence in models; *model maturity level (MML)* and *impact* from using the model, on a colour-gradient background. The reason for using MML

and impact is to be able to represent uncertainty and imprecision as well as an expected consequence the decision has on the performance of the project.
MML depicts a distance, or compromise, between the actual (i.e., current value) and ideal certainty level to be expected from the model. Similarly, as with other maturity constructs in literature, MML is envisioned to follow a levels-scale, from low to high maturity.
Impact is here defined as the effect the model has on the framing of a question of the development activity. In a trade-off decision situation, some aspects (e.g. models or other design activities) have greater influence on the end result than other aspects. This is especially evident in a multi-model situation and with many parallel models, where decision makers should be informed about how to best spend resources, on high impact-level aspects, to improve the situation.
With the colour-gradient background (red, yellow, green), acceptance thresholds – the combined uncertainty and impact where you trust to move forwards – can vary from one project to another, and also through different project phases. In early phases and in low-risk projects, more uncertainty can conceptually be allowed, whereas closer to product release and in important decisions with higher stakes, the threshold to pass will be higher. This can be visually represented with different gradients, as is exemplified in Figure 1.

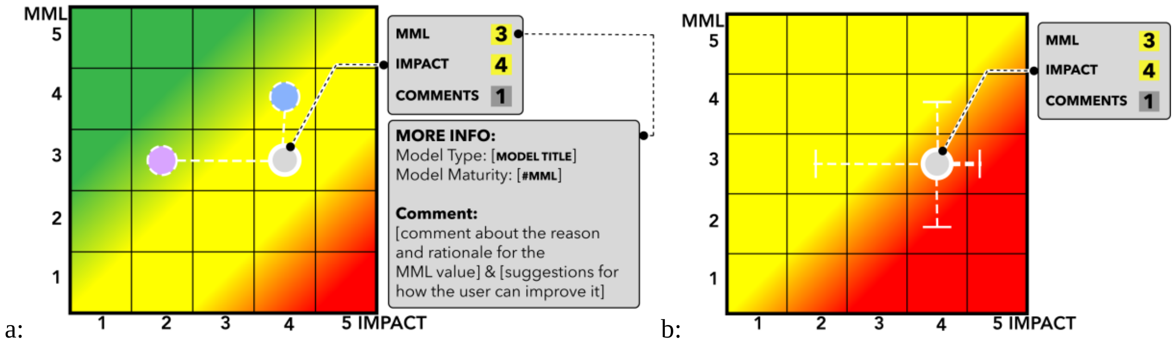

Figure 1. Two examples (a and b) of visualisation of model maturity

To reduce risk of information overload and a cluttered interface, the visualisation is suggested to be interactive, where users explore the reasons for the levels. Also, the idea is to support the user with suggestions on actions to take to move up from the current level. These are presented as the grey callout boxes in Figure 1. For instance, a preliminary model for an early phase might need to be superseded by a more detailed model if a more certain result quality is required in later phases.
Aggregation of models can be represented visually, where the source models' maturity contribution can be traced. In Figure 1 (a), sub-models are connected to the aggregate level by visual leads. Borrowing from the PCMM approach (Oberkampf et al., 2007) reviewed earlier, it is suggested to present an aggregate value as three parts (see Figure 1 (b)); the *minimum* MML of all ingoing models, the *average* levels of all of the, and finally also the *maximum* level, instead of just one value.
Finally, the gradient background can be animated (i.e., difference between Figure 1 (a) and (b)) to depict how the project's criteria is expected to develop during the project, thus allowing the users to decide if another model would be needed further on in the project.

4.3 Test scenario

The presented visualization concept for model maturity has been applied to a case of a 1.7-ton asphalt compaction roller (Figure 2 (a)). The case focuses on the design of the front of the machine considering seven subsystems or components: drum, frame, forks, bearings, engine, engine hood, and eccentric. Taking a lifecycle-value perspective on design with perceived customer value in focus, a multi-disciplinary system model of the roller is developed. The model integrates engineering analysis with value-driven design in a hybrid simulation environment including several different software.
The functional model, a structured representation of the functions needed for successful operation, is developed in order to evaluate system performances, such as compaction capacity, of the design concept. Here the main functionality is soil compaction. However, to be able to compact soil, additional functionality such as, power supply and transmission is needed. A simplified schematic description of the functional model developed in the case study is given in Figure 2 (b).

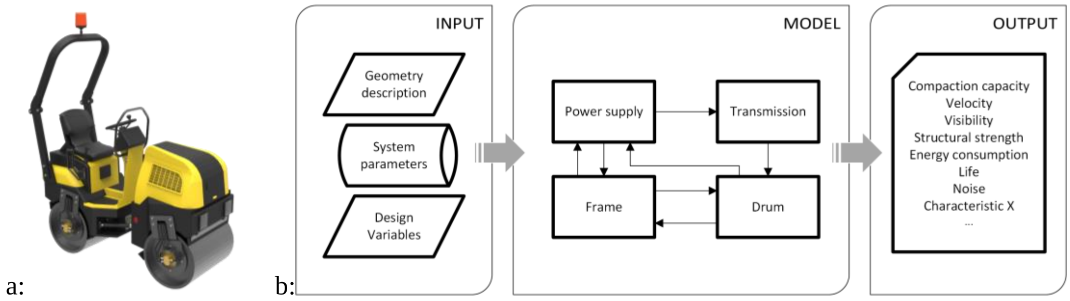

Figure 2. (a) Asphalt compaction roller and (b) functional model of asphalt compaction

This functional model is populated by engineering models (for example in the form of differential equations, algebraic equations and mathematical logic) in order to estimate the performances of the system (listed on the right side of Figure 2 (b)). In the case study, for a given system configuration, a compaction model calculates the amount of energy per time unit that is transferred to the ground through the drum. An energy model calculates required energy and associated fuel consumption for the suggested machine design, and a finite element model of the frame verifies the structural strength to avoid structural failure during operation. For the population of such engineering models, geometric and technical descriptions of the major sub-systems and components under analysis is required. This information is supplied through a parametric CAD-model. Geometric information from the CAD model is also used to assess visibility from the operator's seat.

A value function, total cost of ownership (TCO), is defined to cover the relevant monetary impacts throughout the system lifecycle and builds on three major cost drivers (TCO items); unit cost, operation cost, and maintenance cost. The unit cost is estimated as the sum of all purchase costs and the manufacturing costs, which are estimated by use of a generic factory cost model.

The results from the simulation of the functional/engineering and the factory models are used as input to the development and simulation of ‘lifecycle performance’ models. In the case study, these consist of two modules based on a discrete-event simulation (DES) technique. The first is an ‘operation model’, calculating measures such as, net utilization time, net distance covered, net total fuel consumption, and number of transport operations between work sites. The second module is a maintenance model, predicting the impact of design choices on maintenance and repair costs.

A simplified schematic description of the multidisciplinary model hierarchy, showing typical model interaction is shown in Figure 3. The model hierarchy has three levels with the TCO model on top (level 1) and the system performance models in the bottom (level 3).

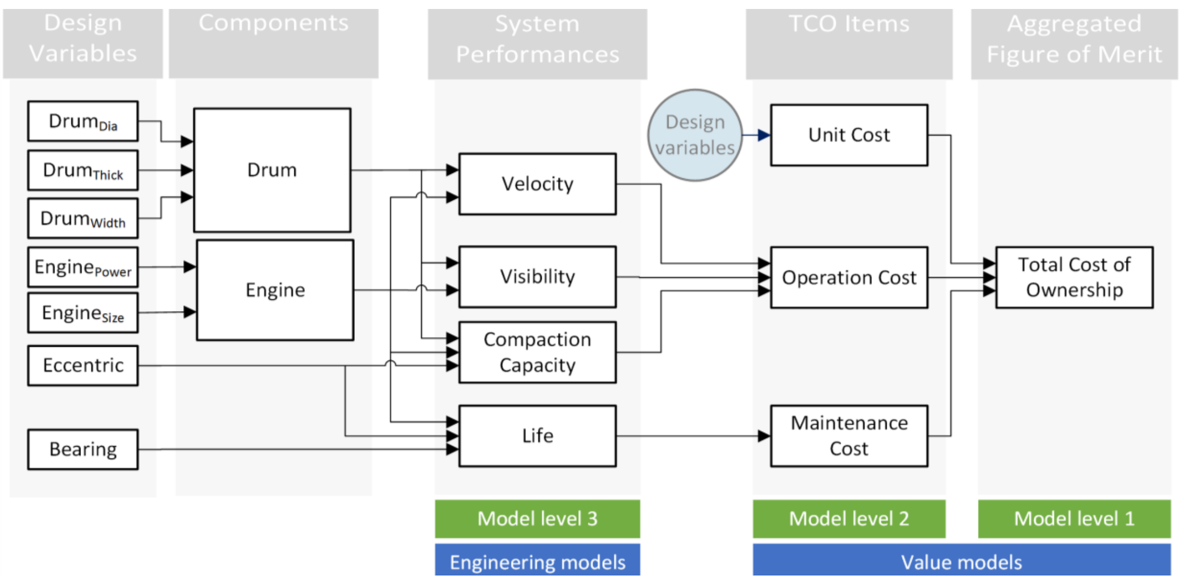

Figure 3. Hierarchical decomposition of value model and sub-models on three levels

The complete system model is hierarchical with interlinked models (Figure 3). For example, to calculate operation cost, the operation cost model must be executed. However, this model is fed by several other models, such as, the velocity, visibility, and compaction capacity models. In such an interlinked multi-level model hierarchy, uncertainties propagate through the system. To be able judge the high-level output (operation cost), the decision maker must be aware of eventual uncertainties at lower levels and how they propagate through the system. In this context, the decision maker needs to trade-off uncertainty in the models against their overall impact on value to be able to make a confident decision on a design concept.

To exemplify sub-model impact on model response, an assessment based on a sensitivity study is made. The input variables from the sub-models that compose the operational model (velocity, visibility, and compaction-capacity) are varied a small amount around a nominal value and the model response (operation cost) is calculated. The result is plotted as a tornado diagram (Figure 4) showing to what extent sub-model variation affect model response.

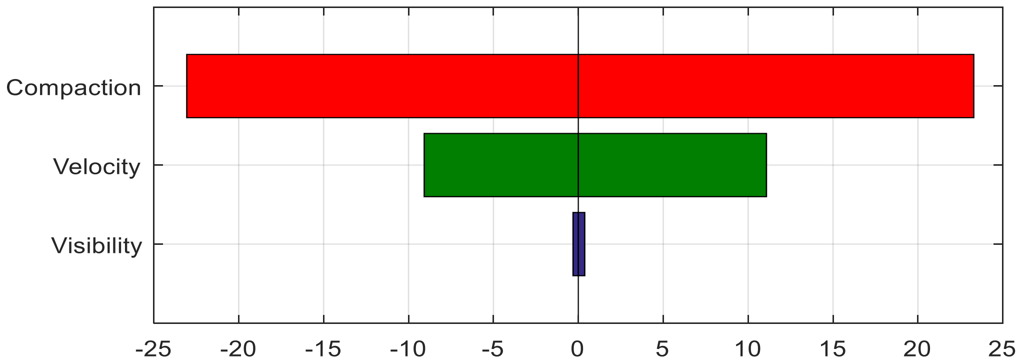

Figure 4. Results from sensitivity analysis

Quantifying sub-model impact on model response through a scale is not a trivial task. One example could be, assuming results of the sensitivity study is normally distributed, a scale based on percentiles, (e.g., similar to relative grading applied in some school systems). Expected small sample sizes in the intended application will render low confidence levels in these predictions although this might be acceptable due to the relative nature of the sought impact measure. In the example, impact is graded on a scale from 1 to 5 evenly distributed across 0-100%. The results are summarised in Table 1 and visualized according to the proposed format in Figure 5.

Table 1. Results from test case

Model	Impact	MML	Comment
Compaction	5	3	Modification of validated model previously used
Velocity	3	4	Experimentally verified. Used within the firm for many years.
Visibility	1	1	Only account for operator sight in one direction. Do not follow international standard ISO5006:2006.

The visualisation for the test case can be seen below in Figure 5. The MML and impact relative to a threshold combination is visualised with use of colours. For instance, impact for compaction is red, whereas both MML for the velocity model and impact for the visibility model is green. Clicking on the visibility model provides additional rationale and suggestions for how to improve the result.

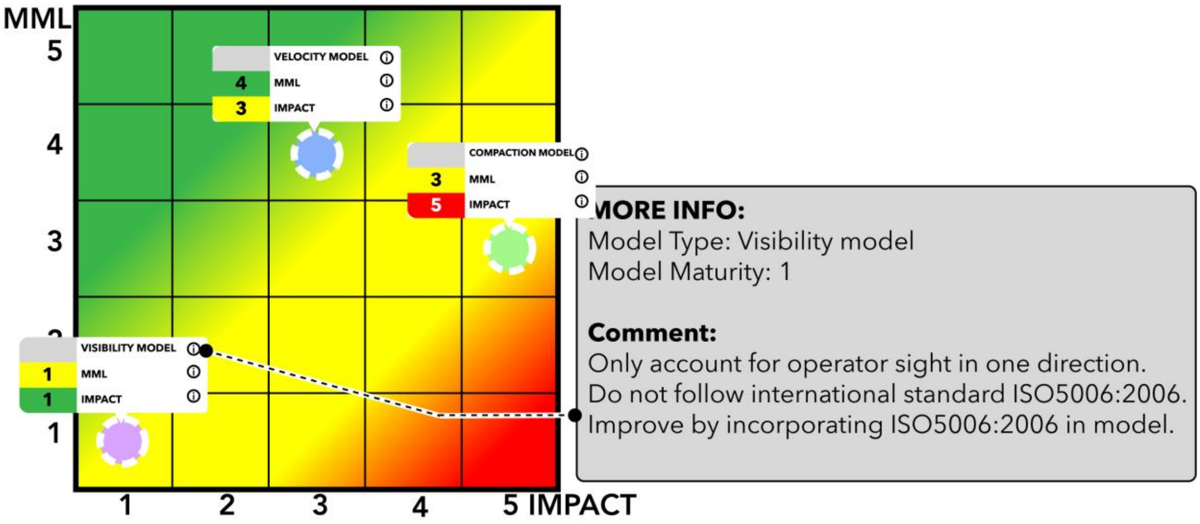

Figure 5. Visualization of MML and impact for test scenario

The example illustrates that a low MML not necessarily requires an action. The visibility model has MML 1, but because its impact on the response is low it can still be acceptable. On the other hand, the compaction model has MML 3, but because it has significant impact on the response, the decision maker is cautioned and able to account for this in a decision scenario.

5 DISCUSSION–INTEGRATED DECISION SUPPORT OF UNCERTAINTY MANAGEMENT

The design process paradox (Ullman, 2010) effectively states that having more knowledge available, sooner in a project allows more informed decisions about the design project before it is too late. The findings from the study indicates that having 'knowledge about the knowledge' would also allow for more informed decisions, not necessarily because the product is better, but because there is more knowledge about its potential imperfections.

A challenge in a multi model environment, is to have a consistent and representative way to deal with aggregation and propagation of model immaturity. Outputs from one model leads to inputs in another model in the hierarchy, and uncertainties will propagate through this complex system. In such a context, engineers have the difficulty of understanding how uncertainties of models propagate. As a result, engineers will direct personnel and time to improve the maturity of all the models, hence delaying the decision moment. In this discussion, the '*cost of modelling*' is of interest. In product development, resources are scarce and it is important to know how to spend those in the best way possible. In M&S and applying the MML/impact measures, it is of interest to know on which model(s) to best spend resources to improve the outcome, and thus not evenly distribute efforts onto models that can already be executed with sufficient confidence to deliver a product. With the presented visualization support, engineers can direct resources to the improvement of the maturity only of those models that have greater impact on the overall results. Others can be considered as '*satisficing*' (Simon, 1979) even with a low maturity level.

Although a sensitivity analysis provides a feel for the robustness of the models, when aggregating several layers of models and one serving as input to the next, 'faulty' models can skew the results from a variation on inputs in a similar fashion, providing a false positive on a robustness response. The idea is that the combination of MML and impact will capture this, but it needs to be further elaborated.

M&S is part of a greater whole in product development, where it is contributing to the uncertainty of product development at large (Johansson, 2014) in projects, which contains other knowledge elements. Part of the ongoing work is therefore also to relate and expand on the knowledge maturity scales which were elaborated (Johansson et al., 2011) to support decision making in a gated process, based on the evaluation of input information, tools, and user experience and expertise. On this note, M&S capability is not just about the simulation tool, but also requires the right infrastructure and user expertise and qualification (Clay et al., 2008) to be effective. For instance, what reality to model is defined by the user's state of knowledge (Walter et al. 2014), where an engineer is likely to perceive reality differently from a business developer, and allowing both (Ericson et al., 2007) to perceive the relevant information accordingly is important.

A strong belief with the application of a maturity construct is that it, as identified by other authors (Graettinger et al., 2002; Oberkampf et al., 2007), also allows the stakeholders to stimulate discussion and communication about issues that are on a meta-level. It essentially is a boundary object (Johansson, 2009; Panarotto, 2015). This relates to more fundamental issues of knowing, and is not directly related to satisfying the specific application expectations. Maturity is about figuring out and valuing some relevant sets of meta-information, with a view towards making informed decisions; What activities (how well) have been performed? What are the processes? Whom are involved? How can information be characterised?

6 CONCLUDING REMARKS AND FUTURE WORK

The aim of this paper has been to conceptualize a design support for improving confidence and validity in models, by communicating uncertainties from modelling and simulation to relevant stakeholders. This has stemmed from the need of firms that want to move towards using models as a first and only mode of attack, as this would allow to avoid testing physical models (thus accelerating the development process). Also, firms want to be able to incorporate new modelling approaches stemming from research (such as for value and sustainability) sooner in their product development processes.

This paper has developed and suggested an approach to visualization of model maturity level (MML) as well as impact level in relation to one or several aggregated models. This was exemplified by a test scenario where a multi-disciplinary modelling and simulation of an asphalt roller, was presented.

The main findings indicate that a way of representing some relevant meta-information of the use of models is needed in order to better comprehend the results of the model hierarchy. With such representation, engineers can direct their action on improving the maturity of models that highly affect the end result, while under prioritizing the maturity of models with low impact on the end results.

We can also conclude that there are more research efforts needed to be able to move closer towards industrial adoption of this approach. More empirical work with the partner firms is needed to further understand their problems and hesitations from going all-out on the M&S track. Here we see that there is a need to do some ‘model archaeology’, where we can review past cases – both successes and misses – to see what were the actions taken, with what rationale (also in retrospect), and the outcomes from these projects. Also, a method for assigning impact levels needs to be further researched. Based on this, together with best practice from literature, a framework of MML can then be further elaborated and even expanded beyond M&S into an improved Knowledge Maturity framework for managing the meta-level of ‘knowledge about knowledge’ discussion in the projects.

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