Credit to SMEs?

Robust Lending Decisions with Exploratory System Dynamics Modelling & Analysis

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Master Thesis

CREDIT TO SMEs?

- Robust Lending Decisions with Exploratory System Dynamics Modelling & Analysis -

Engineering and Policy Analysis Master Thesis

Delft University of Technology
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PREFACE

The pile of papers in front of you serves multiple purposes.

Why would You read it?

This is first and foremost a master thesis, reporting on applied research in the field of exploratory modelling. **If you are a methodologist in the fields of modelling, data analysis, decision-support or risk and uncertainty**, then you may find state-of-the-art combinations of modelling and analysis tools. Read chapters 1 and 2 and jump to the referred journal articles and books for more! You are welcome to contact me with questions/feedback.

The methods and tools presented here are supposed to support lending decisions in the context of commercial banking. Therefore the project was performed in collaboration with bankers. **If you are involved in banking, equity research, business model analysis or financial management of a company**, you will find innovative ideas to handle risk and uncertainty in your work: read chapters 1, 2(a) and 4! Give this to an analyst as a manual, send her/him to training at TU Delft or RAND Corporation and then let her/him do the work for you: help you make more robust decisions in the face of future uncertainties. Contact me if you want to set up an implementation strategy and you don't know where to start.

If you are a System Dynamicist you will find new ways to explore and use (and torture) your model. Read chapters 1-3. Then go and make your models tell you more! Contact me if you are struggling with that.

If you are one of my friends or my wife, here you can read about what kept me busy in the last 6 months. It should prove that I have learned and done lots of things, but don't hesitate to ask the 'Why on earth…?' question. Contact me with holiday offers/invitations.

Acknowledgements

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Erik and Anna! Without you …

András Kővári

Delft, 2013

Executive Summary

This project's commissioner, the head of ING's emerging markets credit trading desk developed a loan structure called Revenue Participation Loan to fit the needs of SMEs in emerging markets. He now wants to combine this new product with innovation in his approach to uncertainty. With these types of loans SMEs agree to pay a fixed percentage of their revenues (a 'cut') to the lender until an agreed multiple of the principal is reached. The advantage of this structure is that it tolerates the sales fluctuations, but the implication is that it is unknown how long it will take to repay the loan. In the face of this uncertainty the bank needs analytical tools to select the best candidates and make robust lending decisions.

No analytics can exactly predict the future. However, a good model-based analysis usually leads to better decisions than flipping a coin. But that too depends on good quality models and on how they are treated. A good addition to the well-established accounting models seems to be System Dynamics (SD) modelling. SD's dynamic approach allows building and simulating stock-flow models that better represent the non-linear systems of companies. To make sense of the uncertainties in these models the Exploratory Modelling and Analysis (EMA) tools are proposed. The objective of this project is to investigate in what ways SD modelling combined with an exploratory approach could support lending decisions and monitoring of an SME credit portfolio.

Traditional business plans aim to create *the* model that most accurately predicts the future performance of the company. Lending decisions based on such best-guess models are problematic given the deep uncertainties inherent in the mid- to long-term future. Opposed to this 'consolidative' approach, an exploratory study aims to systematically analyse a wide range of plausible future scenarios. The aim becomes to better understand the nature and implications of uncertainties and to devise robust measures that perform well over a wide range of possible futures. Such analyses can be supported by existing EMA tools also developed at TU Delft.

Two case studies based on existing loans are presented to explore how SD modelling of SMEs could be performed and to illustrate the capabilities offered by the EMA workbench. Although these cases featured two very different companies a relatively similar framing of the problem can be recognized: the availability of cash balance is a critical enabler of these companies' growth. Based on the SD models and their uncertainties considered the EMA tools can plot the range of scenarios that can occur. The most important indicator from the point of view of the bank is the time it takes to repay the loan. Using plausible uncertainty ranges for each input parameter the possible outcomes range from around 4 years to infinite repayment time. Feature selection algorithms then can be used to understand what are the most influential model parameters determining this outcome. Further analysis can reveal what combinations of uncertainty ranges will likely lead to the most (un)desirable scenarios. Finally, a robust optimization tool is introduced that can determine the optimal loan size and cut taking into account the uncertainty surrounding key exogenous variables.

The study performed on the two cases could be performed during the assessment of the companies that are willing to receive a loan. However, this has some implications on the nature of the assessment. It became clear that more information needs to be asked and the nature of questions has to be broadened to what is commonly considered 'soft information'. Although SME managers might not be used to it, explicit, clear and quantitative expression of causal relationships is at the core of SD modelling. Historical data records and a skilled modeller can make the inquiry manageable. The detailed modelling might be demanding for both the bank and SMEs, but the effort can pay off when more company models are analysed together. A combined analysis is envisioned in which the company models are embedded into the relevant macroeconomic environment, therefore allowing a consistent portfolio-level analysis. A higher level of detail allows for broader detection of weak signals of change and can also lead to more efficient monitoring through shared understanding between bank and company.

It is recommended that the steps presented in the case studies are performed for a real company assessment to gain real-time experience with the EMA tools. The insights gained should be used to continually develop and improve the process of application. Despite its added value, the EMA approach and analytic tools probably cannot replace the need for good human judgement. But as a supporting companion for decision-making, they can give a sharper and more colourful picture of the uncertain future.

CONTENTS

Executive Summary 1

1. Introduction 3

   1.1 Motivation 3

   1.2 Background 3

      1.2.1 RP Loan basics and current lending practice 3

      1.2.2 What is System Dynamics and how can it help? 5

      1.2.3 What is EMA and how can it help? 7

   1.3 Research question and objectives 9

   1.4 Research scope and paper structure 9

2. EMA Methodology and its Tools 10

   2.1 Descriptive Tools 11

   2.2 Search Tools 12

3. Case Studies 13

   3.1 Case 1: Plastic Production Company 14

      3.1.1 Preparation 14

      3.1.2 Model Description 15

      3.1.3 “What if…” Analysis 21

      3.1.4 Structured Analysis 24

   3.2 Case 2: High-End Shoe Retailer 33

      3.2.1 Model description 33

      3.2.2 Structured Analyses 37

4. Recommendations, Implications and Reflections 40

   4.1 On Information Gathering: A Culture of Transparency? 40

   4.2 On SD Modelling of SMEs 41

   4.3 Outlook for Combined Analysis and Monitoring 42

   4.4 The EMA Workbench within a Bank: A Bold Vision and Limitations 44

5. Conclusions, Future Work 45

6. References 46

Appendix 1 49

Appendix 2 53

Appendix 3 55

Appendix 4 60

1. INTRODUCTION

1.1 Motivation

Small and Medium-sized Enterprises (SMEs) are the backbone of growth and employment in emerging economies. They represent 95% of all companies, and employ two thirds of the labour force. A report by McKinsey & Co. estimated that SMEs in emerging markets (EM) account only for 7% of the total value of loans, bonds and public equity outstanding (Stein, Goland, & Schiff, 2010). Despite their huge share in job creation, SMEs' capital employed in some form of credit is just a fraction of the loans that the large corporations use. This lack of capital is found by some to be the biggest constraint on these companies' growth (Beck & Demirguc-Kunt, 2006) .

Lending to SMEs is riskier, but the yields that investors can get from larger companies have long reached a plateau. There is a huge unmet credit demand from the SME side. Therefore, banks that can develop a sound business model for lending to them could find great alternatives for future revenue streams while contributing to economic development and job creation. However, confidence in banks' sound business models and risk management in general has hardly ever been lower. Bankruptcies and bail-outs during the crisis to high-profile scandals[1] all undermine bank's credibility in proper risk management. Economists also talk about financialization of industry, warn about debt deflation and call for the restoration of banks' role as a service to industry (Hudson, 2012). KPMG reports on the capabilities of risk management being outpaced by expectations (KPMG and The Economist, 2013), while another survey calls for the rethinking of risk strategies within banks (Ernst & Young, 2010). The European Central Bank stated that there is an enormous need for further research into the management of financial systems and systemic risks (ECB, 2010). Novel analytical tools aiding banks' decision-making may help restoring confidence and reconcile finance and industry.

Banks' need for novel ways of risk approaches and a vast unmet demand for credit from SMEs in emerging markets inspired a pilot project within ING Bank. The head of ING's emerging markets credit trading desk developed a loan structure called Revenue Participation Loan (RPL) to fit the needs of SMEs in emerging markets (see details below). He now wants to combine this new product with innovation in his approach to uncertainty and risk. Already having a background in operations research he recently encountered the Exploratory Modelling and Analysis (EMA) tools developed at TU Delft's Technology Policy & Management faculty. Seeing a potential fit with his interests, he commissioned a project investigating the possible uses of the EMA tools in his team's investment practices. The findings of this project are reported in this master thesis. This document also serves as a final report to the commissioner aiming to serve as a useful reference for any further application of the EMA approach in his work.

Within scientific research this work fills the gap of applying SD modelling with an exploratory approach to the study of RP Loan performance. Chapter one continues with explaining the three key pillars that define this gap: (1) RP Loans and what could be improved in the lending process, (2) what is SD and how existing SD work supports its application to this topic and (3) what is the EMA approach and why is it a useful support to decision-making related to the future performance of loans. With these background elements explained the research question and scope can be formulated at the end of this chapter.

1.2 Background

1.2.1 RP Loan basics and current lending practice

The idea of a Revenue Participation Loan emerged from experience of working with SMEs in emerging markets. It is offered to small companies with a sound business model and potential for growth within the markets they operate in. The structure of the transaction is presented in Figure 1.1. At the start the lender gives the company a certain amount, that is the capital provided. The company agrees that a fixed percentage of all its revenues are directly transferred to a debt repayment account. This percentage will be referred to as the 'cut' in

[1] Think of insider trading, HSBC money-laundering, Barclay's Libor fixing, JP Morgan's recent 6bn losses

this report. The loan is considered to be repaid when the accumulated repayments reach an amount equal to the capital provided times an agreed factor that can be called the premium.

There are some obvious differences between an RPL and a traditional loan structure. First, there is no interest rate by which the amount left to be repaid could grow over time. The actual monthly repayments are not fixed upfront, but they depend on the actual sales. Therefore it is not known upfront how long the repayment will take. Furthermore, an RPL is not dedicated only for working capital or long-term asset acquisition. Instead, it is meant to be a comprehensive package covering all the capital needs of the company that will enable them to grow. Therefore the company has to repay other debts at the moment of receiving the RPL and is restricted in the amount of additional debt it can take over the duration of the repayment.

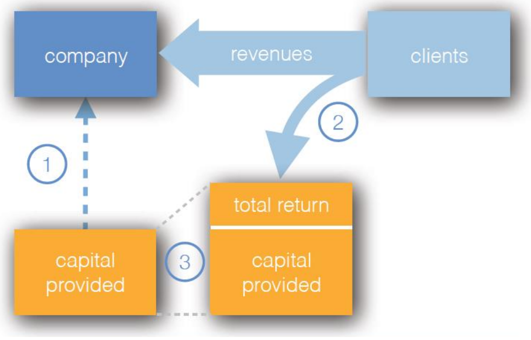

Figure 1.1 Structure of an RP Loan

Small companies usually face higher volatility in their sales revenues and also in the interest rates that they can get to refinance their debts. Under an RPL structure the sales volatility is tolerated and there are no additional loans to manage. It is therefore mainly the flexibility of the repayment that appeals to SMEs in this structure. Moreover, once the RPL is repaid, the owners are left with a company with virtually no debt, hence more equity. The interests of the bank and the company are more closely aligned: if the company grows quicker, the repayment will also take less time, meaning a higher internal rate of return.

Before awarding an RPL, the bank tries to thoroughly assess the companies interested. After an initial screening, the bank chooses to visit the most promising candidates. Such a visit and discussion has two main goals: (1) **to understand the business model of the company** and (2) **to assess whether it is sustainable in the future**. First, the company directors present to the bank representatives how the company works, they discuss historical financial data and explain their plans for the future. Then the main drivers and barriers to growth are discussed to see where the future revenues will come from. The discussion is of course supported by calculations which roughly go through the following steps:

1. The potential for future sales revenues is calculated by looking at the potential growth of the market in which the company operates. The main clients are assessed and forecasts are made about the expected growth of sales to existing or new clients. Indicators of the economic environment (such as GDP, urbanization, credit card penetration, internet penetration, consumer spending, etc) are described and an assumption is made about how its environment will support the revenue growth of the company.[2] All this is translated to a forecasted sales volume for the next years.
2. Given the expected sales volume, the cost of investments necessary to supply this volume is calculated. Costs are calculated using historical unit cost data and assumptions about how the main cost elements will evolve in the future.
3. Given the revenues and costs, the net income can be calculated as the difference between the two. If it results that the cash flow from this net income is positive and also large enough to support an RPL repayment, then the company is a strong candidate for the loan.

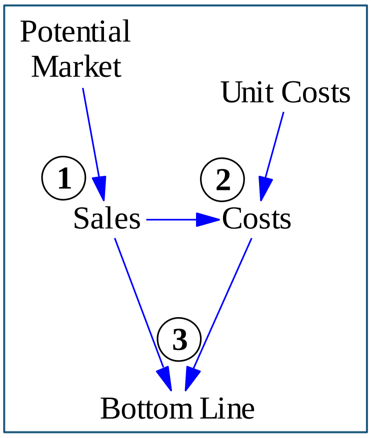

Figure 1.2 Usual forecasting steps

If the above calculations look promising, the loan size and the cut have to be agreed upon. The loan size needs to be enough to repay existing loans and support future spending, while the cut has to be large enough to repay the loan in a reasonable time, but also bearable for the company. Overall, the loan is usually designed such that under a no-growth scenario it would be repaid in approximately 10 years. It is expected though, that given

[2] The assumption of how these indicators translate to sales revenues growth is not necessarily explicit. It is usually implied that there is a positive correlation between these indicators and the company's revenue growth.

the potential to grow the company will utilize the capital provided to increase sales and repay the RPL in 6-7 years.

When deciding to give the loan, the basic questions faced by the bankers are: When will the full repayment happen? How likely is it that it will take less than 10 years? What amount is enough to put the company on a growth path? Under what conditions will the repayment be successful? One of the purposes of financial modelling is to give an indicative answer. The knowledge gathered about the company is usually recorded in a report and the forecasting of the debt repayment is done using accounting models in spreadsheet form. However, much still relies on intuition according to the bankers involved in the origination. The accounting models used during the assessment are high-level and simplistic. Often the comprehensive model is only built after the loan has already been given. All these models contain many assumptions about future prices, conditions and parameters of the company and economy, but there is no systematic assessment of the effects of all these assumptions, the sensitivity of their outcomes to these assumptions, and the overall robustness of the loan. The traditional spreadsheet models and the currently used software tools hardly allow for that.

The reliability of any forecasting depends heavily on the type and quality of the underlying models used. The usefulness of these models then depends on the analytic tools, indicators and representation methods applied. According to the commissioner of this project both an alternative modelling approach and novel analytical tools could greatly support robust lending decisions. System Dynamics models can provide an alternative to spreadsheet models, while the EMA workbench contains tools for scenario generation, uncertainty exploration and robust optimization that could be valuable additions to current lending practices. The two concepts (SD +EMA) are introduced below.

1.2.2 What is System Dynamics and how can it help?

System Dynamics is a continuous modelling approach to represent the dynamics of systems. Having its roots in control systems engineering, it is based on models consisting of stocks and flows. Any system that can be conceptualized as a collection of stocks and flows can therefore be modelled with SD. The stock-flow structure is interlinked with auxiliary variables and explicitly defined causal relations often forming feedback loops.

Traditional accounting models are a collection of linear relationships. Investors usually try to understand the businesses and make decisions through the lens of such accounting models. However, there are many reasons why such models cannot adequately represent what drives business performance. Business processes are often characterized by accumulation of resources over long time periods and substantial delays between action and result. There are many complex interdependencies that often create feedback loops that accelerate or hold back changes in the system. Other non-linearities that linear models cannot deal with include thresholds, tipping points and finite resource uses. Financial reports therefore are often complemented with a text description of these additional ‘soft information’.

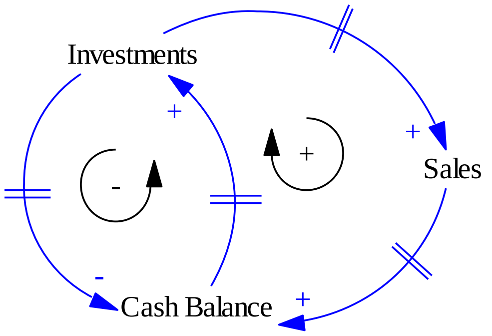

Figure 1.3 Generic business model

SD allows building and simulating quantitative models that can deal with all the above mentioned features of business processes. An SD model is well suited to represent the delayed interrelationships between a company’s sales, cash balance and investments. Any business can be viewed as a system that continuously invests money into resources that can generate sales over time, that in turn generate cash income again, and so on... often characterized by delays all along these relations (see Figure 1.3). SD modelling is well-suited to capture such (and much bigger) dynamic complexities and is therefore a promising approach to provide a more reliable alternative to linear accounting models. Another advantage of using the SD methodology is its focus on modelling the decision-making processes that bring about change in a system. Whereas spreadsheet models simply state the expected future financial results, an operational SD model of a company is essentially a hypothesis about *how* business decisions bring about the financial performances reported. The fact that SD models are built to be 'simulated' means that business performance over time can be studied under a variety of alternative assumptions about the systemic relations and their parameterization.

SD's usefulness for the study of business performance over time was proven extensively by leading scholars in the operations research, management and strategy fields (Morecroft, 2007; Sterman, 2000; Warren, 2008).[3] Given its aforementioned strengths SD modelling is applied also in this thesis, since the aim of this project is the study of RP Loan performance over time. Further references that support the application of SD to the study of RP Loans are enumerated below.

SD allows building and simulating dynamic models with a stock-flow structure. Since the elements of an accounting model are also stocks (on balance sheets) and flows (on income statements and cash-flow statements), one would expect that SD has been widely applied to build, study and report on accounting systems. However, reports on SD applications in the scientific literature do not reflect a significant focus on accounting. Models of cash flows and profits were part of SD models from the early years of the field, although it was not the starting point or main focus of initial studies (Forrester, 2003). While Forrester's *Industrial Dynamics* only treats the 'Money'-part of his models as indicators (Jay W. Forrester, 1961), later works based on his models integrate the cash flows into the feedback loops of the system, applying SD to study the performance of large companies (Lyneis, 1980; Richardson & Pugh, 1981)

Yamagouchi claims that his searching review of the SD literature resulted in no comprehensive accounting model, therefore he started building one from scratch (Yamaguchi, 2012). Based on scholarly accounting books he assembled the stock-flow representation of an accounting model covering a wide range of financial indicators and relations related to a firm. His simplified representation of a balance sheet is shown on Figure 1.4. The basic elements of asset and liability stocks of a company can be recognized. The flows going in and out of the 'Cash/Deposits' stock can constitute the cash-flow statement. The rest of his model goes into more details of inventories, cash flow statements, income statements and ratio analyses.

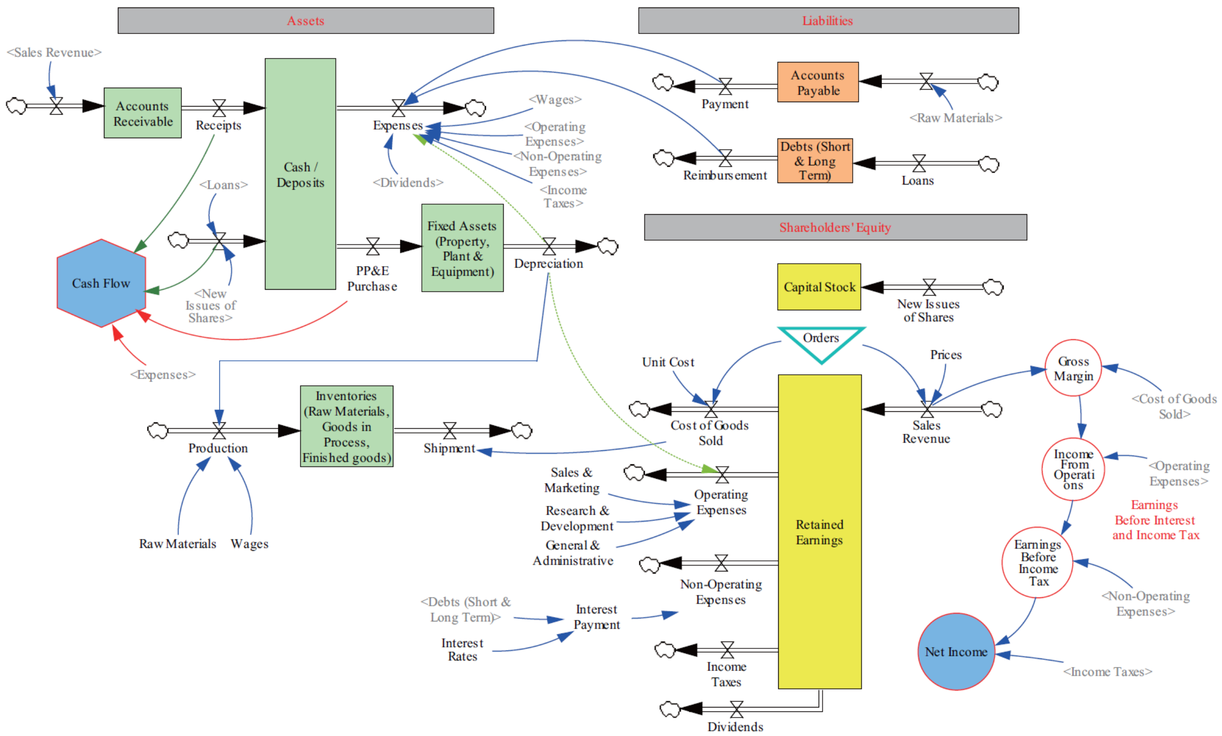

Figure 1.4 Yamagouchi's simplified accounting model (quoted with permission from the author)

[3] It is out of the scope of this report to further introduce the notions of SD, since it is an extensive scientific field of its own. However, some parts of this report presuppose familiarity with SD's basic concepts and methods. The referred books and various short online courses can greatly help whenever the reader feels that a figure or text in this report is unclear due to a lack of SD background.

Most of Yamagouchi's accounting model is nothing more than the stock-flow representation of the linear relations that are usually represented with spreadsheets. He explains that the flows of the model should be driven by flows related to 'real' transactions. He provides the example of inventory valuation: the actual stocks and flows of material together with the prices and unit costs determine the valuation flows appearing in accounting models. Hence it is the behaviour of the underlying 'real' stock-flow model that will determine the behaviour observed on the accounting indicators. More exactly there is an interaction between the two: business managers often use financial data (among other things) to make decisions regarding their everyday operations and strategic moves.

Clearly it was not the fields of finance, valuation or accounting in which SD has first established itself as a research method. Related to business, SD was mostly positioned within operations research and management. The real-world applications reported in books and in the System Dynamics Review (the field's journal) mostly deal with high-level advice to large corporations (Campbell, 2001; Weil, 2007). They deal with specific strategic issues and money flows or shortages are rarely the main focus except their role as an indicator of performance. There are only a few SD cases that relate to modelling work with SMEs. According to (Bianchi, 2002) there are a number of reasons for this. First, the consulting costs of building up a model from scratch for the firm are considered too high for a small company. Secondly, SMEs might not be able to devote the time and human resources necessary to familiarize with SD and facilitate the project. And thirdly, the quality and scope of data that can be gathered from company records to support the modelling is usually poor and limited in SMEs, especially in emerging markets. This did not stop Bianchi from devoting years of research and engagement with SMEs. The lessons he learned and described in his paper are very insightful for any modeller trying to work with SMEs. One of his main contributions is to show how a standard structure of the accounting part can be complemented and customized to fit many of the simple business models of SMEs. Working with generic model parts therefore could substantially speed up the modelling process and make it feasible for modelling SMEs – a view shared also by others (Morecroft, Lane, & Viita, 1991; Winch & Arthur, 2002).

From all the above listed sources on SD the following ideas are most relevant to this project:

- There are many business-process related SD studies from which models or model parts can be gathered and re-used to model a small company
- It is a good idea to try fitting generic models together and customize them for an SME case, instead of starting a new model from scratch
- With minor modifications, the accounting part of the model could be such a common structure present and fitted to any SME model. Yamagouchi's accounting models can be a good starting point.

There are also a few contrasts appearing when trying to relate the traditional SD approach with this project's context and goals. First of all, from the bank's perspective it is crucial to focus on the cash flows of the company to see where the loan repayments will come from. Although it is usually not the main focus in the case of big companies, the cash balance and liquidity are crucial for SMEs and are often also the main concern of their CEOs. Secondly, usual SD modelling engagements focus on learning and understanding specific strategic phenomena through capturing mental assumptions into endogenous models. In contrast, the aim of investors is not only to understand how the business works, but also to assess the possible future scenarios in depth to support robust investment decisions. SMEs are usually least in the position of shaping their market environment and there are many external influences that can have a high impact on their business. For this reason many exogenous factors can drive the system and they need to be taken into account in the uncertainty analysis. Finally, to connect to the established lens of SME accountants, auditors, analysts and potential investors, it might be a good idea to communicate the results through the usual accounting concepts.

1.2.3 What is EMA and how can it help?

Once the analyst has a powerful modelling method to represent the business, the next crucial step is how to use the model(s) built. What to do with them to understand the future of the company and make robust decisions? Financial reports offered to investors usually have one version of an underlying model and show one particular scenario, a 'base-case'. Simply building SD models instead of spreadsheet models does not necessarily change the way the model is used. Historically, models have usually been built with the aim of consolidating the available knowledge into a single model that can later be used as a realistic representation of the real system, i.e. a surrogate for it. This quest for a best-estimate model was termed the *consolidative* approach to modelling by (Bankes, 1993). Such an approach is often used for prediction (Hodges & Dewar, 1992; Hodges, 1991) and – just as with business plans used to decide on RP Loans – the assumption is that such a prediction is a good basis for deciding the actions to be taken (in our case to give or not to give a loan, and if yes, then how much and under what conditions). Such an approach may work in some cases, however it is severely limited when there is insufficient knowledge, inherent uncertainty and/or disagreement among stakeholders about the 'correct' model representing the real system.

Accurate prediction would need strict validation of the model used through experimentation. In the case of models predicting financial performance of a company this is impossible to do for a very simple reason: they relate to the future and the future did not yet happen at the moment of building the model. There is no historical data available for comparison with the model behaviour. The bankers cannot wait until they can confirm that their predictions for the next 5-10 years are true: they need to decide whether to award a loan or not soon after a model is built. Therefore they are left to deal with uncertainty that is inherent in the future.

Opposed to the consolidative approach, an *exploratory* approach views models as plausible hypotheses about the real system that can be used to perform computational experiments therefore looking at how the system would behave under different assumptions (Bankes, 1993). These varying assumptions are taken as plausible guesses about the target system instead of being considered a reliable representation of it. Under conditions of 'deep uncertainty' these guesses cannot be meaningfully ranked according to their probabilities (Lempert, Popper, & Bankes, 2003). The range of plausible models that can be built is constrained by what is known about the system. However, what is unknown can possibly be infinite therefore the ensemble of possible future models that can be built to represent the future system can also be infinite. The challenge in the EMA methodology is to design a search or sampling strategy over this possibly infinite ensemble such that it leads to reliable and meaningful insights.

Banks deciding to give loans to companies for 5-10 years face inherent uncertainties in their decisions, possibly more so in emerging markets. Currently the approach is to 'predict-and-act' and there is hardly any systematic analysis of all the uncertainties related to the model used. However, as Porter et al. put it, "there are many irreducible uncertainties inherent in the forces driving toward an unknown future beyond the short term and predictions need not be assumed to constitute necessary precursors to effective action" (Porter et al., 2004). The EMA methodology's aim is not to reduce uncertainties or make better predictions. It looks for actions that could lead to acceptable performance over a wide range of uncertainties. It aims to explore assumptions made about system uncertainties, thereby supporting a better-informed and more robust decision-making.

To apply the EMA methodology, researchers can use various existing tools, such as Monte Carlo sampling, factorial methods, optimizations techniques and other data-mining and machine-learning algorithms (Agusdinata, 2008; Lempert et al., 2003; Miller, 1998). The EMA workbench is a software toolbox that implements these techniques in addition to the relevant visualisation tools. Its open-source code was developed at TU Delft's Policy Analysis section[4]. The paper by (Pruyt & Kwakkel, 2012) lays out the vision for the coupling of the EMA approach with SD modelling. With the development of the EMA workbench studies appeared exemplifying the use of these tools, being applied to bank run analysis (Pruyt & Hamarat, 2010a), the study of copper futures (Auping, Pruyt, & Kwakkel, 2012), energy transitions (Hamarat, Kwakkel, & Pruyt, 2013), influenza pandemic exploration (Pruyt & Hamarat, 2010b) and airport adaptive planning (Kwakkel & Pruyt, 2013; Kwakkel, Walker, & Marchau, 2012) among others.

The EMA workbench contains tools for parameter influence measurement, scenario discovery, robust optimization and adaptive policy design. Related to RP Loans, these tools can answer questions including, but not limited to:

[4] The code can be downloaded from the github account of the lead developer, Jan Kwakkel, https://github.com/quaquel/EMAworkbench

- Which parameters and structural assumptions are most influential in determining the repayment time?
- What combinations of uncertainties lead to undesirable scenarios such as too long repayment time?
- Given the future uncertainties, what is a robust decision in terms of loan size and cut?
- How can we dynamically adapt the loan conditions given how the future unfolds and what is the least regrettable policy to perform now?

For all these capabilities, the EMA workbench can be a useful toolbox on the desk of the analyst who tries to support lending decisions or to monitor the progress of a loan over time. To the knowledge of this author, the EMA approach coupled with SD models have not yet been applied for these purposes. The methodology and its tools are explained in more detail in chapter 2.

1.3 Research question and objectives

The objective of the project is to investigate in what ways SD modelling combined with an exploratory approach could support lending decisions and monitoring of an SME credit portfolio. Therefore the main research question can be formulated as:

How can exploratory SD modelling and analyses improve lending decisions and the monitoring of credit portfolios?

Related sub-questions that would allow us to answer this question are:

a) How can the companies and the portfolio as a whole be modelled using the SD approach?
b) Based on these models what insights can be gained using EMA tools?
c) How could the analytic tools be used to monitor the progress of a loan repayment?

To answer these questions, the following five research objectives were formulated:

1) Describe the relevant scientific literature that supports the project goals
2) Provide example SD models for existing cases from which the model parts could be easily reused in similar cases
3) Perform and document analyses with the EMA workbench and the SD models illustrating their use and commenting on their strengths and weaknesses
4) Reflect and document the lessons learned from applying these tools on the cases
5) Formulate recommendations on possible future application in the lending and monitoring process

The research questions show that the project is mainly about combining existing methods and applying them in the context of loan performance analysis. The goal is to build and document knowledge for the commissioner of this project who can be considered the 'problem owner' in policy analysis terms. There is also a 'design and recommend' element in the work presented here: not only models have to be designed, but recommendations on the integration of these tools into the lending practices are also given.

1.4 Research scope and paper structure

The first objective stated above has been mostly reached by the description of the project motivation and background, leading to the identification of the research gap to be filled. This research is in a sense explorative: tools and methods were tried out and regularly presented to the commissioner to discuss their value and potential uses. The range of tools and possibilities offered by the EMA workbench were far from fully covered. Only a few selected algorithms and visualization methods were tried and exemplified in this report with the aim of a well-grounded and detailed illustration on some questions relevant to RP Loans. This implies that there could still be plenty of unexplored methods that can be quite relevant in supporting lending decisions.

It also has to be noted that the research is limited to two company-cases, and the notion of credit portfolios is only touched upon at the end of the thesis, giving recommendations based on the existing cases. Furthermore, the research question refers to possibilities for 'improvement', which implies that there is an existing process that has clear weaknesses that should be improved. Interviews with the bankers involved in the origination expressed the need for a novel approach and improved analytic capabilities, and the reasons for this need were mostly explained in the sections above. However, the ‘weaknesses’ of their current approach cannot be ‘demonstrated’, let alone expressed in numbers, since the RP Loans themselves are a very recent development in their practice. There are no available historical default rates, or other relevant descriptive knowledge, other than what is mentioned throughout this report. Hence some questions that are out of the scope of this research are:

a) To what extent does EMA improve decision-making?
b) Is it worth doing the analysis?
c) Can it be turned into an efficient method for actual commercial use?

Although related lessons are distilled and recommendations are given, this research is not meant to categorically answer these questions. Further research can later treat them as experience with the EMA tools will be built up in the bank over the future.

The rest of the document is organized in line with the research objectives. Section 2 explains the EMA methods and tools used throughout the case studies, also extending the list of knowledge sources used. An extensive Section 3 covers two case studies to illustrate the modelling process and the application of the EMA tools for individual companies. The blue boxes in this section immediately provide some reflections on the matters discussed. The experience gained from the case studies provides the basis for the lessons learned and the recommendations presented in Section 4. Section 5 formulates the conclusions and indicates possible future tracks of this research.

2. EMA Methodology and its Tools

As explained in section 1.2.3, EMA is about the use of multiple models to perform computational experiments exploring various assumptions about the uncertain future to see how they could affect the performance of the system of interest. The ensemble of possible models that cover the uncertainty can be thought of as all the models that could be built that are consistent with what is *known*. This uncertainty, i.e. this ensemble of models should be explored in a meaningful but practical way. In future-oriented studies there are only a few things that are known for sure in advance (mostly the universal constants such as e and π). Therefore – as Bankes notes – *“In general, a mathematically rigorous strategy for sampling* [the whole uncertainty space] *will not be available. Instead, a sampling strategy may involve using human judgement to prioritize the investigation of the uncertainties involved*” (Bankes, 1993).

There are a number of ways to classify uncertainties in order to help establishing an exploratory strategy (Kwakkel, Walker, & Marchau, 2010; Walker et al., 2003). Uncertainty can reside in different ‘locations’ regarding the model:

- Parameter uncertainty: the value of the model parameters is not precisely known
- Structural uncertainty: the exact formulation (equation) of the model relations is unknown
- Outcome uncertainty: it is unknown how the different stakeholders will value different outcomes

A second classification of uncertainties is given by their ‘level’. It can be thought of as a scale between perfect knowledge and complete ignorance, i.e. ‘we don’t know that we don’t know’. Closer to the first end are the shallow uncertainties, where the range of possible futures can be well-described with sensitivity graphs and/or probability distributions. This category is usually referred to as risk, and it is studied by statistical analysis. However, uncertainty can be thought of as a wider domain encompassing risk, but also having deeper levels (see figure 2.1). Somewhere in the middle of the scale are those uncertainties that can be ranked according to their perceived likelihood, but an exact probability

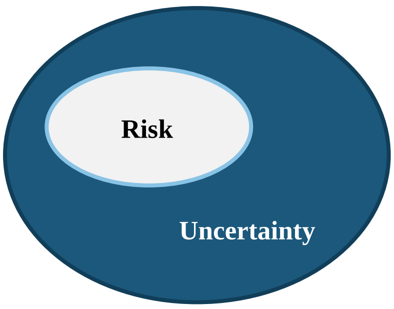

Figure 2.1 Uncertainty and Risk

cannot be assigned to them. Finally, at the other end of the scale is ‘deep’ uncertainty, where alternatives cannot be treated probabilistically and/or stakeholders cannot agree on a meaningful ranking of the future alternatives. When performing an EMA study, analysts should consider these different levels and treat uncertainties accordingly. Whereas risk analysis methods are widely used already, this project focuses on methods that can be deployed to treat uncertainties in the ‘deeper’ domains.

In case of deep uncertainty, the first step to its exploration is the enumeration of plausible alternatives. For parameters, this is usually an interval of numbers. For structural uncertainties the analysts can build a number of alternative model formulations perhaps even with different modelling approaches (continuous, agent-based, etc.). If it is known that variable A depends on B and C, but it is unknown what the exact relation is, then there could also be ways of generating a wide range of possible relations using generic mathematical functions (polynomials, Fourier series, etc.). This way, a range of models is generated that could be sampled or searched on the basis of the mathematical function used. Finally, in case of outcome uncertainties, the possible future configuration of actors and their possible preference variations should be captured. In this project no outcome uncertainty is explored, the focus remaining on the repayment time of an RP Loan and assuming that a quick repayment time is equally desirable by all actors considered (the bank and the SMEs). More attention is devoted to parameter uncertainties and some simple forms of structural uncertainties: switching causal relations on/off and a variety of table (lookup) functions between variables.

The uncertainty ranges of parameters and the model versions together define a multi-dimensional uncertainty space. Each point in this space is one particular set of parameter values and a model version. Each point defines an experiment, i.e. a simulation run on the selected model specification with the selected parameter values. The first difficulty in exploring this uncertainty space arises from the fact that it usually contains an infinite number of points. Broadly speaking there are two possible things to do with the ensemble of experiments to gain some useful information from it. One can try to infer properties of this ensemble or search for experiments with special properties. The methods used in this project can be broadly categorized in these two classes, in practice they are usually combined and used interchangeably.

2.1 Descriptive Tools

There are a number of ways to describe the ensemble of experiments generated by the definition of uncertainties. Since they are infinite in number, some kind of sampling strategy has to be involved to make a meaningful selection of simulation runs to be performed. Furthermore, relevant visualisation techniques can help conveying the findings about the experiments. If SD models are used, then a simulation run generates time-series data that can be plotted on a time-chart. Figure 2.2 shows such a chart for the variable that shows how much debt (in euros) is still to be paid at each point in time. Once the debt level reaches zero the repayment stops and the repayment time can be read on the horizontal axis (around 68 months in the case below). The chart on the right plots not one but several model runs, each representing one experiment with one particular setting of parameters. Here only one model structure was used and only the parameter intervals had to be sampled. The violet shaded background fills the range between the two extreme outcomes.

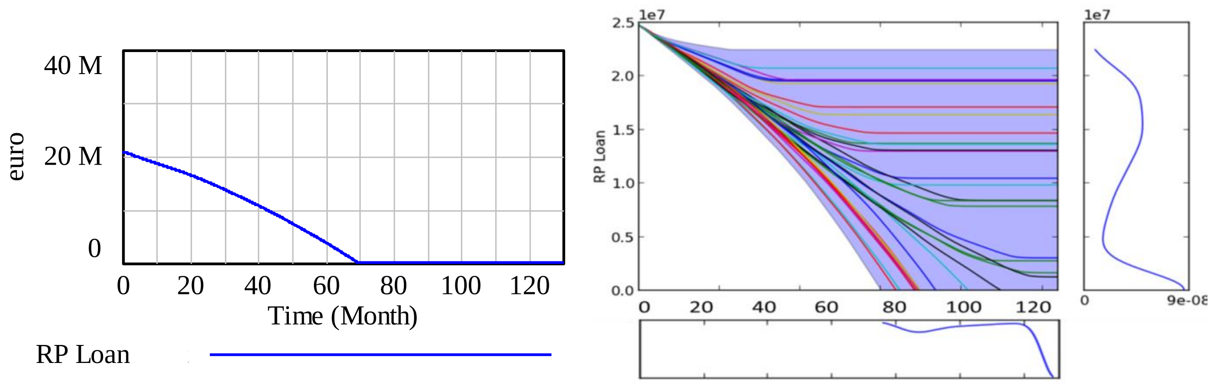

Figure 2.2: Left: one model run produces a time-series data of debt remaining; Right: several model runs of the same indicator

The chart on the right on Figure 2.2 also uses simple descriptive statistics to show more information about the uncertainty space sampled. The kernel density estimates (KDEs) below and to the right of the chart show the distribution of the end-values of the repayment times. These can be used to see whether the model runs tend to end up in certain regions of the output range and to guide further searches over the experiments. If probabilities were not assigned to the reliability of the model structure and the parameter ranges used, then these KDEs cannot be interpreted probabilistically. Depending on the model runs and the insight to be extracted, the KDEs can be replaced by histograms or box plots.

Another way of describing the uncertainty space is to examine what are its most influential dimensions. Is it the value of a few parameters that determine the outcome? Or is it the model version used that makes the difference in most cases? Feature selection algorithms are usually explored to answer such questions. They are commonly used in the study of genes or in other areas where data-mining is required (Liu & Motoda, 2007). The central tenet in feature selection is that among a large number of parameters there are some of them that have an insignificant contribution towards the outcome generated. These can be separated from the more influential ones in order to arrive to a more manageable and meaningful list of ‘features’ thereby simplifying further studies. Algorithms used for feature selection usually employ some search techniques - such as classification and regression trees (Breiman, 1984) or random forests (Breiman, 2001) – in combination with an evaluation measure that gives the scoring of the parameters. Based on the scores a ranking can be established that lists the various features according to their influence in determining the outcome measured. In the case of company models such lists can indicate where the management’s attention and efforts should be concentrated.

2.2 Search Tools

One useful analysis to perform in an EMA study is the search for scenarios with specific attributes. Visualizing all the scenarios generated as in Figure 2.2 gives an idea of the various behaviour modes and outcomes possible, but one might be interested in what generates specific groups within the whole ensemble. One of the simplest ways to distinguish some scenarios is to look at their end values. The search task then becomes: “what scenarios lead to outcomes with an end value above (or below) X?” Scenarios mean a combination of parameter values and model configurations, i.e. points in the uncertainty space.

One of the tools that can be used for scenario discovery is called the Patient Rule Induction Method (PRIM) (Friedman & Fisher, 1999). It has been successfully applied to scenario discovery (Dixon, Lempert, LaTourrette, & Reville, 2007) also in cases such as water resource planning in California (Groves & Lempert, 2007) and impact study of renewable energy requirements in the US (Lempert, Groves, Popper, & Bankes, 2006).

PRIM is useful to find which combination of uncertainties lead to (un)desirable scenarios. What is desirable or not is usually defined as a limit for the end state of an indicator. For example PRIM can look for scenarios with a repayment time of more than 120 months. The algorithm then looks for so called boxes in the uncertainty space that have at least a minimum density of those interesting cases and containing a minimum number of scenarios (usually referred to as a minimum mass).

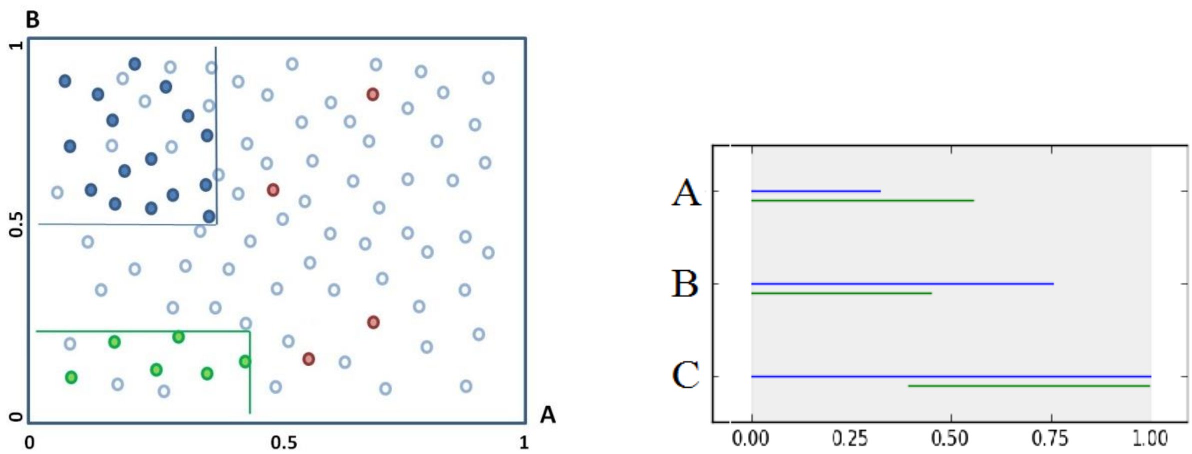

Figure 2.3: Left: PRIM illustrated on a 2-dimension case; Right: another PRIM analysis example with 3 dimensions

Figure 2.3 illustrates the algorithm for two hypothetical searches. For a two-dimensional uncertainty space (left side image) the scenarios can be plotted on a 2D plane. Here A and B are the two uncertainty dimensions and their pre-specified ranges are normalized to a 0-1 scale. The coloured dots are identified as the interesting cases, while the blank ones are outside the pre-specified limit. The algorithm then 'peels' along each of the dimensions, a tiny slice at a time (this is why it is called 'patient'). Once a box with the desired minimum density and mass is identified the search starts again for another box, this time considering only the remaining points. The algorithm stops when no more boxes with the pre-set minimum conditions can be found (66% density and minimum mass of 9 points for Fig 2.3). This means that some interesting cases (red ones on Fig. 2.3) will not appear in any of the boxes.

The resulting boxes can be seen as sets of variable ranges. If there are three uncertainties considered, then the ranges found by PRIM could be visualized as a box in a 3D space. For more than two dimensions the output format of a PRIM analysis is better visualized as shown on the right-side image on Figure 2.3. It shows that two 'boxes' (blue and green) were found that contain at least *m%* of the total scenarios of which *d%* is interesting (*m* is the mass limit and *d* is the density limit specified by the analyst). At the end the algorithm prints the density of each box found and their 'coverage': a percentage of the interesting cases that can be found in each box. Knowing that the lines are plotted on a normalized range, the limits of the boxes on each variable can be read. After running the algorithm the exact values of these limits can also be printed out.

With a PRIM algorithm the search will usually have to make a trade-off between density and coverage. A process called 'pasting' is usually employed within the algorithm to extend the boxes on dimensions which were initially unnecessarily constrained. Its 'patience' means that the algorithm is fairly accurate in identifying the most optimal uncertainty ranges. However, it can also unnecessarily clip the end of some dimensions, thereby introducing some insignificant parameters into the final displayed list. Further assessment of PRIM's strengths and weaknesses and comparison to other methods is given in (Lempert, Bryant, & Bankes, 2008). PRIM can also be applied in a more participatory way described by (Bryant & Lempert, 2010), where statistical measures to assess the reliability of PRIM are also suggested.

Scenario discovery can support robust decision-making through identifying the vulnerabilities of the candidate robust alternative policies (Bryant & Lempert, 2010). Within the search methods there are other tools such as optimization that can also be applied in the context of uncertainty analysis. Using a single model with no uncertainty in its parameters, an optimization problem would mean the calibration of some control parameters such that the best outcome is reached on the key indicator(s). However, an optimal measure in the face of uncertainty can also be defined as the measure that performs *well enough* over the widest range of possible future scenarios. Such a measure will probably not be strictly the best in the scenario that will actually happen. However, at the time of decision-making it may well represent the most robust decision given the uncertainties surrounding the decision. Such 'robust optimization' algorithms can also be considered as part of the EMA toolset. An example of a robust optimization run will be given in the first case study.

The above described tools are just some of the existing ones that can be employed in an exploratory study. They are the ones used in the case studies below, however it is up to the analyst's imagination and skills to devise further scenario analysis and visualization techniques. Ultimately the methods used might well vary according to the needs of the actual cases and the questions that need to be answered about future uncertainties.

3. CASE STUDIES

Having all the above listed tools in mind the following process was envisioned on how to apply SD and EMA to real-life RPL lending processes:

1. During the initial company visit the bank gathers information about the company
2. Starting from a pre-existing generic company model the bank analysts create a tailor-made SD model about the SME in question

3. The customized SD model is analysed with the EMA workbench to assess the growth potential under different scenarios and to indicate the key conditions for a successful deal.
4. After the deal is struck the bank can monitor the repayment by comparing the most recent company data to scenarios developed during the previous step.

The envisioned process was tried with two case studies involving two different types of companies. The two companies were already given an RP Loan less than a year before the start of the project. This meant that there was some information available about them ready to be used to develop the cases. The cases illustrate how a company model can be built using information available in different forms and how the models can be treated with the EMA workbench tools.

3.1 Case 1: Plastic Production Company

The core business of the first company – as the title shows – is to produce and sell plastic products. In essence the company acquires raw materials and turns them into different types of finished products using a few types of machines and employing a few hundred workers. The company is the sole supplier of some specific plastic parts for one big client that accounts for around three quarters of the sales. The rest of the sales are coming from food packaging products (fpp) sold to numerous smaller clients in the yoghurt production industry. The company and its clients are located in Turkey, while some of its raw material suppliers are in Europe.

3.1.1 Preparation

Information about the company and the loan was available in the form of a text report (further referred to simply as 'the report') and an attached accounting model in a spreadsheet. At the start of the project the EMA tools were tried out with a series of very simple SD models representing an abstract view of a company with an RP Loan. This was done in order to familiarize the commissioner with the tools at an early stage and to support discussion on what are interesting further tracks to take (see models and some analyses in Appendix 1). For these initial studies data from the aggregated financial statements were used. As questions arose about how to introduce the available data into the simple SD models, the models became more and more detailed to distinguish between different assets and introduce some relevant delays. These initial simple modelling studies already uncovered assumptions that were worth investigating in more detail about the case (for example how can the ratio [cost of goods sold/fixed assets] almost double over the next 5 years? Why was this assumption implied in the accounting model?).

The initial model versions contained only stocks and flows of valuation expressed in the relevant currency. At a next stage a model for the 'real' part was added to incorporate more detailed assumptions and to show how the company operations link to the accounting part. Some information about this 'real' part (prices of materials and machines, initial numbers of employees and machines) were readily available in the report, including future forecasts for them. However, in order to build this operational part of the model, more information was needed about how the company operates, how it is organized, and what are the delays in its system. The report hardly contained any such information.

Knowing that it was essentially a production company, a possible operational structure of the company was sketched based on earlier SD models, for example Forrester's *Industrial Dynamics* (Forrester, 1961). From the financial statements it was clear what the main cost elements were: raw material, machines and wages. Having an initial possible structure linking these main elements, an interview was conducted with the equity research analyst who helped to assess the company, wrote the report and built the accounting model. A list of questions was prepared for the interview (see questions in Appendix 2) and the goal was to clarify how the company works and how to modify the production model to represent our company at hand. Colour coding the initial model helped highlight the parts for which information was still missing or its quality could be improved.

During the interview it became clear that the research analyst is very knowledgeable about the company. The reason for missing information in the report was mostly not that the analyst didn't know, but that they were deemed irrelevant or too detailed. Indeed, it wouldn't make too much sense to describe in a text how inventories are managed, what delays are there in the system, how decisions are made, etc. if the reading investors are not expected to be systems thinkers. Even if they are, it is hard to mentally simulate all those details. There were however also a few questions that were not asked from the company, but were important to know to build the SD model. Some of the missing information was gained from the CEO of the company during a brief phone conversation. After that there were still some uncertainties remaining related to the model, but the knowledge gained was considered enough to have a reasonably realistic model of the company. Having in mind that an uncertainty exploration would follow anyway, it was not necessary to have all the parameters tuned to a fixed real value.

3.1.2 Model Description

In this section a detailed description of the model is provided. As explained in the previous sub-section, the model went through several versions. The version presented below – actually with minor structural variations included - is the one used to illustrate the EMA tools in this document. The description below is provided to explain how the structure and equations of the model were obtained, but it is not meant to spell out every equation in detail.

Orders

The *incoming orders rate* is an exogenous variable to the model: it is assumed that orders will come. There is no model part that details why and where do they come from. It comprises the total of the big customer's orders and the small customers' orders. It is expressed in tons and its initial value is based on the 2012 sales volume. The *orders increase rate* is calibrated such that the *incoming orders rate* will be equal to what is forecasted in the report. This assumption can later be changed to test demand constraints. The information on *incoming orders rate* is then used in different departments for different decisions.

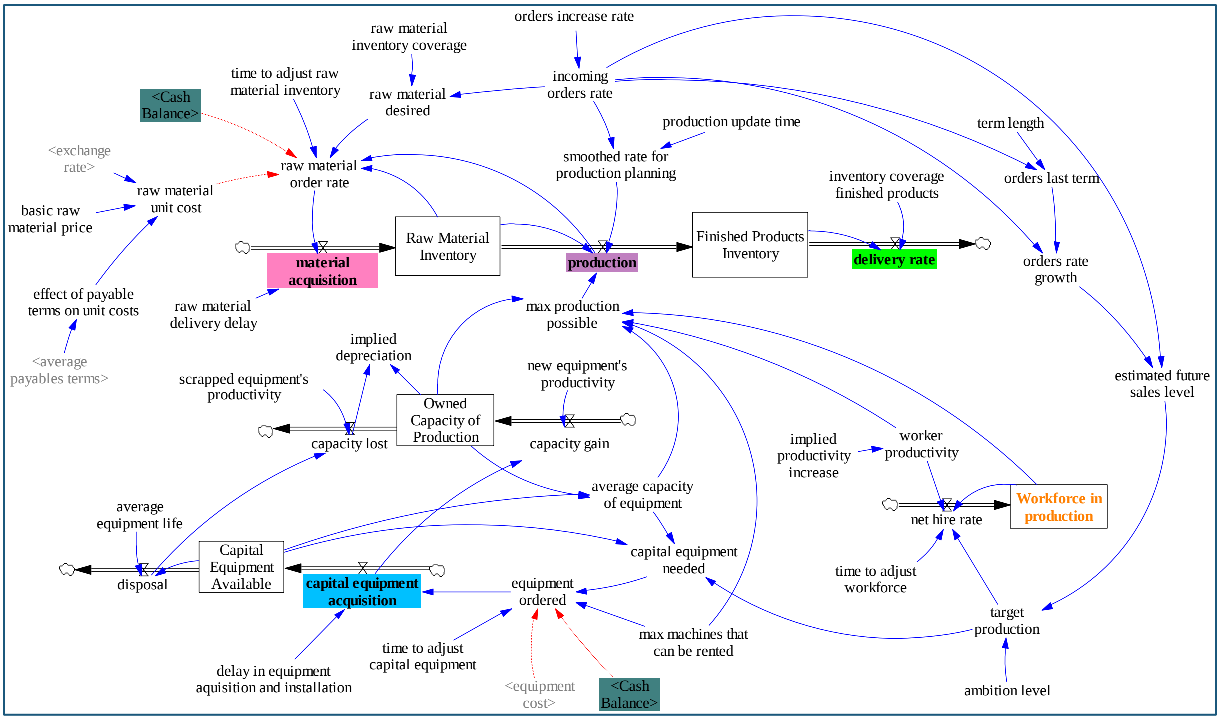

Figure 3.1: The "real" part; model of the main company operations: inventory, workforce and capacity management.

Raw Materials

The *incoming orders rate* is used to estimate the raw material needed for inventory. There is no exact target for coverage in the company, but from the verbal description it appears that they could cover roughly 2 weeks' production with the existing *Raw Material Inventory* at any time. Therefore the *raw material inventory coverage* is set to half a month. There are two main sources of raw material: (1) ordered from Europe, paid within 5 days mainly to cover the production for the small clients, and (2) provided by the big client, the cost of which is netted out against the sales to the big client. There are also occasional trade activities in raw materials with the local providers, but that happens only in smaller quantities and only when a better deal can be made than with the usual providers. Orders for materials from Europe are placed on a monthly basis with a schedule of when they want the parts of the order to be delivered. The material bought from the big client is just taken from the client's warehouse whenever needed. The raw material provided by the big client usually covers around one third to a half of the volume sold to them. Overall, the average *raw material delivery delay* is one month from the placing of orders.

The *raw material order rate* represents what is the actual order placed by the company. It is usually constrained by the *Cash balance*, such that only that amount is ordered that could be paid from the actual available cash. This constraint (indicated by the red dotted arrows) is a structural option to be investigated. The amount of raw material ordered is equal to what is used in *production* plus the adjustment for inventory coverage. The average *raw material unit cost* changes based on what is the *average payables term* agreed with the provider. The *effect of payable terms on unit costs* - a lookup function estimated by the CEO – is applied on a *basic raw material price* expressed in euros. Raw material prices are determined by the global market prices therefore they are influenced by the exchange rate.

Production

Production turns raw material into finished products. The plan for the production quantity is prepared every week based on orders. Only products on order are produced, so the company doesn't have a target for *Finished Products Inventory* coverage. Nevertheless, changes in ordered amount can occur within the weeks, so whatever is not sold still goes to an inventory of finished products. *Production* is constrained by three factors: the available raw material, the available machines and the available production workers. The work itself is not very labour intensive according to the company therefore the output per person is quite flexible. To express a monthly maximum, *worker productivity* is introduced as a proxy. This was calculated from [sales volume/production workers] from the report where it was assumed that this ratio will grow: while sales volumes almost doubled over the 5 years forecasted, the number of production workers was only growing by 20%. Conversely the output per person was implied to grow. This is again an assumption that will be investigated whether it has a significant impact.

Workforce and Capital Equipment

The planning for capital equipment and hiring takes place every December. The company forms an expectation of sales volumes for the next year – *estimated future sales level* – which will usually also represent the *target production*. The big client provides its own forecast every year. Overall it is assumed – rather simplistically - that the growth expectations are formed based on last year's growth. The *ambition level* is introduced to see what could happen if the targeted production is different from the estimated orders level: the company could – for caution or because of optimism – decide to invest less or more than what the demand is expected to be from his clients[5]. The yearly planning for workforce and machines essentially smoothens the seasonal fluctuations, so that they are not observed on the number of machines or on the workforce. It is the intensity of work and the utilization of machines that changes from month-to-month with the fluctuations.

The *target production* together with the *worker productivity* defines how many workers will be needed to reach the target. The difference between what is needed and how many are available gives the number of people hired. From the moment a decision is made to hire people, it takes about 2 months to get a fully productive worker. This is all reflected in the *net hire rate.*

The *target production* together with the *average capacity of equipment* will determine the *capital equipment needed* to satisfy the target. The company has the possibility to outsource some of its production to neighbouring factories. The *maximum machines that can be rented* from neighbours is around 15 and is assumed to remain constant over the forecasted period. When the *Capital Equipment Available* plus the *maximum machines that can be rented* would not be enough to reach the *target production,* then additional equipment is ordered. Usually this

[5] This mechanism about how decisions are made about investments into machines and hiring is an uncertain one. The early model versions assumed that any available cash will be reinvested in an optimal way.

is done by leasing, but that would represent additional long term debt and that is quite limited in case of an RP Loan. Therefore the *equipment ordered* can be considered here to be constrained by the *Cash balance* available: only that amount is ordered that can be paid by the actual available money in the bank (red dotted arrows). The *time to adjust capital equipment* represents the time spent from the need for additional equipment arising until the actual placing of the order. No measurement or observation was available for this parameter, but it is estimated as 2 months for a start. Ideally the modellers could look at historical data and cross-check with managers' answers to find out how exactly decisions are made on this issue and to estimate these time delays. The inverse of this parameter can also be thought of as the fraction of equipment needed that is actually ordered at any point in time. From the moment of order it is estimated to take around 6 months for the machines to arrive and be fully operational. With the acquisition of new machines the *Owned Capacity of Production* grows in parallel. The machines have an estimated average life of 20 years. With the scrapped machines capacity of production is of course also lost. There was no exact data available on the *new equipment's productivity* and the *scrapped equipment's productivity,* therefore the values are just estimates.

Balance Sheet and Income statement

All the flows modelled above generate accounting flows somewhere in the balance sheet. These are described below. Many of these relations presented are well-known accounting equations. The colour coding here indicates which variables from other parts of the model connect to this part (shadow variables in SD).

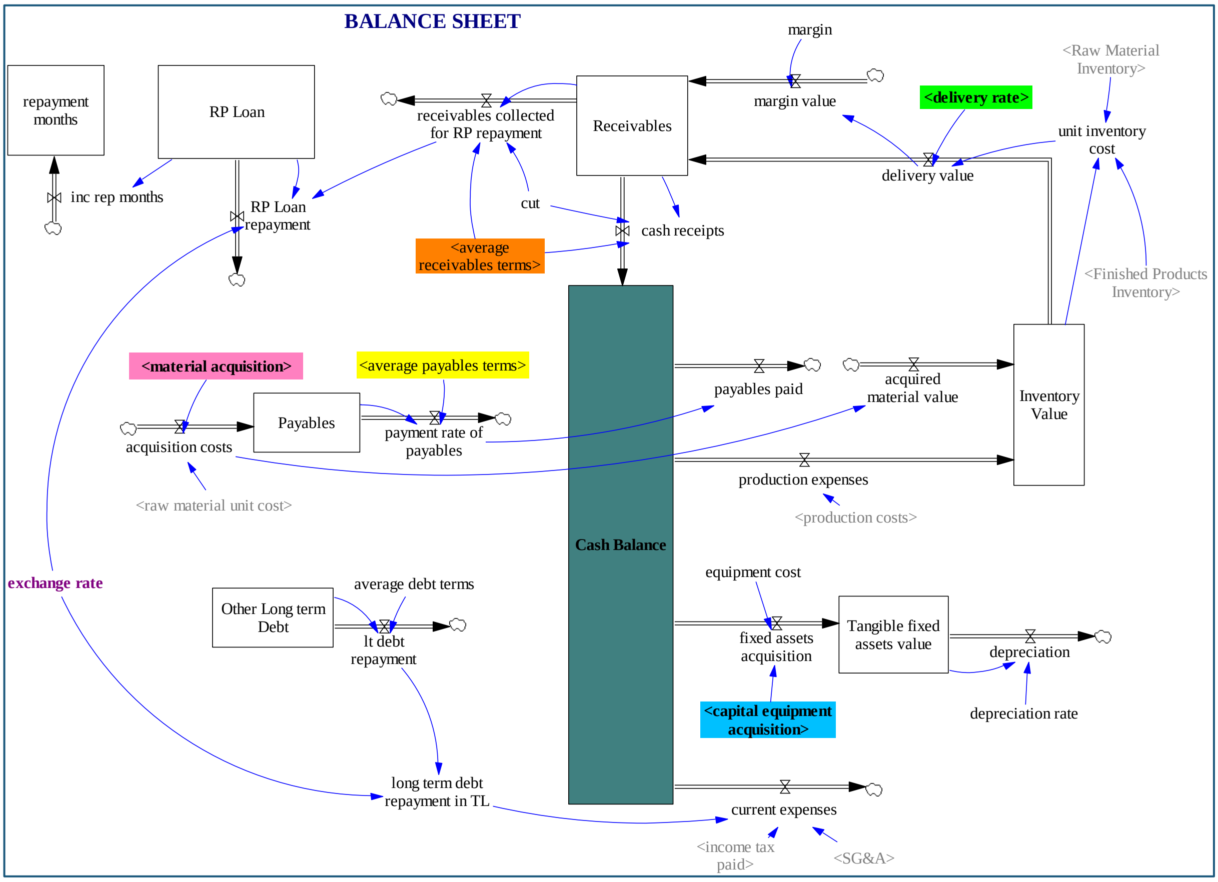

Figure 3.2: The balance sheet stocks will be very similar for every model, while the link with the "real" part will change.

The stock of *Cash Balance* is in the centre, since we are interested in where the cash is flowing and at what rate it will come back. There are many cost elements that generate an outflow of cash at a company. *Fixed assets acquisition* is one of them: *capital equipment acquisitions* multiplied by the *equipment cost* generate the cash outflow and an increase in *Tangible fixed assets value.* To this latter stock an annual depreciation rate of 6.6% is applied. The *equipment cost* and the *depreciation rate* were derived from data from the report.

Material acquisition multiplied by the *raw material unit cost* defines the *acquisition costs* which generate both an inflow of *Payables* and an inflow of *Inventory Value. Payables* are then paid and the *payment rate of* *payables* is defined by the *average payables terms.* This structure is essentially a delay between the moment of raw material acquisition and cash outflow.

The *Inventory Value* captures the value of both raw materials and finished products. Therefore its value can increase in two ways: acquisition of raw material and added value through production. This added value is represented by the *production costs* which capture the payroll, energy and overhead costs. Data and forecast on these three forms of cost were readily available in the report: energy and overhead costs per ton are expected to remain flat and the company adopted a policy for the *payroll increase* to be 2 times *inflation*. The *unit inventory cost* is calculated as *Inventory Value / (Raw Material Inventory + Finished Products Inventory).* Together with the delivery rate, this gives the *delivery value:* the value flowing out of the inventory with sales.

Box 1: The dilemma with inventory valuation

Figure 3.2 and the related explanation presents one way of modelling inventory valuation. The raw material valuation is quite straightforward, but the added value through production could be modelled differently. In this version the problem could arise if actual production stops, but the company continues to pay the wages of workers. Then those wages are continuously added to the inventory value, but they might not actually increase the gains expected from sales of finished products. This mismatch becomes more significant for companies with relatively low inventory levels. An alternative formulation for calculating the inventory value is to tie it to actual production through the *worker productivity* parameter. That has its drawbacks if wages have to be paid regardless of output, if the work is not so labour-intensive and if *worker productivity* is a fluctuating and flexible concept – as in the case of our company at hand.

Sales revenues are usually calculated as sales volume times average price. This is also how it is calculated in the report, but there are reasons to deviate from this representation in this model of the company. The main reason is that there is a pricing agreement with the big client which applies a margin on the costs of the company. The *margin* in the model can be thought of as the weighted average of this agreed margin and the margins realized on the food packaging side. Another reason is simply for the sake of visualization: to identify explicitly the flow of cash into the system.

The *sales revenue* is then the sum of the *delivery value* and the *margin value.* They generate revenue first in the form of *Receivables*, which are then collected according to the *average receivables terms.* Part of the collections from receivables goes directly to *RP loan repayment.* The *cut* represents what percentage is deducted for this purpose. The remaining income from collections will be a cash inflow that will appear on the company's *Cash Balance.* After the RP Loan is fully repaid, the cut is not applied anymore and the receivables collected fully go into the *Cash Balance.* There are three more items that add up to generate *cash outflow: taxes paid*, *SG&A* and *long term debt repayment.* The *Other Long-term Debt* stock represents the leasing debts that the company already had on his books and was allowed not to repay immediately after the RP Loan. These are mostly tied to euros therefore their gradual repayment is affected by the *exchange rate*.

SG&A is expected to increase partly with the growth in sales volume (delivery rate). The *SG&A wages* are tied to inflation (see Figure 3.3), while there are some *other general costs* that are assumed to grow 5% per year. The last outflow of cash represented here is the *income tax paid* which is calculated from the *pre-tax profit* at the given *tax rate.* The *tax rate* in the country is 20% and is expected to remain the same over the forecasted period.

Finally, the *RP Loan* stock keeps track of what is remaining to be paid for the RP loan. Its initial value is the sum of the principal value and the premium. Once this stock is emptied, a counter is stopped to calculate the *repayment months.*

In the end an income statement is compiled using standard accounting equations. *Finance expense* and different versions of profits (gross, EBIT, EBITDA, pre-tax, net-) are calculated here for reporting and comparison. These variables are the common elements of an income statement. Since the model is formulated in months, the income statement variables will also be generated in monthly terms. However, to be compared with the annual statements they are multiplied by 12 to be ready for an annual report (see Figure 3.4). Finally, some well-known leverage ratios and profitability ratios were modelled which will likely have the same formulation for any future model built. These indicators can be added to a separate list and exported in a spreadsheet format after simulation. This allows comparison with the existing accounting spreadsheets for the eye of an accountant.

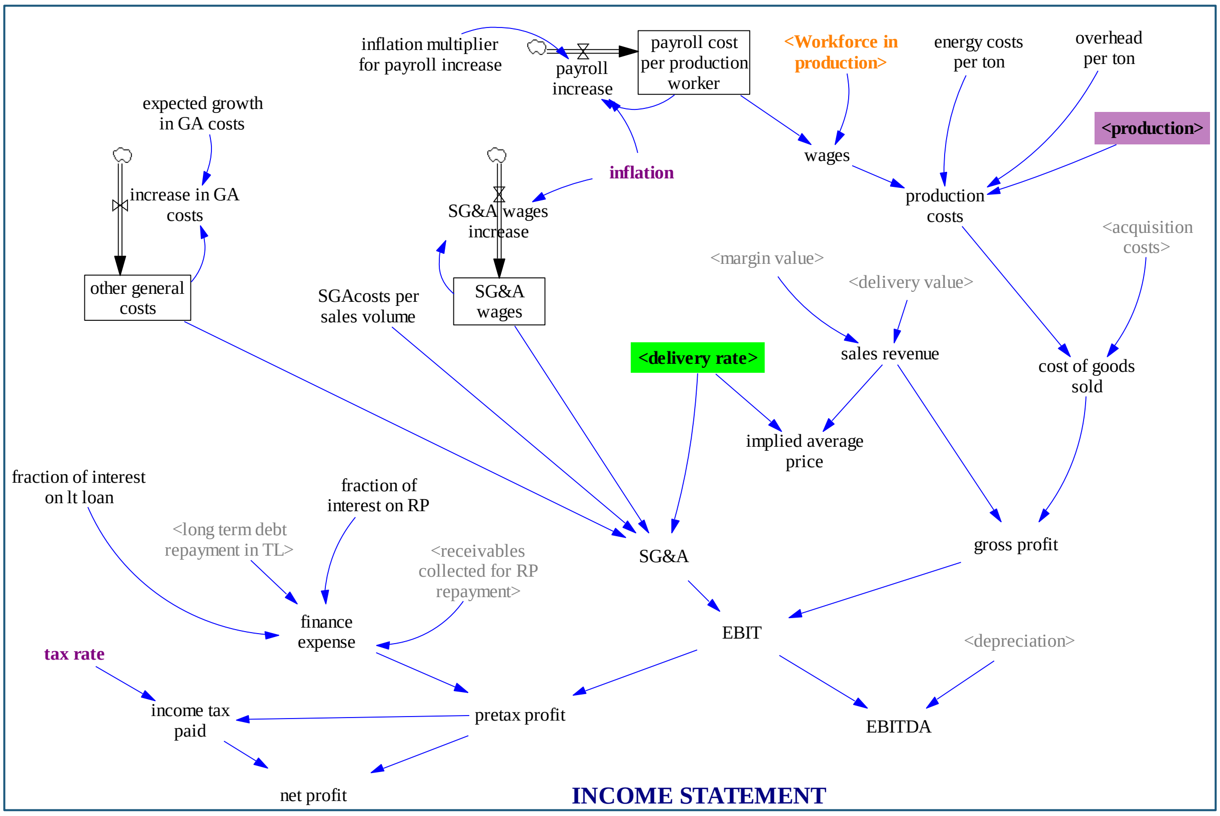

Figure 3.3: Cost elements and income statement model. The lower half of this model is readily reusable for future models.

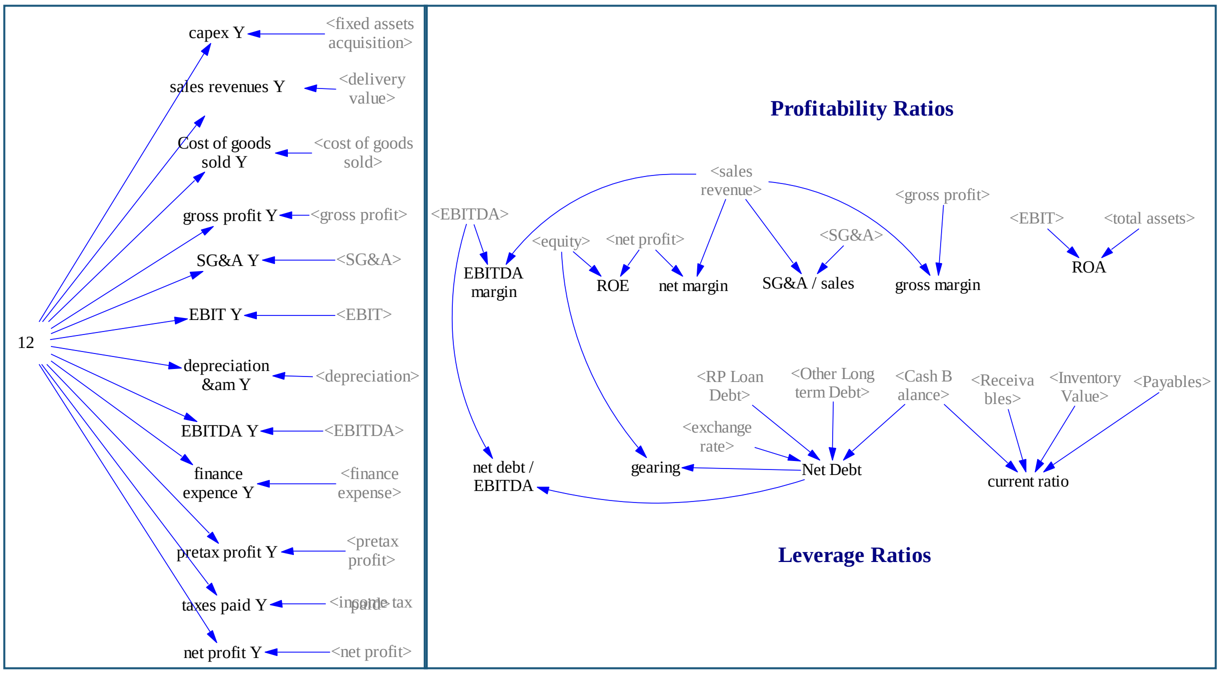

Figure 3.4: Yearly values and well-known profitability and leverage ratios.

Receivables and Payables Terms

The average terms of payment agreed with customers and suppliers can have a substantial effect on the cash balance of the company. Since the company is limited in the additional debt it can take, cash shortage is an issue that should be avoided for the smooth running of the company. Therefore the way the average payables and receivables terms are obtained is crucial and more attention was paid to its details. There are three main defining factors. First, the receivables terms on the food packaging side were relatively high, more than 3 months. Secondly, there are the payment terms to the raw material suppliers which the company tries to keep buying from Europe with payment required within days. Finally, the payment terms with the big client are important because they will define both the payables and receivables terms for the products they buy: they are netted out against each other after the agreed periods.

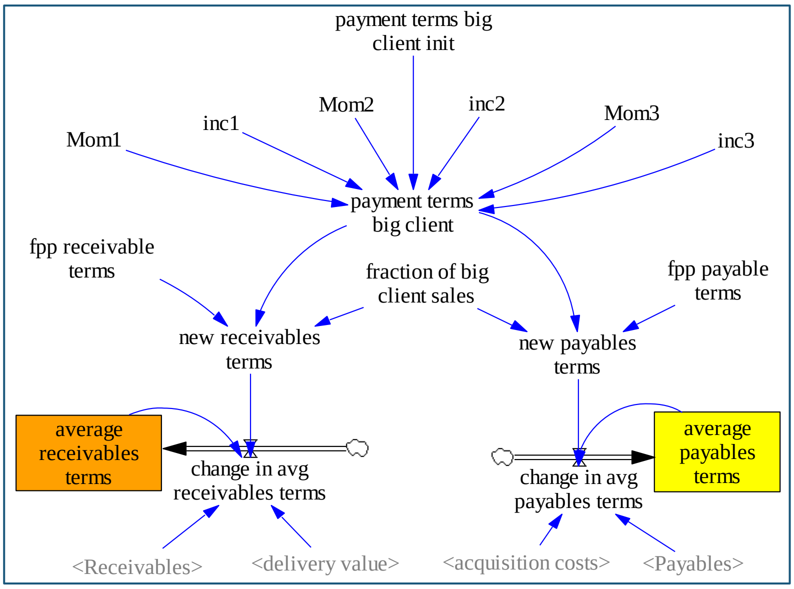

Figure 3.5: Calculation of average receivables and payables terms considering possible future changes in agreements

After the RP Loan was given, the company revised its agreements with the big client and changed its raw material suppliers. Therefore at the start of the simulation period, significant changes occurred in the average terms with the introduction of newly agreed receivables and payables terms. Since the new terms affect only the new transactions and there are still some remaining old payables and receivables, the average terms will only change gradually. Furthermore, the big client agreed to reduce the payment terms, but only temporarily: it wants to gradually increase the terms back from 7 to 45 days. Some options were modelled to analyse the effect of different increases at different moments of the payment terms with the big client.

Initial Values

Setting accurate initial values for the stocks of the model is crucial for the validity of the simulation results. Choosing how to set them is not always straightforward. The choices made for the simulations in this report are explained here.

The simulations should start from a moment close to the receipt of the RPL. Since the loan was given in mid-2012, and many of the financial data in the report referred to the year-end values, it was decided to set the start of the simulation to the start of 2013. Therefore the year-end data for 2012 provided most of the initial values. Since the report containing these values was written at the end of 2012, the year-end values were only estimates, but mostly close and reliable ones.

Box 2: Initialization choices

Initialization should not necessarily start in balance, like many of Forrester's studies present. As Bianchi says, they are good in case the purpose of the study is to understand a certain behaviour or phenomenon in the system (Bianchi, 2002). However, when the purpose is to study an actual situation, the initial values should reflect the actual values at that time as closely as possible. In this report mostly the year-end data were used for the simulations. In future practice, if the study is carried out before the giving of the loan, then initialization should reflect the status at the moment of receiving the loan. Then the model could include one-time actions too, that are performed at the start of the simulation (for example repayment of previous debt)

On the “real” side, numbers for *Initial Capital Equipment Available*, *Initial workforce in production* and *Initial average productivity per equipment* were readily available in the report. The year-end inventory value from the balance sheet and the raw material prices were used to estimate the tons of material that should sit initially in the *raw material* and *finished products inventories*. The estimated inventory coverage values were used to decide how to divide the resulting number between *Initial Raw Material Inventory* and *Initial Finished Products Inventory*. This makes sure that the simulation for the two stocks starts in balance.

For the balance sheet stocks the initial values were set as those of the estimated 2012 year-end values from the report. There was more recent exact data available for the *Initial Cash balance* and *RP Loan Initial value.* They were very close to the previous estimations so probably the rest of the initial values were also quite accurate. *Initial payroll costs per person* and *Initial SG&A wages* were also available in the report, while the *Initial GA others costs* was calculated by aggregating the remaining detailed cost elements.

3.1.3 “What if…” Analysis

Modelling the chosen parts of the company operations already helps **understanding the business** by giving a comprehensive “map” of the company. Looking at the simulation runs of the model helps gaining even more insight into the business model. Simulation also helps **investigating whether the business model is “sustainable”** by asking “what if…” questions. The model contains many assumptions. What happens if these assumptions change?

A first “base-case” run uses the parameters obtained from the report. The cash constraints are disabled for this run. Such a “base-case” run shows that the RP Loan is repaid in 70 months (indeed within the 6 years estimated in the report). As the company’s revenues grow, more and more money flows for debt repayment, accelerating the repayment towards the end. The small fluctuations in repayment between months 9 and 15 are caused by the 3-step changes in the payment term agreements with the big client.

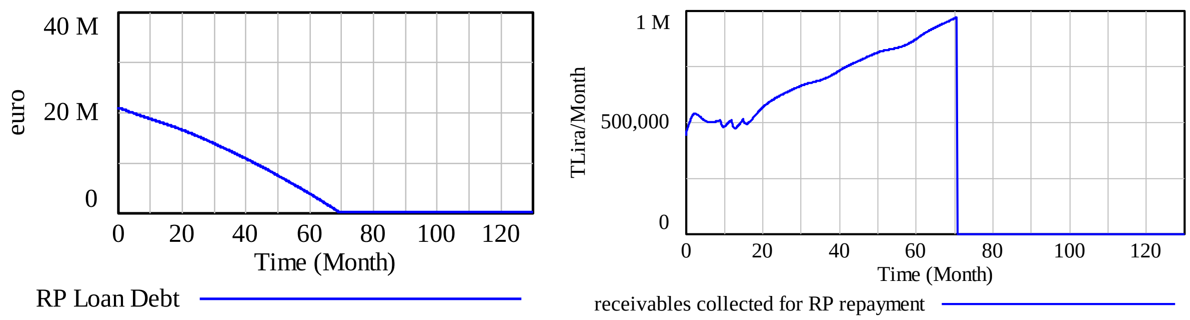

Figure 3.6: The RP loan is repaid within 6 years and the cut is no longer applied when debt is repaid

The incoming orders rate drives the model in this case. It sets the target for equipment acquisition and workforce hiring, and they are mostly acquired in time to satisfy the demand. Delays in the acquisition of equipment mean that there are still a few times when the production is limited by capacity. The figure below shows how the equipment base grows periodically, determining the company’s capacity of production. This kind of behaviour is likely to happen with the company’s policy of year-end planning and ordering of machines.

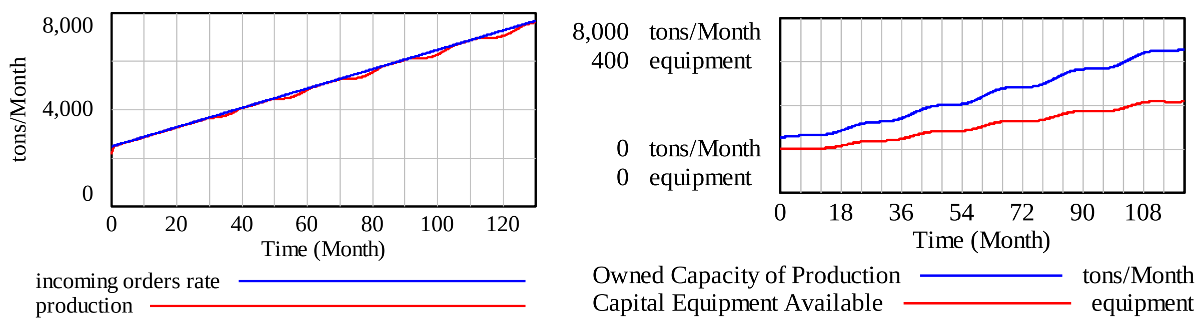

Figure 3.7: production is mostly able to keep up with the incoming orders rate; the equipment base is growing periodically

To get a sense of validity for the model, the balance sheet data from the report can be compared to the base-case simulation runs. Validating the model means building confidence in that the model represents the real system realistically. Therefore we talk about “a sense of validity” instead of “to validate”, because the forecasts from the report might not necessarily represent what ought to happen. Also, the aim is not to reproduce the forecasts from the report. It is actually expected that there will be some deviations given that the underlying model is a non-linear dynamic one, instead of a static linear one. Nevertheless, the behaviour of some of the main indicators should be similar and their order of magnitude should be the same, given that the input parameters are the same.

The left-side graph on Figure 3.8 plots the forecasted year-end values from the report for the 6 selected balance sheet stocks. With the same colours, the right-side graph shows the runs of the SD model simulation. Since forecasts were made for 6 years, the simulation is also stopped after 72 months for this comparison. The initial values for all 6 variables are the same, while they also remain numerically close to each other. Starting from the top, the fixed assets value grows on both graphs, although the simulation run shows the fluctuations that reflect the periodical equipment acquisitions. Receivables and Payables grow in parallel, the expected dip in their level at the start of the period appears on both graphs. This is caused by the change in payment terms over the initial 2 years. The RP loan level has the same shape, their value is slightly different, since the accounting model includes only that part that is categorised as long-term debt.

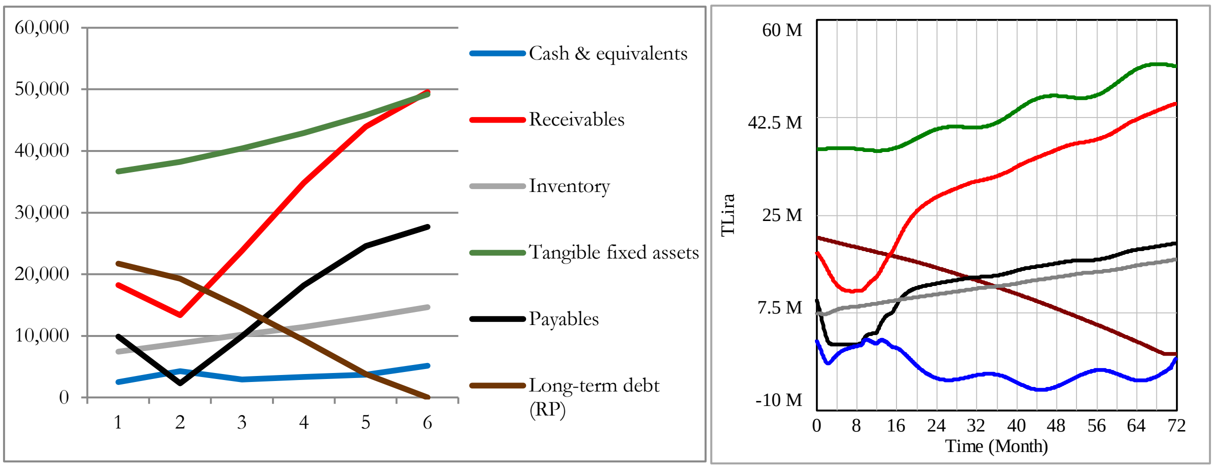

Figure 3.8: Six stocks from the balance sheet: data from the report on the left and SD model runs on the right.

As typical with many companies, the year-end cash level hovers close to the zero line. In this, the two graphs are similar, although the SD model run goes significantly below zero. It touches minus 6 million at its lowest point. In order to keep up with the set order rate, the company would need to go significantly into negative territory. This should not happen during the course of the RP Loan. A first constraint is introduced into the model: new equipment is ordered only when there is cash available for it. Figure 3.9 below shows the possible effect of such a policy.

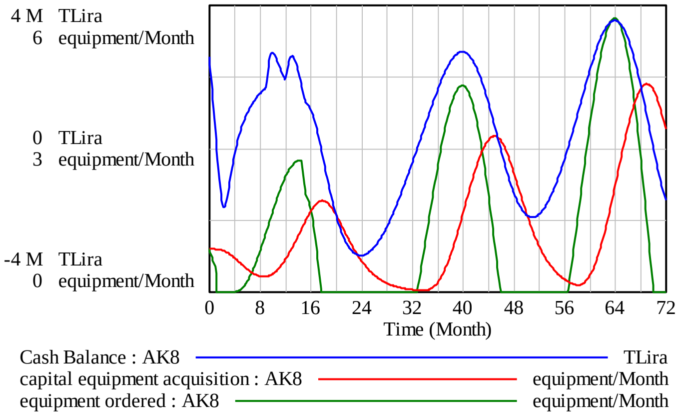

Figure 3.9: Although orders stop when the cash balance becomes negative, the delivery and payment takes place later

Even with the constraint on equipment acquisition, the cash balance will sometimes go negative due to the delay between the order taking place (when money is still available) and the delivery and payment of equipment. Equipment ordering (green line) stops when the cash balance (blue) hits zero, but the delayed deliveries create continuing outflow of cash.

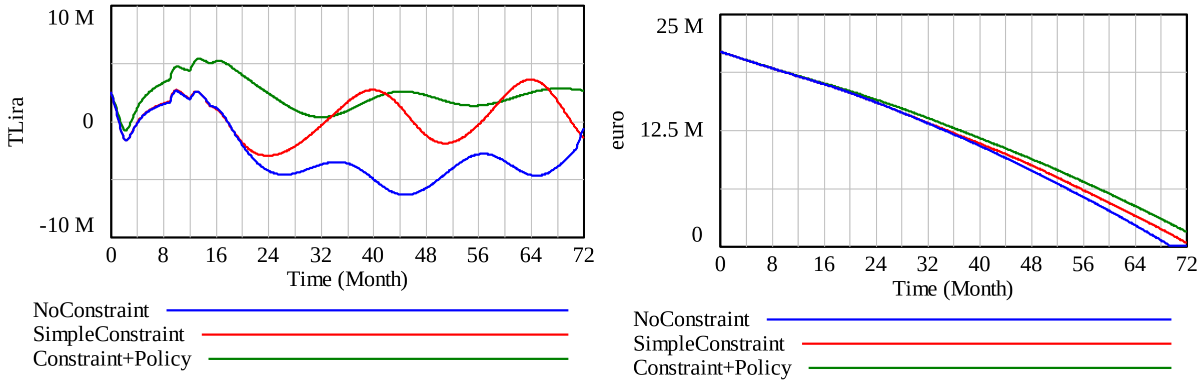

Figure 3.10: Cash balance on the left and RP Loan on the right: the constraint and parameter changes extend the repayment time

The company could think of policies for managing the tricky repayment time, when the cash constraint can be very real and pressing. A third scenario is simulated, to see whether some parameter changes could keep the behaviour of the cash balance in positive territory. The *time to adjust capital equipment* is increased to 4 months, the *ambition level* is set to 90% and the *delay in equipment acquisition and installation* is reduced to 5. The reduction of the *ambition level* slightly reduces the overall investment level, while the other two modifications somewhat dampen the fluctuation. This is a simple policy option that can give some guideline on how to avoid cash shortage. As it could be expected, the constraint and a lower-ambition policy come at the cost of longer repayment. The plausibility of this advice could not be checked with the company. Ideally the way capital investments are handled should be discussed in more detail with the company managers. However, the model was useful to point to a potential problem and provide a basis for discussing possible policy levers to avoid it.

Just after the company model presented here was completed, the company contacted the bank signalling a possible cash shortage in the near future. The cause of it – they explained – was the sooner-than-expected introduction of new payment terms with the big client. This client proposed a 3-stage gradual introduction of longer payment terms and the company feared that this would push them below the allowed cash balance. They needed the bank to check their calculations and advice on how to resolve this issue. To investigate this problem the above presented model was not so useful due to its stylized assumptions concerning cash flows and its longer-term focus. Therefore a special-purpose model was created using also the structure from Figure 3.5. The model aimed for a more accurate short-term simulation of the actual cash flows, also taking into consideration the monthly fluctuations in sales. The model helped identify where more accurate short-term forecast is needed. The company was asked to provide more details to calculate the exact magnitude of the shortage. Even before more accurate data could arrive, model simulations showed that if there was ever a good time to start implementing the 3-stage change, then it was in the early autumn of the year. Given the nature and timing of the fluctuations, that was the time in which the effect of new payment terms would least likely push the cash balance below the zero line.[6]

Many more “what if” analyses could be performed on a model with so many external variables and initial values. Most of these parameters are not fixed for the future, but are uncertain. Combinations of assumptions could be simulated and their effect on different indicators could be further investigated to learn more about the system’s behaviour. Vensim’s SyntheSym mode allows for real-time visualization of parameter changes and it can be a handy tool as long as the model is not too big relative to the computer’s processing and displaying capacity. In what follows, the traditional SD tools are coupled with some machine-learning and data-mining algorithms to perform a more structured analysis of parameter uncertainties.

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[6] No further details or graphs are given on this confidential issue, since it was not yet fully settled at the time of writing.

3.1.4 Structured Analysis

By a more structured analysis we mean a systematic consideration of all the external parameters of the model. There are dozens of these constants that have some influence on the model's behaviour, therefore also on the possible future scenarios. With the introduction of the EMA tools we first look at the model's sensitivity to all the external variables. Then we try to reduce the list of variables to the most influential ones with the help of algorithms that can automatically rank them. Considering the perspective of the bank, we then ask what would be a robust *loan size* and *cut* to offer in the face of the relevant uncertainties. Finally we seek the safe operating boundaries for the firm to repay within the desired time frame.

Before we move to the experiments it is worth looking at the list of external variables we are dealing with. They are called 'external', because they remain constant and they are not influenced by any other variable in the system. This does not mean that there is no link between them in reality. For example, it is quite reasonable to assume that there is a negative correlation between the 'margin' and the 'orders increase rate'. Such and many other feedback links probably do exist in reality and connecting them would make the model more endogenously driven. Due to the lack of any quantitative knowledge these additional relations were left out of the models used here. Alternatively, several plausible links could be formulated among them and their impact could be further investigated. To keep things simple for the start, we chose not to do that here. Also, the upcoming experiments all deal with the model version in which both cash constraints are turned *on.*

There are 31 external variables that we consider if we treat the initial values fixed. Different combinations of them can be used to perform different kind of experiments. It may be worth classifying them in three categories according to what influence the company has on the future values of these variables. Table 1 shows such a possible classification for our case. The three categories are defined as follows:

- **High**: the variable refers to the internal organization of the company and its work processes. The value taken by this variable is mostly to the discretion of the company's management. In other words, the company cannot be blocked to set the parameters of these values.
- **Some**: the company does have significant influence on the variable, but its environment also plays a role. In most cases there are other actors with whom the company has to negotiate and agree on the variable: a client, a supplier or a lender.
- **None**: the company has virtually no influence on these variables over the forecasted period. They are determined by the environment in which the company operates. These are mostly determined on the global market in which the company – being a small player – has no power, or they are set by another actor (for example the government) on which the company has neglectable influence.

It has to be noted that the classification is not a definite one, discussing them with the company might change some of them. The company's influence within the 'Some' category is also varying. These are the variables that are the likely candidates for adding more causal effects into the model structure. Also, one might try to

Variable name	Company's influence
ambition level	High
inflation multiplier for payroll increase	High
inventory coverage finished products	High
production update time	High
raw material inventory coverage	High
term length	High
time to adjust capital equipment	High
time to adjust raw material inventory	High
average debt terms	Some
average equipment life	Some
cut	Some
delay in equipment acquisition and installation	Some
depreciation rate	Some
fpp payable terms	Some
fpp receivable terms	Some
implied productivity increase	Some
payment terms big client init	Some
margin	Some
new equipment's productivity	Some
orders increase rate	Some
overhead per ton	Some
raw material delivery delay	Some
scrapped equipment's productivity	Some
time to adjust workforce	Some
basic raw material price	None
energy costs per ton	None
equipment cost	None
exchange rate	None
inflation	None
max machines that can be rented	None
tax rate	None

Table 1: List of external variables classified according to what influence the company has on their value.

find a continuous ordering of these variables instead of the 3 categories. Nevertheless such a classification proved helpful in articulating what combinations of uncertainties to focus on when designing different experiments. These considerations will appear in the experiments performed below.

Experiment 1: A sense of sensitivity

The 31 external variables each encompass an assumption about the parameters of this business model for the future. The financial modeller might be interested how sensitive the key indicator is to all these assumptions. To get a sense of the answer, the results of the first experiment are presented on Figure 3.11. All parameters were varied with maximum ±10%, similar to what a sensitivity analysis would do. However, it's not the same as a traditional univariate sensitivity analysis. That would mean changing one parameter at a time and measuring the difference it makes on the key performance indicator. Instead, all the parameters are assigned an uncertainty range of ±10% here. 15000 scenarios were then generated with different combinations of parameter values sampled from the given ranges with the Latin Hypercube sampling method. The time series of the RP Loan level from these scenarios are plotted on Figure 3.11 below. The blue envelope shows the range of possibilities. On their right side each graph has a histogram of the end-states of scenarios.

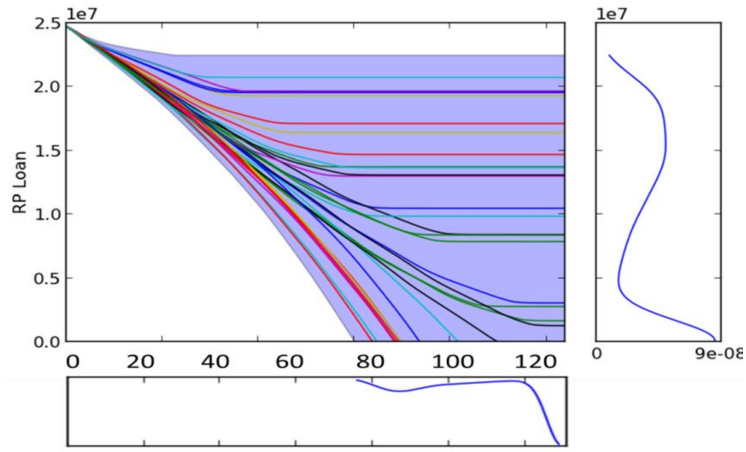


Figure 3.11: RP Loan repayment months: possible scenarios with a ±10% variation for all the variables.

On the above figure there are a group of scenarios in which the loan is repaid sometime after about 75 months. There is also a second class of scenarios in which the loan starts to be repaid at the beginning, but stops and reaches a plateau at some point, with the remaining amount not seeming to be repaid at all. In the words of the actual case this means that the company gets into such a cash shortage at some point that it doesn't manage to order raw material. Its inventories quickly deplete, after which sales stop and there remains no source of recovery. There also seem to be a few scenarios that start out well, but then are outperformed towards the end by scenarios that had a worse start. With a 10% change in the input variables, there appears to be quite some room for change in the outcome of the repayment time. The figure shows that most of the scenarios end up in a repayment time higher than 10 years.

A PRIM analysis (see Ch. 2.2) can be performed to see what combinations of the uncertainties cause the repayment time to be in a given range. For the PRIM analyses performed below usually their density and coverage will be discussed in the main text, while all the outputs can be found in Appendix 3. The first one (figure 3.13) looks for boxes with at least 80% density of repayment time less than 90 months. There are only 2289 such cases out of 15000 and 31% of those cases are in the only box found, its density being 93%. Out of all the variables, a relatively small number of them seem to contribute significantly to such a preferable outcome.

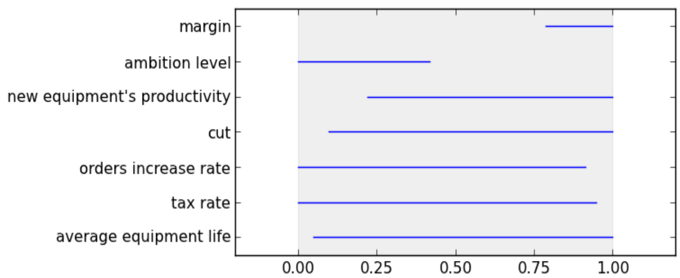


Figure 3.13: PRIM for repayment months < 90

The second PRIM analysis (figure 3.14) looks for boxes of the uncertainty space with at least 80% density of repayment time more than 120 months. There are 10237 cases (roughly two thirds of the total) that do not make it within the desired 10 years. The first box (blue) covers 65% of the cases having a density of 91%, while the other box (green) covers only 6% and has a density of 82%.

From these PRIM results it can be discerned that the model is probably most sensitive to the margin and ambition level variables. A combination of these two variables can strongly determine whether the scenario will be that of repayment or not. However, this experiment only gives an indication of the *model's* sensitivity to the given parameters. It tells nothing about the plausibility of these outcomes. The results have to be interpreted in light of the fact that the ranges were ±10% around a very specific scenario that was picked to be the 'base-case'. A 10% variation in the tax rate over the forecasted period might be as plausible as a 50% variation in the margins. Or a 10% change in the payable terms that were already on the lower extreme (5 days) does not make as much sense to investigate as a 10% change in the exchange rate. For these reasons the remaining experiments will work with *the plausible values that the variable can take* in the forecasted period.

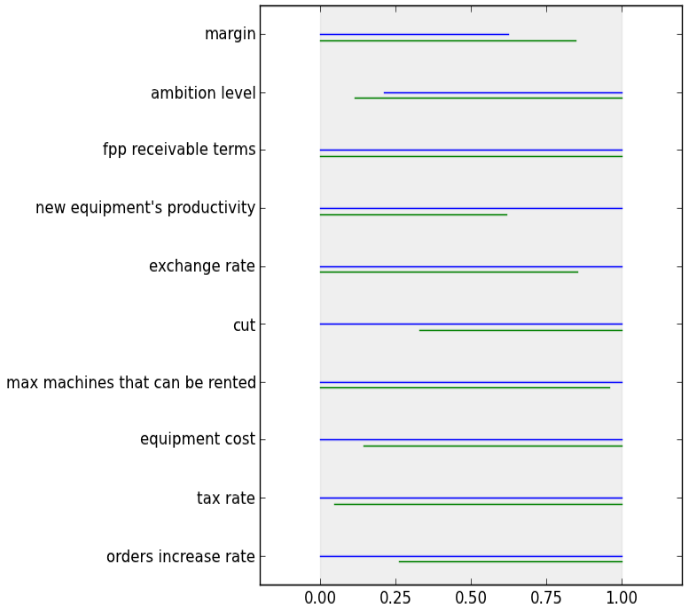


Figure 3.14 PRIM for repayment months >120

Experiment 2: Plausible future ranges

For the second set of experiments, all the variables are considered again for the last time. The aim is first to see the range of plausible outcomes that can occur given the plausible uncertainty ranges assigned to the external variables. Next, the PRIM is used together with two feature selection algorithms to see which parameters are the most influential in determining the repayment months. Cross examination of these results and knowledge about the case is used to narrow down the set of uncertain variables.

Box 3: How to define plausible ranges?

When assigning uncertainty ranges, one would want to avoid bias towards optimism or pessimism. Some variables have physical limitations, or can be bound by the definition of their meaning. Zero is a common upper or lower limit. But zero can also be a minimum limit never reached, just like infinity as a maximum. The assigned ranges have to be practical and meaningful too, therefore knowledge about the actual case will inevitably be used. Ideally, to avoid bias, a fair range should be assigned to every variable, such that these uncertainty ranges are 'equally plausible'. In practice that is impossible to do, since 'equally plausible' is an oxymoron itself. We intend to define plausible ranges, since we cannot or don't yet want to quantify the probability of the variable staying within those ranges. Therefore it is impossible to say that they are 'equally plausible'.

Nevertheless, one should strive for 'similar plausibility' while accepting that the resulting ranges will always be subjective and debatable. One guiding question could be: "What values can variable A take, given the ranges assigned to the rest of the variables?" This question suggests a circular and iterative process of plausible range definition. In the absence of more strictly verifiable ways it is sometimes helpful to ask several experts to go over this process.

The uncertainty ranges assigned to the external parameters of the model can be found in Appendix 3. As Box 3 elaborates, the choice for the intervals is subjective and it relies mostly on knowledge about the actual case. Choosing a plausible range usually means a wider interval than ±10% for the input parameters. Figure 3.15 shows that the generated range of outcomes also becomes wider in this case. Looking at the time series it is apparent that the trends remain the same: a class of scenarios that tend to repay, a class of scenarios that never seem to repay, and the fact that some of the well-starting time series are eventually overtaken by initially slower ones.

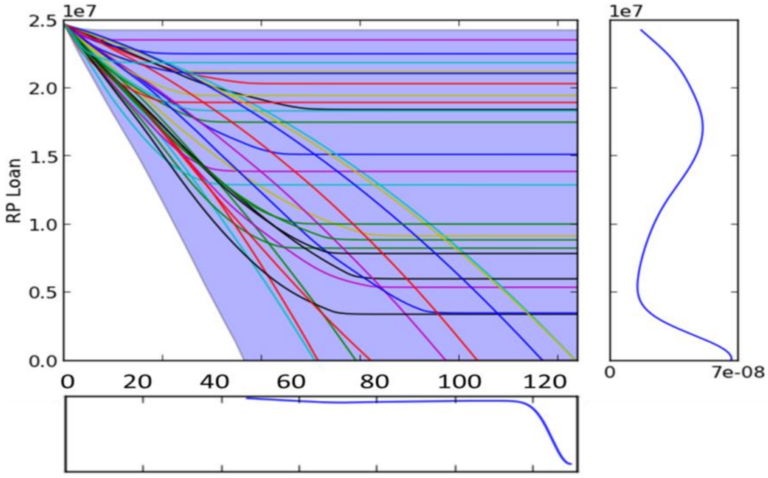


Figure 3.15: Range of possible outcomes given the plausible ranges of external parameters

We can now ask which variables are most influential in determining the outcome. If we classify the outcomes into 2 sets, then PRIM can be used again to see which combination of uncertainties determine the outcome. Figure 3.16 below shows the results of PRIM for repayment time greater than 120 months. Out of the 20.000 runs, 15.100 are above 120. There are 3 boxes found covering 73% of the cases. The first box (blue) is an interesting one: only margin seems to be contributing and this box alone covers 60% of all the interesting cases. From this it appears that on the long run, it is the margin that is mostly determining whether the loan will be repaid in 10 years. However, there are also 2 other interesting boxes in which it seems that the margin can be almost anything in the given range, but other combinations of uncertainties become relevant.

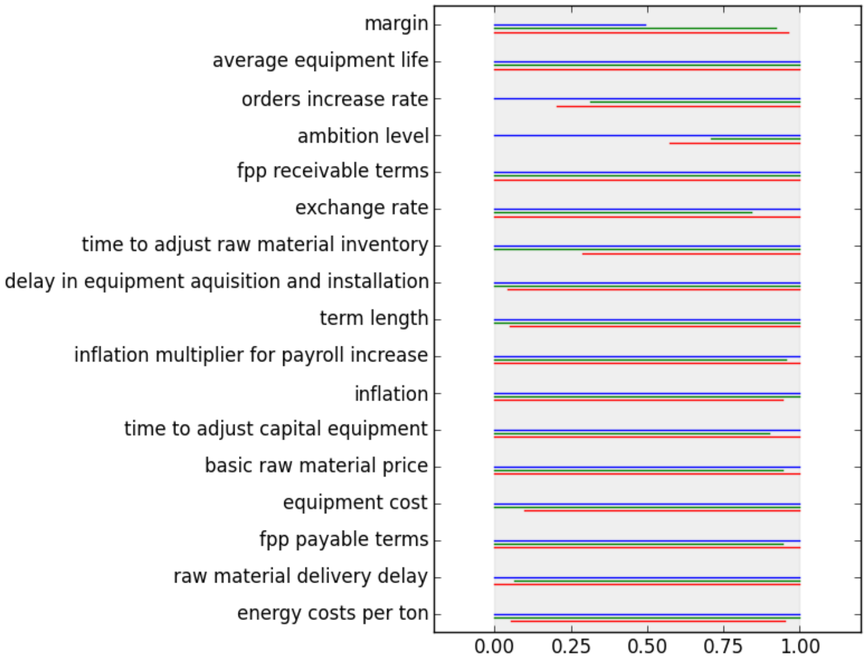


Figure 3.16: PRIM with repayment months>120, density limit 0.8 and mass limit 0.05

Interestingly, the variable ‘cut’ did not even show up on the above figure. It means that in the covered cases it is not influential in determining whether the repayment will pass the 120 month mark. This shows how important it can be the way we set the classification for PRIM. Another run where we ask which combinations of uncertainties lead to repayment less than 72 months is shown on Figure 3.16. ‘Cut’ features prominently here, which means that it can be quite important in determining the success of a short repayment time.

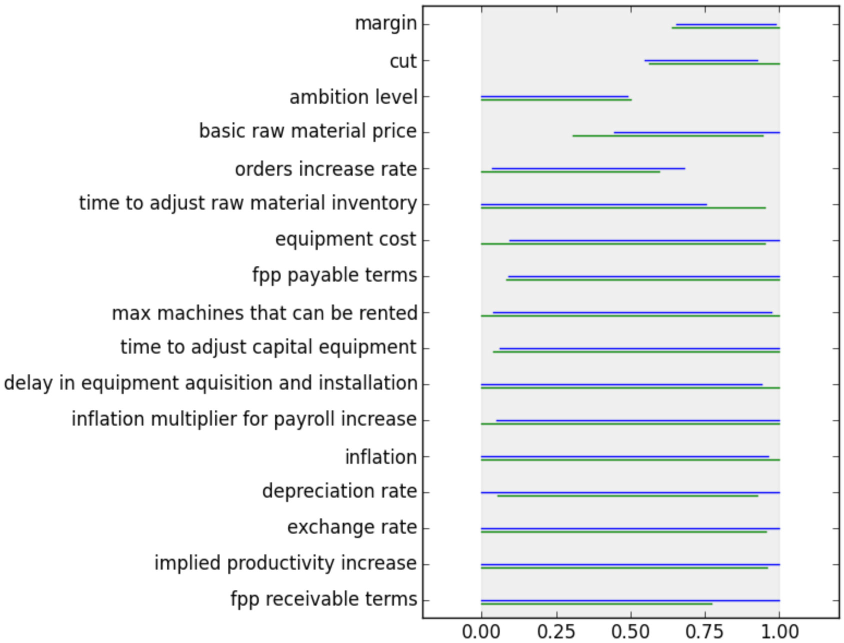


Figure 3.17: PRIM with repayment months<72, density limit 0.8 and mass limit 0.01

Figure 3.17 above is an example where PRIM was looking for outcomes on the lower extreme: below 72 months. There are only 1.355 such cases out of the 20.000 scenarios and the above two boxes only cover 26% of them. The mass limit was set to 0.01 instead of the default 0.05, because otherwise the algorithm did not find any boxes with the required density of 80%. Further trials show that the coverage can hardly be increased even if the mass limit is lowered to 0.001 (see Appendix). This is due to the very small number of desirable scenarios and those existing ones being unique combinations of parameter values. For now what is useful information here is the ranking of the variables. The ones that didn’t appear on any of the two PRIM figures are probably not very influential in determining the outcome of a simulation. This gives a first indication of which variables can be left out when we try to reduce the number of variables to work with.

There are two more algorithms presented here that can give further indication about the influential variables. They are both part of the current EMA workbench’s toolbox and their results will be compared to the PRIM results to finally arrive to a reduced list of ‘most influential variables’. Both of these algorithms are meant to calculate – in two different ways - which variables are the most influential in the categorisation of the outcome. They both have a user-defined categorization of the key indicator as an input. For our example this means that we can define categories of repayment months, say ‘less than 72’, ‘between 72 and 96’, ‘between 96 and 120’, and ‘over 120’. The algorithms will then rank the variables according to their influence on the outcome’s classification into one of these 4 categories. Note, that the PRIM analysis only allowed for a binary classification: above or below a specified limit.

The first algorithm uses random forests (Breiman, 2001) to measure a parameter’s importance. The idea is that a random change in an important variable would greatly affect the outcome’s classification, while the change of an unimportant variable will not have much effect on it. The second algorithm uses the ReliefF (Kononenko, 1994) metric to determine which parameter has the highest influence on the classification. The results of the two algorithms are displayed in Table 2 below.

Random forest measure		Feature selection with ReliefF	
margin	**8,205**	**margin**	**0,07602**
cut	**7,570**	**cut**	**0,05193**
orders increase rate	**4,699**	ambition level	0,02821
ambition level	3,438	**orders increase rate**	**0,02643**
basic raw material price	**0,720**	time to adjust raw material inventory	0,00783
time to adjust raw material inventory	0,272	**basic raw material price**	**0,00649**
time to adjust capital equipment	0,158	time to adjust capital equipment	0,00335
fpp payable terms	**0,083**	**fpp receivable terms**	**0,00260**
fpp receivable terms	**0,082**	**fpp payable terms**	**0,00193**
exchange rate	**0,037**	raw material inventory coverage	0,00169
equipment cost	**0,036**	term length	0,00149
max machines that can be rented	0,032	new equipment's productivity	0,00109
average debt terms	0,022	production update time	0,00105
inflation multiplier for payroll increase	0,019	delay in equipment aquisition and installation	0,00051
time to adjust workforce	0,017	average equipment life	0,00028
implied productivity increase	0,014	**exchange rate**	**0,00010**
payment terms big client init	0,014	**energy costs per ton**	**-0,0002**
new equipment's productivity	0,006	inventory coverage finished products	-0,0003
energy costs per ton	**0,005**	average debt terms	-0,0006
depreciation rate	0,004	**max machines that can be rented**	**-0,0007**
inflation	**0,003**	implied productivity increase	-0,0007
raw material delivery delay	0,002	depreciation rate	-0,0007
inventory coverage finished products	-0,001	overhead per ton	-0,0011

Table 2: Rankings of variables based on their importance according to two algorithms; bold: variables selected for further analysis

In Table 2 a higher score for a variable means a higher influence. The algorithms calculate their scores differently, so the two scores for the same variable should not be directly compared. A negative score means no influence, therefore the variables lower down the ranking were left out of the table. The rankings generated by the two algorithms show some similarities: the first four variables appear to be most influential. There is a considerable gap between them, ‘the big four’, and the rest of the variables. A trial of running the algorithms with different categorizations or on a higher number of generated scenarios did not change the ranking of the first four. However, the small difference among the rest makes their ranking vary with different categorizations or number of scenarios.

These tables and the initial PRIM analyses with all the variables included can support decision on which variables to leave out for a more focused study. One method used only with one setting can hardly give a reliable indication of importance, therefore it is advisable to try out multiple methods and settings. Ultimately knowledge about the case, the model structure and the type of particular question we try to answer will also control the choice of uncertain parameters to work with. The next two sets of experiments show two examples of such more focused analyses.

Experiment 3: Robust optimization

To illustrate the robust optimization tool of the EMA workbench, one such experiment is described here. The tool can be used to find robust policies in the face of uncertainties. Here we take the simplest case: the policy we discuss is a pair of parameter values and the objective that we measure and try to reach is measured on a single outcome.

Taking the perspective of the bank, the two variables that it can mainly influence are the size of the loan and the cut. Hence, the lender might ask: in the face of all the influential uncertainties, what is a robust pair of loan size and cut that will most likely lead to less than 10 years repayment time? To ask this question to a computer, all the assumptions around the question need to be clearly specified.

The first assumption is the **measure of success**: 'less than 10 years' was mentioned above, but other limits can also be tried out probably leading to different optimal results. Instead of the single objective of repayment time, there can be multiple objectives too. In that case the multi-objective robust optimization returns a Pareto-front[7] of answers instead of a single optimal outcome. The measure of success will be closely linked to how we define robustness – the objective function for the algorithm. We can ask: (1) which combination of loan size and cut will lead to **success** in the highest percentage of scenarios? This is the way robustness was defined for our experiment below. But alternatively we may ask: (2) which combination of loan size and cut leads to the lowest average repayment months over all the scenarios? Or instead of average we can (3) ask for the median. These three options are slightly different ways of telling the computer what we mean by robustness.

Assumptions also need to be made about the parameters considered and their uncertainty ranges. Here we can make use of the classifications obtained in the previous experiments. From the lender's perspective it is interesting to consider mostly the uncertainties that are totally out of the influence of the company (ranked 'none' in the initial classification). To simplify matters a bit further, we assume that the three most influential variables that concern the internal workings of the company – ambition level, time to adjust raw material inventory and time to adjust capital equipment – remain fixed. One reason for that can be that after the modelling and what-if analyses, the company gained a good understanding of what value works best for these parameters. But there are also other reasons for this simplification: the effects of 'ambition level' and 'orders increase rate' on the model are very similar and the latter variable will be included in the list of uncertainties. They were also ranked relatively close on the feature selection results. From the PRIM analyses we saw that the 'time to adjust raw material inventory' becomes problematic if it is on the higher half of the given range of (0.5, 2), but there is no real reason for the company to deviate from the current value of 1 month. Finally, we saw at the "what if" analyses that a higher value for the 'time to adjust capital equipment' than in the base case would probably help avoid default, since this would represent a more cautious spending schedule on machines. Hence the most influential uncertainties that were selected for the robust optimization are: margin, orders increase rate, fpp receivable terms, fpp payable terms, exchange rate, inflation, energy costs per ton, tax rate, basic raw material price and equipment cost. In terms of how much influence the company has on these parameters, the first four are on the 'some influence' category, and the latter six are on the 'none' list. This arrangement matches the lender's interest in considering mostly non-influentiable uncertainties for this exercise.

Finally, the robust optimization algorithm needs to know in what range it should look for the optimal values. For the size of the loan it was apparent from the first simulations that the 'base case' initial value might not be enough to set the company on a growing path. Therefore we define here a 'Hypothetical extra loan' that is added to the base-case initial value of both 'Cash Balance' and 'RP Loan'[8]. We let the algorithm look for a value between 0 and 5 million euros for this extra loan. The range for the cut is set to (1% - 10%). Anything above 10% is considered to be too much burden on the company.

Once all these assumptions are clarified and formulated, the robust optimization algorithm can be set to run. The robust optimization implemented in the EMA workbench has a genetic algorithm at its core. This means that it generates the scenarios with the given uncertainties and tries them out with different combinations of 'Hypothetical extra loan' and 'cut'. Then the pairs with the highest score on the objective function are repeatedly mutated and replicated to see if any higher score can be obtained. After a pre-defined number of generations the algorithm stops and outputs the pair(s) that resulted in the highest score on the objective function.

Appendix 3 contains a quick overview of all the settings used to run the robust optimization algorithm. Two runs were made with different population sizes and generation numbers. With these settings the robust optimization algorithm resulted in multiple pairs that scored equally on the objective defined. The pairs of Hypothetical extra loan and cut for the two runs are plotted on Figure 3.18 below.

[7] Pareto optimality means that it is impossible to improve on any of the objectives without leaving another objective worse-off

[8] Initial value RP Loan = base case initial value + hypothetical extra loan*1.5, where 1.5 is due to the premium

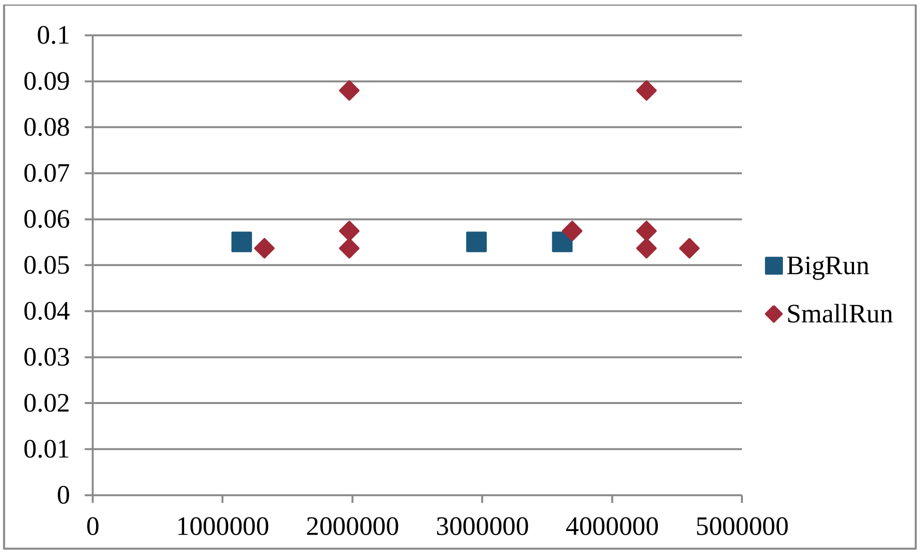


Figure 3.18: Results of two robust optimization runs

The above results give a strong indication that a loan with a 5-6% cut would be most likely to be repaid within 10 years, given the uncertainty ranges considered. As for the extra amount, the small run is spread from 1.3 million to 4.6 million, while the big run is also above 1 million, but doesn't go above 3.6 million. From this there is no strong indication for a certain amount, however the results do lightly suggest that at least 1 million extra loan would increase the likelihood of a timely repayment.

As with the previous analyses in this chapter, running a robust optimization algorithm only once will leave some doubt in the validity of the results. Although these results reflect thousands of runs, in some sense we would still need to base our decision on two observations only: the algorithm was only run with two sets of settings. Similarly to the rest of the EMA tools, the analyst would want to try out several experiments in order to gain more confidence in the advice finally presented to decision-makers.

Experiment 4: Safe boundaries

Once a robust loan size and cut are agreed upon, these two parameters can be considered fixed and the remaining influential parameters can be explored further. A fourth set of experiments are shown here with the loan size and the cut being fixed, while some of the most influential variables remaining uncertain. The selection of the variables and their ranges can be found in Appendix 3. They are a mix of the three categories defined, from highly influentiable to no influence at all by the company. Figure 3.19 shows the possible range of future scenarios. It is quite wide, as expected, but still narrower than before, when all the variables were considered uncertain. It is apparent, that there are only a few scenarios below the 120 month limit.

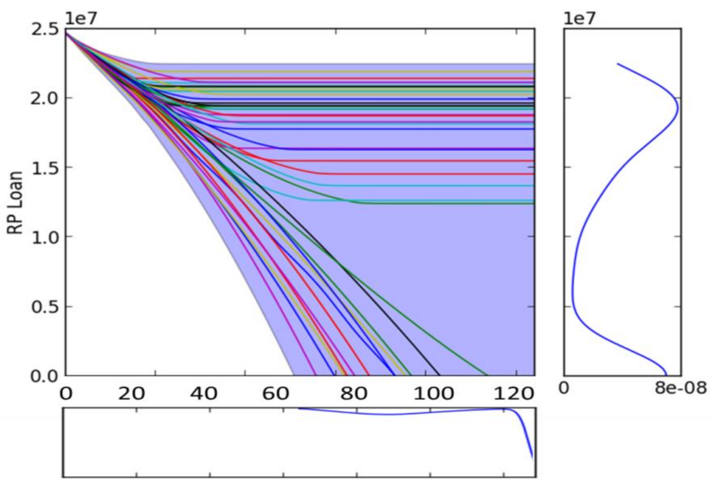


Figure 3.19: Range of scenarios with fixed loan size and cut and a few uncertainties.

PRIM analysis can be performed again to get a sense of 'safe boundaries' within which the scenarios are likely to end up in a certain range. With the same number of scenarios generated (in this case 20000), the reduced number of uncertainties is expected to lead to more accurate results. Figure 3.20 shows the PRIM results for repayment time less than 6 years. There are 251 such cases (1.25% of the total 20000) therefore the mass limit had to be lowered to 0.2% to find at least two boxes with densities of at least 80% (see Appendix3 for all the settings and results).

The coverage of the two boxes together on Figure 3.20 is 39%, which means that there are still 61% of the cases that repay within 6 years unrepresented. It is interesting to see what the interpretation of this figure means. It suggests that basic raw material prices should be on the higher end (around 1500 euros instead of 1300) – a result that might be counterintuitive, since raw materials form the bulk of the costs for the firm. However, here we have to remember how we modelled the sales revenues: a margin was applied to the inventory value outflowing. Applying the same margin on a higher cost of goods sold means higher profits, all others being equal. Therefore a high raw material price would be highly beneficial for the firm, but only with the condition that it can keep the same margins in his contracts. The rest of the results are straightforward: high margins, order rates, and payable terms should be coupled with the normal or more frequent time to adjust raw material inventory, while in some scenarios low receivable terms are also necessary.

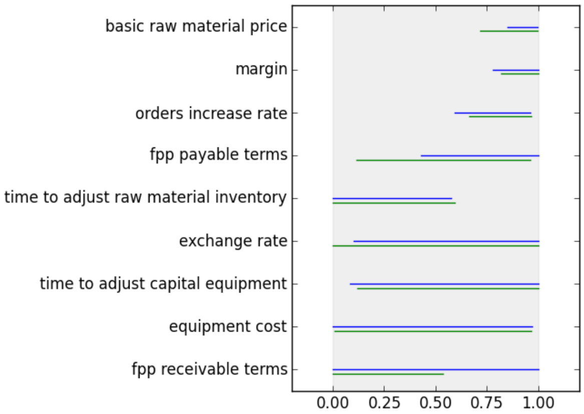


Figure 3.20 PRIM with repayment months <72, mass limit 0.002

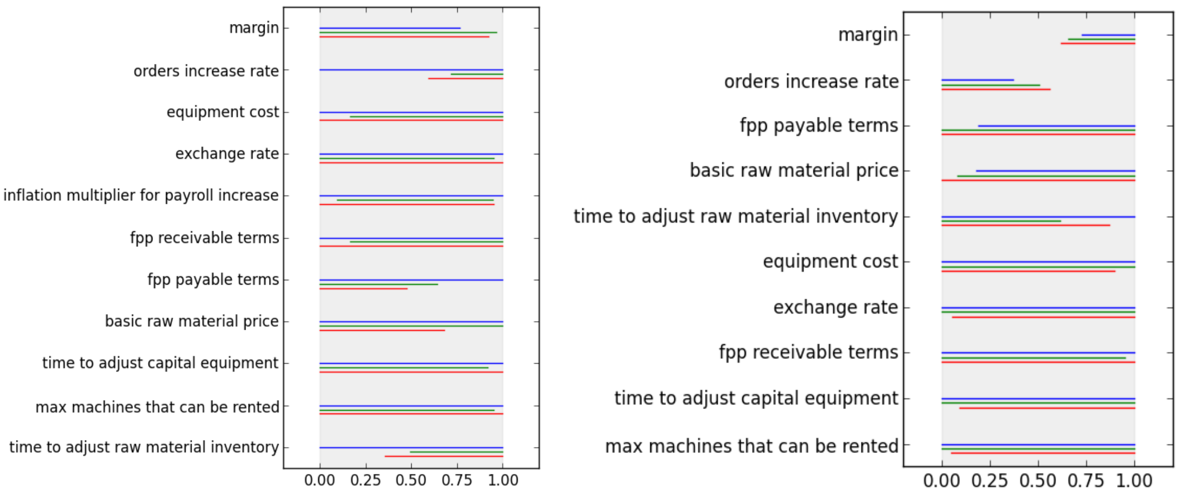


Figure 3.21 Left: PRIM with repayment months >120, mass limit 0.01; Right: repayment months <120, mass limit 0.05

Finally we look at the other end of the range: repayment time *greater* than 10 years. It can hardly be called an extreme, since more than 2/3 of the scenarios are in this group. The left-side figure above shows the results. The first box (blue) covers 92% of all the undesirable cases and it only restricted one dimension, the margin. Looking at the exact number (Appendix3) it reads that any scenario that has a margin of 18% or lower will likely end up in a repayment time more than 10 years. There are two more boxes which show that even if the margin is above 18%, there are combinations of uncertainty ranges that still lead the scenarios to an undesirable end. The right hand side figure shows the PRIM results if we look for what would lead to repayment time *less* than 10 years (1/3 of the cases). It is interesting to notice that the result is far from being 'the inverse' of the previous result. In this case the three boxes found are roughly of equal coverage and together they cover only about half of all the desirable cases. The third box (red) shows that even with a margin of 16% the loan can be repaid within 10 years if the other set of conditions apply. It's also interesting to note that it's safer to have the orders increase rate on the lower end of the range. Higher order rate increases would probably lead to higher investments at the beginning of the simulation and a more likely overspending. Once the cash balance goes below zero it is unlikely that the company recovers since the raw material acquisition stops. In this case study this was a recurring theme for this company. If the cash balance is indeed so important then it is crucial to be precise when modelling the cash-related activities. Our simplistic model is not so detailed on that issue and further improvements could make the interpretation of all the above results more reliable.

3.2 Case 2: High-End Shoe Retailer

The previous case was developed in a quite extensive manner and led the reader through with detailed explanations of the model and its analysis. Even so the model was kept simple relative to the real conditions of the company and also relative to the factors that could have been considered in a 'real-time' assessment. With that we already went a long way towards fulfilling the 2nd, the 3rd and partly the 4th research objective. Yet, there are at least 3 reasons to include this 2nd case study:

- To show that for a totally different type of company there are still some similar issues that appear in the model and the framing of the problem
- To show how (mainly the accounting) parts of the previous model can be reused with only minor modifications
- To extend the set of documented SD structures for the commissioner with an example of the use of subscripts and a common way of dealing with uncertainty in the Lookup functions and structural uncertainty in general

3.2.1 Model description

The company in this case is a high-end shoe retailer, having almost nothing in common with a plastic parts production company, except that they both operate in the same country. The information available on this company was much scarcer: only an incomplete and preliminary version of a report and accounting model together with a one-hour discussion with the equity research analyst were used. For this reason it is even harder to validate it against the 'real case', nevertheless it is quite detailed and realistic in many aspects. The following description provides the information needed to understand the model and the main issues of the case.

The company is a well-established retailer in Turkey with a high brand-recognition among Turkish women. It works with many designers and sells more than a hundred types of shoes and some accessories. At the time of receiving the RP loan, the company closed down its only production facility, thus becoming a purely retailer company. It has almost one hundred stores in the country, part of them being its own stores, while the rest are franchises. Additionally the company exports to a few foreign stores and also opened a line of online sales that are offered on popular Turkish shopping websites. These latter two channels constitute a small fraction of the total sales at present.

The fact that the company has four main sales channels made it complicated to build the accounting model. The two types of stores have different attributes such as sales volume per square meter, average store size, average price of shoes and percentage of returned shoes. The shoes sold on the internet can also be returned, while the exported ones can not. The mix of shoes sold over the four channels is different, leading to different costs of acquisition and sales revenues. Modelling all the complexities of this company with separate stock-flow structures for all these channels would quickly make the model too big to give a quick overview. However, although the sales channels have different aspects and attributes, there are still some common structures that can be recognized. This is where subscripts become useful: they can make the model more comprehensible by hiding the complexity of the case.

Figure 3.22 shows the stock-flow diagram of the 'real part' considered for this retailer company. Monthly sales volumes from the domestic stores are calculated from the *number of stores* times the *sales volume per store*, which in turn is equal to the *average store size* times the *actual sales per sqm.* Subscripting here means that each of these mentioned variables actually contain two numbers at each point of time: one for the franchises and one for the company's own stores. Similarly, the flow *new stores added* contains two equations: one for own stores which are also constrained by the actual cash balance, and one for the franchise stores, which are not constrained by liquidity, only by the company's willingness to open additional franchises that might be harder to supervise.

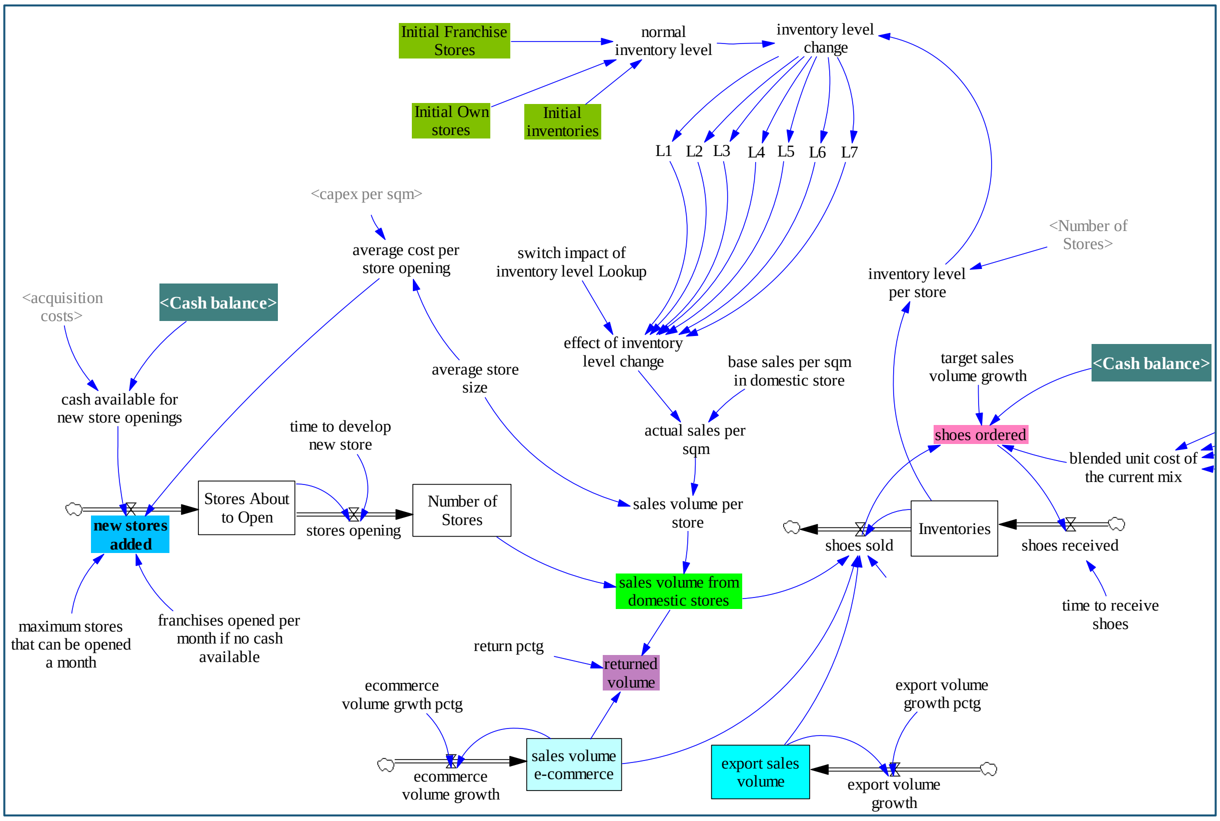


Figure 3.22 Store openings, inventory orders and the resulting sales volumes for the company's four sales channels.

From the discussion with the research analyst it became clear that the sales per stores can be significantly affected by the inventory levels. The variety and quantity of shoes offered increases the sales volumes. Therefore it is important to be able to order enough pairs to keep the inventory levels. At the time when the company closed its production, it found it harder to supply all the needed quantities for all of its stores, therefore its sales took a substantial hit. From all these it is clear that higher inventory levels should lead to higher sales per square meter. However, the quantification of this relation is not known, it is uncertain. A small change in inventory levels can cause a big change in sales per sqm, or it can happen that a big decrease causes only a minor dent in the sales level. This uncertainty was modelled using seven versions of lookup functions that capture the above described range of possibilities (see figure 3.23). The inventory level was normalized using the starting condition. Knowing that zero inventories should mean zero sales, the uncertainty lies in how the two points are connected. The seven versions here capture a few possibilities, but there are of course many other tracks that this elasticity could take. Above the normal level, they all continue in different increasing and linear shapes.

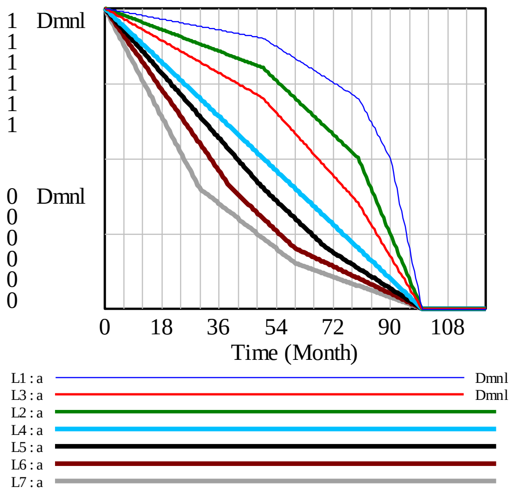


Figure 3.23 7 possible relations inventory levels->sales

The simple assumption is made that the company tries to make orders to supply the current sales level (*shoes sold*) times a *target sales volume growth*. The *shoes ordered* are constrained by the cash balance available: only that amount is ordered that can be paid given the overall unit costs of the current mix of sales. Whatever is not spent for these orders remains available for spending on store openings. After the orders are made it takes a few months until the shoes arrive into the inventories, and this could best be modelled as a fixed delay. The monthly sales volume through exports and e-commerce are assumed to grow with a constant (although uncertain) average growth rate over the next years.

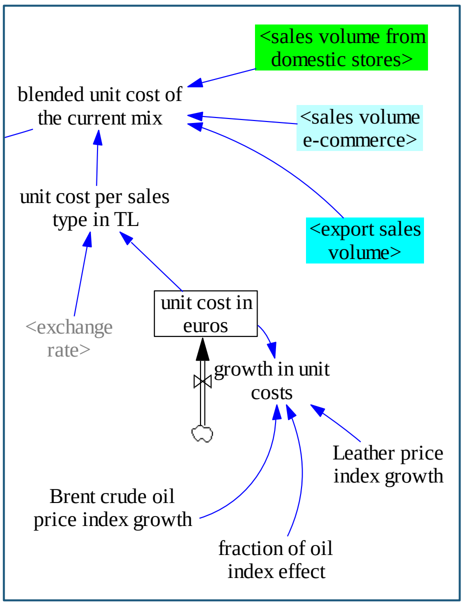


Figure 3.24 Calculation of acquisition unit costs

Figure 3.24 shows how the *blended unit cost of the current mix* of sales is calculated. It is the average of all the unit costs of the four channels weighted by their respective sales volumes. Cost of shoes and related products are expected to grow together with the *leather price index* which is determined on the global market. A fraction of the shoes are made of high-quality plastic, therefore the change in crude oil price also influences the acquisition costs.

Figure 3.25 below shows how the overall monthly sales revenues and returned shoes' values are calculated. The colour coding helps again to track the links between the 'real' part and the valuation part of the model. Mirroring the assumptions made in the accounting model, the average prices for the four sales channels are increasing with inflation. The *average price domestic* stock contains three average prices: two for the store types and one for the e-commerce side which also sells for Turkey. With this we have now created the link to the balance sheet – at least on the revenue side.

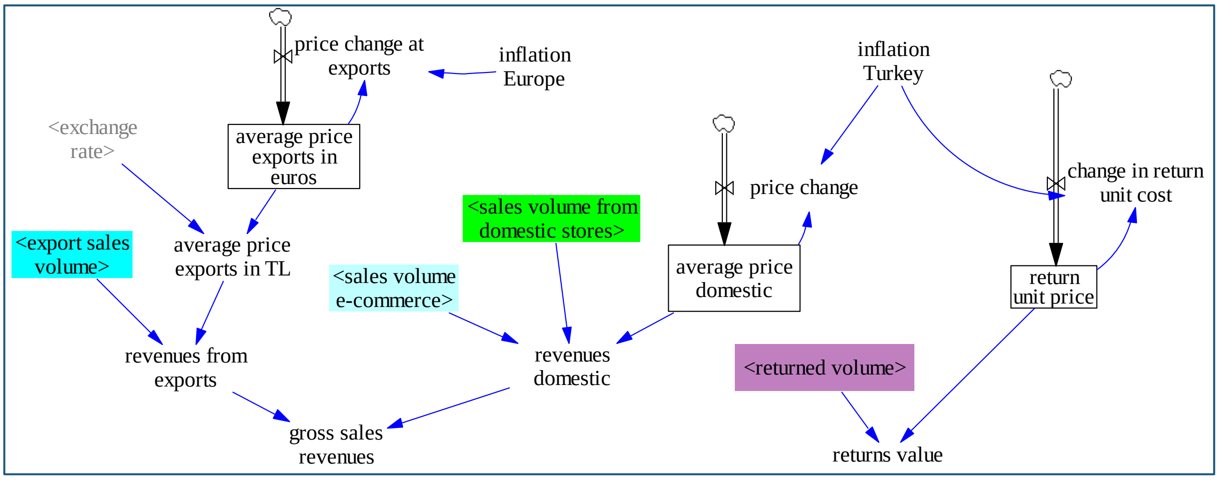


Figure 3.25 Calculation of the net sales revenue elements: returns value is deducted from gross sales revenues

Figure 3.26 shows the balance sheet model for this company. The stocks are unsurprisingly the same, while the link with the 'real' part is slightly different. One major difference is that there are no production expenses: no direct flow between cash balance and inventory. This time the sales revenue calculation was done according to the traditional sales volume times price formula (see above), therefore the margin is not a constant one anymore.

Since the sale of the production facilities the only tangible fixed assets of the company are the decoration and the facilities in its own stores and its headquarters. They depreciate fairly quickly, they are replaced on average every 5 years, hence the depreciation rate of 20%. All the company's own stores are rented, and these expenses are booked in the SG&A category (see figure 3.27). *Rental expenses* depend on the number of 'own' stores and on their average size, while the rent per sqm is expected to grow in line with inflation. Expenses related to sales are substantial in the case of any retailer, therefore they are detailed also in our model. One of the big parts of these expenses is the personnel expenses. Average wages per employee are different for those at the headquarters and those at the stores, however their targeted wage growth is the same. Therefore the stock *wage per employee* is again subscripted, containing the numbers for the two categories. The rest of the relations is left according to the preliminary accounting model, notably with the company having a fixed target percentage of revenues for advertising. In terms of causality there is probably a strong link also in the other way: advertising expenses affecting the net sales revenues. A more detailed modelling of customer acquiring and retention due to advertising would be a worthy addition to investigate. The company had no knowledge of its number of customers and the number of sales per customers.

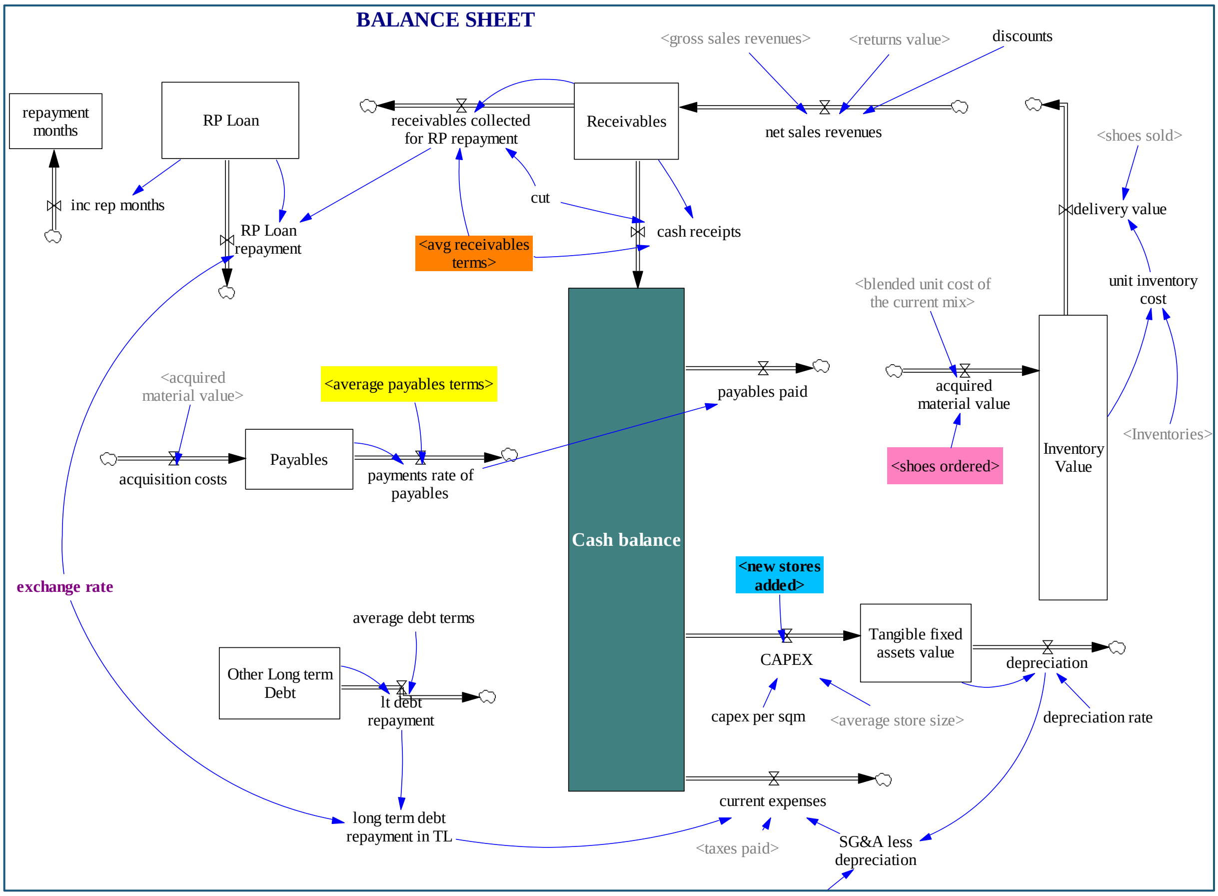


Figure 3.26 Balance sheet and cash flows for the shoe retailer

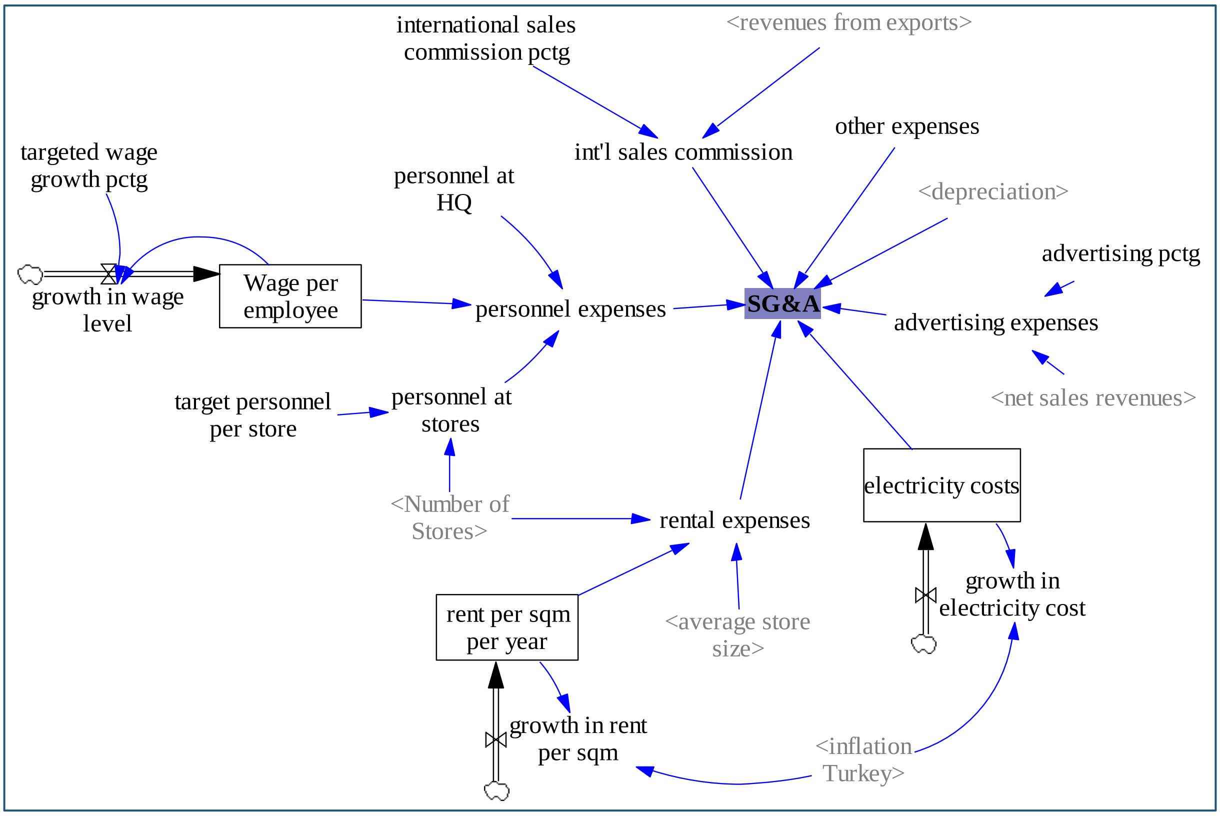


Figure 3.27 Calculation of the Sales, General and Administrative costs

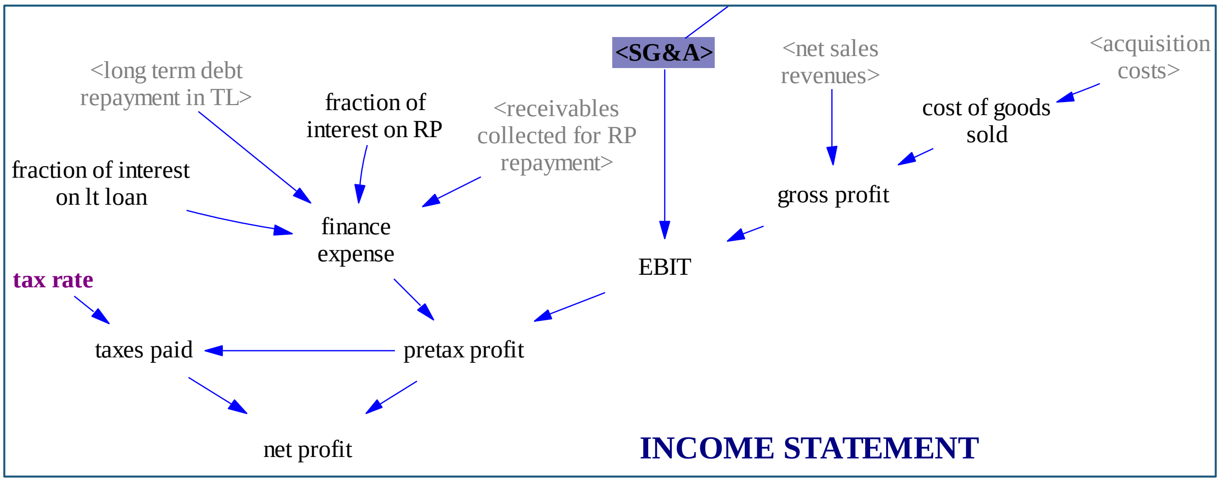


Figure 3.28 Deriving the income statement: standard accounting equations.

Figure 3.28 shows the income statement calculations for this case. Since they are standard accounting relations, the structure is the same as the lower half of figure 3.3. In fact the whole model building for this case could be started by keeping the balance sheet and income statement from the previous case and making the necessary modifications to fit the case of the retailer.

One last detail to be mentioned about the model is the calculation of the average receivables terms and the average payables terms (figure 3.29). They greatly affect the flows of cash therefore they deserve some detailed modelling. The complicating thing on the receivables side is again the different sales channels. At the stores a fraction of the customers pays in cash, others pay by card for which the payment terms are different from those of online sales and exports. The latter two can take 4 to 6 months. On the supply side the company works with more than 60 suppliers. For a part of the orders the payment has to be made upfront, while the rest can sometimes allow even a 12 months payment period.

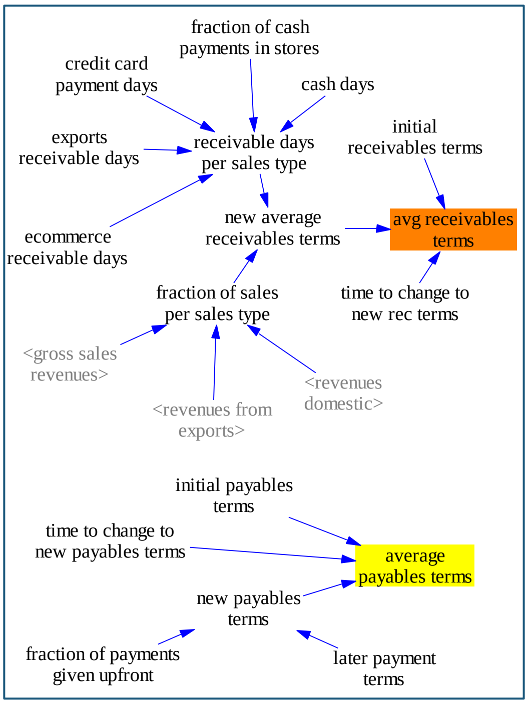


Figure 3.29 Calculation of payment terms

With this the model is now complete, i.e. the issues considered relevant for the case were captured in this model. From the talk with those who assessed the company it emerged that important barriers to growth in this case are very similar to the production company's case. There the company had to buy raw material and invest into production capacity (machines) in order to grow, and both of these substantial investments were limited by the available money. Similarly, the shoe retailer has to order shoes in time for the sale season and has to build up 'selling' capacity through opening stores. Since the company aimed at only opening stores managed by themselves ('own' stores), they have to make these investments from their own available money. Additionally they also have to hire their own store personnel. An alternative narrative could have been to focus on branding and advertisement, instead of new store openings. However, the only information available on that topic was that the company prepares its annual budget for advertisement as a percentage of revenues.

3.2.2 Structured Analyses

From the model presented above it can be seen how subscripts help managing the complexity of the case. However, all the variables that impact the company are not reduced in number. In this section we quickly run through the EMA tools presented earlier and apply them in a similar fashion to the shoe retailer case.

We start again from considering all the constants, this time assigning the wider plausible ranges from the beginning (see Appendix 4 for the exact settings in this section). Figure 3.30 shows that the range of possible future scenarios is quite wide.

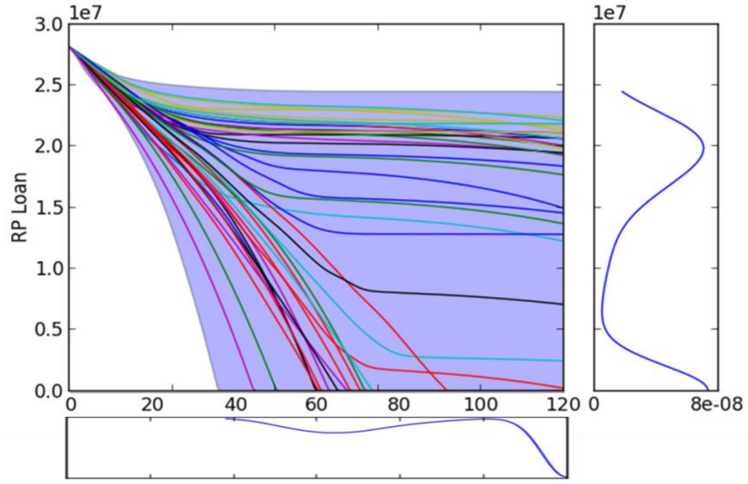


Figure 3.30 Range of possible future scenarios with all the variables considered for the shoe retailer case

The 36 variables are then ranked again based on their influence on the outcome classification:

Random forest measure		Feature selection with ReliefF	
exchange rate	**9.749**	**exchange rate**	**0.10488**
switch impact of inventory level Lookup	**2.329**	**switch impact of inventory level Lookup**	**0.03891**
fraction of payments given upfront	**1.152**	**fraction of payments given upfront**	**0.02196**
Leather price index growth	**0.623**	**Leather price index growth**	**0.01799**
base sales per sqm Own	**0.574**	**base sales per sqm Own**	**0.01547**
credit card payment days	**0.544**	**credit card payment days**	**0.01319**
average own store size	**0.215**	return pctg Own	0.01268
maximum stores that can be opened a month	0.134	**average own store size**	**0.00883**
target sales volume growth	0.113	exports receivable days	0.00712
targeted wage growth pctg	0.112	base sales per sqm Franchise	0.00663
other expenses	0.109	target personnel per store	0.00642
target personnel per store	0.097	other expenses	0.00512
later payment terms	0.090	fraction of oil index effect	0.00472
base sales per sqm Franchise	0.089	franchises opened per month if no cash available	0.00309
ecommerce volume growth pctg	0.086	Initial electricity costs	0.00265
return pctg Own	0.080	time to change to new payables terms	0.00202
advertising pctg	0.065	Initial rent per sqm per year	0.00180
Initial electricity costs	0.062	advertising pctg	0.00169
time to change to new payables terms	0.050	maximum stores that can be opened a month	0.00132
time to develop new store	0.038	average franchise store size	0.00123
personnel at HQ	0.028	fraction of cash payments in stores	0.00098
Brent crude oil price index growth	0.023	time to change to new rec terms	0.00063
ecommerce receivable days	0.018	later payment terms	0.00062
average franchise store size	0.010	return pctg Franchise	0.00061
inflation Turkey	0.010	inflation Turkey	0.00053
franchises opened per month if no cash available	0.005	Brent crude oil price index growth	0.00044
export volume growth pctg	0.003	ecommerce receivable days	-0.00019
inflation Europe	0.002	targeted wage growth pctg	-0.00052

Table 2: Rankings of variables based on their importance according to two algorithms

The ranking shows that the exchange rate is the most influential according to both of the algorithms and the rest of the variables are at quite some distance from it. Although the same uncertainty range was assigned to it, this time the exchange rate is much more influential than in the previous case. Since it affects many parts of the model (the supply costs, debt repayment, etc) it is easy to lose track of what trend would be more beneficial in the exchange rate, if one tries to simulate the business model mentally. The first seven most influential variables were selected for a closer investigation of their effects. Figure 3.31 shows that the range of possible scenarios is slightly reduced with such a selection.

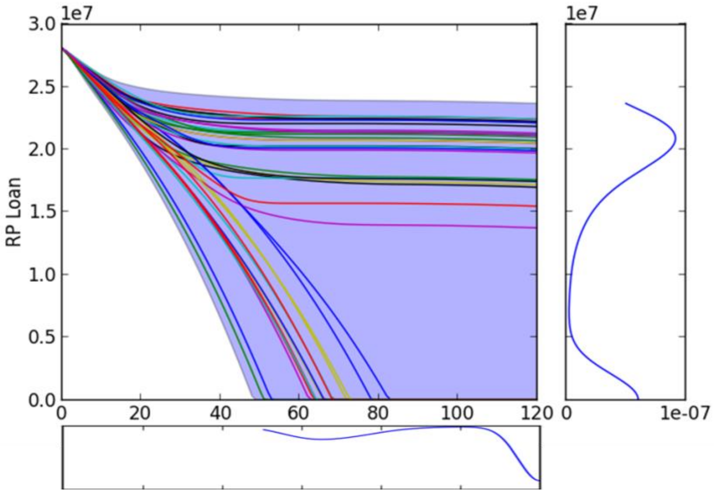


Figure 3.31 Range of possible future scenarios with 7 of the most influential variables considered

Next a PRIM analysis is performed to see what combination of parameter ranges will lead to a desirable repayment time of less than 6 years. Around 22% of the 10000 scenarios end up within that limit. Even so, a mass limit of 5% set for the first PRIM (on the left) only finds one box that covers only 22% of the desirable cases. Decreasing the mass limit to 2% reveals 3 boxes, together covering 31% of the desirable cases. This could mean that the rest of the desirable cases are generated by numerous other combinations of parameters that are scattered in the uncertainty space. PRIM with the current visualizations is not so handy in handling such cases.

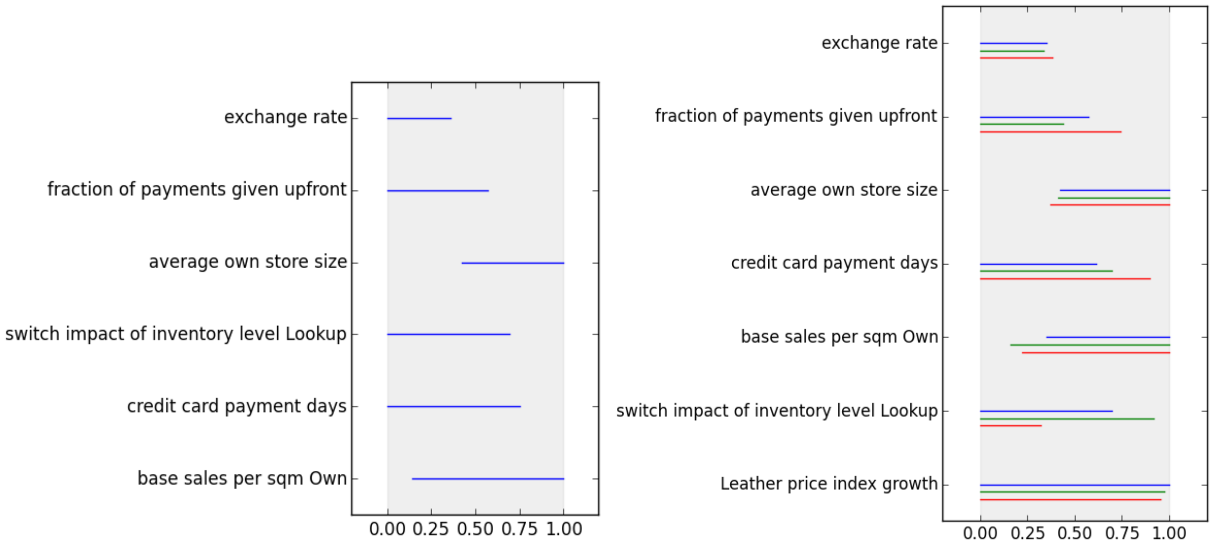


Figure 3.32 Left: PRIM for repayment months <72, mass limit 0.05 and Right: repayment months <72, mass limit 0.02

These PRIM results reinforce that the exchange rate is the most influential parameter. A low exchange rate is desirable, since it means that the cut deduced translates into a higher repayment of the RP loan, which is denominated in euros. It also appears from the above results that the ‘switch impact of inventory level Lookup’ variable can be important to stay on the lower end. Translated to the case this means that the sales levels per sqm should be inelastic to the change in inventory levels. Furthermore, the figures suggest that the leather price index growth is least influential among the seven. Since the margin was not modelled to be constant over the scenarios, this time a higher input cost does not help in generating more revenues.

We can also look at the other end: what leads to a repayment time of more than 10 years? 69% of the 10000 scenarios end up in this undesirable state. The two boxes found cover 69% of them, although there is an imbalance between the two: the blue one covers 62%, while the green box only the remaining 7%. The green box is still interesting since it shows that even if the exchange rate is on the most favourable lower end, there is still a combination of parameters that lead to an undesired long repayment time.

Figure 3.33 Left: repayment months> 119, mass limit 0.05 and Right: repayment months <72, mass limit 0.01, FX fixed to 2.33

Finally, one might not like the high influence of the exchange rate, especially that the estimated boundaries of success hardly ever cover the forecasted numbers. Therefore another experiment was developed with the exchange rate being fixed to the forecasted 2.33 TL/euro value. Given the remaining 6 uncertainties, what combination of their ranges can still lead to a desirable repayment time of less than 6 years? The right-hand side figure shows these combinations. Only 11% of all the cases end up in this state and the five boxes cover only 52% of them. The boxes are comparable in size with the smallest one being twice smaller than the largest one.

The above mix of seven parameters used contains both non-influentiable and influentiable parameters. Robust optimization experiments could be useful to explore different strategies (i.e. combinations of parameter values that the company can partly affect) under uncertainties in the parameters that are harder to influence. However, the analysis performed and presented in this chapter already provides adequate material to draw some lessons from.

4. Recommendations, Implications and Reflections

Section 3 started with a very *rough* vision on how the EMA workbench tools could be applied to support decision-making in the lending processes of RP loans. In this section those four topics are revisited and discussed in light of the experiences with the case studies. Through these reflections and recommendations, the rough vision is developed into a *bold* one.

4.1 On Information Gathering: A Culture of Transparency?

The first topic is: what information should be gathered about a company to make better lending decisions? As mentioned in the introduction, much of the assessment currently looks through the lens of financial statements. But there is also an equally important element that is the understanding of the business, in other words *how* does it generate the financial outputs. During the assessment the bank representatives try to learn this from the company directors. Later it is reported in a text form to which the spreadsheet models are attached. Trying to build simulation models based on the reports it became clear that a lot of information is lost about how the company operates. Additional information had to be collected from the analyst who knew the company. Even then there were information missing about how the company manages its most important assets and its inventories and what the numerical values of the decision parameters were.

Trying to build an operational SD model showed that the way decisions were made in the company was fairly unknown. The implication of this experience is that ideally, more information needs to be collected and recorded and also the nature of the information has to be broadened to include a more structured expression of soft knowledge in the form of causal relations and equations. However that is easier said than done and it is not yet clear to what extent it is worth making the additional effort. The SMEs – who may or may not be used to reporting to investors – have to get used to the fact that they are asked more questions about how the company is run. They need to provide more data from the operational records and also talk about how they would make decisions in the future, although they might not be so used to planning and control processes at all. A common pitfall is that companies prepare one version of the future plan for the bank, while they work with another version for their internal operations (Bianchi, 2002).

The debate on how to improve reporting to investors is on-going in the finance industry ("Better Business Reporting," 2013). Investors seem to agree that 'integrated reporting' is needed to give more insight and understanding to investors about the businesses they lend to (KPMG, 2013). There is no agreement about what this integrated reporting should entail, only the realization that there is a need for capturing *how* the business creates value and convey this in a simple way to investors. On one hand this would inevitably lead to more transparency about how businesses are run and what structures and parameters are in place to drive their performance. On the other hand, investors need a way to structure and analyse the additional volume of (soft) information. The case studies in this report showed how to capture information in SD models. Hence it can also be considered an alternative for more integrated reporting. An example of what questions to prepare for an interview was also given (Appendix 2).

Overall, SD modelling proved to be a useful tool in capturing big amounts of information of different natures. Some companies might feel that they are too much exposed by the rigorous information-gathering that a modelling study requires. Managers need to be assured that the elicitation of their mental models on decision-making will be used for their advantage: to come up with robust lending decisions and perhaps some useful strategic advice to the company. The EMA approach also presents an unexpected opportunity to please company managers who are reluctant to give away sensitive company data[9]. In view of the uncertainty analyses to be performed, it is no longer required to reveal the exact historical data or to come up with the best estimate. It is enough to have a range of plausible values that the company is comfortable to disclose (as is the case with governments' classified numbers that are often communicated to the public in orders of magnitude). Of course, the disclosed range has to be narrow enough to reflect the strategic importance of the parameter.

4.2 On SD Modelling of SMEs

It's hard to draw a clear line between information gathering and modelling. Building a SD model can actually help a lot in structuring the inquiry about the company during the assessment period. The model is also a powerful documentation tool helping to keep track of numbers and also soft information. Generic structures can be useful to structure an initial discussion and quick model building session with the company, just as it helped preparing the interview for the first case in this report. Learning about the company through modelling can also point to possible missing information.

SMEs are not used to active planning and control for their organizations (Bianchi, 2002). They might not have well-established and/or formalized policies therefore there might be a lot of structural uncertainty in the model to be built. They might not be used to quantifying their decision processes into models, but going through historical data records can facilitate the discussion. Uncertainties might remain about how decisions will be

[9] Often the most influential parameters are rightly perceived as strategic and sensitive by managers, therefore they might want to withhold crucial information about them.

made in the future and how the structure of the model will evolve. Even so it can be worth adding the 'real' part and capturing these uncertainties in alternative models, since the multi-model approach is one of the core features of the EMA approach and can also be well handled by the EMA workbench.

Receiving an RP loan usually triggers many kinds of changes in a company. Previous debts are repaid, supplier contracts renegotiated, parts of the business might be shut down, other parts restructured and new investments are made. The aim is to model the system as it will behave after the receipt of the loan to explore its performance of repayment. This has some consequences also on the modelling study that should be performed. First, on the initialization: as explained in Box 2, things do not necessarily have to start in a balance. Secondly, on the validation of the model(s): there might hardly be any relevant historical data to compare the behaviour to. The model can be best validated by showing its assumptions to the company managers and asking them whether the behaviour generated by each model part makes sense to them and in what conditions would they expect deviations. If each equation seems realistic to the managers and the behaviour of the model parts also makes sense to them, then the model as a whole can also be valid, even though the overall behaviour is somewhat unexpected (assuming that all the relevant parts were included into the model). This does not mean that historical data is completely useless. Quite the contrary, it can validate those model parts that remain unchanged. Finally, if cash is such a constraining issue – as it proved to be – then it is important for the validity of the results that the flows related to cash balance are numerically as accurate as possible. Equally important is to model realistically how decisions are made based on cash availability. This is an area where the models presented in this report could be greatly improved.

There is a similar trade-off in more extensive modelling as with information gathering. A high-level modelling with aggregated data from financial statements can be performed without much involvement of the company and it can give a quick estimation of the repayment time within minutes. More detailed, tedious modelling involving the company can make the modelling study more realistic and the analysis results more reliable *if* the contact hours with the company are used to reduce the uncertainties about the future. Trying to build the simulation models with the company *can* have the effect of reducing uncertainty in the sense that the uncertainty space is restricted to either a single model formulation, or – more probably – a finite set of possible future models. Performing the modelling in close collaboration with the company can also have a good side-effect: the managers themselves learn the systemic view of their own company and how to make better decisions, where to focus their efforts. Not only model uncertainties can be reduced this way, but also parameter uncertainties, if the company learns how important it is to maintain some parameters in a certain range. Of course, the drawback is that such a collaborative approach would take more time even for the quickest modellers.

The cases presented in this report show how a SD model of the accounting relations can be coupled to the operational model of the company. This approach is recommendable, since it includes the well-known key accounting indicators and also provides a more realistic model of the company. One additional reason for making the detailed operational model is that it can make the relations to macroeconomic variables more explicit. In the two cases treated here we encountered such variables as exchange rate, tax rate, oil price index, leather price index and energy costs, all of them being non-influentiable by the company or the bank alone. When models of several companies are analysed together, such an approach makes it easier to embed all these models into one model of the macroeconomic environment.

4.3 Outlook for Combined Analysis and Monitoring

A combined analysis would mean that several company models are put into one big model to analyse them together as a portfolio. Since the companies in a country all share the same macroeconomic environment, they can be embedded in a country-model which includes the main macroeconomic indicators relevant to the individual models. These country-specific and global market indicators would then be external inputs to the company models, just as they were in the cases presented.

A combined analysis would have the following advantages. First of all, it would make sure that the assumptions about the shared external variables would be consistent over the whole portfolio. Secondly, an aggregated RP Loan remaining and repayment cash flow could be calculated. This would allow analysing the effects of uncertainties on the overall internal rate of return of the portfolio. Finally, new investments could be based on the existing portfolio, such that a new company would reduce certain exposures and maybe even narrow down the uncertainty around the overall performance of the portfolio.

The case analyses gave examples of the use of PRIM for finding ‘safe boundaries’ for a given company. The algorithm can answer the question: “What combination of parameter ranges leads to the (un)desirable scenarios?” It was used to look for desirable scenarios such as a repayment time less than 6 years and undesirable scenarios such as repayment longer than 10 years. The output is always a list of variable ranges that lead to the previously specified outcome. The resulting boundaries intuitively point to a possible automated monitoring system in which the conditions for ‘alarm’ are read from the PRIM outputs and they are constantly compared against the numbers reported by the company. For example we may take figure 3.32 (left) and whenever all the listed variables’ value get into the ranges specified by the blue lines, the monitoring system might automatically trigger a message saying something like:

“It will probably take less than 6 years to repay this loan.”

However, the interpretation of the PRIM results is hardly ever so simple and a monitoring system with such a simple output may never be reliably reached. There are several things that any attempt for such a monitoring system should take into account. First of all, the word ‘*probably’* from that message means nothing to an analyst if it is not translated to an actual number. One might then ask: with what probability will it take less than 6 years? The first thing to look at then is what the density of that box was from which this message was triggered. In our case that was 95% (Appendix 4). Then the next question is: what if the variables are just outside of the given boundaries on a few of those variables considered? Does that mean a sure repayment time longer than 6 years? The low (22%) coverage of the box in question shows that the answer is most probably ‘no’. There are many of the desired scenarios not represented by this single box. Therefore it is sure that other combinations of the parameters can also lead to less than 6 years repayment time. And finally, what is the probability that at least one of the underlying models used reflect the future behaviour of the system?

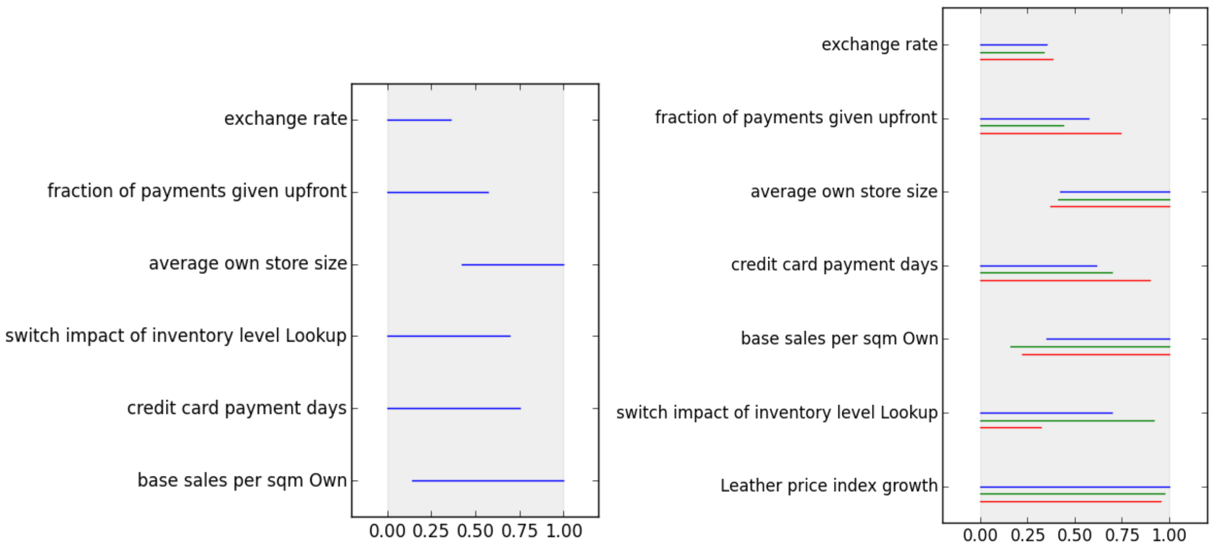


Figure 3.32 (again) Left: PRIM for repayment months <72, mass limit 0.05 and Right: repayment months <72, mass limit 0.02

To make matters further complicated, a probabilistic interpretation can only happen if the uncertainty ranges have a probability distribution assigned and the rest of the variables will remain fixed with 100% certainty. Hence, the validity of the whole model has to be checked constantly and if changes happen in the system, then the adjustments have to be made. Considering all these complications it appears that these tools are not (yet) suitable for making probabilistic judgements about the future of companies. This is not unexpected, nor were they meant to be used in that way. A *semi*-automated system based on some rules of thumb can probably be set up that would monitor parameter changes and warn for a re-examination when receiving signals of change. In those cases a shared understanding developed with the company based on previous detailed modelling can help in the efficient discussion of the emerging issues. A periodical update to the model can then be applied and the relevant uncertainty analyses can be performed to update the future picture.

What Forrester wrote about the 'process of modelling' can be analogous to the 'process of monitoring' with the EMA workbench: "*I believe we are proposing the 'Process' of modelling rather than particular frozen and final models. The difference in viewpoint becomes especially important as we move into the implementation phase. It seems to me that the average person will be greatly concerned if he feels that the future and alternatives are being frozen once and for all into a particular model. Instead, we are suggesting that models will help to clarify our processes of thought: they will help to make explicit the assumptions we are already making and they will show the consequences of the assumptions. But as our understanding, our assumptions, and our goals change, so can the models.*"(Forrester, 1985). …and so can the experiment settings that are applied to the models with the EMA tools.

4.4 The EMA Workbench within a Bank: A Bold Vision and Limitations

Through the case studies and the lessons learned a bold vision emerges about the role of EMA in the bank's lending processes. First stage in this vision is the initial inquiry about the company. Skilled modellers gather knowledge about the SMEs and capture them in SD models through a collaborative process with the company managers. A relatively big amount of historical records – both accounting and operational – supports the validation of each model part. However, besides looking at historical performance, brainstorming on possible alternative models for the future behaviour of the company would generate a range of models to cover the relevant uncertainties. Such a process with SD models could even be considered as a prerequisite for giving a loan, as Bianchi suggests: "*…banks and public trusts financing business start-up could embody the feedback approach as a necessary prerequisite in defining standard requirements to accept a business plan as eligible for a grant*." (Bianchi, 2002)

Second stage is the preparation of alternative company models for a treatment on the EMA workbench. The use of EMA tools puts additional demands on how SD models should be built. Since the models are often stressed to their limits, some effort should be made to make sure that the equations remain valid under extreme parameter values. Combinations of uncertainty ranges are fed into the SD models to generate a wide range of possible future scenarios. The most curious ones are then selected and examined to see what combination of parameters generate them. Impossible scenarios are filtered out and modifications in the models are made not to allow those impossible scenarios to appear any more. Impossible assumptions that were previously thought possible can thus be filtered out. Multiple methods are then used to make a list of the most influential variables. A more focused analysis on the most critical ones can give a sense of the safe boundaries within which the company should operate to reach its repayment target. Additionally, the latest company model is embedded into the model of all existing client companies to see what would be the effects on the portfolio as a whole. The key lessons learned through this whole process are written down in a contract and key conditions are formulated to strike the deal.

Stage three is the signing of the deal and the monitoring afterwards, where all the contact between the company and the bank rests on a shared understanding of the business developed through the modelling exercises. With more experience, a semi-automated reporting and monitoring system can be set up which prepares updated analyses based on the latest company data and macroeconomic indicators.

In terms of content, the necessary ingredients for the above presented bold vision already exist: SD modelling of SMEs has already been done, while the application of some key EMA tools to this type of problem has been described in this report. The process-related elements – such as the interaction during real company assessments, the writing of contracts based on this kind of study and the monitoring process – are yet to be tried out and explored. It is recommended that the steps presented in the case studies are performed for a real company assessment to gain real-time experience with the EMA tools. The case material and lessons learned from this report should serve as a good preparation for such an experiment. The insights gained from real applications should be used to continually develop and improve both the EMA tools and lending processes.

While the individual explanation of the EMA methods could be presented in this report, an attempt was made to explain how they should be used in combination and in a highly iterative process. From all the SD models built and all the analyses that were run with the EMA workbench, only a fraction of them could be fit into this master thesis project report. Similarly, an actual company assessment with an EMA study would require several iterations in a highly interactive setting with the company. One limitation of this research was the restricted interaction with the actual companies. The case studies 'simulated' the hypothetical EMA studies that could be performed based on the information available about the existing companies on the portfolio. Therefore they focused more on the explanation and exemplification of the EMA tools available, but could not tell much about how an *actual* EMA study could be *most efficiently* performed. A further resulting limitation is also that the suggested multi-model approach to uncertainty exploration was only briefly exemplified in the case studies.

As it was made clear in the beginning chapters, an exploratory approach to modelling and analysis is the art of devising practical and insightful search and description strategies over a relevant portion of the infinite uncertainty space. There are tools available to do that and their thorough understanding is essential in performing this art. This study aimed mostly at creating that thorough understanding, focusing on the 'How?' question. But what makes a study insightful, practical and relevant? That depends very much on the bankers and company managers involved in the decision-making, their goals, attitudes and perceptions, partly because deep uncertainty is not quantifiable by its nature. Channelling these perceptions into an EMA study that in the end is deemed relevant is what makes EMA an art.

5. Conclusions, Future Work

The motivation behind this project was a need for a broader set of analytical tools to better understand and handle the uncertainty related to future repayment of RP loans. The commissioner's preference for SD modelling and his interest in the EMA tools developed at TU Delft led to the following research question:

How can exploratory SD modelling and analyses improve lending decisions and the monitoring of credit portfolios?

Through two case studies of existing client companies the application of SD modelling and the tools of the EMA workbench were exemplified. A SD representation of accounting relations was provided that can be reused in future models, while two examples were given on how to attach an operational model of the company to these accounting parts. The capabilities offered by the SD models and EMA tools demonstrated in this thesis are:

- understanding the business model through modelling
- what if analysis supported by simulation
- finding influential parameters
- finding safe boundaries with PRIM
- Robust Optimization: finding the right mix of cut and loan size under uncertainty

Understanding of the individual tools alone is not enough to perform an exploratory study. The EMA approach and how it relates to earlier modelling studies needs to be well-understood. For this reason the beginning chapters elaborated on what it means to explore future uncertainties using simulation models. From the vast number of conceivable analytic tools that can support such an exploration, a few were presented in more detail and related to the case studies at hand.

Reflections on the use of the EMA methods and their potential were provided throughout the cases and recommendations were formulated afterwards. These materials could serve as a basis for more elaborate studies, preferably in the context of actual company assessments. A roadmap to build these capabilities into the bank's team is not yet outlined, since the institutional and organizational complexities of such a plan were out of the scope of this study. Certainly there are actors such as investors, co-workers, consultants and the borrower companies that all have an influence on the successful use of these capabilities. Without those considerations, any plan of introduction would be a meaningless exercise. What would be the best application process of the tools demonstrated here could be a logical next topic of inquiry.

Given the limited exemplification of the multi-model approach in this study, further research could be performed to analyse a variety of model versions. The case studies were selective in the modelling of relevant model parts hence there is room for more SD model development based on the same companies. This would be worth performing in a more interactive manner with the company. Further analysis could then compare the results of different model analyses to demonstrate the benefits of different levels of detail, different model complexities and perhaps even different modelling approaches.

Meanwhile there is still room for demonstrating other capabilities of the EMA tools that were not included in this project. Clustering of similar scenarios and the adaptive design of robust policies are two of the promising tools that could further support decision-making. Furthermore, the effect of random variations in the parameter inputs could be further investigated, as it was done with early model versions of this project but left out from the analysis of more elaborate models.

With the state-of-the-art data-gathering, modelling and analysis tools we are still nowhere near the exact prediction of what will happen in the future. The development and use of the EMA tools will probably not change that, its focus being not the reduction but the exploration of uncertainty. These analytic tools are not meant to replace the need for good human judgement. But as a supporting companion for decision-making, they can give a sharper and more colourful picture of the uncertain future.

6. References

Agusdinata, D. B. (2008). *Exploratory modeling and analysis: A promising method to deal with deep uncertainty*. Delft University of Technology. Retrieved from http://www.nextgenerationinfrastructures.eu/download.php?field=document&itemID=433706

Auping, W., Pruyt, E., & Kwakkel, J. (2012). Analysing the Uncertain Future of Copper with Three Exploratory System Dynamics Models. *Proceedings of the International Conference of the System Dynamics Society*.

Bankes, S. (1993). Exploratory Modeling for Policy Analysis. *Operations Research*, *41*(3), 435–449.

Beck, T., & Demirguc-Kunt, A. (2006). Small and medium-size enterprises: Access to finance as a growth constraint. *Journal of Banking & Finance*, *30*(11), 2931–2943. doi:10.1016/j.jbankfin.2006.05.009

Better Business Reporting. (2013). Retrieved from http://betterbusinessreporting.com/

Bianchi, C. (2002). Introducing SD modelling into planning and control systems to manage SMEs' growth: a learning-oriented perspective. *System Dynamics Review*, *18*(3), 315–338. doi:10.1002/sdr.258

Breiman, L. (1984). *Classification and regression trees*. Chapman & Hall.

Breiman, L. (2001). Random Forests. *Machine Learning*, *45*(1), 5–32. Retrieved from http://link.springer.com/content/pdf/10.1023/A:1010933404324.pdf

Bryant, B. P., & Lempert, R. J. (2010). Thinking inside the box: A participatory, computer-assisted approach to scenario discovery. *Technological Forecasting and Social Change*, *77*(1), 34–49. doi:10.1016/j.techfore.2009.08.002

Campbell, D. (2001). The long and winding (and frequently bumpy) road to successful client engagement: one team's journey. *System Dynamics Review*, *17*(3), 195–215. doi:10.1002/sdr.214

Dixon, L., Lempert, R. J., LaTourrette, T., & Reville, R. T. (2007). The Federal Role in Terrorism Insurance. RAND Corporation. Retrieved from http://www.rand.org/pubs/monographs/MG679.html

ECB. (2010). Towards Macro-Financial Models with Realistic Characterizations of Financial Instability. *Financial Stability Review*, (December), 138–146. Retrieved from http://www.ecb.europa.eu/pub/fsr/shared/pdf/ivdfinancialstabilityreview201012en.pdf

Ernst & Young. (2010). Recover , adapt , advance - Back to business in an uncertain world. Retrieved from http://www.ey.com/Publication/vwLUAssets/Recover,_adapt,_advance:_back_to_business_in_an_uncertain_world/$FILE/Recover-adapt-advance_back-to-business-in-an-uncertain-world.pdf

Forrester, J. W. (1961). *Industrial Dynamics* (p. 479). Productivity Pr. Retrieved from http://www.amazon.com/Industrial-Dynamics-Jay-Wright-Forrester/dp/0915299887

Forrester, J. W. (1985). “The” model versus a modeling “process.” *System Dynamics Review*, *1*(1), 133–134. doi:10.1002/sdr.4260010112

Forrester, J. W. (2003). Dynamic models of economic systems and industrial organizations. *System Dynamics Review*, *19*(4), 329–345. doi:10.1002/sdr.284

Friedman, J. H., & Fisher, N. I. (1999). Bump hunting in high-dimensional data. *Statistics and Computing*, *9*, 123–143.

Groves, D. G., & Lempert, R. J. (2007). A new analytic method for finding policy-relevant scenarios. *Global Environmental Change*, *17*(1), 73–85. doi:10.1016/j.gloenvcha.2006.11.006

Hamarat, C., Kwakkel, J. H., & Pruyt, E. (2013). Adaptive Robust Design under deep uncertainty. *Technological Forecasting and Social Change*, *80*(3), 408–418. doi:10.1016/j.techfore.2012.10.004

Hodges, J. S. (1991). Six (or So) Things You Can Do with a Bad Model. RAND Corporation. Retrieved from http://www.rand.org/pubs/notes/N3381.html

Hodges, J. S., & Dewar, J. A. (1992). Is It You or Your Model Talking? RAND Corporation. Retrieved from http://www.rand.org/pubs/reports/R4114.html

Hudson, M. (2012). *THE BUBBLE AND BEYOND*. ISLET. Retrieved from http://www.amazon.co.uk/THE-BUBBLE-AND-BEYOND-ebook/dp/B009M5TBMW

Kononenko, I. (1994). Estimating attributes: Analysis and extensions of RELIEF. In F. Bergadano & L. Raedt (Eds.), *Proc. European Conf. on Machine Learning (ECML-94)* (Vol. 784, pp. 171–182). Berlin, Heidelberg: Springer Berlin Heidelberg. doi:10.1007/3-540-57868-4

KPMG. (2013). *The future of corporate reporting*. Retrieved from http://www.kpmg.com/Global/en/IssuesAndInsights/ArticlesPublications/Documents/future-of-corporate-reporting.pdf

KPMG and The Economist. (2013). Expectations of Risk Management Outpacing Capabilities - It’s Time For Action. Retrieved from http://www.kpmg.com/Global/en/IssuesAndInsights/ArticlesPublications/risk-management-outpacing-capabilities/Documents/expectations-risk-management-survey.pdf

Kwakkel, J. H., & Pruyt, E. (2013). Exploratory Modeling and Analysis, an approach for model-based foresight under deep uncertainty. *Technological Forecasting and Social Change*, *80*(3), 419–431. doi:10.1016/j.techfore.2012.10.005

Kwakkel, J. H., Walker, W. E., & Marchau, V. a W. J. (2012). Assessing the efficacy of dynamic adaptive planning of infrastructure: results from computational experiments. *Environment and Planning B: Planning and Design*, *39*(3), 533–550. doi:10.1068/b37151

Kwakkel, J. H., Walker, W. E., & Marchau, V. A. W. J. (2010). Classifying and communicating uncertainties in model-based policy analysis. *Int. J. of Technology, Policy and Management*, *10*(4), 299–315. doi:10.1504/IJTPM.2010.036918

Lempert, R. J., Bryant, B. P., & Bankes, S. C. (2008). Comparing Algorithms for Scenario Discovery. RAND Corporation. Retrieved from http://www.rand.org/pubs/working_papers/WR557.html

Lempert, R. J., Groves, D. G., Popper, S. W., & Bankes, S. C. (2006). A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios. *Management Science*, *52*(4), 514–528. doi:10.1287/mnsc.1050.0472

Lempert, R. J., Popper, S. W., & Bankes, S. C. (2003). *Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis*. (RAND, Ed.). Santa Monica, California.

Liu, H., & Motoda, H. (2007). *Computational Methods of Feature Selection*. Chapman and Hall.

Lyneis, J. M. (1980). *Corporate planning and policy design: A system dyamics approach*. Pugh-Roberts.

Miller, J. H. (1998). Active Nonlinear Tests (ANTs) of Complex Simulation Models. *Management Science*, *44*(6), 820–830. doi:10.1287/mnsc.44.6.820

Morecroft, J. D. W. (2007). *Strategic Modelling and Business Dynamics: A Feedback Systems Approach*. Chichester: John Wiley & Sons, Ltd.

Morecroft, J. D. W., Lane, D. C., & Viita, P. S. (1991). Modeling growth strategy in a biotechnology startup firm. *System Dynamics Review*, *7*(2), 93–116. doi:10.1002/sdr.4260070202

Porter, A. L., Ashton, W. B., Clar, G., Coates, J. F., Cuhls, K., Cunningham, S. W., … Thissen, W. (2004). Technology futures analysis: Toward integration of the field and new methods. *Technological Forecasting and Social Change*, *71*(3), 287–303. doi:10.1016/j.techfore.2003.11.004

Pruyt, E., & Hamarat, C. (2010a). The Concerted Run on the DSB Bank : An Exploratory System Dynamics Approach. *Proceedings of the International Conference of the System Dynamics Society*.

Pruyt, E., & Hamarat, C. (2010b). The Influenza A(H1N1)v Pandemic: An Exploratory System Dynamics Approach. *Proceedings of the International Conference of the System Dynamics Society*.

Pruyt, E., & Kwakkel, J. H. (2012). A Bright Future for System Dynamics : From Art to Computational Science and Beyond SD Modeling : Recognizing the Core and Cherishing the Diversity. *Proceedings of the International Conference of the System Dynamics Society*.

Richardson, G., & Pugh, A. L. (1981). *Introduction to System Dynamics Modeling with Dynamo*. Pegasus Communications.

Stein, P., Goland, T., & Schiff, R. (2010). Two trillion and counting. Retrieved from http://www.mspartners.org/download/Twotrillion.pdf

Sterman, J. D. (2000). *Business Dynamics: Systems Thinking and Modeling for a Complex World* (p. 1008). McGraw-Hill/Irwin. Retrieved from http://www.amazon.com/Business-Dynamics-Systems-Thinking-Modeling/dp/007238915X

Walker, W. E., Harremoes, P., Rotmans, J., Sluijs, J. P. van der, Asselt, M. B. A. van, Janssen, P., & Krauss, M. P. K. von. (2003). A Conceptual Basis for Uncertainty Management. *Integrated Assessment*, *4*(1), 5–17.

Warren, K. (2008). *Strategic Management Dynamics*. John Wiley & Sons, Ltd.

Weil, H. B. (2007). Application of system dynamics to corporate strategy: an evolution of issues and frameworks. *System Dynamics Review*, *23*(2-3), 137–156. doi:10.1002/sdr.373

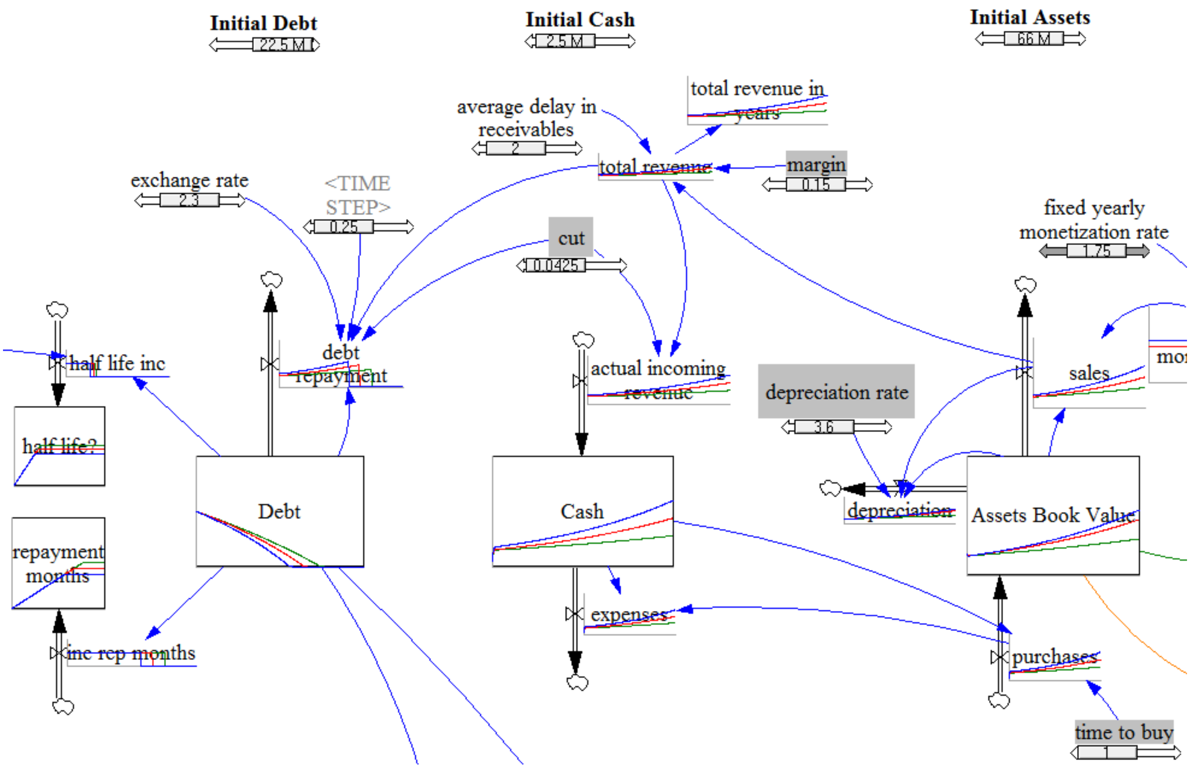
Winch, G. W., & Arthur, D. J. W. (2002). User-parameterised generic models: a solution to the conundrum of modelling access for SMEs? *System Dynamics Review*, *18*(3), 339–357. doi:10.1002/sdr.252

Yamaguchi, K. (2012). *Macroeconomic Dynamics*. On-going Draft Version 4.

APPENDIX 1

This appendix relates to section 3.1.1 and it shows the early studies made to familiarize with some EMA tools on some highly aggregated models. The evolution of the models and their behaviour can be tracked through the versions created.

Stage 1 – first model

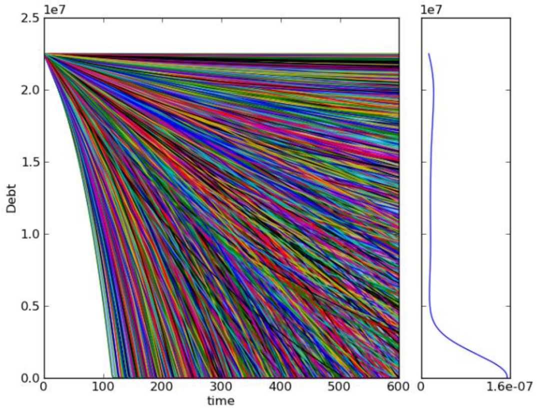


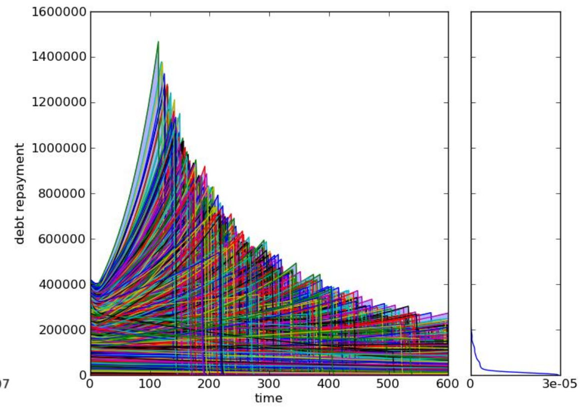
Stock-flow diagram showing structure and initial values used for the 3rd scenario: higher margin + higher monetization rate

Experiments1

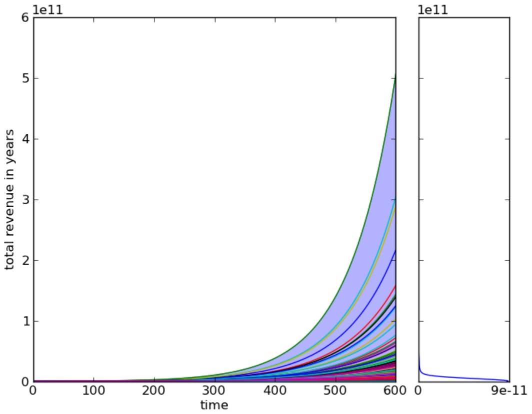
margin	0-40	%
depreciation rate	1-20	%/year
monetization rate	0-300	%/year
average delay in receivables	0,1-6	Months

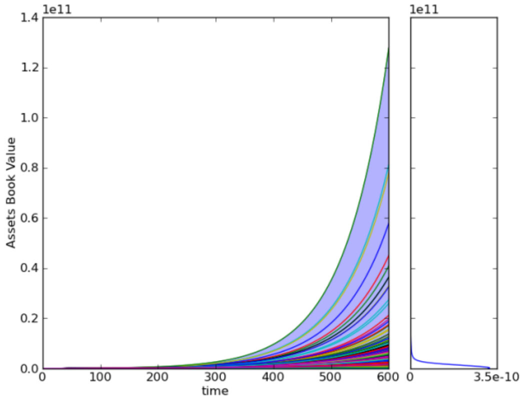
All uniformly sampled, Latin Hypercube, 2000 Runs

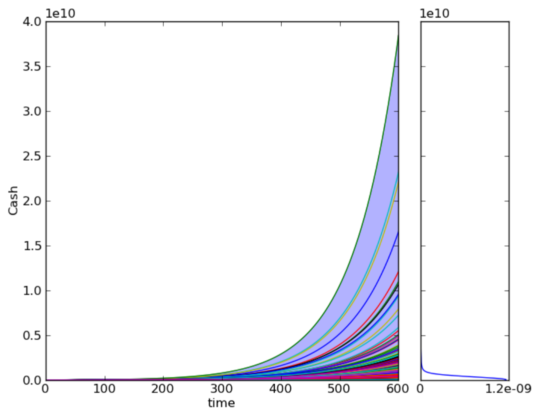


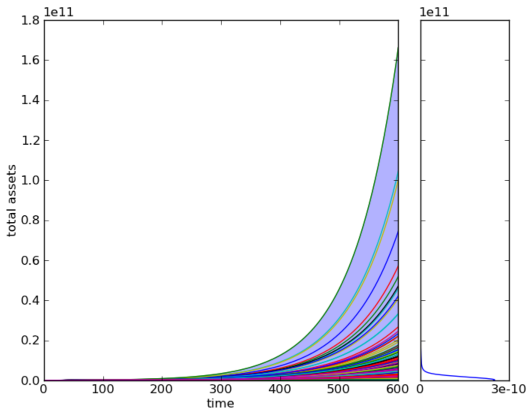


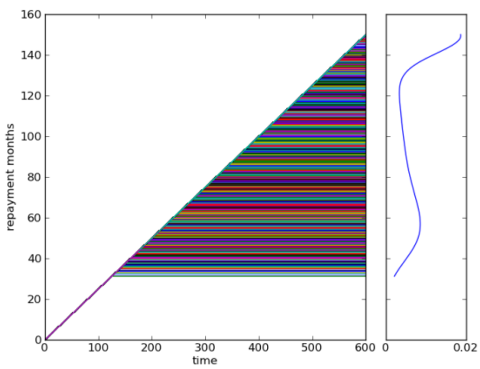
Time scale is 0-150 months (not 0-600): always divide ‘time’ by 4

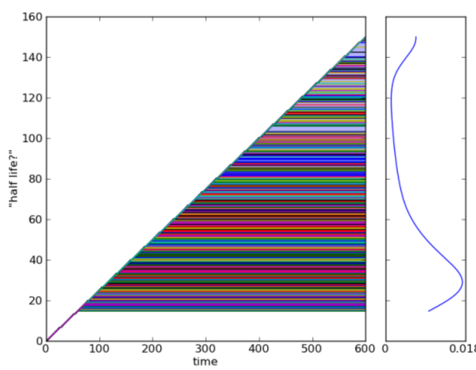












Stage 2

In this briefing the model is extended with stocks of receivables and payables. The Assets are split into Fixed Assets and Inventories. The available cash is divided between these two. For both investments there is a delay.

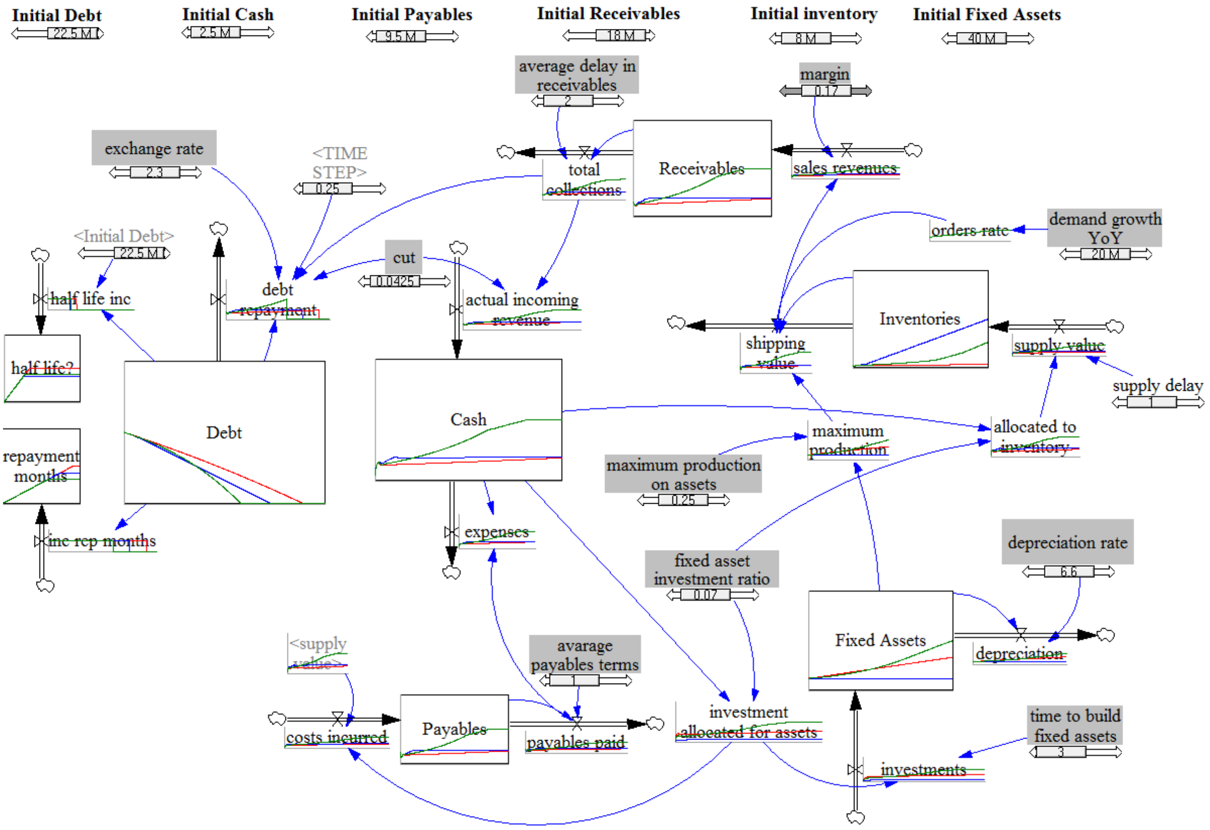


Fig1. Fixed asset investment rate: green 7%, red:0.1, blue:0.02 => Less is More!

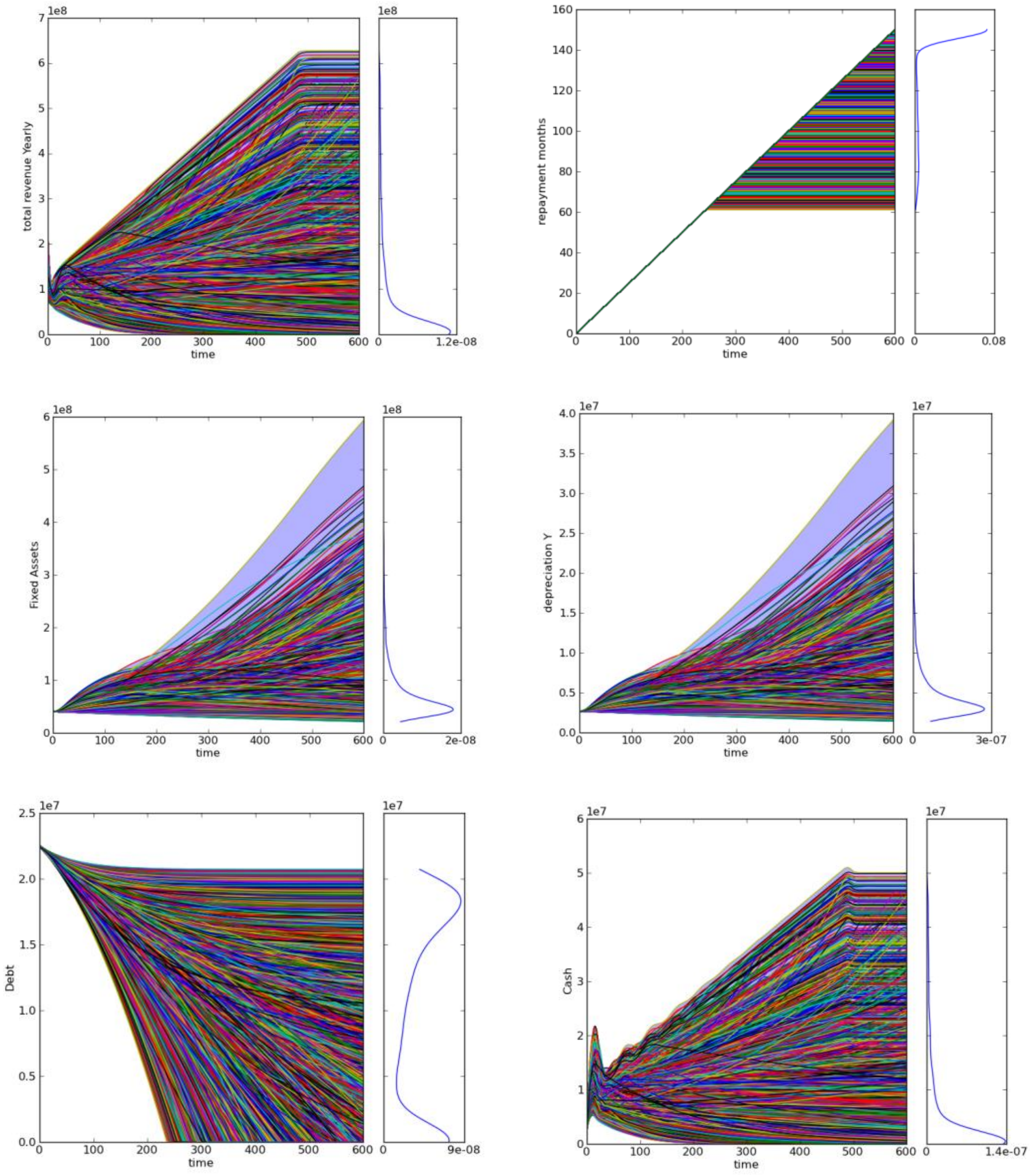
Model used in this briefing and some runs. It suggests that there is an ‘optimal mix’ of investment into assets or inventory. In practice this could mean investment into machines, wages versus using money to buy raw material for production. Both are needed, but too much spent for either of them leads to lower performance. This is because a good mix of both is needed to create the products.

Experiment 2

Initial play with the two delays related to supply and fixed assets showed that numerical sensitivity on these variables is very low if a realistic range is considered (0.1-12 months). They are left out from further analysis.

margin	1-25%
average delay in receivables	1-3Months
max production on assets	10-40%
average payables terms	1-3%
fixed asset investment ratio	1-30%
demand growth YoY	0-40million

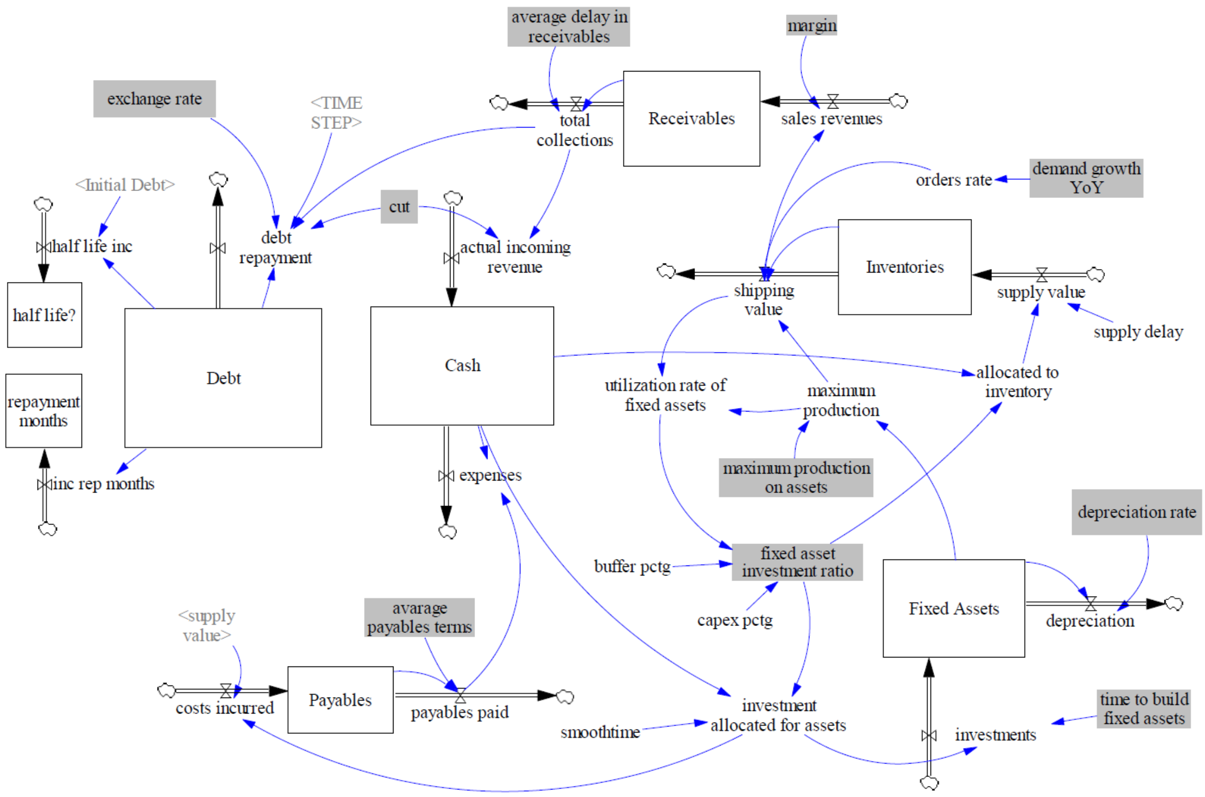
These are the parameters and ranges fed into the uncertainty analysis.

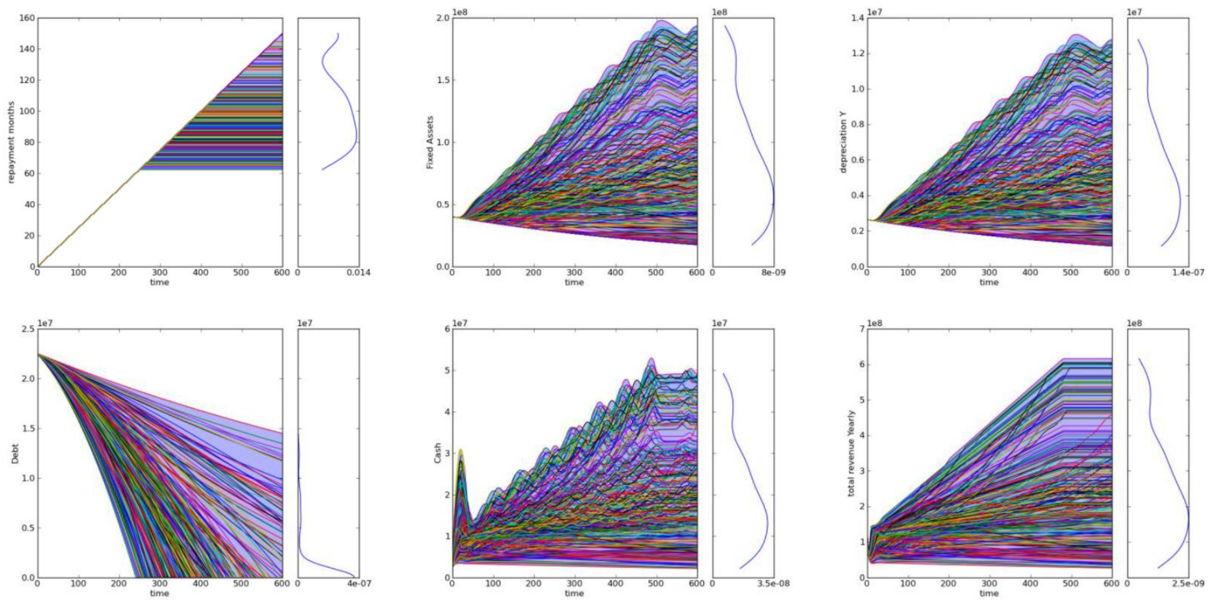


In this first experiment 6 dimensions were considered and a plausible range was taken. Graphs show that most of the scenarios end up in a default.

Stage 3

Here the model from briefing 2 is slightly modified to try out 2 possible rules of thumb that the company might use to optimize its cash allocation.





APPENDIX 2

This appendix relates to section 3.1.1. In the table below the questions prepared for the interview with the equity research analyst are shown. Many of them could be answered by the analyst, a few of them by the CEO and some of them were left unanswered. Even so they helped to build a reasonably realistic model for the first case.

Topic	Question to ask	Possible follow-up question (if significant)	Goal	Whom to ask?	Answer's expected unit
Inventory management and production	What is your current inventory volume?	detailed on different inventories?	get initial value	Production department manager(s) + financial dep.	tons
	Are there any flow rate records available?	like aquisitions, production, shipping rates	get historical data to back up soft data		tons/(day or week or month)
	How do you decide on replenishing raw materials inventory? based on what information?	open questions with many possible follow-up questions	get insight into existing/future policies		soft data
	What could constrain the aquisition?	delays in decision-making or shipping?	see if there could be significant delays and/or extreme situations		soft data + time delays
	How is the production rate planned?	How is the work organized?	get insight into existing/future policies		soft data
	What determines the actual production rate?	what could constrain it?	get insight into existing/future policies, also in extreme conditions		soft data
	What is your maximum inventory capacity now?		see the utilization of space and possible needs for expansion		tons
	How do you plan to extend it when you run out of space?				soft data
	How much would it cost to extend / tons?		needed for cost forecasts		Tlira/tons
	What are the costs related to inventories and their management?		needed for cost forecasts		Tlira/something
	Who else is using the information you report	and for what decision?	decisions in other parts of the company		soft data
	Do you experience fluctuations in inventory levels, production or aquisition rates?	what's the reason for that?	double-checking validation question		description of dynamics
Workforce and hiring	What is the current workforce?	machine type or whatever classification	get initial value	workforce manager(s) + finance dep.	# of employees
	How do you decide on hiring new people? Based on what information?	where will those additional people be hired?	get insight into existing/future policies		soft data
	How often do you adjust the workforce?	based on a rule of thumb, or based on need? Or a mix of the two?	get decision parameters		soft data + time delays
	How much flexibility do you have for extra work hours before hiring more?	any extra costs?			%
	What constrains the hiring?	cash balance, manpower shortage, etc?	check decisions in extreme conditions		soft data
	What are the costs of hiring/firing?		needed for cost forecasts		Tlira/person
	productivity associated?	how much time and money does it cost?			soft data+costs+delays
	Is worker productivity measured/monitored/managed?	are there records?	get insight into existing/future policies		soft data+ tons/month/employee
	do workers switch btw facilities sometimes?				
	Do you experience significant fluctuations in employees/working hours?	what's the reason for that?	double-checking validation question		description of dynamics
Equipment aquisition and maintenance	Current number of machines?	detailed on different types?	get initial value	Technical department manager(s) + finance dep.	# of machines
	are there aquisition records?		get historical data to back up soft data		machines bought/month
	What is the utilization rate? Are there records?				%
	What is the maximum productivity of machines?	what is it for new machines? Is it fully used?			tons/month/machine
	How do you decide on new aquisitions/outsourcing?				soft data
	What are the constrainst on new aquisitions? or on outsourcing?	quality? How is it decided?			soft data
	what are the delays in aquisitions/outsourcing?				time delays
	Is there maintenance performed? Why?	What effect does it have? What costs?			soft data+Tlira/month
	how much wear and tear is experienced?				capacity decrease or cost increase
	How and when do you dispose of machines?	could you sell it? at what price?			soft data+price

APPENDIX 3

This appendix relates to section 3.1.4 and it contains the complete settings for the experiments performed in the section.

Experiment Set 1: Sensitivity, variables and 10% ranges

15000,L,1234,,0
exchange rate=RANDOM_UNIFORM(2.07,2.53)
tax rate=RANDOM_UNIFORM(0.18,0.22)
orders increase rate=RANDOM_UNIFORM(36,44)
raw material inventory coverage=RANDOM_UNIFORM(0.45,55)
time to adjust raw material inventory=RANDOM_UNIFORM(0.9,1.1)
basic raw material price=RANDOM_UNIFORM(1170,1430)
raw material delivery delay=RANDOM_UNIFORM(0.9,1.1)
production update time=RANDOM_UNIFORM(0.225,0.275)
inventory coverage finished products=RANDOM_UNIFORM(0.315,0.385)
term length=RANDOM_UNIFORM(10.8,13.2)
average equipment life=RANDOM_UNIFORM(18,22)
ambition level=RANDOM_UNIFORM(0.9,1.1)
implied productivity increase=RANDOM_UNIFORM(0.072,0.088)
time to adjust workforce=RANDOM_UNIFORM(1.8,2.2)
max machines that can be rented=RANDOM_UNIFORM(13.5,16.5)
time to adjust capital equipment=RANDOM_UNIFORM(1.8,2.2)
delay in equipment aquisition and installation=RANDOM_UNIFORM(5.4,6.6)
new equipment's productivity=RANDOM_UNIFORM(27,33)
scrapped equipment's productivity=RANDOM_UNIFORM(18,22)
margin=RANDOM_UNIFORM(0.144,0.176)
cut=RANDOM_UNIFORM(0.03825,0.04675)
equipment cost=RANDOM_UNIFORM(280800,343200)
average debt terms=RANDOM_UNIFORM(54,66)
depreciation rate=RANDOM_UNIFORM(5.94,7.26)
energy costs per ton=RANDOM_UNIFORM(179.1,218.9)
overhead per ton=RANDOM_UNIFORM(81,99)
inflation=RANDOM_UNIFORM(0.045,0.055)
inflation multiplier for payroll increase=RANDOM_UNIFORM(1.8,2.2)
fpp payable terms=RANDOM_UNIFORM(4.5,5.5)
fpp receivable terms=RANDOM_UNIFORM(99,121)
payment terms big client init=RANDOM_UNIFORM(6.3,7.7)

Output of PRIM1: repayment months < 90, density threshold 0.8, mass threshold 0.05;

box	mean	mass	coverage	density	res dim
1	0.93	0.051	0.31	0.93	7
rest	0.11	0.95	0.69	0.11	0

uncertainty	box 1 min		box 1 max	rest box min		rest box max
margin	0.17	-	0.18	0.14	-	0.18
ambition level	0.90	-	0.98	0.90	-	1.10
new equipment's productivity	28.28	-	33.00	27.00	-	33.00
orders increase rate	36.00	-	42.45	36.00	-	44.00
cut	0.04	-	0.05	0.04	-	0.05
energy costs per ton	179.10	-	216.62	179.10	-	218.90
tax rate	0.18	-	0.22	0.18	-	0.22

Output of PRIM2: repayment months >120, density threshold 0.8, mass threshold 0.05

1	0.91	0.49	0.65	0.91	6
2	0.82	0.051	0.062	0.82	9
rest	0.43	0.46	0.29	0.43	0

uncertainty	box 1		box 2		rest box	
	min	max	min	max	min	max
margin	0.14 -	0.16	0.14 -	0.17	0.14 -	0.18
ambition level	0.94 -	1.10	0.92 -	1.10	0.90 -	1.10
fpp receivable terms	99.01 -	121.00	99.00 -	121.00	99.00 -	121.00
new equipment's productivity	27.00 -	33.00	27.00 -	30.71	27.00 -	33.00
exchange rate	2.07 -	2.53	2.07 -	2.46	2.07 -	2.53
cut	0.04 -	0.05	0.04 -	0.05	0.04 -	0.05
max machines that can be rented	13.50 -	16.50	13.50 -	16.37	13.50 -	16.50
equipment cost	280802.00 -	343198.00	289915.50 -	343198.00	280802.00 -	343198.00
tax rate	0.18 -	0.22	0.18 -	0.22	0.18 -	0.22
orders increase rate	36.00 -	44.00	38.10 -	44.00	36.00 -	44.00

Experiment Set 2 (E2)

All variables, plausible ranges

15000,L,1234,,0
exchange rate=RANDOM_UNIFORM(1.8,2.8)
tax rate=RANDOM_UNIFORM(0.18,0.22)
orders increase rate=RANDOM_UNIFORM(0,50)
raw material inventory coverage=RANDOM_UNIFORM(0.3,0.7)
time to adjust raw material inventory=RANDOM_UNIFORM(0.5,2)
basic raw material price=RANDOM_UNIFORM(1000,1600)
raw material delivery delay=RANDOM_UNIFORM(0.5,2)
production update time=RANDOM_UNIFORM(0.15,0.5)
inventory coverage finished products=RANDOM_UNIFORM(0.2,0.5)
term length=RANDOM_UNIFORM(6,18)
average equipment life=RANDOM_UNIFORM(17,25)
ambition level=RANDOM_UNIFORM(0.8,1.2)
implied productivity increase=RANDOM_UNIFORM(0,0.08)
time to adjust workforce=RANDOM_UNIFORM(1,2.5)
max machines that can be rented=RANDOM_UNIFORM(10,20)
time to adjust capital equipment=RANDOM_UNIFORM(1,6)
delay in equipment aquisition and installation=RANDOM_UNIFORM(4,7)
new equipment's productivity=RANDOM_UNIFORM(27,33)
scrapped equipment's productivity=RANDOM_UNIFORM(18,22)
margin=RANDOM_UNIFORM(0.1,0.21)
cut=RANDOM_UNIFORM(0.02,0.1)
equipment cost=RANDOM_UNIFORM(280000,380000)
average debt terms=RANDOM_UNIFORM(54,66)
depreciation rate=RANDOM_UNIFORM(4,8)
energy costs per ton=RANDOM_UNIFORM(180,240)
overhead per ton=RANDOM_UNIFORM(81,99)
inflation=RANDOM_UNIFORM(0.02,0.08)
inflation multiplier for payroll increase=RANDOM_UNIFORM(1,2.5)
fpp payable terms=RANDOM_UNIFORM(5,150)
fpp receivable terms=RANDOM_UNIFORM(70,150)
payment terms big client init=RANDOM_UNIFORM(7,45)

PRIM settings

E2B (20000 runs) repayment months >120

box	mean	mass	coverage	density	res dim
1	0.93	0.49	0.6	0.93	7
2	0.94	0.055	0.069	0.94	10
3	0.85	0.052	0.059	0.85	9
rest	0.51	0.4	0.27	0.51	0

uncertainty	box 1		box 2		box 3		rest box	
	min	max	min	max	min	max	min	max
margin	0.10 -	0.15	0.10 -	0.20	0.10 -	0.21	0.10 -	0.21
average equipment life	17.00 -	25.00	17.00 -	25.00	17.00 -	25.00	17.00 -	25.00
orders increase rat	0.01 -	50.00	15.75 -	50.00	10.15 -	50.00	0.00 -	50.00
ambition level	0.80 -	1.20	1.08 -	1.20	1.03 -	1.20	0.80 -	1.20
fpp receivable terms	70.01 -	150.00	70.00 -	150.00	70.00 -	150.00	70.00 -	150.00
exchange rate	1.80 -	2.80	1.80 -	2.64	1.80 -	2.80	1.80 -	2.80
time to adjust raw material inven	0.50 -	2.00	0.50 -	2.00	0.93 -	2.00	0.50 -	2.00
delay in equipment aquisition and	4.00 -	7.00	4.00 -	7.00	4.13 -	7.00	4.00 -	7.00
term length	6.00 -	18.00	6.00 -	18.00	6.60 -	18.00	6.00 -	18.00
inflation multiplier for payroll i	1.00 -	2.50	1.00 -	2.43	1.00 -	2.50	1.00 -	2.50
inflation	0.02 -	0.08	0.02 -	0.08	0.02 -	0.08	0.02 -	0.08
time to adjust capital equipment	1.00 -	6.00	1.00 -	5.51	1.00 -	6.00	1.00 -	6.00
basic raw material price	1000.02 -	1599.98	1000.02 -	1566.34	1000.02 -	1599.98	1000.02 -	1599.98
equipment cost	280003.00 -	379998.00	280003.00 -	379998.00	289789.50 -	379998.00	280003.00 -	379998.00
fpp payable terms	5.00 -	150.00	5.00 -	142.01	5.00 -	150.00	5.00 -	150.00
raw material delivery delay	0.50 -	2.00	0.60 -	2.00	0.50 -	2.00	0.50 -	2.00
energy costs per ton	180.00 -	240.00	180.00 -	240.00	183.23 -	237.08	180.00 -	240.00

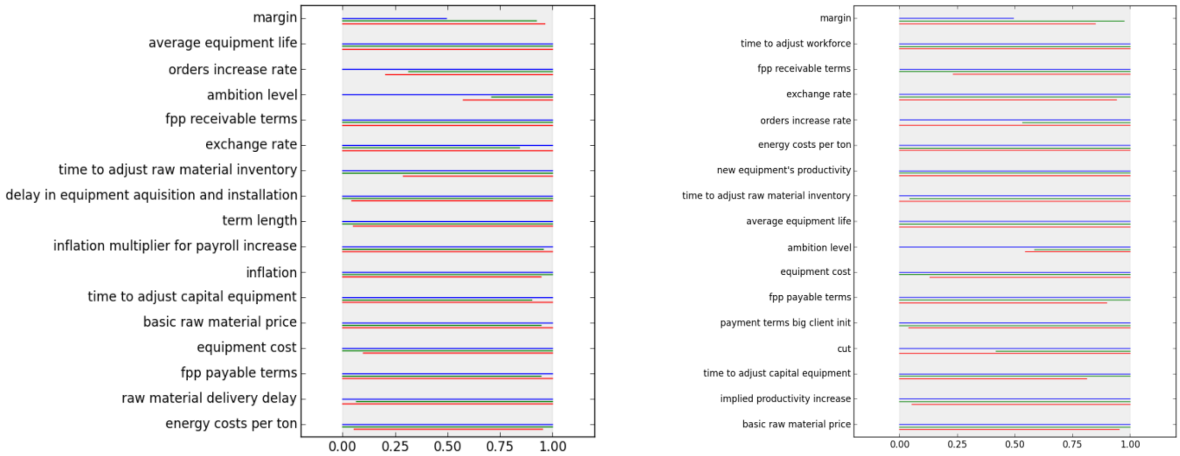


Figure shows the difference between working with 20k or 25k runs with the same PRIM settings.

E2BB (25000 runs) repayment months >120, almost the same as above

box	mean	mass	coverage	density	res dim
1	0.93	0.49	0.61	0.93	9
2	0.98	0.053	0.069	0.98	5
3	0.86	0.05	0.057	0.86	10
rest	0.5	0.4	0.27	0.5	0

uncertainty	box 1		box 2		box 3		rest box	
	min	max	min	max	min	max	min	max
margin	0.10 -	0.15	0.10 -	0.21	0.10 -	0.19	0.10 -	0.21
time to adjust workforce	1.00 -	2.50	1.00 -	2.50	1.00 -	2.50	1.00 -	2.50
fpp receivable terms	70.01 -	150.00	70.00 -	150.00	88.59 -	150.00	70.00 -	150.00
exchange rate	1.80 -	2.80	1.80 -	2.80	1.80 -	2.74	1.80 -	2.80
orders increase rate	0.01 -	50.00	26.70 -	50.00	0.00 -	50.00	0.00 -	50.00
energy costs per ton	180.00 -	240.00	180.00 -	240.00	180.00 -	240.00	180.00 -	240.00
new equipment's productivity	27.00 -	33.00	27.00 -	33.00	27.00 -	33.00	27.00 -	33.00
time to adjust raw material inven	0.50 -	2.00	0.57 -	2.00	0.50 -	2.00	0.50 -	2.00
average equipment life	17.00 -	25.00	17.00 -	25.00	17.00 -	25.00	17.00 -	25.00
ambition level	0.80 -	1.20	1.03 -	1.20	1.02 -	1.20	0.80 -	1.20
equipment cost	280002.00 -	379998.00	280002.00 -	379998.00	293160.00 -	379998.00	280002.00 -	379998.00
fpp payable terms	5.00 -	150.00	5.00 -	150.00	5.00 -	135.35	5.00 -	150.00
payment terms big client init	7.00 -	45.00	7.00 -	45.00	8.48 -	45.00	7.00 -	45.00
cut	0.02 -	0.10	0.05 -	0.10	0.02 -	0.10	0.02 -	0.10
time to adjust capital equipmen	1.00 -	6.00	1.00 -	6.00	1.00 -	5.06	1.00 -	6.00
implied productivity increase	0.00 -	0.08	0.00 -	0.08	0.00 -	0.08	0.00 -	0.08
basic raw material price	1000.01 -	1599.99	1000.01 -	1599.99	1000.01 -	1571.20	1000.01 -	1599.99

E2B repayment months <72, mass limit 0.01

box	mean	mass	coverage	density	res dim
1	0.92	0.01	0.14	0.92	13
2	0.83	0.01	0.12	0.83	13
rest	0.051	0.98	0.74	0.051	0

uncertainty	box 1		box 2		rest box	
	min	max	min	max	min	max

margin	0.17 -	0.21	0.17 -	0.21	0.10 -	0.21
cut	0.06 -	0.09	0.06 -	0.10	0.02 -	0.10
ambition level	0.80 -	1.00	0.80 -	1.00	0.80 -	1.20
basic raw material price	1267.81 -	1599.98	1184.15 -	1567.40	1000.02 -	1599.98
orders increase rate	1.79 -	33.98	0.00 -	29.81	0.00 -	50.00
time to adjust raw material inventory	0.50 -	1.63	0.50 -	1.93	0.50 -	2.00
equipment cost	289419.00 -	379998.00	280003.00 -	375126.50	280003.00 -	379998.00
fpp payable terms	18.15 -	150.00	17.12 -	150.00	5.00 -	150.00
max machines that can be rented	10.39 -	19.75	10.00 -	20.00	10.00 -	20.00
time to adjust capital equipment	1.30 -	6.00	1.20 -	6.00	1.00 -	6.00
delay in equipment aquisition and installation	4.00 -	6.82	4.00 -	7.00	4.00 -	7.00
inflation multiplier for payroll increase	1.07 -	2.50	1.00 -	2.50	1.00 -	2.50
inflation	0.02 -	0.08	0.02 -	0.08	0.02 -	0.08
depreciation rate	4.00 -	8.00	4.22 -	7.70	4.00 -	8.00
exchange rate	1.80 -	2.80	1.80 -	2.76	1.80 -	2.80
implied productivity increase	0.00 -	0.08	0.00 -	0.08	0.00 -	0.08
fpp receivable terms	70.00 -	150.00	70.00 -	131.73	70.00 -	150.00

E2B repayment months <72, mass limit 0.001

box	mean	mass	coverage	density	res dim
1	1	0.0049	0.072	1	13
2	1	0.0041	0.061	1	13
3	1	0.0027	0.039	1	14
4	1	0.0034	0.051	1	16
5	1	0.0019	0.029	1	18
6	0.98	0.0021	0.03	0.98	21
rest	0.05	0.98	0.72	0.05	0

E2B repayment months <72, mass limit 0.005

box	mean	mass	coverage	density	res dim
1	0.99	0.0078	0.11	0.99	13
2	0.94	0.005	0.069	0.94	17
3	0.97	0.0054	0.077	0.97	15
4	0.82	0.0052	0.062	0.82	17
rest	0.047	0.98	0.68	0.047	0

E2B <72, mass0.005, density 0.6

box	mean	mass	coverage	density	res dim
1	0.99	0.0078	0.11	0.99	13
2	0.94	0.005	0.069	0.94	17
3	0.97	0.0054	0.077	0.97	15
4	0.82	0.0052	0.062	0.82	17
5	0.71	0.0052	0.054	0.71	18
6	0.67	0.0051	0.05	0.67	17
rest	0.04	0.97	0.57	0.04	0

Experiment 3 (Robust Optimization)

Ranges for the policy levers: *'Hypothetical extra loan'*:(0, 5000000) and *'cut'*:(0.01, 0.11)

Settings for the genetic algorithms, **Small Run**:
cases=1000,
nr_of_generations=15,
pop_size=40,
crossover_rate=0.5,
mutation_rate=0.01,

Big Run:
cases=30,
nr_of_generations=100,
pop_size=120,
crossover_rate=0.7,
mutation_rate=0.05,

The uncertainties considered were:

ParameterUncertainty((1.8, 2.8), *"exchange rate"*),
ParameterUncertainty((0.1, 0.21), *"margin"*),
ParameterUncertainty((0.02, 0.8), *"inflation"*),
ParameterUncertainty((0, 50), *"orders increase rate"*),

ParameterUncertainty((10, 20), "max machines that can be rented"),
ParameterUncertainty((280000, 380000), "equipment cost"),
ParameterUncertainty((180000, 240000), "energy costs per ton"),
ParameterUncertainty((1000, 1600), "basic raw material price"),
ParameterUncertainty((4, 150), "fpp payable terms"),
ParameterUncertainty((70, 150), "fpp receivable terms")]

Experiment Set 4 (ESB2)

20000,L,1234,,0
exchange rate=RANDOM_UNIFORM(1.8,2.8)
equipment cost=RANDOM_UNIFORM(280800,360000)
basic raw material price=RANDOM_UNIFORM(1000,1600)
max machines that can be rented=RANDOM_UNIFORM(10,20)
time to adjust raw material inventory=RANDOM_UNIFORM(0.5,2)
time to adjust capital equipment=RANDOM_UNIFORM(1,6)
inflation multiplier for payroll increase=RANDOM_UNIFORM(1,2.5)
orders increase rate=RANDOM_UNIFORM(10,50)
fpp payable terms=RANDOM_UNIFORM(5,150)
fpp receivable terms=RANDOM_UNIFORM(60,150)
margin=RANDOM_UNIFORM(0.08,0.21)

PRIM <72 0.8 0.002

```
[INFO/MainProcess] 20000 point remaining, containing 251 cases of interest
box         mean      mass  coverage   density   res dim
1           0.97    0.0031      0.24      0.97         8
2           0.82    0.0022      0.15      0.82         8
rest      0.0077      0.99      0.61    0.0077         0


uncertainty                                 box 1                    box 2                    rest box
                                              min          max         min          max          min          max
basic raw material price                  1511.02 -    1599.18     1429.68 -    1598.76      1000.02 -    1599.98
margin                                       0.18 -       0.21        0.19 -       0.21         0.08 -       0.21
orders increase rate                        33.84 -      48.46       36.51 -      48.63        10.00 -      50.00
fpp payable terms                           67.34 -     150.00       21.91 -     144.21         5.00 -     150.00
time to adjust raw material inventory        0.50 -       1.37        0.50 -       1.39         0.50 -       2.00
exchange rate                                1.90 -       2.80        1.80 -       2.80         1.80 -       2.80
time to adjust capital equipment             1.43 -       6.00        1.60 -       6.00         1.00 -       6.00
equipment cost                          280802.00 -  357701.00   281420.00 -  357284.75    280802.00 -  359998.00
fpp receivable terms                        60.00 -     150.00       60.00 -     108.30        60.00 -     150.00
```

PRIM >120 0.8 0.01

```
[INFO/MainProcess] 20000 point remaining, containing 13642 cases of interest
box         mean      mass  coverage   density   res dim
1           0.82      0.77      0.92      0.82         2
2           0.95     0.011     0.015      0.95        10
3           0.88      0.01     0.013      0.88         6
rest        0.17      0.21     0.051      0.17         0


uncertainty                          box 1                    box 2                    box 3                    rest box
                                       min          max         min          max         min          max         min          max
margin                                0.08 -       0.18        0.08 -       0.21        0.08 -       0.20        0.08 -       0.21
orders increase rate                 10.00 -      50.00       38.68 -      50.00       33.86 -      50.00       10.00 -      50.00
equipment cost                   280802.00 -  359998.00   293841.55 -  359998.00   280802.00 -  359998.00   280802.00 -  359998.00
exchange rate                         1.80 -       2.80        1.80 -       2.75        1.80 -       2.80        1.80 -       2.80
inflation multiplier for payroll  1.00 -       2.50        1.14 -       2.42        1.00 -       2.43        1.00 -       2.50
fpp receivable terms                 60.00 -     150.00       74.97 -     150.00       60.00 -     150.00       60.00 -     150.00
fpp payable terms                     5.00 -     150.00        5.00 -      98.14        5.00 -      74.07        5.00 -     150.00
basic raw material price           1000.02 -    1599.98     1000.02 -    1599.98     1000.02 -    1408.22     1000.02 -    1599.98
time to adjust capital equipment  1.00 -       6.00        1.00 -       5.58        1.00 -       6.00        1.00 -       6.00
max machines that can be rented  10.00 -      20.00       10.00 -      19.53       10.00 -      20.00       10.00 -      20.00
time to adjust raw material invent0.50 -       2.00        1.24 -       2.00        1.03 -       2.00        0.50 -       2.00
```

PRIM <120 0.8 0.05

```
[INFO/MainProcess] 20000 point remaining, containing 6358 cases of interest
```

box	mean	mass	coverage	density	res dim
1	1	0.066	0.21	1	5
2	0.98	0.056	0.17	0.98	5
3	0.86	0.052	0.14	0.86	7
rest	0.19	0.83	0.48	0.19	0

uncertainty	box 1		box 2		box 3		rest box	
	min	max	min	max	min	max	min	max
margin	0.17 -	0.21	0.17 -	0.21	0.16 -	0.21	0.08 -	0.21
orders increase rate	10.00 -	24.77	10.00 -	30.32	10.00 -	32.33	10.00 -	50.00
fpp payable terms	32.19 -	150.00	5.00 -	150.00	5.00 -	150.00	5.00 -	150.00
basic raw material price	1107.40 -	1599.95	1049.42 -	1599.98	1000.02 -	1599.98	1000.02 -	1599.98
time to adjust raw material inventory	0.50 -	2.00	0.50 -	1.42	0.50 -	1.80	0.50 -	2.00
equipment cost	280802.00 -	359998.00	280802.00 -	359998.00	280802.00 -	351927.60	280802.00 -	359998.00
exchange rate	1.80 -	2.80	1.80 -	2.80	1.85 -	2.80	1.80 -	2.80
fpp receivable terms	60.00 -	150.00	60.00 -	145.51	60.00 -	150.00	60.00 -	150.00
time to adjust capital equipment	1.00 -	6.00	1.00 -	6.00	1.45 -	6.00	1.00 -	6.00
max machines that can be rented	10.00 -	20.00	10.00 -	20.00	10.49 -	20.00	10.00 -	20.00

APPENDIX 4

This appendix is related to section 3.2.2

Experiment 1: All variables

2000,L,1234,,0
maximum stores that can be opened a month=RANDOM_UNIFORM(0.25,2)
franchises opened per month if no cash available=RANDOM_UNIFORM(0,0.5)
time to develop new store=RANDOM_UNIFORM(2,8)
ecommerce volume grwth pctg=RANDOM_UNIFORM(0,20)
export volume growth pctg=RANDOM_UNIFORM(0,20)
time to receive shoes=RANDOM_UNIFORM(2,5)
target sales volume growth=RANDOM_UNIFORM(1,2)
base sales per sqm Franchise=RANDOM_UNIFORM(65,80)
return pctg Ecommerce=RANDOM_UNIFORM(8,12)
return pctg Franchise=RANDOM_UNIFORM(8,12)
return pctg Own=RANDOM_UNIFORM(3,10)
switch impact of inventory level Lookup=RANDOM_UNIFORM(1,8)
Brent crude oil price index growth=RANDOM_UNIFORM(-5,15)
fraction of oil index effect=RANDOM_UNIFORM(0.05,0.5)
fraction of cash payments in stores=RANDOM_UNIFORM(0.15,0.35)
exports receivable days=RANDOM_UNIFORM(90,270)
ecommerce receivable days=RANDOM_UNIFORM(60,180)
time to change to new payables terms=RANDOM_UNIFORM(1,6)
time to change to new rec terms=RANDOM_UNIFORM(1,6)
fraction of payments given upfront=RANDOM_UNIFORM(0.1,0.5)
later payment terms=RANDOM_UNIFORM(300,400)
inflation Europe=RANDOM_UNIFORM(1,5)
inflation Turkey=RANDOM_UNIFORM(4,6.5)

target personnel per store=RANDOM_UNIFORM(5,8)
targeted wage growth pctg=RANDOM_UNIFORM(5,12)
personnel at HQ=RANDOM_UNIFORM(70,85)
other expenses=RANDOM_UNIFORM(600000,1000000)
advertising pctg=RANDOM_UNIFORM(0.5,2)
Initial electricity costs=RANDOM_UNIFORM(450000,600000)
Initial rent per sqm per year=RANDOM_UNIFORM(95,125)
average own store size=RANDOM_UNIFORM(150,200)
average franchise store size=RANDOM_UNIFORM(130,150)
base sales per sqm Own=RANDOM_UNIFORM(85,105)
exchange rate=RANDOM_UNIFORM(1.8,2.8)
Leather price index growth=RANDOM_UNIFORM(-5,10)
credit card payment days=RANDOM_UNIFORM(40,100)

Experiment 2: A few selected

2000,L,1234,,0
switch impact of inventory level Lookup=RANDOM_UNIFORM(1,8)
fraction of payments given upfront=RANDOM_UNIFORM(0.1,0.5)
average own store size=RANDOM_UNIFORM(150,200)
base sales per sqm Own=RANDOM_UNIFORM(85,105)
exchange rate=RANDOM_UNIFORM(1.8,2.8)
Leather price index growth=RANDOM_UNIFORM(-5,10)
credit card payment days=RANDOM_UNIFORM(40,100)

PRIM <72 0.8 0.05

```
 [INFO/MainProcess] 10000 point remaining, containing 2184 cases of interest
box          mean      mass   coverage   density   res dim
1            0.95     0.051       0.22      0.95         6
rest         0.18      0.95       0.78      0.18         0

uncertainty                                    box 1              rest box
                                             min        max      min        max
exchange rate                               1.80 -      2.16     1.80 -      2.80
fraction of payments given upfront          0.10 -      0.33     0.10 -      0.50
average own store size                    171.09 -    200.00   150.00 -    200.00
switch impact of inventory level Lookup     1.00 -      5.87     1.00 -      8.00
credit card payment days                   40.00 -     85.27    40.00 -    100.00
base sales per sqm Own                     87.89 -    105.00    85.00 -    105.00
```

PRIM <72 0.8 0.02

```
[DEBUG/MainProcess] loading C:\Users\tudelft\workspace1\EMA
box          mean      mass   coverage   density   res dim
1               1     0.031       0.14         1         6
2            0.95      0.02      0.087      0.95         7
3            0.93     0.021      0.087      0.93         7
rest         0.16      0.93       0.69      0.16         0

uncertainty                            box 1               box 2               box 3               rest box
                                     min        max      min        max      min        max      min        max
exchange rate                       1.80 -      2.15     1.80 -      2.13     1.80 -      2.18     1.80 -      2.80
fraction of payments given upfront 0.10 -      0.33     0.10 -      0.28     0.10 -      0.40     0.10 -      0.50
average own store size            171.27 -    199.95   170.70 -    200.00   168.69 -    200.00   150.00 -    200.00
credit card payment days           40.00 -     76.96    40.00 -     81.75    40.00 -     93.89    40.00 -    100.00
base sales per sqm Own             92.01 -    105.00    88.25 -    105.00    89.46 -    105.00    85.00 -    105.00
switch impact of inventory level L 1.00 -      5.87     1.00 -      7.42     1.00 -      3.25     1.00 -      8.00
Leather price index growth         -5.00 -     10.00    -5.00 -      9.60    -5.00 -      9.34    -5.00 -     10.00
```

PRIM >119 0.8 0.05

[INFO/MainProcess] 10000 point remaining, containing 6893 cases of interest

box	mean	mass	coverage	density	res dim
1	0.92	0.47	0.62	0.92	4
2	0.96	0.051	0.071	0.96	7
rest	0.44	0.48	0.3	0.44	0

uncertainty	box 1		box 2		rest box	
	min	max	min	max	min	max
exchange rate	2.15 -	2.80	1.82 -	2.80	1.80 -	2.80
switch impact of inventory level Lookup	2.94 -	8.00	2.00 -	8.00	1.00 -	8.00
base sales per sqm Own	85.00 -	104.92	85.00 -	98.53	85.00 -	105.00
average own store size	150.00 -	199.99	150.00 -	176.11	150.00 -	200.00
credit card payment days	40.00 -	100.00	50.60 -	100.00	40.00 -	100.00
fraction of payments given upfront	0.10 -	0.50	0.28 -	0.50	0.10 -	0.50
Leather price index growth	-5.00 -	10.00	-2.74 -	10.00	-5.00 -	10.00

PRIM <72 0.8 0.01, FX fixed

[INFO/MainProcess] 5000 point remaining, containing 558 cases of interest

box	mean	mass	coverage	density	res dim
1	0.99	0.016	0.14	0.99	6
2	0.88	0.012	0.095	0.88	6
3	0.92	0.012	0.097	0.92	6
4	0.93	0.013	0.11	0.93	6
5	0.85	0.01	0.079	0.85	6
rest	0.057	0.94	0.48	0.057	0

uncertainty	box 1		box 2		box 3		box 4		box 5		rest box	
	min	max	min	max	min	max	min	max	min	max	min	max
average own store size	180.09 -	192.63	176.58 -	195.51	164.17 -	198.99	170.25 -	199.88	191.96 -	200.00	150.00 -	200.00
fraction of payments given upfront	0.10 -	0.27	0.11 -	0.22	0.10 -	0.24	0.10 -	0.37	0.10 -	0.32	0.10 -	0.50
switch impact of inventory level Lookup	1.00 -	4.11	1.00 -	6.02	1.00 -	7.03	1.00 -	2.68	1.20 -	3.70	1.00 -	8.00
base sales per sqm Own	93.08 -	105.00	97.70 -	105.00	99.37 -	104.88	96.62 -	105.00	92.36 -	105.00	85.00 -	105.00
credit card payment days	40.01 -	81.32	40.01 -	91.64	40.01 -	62.31	40.01 -	78.78	40.01 -	90.23	40.01 -	99.99
Leather price index growth	-5.00 -	8.67	-5.00 -	6.89	-5.00 -	7.37	-5.00 -	7.00	-5.00 -	8.12	-5.00 -	10.00