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UNCERTAINTY AND RISK REDUCTION IN ENGINEERING DESIGN EMBODIMENT PROCESSES

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1. Introduction

Uncertainty is often considered as a lack of knowledge that may introduce risks to the outcome and execution of a process. In the use of formal information systems such as Product Data Management (PDM) the tacit appreciation of uncertainty needs to be made explicit and as objective as possible such that various parties can share information with minimal risks. Document lifecycle management is commonly used to control versions and iterations but the uncertainty in data is still not represented explicitly. At present, the uncertainty may be reflected in contextual clues like the product lifecycle stages, status of work (in progress, draft etc.), but uncertainty in data is still not clearly defined or expressed.

The authors are particularly interested in the uncertainties occurring during the embodiment design phases. The main activities in this phase consist of systematic transformations or from the physical domain (design parameters) into the functional domain (performance parameters, design targets) to evaluate how well a design will satisfy the required functions. A common form of mapping from the design parameters into the performance parameters in today's virtual product development is based on simulation models such as the finite element method (FEM).

It is common to have coupled and conflicting design requirements thus introducing ambiguity in the product definition. In concurrent engineering, multi-disciplinary teams work collaboratively to resolve the design problem as well as to satisfy these trades-offs. These teams may utilise different methods and tools to perform their work, and exchange information with inter-dependent teams. In order to reduce development time, individuals and teams usually need to proceed with assumptions and continuous iterations when new information becomes available. The uncertainty associated with the method and information will have impact on these activities, and needs to be quantified and assessed. This temporal issue introduces additional risks due to the need to provide and receive uncertain information.

This paper builds on previous work on a maturity framework [1]. The information maturity refers to invalidated information or that of uncertain conformance to the required quality where this may have critical consequences on the product and the process. The uncertainty refers (in this paper) to data that are imprecise, subject to errors or unstable. This paper will look in particular into the correlation between uncertainty in data and perspectives on its maturity related to the design process in order to assess the resultant risks of design iteration.

The remainder of this article is organized as follows. The authors first review different types of uncertainty in the literature (Section 2). As the aim of the present paper is to assess the risk within the engineering design, the section 3 is dedicated to the presentation of different risk assessment approaches provided in the literature. Section 4 represents the description of the proposed maturity-based framework as an answer to some the main shortcomings highlighted in section 3. In order to illustrate the potential contributions of the proposed approach, a scenario based on a fragment of the engineering analysis process in the area of aircraft design, is presented in the section 5. Section 6 puts forward some of the main challenges that the risk assessment approaches face in the engineering design context. The paper is rounded up with conclusions and further work in the section 7.

2. Literature Review

2.1 Uncertainty

This section doesn't aim to represent a consistent definition of uncertainty. The focus here is on three types of uncertainty particularly important in engineering analysis, i.e. errors, imprecision and instability.

There is no consistent definition of uncertainty in the literature; its usage depends greatly on the context of discussion. In general, uncertainty "applies to predictions of future events, to physical measurements already made, or to the unknown" [2]. In engineering, several authors attempt to clarify its taxonomy and meaning. For example, Earl [3] distinguishes between known and unknown uncertainties. The known uncertainties are those can be described and handled well based on past cases. The unknown uncertainties are those where the specific event or type of event could not have been foreseen, e.g. the occurrence of the peak oil price of 2006 and its impact on the automotive manufacturing industry. A well-accepted classification in engineering analysis is the distinction between reducible and irreducible uncertainty [4]. Reducible or epistemic uncertainty can be decreased through further studies, measurements and expert consultation. However, the irreducible or stochastic variability is inherent to the physical system such as the dimensional variation in the manufactured components and cannot be reduced through additional studies or measurement. Although useful for modelling purposes, the separation of effects of the two types of uncertainty is not always possible in practice. Furthermore, in addition to these two categories, Pon [5] introduces the notion of abstraction uncertainty in engineering – uncertainty introduced by the abstractions used by engineers. Uncertainty can arise due to information abundance or ignorance. Zimmermann [6] suggested uncertainty can be caused by the lack or abundance of information, conflicting evidence, measurement uncertainty, or ambiguity and belief (or subjectiveness).

The above definitions of uncertainty are concerned with the information content (incompleteness, imprecision and vagueness). In [7], uncertainty may concern data (e.g. incompleteness, inconsistency or lack of quality of measurement) or the description of the data (e.g. ambiguity of descriptions, the selection of parameters and the lack of clarity in their scope). This classification overlaps with Eversheim's categorization of uncertainty: content-uncertainty (incompleteness, imprecision and vagueness) and context-uncertainty (unreliability, invalidity and instability) [8]. Both lack of knowledge and lack of definition are similar to Earl's uncertainties in the description. The lack of knowledge is the "facts that are not known, or are known only imprecisely, that are needed to complete the system architecture in a rational way" and the lack of definition represents "things about the system in question that have not been decided or specified". Lack of knowledge and ambiguity of definition (lack of definition) are reducible. However, the stochastic variables are inherent uncertainty such as the material characteristics of the manufactured components as well as the unknown uncertainties (such as the occurrences of unexpected event) that are irreducible.

From the literature, one can notice that the sources and types of uncertainty and the uncertainty effects are often confused. In this article we use Eversheim's content and context-dependent classification of uncertainty. Content relates to the uncertainty in the information, such as: imprecision, incorrectness (errors), vagueness (unspecific or fuzziness) and the context-dependent uncertainty is due to the complexity of the context such as the instability. However, inconsistency, invalidity, unreliability, robustness and lack of quality represent metrics for assessing the information readiness for a specific task, given the level of uncertainty. In [9], these indicators are called maturity indicators. Some other authors consider maturity indicators to assess the process readiness given the information uncertainty.

For instance, Krishnan [10] defines task sensitivity as a criterion to assess the effect of the upstream variability on the downstream task. Bhuiyan and Thomson [11] consider completeness as the probability of churn and the probability of design versions. Churn iteration corresponds to the frequent, minor changes during an activity, whereas the design version iteration is the time-consuming and costly rework across phases [11]. This rework is due to uncertainty of the processed information. In this paper, we use these maturity indicators in a risk assessment framework.

As mentioned above, one of the reasons for uncertainty classification is for modelling purpose. The uncertainty and maturity modelling is one of the important steps towards the development of the present framework for risk management. Although, the authors have been investigating different techniques and methods for uncertainty and maturity modelling in the design process, the purpose of the present article doesn't present this research but rather concentrates on the further step which is the risk assessment and reduction. The description, and the justifications of the modelling methods used, will be presented in future publication.

2.3 Methods for risk identification and assessment

Risk can be defined as potential impacts due to the consequence of uncertainty. Risk management usually aims to translate uncertainty into estimates of project time and cost, and safety. Regarding cost, risk management serves to clarify the risks associated with project costs and provides a means of validating the budget's contingency. However, regarding the time, risk management serves to clarify risks to the project's schedule allowing for contingency plans to be established early when such risks affect the critical path. As indicated in [12] the costs due to the timeliness of delivery often have an important impact on profitability (more than the development or the production costs). Thus the present work is motivated by the need for project time control and by the reduction of the design iterations [13].

In a systematic probabilistic risk assessment (PRA) [14], the aim is to quantify the risk that could be used to define and measure acceptable levels of risk, calculate the cost of reducing risk, and optimise the balance of cost versus risk. Different methods are employed in order to identify risk and to assess the probability of risk occurring, the uncertainty of estimates and their impact/severity. For example, failure mode-based methods, such as Failure Modes and Effects Criticality Analysis (FMECA) [15], can be used as a part of the design project to identify problems (failures) throughout the design process and to prioritise corrective actions. Such methods allow engineers to consider any potential issues beforehand but the main shortcoming is that they do not allow for risk to be mitigated during the task/operation. The approach proposed in the present paper uses uncertainty factors and the maturity indicators to evaluate the occurrence and the impact of the iteration risk, respectively. The risk is considered within a collaborative framework.

3. Maturity-based approach for risks assessment

In a concurrent engineering context with cost and lead-time constraints, the information supplier and receiver will not wish to wait until the completion of associated tasks for information to be released and for their tasks to be started. Preliminary releases of immature information have to take place, and compromise is needed about the uncertainty level of the exchanged information. This is not done without additional risk of rework and cost overrun.

The assessment of the iteration risk follows the steps of any risk assessment method which consist of answering the following questions: (1) what are the initiators or initiating events that lead to adverse consequence(s)? (2) What and how severe are the potential detriments that the process or the product may be eventually subjected to as a result of the occurrence of the initiator? (3) How likely to occur are these undesirable consequences, or what are their probabilities? How the risk could be mitigated?

The questions about the costs associated to the risk reduction actions and the assessment of the residual risks are not considered in this paper. The answers to the questions above are described through the steps of the proposed maturity-based approach for risk assessment (figure1). We assume that risk likelihood is a function of the uncertainty levels because risk is caused by information uncertainty and risk impact is a function of the maturity levels because its impact relates to the context of the task. The authors made the choice to organize the description of this approach within the following sub-sections as shown in the figure 1.

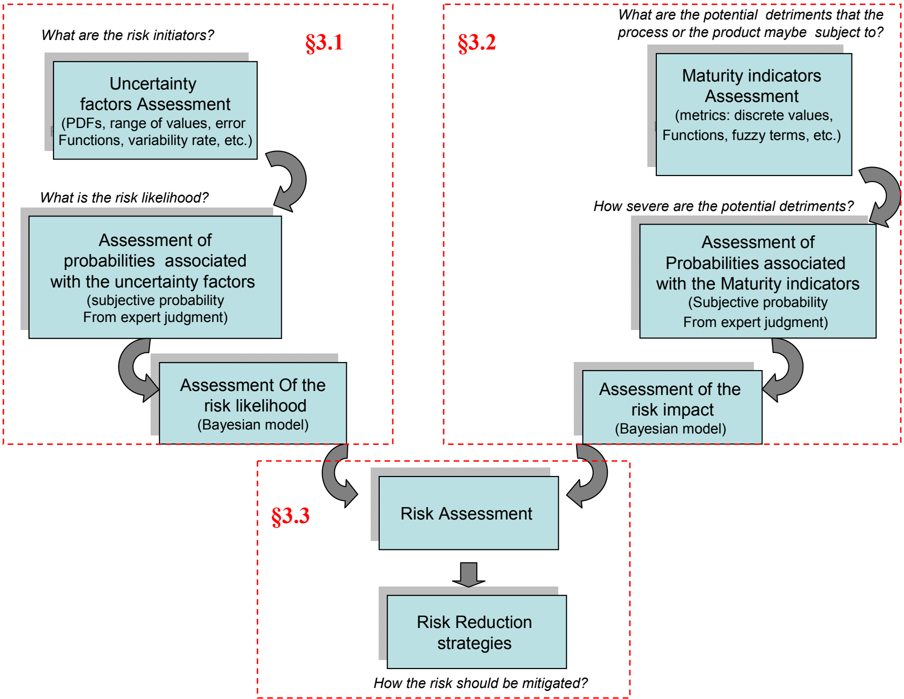

Figure 1. Maturity-base approach for risk reduction

Although the assessment is meant to be done at the beginning of a project, it is important to emphasise on the fact that the uncertainty and the risk assessment are time dependent; their values might change throughout the engineering design process.

3.1 Uncertainty factors and iteration risk likelihood

The questions targeted in this section are: (1) what are the risk initiators or factors? and (2) what is the risk likelihood? (Figure 1)

Obviously, the uncertainty factors associated with the inputs are the initiator of the risk in the engineering process. The key subsequent questions are what the uncertainty factors are and how to assess them? The answer to the former question is provided in the context of engineering analysis processes, where the information created, modified and exchanged are mainly design parameters or performance parameters (material properties, component dimensions, loads, stress, etc.). Hence, the authors argue that the uncertainty in this stage of the engineering design corresponds to the factors: imprecision, errors and/or instability. These factors reflect, respectively, the extent of data that describe the considered parameter (imprecision) [16]; the discrepancy measured between predicted parameters and evidence in the presence of uncertainty (errors) [17] and the likelihood that the data provided by one task would change after being released due to contextual effects (task interdependence, customer requirement, unexpected events, etc.) (instability) [10] [18].

The imprecision often results from a lack of knowledge or information or from deliberate modelling decisions due to resource limitation. The imprecision may be represented and assessed in design by fuzzy terms, ranges of deterministic values or by Probability Distribution Functions (PDFs). Level of

imprecision may be assessed in each of these representations (e.g. “imprecise”, “moderately precise” or “precise”). However, according to the available knowledge about the imprecision of the data representing the considered parameter, the engineer may assign different level of probability regarding the level of imprecision (Figure 2).
In [17], Goh describes error functions applied to design spaces with a large gathering of experience from analysis and evidence from many variants, including the representation of systematic and random uncertainties. The analysis of errors needs to be supported by a company’s Verification and Validation (V&V) activities such that it is possible to classify modelling approaches according to their accuracy for specific types of problems. Thus, according to the classification of modelling approaches used and the values derived from these approaches, different levels of uncertainty may be associated with the errors (e.g. “low”, “medium” or “high” errors in Figure 2).
Instability is considered as uncertainty due to contextual effects on the information. Different mathematical models have been proposed to represent information instability [18]. For instance, Krishnan [10] uses evolution rate to assess the probability that the actual value (at the time t) of a parameter approaches its final value at the ending time of the task (Figure 2). Here also, according to the knowledge about the likelihood of future changes, the engineer can judge the probability of the instability as, for example, “low”, “medium” or “high” (Figure 2).

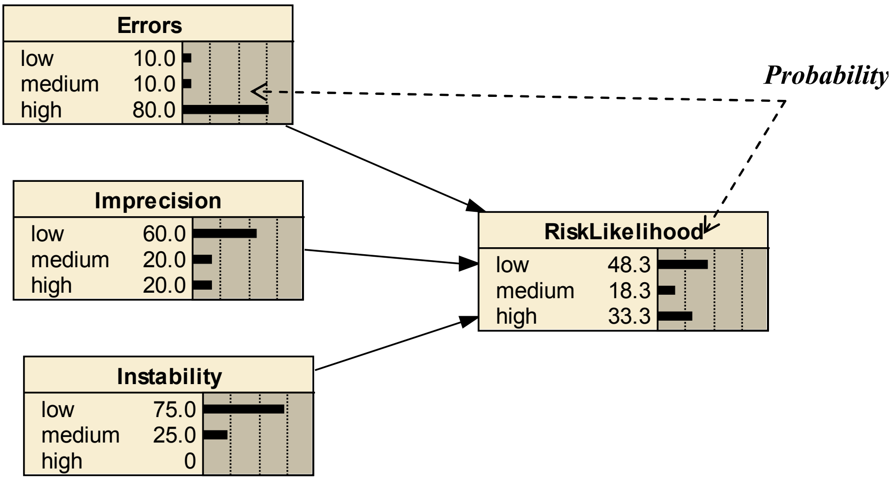

Figure 2. Example of likelihood assessment from uncertainty factors (errors, imprecision and instability) associated with a parameter “P”

The figure 2 corresponds to an example of risk likelihood assessment where the factors Instability, Imprecision and Errors are estimated using a set of metrics, namely: variability rate (instability), standard deviation and standard mean (imprecision), and systematic and random errors. For instance values of the variability rate (ε_t) are judged “low” within the interval $0 \leq \varepsilon_t \leq 0.25$ “medium” within the interval $0.25 < \varepsilon_t < 0.75$ and “high” within the interval $0.75 \leq \varepsilon_t \leq 1$
However, as the knowledge about the design context is difficult to predict and to replicate, it is often difficult to judge or evaluate the confidence about information uncertainty without relying on expert judgment or experimental knowledge. Thus, subjective probabilities are used to represent the level of confidence the expert would have regarding each level of imprecision, error and instability. For example, the instability is judged “high” with 75% of probability (figure 2, left-hand side and down). The subjective approaches for probability assessment are meant to be repeatable and the attempt is to provide objective quantification approaches, such as metrics. Indeed, values of the variability rate

(ε_t=0,95) could be associated with fuzzy terms (e.g. “Low”). These fuzzy terms would be selected (by experts) and subjective probability (grade of membership) would be then estimated to represent how likely the given value(s) of εt corresponds to those fuzzy terms (e.g. “low”). To reflect the fuzziness of the probabilities evaluation, a probability “1” describes a fully included member whereas values strictly between “0”and “1” characterize the fuzzy members.
The probabilities associated with the levels “low”, “medium” and “high”) are highly important for the engineer’s decision making. They actually help the engineers to make up their mind about the risk. For example, the confidence could drop even though the performance parameters meet the criteria. This might be the case if the performance parameter which seems to meet the criteria is derived from deductions and approximate calculation methods, the parameter is still uncertain because it was based on a low validity of the transfer function.
The risk likelihood is derived from the probabilities of the uncertainty factors (figure 2). Indeed, high probability for “high” errors in the parameter reveals high likelihood of iteration. Similarly, a high probability for “high” imprecision or instability means high likelihood of iteration owing to limited data, modelling assumptions, numerical methods or further uncertainty occurrence. A Bayesian model with conditional probabilities of equal weight is applied in the figure 2 in order to derive the risk occurrence probability from the probabilities of the uncertainty factors (the method for this mapping will be described in future publication). Different weights of the conditional probabilities reflect how much the design actors are pessimistic or optimistic about the risk occurrence. The mathematical description of the Bayesian model is well described in [19]. The calculations are performed using the Bayesian network development software “Netica” 1 (figure 2).

3.2 Maturity indicators and iteration impacts assessment

The questions targeted in this section are: (1) what are the potential detriments that the process may be subject to? How severe is the effect of these detriments? (Figure 1)
The authors, in previous work [9] claim that the severity of the possible adverse consequences (design iteration impact) depends on the levels of the maturity indicators associated with the design tasks in the presence of uncertainty (figure 3). In previous work [9], the authors describe the maturity indicators in terms of: “data quality”, “validity” and “sensitivity”.
The data quality reflects the accuracy, consistency, completeness and currency as well as scalability, reliability, provenance and trust on the output. [20]. The evaluation of this criterion consists of the answers to different questions such as: what is the quality of the methods used to derive the output? What is the provenance of the input data required to perform the output? How has the utility of the input been evaluated? etc [9]. The assessment of this indicator would indicate the impact of the input errors on the output errors. For instance, given the provenance of the data used in the analytical equation (estimation based on hypothesis), high errors in the inputs would generate high inconsistency and errors in the output.
The validity indicates the quality of task, and for engineering analysis processes, this can be indicated by the type of model used (e.g. physical law, empirical model), the analysis method applied (e.g. analytical equation, finite element model), the maturity of the technology used (turbulence model in computational fluids dynamics), the evidence used for validation (benchmark experiments), etc. The assessment of the validity would indicate the impact of input errors/imprecision on the output errors and imprecision (e.g. the use of an analytical equation to derive a performance parameter would implies more important invalidity on the output in the case of errors in the input than the use of a finite element model).
The number of relevant metrics for describing the data quality and the validity indicators needs to be established specifically for a group of people within a shared domain [9].
The sensitivity indicator is considered as the measure of additional work within the task necessary to absorb the input change [10]. For instance, the additional work might be the additional duration “d” necessary to the task in order to absorb the uncertainty in the input. The metric “d/additional

1 http://www.norsys.com/

uncertainty” or “d/iteration” could be used to assess the value of the task sensitivity . This indicator helps to assess the impact of the input uncertainty on the current task.
Thus, the impact of iteration generated from a task in the presence of input uncertainty is considered “low” if the values of the data quality, validity and sensitivity imply “low” risk of harmful consequences to design iteration (“high” errors, imprecision on the output or costly iteration). The maturity indicators provide a basis for evaluating probabilities associated with impact on design iteration risk.
Using the Bayesian network software (Netica), figure 3 shows an example of impact estimation based on the subjective probabilities associated to the quality, the validity and the sensitivity. Metrics could be used to assess the these factors such as:

- Data Quality: “completeness” (exploration of design/performance space), “appropriateness” (direct or indirect evidence), “accuracy” (frequency of data updating) and “consistency” (common identification and data definitions across the organisation)
- Validity: High: Have applied on the same scenario many times and obtained reliable outcome “Medium”: Have applied on different scenario and obtained reasonable outcome and “Low”: New application with no prior evidence of outcome when applied
- Sensitivity: “duration of changes/iteration” (sensitivity)

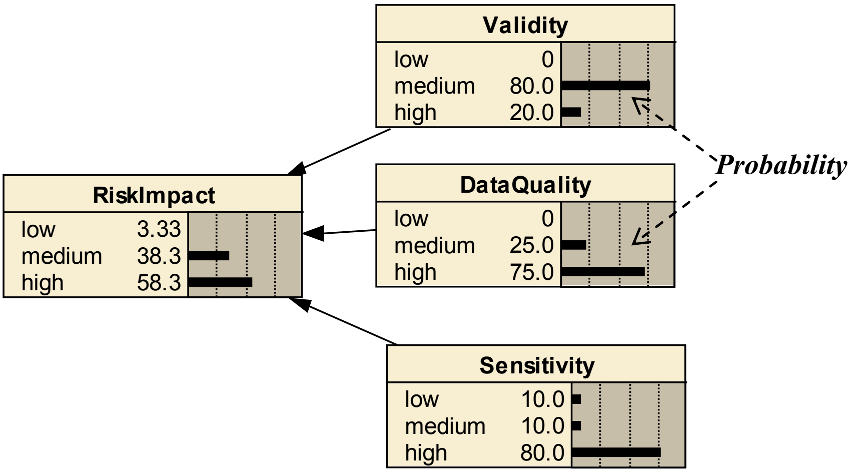

Figure 3. Example of risk impact assessment from the maturity indicators associated with of a given task

For instance, depending on the circumstances, the duration of change/iteration could be judged “low” if the value is between 1 day/iteration and 7 days/iteration “medium” if the value is between 1 week/iteration and 1month/iteration and “high” if the values are over 1 month/iteration ”. Here also the numerical example of the impact probability is derived from a Bayesian model with conditional probabilities of equal weights for illustration.

3.3 Risk reduction strategies

Once both the likelihood and the impact probabilities have been assessed, that means the risk can be prioritised. The remaining question is what are the strategies for reducing the risk? (Figure 1).
To answer the latter question, one considers the information exchange between upstream task and downstream task (Figure 4, left-hand side). Based on the analysis done in the previous section, the approach consists of the assessment of the iteration risks resulting from the release of the upstream information to the downstream task. For illustration purposes, the risk graph of figure 4 represents

different simulated values2 of risk occurrence probability (on the input or output) and risk impact probability (in the downstream or upstream).
Information as an input (Input in figure 4) is judged “mature” if it is ready to be used in the downstream task, that means if the iteration risk generated by processing this information is “low” (risk likelihood value is towards the bottom left rectangle in the risk diagram, figure 4). In this case, the maturity indicators (validity, data quality and sensitivity) associated with the downstream tasks have already reached levels that the design engineers consider (via subjective probabilities) harmless in term of generating downstream iterations.
In the same way, information as an output is judged “mature” if it is ready to be released from the upstream task (figure 4) without generating risks of upstream iterations; that means the iteration risk in the upstream after releasing this information is “low”. If the maturity indicators associated with the upstream task have reached levels that the design engineers consider harmless in term of re-generating the considered output, the supplier of the information would release this latter to the downstream. However, if the upstream iteration risk is high that means the maturity indicators show unfavourable values e.g. “high” sensitivity or “low” quality then the retention of the information should be applied until the upstream risk deceases.

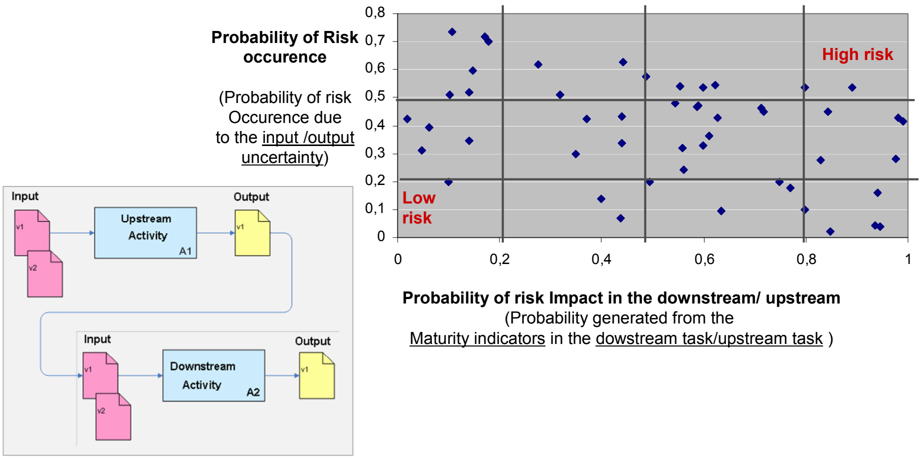

Figure 4. Risk graph

In concurrent engineering, the engineer supplying/receiving the information needs to decide when he or she is willing to commit resources to provide the information or to use the information supplied by other. The commitment of resources based on uncertain information should be delayed if the information provided/received generates high probability of instability, errors and/or imprecision after being released. Taking into account this argument, the authors propose a set of communication patterns (inspired from the literature [23] [18]), which consist of strategies for information release between dependent tasks. These strategies represent mitigation actions that might be taken according to the acceptability of the risks, mitigation actions.
Depending on the combination between the evolution of both the uncertainty factors and the maturity indicators, the information supplier and receiver face different types and levels of risk in the process. For instance, if “low” sensitivity in the downstream coincides with “high” instability of input that means the probability of extended iteration is “high”. Therefore, an “iterative” release strategy (several intermediate releases) would seem to be the most desirable pattern of information communication [18].

[2] Using a discrete-event simulation method.

However, if the sensitivity in the upstream is “high”, that means each output release would cost important effort/time in the upstream task and this is a good argument for the supplier to retain the information from releasing it. Thus a compromise has to be achieved about the number and dates of intermediate releases of the information according to the risk levels that both the information supplier and receiver are willing to take. The greater the distance between the upstream risk and the downstream risk (see the risk card in the figure 4), the more a compromise is difficult to achieve. This is particularly the case when the downstream risk is higher than the upstream risk.

Another example communication strategy is when the input instability is high and the downstream sensitivity is high. In this case, the risk of an extended iteration impact is high in the downstream task. Thus an early freezing of the information would seem suitable and a “pre-emptive” communication would be convenient [23]. That means one preliminary release is allowed and one final release of stable information is required. Here also, the upstream risk should be considered and a compromise on the intermediate and early freezing date should be achieved.

Furthermore, the consideration of the set of uncertainty factors and the maturity indicators requires sometimes a combination of different communication patterns or a compromise between some of them. For instance, pre-emptive communication is not appropriate in a situation where the upstream information is characterised by a high error and low instability. In this case, “set-based communication” is required [23]. This strategy aims to cope with the risk of starvation (design blocking). It consists of communicating different design alternatives with low instability from the upstream to the downstream. For a summary of different strategies of information release, the reader is invited to refer to [9].

4. Case study

In this section, we illustrate the application of the maturity framework in a structural analysis process in a typical aircraft design [24]. The main activities within this phase consist of systematic transformations or mapping from the physical domain (wing geometry, loads, material properties) into the functional or performance domain (stability, reparability, damage tolerance, etc.) [24] to evaluate how well a design will satisfy the required functions. A common form of mapping from the design parameters into the performance parameters in today’s virtual product development is based on simulation models such as the finite element method (FEM). The present case study is a scenario based on a fragment of the structural analysis process in the design of an aircraft (Figure 5). Two main tasks, concerning the wing structure analysis, are represented using the dynamic modelling technique which is the extended3 Signposting model (more justifications and details about the Signposting model are provided in [25]). The first task is the “Wing assembly and solve” within which the components: wing-box spars, wing-box cover, wing-box ribs and the landing gear attachments are assembled in a coarse generic Finite Element Model (FEM) (figure 5). Under the static and fatigue loads, stress calculations are performed using the FEM according to the loads distribution model of the whole aircraft. The “structure analysis” task corresponds to the optimization analysis of the assembly/component levels. The components are thus analysed in sequential process and with different analysis methods. During and at the end of the “structure analysis” task, the reserve factors and the different sizing of the wing components are checked (figure 5).

A number of decisions about the wing design have to be made during the assembly and the structure analysis tasks based primarily upon uncertain information obtained from field analysis (loads) and from simulation processes. Furthermore, high interdependencies are highlighted between the wing components (between the covers, the spars and the ribs) which introduce instability into the components geometry and into the FEM. The wing stresses resulting from the “structure analysis” are also highly dependent on the FEM. Thus, high risk of iteration is expected between the global FEM

[3] The tasks representation, in the figure 5, extends the original Signposting model by replacing the confidence representation of the input and output by multiple uncertainty indicators (errors, imprecision and instability). The maturity indicators, associated with the tasks, are also an extension of the original Signposting model.

and wing components (within the assembly task) and between the global FEM (output of the assembly and solve task) and the wing stress (output of the structure analysis task). Our interest concerns the reduction of the latter risk of iteration.

In order to assess this risk, the uncertainty associated with the loads, the FEM and with the stress and the maturity indicators associated with the "structural analysis" task are estimated (figure 5). The loads are shown with rather a high level of error-risk (probability of 80% "high") and low level of instability (probability of 75% of "low") (according to the estimation of the systematic and the random values θ=0,30 and δ=0,70 and of the variability rate ε_t=0,95, respectively). The risk of errors is due to the fact that at the beginning of the structural analysis process, the engineers use broad information about the partition of loads among the components. However, the low instability is due to the fact that the loads are rarely re-estimated because of the high cost of doing so.

Using the method of risk assessment proposed above, the resulting risk likelihood associated with the FEM is relatively high (55%) (Figure 5, upper left-hand side). Indeed, there is a high risk of FEM error which is due to the sensitivity of the wing assembly task (sensitivity of the forces) to the load errors. On the other hand, the interdependence of the wing components (e.g. spars and skins) makes the wing assembly task sensitive to every variation in the inputs or in the output (FEM). Thus, the instability of the FEM is largely recognised to be high (85%).

Similarly, a relatively high-risk likelihood (probability of 62% "high") is also found on the wing stress, (Figure 5 lower right side). This is due mainly to the high risk likelihood in the input (loads and FEM) but also to the relatively high risk of impact (58%). The main impact risk is associated to the risk of time/effort overrun due to the high value of the sensitivity indicator (80%) towards the loads and the FEM uncertainty. For example, within the structural analysis task, the loads data (air pressure, fuel pressure, etc.) are used for the sizing of the cover region and the estimation of the cover data (Rib Pitch/material selection, etc.). These data are, in their turn, the basis of optimization for the generic skin and stringers of the wing and thus they have an impact on the overall definition of the FEM. The applied programmes for analysis depend on the sizing of the FEM. Hence, changing the loads (errors) would have an impact on the wing sizing and consequently on the programmes used for the wing stress analysis.

Consequently a high probability of iteration on the wing stress is estimated due to the high errors in the loads (80%). The iterations risks on the stress would be also generated from the instability (85%) and the errors (60%) of the FEM, since this latter represent the main input to the generic sizing loop of the wing.

The high instability of the FEM, the high errors of the loads and the high sensitivity of the stress analysis task could imply important delays in the stress analysis task. On one hand, as the upstream task (Wing assembly & solve) is highly sensitive to the input uncertainty that means the release of highly uncertain FEM would suggest extended future iterations within the upstream task. Thus the engineer in charge of the wing assembly would not release the FEM before achieving a certain probability level regarding the instability and the correctness of the FEM.

On another hand, high risk of iteration has been estimated in the downstream activity. Thus the receiver of the FEM would wait until a lower risk likelihood on the FEM is reached. In this case, both the supplier and the receiver of the FEM agree on the reduction of the risk of iteration by reducing the errors of the loads and/or the instability of the FEM. The aerodynamic engineer responsible for providing the load cases can reduce the errors using more advanced models and accurate technology to simulate the loads on the aircraft wing (e.g. turbulence model in computational fluid dynamics). The aerodynamics engineer may also adopt a conservative approach and provide increased safety factors on loads. Regarding FEM communication, a strategy of release that permits a stable FEM is required. As the FEM is most likely to contains errors and the sensitivity of the stress analysis is high, the engineers would agree on a stable release of the FEM from the assembly task to the stress analysis task (e.g. one final release in sequential way) with an agreed level of errors (by adopting a safety factor method or the estimation of design failure probability).

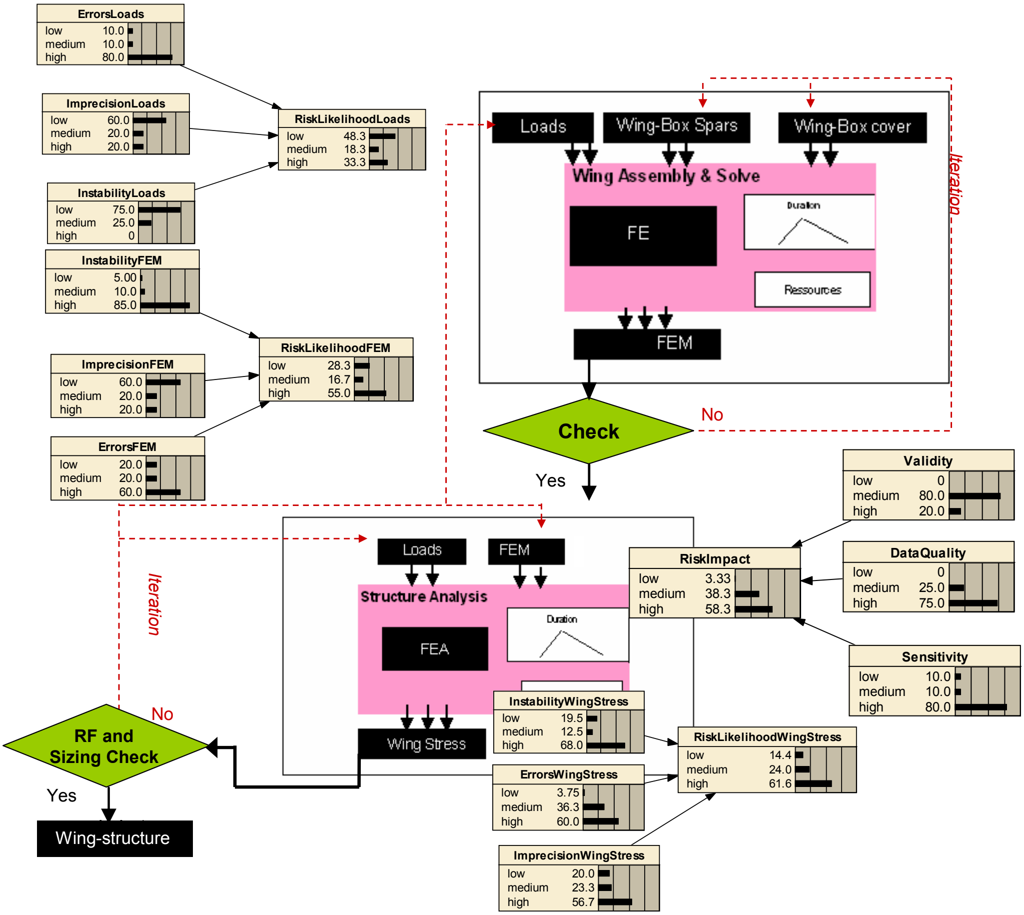

Figure 5. Example of information exchange between the finite element task and the structure analysis task in aircraft engineering design

5. Discussion

5.1 Level of process granularity

The work described in the paper involves tasks that are defined to a fine level of granularity (structural analysis). The levels of granularity whereby processes are defined can affect the type of maturity indicators and uncertainty factors that are most applicable. We argue, however, that perhaps maturity indicators can be used to make the distinctions between process layers more apparent due to emergent rather than predefined qualities.

The level of granularity also dictates the way maturity is applied to manage risks. In a fine level of granularity, maturity can be used to reduce local risks between actors performing operational tasks, such as high risk of errors in the parameters and high risk of churn iteration due to multifunctional interactions [11]. Maturity indicators could also help to plan, monitor and control the tasks at tactical and strategic level, giving cost, time and resource availability. The maturity could be used as a means for aggregation to a higher level of process granularity.

5.2 Unplanned design process (proportion of the unplanned activities in aircraft design)

Many activities during the design process have a potential to occur in an unplanned way or to reveal unplanned iteration. A dynamic model of process behaviour and risk assessment and impact analyses should include such possibilities. However, the difficulty is in fully enumerating the potential sources of errors, of instability, imprecision or ambiguity and also their different impacts in both the design process and the product definition and performance. In practice, the potential failures or sources of uncertainty that are considered must be selected subjectively, often based upon judgment of risk or potential impact based on recent experience. Additionally, predictions of the conditions under which unplanned tasks or iterations occur must be based on expert judgment of uncertainty; this may be biased by many factors.

5.3 Limitation of the modelling methods

The use of the Signposting model is appropriate in the modelling of adaptive or variant design processes; in such scenarios the majority of tasks and parameters are well delimited and may be identified in advance. However, the very nature of design process models also restricts robustness analysis for two main reasons. Indeed, models are always simplifications of reality and modellers, who can never fully capture the complexity of uncertainty inherent in design, must subjectively identify the most important factors to be included in any analysis. Uncertainty stemming from the model itself is another important limitation in process robustness analysis. While evaluating the influence of uncertainty on the process, the modeller has to take into account the structure of the model and the assumptions made in order to draw reliable conclusions with regard to process robustness.

5.4 Information value

Dealing with the uncertainty and the maturity evaluation and evolution means dealing with the knowledge capture and reuse question. Among problems encountered in the recording of information is information overload. Indeed, with the great growth of information volume (detailed drawings, geometry of the product, spreadsheets, different versions of analysis programs, etc.), it is more and more difficult for a single person such as a project manager or even the core project team to understand each piece of information produced during the design process. One of the questions that might be asked in this case is what will be the purpose of the record and when is it worthwhile to record the information? The determination of the information maturity should be necessary to highlight the level of trust or confidence in the information and the appropriate time of information capture as the product development process evolves. However, this is not enough to assess the level of aggregation that provides a balanced compromise between the expense of acquiring additional information maturity and its benefits of uncertainty reduction. The utility or the value of the information should be the other criteria used for the information record and use.

6. Conclusion and future work

This paper has presented an approach for expressing uncertainty factors and maturity indicators for exchanged information that might improve confidence and the level of commitment of design actors. The main expected outcome of this framework is the opportunity for risk assessment and updating as the engineering design proceeds. The maturity-based approach consists of a dynamic method to assess the uncertainty factors and their effects on the project monitoring. Current empirical work is being undertaken in the area of aircraft engineering design in order to assess the validity of the framework. Along with the flexible modelling technique (adapted Signposting), the proposed method may be the means by which process execution may be enhanced. In future work the authors propose simulation models that allow the derivation of task status and the task selection functionalities. Potential implementations within the current Signposting modelling tool(s) are envisaged.

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