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INVESTIGATING DESIGN PROCESS PERFORMANCE UNDER UNCERTAINTY

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ABSTRACT

This paper explores how uncertainty can be modelled in engineering design processes as a route to improving their robustness, which we view as the likelihood that they will have acceptable duration despite uncontrollable noise factors and other uncertainties. We introduce this concept by drawing parallels between the robust design of design processes and the robust design of products. We then discuss a case study of an aero-engine design process, in which we constructed a 200-task Applied Signposting Model and used Monte-Carlo simulation to explore the impact of uncertainties on this process. This highlighted that the apparent robustness of a process depends on the number and types of uncertainty sources incorporated in the model, and that the computational expense of simulation analysis is too high to identify robust configurations via factor-by-factor perturbation. We therefore explore how the structure of information flows in an NPD process can affect its response to delays, with the objective of identifying a more practical approach to finding robust process configurations. This highlighted certain patterns of interactions between tasks which cause delays to be absorbed, reduced, propagated or accumulated. To conclude, we propose that one approach to robustness improvement is to develop management policies which reduce the incidence of those task configurations which accumulate delays.

KEYWORDS

Uncertainty, design process simulation, process robustness, process scheduling, applied signposting model (ASM)

1. INTRODUCTION

Increased performance requirements and more complex products have led to growth in the complexity of NPD projects, for example through increased task concurrency. This complexity has increased uncertainty about process behaviour (Tatikonda, Rosenthal, 2000; Nightingale, 2000) and may contribute to the high number of projects that have failed to deliver on their early promises (Matta, Ashkenas, 2003). Mitigating the impact of process uncertainty in NPD is therefore becoming increasingly important[1].

Mitigating the impact of process uncertainty in NPD is challenging, particularly in the design phase as design activities are characterised by novelty, creativity and unpredictability of outcome (Reza, Wang, 1999, p. 236; Browning, Eppinger, 2002). With the introduction of Taguchi methods (Phadke, 1989; Taguchi, Clausing, 1990) much research on handling uncertainty in NPD has shifted towards the principles of robust design (Swan, et al., 2005). Fundamentally, robust design is concerned with minimising the effect of uncertainty or variation in design parameters without eliminating the source of the uncertainty or variation (Hacker, Lewis, 1999; Kalsi, et al., 2001; Phadke, 1989).

However, the focus of these approaches has been almost exclusively on the product domain or on manufacturing where uncertainty is easier to quantify and

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[1] In the context of this paper we define process uncertainty as the uncertainty associated with executing a process, i.e. coordinating people and other resources to carry out the plan (PMI, 2004).

mitigate than in design. Despite the potential benefits of applying such concepts to mitigating uncertainty in the design process (Yassine, 2007), the robustness of the design process is recognised as an under-researched area (Floricel, Miller, 2001). For example, due to the lack of a precise definition of robustness in the process domain the principles of robust design have been often used to denote different meanings and encompass different attributes of a process, such as its reliability or flexibility (McManus, Hastings, 2005). Moreover, the robustness of the design process is commonly viewed as its ability to deliver robust products.

This brief review illustrates that design process robustness merits further investigation, since it is not thoroughly addressed in academic research. Similarly, the common process modelling/simulation tools do not incorporate robustness analyses. The objective of this paper is therefore to explore three main research questions which must be addressed to develop more robust design processes:

- *What are the uncontrollable noise factors and other uncertainties which affect the design process, how can they be modelled and what are their effects?*
- *What are the 'process design variables' which can be changed to find more robust processes?*
- *How can these process design variables be chosen to identify a more robust configuration?*

Answering these questions in full is the subject of a 3-year Ph.D. project and is beyond the scope of this paper. In the following sections, we begin to explore these questions by showing how design processes can be modelled, highlighting the insights for robustness analysis which can be drawn from simulation using these models, and discussing the limitations of such analysis.

1.1. Paper overview

Following a brief discussion on process robustness in Section 2, Section 3 introduces a simulation-based approach to investigate process response to uncertainty using sensitivity analysis. In Section 4, we discuss a case study of aero-engine design to illustrate and evaluate this approach. The case study revealed that it is impractical to explore all aspects of process robustness using sensitivity analysis alone. In Section 5, we analyse how the structure of information flows in a process can affect its response to delays in individual tasks. In Section 6, we propose that this type of analysis could be used as the basis for future research in this area. Section 7 highlights key conclusions of the paper.

2. BACKGROUND

This section sets the paper in context by drawing parallels between *product robust design* and *process robust design*.

2.1. Product- vs. process robust design

Product robust design can be defined as a set of design rules that help to manufacture a product of desired quality despite uncontrollable noise factors that influence the manufacturing process[2] (e.g. Hernandez, et al., 2001).

By analogy, process robust design can be summarised as finding process configurations such as plans or parallelisation strategies that ensure expected process performance despite uncontrollable noise factors during its execution. Since those factors might include different types of uncertainty within and outside the system (Sanchez, 1994), we define the robustness of a process as its *ability to deliver acceptable outcomes despite uncertainty.* The comparison between product- and process robust design is highlighted in Figure 1 below.

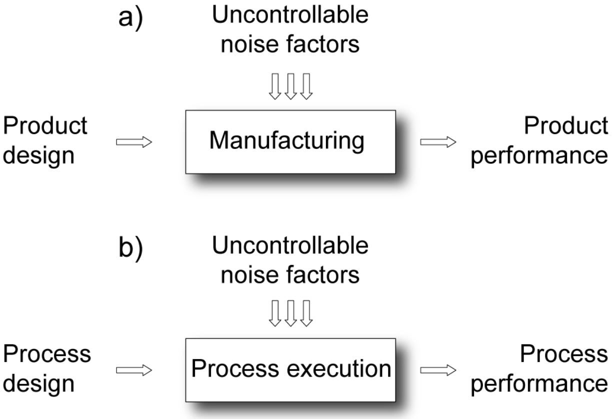

Figure 1 The principles of robust design in a) the product domain and b) the process domain

One approach to analyse the robustness of a system is to use formal mathematical or heuristic models to analyse the influence of the noise factors on the system's performance for given design variables.

However, such models can become intractable as the complexity of the system increases and the numbers

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[2] Product robust design is also used to refer to making a design's performance insensitive to uncontrollable environmental variation during use.

of variables grow. Predicting the performance which different configurations might yield can thus be difficult without making many simplifying assumptions. Monte-Carlo simulation methods may be used to evaluate the robustness of complex systems such as manufacturing processes, with respect to certain input variables. Although these models are useful for evaluation, they cannot be used to find optimal solutions on their own (Shannon, 1992).

This paper proposes that an analogy may be drawn between 1) the application of simulation to enable robust design of products and 2) the application of simulation to support the design of more robust design processes. This is based on the assumption that complex design processes can be adequately represented in task-based simulation models analogous to models of a manufacturing system. This may be justified by reference to the large body of literature on design process modelling and simulation, as discussed by Browning, et al. (2006) and comprehensively reviewed in Browning, Ramasesh, (2007). Since it is widely accepted in the literature this assumption will not be explored here.

3. INVESTIGATING ROBUSTNESS USING SIMULATION

In this section, we discuss the application of simulation modelling to analysing design process robustness. This will be illustrated in section 4 by application to a case study of aero-engine design.

3.1. Simulation modelling

Shannon, (1992) describes simulation modelling as "*the process of designing a model of a real system and conducting experiments with this model for the purpose of either understanding the behavior of the system and/or evaluating various strategies for the operation of the system*". We therefore discuss the principles of building such models of the engineering design process with a particular focus on task network models. Then, we discuss how they can be simulated and used to support process robustness analysis. In particular, relationships between process uncertainty captured in the model and simulation results are investigated, and we show that understanding these relationships is a necessary precursor to robustness analysis.

3.2. Task-based simulation models

Many task-based process models have been proposed in the literature. For example, Browning, Ramasesh, (2007) identify over 400 publications concerned with the development and analysis of such models. Much of the research presented in this paper could be viewed in terms of any of these approaches, which differ in their assumptions about process behaviour but can all be viewed as 'black box' simulation models which calculate expected process performance from a particular set of input variables and noise factors. In this context, an input variable could be the planned duration of a task, and a noise factor the uncertainty in this duration.

Although the key concepts of this paper could thus be introduced in terms of any simulation framework, or indeed in more abstract terms, the task-based modelling approach used for the case study is introduced here to clarify the forthcoming discussion. This approach, termed the *Applied Signposting Model (ASM)* is based on the following assumptions:

- Design processes may be decomposed into discrete tasks, which interact via their input and output information.
- Tasks are available to begin only when their input information is available, and release their output information upon completion.
- Tasks cannot be started until sufficient resources are available. If multiple tasks are have sufficient information to start but compete for limited resource, a single task is prioritised to begin first and the others must wait upon its completion. In this situation, the simulation assumes task prioritisation is governed by a *task selection policy*. For example, the *shortest-task-first* policy assumes that the task with shortest duration is always attempted first.
- Tasks must be re-attempted when input information changes following the discovery of rework. Since rework of one task also requires any downstream tasks to be re-attempted, the simulation accounts for this propagation of rework by dynamically identifying and interrupting any downstream tasks when a change to any task's input information is detected. These downstream tasks are automatically re-attempted once all their upstream dependencies have been completed.
- Tasks do not affect process behaviour during execution, e.g. by releasing information prior to completion.

The ASM approach is described in full by (Wynn, et al. 2006). It allows simulation of relatively complex processes, including concurrent tasks, unplanned rework, refinement iterations, resource limitations, and conditional or unconditional probability distributions which specify task durations. The model is based on the intuitive graphical notation illustrated in Figure 2. Wynn, (2007) discusses a number of case studies in which the approach was applied, arguing that this intuitive notation was critical in validating simulation models by discussing the assumptions with process participants, and thereby in generating buy-in to the simulation approach.

The ASM is implemented in the *P3 Signposting* software platform.[3] This provides the discrete-event Monte-Carlo simulation code used by the case study in this paper.

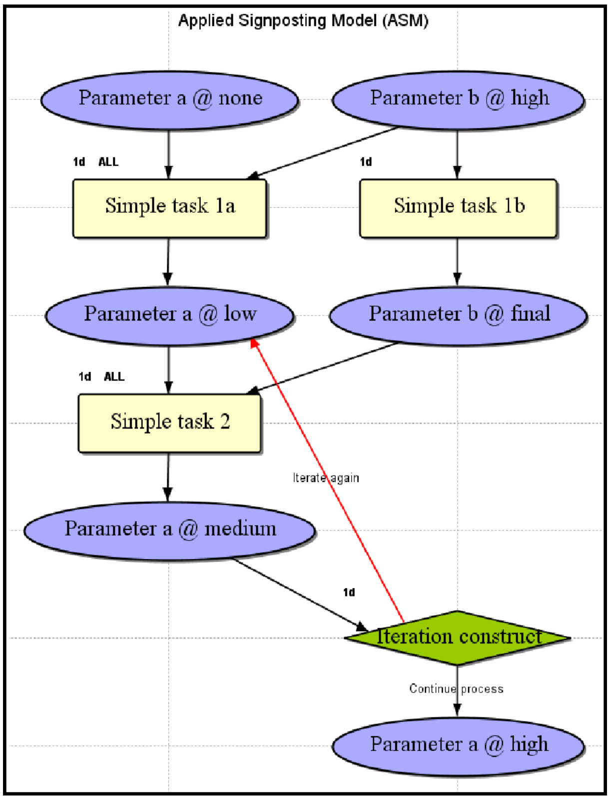

Figure 2 The Applied Signposting Model assumes that design tasks (yellow rectangles) start when all inputs (blue ellipses) are made available, and must be re-attempted if one or more is updated by rework. In this example, rework would be caused by failure of the evaluation task (green diamond)

3.3. Effects of uncertainty on simulation

Process modelling frameworks such as the ASM typically allow uncertainty to be represented in several input variables, such as the availability of resources and the durations of individual tasks. However, De Millo argues that uncertainty is often not incorporated in models when modellers have a limited knowledge of a system, perfect information cannot be accessed or is prohibitively expensive to seek out (De Millo, 2005). In other cases, uncertain values of many variables may be incorporated in an *ad-hoc* way based on the modeller's estimates, judgements and experience from similar projects.

In practice, it is important to carefully consider how uncertainty is modelled since the number and types of sources of uncertainty explicitly captured in a process model has a fundamental effect on its simulation results. This is illustrated by example in Figure 3. In the case of a process model with no uncertainty, the entire population of simulated processes will have the same duration (Figure 3, top). Including sources of uncertainty in a model spreads the simulation results into a profile of outcomes which depends upon the numbers and types of uncertainty sources (Figure 3, centre). In general, the more sources of uncertainty which are incorporated in the model, and the more interdependencies which are incorporated between them, the more difficult it is to interpret the profile of outcomes (Figure 3, bottom).

3.4. A sensitivity-based approach to evaluating process robustness

The way in which a system's uncertainty is modelled affects how its robustness can be evaluated. As indicated above, the uncertainties of interest are often not recognised or captured in a design process model. The input variables of such models must therefore be perturbed to assess the robustness of the process.

For example, to assess the robustness of a process with respect to changes in the execution time of certain activities, new task duration estimates can be used as the model's input variables and a new population of simulated processes obtained. Comparing this new set of processes with the original one indicates the robustness of the process. The smaller the difference between the two distributions, the more robust the process is with respect to uncertainty in the durations of the perturbed tasks (Figure 4). This example illustrates how process robustness may be evaluated using sensitivity analysis. Indeed, the robustness of a process can be viewed as the insensitivity of its performance to certain sources of uncertainty.

Uncertainty in a process can also be represented using probability distributions of the simulation

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[3] See http://www-edc.eng.cam.ac.uk/p3.

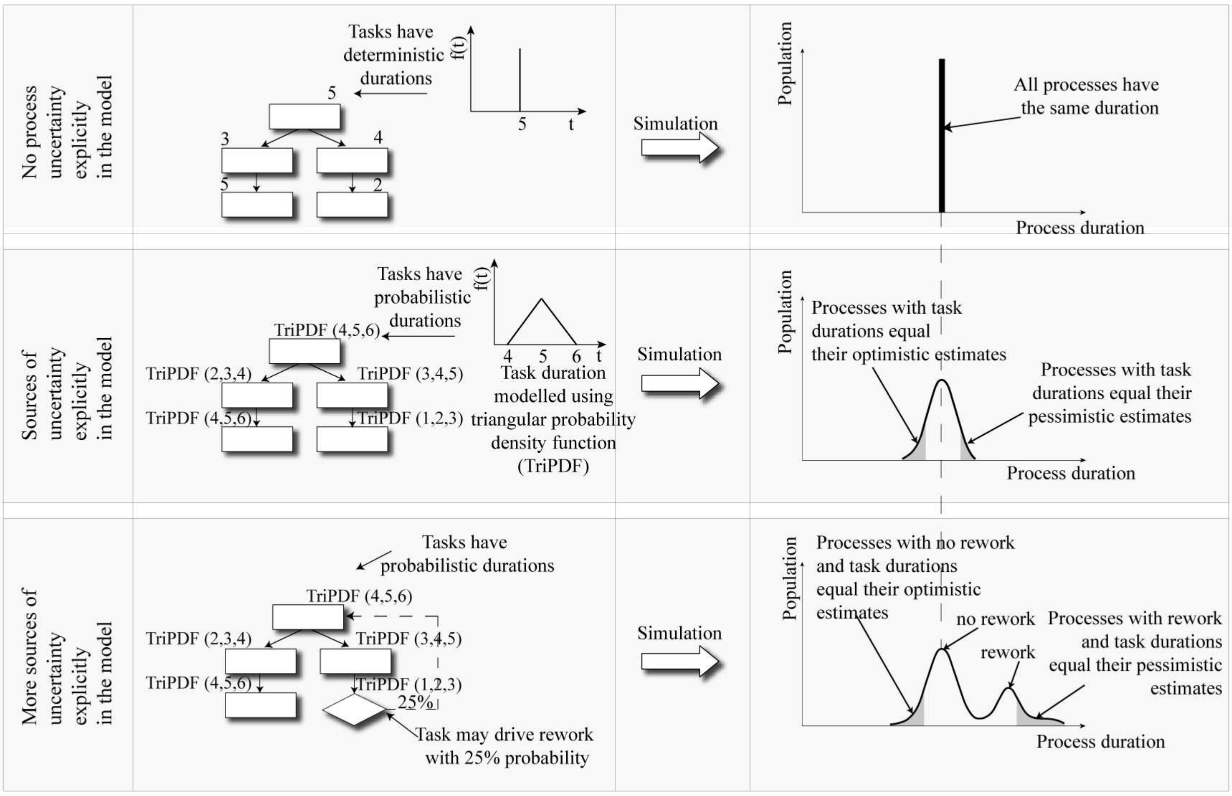


Figure 3 The apparent robustness of a simulated process is influenced by the uncertainty which is captured in the model

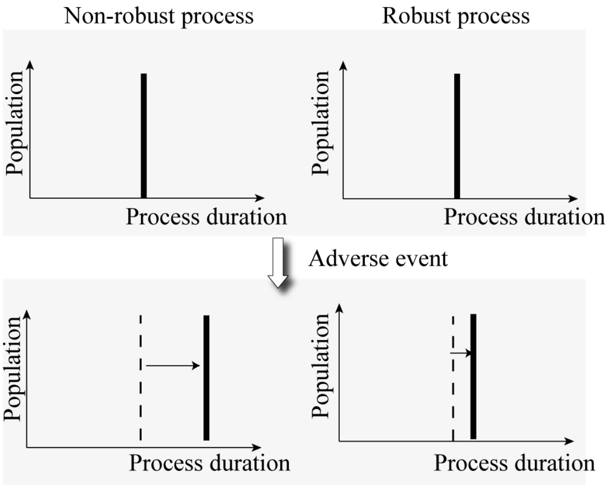


Figure 4 Evaluating the robustness of a simulated process using a sensitivity-based approach and a step change in one input variable

model's input variables. For instance, the possibility of delay in a task's completion can be captured using a triangular probability density function (PDF) which characterises the distribution of that task's duration. Likewise, the possibility of rework can be modelled using tasks with alternative failure modes which are selected stochastically. The profile of simulation results then incorporates information about the sensitivity of the process to all sources of uncertainty in that model configuration.

Accordingly, only one simulation experiment is needed to assess the robustness of a process with respect to a set of uncertainties: the wider the spread in the distribution of process performance values, the less robust the configuration is with respect to the uncertain input variables (Figure 5).

3.5. Limitations of simulation

As shown in the previous sections, including more sources of uncertainty in a model can have a significant influence on its simulation results. This demonstrates that the validity of recommendations for process improvement can be sensitive to changes in the type and number of uncertainty sources included in the model. For instance, overlooking the possibility for rework following a design evaluation will distort the profile revealed through simulation. Such modelling omissions are probably inevitable given the incompleteness of data available in practice, especially in the case of large-scale models.

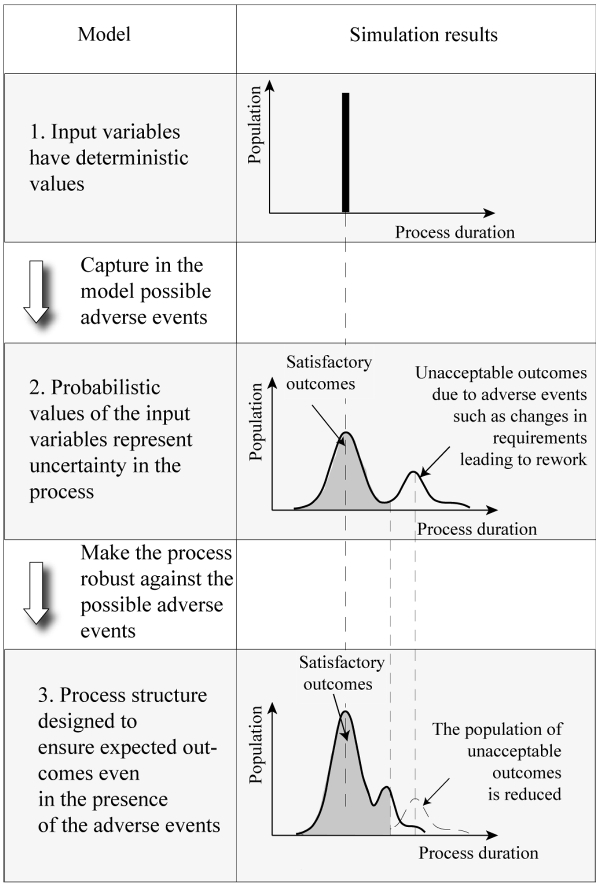


Figure 5 Evaluating the robustness of a simulated process using a sensitivity-based approach and varying multiple factors at a time, using probability distributions

In general, incorporating more detail and additional sources of uncertainty in a model can facilitate more comprehensive analysis of the underlying system. Despite the apparent benefits of using detailed models to maximise the fidelity of simulation analysis, constructing comprehensive models of design processes can be difficult since:

- The availability of data is usually limited, particularly if the design process being investigated is extremely innovative (this is often not the case in the complex design processes we study, since complex products such as aero-engines are designed in large part by modification of previous versions).
- The cost of modelling and knowledge acquisition is often prohibitive.
- Limitations of the modelling framework can prevent the representation of phenomena which are known to occur in practice.

Due to the difficulties of developing a comprehensive model and the impact of deciding which uncertainties to incorporate upon simulation results, a number of authors argue that simulation should be used primarily as a tool to facilitate a better understanding of the process (Kwak, Ingall, 2007; Saltelli, 2002). Recommendations for improvement which are derived from simulation results should therefore be carefully considered in the light of experts' opinions.

4. CASE STUDY

In this section, we investigate whether a design process' response to uncertainty can be evaluated using the sensitivity-based approach outlined in Section 3.4 above. We discuss a case study of aero-engine development which forms the basis of an ASM simulation model. A simulation experiment was then conducted in which sensitivity analysis was used to investigate the impact of uncertainty in tasks' durations, resource availability and rework on total process duration.

4.1. A model of aero-engine design

The aero-engine is one example of a complex product which has a correspondingly complex design process. For this case study, an ASM simulation model was developed to represent the design of two major subsystems in a civil aero-engine. The model was based on data provided by a UK aerospace manufacturer with whom we have previously conducted several in-depth case studies. This background knowledge helped the researchers to interpret the product- and company-specific terminology in the data set. All numeric information from the case study has been modified to protect commercial sensitivity. While the structure of the model is representative of an industry design process, the numeric simulation results presented in forthcoming sections do not reflect the specific process which was investigated.

The data was initially formatted as Excel spreadsheets which listed design tasks and their deliverables, together with due-dates and resource constraints. As is typical with dependency-based data, this was strongly connected and thus difficult to represent using the graphical network view of the Applied Signposting Model. To address this issue, the names of all tasks were printed on small rectangles and arranged manually on large sheets of paper (Figure 7). This allowed a suitable layout for the process network to be developed. Cases of redundant

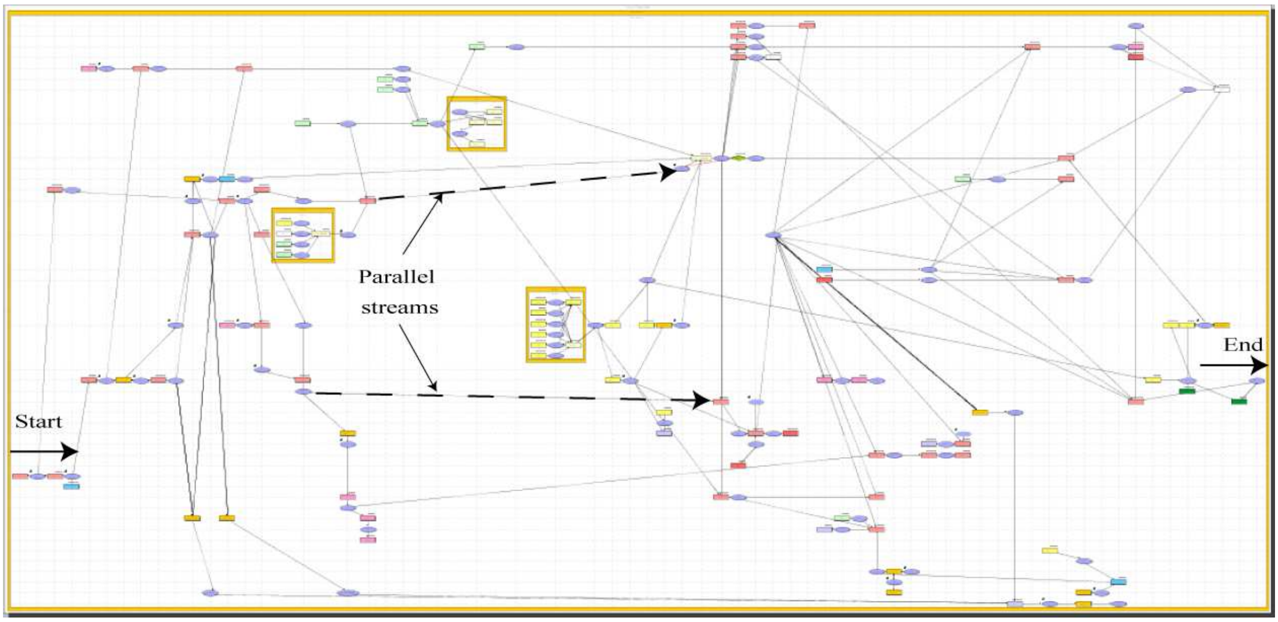


Figure 6 A flowchart view of part of the aero-engine development process model

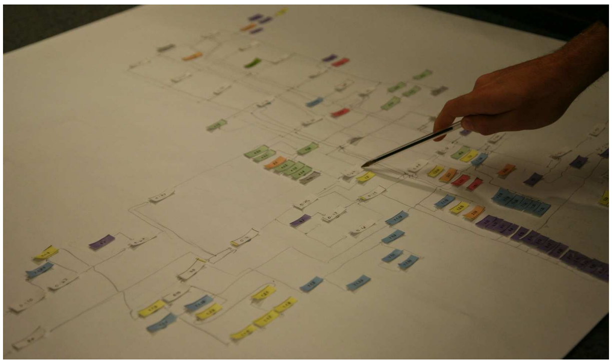


Figure 7 A paper-based approach was used to develop the structure for the ASM process model

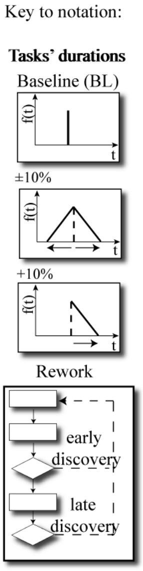
feed-forward of information between non-adjacent tasks were identified by inspection. These interactions were then removed since they could not affect task ordering and thus unnecessarily complicated the process network. Finally, the paper-based model was used as the template for constructing a formal model in the P3 Signposting software tool. This model, shown in Figure 6 above, formed the basis of the simulation experiment.

4.2. The simulation experiment

In overview, the simulation experiment was conducted by introducing different sources of process uncertainty into the deterministic process model described above to explore their impact on its simulated duration. The experiment proceeded in four high-level steps. These are discussed below and summarised in Table 1.

Table 1 Details of steps in the simulation experiment: '-10%' in resource availability – a 10% decrease in the pool of available resources. Early discovery of rework reduces the number of reattempted tasks by 50%

Step	Config.	Uncertainty in:		
		All tasks' durations	Resource availability	Rework likelihood
0	Baseline	BL	BL	0%
1	a	±10%	BL	0%
	b	±20%	BL	0%
	c	+10%	BL	0%
2	a	BL	-10%	0%
	b	±10%	-10%	0%
3	a	BL	BL	10%
	b	BL	BL	50%
	c	BL	BL	50% + early discovery
	d	±10%	BL	50%
	e	±10%	-10%	50%
	f	±20%	-10%	50%
	g	+10%	-10%	50%
	h	±20%	-10%	50% + early discovery



In Step 0, the baseline configuration of the process was simulated with no uncertainty explicitly modelled. The only variability in this configuration arises from the assumption that, when many tasks are possible but only one may be attempted first due to resource constraints, a task is selected at random to begin first. This source of uncertainty reflects no knowledge about how tasks would be chosen in practice. All tasks in this configuration are assumed to have equal deterministic durations and to require a single unit from a common resource pool during their execution. When each task is completed, its resource is returned to the pool. Each of the remaining three steps focused on one type of uncertainty and its impact on process duration. In Step 1, uncertainty in all tasks' durations was incorporated; in Step 2 – uncertainty in resource availability; and in Step 3 – uncertainty in the likelihood and magnitude of rework caused by failure of one key task.

Several minor configurations of each step were simulated to illustrate the effect of changes in the magnitude of the introduced source of uncertainty and to explore possible interactions with other types of uncertainty. 1000 simulation runs were executed for each experiment.

4.3. Results

Step 0 – Baseline configuration

Simulation results for the baseline configuration indicate that process duration would be between 5.4 and 5.9 months, with the most likely value being 5.8 months (Figure 8).

This shows that at least four possible process execution paths exist. These arise from the *random-task-first* policy, as discussed above.

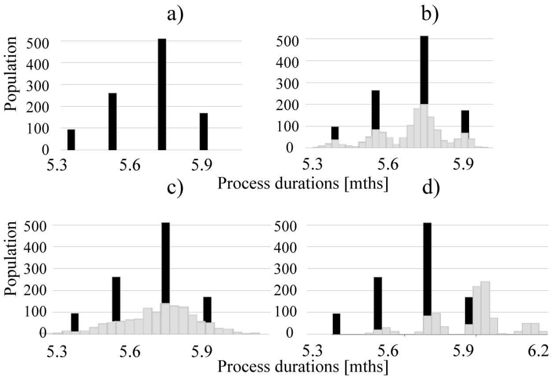


Figure 8 Simulation results of the impact of uncertainty in tasks' execution times on process total duration: a) step 0 –baseline configuration, b-d) accordingly steps 1a-c (±10%, ±20% and +10% uncertainty); the black bars denote the baseline configuration

Step 1 – Tasks' durations

Simulating process configurations with a symmetrical distribution of the probability density function (PDF) of tasks' durations yields populations of process duration values symmetrically distributed around the bars of the baseline configuration (Figure 8b and 8c, Steps 1a vs. 1b). In terms of duration variability and expected duration, these configurations are very similar to the baseline.

Simulation results of a process configuration with asymmetric distributions of the task duration PDFs differ in that the resulting duration modes is shifted to the right of the bars of the baseline configuration (Figure 8d, Step 1c). This indicates an increase in the expected process duration, as would be expected when all tasks' durations may be extended.

To summarise, the impact of uncertainty in tasks' durations on process performance was found to depend upon the magnitude and distribution of this uncertainty.

Step 2 – Reducing resource availability

Reducing the resource availability by 10% from the baseline (Step 2) revealed that simulated process execution times become longer (Figure 9a). This occurs since fewer tasks may be attempted concurrently. Furthermore, the variability in duration of the under-resourced process is higher than that of the baseline configuration. This arises from the increased number of prioritisation decisions which must be made when previously concurrent tasks must be performed sequentially.

Introducing uncertainty in tasks' durations results in the peaks of the process duration distribution being symmetrically distributed around the bars of the *limited-resource-availability* configuration (Figure 9b). The total variability of the new population, however, does not undergo any significant changes; instead, uncertainty in tasks' durations alters the type of the distribution from discrete into continuous (Figure 9b).

Step 3 – Rework

Unlike adding uncertainty in tasks' durations, uncertainty in the amount of rework has a significant impact on the expected value and variability of the total process duration. Similar to the limited availability of resources, this type of uncertainty leads to an increase in the values of both the variability and expected value (Figure 10). The degree of such in-

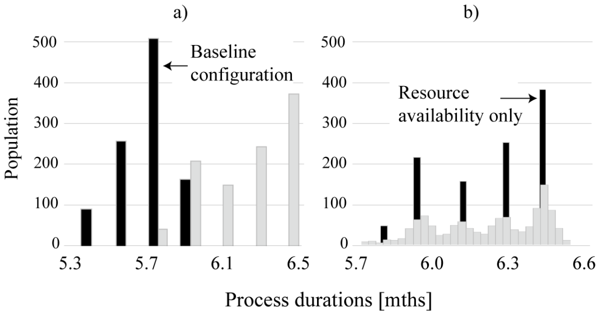


Figure 9 Simulation results showing the impact of limited resource availability on process duration: a) step 2a (limited resource availability only) b) step 2b (limited resource availability and uncertain tasks' durations)

crease depends on the probability of rework and the impact if it occurs, i.e. how many tasks must be reattempted. In the simulation results, the effect of this possible rework is visible in the appearance of a second mode in the duration distribution. The relative height of the mode is determined by the probability of rework (compare Figures 10a and 10b for Steps 3a vs. 3b) and the distance between the first and second modes is proportional to the magnitude of rework (compare Figures 10c and 10d for Steps 3b vs. 3c).

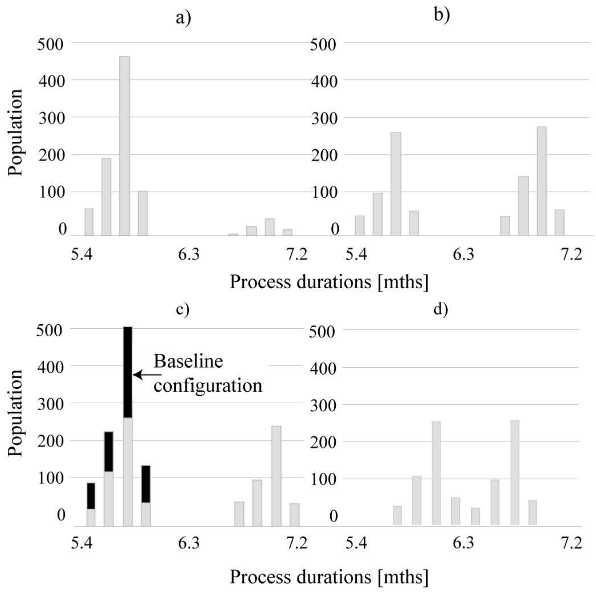


Figure 10 Simulation results indicate the effect of altering the likelihood and impact of rework in the baseline configuration

While the magnitude and likelihood of rework play an important role in determining the expected value of process duration, the subsequent addition of symmetric uncertainty in tasks' durations does not have significant impact. Likewise, introducing such uncertainty does not have any significant impact on the variability (Figures 11a, 11b and 11d).

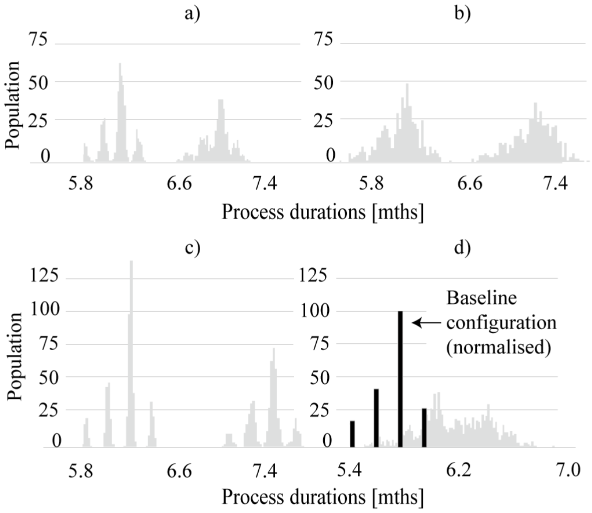


Figure 11 Simulation results showing the impact of the uncertain amount of rework on process duration combined with: a) ±10% uncertainty in tasks' durations (step 3e), b) ±20% uncertainty in tasks' durations (step 3f), c) limited resource availability and +10% uncertainty in tasks' durations (step 3g), and d) limited resource availability and ±20% uncertainty in tasks' durations (step 3h)

However, uncertainty in tasks' durations has influence on other characteristics of the distribution, such as the number of distinct secondary modes that indicate differences in duration which can arise from different task prioritisations. This is because an increase in the variance of the secondary modes leads to smoother distributions in which those modes are no longer distinguishable. Coupled with a reduction in the scope of rework, an increase in variability of the secondary modes leads to a distribution in which the primary modes are difficult to identify. In this distribution, effects of both rework and different tasks' ordering are nearly imperceptible (Figure 11d).

5. STRUCTURE AND ROBUSTNESS

The aim of the case study presented in the previous section was to investigate the practical applicability of incorporating different sources of process uncertainty in a simulation model to investigate their effects on the process duration. The study revealed that, while it is possible to gain some understanding of a process' response to specific uncertainties in this way, the expense of simulation and difficulty of interpreting results mean that only a very limited set of questions could be explored. The case study model, for example, comprises far too many variables to investigate each individually. The response of the model to combinations of noise factors would be even more difficult to evaluate exhaustively.

Instead of attempting to exhaustively evaluate the system's response to uncertain input variables, in this section we propose that studying the structures of information flows between tasks in a process can provide helpful insight into that process's response to uncertainties. In particular, the discussion highlights four distinct 'structural patterns' which can arise in practice, and shows how each pattern responds in a more robust or less robust way to the delay in completion of a constituent task. The paper will thus conclude that it may be possible to evaluate process robustness by searching for such patterns within the process, thereby placing less emphasis on computationally expensive simulation.

5.1. Task delays and process structure

The way process duration is affected by delayed tasks is dependent on the structure of information flows as well as the duration of the delay. Short delays are often unlikely to cause a process slippage regardless of the type of the task and its position on the critical path. Conversely, long delays may cause disruption of the entire project even if the task is not originally on the critical path (Eden, et al., 2000).

Although such delays can arise from a number of causes such as overoptimistic estimates or subcontractor's late delivery (Eden, et al., 2000), their ultimate effect is determined by the structure of information flows, resource constraints and management policies, such as the task selection policy in the ASM approach. How process structure responds to a delay is illustrated in four example patterns below.

5.2. Structure absorbs delay

For a process structure to absorb a task delay, i.e. to ensure that total process duration remains unchanged or at least does not exceed the maximum permitted value, the task should not be on the critical path of the project, which means that there are no downstream tasks whose execution immediately waits on the release of the task output. To illustrate this point, consider Figure 12 in which tasks 1, 3 and 4 are on the critical path and the deferral of any one will delay the whole process. In contrast, task 2 is an example of an activity that is not on the critical path.

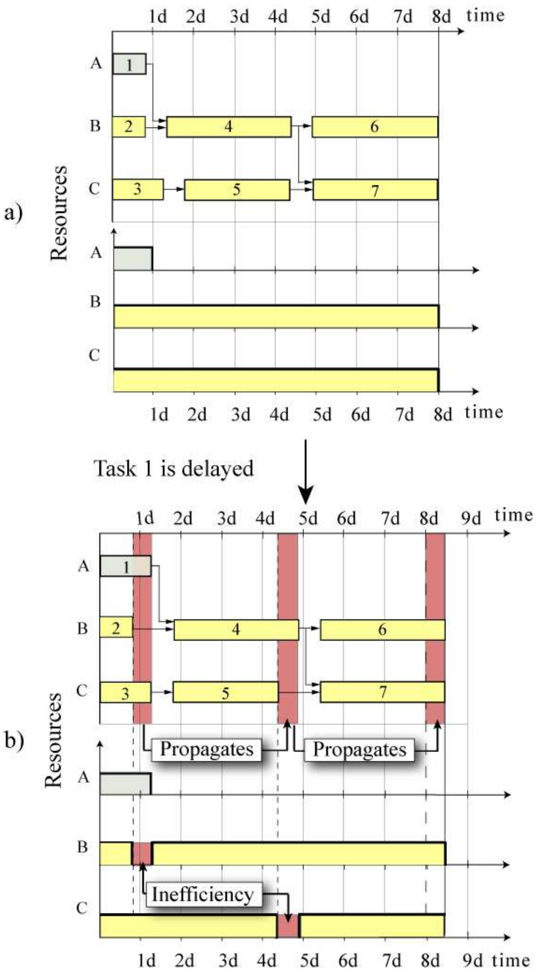


Figure 12 The propagation of a task delay across the project (top row) and a resource usage profile illustrating inefficiencies due to the delay (bottom row): a) original project b) project with a task delay. A, B and C represent different types of resources

Among other conditions that have to be met for process duration to remain unchanged following task delay is that the overdue task should not cause any risk, cost or quality perturbations that may eventually result in process slippages.

5.3. Structure propagates delay

Once a task is on the critical path its delay will propagate through the process. For example, if subsequent tasks are executed according to Figure 12, the propagated delay will reach the end of the task chain, whose length depends on the number and capacity of buffers in the process

Rescheduling one task can cause inefficiency in resource usage in addition to delays in subsequent tasks. As illustrated in Figure 13, an initially continuous profile of resource usage can become disjoint following a task delay. The resulting discontinuities represent resource inefficiency. This example shows that simple task rescheduling can have bearing not only on a timely accomplishment of the project but also on other common measures of process performance (see the discussion on resource-constrained project scheduling in Tormos, Lova, 2001).

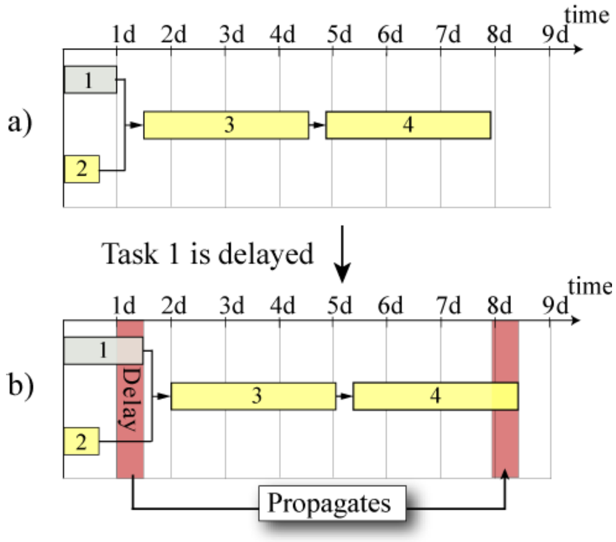


Figure 13 An illustration of a task on the critical path

Propagated delays may be commonly observed in industrial practice and are intuitive to understand in principle. In their simplest form, the possibility of such delays can be recognised and mitigated in a plan (e.g. using buffers) without requiring sophisticated analysis. However, efficient application of buffers to mitigate uncertainty can become significantly more complicated if multiple dimensions of process performance are taken into account. For example, there may be a trade-off between minimising the expected duration (achieved using few buffers) and duration variability (achieved using many buffers).

5.4. Structure accumulates delay

The concept of delay-accumulating structures is similar to that of delay-propagating structures, as it also relates to the impact of a delay in one activity upon tasks that are downstream in the process. In accumulated delays, however, a delay is magnified as it propagates through the process. For example, this can occur following rework. The ultimate magnitude of the knock-on delay depends on the particular characteristics of the reworked tasks. Even if rework does not take place, process or milestone completion may be delayed since the initial delay will *propagate* to the subsequent tasks that are not in the rework cycle (Figure 14).

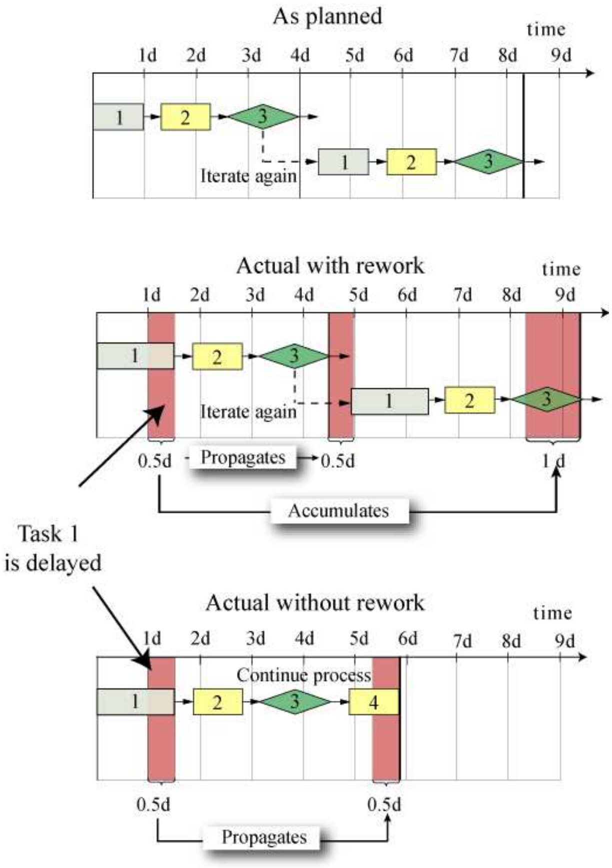


Figure 14 The accumulation of delays due to rework

This type of response may be difficult to distinguish from propagated delays in practice. However, distinguishing between these behaviours is useful since recognition of accumulation patterns could help identify tasks whose failure or postponement could affect the outcomes of processes with significant rework. This is a common structure in engineering design processes.

In the propagation and absorption patterns, the originating delay can arise from either rescheduling or extended task duration. However, rescheduling to first attempt of a task does not necessarily result in *accumulation* of delay, since the execution of reworked tasks may be on schedule and the initial postponement will simply *propagate* without further amplification.

5.5. Structure causes process duration to reduce following delay

As already demonstrated in the case of propagated delays, resource constraints tend to create additional complexity in a structure's response to delay. In particular, they can cause counter-intuitive behaviour and trade-offs in process performance. To illustrate, Figure 15 shows a case in which resource constraints cause a *reduction* in total process duration following a delay in execution of one task. In this example, a management policy regarding resource utilisation (aim for continuous utilisation of resource B) and/or a policy concerning activity prioritisation influence the outcome. The reduction mechanism can occur whenever tasks are structured such that a delay in a single task allows later tasks to be more efficiently interleaved.

This example also illustrates that locally-optimal management policies may not be globally effective. Consider the resource profile depicted in Figure 15a, where the policy favouring efficient and continuous utilisation of resource B leads to inefficiency in total resource use and, consequently, to the longer duration of the process.

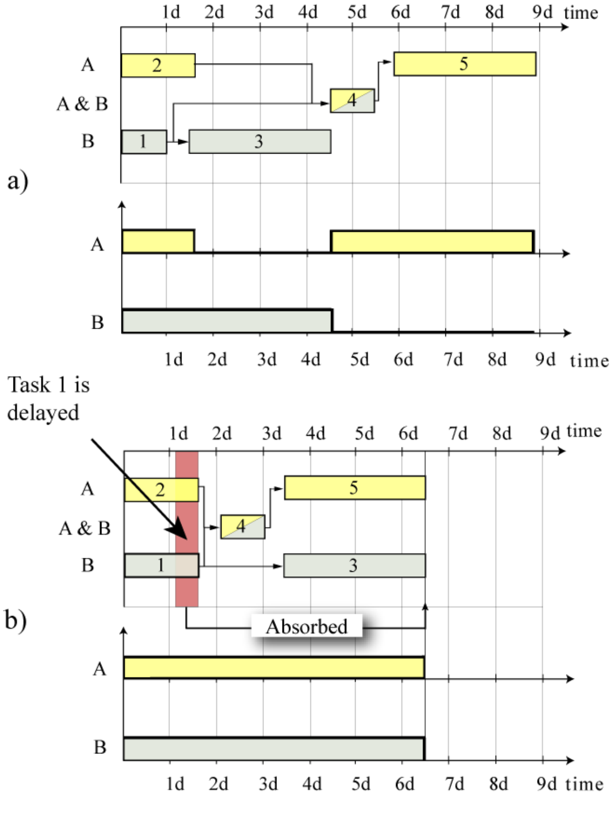


Figure 15 Counter-intuitive process behaviour due to a task delay (top row) and a resource usage profile illustrating more efficient usage due to the delay (bottom row): a) original project b) project with a task delay. A and B represent different resources

6. DISCUSSION AND FUTURE WORK

The experiment in Section 4 has demonstrated that simulation-based analysis can provide a useful approach to evaluate the behaviour of complex design processes. In particular, we have shown how three different sources of noise, i.e. uncertainty in tasks' durations, resource availability and rework behaviour can impact on the duration of the design process. We argue that understanding these relationships between sources of process uncertainty and process behaviour can provide insight to support the design of more robust processes.

Although the simulation results were qualitatively consistent with the theoretical analysis presented in Section 3, difficulties in interpreting them arose when more than one source of uncertainty was simultaneously introduced to the model. In addition, due to the computational expense of experimentation, only a very limited number of scenarios (combinations of the values of the three noise variables) could be investigated. This shows that the first research question of Section 1 cannot be fully answered using this approach in isolation. It is also difficult to reason about possible process design variables because the effect of one variable might not be distinguishable from the effects of other variables, or could be cancelled out by factors not included in the experiment. This shows that a more sophisticated approach is necessary for the identification of process design variables to be practicable.

To explore this, Section 5 illustrated some relationships between sources of uncertainty and the outcomes of simple process structures. This showed that process robustness can be viewed as a derivative of structural patterns which are easy to understand. More specifically, the absorption and reduction structures may be viewed as having a positive effect on process robustness (task delays do not result in process delays) and the accumulation and propagation structures as having a negative effect on process robustness (task delays result in process delays). Accordingly, in the light of the second and third research questions of this paper, it may be concluded that one way to identify robust configurations of design processes is to identify management policies (e.g. regarding resource allocation or task execution) which minimise accumulation and propagation while maximising absorption and reduction. This is summarised in Table 2.

Finding a way to identify such policies requires significant future research. One challenge is that process structures cannot be viewed in isolation since they could interact to amplify or buffer one another's response. It would therefore be necessary to explore the effects of these structures in combination.

Table 2 Process structures and their effects on process robustness

Pattern		Process delay/ task delay	Likely effect on process robustness
Reduction		*<0*	++
Absorption		*0*	+
Propagation		*(0,1>*	–
Accumulation	*Low probability of rework/few iterations*	*>1*	– –
	High probability of rework/many iterations	*>>1*	– – –

7. CONCLUSIONS

This paper has argued that the principles of Robust Design, which are most typically associated with the product, may be applicable to improve the ability of a design process to deal with uncertainty. This is currently an under-researched area which this paper has begun to address. In conclusion, this paper has focused on the following research questions stated in Section 1:

1. *What are the uncontrollable noise factors and other uncertainties which affect the design process, how can they be modelled and what are their effects?*

   The paper argued that uncertainty in process execution can be viewed as delays in individual tasks and in rework behaviour, as well as variations in resource availability. These factors can be incorporated in a simulation model and their effects estimated by a one-factor-at-a-time perturbation analysis.

2. *What are the 'process design variables' which can be changed to find more robust processes?*
   By analogy to product robust design, finding robust design process can be viewed as identifying process design variables which maximise process robustness. We have shown that one such variable is the management policy regarding resource allocation and task prioritisation in resource-limited scenarios. These could potentially be influenced to maximise the occurrence of 'robust structures' in the process.

3. *How can these process design variables be chosen to identify a more robust configuration?*
   Due to its computational expense, simulation-based analysis of complex design processes has been shown to be impractical as a method to identify more robust configurations. Investigating how a process' structure affects its response to delays in constituent tasks has been proposed as an alternative, more general method of identifying process design variables. Exploring how this could be achieved in practice is an opportunity for further research. Another such opportunity is to determine whether, and how, the ideas in this paper could be applied to improve innovative design processes, which are more difficult to model and analyse than the adaptive design considered in this paper.

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