Query-based Risks Management of Manufacturing Processes

Christophe Ponsard¹, Renaud De Landtsheer¹, Gustavo Ospina¹,

Stephan Printz² and Johann Philipp von Cube³ ¹CETIC Research Centre, Charleroi, Belgium

²Institute for Management Cybernetics (IfU), RWTH Aachen University, Aachen, Germany ³Fraunhofer Institute for Production Technology (IPT), Aachen, Germany

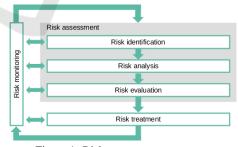
Keywords: Discrete Event Simulation, Manufacturing, Supply Chain, Procurement Risks, Risk Management.

Abstract: Managing risks in supply chains is challenging for most companies, given the globalisation process which is strengthening the production constraints and also introducing more procurements risks. This is especially difficult for smaller companies because they generally lack resources to develop a specific expertise or buy expensive tools. Our research aims at addressing those issues by proposing an easy to use, yet powerful simulation framework based on Discrete Event Simulation. In our previous work we demonstrated the expressiveness of our modelling language and the efficiency of our simulation framework. The focus of this paper is on the usability dimension of the developed tool. We describe the global process driving the company through the whole risk control process, from identification, modelling, simulation and analysis. We demonstrate our ideas on a web-based prototype composed on a number of wizards and component supporting the structured analysis of simulation outcome in direct relation with the risks.

1 INTRODUCTION

Supply chain risk management (SCRM) is the implementation of strategies to manage both everyday and exceptional risks along the supply chain, based on continuous risk assessment with the objective of reducing vulnerability and ensuring the process continuity (Wieland and Wallenburg, 2012). Such risks can occur for several reasons, both external (procurement risks of geographic, political, social nature, etc.) or internal (machine reliability, nature of specific operations, etc.). Helping company managers make the right decisions in the face of risks is not an easy task. Small and medium enterprises (SMEs) are especially challenged, because they have limited resources, and failing to address such risks can have dramatic effects on their business. This was confirmed by a survey we conducted on-line, related to the practice of evaluation of risks in an industrial context (Printz et al., 2015). The results of this survey showed that nearly 66% of the companies consider risk evaluations, but only 10% rely on dedicated software tooling and most of SMEs only rely on spreadsheets as tools.

Whilst analytical reasoning is impractical, modelbased simulation has proved to be a adequate approach (Deleris and Erhun, 2005). A common characteristic is that the impact of risks can generally only be assessed at the output of the supply chain while some risks, like procurement risks, occur at the very beginning. Therefore, this requires to be able to reason throughout the whole manufacturing process.





Our ultimate goal is to produce a user-friendly, tool-supported methodology that will guide the user through the whole process of risk assessment shown in Figure 1. In order to reach this goal, our research is structured as follows:

• Identifying a taxonomy of risks related to supply chain in manufacturing, based both on literature review and feedback from our survey (Printz et al., 2015).

Ponsard, C., Landtsheer, R., Ospina, G., Printz, S. and Cube, J.

Query-based Risks Management of Manufacturing Processes.

DOI: 10.5220/0006011103390344

In Proceedings of the 6th International Conference on Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH 2016), pages 339-344 ISBN: 978-989-758-199-1

Copyright (C) 2016 by SCITEPRESS - Science and Technology Publications, Lda. All rights reserved

- Developing a modelling and simulation tool for identifying risks, quantifying them and deciding on how to mitigate them. This technical part of the work relies on a Discrete Event Simulation (DES) engine provided by the OscaR library (OscaR, 2012) and combined with Monte Carlo Simulation (MCS) techniques. It is fully described and benchmarked in (Landtsheer et al., 2016).
- Building a user-friendly interface to support the global risk management workflow depicted in Figure 1. This is the scope of the present paper.
- Validating our work through a group of companies that are already trying out the tool.

Our modelling framework includes concepts such as *storages* and several types of production *processes*. In addition, we defined a query language on models. It is fully declarative and includes arithmetic, temporal, and logic operators, as well as basic queries on the elements of our factory model (contents of a storage, running state of a process, etc). Based on this query language, the software tool is able to estimate the probabilities of different scenarios (e.g. delay in deliveries, defective parts or poor quality) and their impact.

In this paper, we show how the modelling concepts and simulation tool are supporting the global risk management process in an efficient, consistent and user-friendly way using a web-based interface. The main steps of the process support are as follows:

- *Risk-oriented process modelling:* the model is built with the aim to express the required risks and not especially to be a full scale model. As risks are fully identified in the next step, it may need to be refined to reach the right granularity.
- *Risk identification:* in this key step, a hierarchical risk model is defined using a structured wizard covering major risk categories such as quality, quantity and delay risks. Different queries are used to express the risks for each category.
- *Risk-oriented simulation:* the model instrumented with queries is run using the DES and MCS, and raw results (collected traces or statistics) can be explored directly in the tool.
- *Risk analysis and measures:* the measurements collected using the risk queries are presented in a risk dashboard according to the structured risk model. It allows the risk analyst to zoom in specific risk categories or look at the behaviour of specific element according to specific risk categories. Based on this, some risk control measures can be identified and validated using a new round of simulation. The best value of specific parame-

ters can also be determined, e.g. the threshold or the quantity for an order policy.

The paper is structured as follows. Section 2 gives some background on our framework. Section 3 describes a short case study consistently used in the next sections. Section 4 to 7 describe our modelling, risk identification, simulation and analysis steps, respectively. Finally, section 8 draws some conclusions and describes some future work.

2 BACKGROUND: SIMQRI SIMULATION META-MODEL

All the main elements of manufacturing processes are represented in our simulation meta-model, which allows us to define concrete models that are simulated in a DES engine. In addition to this, we designed a Query Language over concrete simulations in order to collect and analyse data.

2.1 Meta-model Overview

This section introduces the basic blocks for representing factories. Figure 2 summarises the meta-model of concepts used at that purpose. It is composed of activatable components such as storages and processes through which items can flow.

- *Storages* represent any kind of storage device or place for raw materials, like a warehouse, a barrel or a silo. They have a maximum capacity. When this capacity is reached, they either overflow, or processes trying to put more items into them are blocked, depending on the settings of the storage. If a full storage overflows, any exceeding material is lost.
- *Batch processes* are factory processes that work in a batch fashion; supplies are collected from various storages, the process then runs for some time, and finally the produced outputs are dispatched to their respective storages before this whole cycle starts again. They exist in different flavours: with a single or multiple production lines.
- *Splitting processes* are similar to batch processes, except that they have several sets of outputs that can be selected according to some rules. It can be used to model failing processes and quality assurance process.
- Continuous processes are factory processes that typically run on a conveyor belt. Items are continuously picked from input stocks and undergo the process taking some time. Continuous processes



Figure 2: Meta-model of our tool.

act like pipeline; they can process several items in a queue.

The flow is controlled through activation rules that relates to order books and procurement policies.

- On Order activation represents on-demand production triggered by a specific order book.
- *Stock monitoring* are used to implement different procurement policies (or possibly internal stock transfers) based on different possible models.

2.2 Query Language Overview

We remind here the main operators that can be used to express queries allowing the risk analyst to evaluate specific risks on the model. The language can also be used to collect other kinds of Key Performance Indicators (KPIs) that are also useful to quantify and reason about the risk impacts.

Queries for Processes

These are atomic operators that extract basic metrics from processes of the simulation model. Suppose that p is such a process:

- *t* ⊨ completedBatchCount(*p*) the total number of batches performed by *p* until time *t*.
- *t* ⊨ startedBatchCount(*p*) the number of batches started by *p* until time *t*. For a multi-line process, it sums up the started batches of each line.
- t ⊨ totalWaitDuration(p) the total duration where p was not running until time t. For a multi-line process, it sums up the waiting time of each line.
- t ⊨ meanLoad(p) is the ratio between of the completed batches and the total capacity until time t.
- *t* ⊨ anyBatchStarted(*p*) true if a batch was started by the process at time *t*.

Queries for Storages

These are atomic operators that extract basic metrics from stores of the simulation model. Suppose that *s* is such a store:

t ⊨ empty(*s*) true if *s* is empty at time *t*, false otherwise.

- $t \models \text{content}(s)$ the number of items in *s* at time *t*.
- $t \models$ capacity(s) the (fixed) maximal capacity of s.
- t ⊨ totalPut(s) the number of items put into s until time t, not counting the initial ones.
- *t* ⊨ totalFetch(*s*) the number of items fetched from *s* until time *t*.
- *t* ⊨ totalLostByOverflow(*s*) the number of items lost by overflow from *s* until time *t*.

Operators

Complex queries can be built using following operators, some of them also referring to one or more states of the considered trace:

- logical: true, false, *not*(!), *and*(&), *or*(||), *<*, *>*, ...
- temporal logic: hasAlwaysBeen, hasBeen, since, ...
- arithmetic: +, -, *, /, *sum*, ...
- temporal arithmetic: delta, cumulatedDuration, time, min, max, avg, integral...

3 COMPLEX ASSEMBLY CASE STUDY

The product under investigation is relatively simple, it consists of three components, which are procured externally. The production process can be characterised as an order-driven, small batch, job shop production as depicted in Figure 3.

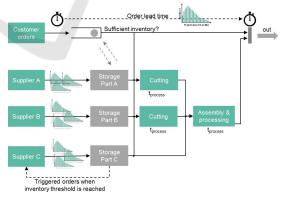


Figure 3: Complex Assembly Case Study.

Materials A and B are delivered on a regular basis and kept on stock, whereas component C is ordered based on the current demand. Whenever a new customer order arrives, inventory is checked. If enough parts are available, the order is released and the production process starts. If not, the order has to wait until new supplies arrive causing a delayed start of production and potentially delayed deliveries. Materials A and B are polymer materials stocked as mats out of which single components need to be cut in a first production step prior to assembling and processing all three components. Completed orders are directly shipped and no final products are kept in stock.

4 RISK-ORIENTED MODELLING

The modelling tool is based on a web-based graphical editor using the JointJS (ClientIO, 2016) JavaScript library. The modelling is done using drag and drop and a property editor can be used to specify the required parameters. Figure 4 shows the modelling tab of the user interface for our case study.

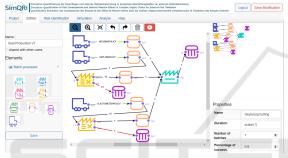


Figure 4: Risk-oriented modelling.

Stochastic values can be introduced in several places, either integer (e.g. delivered quantity) or real (e.g. delay) data types can be instantiated using respectively discrete and continuous probability distributions. Specific components also have a native stochastic behaviour (e.g. processes with a failure rate).

5 RISK IDENTIFICATION

After modelling a factory, the analyst can then move to the risk identification tab of the interface. The tool includes a wizard helping the user to express risk using our query language. A succession of screenshots of this wizard is shown in Figure 5. It starts from the main risk categories (quantity/quality/delay), then guides the user into specifying how the risk can be measured both at system level and then at component level. At system level, the risk impact will be measured in monetary terms in order to allow the aggregation and comparison of different kinds of risks. Of course, component level risks does not always involve a system: the goal is actually to design the system to be resistant to component level risk occurrence. Figure 6 shows our simple generic risk model. With this

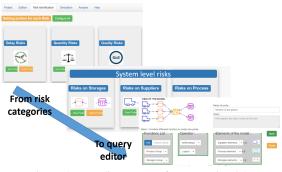


Figure 5: Encoding a query for a quantity risk.

model, generic queries can be defined for component level while the risk analyst has to provide problem specific queries that computes the mitigated risk at system level.

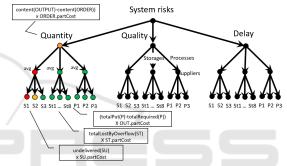


Figure 6: Overview of our generic hierarchical risk model.

In the context of our case study, we defined the following quantity risks:

- at system level, the global OUTPUT storage can be compared with an ORDER book: (content(OUTPUT) - content(ORDER)) * ORDER.partCost. We here use the agreed order cost which may differ from the production cost.
- at component level, specific risks indicators might, for a storage can be an overflowing or full storage, raise quantity risk flags with totalLostByOverflow(ST) * ST.partCost. A supplier might also fail to deliver the required quantity undelivered(SU) * SU.partCost. For a process, meanLoad(P) can be an indicator if it is saturating at 100%. The loss can be evaluated using the difference between measured and expected production for a given process: (totalPut(P) totalRequired(P)) * OUT.partCost

A number of predefined queries are available in each context. Queries can also be edited and designed from scratch using a plain text editor. Figure 5 shows the encoding of a quantity risk measuring the number of lost pieces in a factory.

6 **RISK-ORIENTED SIMULATION**

The next tab is devoted to running the simulator on the model together with the queries to collect all the required risk information. The simulator can be run in two modes that are detailed in the rest of this section:

- *in "One Shot" mode*, the simulator will return a single trace with no statistical meaning. The trace can be analysed to make sure about the general behaviour of the supply chain and factory.
- *in "Monte Carlo" mode*, the simulator will not collect individual traces. Instead, it will compute statistical information over the set of traces.

6.1 Trace Analysis

Different tools are available for trace analysis. The first tool enables to explore a single trace using a slider. At each event occurrence, the slider shows the time and what occurred at that specific time. Time is continuous, and expressed in an arbitrary unit, decided for the whole model (it can be hours, seconds or milliseconds depending on the domain and the risks). Figure 7 shows the trace tool displaying a specific time of a simulation of our case study.

Simulation of Seal Production V1
.:Simulation Trace:.
Grid Time:
Events At Time : 15
 ElestometerFrocess chain 1 : Finished batch, outputting to 1 ElestometerFrocess chain 1 : Finished outputting ElestometerFrocess chain 1 : Start new batch ElestometerFrocess chain 2 : Finished batch, outputting to 1 ElestometerFrocess chain 2 : Finished outputting ElestometerFrocess chain 2 : Start inputting ElestometerFrocess chain 5 : Start inputting
Figure 7: Trace analysis tool.

Focusing on this specific time, it is possible to zoom on any specific element or any query. Figure 8 shows the state of the final storage for *ProducedGoods* at time 11.

6.2 Statistics Overview

In Monte Carlo mode, the risk analyst can check some key statistic indicators of the model elements and queries, such as minimum, maximum, mean and standard deviation (Figure 9). The full distribution of the simulation data is available to the client for more complex analysis.

ProducedGoods
ElastometerStorage
HousingStorage
4

Figure 8: Element detail at a specific time of a trace.

Monte V1	Carlo	Simulation	of	Seal	Production
On 100 itera	tions				
	9539072 449945 1543438872.0562 Lion Ele				
Probe				Value	
LipStorage : Mi	nimum relative s	tock level (Basic Probe)		• Ma • Mi	an : 0 ximum : 0 nimum : 0 riance : 0
ProducedGoods :	: Average relativ	e stock level (Basic Probe)		• Ma • Mi	an : 0.00004990909090909090923 ximum : 0.0000935000000000001 nimum : 0 riance : 2.1547560275852463e-13

Figure 9: Overview of statistical data on queries and elements.

7 RISK ANALYSIS AND MITIGATION ACTIONS

7.1 Risk Dashboard

Figure 10 shows the risk management dashboard at the top-level for our case study. It displays a pie chart representing the relative importance of the three main risks (quality, quantity and delay) estimated at the system level. The probability distribution of those three risk factors are displayed in the bottom part. A diagram on the left part also displays the evolution over time of specific queries (by default the total risk). Two curves are drawn: one displaying the expected value (mean) of the indicator and the other displaying the Value at Risk (VaR), i.e. the threshold loss value, such that the probability that the loss over the given time horizon exceeds this value is p (e.g. 5%) (Jorion, 2006). It is then possible to zoom in specific risk categories and explore how specific processes, storage or

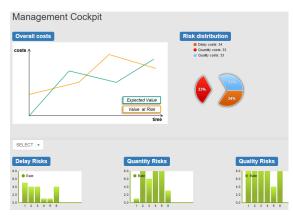


Figure 10: Top-level dashboard of the risk analysis.

suppliers behaves with respect to a specific risk.

7.2 Risk Control

Controlling the risks requires tuning the model in order to minimise the estimated costs induced by risks. However, changing a parameter in the model might have multiple and possibly conflicting effects. The tool supports a simple way to change the values of some parameters to find out their optimal values, given that other parameters remain constants. The risk analyst can then perform a tuning-simulationanalysis process on the model in order to find out the best alternative to control the risk.

Ordering Threshold Size	Process Idle Time
0 (wait empty)	70%
10	34%
20	5%
30	0.01%
40	0%

Table 1: Optimisation of the ordering threshold.

Table 1 shows the effect of the ordering threshold on the idle time of the process directly fed by that supplier. A zero threshold will result in a quite high idle time as the process will have to wait the whole delivery time. As the threshold is increased, the process idle time is decreasing, but beyond the threshold of about 30 parts, it reaches its full rate. There is no reason to increase it more, since it will result in more frequent deliveries and thus higher procurement costs.

8 CONCLUSIONS

In this paper, we presented a web-based interface allowing to support risk assessment for supply chains based on a simple risk model and a supply chain model instrumented with risk queries. The risk model can be easily instantiated using wizards and results in an easy to interpret risk dashboard after the model simulation. The tool relies on an efficient engine able to perform large number of simulations including stochastic parameters.

Our current experience with the tool is quite positive. We are carrying out a validation of the tool on real-world cases provided by SMEs from Wallonia and Germany. We are also enhancing the wizards to help formulating common system-level risks. Another demand is to support a desktop-based interface. To this purpose, we are implementing another frontend relying on the Eclipse using EMF modelling and the Sirius editor (Obeo, 2016).

ACKNOWLEDGEMENTS

This research was conducted under the SimQRi research project (ERA-NET CORNET, Grant No. 1318172). The CORNET promotion plan of the Research Community for Management Cybernetics e.V. (IfU) has been funded by the German Federation of Industrial Research Associations (AiF), based on an enactment of the German Bundestag.

REFERENCES

ClientIO (2016). JointJS website. http://jointjs.com.

- Landtsheer, R. D., Ospina, G., Massonet, P., Ponsard, C., Printz, S., Hrtel, L., and von Cube, J. P. (2016). A Discrete Event Simulation Approach for Quantifying Risks in Manufacturing Processes. In *Int. Conf. on Op. Research and Enterprise Systems (ICORES).*
- Deleris, L. and Erhun, F. (2005). Risk management in supply networks using Monte-Carlo simulation. In 2005 *Winter Simulation Conference*, Orlando, USA.
- Jorion, P. (2006). Value at Risk, 3rd Ed.: The New Benchmark for Managing Financial Risk. McGraw-Hill.
- Obeo (2016). Sirius Obeo Designer. http://www.obeodesigner.com/sirius.
- OscaR (2012). OscaR: Scala in OR. https://bitbucket.org/oscarlib/oscar.
- Printz, S., von Cube, P., and Ponsard, C. (2015). Management of procurement risks on manufacturing processes survey results. http://simqri.com/uploads/media/Survey_Results.pdf.
- Wieland, A. and Wallenburg, C. M. (2012). Dealing with supply chain risks: Linking risk management practices and strategies to performance. *Int. Journal of Physical Distribution & Logistics Mngmt*, 42(10).