A Systemic Approach Framework for Operational Risk

– SAFOR –

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Abstract

This thesis attempts to describe the essential systems features of a complex real-world domain of operational risk (OR) in banking, by employing general systems theory (GST) as the guiding method. An implementational framework (SAFOR) is presented for operational risk management (ORM), the target of which is to manage and mitigate the risk-around-loss causes. Since reasoning about OR is often scenario based, the framework also includes methods for decision making in addition to Value at Risk (VaR) and Conditional Value at Risk (CVaR). Other computational models that yield prediction intervals are discussed as well. Because the banking industry is one of the most mature sectors when it comes to OR, and contains the most data points, the discussion in this thesis evolves around such institutions. The present state-of-the-art in OR management for banking is surveyed using a systemic-holistic approach and the model framework is presented against this discussion. Tools and concepts from systems theory and systems thinking are employed for assessing systems properties and gaining insights into the interaction of various components. This brings about a number of advantages. This is not in disagreement with current suggestions such as those of the Basle Committee (Basel II), which is doing an excellent job in proving the state-of-the-art in best practice for banking institutions. Rather, this thesis offers a complementary perspective, looking at essentially the same problems but in a broader context and with a differing view.

OR data has been hard to come by in banking. Confidentiality and difficulties in quantifying OR as well as the short time data has been gathered in a consistent way are some of the reasons for this. Moreover, OR is often not clearly discernible from market or credit risks and is not diversifiable. Therefore, no case study has been done. Instead, we have chosen to look into a published bank application of an advanced OR model. The application shows that the technique holds as validation of the SAFOR modules, but contrary to SAFOR the application has no discriminating interval method for decision making, nor does it say much about how to find and control correct data.

Furthermore, the term risk is a very important concept in the literature on economic, political, social and technological issues. In this thesis we mainly concentrate on ORs
and OR measures. The thesis research strategy is both explanatory and descriptive. It is explanatory since it rests mainly on literature surveys of the latest and most important research that we have found with significance for building our SAFOR model. But, the strategy is also descriptive, since the model describes a systemic approach. The concept *system* is here seen as an epistemological device to describe systems as wholes. Therefore, the systemic approach is viewed as an epistemology or a meta-science used for communication between sciences, and which at the same time states criteria for control.

In general, by meta-science is meant a formalised (simplified) linguistic model whose mechanism is the hierarchical system of concepts. Meta-science constructed in a formalised manner can go beyond general statements. It can create the natural meta-system transition, where the objects of the study formalise languages as a whole - for their syntax, their semantics and their applications to description of the reality. A meta-system transition can be used even if the exact structure of the systems involved is not known. For instance, a system of any kind can be copied with some variations, and as a result of consecutive metasystem transitions a multilevel structure of positive and negative feedback mechanisms arises. These feedbacks create understanding for the needed balance between development and control, which are the two main functions involved in the survival of a system.

Moreover, this systemic approach asks for interdisciplinary competence. For example, it is important that the project leader, the senior management and the board of directors understand the relation between the different areas, such as Information Technology (IT), security, risk transfer and finance, and how they integrate. But, it is not easy to find or educate people for such a broad competence.
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1 Introduction

This thesis deals with systems theory and its applications to a real-world domain – the domain of operational risk (OR) in banking. It is an attempt to capture and describe essential system features of a complex domain by employing general systems theory (GST) as a guiding method. It structures and compiles OR knowledge and methods for handling OR under a systemic\(^1\) umbrella, called *A Systemic Approach Framework for Operational Risk* (SAFOR) synthesised in Chapter 9. The domain was chosen because the author has spent more than 30 years working in banking, as a credit manager at one of the four big banks in Sweden.

OR has always existed in business, but the developments in information technology (IT) and risk management tools in recent years have specifically forced the actuaries (mathematicians and statisticians) in insurance to be more engaged in this sort of risk. But, today both financial and non-financial businesses are studying OR to uncover the risks of future process failings and to develop solutions. With the information and available resources the objectives of the business processes can then be managed to reach *acceptable* results.

Furthermore, shareholders and regulators have gradually asked for more risk information about organisations. Accordingly, a new comprehensive risk management approach is developing, where the trend is towards strategic risks and ORs, instead of seeing the risks in isolation, as hazards or financial risks. This new management framework is called enterprise risk management (ERM) [185], [186], [187]. ERM is then further divided into core business risk and OR, which in turn is also subdivided. In this thesis, we focus on the OR part. A common definition of OR is not yet established, but there is a significant definition prescribed by regulators, and which has to be used for regulatory purposes in financial institutions. This definition of the OR is: *The risk of loss resulting from inadequate or failed internal processes, people and systems or from external events* [112] (Basel II\(^2\)). It is important to note that for management objectives this definition is not sufficiently comprehensive. Management

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1 See Footnotes 3 and 56.
2 Basel II is described in Section 3.2.
must also investigate risks like strategic and reputational ones as well as systemic risks\textsuperscript{3}.

In regard to OR regulation in financial industries, the further OR categorisation is based on the causes of losses. These OR categories concern how a business operates, which generally means the day to day operations of the firm, while the core business risks concern what a business is, i.e., the overall strategy [185], [187], [188].

Many financial regulators have recommended different degrees of the ERM processes in their guidelines, e.g., the Turnbull Report, the Basle Committee (Basel II), and the Australian/New Zealand Standards\textsuperscript{4} [185]. These new guidelines also include ORs that in the last fifteen years have been shown to be an important reason for large financial disasters. Therefore, ERM\textsuperscript{5} calls for new implementation of a firm-wide risk management system. For financial institutions, like banks, credit and market risk management is already well established [1], [26], [185]. But, according to operational risk management (ORM), there is still a need for a reliable approach, especially for the banking regulators.

For a long time, the definition of risk management has been different in financial and non-financial industries. There have also been different ERM skills among different persons within a firm, and sometimes different firms have shown more interest in some ERM categories than in others. Accordingly, until recently there have been different kinds of risk managers within financial and corporate risk management, and often these people have different educations and different responsibilities. Corporate risk management traditionally asks for practical business experience and good knowledge of insurance businesses, while financial risk management calls for

\textsuperscript{3} Strategy risk deals with the existing base of a bank and its options and it is based on a what-if analysis. With strategy is meant doing the right thing at the right time ([123] p. 23). Reputational risk is all aggregated risk outcomes plus other internal and external factors. It is the mix of doing the right thing and doing things right over an extended period. For instance, it could be relative to share performance, revenue growth, number of clients’ growth and keeping good staff. ([123] p. 23). Systemic risk is defined in the financial services industry as the likelihood of a major failure or disruption in one institution or segment of the market, which may affect other institutions and lead to a breakdown of the financial system [123] (see systemic thinking, Footnote 56). The systemic approach used in the systems science is different to this financial term, but both terms emphasise the whole.

\textsuperscript{4} These three guides are related to internal business control for Institute of Insurance and Finance in England & Wales, Bank for International Settlements (BIS), Basle and Australian/New Zealand and the Asia Pacific region [185].

\textsuperscript{5} Enterprise Risk Management is defined as a systematic method of identifying, assessing, communicating, managing and monitoring risks across activities, affiliates, functions or products, in a way that will build shareholder value over the long run. [185] (See Footnote 57).
specialists who are well informed in derivative trading and can manipulate statistical models. But having these two sides of risk management can be problematic if they overlap and result in a piecemeal approach. Furthermore, banks have learnt that operational problems, which have been observed in the last fifteen years (e.g., Barings Bank⁶), can be much more dangerous than financial risks [123].

Therefore, it is important that the ORM results in a comprehension of the whole company’s structure without overlapping. Holism, which means that a system is investigated as a whole, is discussed in Chapter 2.

Specifically, until recently this uncertainty about defining and managing risks has been characteristic of the financial sector. The well-known statistical approach to risk analysis, Value at Risk (VaR), in some core business risks (e.g., credit risk and market risk), has in the international financial industry in 2005 resulted in the use of probabilistic models even for strategic decision-making and OR⁷. This is even though the latter approaches are still under development and not yet proven in practical terms. But, how the evaluation of larger ORs in banking should be managed is seldom described in the literature. Using a systemic approach to OR, and how larger ORs might be evaluated and prevented, is further discussed in Chapter 4.

**Research Strategy**

Our research strategy is both explanatory and descriptive. We seek to explain situations and relationships among different phenomena where enough research already exists for studying details, but only a little research has been done with reference to OR in banking. Indeed, our thesis rests mainly on literature studies. But, our strategy is also to describe a systemic-holistic approach as a communication between sciences. For such an OR approach to be viable it is necessary that the project leader understands the relations and co-operations between the different areas. Therefore, we first give some overview explanations, with literature references, of what is included in our different SAFOR modules. Then, Chapter 9 synthesises our suggested framework for an OR implementation.

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⁶ Barings Bank was Britain’s oldest merchant bank. It collapsed in February 1995. Over a few days, the bank went from apparent strength to bankruptcy. It was a single trader in a small office in Singapore who caused the failure.

⁷ see http://support.sas.com/papers/sug30/opriskvar
1.1 OR Management

ORM is a whole business process, including risk analyses and risk mitigation processes. It works in a closed loop for identifying and controlling hazards at all levels of the firm and its purpose is to lower risks to acceptable levels [187]. A business risk analysis includes the identification of the assets, the threats, the level of business impact of realised threats and the vulnerabilities in the protection. The business purpose of the risk mitigation process is to reduce vulnerability through suitable controls on individual loss events, after considering such things as security and costs [106]. These controls can be both technical and procedural and must be integrated into the whole organisation, since it is important to know what might go wrong for the business process [125]. Chapter 3 describes the Basel II proposal for ORM in banking.

The discipline used for such an approach is called information systems (IS). IS is concerned with the development, use, application and influence of the information in the system and is a technological implementation for recording, storing, and disseminating linguistic expressions, as well as for drawing conclusions from the information. In this discipline information is protected by six security measures; availability, utility, integrity\(^8\), authenticity, confidentiality and possession. Traditionally, IS has been used in programming, but today IS even includes the system environment. By data integrity is meant the quality of correctness, completeness and compliance with the intention of the data producer. Implications of this approach are discussed in Chapter 5.

Accordingly, if we look into ORs as IS, we have to start with classifying these systems into business risks. These risks can be fire, fraud, error, delay, service interruption and so on, and they can vary much in degree, from small to large. Therefore, the analysis must be carefully accomplished to find out the implied estimate of the risks. If the IS is incorrectly analysed, it can cause service and operating problems as well as sabotage or malicious interference [106].

Indeed, integrity of information is different in different business systems. Therefore, it is important to understand what is meant by security, which only has meaning in

\(^8\) Integrity is related to integer (whole, complete). It comprises several contents, e.g., integrity in modern ethics, the law, science, mathematics and other integrities. For more details see en.wikipedia.org/Information System.
relation to something that is valuable, at risk, and needs to be secured. This means that security can only be understood after a closed risk analysis. GST, described in Chapter 2, proposes that the risk analysis should be independent of the actual workflow. An approach from a high level should therefore be used for reaching an indicated estimate of the risk in the whole business [110].

In all businesses there is unpublished confidential information, private or secret, published information, copyright and patents that have a value, all of which require protection. Computerised IS is very sensitive to error, failure or delay, which can have serious consequences for the whole company and its employees. Therefore, it is very important that after the OR categorisation is done, all possible risks are immediately mapped.

Further it is important that OR categorisation starts with a high-level list of headings, where the proposed threats are integrated. To avoid a check-list mentality instead of creative thinking, this list of threats must not go into too much detail. Therefore, people who carry out the risk analyses have to spend considerable thought over the proposed dangers. If there is reliable statistical OR information available, threats can be assessed with the help of their expected probability. Also, the use of subjective probability can, as demonstrated in this thesis, greatly extend the applicability of such approaches.

1.2 History of ORM

Over the years, the armed forces have gradually developed the principles of managing OR. These ORM principles have then stood as models for other organisations, e.g., the manufacturing. Over the years, certain control principles for managing ORs have been devised. Today, OR development is found in all activities in society and occurs principally through experience. Only in the last five years have banks and their supervisors started to discuss analytical ORM for their activities. For a long time, the analytical ORM has been the main approach for managing OR, but this approach only reduces complex problems into parts, which can bring about the loss of important properties. Moreover, OR changes with time in the new environments and these changes are different for different organisations. But, it will take many years of OR adjustments before an acceptable ORM method can be obtained in the banking industry. This is further investigated in this thesis.
The military ORM purpose is to eliminate or diminish risks to an acceptable level. This is normally done by improving the identification of the hazards in the operational environment. Therefore, it has developed some tools for the leaders to make sound, logical decisions in order to manage future OR. Military ORM is a closed loop process, broken down into key elements and rules for managing OR. All units have the same structure, but with different specifications and implementation [123].

1.3 Recent Trends

Quite recently, some managers of larger organisations have taken a more holistic approach to the ORM process. They use the traditional analytical qualitative OR approaches together with new methods for monitoring OR and, thereby make more informed decisions. Qualitative methodologies and tools are used to identify, assess, and mitigate the level of OR and to show the effectiveness of the ORM. On the other hand, quantitative, probabilistic approaches are used to quantify OR in monetary terms, like VaR measures of credit risk or market risk, to show the efficiency of the OR. This statistical approach is described in Chapter 7.

Also some new kinds of key risk indicators have been introduced, which provide the manager with measures for continuous insight into the OR level. As soon as the key risk indicators are identified in a company, its manager can start dynamic control of its OR and store up the loss event data. The necessary integration of the key risk indicators and qualitative and quantitative risk approaches to implement a quantitative ORM process is also under development. This could then be used for calculating the capital allocation and for helping to improve the company’s overall efficiency [112]. However, these attempts do not seem to have been made from any explicit systems perspective. However, in this thesis, it is suggested that ORM can be viewed as a system-based concept. This means, for instance, that a large fraction of the operational mistakes and errors can be avoided through correctly designing the systems.

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9 See for instance Chapter 4.
10 According to Drucker ([110] p. 236): Efficiency is concerned with doing things right (= OR). Effectiveness is doing the right things (= Strategy risk).
11 With systems perspective means that all the behaviours of a system as a whole in the context of its environment is taking into account.
Chapter 1  Introduction

The systemic approach\textsuperscript{12} measures and streamlines how capital, people, and information flow into and out of the enterprise. Contrary to the analytic approach, the systemic approach emphasises the interactions and connections of the different components of a system with the main focus on its self-regulating abilities, also called cybernetics. Moreover, the systemic approach, also called systems thinking, has its origin in multiple sciences and has evolved into a discipline for understanding the operations of systems and the dynamic relations within them and between them and other systems. By using systems and creative thinking managers can learn to identify systems problems and opportunities and to determine system changes. Furthermore, by using processes and life cycle models managers can learn to act efficiently on system changes.

In the financial sector, different management programmes have been introduced at companies like General Electric and Motorola \textsuperscript{114}. There is also the recently introduced SAS OpRisk Solution\textsuperscript{13}, which includes OpRisk Monitor, OpRisk VaR, and OpRisk Global Data. However, if only external data from comparable organisations are used in the statistical models, there is a risk that managers will have no incentive to invest in internal ORM controls. The consequence could then be that the managers fail to anticipate certain internal events that may arise.

1.4 Purpose and Motivation

The main purposes of this thesis are to demonstrate:

1. The applicability of a systemic approach to a complex domain.

2. How this approach can bring knowledge to the domain.

This is done by integrating several methodological approaches into a unified framework covering a number of essential systemic aspects.

The domain selected for the study is OR and the area is the banking sector. This is mainly for two reasons. Firstly, the banking sector has established common practices for considering OR such as national regulatory supervisors (e.g., Finansinspektionen in Sweden). Secondly, there is work in progress among bank institutions to find out more globally acceptable standards (Basel II). These facts point out an area of current

\textsuperscript{12} See Footnote 57.

\textsuperscript{13} www.sas.com.
interest and focus in society. Since we use a systemic approach for implementation of our own model, we can use analogies between systems, which are well-known in GST. This means that experiences of known systems, e.g., VaR and Conditional Value at Risk (CVaR), can stand as templates for modelling OR systems. However, it is important that the model used is relevant for predicting the behaviour and life cycle of the designed organisation.

In the thesis, an implementation framework, SAFOR, for ORM in order to attain greater implementation efficiency is presented. There are several approaches developed for modelling OR, but it is not easy today to implement a comprehensive ORM. One industry sector (banking) was selected and the dominant OR approach (Basel II) reviewed. Basel II is very permissive, and does not give good guidance on which instances of each step to select. But organisations cannot simply wait for a consensus to emerge. Reasonable processes must be implemented. One such implementation framework, adaptable over time, is suggested in this thesis. This model provides a reference point that could be adopted individually and improved over time.

Consequently, we start with a systems perspective, where an implementation framework for OR management in banking is developed. Since banking is one of the most mature sectors when it comes to OR, and contains most data points, the discussion herein revolves around such institutions.

The thesis is interdisciplinary in the sense that it applies a systems perspective to implementation issues of risk handling and suggests some remedies originating from computer science (such as computational decision analysis). Although it deals with risks in banking, its reach is presumably wider since success in ORM in banking will most likely lead to changes in other large sectors in the society [123].

This is not in disagreement with Basel II, which is doing an excellent job in proving to be the “state of the art”¹⁴ in best practice for banking. Rather, this thesis offers a complementary view, looking at essentially the same problems but in a broader multi-scientific context with a systemic-holistic viewpoint.

¹⁴ The “state of the art” is the highest level of development, as of a device, technique, or scientific field, achieved at a particular time. “The state of the art shall be held to comprise everything made available to the public by means of a written or oral description, by use, or in any other way, before the date of filing of the European patent application” according to Art 54. en.wikipedia.org/wiki/State_of_the_art.
According to GST, a systemic procedure is used for important systems related problems and opportunities. This systemic procedure includes processing of energy, information or materials to obtain a product or output for further use in the system or its environment\textsuperscript{15}. In order to avoid overloading this thesis but nevertheless to give a basic understanding of how this SAFOR model works, the knowledge and information is ordered in four modules and two sub-modules that together provide a holistic view of the SAFOR. The thesis’ focus is on the use of systems thinking, where the life cycle management of systems also plays an essential part in building a learning organisation. However, the organisation must be equipped with tools, like computers, for handling complex systems and the management of change.

For many years, systems and cybernetics have used concepts and methods derived from associated research in natural sciences, such as catastrophe theory, chaos and dynamic systems, and different high-level computing applications. In the 1950s models and methods of general systems were static and did not succeed very well in reaching their objectives. But today, with better concepts, tools and methods for modelling complex and dynamic phenomena, systems thinking is much more promising. Consequently, this systemic framework, SAFOR, with its four modules and two sub-modules rests on these cybernetic principles.

Moreover, IT that includes computer science and software engineering has grown substantially in the last decade. In parallel with this, IS has evolved with focus on the development, use and impact of IT in business, society, and organisational contexts. Consequently, there has been tremendous progress in the field of IS, with extensive qualitative and quantitative research reports written on the subject. In the 1990s the management of IS (MIS)\textsuperscript{16} was broadened to include the relationship between IS and organisations as a whole. Today IS includes many issues, such as communication and collaboration between people and organisations, inter-organisational systems, electronic commerce and the Internet. This has led to a great variety of research methods and approaches for studying IS.

Accordingly, in ORM also many disciplines are involved. Therefore, to include them all at the same time in a thesis is very difficult. This is the reason why an approach has been chosen that mainly rests on literature study of the latest and most important

\textsuperscript{15} See Figure 2.2.1.
\textsuperscript{16} See Figure 2.3.1
OR research. Then, from this multitude of perspectives this SAFOR model has been developed.

The investigation starts with a systems perspective. Then a framework is developed for implementing OR handling in banking. VaR and CVaR models are discussed from this point of view. Such particular models are compiled together in an implementation model for risk handling that in all essential respects it harmonises with the Basel II.

To aid implementation, the framework not only considers and discusses the OR models, but also includes a method for decision making. This is important, since reasoning with ORs is often scenario based, and for each scenario, CVaR and other computational models yield prediction intervals, within which losses can be described. But the risk handling does not end there, since a decision has to be made regarding the actions needed to reach desired risk levels. For a finite number of scenarios (typically a small number), there has to be a discriminating principle, which makes use of specific methods and processes for its application. Section 8.1.2 describes this discriminating principle.

1.4.1 The Thesis’ Objectives

The objectives with the thesis are to:

1. develop an implementable systemic framework for OR in banking;

2. point out if the entire set of OR procedures can be used by larger industrial organisations that already use market risk VaR;

3. discuss how decision analysis and interval predictions could be used in connection with VaR and CVaR to compute OR for an internal, advanced measurement approach.

In the following of this section we describe the reasons behind the objectives in this thesis.

GST is the main method used both for identification and classification of the processes and IS, as well as for connecting the interdisciplinary applications to produce the SAFOR model. GST has its focus on the parts of an organisation and the relationship between them by connecting the parts into a whole, and it uses the same concepts and definition of an organisation, independent of the branch of science.
Therefore, it is claimed that even if VaR, CVaR, and other computational models use different methods, it is very important to connect these applications in a dynamic systemic-holistic ORM framework that is changing, moving and evolving. Such a framework is theoretically built on a conception of the firm as a system, where the OR exposures are a subsystem, which provides a more effective alternative than when each OR objects of a firm’s system is investigated separately.

In this thesis, an implementable systemic framework for ORM is developed, namely SAFOR. This is done in the context of the banking sector and its major OR framework, Basel II. Because of regulators’ growing pressure to address OR in banking sector, this is the area which has been chosen for investigation. There are several approaches developed for modelling various aspects of OR. Some of the instruments and methods useful in the analysis of the ORM are reviewed. Because of findings in the analysis of Basel II, it is also the intention to comment on whether the entire set of OR procedures can be used by larger industrial organisations that already use VaR calculating for their market risk [1], [26]. A third objective is to discuss how decision analysis and interval predictions could be used in connection with VaR and CVaR to compute OR for an internal, advanced measurement approach in accordance with Basel II.

1.4.2 Limitations

In the thesis the following limits have been imposed:

- GST appropriateness is not investigated in other risk types, e.g., market and credit risks;
- model and estimation risks are not investigated;
- a bottom-up OR approach is used at the transaction level;
- scenario analysis is to be used, when there is lack of objective data;
- risk is assessed in total by simple addition;
- no stand is taken on whether the indicator-based quantifications methods, BIA and SA, for OR quantification and calculation of the regulatory OR capital requirement (ORR) are acceptable explanatory OR variables;
• no stand is taken on whether ORR is desirable or how the OR assessment and aggregation should be done;

• an industry-wide systemic approach is not studied.

The reasons for the above mentioned limitations are further discussed in this section.

This thesis concentrates on applying a systemic approach to the implementation issues of OR. In doing this, the concentration is on conceptual and theoretical ideas, which are summarised in [183] and [184]. It is not the main purpose to investigate GST appropriateness in other domains, even if some reflections can be made based on the results in the OR domain. Nor is it on the agenda to suggest a replacement for Basel II, which is the leading OR framework at the time of writing. Rather, a complementary perspective leads to complementary insights. Model and estimation risks are not investigated specifically, only mentioned in Chapter 5, even if these topics are important. Moreover, it is pointed out in the thesis that the OR approach in the banking industry is generally bottom-up. This means that risks are measured at the transaction level and by type (credit, market and operational risks) to risk aggregates by business units and for the whole firm17. A bottom-up OR framework includes both a statistical measurement approach used for direct losses from events or accidents, and a scenario analysis derived from expert opinions and used for indirect losses related to a potentially bad future environment. Due to lack of objective data, scenario analysis uses assumptions about how often and what severity indirect losses cause. It has been shown that an identical bottom-up OR approach could be used for global banks and that this approach could also measure any OR [112], [114], [123]. Therefore, banking regulators today use risk assessments by type and in total by simple addition of the requirements to set minimum ORR. However, there are many experts who criticise this assumption of perfect dependency among risk types as unrealistic. In this thesis a stand is not taken on whether ORR, planned to start as of year-end 2007 for the advanced approaches, is desirable or how the type assessment and aggregation of banking risks should be done. This is in line with the complementary approach taken.

Applying a systemic view on the ORM processes leads to many insights. However, one important reason for using the systemic approach is to facilitate the introduction of industry-wide OR mechanisms at a later stage. Only if the individual entities are

17 See Section 5.2.
seen from a systems perspective will an industry-wide systemic view be meaningful. This is not studied in the thesis, but is mentioned in Chapter 10 as something for further study, beyond the current project.

Moreover, writing about OR in banking industry can be difficult, since beginners may find the information, without explanation of basic financial concepts, too complicated while professionals may find the specific concepts insufficiently detailed. However, this thesis tries to satisfy both groups by, on one hand, explaining concepts and providing references, and, on the other hand, incorporating details when necessary for conveying the intended message. It is not only the banking sector and the regulators that are interested in ORM, but many other areas such as securities, insurance, consulting and academics.

1.4.3 Contributions

The thesis’ contributions are:

- mainly to apply a framework with a systemic perspective on OR in banking;
- a discussion of four key implementation areas as a result from literature studies of the OR in banking;
- a discussion of a method for decision making;
- that the systemic perspective may lay ground for an investigation of the entire banking system;
- to synthesise various aspects on OR and mitigate the risk around the loss causes;
- that real applications of theories of the OR in banking are better handled with concepts intended for investigating systems, i.e., systems theory;
- by permitting a different view on the topic, pros and cons of existing approaches are discussed and synthesised in the framework.

The above mentioned contributions are discussed further in the following section.

The thesis’ main contribution is the approach of applying a systemic perspective on the complex domain of OR in banking. To that end, is developed an instrumentally meaningful framework for ORM implementation. The present “state-of-the-art” in ORM for banking is surveyed through literature studies and synthesised from a
systemic perspective and as a consequence, four key implementation areas are discussed.

With Basel II still developing, a problem is that most efforts are concentrated on improving details, while less effort has been spent in trying to see it from a more systemic-holistic perspective. As discussed above, Basel II is also very permissive and is impossible to implement directly as it is.

A model framework based on a systemic perspective is therefore presented herein as a kind of suggested reference point that can be adapted or improved individually. As mentioned above, reasoning with OR is often scenario based, therefore the framework also includes a method for decision making, where CVaR and other computational models that yield prediction intervals are discussed from this point of view. The systemic perspective might lay ground for an investigation of the entire banking system. Section 10.2 gives a short survey of the problems associated with such a future approach.

In this thesis, the target of the implementation framework is to synthesise various aspects of OR and to mitigate the risk of loss causes. To assess systemic properties and gain insights into the interaction of various components, tools and concepts from systems theory and systems thinking are employed. This brings about a number of advantages, where real applications of theories of OR in the banking industry are better handled with concepts intended for investigating systems, i.e., systems theory. By permitting a different view of the topic, pros and cons of existing approaches are also discussed and synthesised in the framework.

1.4.4 Research Methodology

This section provides a short overview of the strategies and methods applied in this thesis. These strategies and methods are then presented further and motivated in the following chapters of the work.

1.4.4.1 Research Strategies

The research approach in this thesis is based on:

- cybernetics and systems science, also called the systemic approach. This approach emphasises the interactions and connectedness of different components of a system, which is contrary to the analytic approach;
• qualitative approach, but it also uses traditional disciplines, such as mathematics;

• a classification of the research character as both deductive, for formulating the problem, and inductive for building the theory, according to how different disciplines are used;

• a classification of the research strategy as both explanatory and descriptive. Explanatory since it mainly rests on literature surveys and is descriptive, because SAFOR describes a systemic-holistic approach.

In the following section a short overview of the chosen strategies is given.

According to Robson (2002) [196], for a reliable research result it is necessary to establish a research methodology that provides a procedural framework, where already approved research strategies are used to satisfy the reliability of the research result. The research strategy can be exploratory, explanatory or descriptive. In short, an exploratory strategy is used in contexts where only little research has been done. An explanatory research strategy seeks to explain situations and relationships among different phenomena, where enough research already exists, and can be used for studying details. Descriptive research strategies try to explain problem but may not identify the causes of the behaviour.

Research character can be classified as deductive or inductive. Deductive research uses already known theories for formulating a problem, while inductive research uses specific local observations. These local data are then connected into general collected data, which are used for building theories. Due to the epistemological assumption, research can also be classified into either quantitative or qualitative knowledge. The quantitative or positivist epistemology with its origin in the natural sciences assumes objectively collected and analysed numerical data [196]. On the other hand, the qualitative approach claims that knowledge can be based on subjective experiences of experts for helping researcher to understand people’s behaviour within their social and cultural contexts. This qualitative research is also called constructivism, or interpretive research, which does not prove that there is an objective reality [196]. It is only a social construction and it is understood by investigating attitudes and behaviour. However, the qualitative research is a detailed view of a social situation and is usually more flexible for changes in the research during the study than the quantitative one, which is more formal and strict.
Our research approach is based on cybernetics and systems science, also called GST or systems research, which touches virtually all traditional disciplines, as for instance, mathematics, technology and biology as well as philosophy and the social sciences. GST is shortly described in Section 1.4.4.2 and Chapter 2. The systemic approach emphasises the interactions and connectedness of the different components of a system, which is contrary to the analytic approach. However, in practice the systemic approach focuses mainly on complex, adaptive, self-regulating systems, which are called cybernetics: information, control, feedback, communication, etc. Even if systems theory has its focus on the structure and the models of systems, and cybernetics has its focus on how they function, the two approaches will be viewed as two facets of the same investigation [197].

The applications of mathematics and cybernetics are both meta-disciplines. By meta-disciplines is meant the abstract structures and processes described and used for understanding and modelling\(^\text{18}\). They consist of models of how to build and use models, as stated by van Gigch (1986) [195]. There are, however, differences between mathematics and cybernetics. Mathematics is characterised by simplicity, regularity, and invariance and uses objective, context-independent knowledge. On the other hand, cybernetics emphasises evolution through complexity, variety and process. By a process is here meant a conceptual scheme or action characterised by a sequence of sub-actions, mostly defined in initial and final stages, which are abstractions limited in space. Moreover, contrary to mathematics the cybernetic approach uses subjective, contextual and value-dependent knowledge. It also stresses open systems with various levels and dynamic interactions between them. Today, with the use of better computer concepts and modelling of complex and dynamic facts the cybernetic approach looks very hopeful. However, it is important to note that cybernetics does not deny the value of mathematics [197].

Consequently, for building models the cybernetic approach functions as a heuristic tool, but does not exclude any other scientific method that can contain an element of trial and error in its formulation and testing of hypotheses.

Therefore, cybernetic epistemology is in essence constructivist, meaning that knowledge from the environment must be actively made context-dependent by the

\(^{18}\) See Footnote 32.
system itself. Cybernetic systems thereby tend to increase in size and complexity. However, a cybernetic system supplies guidelines for adequate modelling with the aim of limiting the complexity [197]. Accordingly, the systems research used in this thesis is mainly based on a qualitative approach. But, since the systems research also touches traditional disciplines, like mathematics, which use quantitative approaches, a mixture of quantitative and qualitative research approaches is used in the thesis.

1.4.4.2 Research Methods

The thesis’ research methods follow van Gigch’s nine principles for sub-optimisation (see below) [195]:

1. According to Basel II, OR data must be systematically recorded in different business lines across the bank. This must be done in a right and consistent way in all banks and the context must include the geographical space expressed as local, national or international. The complexity of the OR requires that models and techniques are used in combination. The aggregation of these different OR components must also ensure consistency of the various models.

2. The excesses over a predefined threshold for OR use the generalised Pareto distribution (GPD) for calculating extreme losses on the tails of the distribution.

3. The cost for the measuring can be significantly reduced by the use of thresholds, since only a fraction of the processes need to be defined for measuring an accurate OR. The thesis proposes a greater integration for a strategic OR model across all business units, using VaR and CVaR. These statistical quantification models can generate a loss distribution for each OR category or sub-category and they can also be reduced into individual business lines.

4. Bayesian and other network models can make complex information understandable through their simplified graphical presentation, if not too many details are added to the model.

5. SAFOR2 – The Valuing Risky Projects Module includes belief networks, which use probability theory for managing uncertainty and interactions among the various sources of uncertainty.

6. The systemic approach described in Chapter 2 is proposed for improving the subsystems as well as the whole system.
7. The thesis’ measuring techniques include the necessary data requirements (SAFOR1) as well as the robustness of estimation techniques (SAFOR2 and SAFOR3) and the validation methods that might be goodness-of-fit (acceptable) tests and interval estimation (SAFOR4). This is done through cybernetics.

8. Specific questions can be answered through a carefully and compliant scenario analysis. Therefore, Bayesian network modelling is a key SAFOR tool.

9. Chapter 2 points out that means and goals are not absolute. For instance can a sales subsystem have an output (a goal), which is the input (the mean) to a production subsystem.

The reasons for the chosen method are shortly described in the rest of this section.

In classical theory the economic man as a producer is assumed to be effective in maximising his utility (profit). This assumption of perfect rationality is, however, not realistic, since goals can be categorised in many different ways. For instance, Perrow (1970) [194] classifies goals as social goals, output goals, systems goals, product characteristic goals and derived goals. Social goals satisfy social needs, output goals satisfy consumers’ needs, product characteristics goals are realised in goods and services and derived goals are an organisation’s social responsibilities. However, systems goals are included in the traditional general systems theory model. Therefore, they belong to the structure and process of the system components and thereby include survival and adaptation to new environment situations as well as the rate of growth and profit, etc. It is important to note that only the system components can be optimised, rather than the total system.

Accordingly, since real-world problems are very difficult to identify and optimise, sub-optimisation, also called the next best solution, is commonly used for identifying an objective function. The systems theorist, van Gigch (1978) [195] points out nine principles for sub-optimising:

1. Criteria of lower systems must be consistent with criteria of higher systems.

2. Use of Pareto optimality, which means that sub-optimisation should be scored and ranked in accordance with the utility of each subsystem without reducing the utility of other systems or the utility of the overall system.
3. Reduce the cost for sub-optimisation through internalisation (integration) of subsystems into the whole system.

4. Do not use too much complexity that may lead to generalisation and loss of accuracy.

5. The interactions and interrelationships with other systems are important considerations in the holistic nature of the system. This is in contrast to the analytical approach that reduces complex problems into parts and thereby may lose important properties.

6. The systemic approach must improve the subsystems as well as the holistic system.

7. Use of Bounded rationality, which means a strategy that is good enough. Organisations, like individuals, can learn to avoid uncertainty, simplify problems, and use feedback and to use alternative goal criteria. This is done through cybernetics, which is a control mechanism which communicates that deviations exist, now or in the near future. Thereby, systems are classified in accordance with their complexity.

8. Sub-optimisation can be improved by using scenarios or alternatives.

9. Means and goals are not absolute. Goals in one instance could be means to other goals in another instance.

An organisation seen as a system embedded in a specific environment includes all activities in the organisation, which also comprise components such as consumers, competitors, government and the public, according to the system being studied. But it is important to note that objects by themselves do not make a system. If the outcomes are quantitative, a model ought to be developed that includes the major components of the problem. On the other hand, if the objectives are qualitative they can be measured in terms of probability. However, different techniques are used for different problems. Therefore, the problem first must be well-structured, which means that variables should be quantified, objectives specified and appropriate algorithms established for numerical solutions. If algorithms cannot be used, a poorly structured problem can be solved by a heuristic tool.
Chapter 1  Introduction

Systems methodology states that most of the causes of uncertainty in systems behaviour depend on changes in the external environment. Therefore, the knowledge of the initial state of the organisation-environment interactive system is very important for the prediction of the final state of the system. This prediction of the future changes in the external environment and how to incorporate this impact into the management strategic plan is a very important managerial task. The more knowledge management has about the external environment the more control it may have over it. Accordingly, external information is necessary to minimise uncertainty about the future consequences of today’s decisions and actions. The system-oriented manager must therefore continually scan the external environment to incorporate potential impacts into the strategic plan.

1.5 Structure of the Thesis

Managing the whole enterprise ORs is such a comprehensive task that it is necessary to be familiar with probability theory, though knowledge of this is not always found among corporate risk managers. Therefore, knowledge of both corporate and financial risk management can be useful, particularly, in investigating ORs.

The material used in this thesis is presented in the following order. Chapter 1 presents the introduction. Part I, Chapters 2 – 4, covers an overview of systems theory, the current frontiers, including the compound knowledge of the banking system in the form of Basel II, which is assessed from a systemic perspective. Problems found are divided into several areas, where improvement is called for. Part II investigates these areas in Chapters 5 – 8. After these investigations, Part III suggests a new framework for implementing OR (Chapter 9). This framework, SAFOR, is then presented and assessed as a synthesis of the findings in the preceding chapters. Chapter 10 uses a bank application of an advanced OR model as validation of the SAFOR. Finally, Chapter 11 ends the thesis with conclusions and suggestions for further research.

In more detail, the following is investigated in this study:

**Introduction**

- Chapter 1.
Part I

- Chapter 2: a systemic approach to OR.
- Chapter 3: ORM and banking, with the tentative rules for modelling OR in accordance with Basel II. This chapter also briefly investigates what is meant by financial risk theory.
- Chapter 4: ORM as system processes and modelling methods for OR, together with an analysis of what is lacking today from an implementation point of view.

Part II

- Chapter 5: OR identification and classification, including a short overview of what is meant by estimation and model risks. However, these risks are not further analysed in the thesis.
- Chapter 6: the meaning behind Bayesian inference and belief networks, which could be used for constructing advanced internal OR models and how risk projects in complete and incomplete markets can be valued using decision theory.
- Chapter 7: some of the most important properties of the VaR and the CVaR. This approach is taken in order to understand quantitative, probabilistic approaches including the use of methodologies to quantify OR in monetary terms, similar to VaR measures of market risk [1], [26]. Today it is common that larger international organisations outside the financial sector (e.g., oil, forest and engineering industries) to use VaR measures to calculate their own financial market risk. Section 1.4.2 suggests that, as a consequence of findings in the analysis of Basel II, it is a sub-goal in this thesis to investigate whether the entire set of OR procedures might be used by larger industrial organisations that already use market risk VaR.

VaR analysis is commonly driven for group-wide and core business risk analysis, but, considerable work is still necessary to achieve greater integration of strategic OR models across all business units with the use of VaR and CVaR.

- Chapter 8: different interval approaches and tests are used to find out if a given interval forecast is to be considered good. Section 8.1 also gives an overview of the main imprecise probability statements in terms of intervals proposed in theory.
Part III

- Chapter 9: the SAFOR model with the four modules, which is the suggested implementation framework for an OR model and how the regulator wants the banking industry to implement ORM in their systems. This chapter uses both epistemological and ontological methodologies to ORM. Thus, when using GST to produce the systemic framework, SAFOR, the identified parts are connected into one whole.

- Chapter 10: the validation of the SAFOR. As a consequence of the confidentiality in the banking system and the lack of availability of material, OR data have been hard to come by for this thesis. Therefore, a bank application of an advanced OR model has been investigated, which is a result of the ongoing Basel II discussions on OR regulation in the banking industry. This application seems to be in line with the SAFOR model, and it may therefore be seen as a validation of the SAFOR. However, in this thesis the pros and cons of the proposed ORR are not investigated.

Conclusions and Further Research

- Finally, Chapter 11 concludes the analysis and points out some possible further extensions. The concluding remarks are mainly on banking regulation and the possible application of a systemic approach to banking supervision and risk assessment. However, the statement that ORM should be treated from a systemic-holistic viewpoint and therefore has to cover several different areas is probably true for larger international banks as well as for larger international organisations.
Part I
2 A Systemic Approach

This chapter gives a short overview of what is meant by systems theory and provides the necessary background for reading the following chapters.\(^{19}\)

The Principia Cybernetica Project is an international organisation, which aims to develop a philosophy based on the principles of evolutionary cybernetics\(^{20}\). This organisation proposed the following definition\(^{21}\) in 1992: *Systems theory is the trans-disciplinary study of the abstract organisation of phenomena, independent of their substance, type, or spatial or temporal scale of existence. This theory investigates both the principles common to all complex entities, as well as the (usually mathematical) models, which can be used to describe them* [191].

The idea that open systems interacted with their environments and, thereby, obtained qualitatively new properties, which could result in continual evolution, was formalised and advocated by the biologist Ludwig von Bertalanffy in the 1930’s. Then, in the 1940’s, he proposed the general systems theory (GST), which was further developed by Ross Ashby. Ludwig von Bertalanffy reacted against reductionism, but attempted in spite of that to reintroduce the unity of science. For the development of this science the technological development of data processing has been an important help in analysis as a whole and in distinguishing interaction. Furthermore, the focus of the systems theory is the organisation of the parts and the relations between them, by connecting the parts into a whole (holism). This view of a problem as a whole is called a systemic approach. Systems theory uses the same definition of an organisation, independent of the branch of science (see below).

The conception that objects should be viewed as wholes and that the whole is more than the sum of its parts – a well-known synergistic principle – can be derived from Aristotle. However, it was Ludwig von Bertalanffy (in his publication in Science in 1950), who formulated the concept GST. He created a new paradigm for the development of theories, which has a greater significance than a single theory that always can be falsified and therefore is often short-term. GST is both a methodology

\(^{19}\) The text in this chapter was previously published by *The Journal of Operational Risk* (2007) ([183] Appendix – Systems Thinking). For more detailed information of systemic approaches we refer to any major introductory work such as Schoderbek et al. [110], Louise Yngström [125] and Albin Zuccato [198].

\(^{20}\) See Figure 2.3.1.

\(^{21}\) This definition is prepared for the Cambridge Dictionary of Philosophy [191].
and a valid framework for viewing the empirical world, where its aim is to integrate all scientific knowledge through the discovery of analogies or isomorphic structures\textsuperscript{22} [110].

Several authors, e.g., J. Klir, Ervin Laszlo and Mihajlo D. Mesarovic, have shown that the development of systems theory is different from other sciences. The differences are specifically noted in conceptualisation and modelling [110]. However, the application of certain laws across a number of different branches of sciences is well known. There are applications of engineering, computing, ecology, management, and family psychotherapy. These isomorphisms have similar structures and operational characteristics when considered in the abstract, and they can be studied by exactly the same mathematical model. However, even if the development of systems analysis is not dependent on systems theory, systems analysis uses systems principles for building a system. It is a step-by-step study with the purpose of determining not only what must be done but also to ascertain the best way to improve the function of the system, together with its risks, costs and benefits [110].

Consequently, there are various approaches to systems thinking. But, systems theory is mainly associated with cybernetics\textsuperscript{23} and system dynamics [197]. System dynamics is the science of feedback behaviour in multiple-loop non-linear social systems\textsuperscript{24}.

### 2.1 General Systems Theory (GST)

As mentioned above, a systemic approach is a philosophy that visualises an enterprise as a set of objects with a given set of relations between the objects and their attributes, including their environment, together forming a whole [110], [126] [191]. Furthermore, systems can be investigated from two different points of views, from the existence of the organisations as systems (systems ontology) and from the knowledge in the organisations as systems (systems epistemology). From the ontology point of view the systems are represented as external, materialistic organisations, and from the

\textsuperscript{22} Isomorphic systems are two systems whose elements exist in a one-to-one relationship in their structures and correspondence with each other. There is also a correspondence between the operational characteristics of the systems [110].

\textsuperscript{23} Cybernetics is the science of control and communication in the animal and in the machine. The quality or property of the system is extreme complex, it is handled through the vocabulary and conceptual tools of probability theory, and by feedback principle it is self-regulated [110] (see Figure 2.3.1).

\textsuperscript{24} Specifically, the world dynamics models by Jay W. Forrester show how a network of coupled variables can change [191].
epistemology point of view the systems are represented as non-deterministic, abstract organisations. The theory of the existence, the ontological view, may then be divided into systems architecture (structure) and system dynamics (processes)\textsuperscript{25}.

Kenneth Boulding attempted in the 1950’s to synthesis the different underlying assumptions of GST. He came to the conclusion that there are five basic premises (postulates) of GST that any general systems theorist might accept without necessary proof [174]. These postulates are still of relevance today. In short GST is a regulative instruction. Like all sciences, GST is based on a systematic search for law and order in the universe. Furthermore, GST tends to extend its reach to a search for an order of order, a law of laws (see P3 below). Moreover, these premises call attention to order, structure and regularities that can be understood and controlled by laws, and which can be found by empirical studies of the real world. Boulding’s five postulates are the fundamental assumptions underlying GST ([110] p.37):

\begin{align*}
P1 & . \textit{Order, regularity, and non-randomness are preferable to lack of order or to irregularity (= chaos) and to randomness.} \\
P2 & . \textit{Orderliness in the empirical world makes the world good, interesting, and attractive to the systems theorist.} \\
P3 & . \textit{There is order in the orderliness of the external or empirical world (order to the second degree) – a law about laws.} \\
P4 & . \textit{To establish order, quantification and mathematisation are highly valuable aids.} \\
P5 & . \textit{The search for order and law necessarily involves the quest for those realities that embody these abstract laws and order – their empirical referents.}
\end{align*}

In addition, there have been different characteristics of GST over the years, which depend on GST trying to uncover the laws and the order inherent in all systems. Therefore, GST has been criticised for having less content than other systems theories. However, in 1969 J. A. Litterer put together the ten most fundamental properties (hallmarks) of open systems proposed by different theorists at that time [175]. And, it is important to note that there still are other qualities to add to this list. The hallmarks are meant to facilitate the understanding of the whole security

\textsuperscript{25} See Chapter 4 and Section 5.2.
organisation, which is necessary for the survival of the systems. Security in GST is a part of management for planning and structuring the organisation. The ten hallmarks are ([110] p. 38 – 42):

1. **Interrelationship and interdependence of objects and their attributes**, which means that there must be relations and dependences between elements in a system.

2. **Holism**, which stresses that a system is a whole, which can never be broken down into parts and analysed.

3. **Goal seeking** (teleology), which is an important management tool – the reason for being. In this process the system uses its energy to maintain itself as a system, where it may borrow energy from one subsystem to help another subsystem to maintain equilibrium.

4. **Inputs and Outputs**. Inputs, e.g. energy and material, transformed (processed) into outputs, e.g. products or services, which will enable the system to reach its final goal. In open systems, inputs enter the system from its environment. In closed systems inputs do not change and can therefore not constitute a living system.

5. **Transformation Process**. The system goal is attained by transformation of inputs into outputs.

6. **Entropy** presumes a closed system state, where maximum entropy is dead. Accordingly, while carrying out a mission, entropy increases and the availability of the system for doing further missions declines. By accepting inputs (people, raw material, capital, etc.) into the system from the environment, living systems can for a finite time move, or are at specific instance in the state of order/disorder (risk), to maximum entropy.

7. **Regulation** (management, control) means that the original design for an action will be maintained through managing the interacting goals in the systems. Then, deviations from these planned objectives must be observed and adjusted, where feedback is the condition of effective control. Consequently, control or cybernetics (the science of information control) is the activities used to evaluate and adjust the processes of inputs, throughputs and outputs.

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26 See Figure 2.2.1.
8. **Hierarchy** is the organisation of nesting smaller subsystems, which constitute a complex whole. Furthermore, the definition of the hierarchy depends on the goal or division of interest. Characteristics of each system are that it can be examined by its subsystems, each of which also has the potential to influence the whole. Therefore, the subsystems have to be examined within the context of the whole. A subsystem can, for instance, be IS, a political system or a workflow system.

9. **Differentiation** is specialised functions in complex systems. It is necessary in all systems and it enables the system to be brought into line with its environment. Differentiation, specialisation, and division of labour are identical concepts.

10. **Equifinality** means that open systems can reach their goals in many different ways. They have equally valid alternative ways to reach the same objectives, which can be reached with inputs of various kinds. For instance, a person might travel by different routes to come to the same place. Equifinality is a very useful concept to show how social systems are managed. Unlike in the physical sciences, in the social sciences there is no single best solution for managerial problems. However, there may be many satisfactory solutions to the same decision problem.

Generally, there are many applications in systems theory. Which application is used depends on the business that is being carried out. Some frequently used applications are [110], [126]:

- **Systems Engineering** is the application that ties together conceptual (designing) and operational systems (optimising). For instance, systems engineering includes definition of objectives, analyses of specifications, management, design of elements, implementation of elements and verification.

- **Systems Quality Management** is the art of managing and optimising systems to its purpose.

- **Systems Programming** is the application used for controlling things in the real world with computers. It includes design, definition, implementation, security, database development, and the use of programming languages and programming systems.

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27 See Figure 2.3.1.
• *System Dynamics* are applications, which show how systems evolve over time. They can be divided into state dynamics and structural dynamics. State dynamics are how system states change over time and structural dynamics are how the relations between systems change over time.

Like whole systems, dynamic systems change, move, and evolve. Many things can be looked at as whole living systems, e.g. nature, an economy, a family, a company, a community or an organisation. Such a view would include all the factors involved and examine how they relate to each other and how they work as a whole. With the use of whole systems it is necessary to use both scientific and artistic approaches, such as intuition. Therefore, holism is said to include both philosophical and conceptual assumptions. However, there is as yet no consensus of what whole systems deal with. Whole systems are time invariant and non-linear by nature, and they may aggregate to meta-systems (the system environment and context). As shown in Figure 2.5.1 the context includes the geographical space expressed as local, national or international. Whole systems also have a life cycle and may disintegrate into new systems [125], [126].

Schoderbek et al. [110] also state that there are several other approaches to systems thinking. For instance, systems engineering that use other approaches, like cybernetics, and techniques, like optimisation models, can also qualify as systemic approaches. Therefore, they propose that systems engineering might be seen as the link between systems theory as such and other operational systems. Another particularised approach to systems thinking is operations research, which also uses models and examines quantitative interrelations of the system. Some authors also include systems analysis as a way of systems thinking. However, there is criticism of this approach for systems thinking. However, Schoderbek et al. ([110] p. 146) mean that if the approach allows researchers to view their work from a holistic point of view, and this leads to a better understanding of the system, then they may qualify as systems thinking.

### 2.2 The System Concept

The system concept has its origin in physics and other exact sciences. Specifically, physics uses exact measurement of matter, energy, motion, and force. But, social

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28 See Figure 2.3.1.
scientists cannot normally use this precise definition of a system. Instead, they will use a verbal, operational definition for the inclusion of their very complex and often multidimensional variables. In spite of that, the definition of a system is as precise and inclusive as that of any exact sciences. According to Schoderbek et al. ([110] p. 13): *A system is defined as a set of objects together with relationships between the objects and between their attributes related to each other and to their environment so as to form a whole.*

By a set is meant any well-defined collection of elements or objects (parameters) within a framework, and it is beyond doubt whether or not a given object or symbol belongs to the mentioned framework. There are three kinds of objects: inputs $I$, processes $P$, and outputs $O$. Figure 2.2.1 below shows the major symbols in diagramming a system$^{29}$.

![Diagram of Parameters, Boundary, and Environment of a System ([110] p. 25)](image)

**System environment**

$^{29}$ In GST the system must be conceptualised. The block diagram in GST uses four basic symbols: the arrow (the signal or command), the block (the mathematical operation on the input signal to the block, which produces the output), the transfer function (the mathematical operation to be performed on the block), and the circle with a cross (where a comparison is made between two quantities, the command signal or desired state, and the feedback signal or actual state) [110].
Chapter 2  A Systemic Approach

Inputs are classified into serial and feedback inputs. Necessary inputs for operating systems may be matter, energy, humans, or information. Serial inputs are outputs from other systems. For instance, a sales subsystem can have an output, which is the input to a production subsystem. While feedback input is a recovery of a part of the output of the system in question. However, cybernetics\(^{30}\) takes into account all kinds of feedback processes\(^{31}\). Therefore, cybernetics is sometimes mentioned as included in GST. Furthermore, a process transforms the input into an output. This process can sometimes be very complex, if it is not known in detail. Outputs are the systems results (the purpose) of the process. These three kinds of objects are then bonded together by relationships. The bonds between both objects and relationships are called attributes. Attributes are the characteristics, which tell us how a process is known, observed, or introduced.

Moreover, an open system is also characterised by the system boundary and environment. The system boundary surrounds the internal system, while the system environment is both what lies outside the control of the system and at the same time significantly influence the system performance. As mentioned above, wholeness is a philosophical and conceptual assumption and as such an attribute of a thing or being. Furthermore, the well-known synergistic principle that the whole is greater than the sum of its parts means that for instance, the family as an independent system is more than the individual members together. If a member is removed, the structure of the family system changes and takes a quite different configuration. Consequently, systems thinking takes a very different approach for a better understanding of the whole than the analytical approach that breaks it down into smaller and smaller parts [110].

To sum up, the idea of a system is figurative and not dependent of any branch of science. The purpose of a system is reflected by the system hierarchy of subsystems, which shows the scalability of the systems plan. It is also necessary for open, living systems and subsystems to interact with their environments to survive. This interacting process is called cybernetics. By reason of this interacting process the whole will be more than the sum of its components. Therefore, with respect to the whole these components are seen as subsystems, and with respect to the components,

\(^{30}\) See Footnote 23.
\(^{31}\) See Figure 2.3.1.
the whole is seen as a super system. Furthermore, an organisation has to be controlled for survival. However, the development of an organisation occurs in different phases. In the first phase the organisation is normally controlled through market results. In the next phase the control has changed towards cost and profit centres, or plans and investment centres.

Finally, this control will end in a joint goal for the whole organisation. As mentioned above, another important characteristic of the GST is the use of analogies between systems, where experiences of a known system stand as a template for modelling another system. However, when using analogies it is necessary to ensure that different situations in the organisation remain in focus, e.g., the life cycle, and that the models used are relevant for predicting the behaviour.

This thesis’ framework is theoretically built on a conception of the firm as a system, and the firm’s financial conditions and OR exposures as subsystems.

2.3 Applying a Systemic Approach

Accordingly, a systemic approach to ORM calls for a methodology for conceptualising and operationalising it. One way to do this is to start with the identification of the systems characteristics. But, it is also important that the designer has some knowledge of the systems history and origin. Therefore, a GST approach to ORM can be said to consist of two phases:

- The knowledge and realisation of GST, through the following steps:
  1. Awareness of the systemic approach. An adequate knowledge of the whole system in focus must be secured first before an elaborated knowledge of the parts can be obtained.
  2. Model building. A well-designed model will help to understand reality.
  3. Simulation. IT will be used for model building and experimentation.

- Implementation. The implementation and the use of an ORM framework are not only expected, but mandatory, to qualify a banking institute for the Committee’s lowest possible capital requirement [112].

The systemic approach or systems approach, when it is dynamic and includes the whole, is illustrated in Figure 2.3.1 below:
Chapter 2 A Systemic Approach

**Systems Approach**

- **General Systems Theory**
- **Particularised Systems Approaches**

**Operations Research**
Concerned with operational-level, short term, manageriakontrol problems. Basically a quantifying body of computational techniques: e.g.,
- linear and dynamic programming
- decision trees
- simulation models of real life situations.

**Systems Analysis**
Concerned with policy level, longer term, strategiplanning problems, poorly understood structurally and not readily quantifiable.
Four basic steps: formulation, search, explanation, and interpretation.
It could be Management Information Systems (MIS) as a collection of the organisation’s information processes that provides decision criteria for the direction and control of organisations (see Section 4.2).
Often mentioned as the first step in systems engineering.

**Cybernetics**
"The science of control and communication in the animal and the machine". That means the subject of inquiry in this class is organisations that are complex systems whose behaviour can only be described in probabilistic terms and are, however, self regulating.
Conceptual skills are the manager’s ability to
1. see the organisation as a whole
2. focus on the relationships among the parts of that whole
3. take a long term view of the organisation’s future.

**Systems Engineering**
Systems engineering starts with definition of the problem, and it includes such things as systems objective, systems effectiveness, systems alternatives, cost/benefit analysis, systems developments etc. The systems engineering bridges the gap between conceptual systems and operational ones.

Figure 2.3.1: Various Systems Approaches ([110] p. 10)

Figure 2.3.1 above begins with the general and proceeds to the specific, i.e., from left (General Systems Theory) to right (Systems Engineering). This approach exhibits growth and control objects. It is well-known that growth is a necessary condition for the survival of any system, and control is a necessary condition for balancing growth. Section 2.2 defines the system environment as being beyond the system control, but this environment must at the same time exercise significant influence on the system performance. That means that the system’s growth and control capacity must be in balance with the environment. Moreover, holism intends that the designer should begin with the general and that the risk manager should go only a little bit further than
what has been interpreted as satisfactory up to now. Consequently, modelling processes can help in analysing an organisation as an open-organic system under constantly alterations. This process has to start with a gross conceptualisation of the planned system, including its relation to the whole organisation and its environment. After that, different calculating techniques can be used for recommended quantified outcomes. A systems-oriented investigation must include many modelling attempts, arranged in an abstract hierarchy; with the purpose of finding a satisfactory model for the relevant systems.

2.4 Holistic Approaches to OR

There are other approaches to risks that are related to the work in this thesis. For example, Magnusson’s approach [109] is a systemic-holistic framework, combining finance, risk transfer, IT, and security in a coherent system, described in Section 2.5. He points out that the ontological (physics and mathematics) sciences’ methodology complements the epistemological methodology, and vice versa. The epistemological methodology emphasises an open, living approach with reasoning processes, weaker evidence for observations and predictions and the consequence of unique event. This approach may create more normative, descriptive models than the ontological sciences, which instead generate good descriptive models of the universe ([109] p. 33).

A common approach in a systemic-holistic framework such as in [109] is to view subsystems, e.g. IT systems, as black boxes, where the system transformation process is unknown and the component is considered in terms of the systems inputs and outputs. This is a method of handling systems with a high degree of complexity ([109] p.172), [110]. Moreover, the systemic-holistic approach often requires interdisciplinary competence, where the project leader must understand the relation between the areas, e.g., IT, security, risk transfer and finance, and how they interrelate. But, it is not easy to find people with such a range of competences.

In finance, however, using the non-transparent black box techniques is not recommended. For instance, the mean-variance analysis, when calculating optimal portfolios with high-risk, high-return investments must be transparent. This is described in Sections 6.5.1 and 7.4. Although important, this black box technique is not considered further in this thesis.
2.5 Related Systemic Approaches

Section 1.3 points out that overall system effectiveness is required in order to meet the requirement of the company to have an efficiently operating control. It is demonstrated in Section 5.2 that the ORM in a bank involves a mixture of physical and logical safeguards and procedures, within and outside the computer system. Therefore, the conclusion of this investigation is to view ORM in a bank as a system. This makes it possible to understand, define and discuss particular risks such as IT security related problems. The system includes organisation, humans, tasks, computers, software, documentation, and data, existing in a real environment including, e.g., customers, other banks and regulations. Yngström argues for Security Informatics, which is a holistic view on OR control [125]. Some details of Yngström’s framework and methodology for security informatics, the Systemic-Holistic Model, are shown in the Figure 2.5.1 below.

![Figure 2.5.1: Details of the Framework and the Methodology for Security Informatics – the Systemic-Holistic Model [125]](image)

In Yngström’s model [125], the content of the Systemic Module, i.e., the technical and non-technical aspects in Figure 2.5.1 above, is based on GST, cybernetics and General Living Systems Theory (GLST). Chapter 2 states that GST derives its origin from observations in much the same way as in many different sciences. But, the concept system is seen here as an epistemological device (an abstraction) to describe systems as wholes. On the other hand, GLST deals with systems that really exist – an
ontological entity. Therefore, Yngström proposes that the Systemic Module may be viewed as an epistemology or a meta-science\textsuperscript{32} used for communication between sciences, and which at the same time states criteria for control. Thereby, it is possible to view a whole system, which can include several subject areas, as well as its details. Moreover, special emphasis must be put on negative and positive feedback mechanisms to create understanding of the balance needed between development and control, which are the two main functions involved in systems survival, described in Section 2.2. Here, this whole process is called the Systemic-Holistic Approach [125], where the three dimensions show the area in focus and the systemic module how to approach them.

However, when ORM is introduced and ORs are studied as general systems, the Systemic Module prescribes that the most important principles are to define [125]:

- the system from its environment;
- the system environment;
- the inflow, throughflow, and outflow; and
- the structure of the in-built control system

so that it can deal with inner and outer variety in accordance with Ashby's Law of Requisite Variety, which claims that if the environment is varying it must be met by equal variety in the system. This means that if there is variety in a problem it must be met by variety in the solution ([110] p. 92).

The proposed OR framework in Chapter 9 is based on studies of structures, theories, methodologies and approaches for OR, security, and the relevant parts of financial risk. However, there are problems in bringing together such disparate topics and studying them in a context – in a system – and not separately. For this, we use a theoretical framework similar to the systemic-holistic approach, described in [109],

\textsuperscript{32} In general, with meta-science is meant a formalised (simplified) linguistic model whose mechanism is the hierarchical system of concepts. Meta-science constructed in a formalised manner can go beyond general statements. It can create a natural meta-system transition, where the objects of the study formalise languages as a whole - for their syntax, their semantics and their applications to description of the reality. A meta-system transition can be used even if the exact structure of the systems involved is not known. For instance, a system of any kind can be copied with some variations, and as a result of consecutive meta-system transitions a multilevel structure of positive and negative feedback mechanisms arises. These feedbacks create understanding for the balance needed between development and control, which are the two main functions involved in the survival of a system [197].
[125], [198]. It is built up of a general open systemic approach, illustrated in Figures 2.2.1 and 4.1, in which the input, processes, and output are considered relative to the boundaries of the system. Specifically, IT related OR processes, which are of high importance in banking, can be scrutinised using methods derived from the interdisciplinary Systemic-Holistic Approach.
3 ORM and Banking

The history of bank institutions, like military and manufacturing companies, shows that these organisations have been using risk management, including ORM for a long time. Especially over the last fifteen years\(^{33}\), when the global market and IT have developed very rapidly, risk management in financial institutions has developed new instruments for risk handling. During these first 10 years, the focus of risk management in banking has been on market and credit risks, which have now reached the quantitative impact stage. During the last five years ORM in banking has come into prominence, but there is still much to do before a full quantitative effect with reliable total figures is attained [112], [123]. The currently most widespread developments for ORM in banking are:

- Increased OR awareness.
- More carefully prepared attempts to identify, define, categorise, measure and quantify OR.
- Increasing attention to OR by regulators, financial analysts and banking managers.
- Growing interest in OR by senior management and boards of directors.
- OR seen in an increasing context, as a system.
- A rapid change of the OR environment, where banks as mediators are diminishing, more non-banks enter the market, and global capital markets grow faster.

Nevertheless, there are several reasons why OR data are hard to come by in banking. Confidentiality and difficulties to quantifying OR and the short time over which data have been gathered in a consistent way are some of the reasons. Moreover, OR is often not clearly distinguishable from market or credit risks and not diversifiable.

3.1 Financial Risk Theory

There has been a tremendous growth in both volume and complexity of products traded in the financial market during the last fifteen years.\textsuperscript{34} Since the early 1990s the general environment of the financial institutions has changed dramatically and will continue to change, due to the globalisation and IT. Under these circumstances simple classical OR theories of how to manage OR are often not enough for the investigation of real risks. In the new risk situation that affects all situations of life it is necessary for the managers to use OR applications, which take into consideration that risk theory is a theory of decision-making under uncertainty, including probability theory. Among the most advanced applications in finance are managing market, credit, investments and business risks. In other markets there are similar ways for handling risk, e.g., health, environment pollution and ecological risks.

One way of classifying risks in banking is in accordance with their sources:

- \textit{Market Risk} – the risk that the value of traded assets will decrease due to volatility in market factors. This risk is commonly established by using a VaR methodology.

  This risk is relatively well-understood even if there still is room for improvement [1], [26].

- \textit{Credit Risk} – the risk of loss that depends on uncertainty in a debtor’s ability to meet his/her financial obligations.

  Even this risk is relatively well-understood, although there is still room for improvement.

- \textit{Operational Risk} (OR) – according to Basel II, the risk of loss resulting from inadequate or failed internal processes, people and systems, or from external events [112].

  It is this risk that is on the Basel II’s agenda, described in Section 3.2. But it is still less expounded than quantitative (mathematical and statistical) approaches. This thesis, however, tries to look into some of these approaches.

\textsuperscript{34} Source BIS: \textit{Global market in OTC derivatives (nominal value) have grown from $47 trillion 1995 to $80 trillion 1998 ($1 trillion = $1 \cdot 10^{12}$). Over-the-Counter (OTC) is a security, which broker/dealers negotiate directly with one another. These stocks are usually very risky and they tend to be traded infrequently.} (http://www.bis.org).
• **Liquidity Risk** – risk that lack of market liquidity cannot be solved quickly enough.

This risk is an important topic for discussion since the failure of the LTCM\(^ {35} \), but it is extremely challenging.

• **Risk Integration** – market-credit risk integration is discussed, but it has not yet been carried out.

Risks in banking can also be categorised into internal and external risks. Credit and market risks are external, i.e., they originate from the environment of the bank and both are driven by revenue. On the other hand, OR originates mostly from within the bank organisation, except for external risks such as natural disasters, terrorism and vandalism, shown in Table 5.1. OR is normally not revenue driven, but when ORM is concerned with quality management, it also contributes to client satisfaction, reputation and shareholders’ value [123].

This thesis looks into the conditions for an advanced, internal OR approach for larger international banks in the future, when there is access to a credible loss event database. The question, then, is whether it is possible to use decision analyses and interval forecast evaluation for OR in connection with VaR and CVaR. Chapters 7 and 8 and Sections 9.1.4 and 9.1.5 investigate this question. But a general systemic approach to ORM calls for a methodology for conceptualising and operating the systems. Such an approach has to start with the identification of the systems characteristics.

### 3.1.1 Financial Economics

Financial risk theory is a large field, mostly studied within the areas of Finance or Financial Economics. The following Figure 3.1.1.1 shows which financial markets, institutions and corporate governances are usually included in Financial Economics:

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\(^ {35} \) LTCM (Long-Term Capital Management) is a very large and prominent hedge fund. In September 1998 the Federal Reserve intervened because it was concerned about possible grave consequences for world financial markets if it allowed the hedge fund to fail (http://www.cato.org/pubs/).
Most endeavours concentrate on improving details in a given structure, e.g., VaR or CVaR computations, or on proving further formal properties for a particular sub-problem. This thesis, in contrast, aims to develop a framework for systems properties of ORM, especially for banks.

### 3.2 Basel II

A number of approaches have been developed for modelling OR. Some of them are related in Section 4.2. In September, 2001, Basel II published a consultative paper that included ORR [111]. This document points out that the banking institutions in the future have to include in their ORM both how they manage and how they measure OR. Moreover, in the proposed regular framework OR must be reported explicitly, and no longer implicitly as hitherto included in other risks, which now belong to credit risk. One reason for a new OR framework is that the measurement of credit risk for calculating credit capital requirement has recently been changed, and there is no longer any buffer for other risks in credit risk. Another reason is that larger international banks are very much influenced by the rapidly increased technology and
the complex new financial products and strategies. Therefore, it is suggested that other risks need to be handled more carefully. But, the pros and cons of ORR are not investigated in this thesis. Moreover, there is an ongoing debate about which OR definitions might be the best. In October, 2002, the Committee provided the following definition of the OR: *The risk of loss resulting from inadequate or failed internal processes, people and systems or from external events*, and therefore includes legal risk, but not strategic, reputational and systemic risks [112].

The definition above is based on the four causes of OR events, i.e., people, processes, systems, and external events, shown in Table 5.1 below. However, the Committee has not yet defined the word *loss*, but its demand is that the banks build up historical loss databases, even if not all indirect losses or opportunity costs have to be covered by capital requirement. Some important questions are how a loss event can be distinguished from a normal cost, e.g., at what point or threshold does the normal cost become a loss event, and how to identify operational losses already taken into account by market and credit risks. Moreover, OR is divided into business, or strategic, risks and internal risks. Strategic risks are those when external factors cause a failure to attain expected returns, as a result of changes in the political, regulatory, and legal environment or as a result of competition. Such risks are best modelled by using scenario analysis\(^3^6\). On the other hand, internal risks can result from losses or non-payment of earnings because of failures in internal processes, people and systems\([112],[114]\).

However, in May 2001, the Committee started mapping the banks’ OR data\(^3^7\). This exercise was repeated in October 2002, and was called the third quantitative impact survey, or QIS 3, and included detailed data for the most recent financial year (2001). More than two hundred banks from forty different countries participated in this survey, the purpose of which was to produce a new Accord, including ORs for banks, by the end of 2006 [112]. As mentioned above, this data includes not only information on banks’ OR losses, but also on different exposure indicators. The Committee would

---

\(^3^6\) Scenario analysis can be a demanding exercise, since the financial environment is normally very complex. It can be difficult to foresee the actual future outcomes and to assign probabilities to them. Then, the outcomes may be modelled mathematically/statistically, where possible variability within single scenarios as well as possible relationships between scenarios must be taken into account [112].

\(^3^7\) See http://www.bis.org/bcbs/qisoprisk.htm. There are the results of the first survey which were published in May 2001 in the paper *The Quantitative Impact Survey for Operational Risk: Overview of Individual Loss Data and Lessons Learned.*
use this information for refinement of the proposed ORR in Basel II. Banks received *spreadsheets* and instructions about how they should carry out the OR survey. The complete surveys were then returned via the respective bank’s national supervisors, by 31 August 2002.\footnote{See http://www.bis.org/bcbs/qis3wkb.xls}

### 3.2.1 Tentative Rules for Modelling OR in the Banking Industry

The extension of the capital requirement to include OR was proposed by the Committee in September 2001\footnote{111}. The proposed accord recommends three approaches to determine the ORR: the *Basic Indicator Approach (BIA)*, the *Standardised Approach (SA)* and the *Advanced Measurement Approaches (AMAs)*\footnote{112}. The first survey of OR data in May 2001, mentioned above, was later included in a second survey, QIS 2. Furthermore, the collected data in the different surveys showed that it was necessary to calibrate BIA and SA further, and that those more qualifying criteria for the AMAs were needed. Therefore, the Committee pointed out after the data collection in 2002, that it would undertake an on-going data collection over the next few years for further refinement of the ORR\footnote{113}.

Consequently, the main aim of the data collection in 2002, was to gather granular (event-by-event) OR loss data. These data were used as a help for determining the appropriate form and structure of the AMAs. A detailed framework classified losses in a matrix consisting of 8 standard business lines and 7 loss event categories, which were also further sub-divided. This is shown in Figure 3.2.1.1 below\footnote{124}. These event categories were then further divided into twenty sub-categories. Furthermore, the Basel II OR framework also included 6 exposure indicators, for example the number of employees and total assets. The purpose of these indicators was to provide the opportunity of relating historical loss data to current business operations, and to fix frequency and severity separately for future ORs. However, the base indicator proposed for the BIA and the SA is the gross income only. A summary of the data collected for the financial year 2001 is presented in\footnote{124}.

Moreover, in the new QIS 3 survey in 2002\footnote{112}, banks were asked to give further information, such as:

- Recoveries received as well as expected.
• Chosen threshold for data collection.

• Losses arising from a corporate centre business.

• Component information on gross income.

In this survey, banks were also asked for information described in simplified spreadsheets, including tests for checking the consistency of the data submitted. Furthermore, banks were not allowed to make any changes to the questionnaire [124].

The Committee pointed out that its proposals were based on a sound quantitative foundation and were aimed at increasing the bank’s risk sensitivity. The data collected were meant to be used later for the development of the ORR. Therefore, it was very important that accurate and complete data were received. Banks using the SA were asked to divide their activities into eight business lines, defined in greater detail in Figures 3.2.1.1 and 3.2.1.2 below [124].
### Business Lines

<table>
<thead>
<tr>
<th>1. Corporate Finance</th>
<th>5. Payment and Settlement</th>
</tr>
</thead>
<tbody>
<tr>
<td>2. Trading and Sales</td>
<td>6. Agency Service</td>
</tr>
<tr>
<td>3. Retail Banking</td>
<td>7. Asset Management</td>
</tr>
<tr>
<td>4. Commercial Banking</td>
<td>8. Retail Brokerage</td>
</tr>
</tbody>
</table>

The principles for business line mapping of the OR must be consistent with the definitions of business lines used for calculations in other risk categories, e.g., market risk.

### Event Types

<table>
<thead>
<tr>
<th>Level 1</th>
<th>Level 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internal Fraud</td>
<td>Unauthorised Activity</td>
</tr>
<tr>
<td></td>
<td>Theft &amp; Fraud</td>
</tr>
<tr>
<td>External Fraud</td>
<td>Theft &amp; Fraud</td>
</tr>
<tr>
<td></td>
<td>System Security</td>
</tr>
<tr>
<td>Employment Practices &amp; Workplace Safety</td>
<td>Employee Relations</td>
</tr>
<tr>
<td></td>
<td>Safe Environment</td>
</tr>
<tr>
<td></td>
<td>Diversity &amp; Discrimination</td>
</tr>
<tr>
<td>Clients, Products &amp; Business Practices</td>
<td>Suitability, Disclosure &amp; Fiduciary</td>
</tr>
<tr>
<td></td>
<td>Improper Business or Market Practices</td>
</tr>
<tr>
<td></td>
<td>Product Flaws</td>
</tr>
<tr>
<td></td>
<td>Selection, Sponsorship &amp; Exposure</td>
</tr>
<tr>
<td></td>
<td>Advisory Activity</td>
</tr>
<tr>
<td>Damage to Physical Assets</td>
<td>Disasters and Other Events</td>
</tr>
<tr>
<td>Business Disruption &amp; System Failures</td>
<td>Systems</td>
</tr>
<tr>
<td>Execution, Delivery &amp; Process Management</td>
<td>Transaction Capture, Execution &amp; Maintenance</td>
</tr>
<tr>
<td></td>
<td>Monitoring &amp; Reporting</td>
</tr>
<tr>
<td></td>
<td>Customer Intake &amp; Documentation</td>
</tr>
<tr>
<td></td>
<td>Customer/Client Account Management</td>
</tr>
<tr>
<td></td>
<td>Traded Counterparties</td>
</tr>
<tr>
<td></td>
<td>Vendors &amp; Suppliers</td>
</tr>
</tbody>
</table>

Figure 3.2.1.1: Business Line and Event Type Level 1 and 2 used in the 2002 Loss Data Survey

((124) Appendix A)
Chapter 3 ORM and Banking

Figure 3.2.1.2: Decision Trees to Determine Event Categorisation ([124] Appendix A)
3.2.2 The Measurement Methodologies

There are, as mentioned before, three methods for calculating a global, consolidated ORR. However, banks are allowed to use the BIA or SA for some business lines only, and AMAs for others. Furthermore, it is not allowed to change from an advanced method back to a simpler one. The three methods for calculating ORR are described in increasing order of sophistication in the following sections in this chapter. Moreover, this SAFOR framework is only compared with the Basel II most advanced approach, AMAs.

3.2.2.1 The Basic Indicator Approach (BIA)

Banks that want to use BIA, the least sophisticated method for the calculation of the ORR, must during the last three years hold capital in one fixed percentage (called $\alpha$ – factor) of the total annual average gross income. Basel II has in QIS3 proposed $\alpha = [15\%]$ [112]. However, if a bank uses current mean risk capital (MRC) $\alpha = [12, 5\%]$ [170].

In accordance with national supervisors and/or national accounting standards gross income includes both net interest and net non-interest incomes. More detailed Rules of how gross income is measured are proposed in [112]. There are no other Rules for the use of the BIA other than that the banks must follow the Committee’s guidance on Sound Practices for the Management and Supervision of Operational Risk, published as a consultative document in February 2003 [170].

3.2.2.2 The Standard Approach (SA)

SA is the next least sophisticated method for the calculation of the ORR. Therefore, Basel II mentions some specific qualitative and quantitative criteria that should be used for calculating SA [112]. Three general qualifying criteria for both SA and AMAs are shown below in Section 3.2.2.3.

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39 The following sections of this Chapter 3 is a summary of the OR guidelines in Basel II about recommended methodologies for calculating ORR [112].

40 The Committee has the intention to look further at the partial use of the BIA in combination with the AMAs [112].
Qualitative Standards for SA

Larger international banks can use the SA method for calculating their ORR, but only if they have a satisfactory ORM system. These are the qualitative criteria for such a bank ([112] p. 119):

- Identify the bank’s OR through bottom-up identification, a process which must be reviewed periodically. This is described in Section 5.3.

- Assess the potential OR impact on the bank’s solvency, specifically low-frequency, high-severity events and high-frequency, low-severity events. This is described in Section 5.1.

- Monitor and control the bank’s OR on an on-going basis, with the help of key indicators, thresholds and limits, or scorecards.

- Implement OR procedures with predefined thresholds for taking appropriate decisions in accordance with the management reports. However, exceptions to the bank’s OR policy must also be reported.

- Communicate the OR information in a consistent way throughout the whole bank.

- Construct OR into processes like pricing and paying decisions. OR should be integrated into the whole bank’s business strategy, and appropriate insurance should be used ([112] p.120).

- Discover relevant OR data by business line, shown in Figure 3.2.1.1.

Business line mapping

In the SA gross income from the different business lines and activities must be mapped in a special way. The criteria therefore must be checked and corrected, when business activities and risks are new or changing [112].

Following these principles, a systemic approach to ORM might appear like that shown in Figure 4.1 below.

Quantitative Standards for SA

Permission to use SA implies that the operations of the bank are divided into 8 standardised business lines, shown in Figures 3.2.1.1 and 3.2.2.2.1. In this case, the bank must during the last three years hold capital in one fixed percentage (called $\beta$ – factor) of the average annual gross income from each of the 8 business lines [112].
The total capital at risk (CaR) is then the sum of the different CaRs of the business lines. However, this way of aggregating business line CaRs has been criticized for assuming perfect positive dependence between the different business lines [108]. However, these precise values of the betas can be changed later on, when the banks have undertaken further analysis and learnt more about OR in different business lines. But before then, the values of the betas are detailed in Table 3.2.2.2.1 below [112].

Table 3.2.2.2.1: The Values of the Betas (Basel II) [112]

<table>
<thead>
<tr>
<th>Business Lines</th>
<th>Beta factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corporate finance (β₁)</td>
<td>[18 %]</td>
</tr>
<tr>
<td>Trading and sales (β₂)</td>
<td>[18 %]</td>
</tr>
<tr>
<td>Retail banking (β₃)</td>
<td>[12 %]</td>
</tr>
<tr>
<td>Commercial banking (β₄)</td>
<td>[15 %]</td>
</tr>
<tr>
<td>Payment and settlement (β₅)</td>
<td>[18 %]</td>
</tr>
<tr>
<td>Agency services (β₆)</td>
<td>[15 %]</td>
</tr>
<tr>
<td>Asset management (β₇)</td>
<td>[12 %]</td>
</tr>
<tr>
<td>Retail brokerage (β₈)</td>
<td>[12 %]</td>
</tr>
</tbody>
</table>

3.2.2.3 Advanced Measurement Approaches (AMAs)

AMAs form the most sophisticated ORR method proposed by the Committee. Therefore, more powerful specific qualitative and quantitative criteria are required for use in AMAs. It is, specifically, AMAs that are of interest in this thesis.

Furthermore, larger international banks that adopt the AMAs must at the same time calculate their ORR in accordance with the existing Accord (with ORs included in credit risks) until year-end 2007.

General Qualifying Criteria for SA and AMAs

The minimum, common qualifications for using SA or AMAs are [112]:

- The ORM process must actively be supervised by the bank’s board of directors and senior management.
- The bank’s ORM system must be conceptualised and implemented in an appropriate environment.
The bank must have an organisation with sufficient staff resources to control and audit the different OR business lines.

Moreover, the OR system must be built in such a way that it creates incentives for improvements of the ORM in the different business lines. Furthermore, under the AMAs, the ORR is equal to the bank’s internal, generated OR. But, for calculating ORR the following qualitative and quantitative criteria must also be taken into consideration:

**Qualitative Standards for AMAs**

In short, the qualitative standards, proposed by the Committee for banks that want to calculate their ORR in accordance with the AMAs are [112]:

- An independent ORM function must be established, which can be made responsible for the ORM design and implementation.
- The oversight of the ORM process must be controlled by the board of directors and senior management.
- The internal system for measurement of the OR must be integrated into the bank’s day-to-day ORM processes.
- A fixed, in-advance reporting system for the OR exposures and the loss experience must be established. This reporting system must include management of the different business units as well as the senior management and the board of directors.
- A well documented ORM system.
- The ORM processes and measurement systems must be controlled periodically not only by internal auditors, but also by external ones.
- The system for measurement of the OR must be validated. This can be done by the bank’s external auditors or by the supervisory authorities, or by both.

**Quantitative Standards for AMAs**

(i) **AMAs Soundness Standard**

There are no specific rules for generating ORR under the AMAs. However, the Committee points out that it expects that banks will make further progress in their
development of the analytical OR framework. But, it is necessary for a bank, which wants to use AMAs for its ORR calculation, to show that the OR framework is capable of managing tail loss events that are possible and severe, but not catastrophic. A catastrophic event is not a question for regulation, but notwithstanding, it is a very important question. A bank must also be able to demonstrate to its supervisor how its own OR calculation meets a standard of soundness, such as that of its internal calculated credit risk approach, which should be expressed in a confidence interval of 99.9% with a holding period of one year. The Committee is going to follow up the development of the advanced OR approaches by the end of 2007 [113].

(ii) **AMAs Detailed Criteria**

Admission to use internal OR measure for the calculation of the ORR under the AMAs requires that the following quantitative standards will be used:

- The bank has to calculate its minimum ORR. This calculation includes the sum of expected loss (EL) and unexpected loss (UL) that is not already captured in the practices of the banks internal business ([112] p. 122). This means that the bank can base its minimum ORR on UL alone, if it can show the national supervisor that it has already taken care of its EL, e.g., in reserves and pricing.

- The OR approach must show which major OR drivers influence the shape of the estimated tail loss events.

- Banks must have sound OR systems implemented with integrity, for measuring empirical correlation between different OR estimates. These assumptions of the correlations must be validated by experience.

- The OR framework must comprise the use of internal and external data, scenario analysis, as well as factors that reflect the system environment and internal control systems. It is important that this approach is internally consistent and that it avoids all forms of double counting ([112] p. 122).

(iii) **AMAs Internal Data**

As mentioned in the paragraph above, under the AMAs, internal loss event data must be used in the development of a reliable OR measurement system. These data can be acquired in different ways, for instance, through empirical risk estimates, through the
validation of the inputs and outputs in the OR framework or through the control systems between loss experience and ORM\textsuperscript{41}.

Historical loss data must be documented, including how they are planned to be used and who has authorisation to override judgment, scaling, or make other adjustments. Future calculating of the ORR must be based on at least a five year historical observation period for both empirical risk estimates and validation. However, when AMAs are first used, a three year period is enough.

The following standards are suggested for using the historical loss data collection [112]:

- A bank’s internal system for measurement of OR must agree with the Committee’s definition of OR.
- In accordance with the definition in Figure 3.2.1.1 above, mapping of the historical internal loss data may be presented, when necessary, to supervisors.
- A comprehensive collection of internal loss data is necessary. This means that all ORs are covered in the whole organisation, including all relevant subsystems and geographic locations. This is in accordance with the systemic approach described in Chapter 2 and Section 9.1. It is also proposed that a bank should determine a threshold for collecting internal loss data, for example [€10,000].
- A bank must give equivalent descriptive information of the causes of the event. This information must also include the size of the gross loss amount and any recoveries, as well as the date of the event.
- Loss data events can happen in different parts of a bank, e.g., in an IT department, or in different business lines. There can also be related events over time. In these circumstances the bank must show that it can allocate loss data by using developed specific criteria.
- A bank’s definition of OR must agree with the Committee’s definition of OR, as well as of its detailed loss event types outlined in Figures 3.2.1.1 and 3.2.1.2. Furthermore, OR losses due to market and credit activities (e.g., fraud in credit cards) must be managed specifically.

\textsuperscript{41} See The Systemic Approach discussed in Section 1.3 and Chapter 2.
(iv) **AMAs External Data**

A bank must have an OR measurement system that includes a systematic process to find reliable external data, from supervision and/or from the whole banking industry. Furthermore, the methodologies used must be reliable in incorporating the data in the process, e.g., where and why the loss events occurred, or qualitative adjustments. Also, the development of the improved scenario analysis has to be disclosed. Like collection of internal data, these methodologies in relation to external data must also be regularly reviewed and documented.

(v) **AMAs Scenario Analysis**

External data are not enough for the evaluation of a bank’s exposure to high severity events. Therefore, the Committee’s proposal also includes expert scenario analysis, which can be assessed by experienced business managers and/or risk management experts, expressed as statistical loss distribution. This scenario analysis should be used to evaluate potential losses, which will then be compared over time with actual loss experience for validation and reassessment.

(vi) **AMAs Business Environment and Internal Control Factors**

As mentioned in the Detailed Criteria above, a bank must also establish in the OR framework what the key business environment and the internal control factors are. These factors are used to help the bank to make risk assessments for future operational events. For calculating the ORR the following standards are stated [112]:

- Each factor must be a meaningful driver of risk, in accordance with an expert judgment and if possible, translated into quantitative measures that can be verified.

- The establishment of the changes in the factors and their relative weighting must be well reasoned. For instance, if there are increasing risks when a bank’s business volume increases and/or when their activities become more complex.

- Like the other criteria mentioned above, the OR framework with all its affected parts must be documented and regularly reviewed independently.

- Processes and outcomes must be validated and if necessary appropriate adjustment made. This is mainly done through comparison with actual internal
loss experience, but relevant external data can also be used for validation ([112, p. 124]).

(vii) AMAs Risk Mitigation

Under the AMAs, insurance might mitigate the OR. Such risk mitigation is limited to 10-25% of the total ORR.

The Committee has identified some criteria for insurance mitigation [112]:

- rating A in paying ability for the insurance provider;
- residual maturity term must not be less than one year;
- max 90 days for cancellation of a contract;
- re-insurance to a third party entity has to be marked specifically in the OR loss exposure;
- reduction of the ORR due to insurance.

Furthermore, the methodology for recognising insurance includes potential:

- lack of payment;
- risk that insurance providers are too concentrated42;
- liquidity risks with time gaps between payments and claims.

Later on, the Committee also intends to accept other capital markets instruments for the mitigation of the ORR [112].

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42 Risks must also be spread between insurance companies.
4 ORM as System Processes

This chapter discusses how ORM can be seen as a collection of system processes making up a system. This is important since in a risk management chain, the weakest link will determine the strength of the ORM endeavour. It does not matter how efficient particular techniques are, if weak components are used in important places.

In the search for a systemic framework, this thesis needs a model of the ORM process as a system\textsuperscript{43}. The primary candidate for such a model is based on the Committee’s definitions in Chapter 3. In studying Basel II and employing a perspective of a general open system in accordance with Figure 2.2.1, the following structure of ORM emerges. The subsequent discussion points out four key areas that are addressed in more detail from an implementation point of view.

The Committee has, in [170], changed its earlier ORM definition to include the four processes; identification, assessment, monitoring and control/mitigation of risk [170], synthesised in Figure 4.1 below. However, OR differs from other types of banking risk, e.g., market, credit and liquidity risks, in that it is not directly a consequence of an expected reward. Instead, OR is included in all businesses and thereby influences the whole bank’s ORM process. The Committee’s new definition of OR is intended to represent the complexity of the OR profiles. Indeed, this identification of ORs in larger international banks is probably a more difficult task than that of identifying other risk types, such as credit risk and market risk.

\textsuperscript{43} The text in this chapter is submitted to Decision Support Systems (2007) ([184]. In the same article the texts of Sections 1.1, 2.2, 3.2.1, and partly 9.1.3 are also included.
System environment  (Factors beyond the bank’s immediate control)

System boundary  (Open systems)

Process

Validation/ Reassessment

Strategy

Objectives

Governance Model

Policy

Identification  Assessment  Monitoring  Control /Mitigation

Infrastructure  (The systems and the management framework that are necessary to support the risk model)

Figure 4.1: A Systemic Approach to ORM

Consequently, this ORM definition in Figure 4.1 above is used. The figure illustrates this systemic approach to the ORM framework, which also incorporates the necessary strategy, process, infrastructure, and environment, described in Sections 2.2 and 3.2.2.3. Such an approach encompasses the overall system and affects nearly all parts and people in the organisation. In this framework tools and technology are used for facilitating the process, together with the culture and language of the bank. As mentioned in Chapter 2, a systemic-holistic framework must always be dynamic, which means that it is changing, moving and evolving. Therefore at all the times, it is necessary to search for new insights, as well as improvements in measures and controls. Moreover, the strategy includes involving the senior management and the board of the directors in the ORM approach. The governance model includes the roles, authority levels and accountabilities of each part of the organisation [112], [190]. This is further described in Section 5.2.
In accordance with [170], OR identification includes mapping by risk type, showing details of all parts of the business and to what degree they are affected. However, actual risk identification must first be established before a feasible OR monitoring and control system can be developed. In these circumstances, internal factors could be changes in a bank’s structure, activities, staff, organisation, computers and documentation. External factors could be changes in customers, banking and technology. On the other hand, since the assessment process is qualitative it must constantly be reviewed and reassessed to reach greater effectiveness. Specifically, this is important for the uncertainty sub-module in SAFOR2, described in Section 8.1.2. However, getting appropriate data for assessing ORs is a hard task. The qualitative analysis of self-assessment and/or expert opinions, which use subjective data in defining OR can thereby be complementary to other quantitative approaches. A qualitative approach using data from different sources, based on both subjective beliefs and objective historical samples is not new. For instance, there is a whole VaR distribution where the uncertainty of VaR arises from subjective beliefs about risk model parameters values. This shows the movement towards using more subjective data for risk assessment. Assessment of operations and activities against potential OR vulnerabilities is an internally driven process. The process often includes checklists and/or other means to find the strengths and weaknesses of the OR environment. Such a categorisation is described in Section 5.1. It is here that scorecards can be used for translating qualitative assessments into quantitative metrics. Thereafter, the quantitative metrics can be applied to a ranking list of the different types of OR exposures. The scores may be very useful, and for example can be used to identify possible risks and controls, in order to mitigate them.

Like systems theory the Committee points out in [170] that it is important that a bank has an effective integrated monitoring process. This means that the manager must be provided with the information necessary for immediate corrections. Such corrections might be shortcomings in OR management, e.g., policies, processes and procedures, for reducing the frequency/severity of a potential loss event. Moreover, as mentioned in Chapter 3, banks should also identify appropriate key risk indicators, which could be statistics and/or metrics. These must be reviewed periodically and are intended to serve as a warning signal of an increased risk of future losses. Furthermore, the Committee mentions six types of measures commonly used: risk drivers, risk
indicators, loss history, causal models, capital models and performance measures [170].

Some larger international banks have already started to develop their ORM, and for some of them real-time monitoring and reporting have been one of the most important parts of the ORM process. However, this is not without problems. Indeed, in certain situations, it might tend to increase systemic risk. For instance, if many market traders act in the same way, systemic risk\(^{44}\) might increase. Therefore, it is very important that monitoring and reporting of risks are independent of the decisions made to control the risk. A way of solving this problem could be to give continuous reports to senior management for timely management of the risk control strategies.

A framework must be established to find relevant historical information on individual loss data. This information will then be used for assessing the OR and finding a policy to control/mitigate it. Therefore, an appropriate control approach must be defined; this could be vertically up and down in the organisation and/or across business units, processes and geography in line with the business objectives (see above Sections 2.2 and 2.5). Validation/reassessment \(^{45}\) is then the final part of the ORM process\(^{46}\) [112]. For all business areas this ORM framework will result in a common risk-reward profile where all components are working together. However, due to the present state of OR, the VaR simulation models, mentioned in Sections 4.2 and 9.1.4 and Chapter 7, cannot be used for back-testing or validation until enough historical OR information has been collected. Another problem is that to introduce an organisational model with the right people and training programme will take time (see Sections 2.4 and 3.2.2).

It is also important that the boundaries between a bank’s main risk categories; market, credit and ORs, are correctly defined, which is not always the case. In a more holistic ORM approach, which includes all risk categories, the traditional boundaries must be relaxed [190]. In this thesis, however, a stand is not taken on the issue of how the type assessment and aggregation of banking risks should be carried out. Infrastructure refers here to the tools, including the necessary technology, used to facilitate the entire ORM process.

\(^{44}\) See Footnote 3.

\(^{45}\) See Chapter 8 and Sections 3.2.2.3, (v) AMAs Scenario Analyses, 9.1.4 and 9.1.5.

\(^{46}\) See Section 3.2.2.3 (vi) AMAs Business Environment and Internal Control Factors.
Such tools can be systems, data, methodologies, policies and procedures. And, in systems theory, environment means the surroundings that significantly influence the systems character and behaviour and are not under the immediate control of the bank, such as, competitors, customers, workforce and regulators, described in Section 2.2. As mentioned before, these external factors must also be monitored and assessed to ensure that the internal processes are brought into line with the expectations. A well-known fact is that the environment is growing more and more complex. Therefore, it is essential to incorporate the environment into the ORM framework.

4.1 ORM Generation Process

In this thesis the purpose of the ORM framework is purely regulatory, which means that the framework is based around the causes of the loss in mitigating risks. However, this is not the only reason for OR modelling. Managers may also wish to do an economic cost analysis in different areas of the business, though in doing this, they will only discover the consequences of the loss. Therefore, bearing in mind the purpose of the ORM framework, the first question should be: Why model OR? Furthermore, when choosing methodology managers must also consider what data are available [112], [123], [187].

The ORM process may also be described through the well-known control cycle in Figure 4.1.1 below:
The synthesis of the framework (SAFOR) is discussed in Chapter 9.

There are three main sources of information for collecting data [187]:

- **Internal loss events** (see Chapter 5).
- **External loss events** (see Table 5.1).
- **Expert knowledge/opinion** (see Section 9.1.3).

For a systemic-holistic approach to OR all three sources of information are needed. But, there are pros and cons to each source. Figure 4.1 at the beginning of this chapter shows the Committee’s proposal for the internal operational losses described as four processes: identification; assessment; monitoring; and control/mitigation. Through these processes a bank can successively build up its own internal loss database. However, it is important that this data collection is consistent across the whole bank,
even if there are differences in the internal business culture. Moreover, in collecting data for internal loss databases there is often a bias for recording high frequency low severity events. Low frequency high severity events, on the other hand, may occur very seldom (e.g., once in 20 years) within a specific bank, but, if they do occur, they may cause considerable damage. Modelling these low frequency high severity events is therefore not easy. One way to handle this problem is to gather data from other banks in so-called external loss databases. This information may then be used to complement internal loss databases. However, external loss databases can also be a cause of problems since the bank may not have enough control of the external loss data. Information from such a source must, therefore, be used very cautiously.

The Committee proposes that loss information recorded in OR systems must have been collected for 3-5 years before the data can be considered reliable\(^47\). Moreover, senior management and risk control groups are important factors in building more objective OR databases. Also risk indicators from historical losses applied to future situations are useful for ensuring that prescribed risk mitigation measures are followed\(^48\).

To sum up, the risk classification and the level of data available over time will determine the methodology chosen for the OR model. As mentioned above, quantitative and qualitative information must also be balanced in the ORM framework. However, several modelling methods have been suggested for quantifying ORs both within and outside the Financial Service Industry. An overview of these OR methods are given in Figure 4.2.1 below.

Furthermore, [187] points out that one of the modeller’s greatest challenges is to choose techniques from a varied extent of OR events. For doing this work the modeller must [187]:

- Aggregate individual risks into one model, to find correlation and diversification, and for ensuring that the overall risk follows the firm’s own prescribed risk level.
- Understand when OR should not be avoided or minimised, for stimulating dynamic management of the organisation.

\(^{47}\) See Section 3.2

\(^{48}\) See Sections 3.2.2 and 9.1.3.
• Know how to bring together heterogeneous data sources for determining frequency and severity events.

• Represent an extent of appropriate historic time series data for calculating future events.

• Collect expert data or opinions systematically.

• Construct a model for recognising relationship between cause and consequence.

• Bring together conflicting management objectives that have different focus on risk.

• Make complex information understandable for non-financial managers. The image formats of the Bayesian and other network models can make this process easier through their simplified graphical presentation, provided too many details are not added to the model.

• Understand that complex stochastic models like VaR take time to construct and validate, specifically, because many simulations must be performed before the cause can be identified. This approach is described in Chapter 7.

4.2 Modelling Methods of OR

Figure 4.2.1 below shows the most important methods used to quantify and model OR.
Chapter 4  ORM as System Processes

Modelling Methods of OR

Data Analysis          Modelling               Expert Input

Best suited when:
- High context dependency
- All types of events
- Observable & qualitative data

Best suited when:
- Low context dependency
- High frequency events
- Many observable data

Best suited when:
- High context dependency
- Low frequency events
- Few observable data

Methods:
- Statistical / Actuarial / Empirical distribution
- Stochastic Simulation
- Fit parameter / Regressions
- Stochastic processes
- Extreme value theory (EVT)
- Factor / Indicator-based / Causal theories
- Decision/Event/Fault trees
- Scenarios / Influence diagrams
- Delphi method
- Relative fractiles assessment
- Preference among bets
- Log of odds assessment
- Bayesian approach

Possible OR application:
- Organisation risk
- Technology risk
- All other categories of OR
  ⇒ using qualitative & quantitative data

Possible OR application:
- Employee risk
- External risk
  ⇒ Using quantitative OR data

Possible OR application:
- Policy / Process risk
- Conflicts of interest risk
  ⇒ Producing qualitative OR data

Source: Credit Suisse Group / GRM, 2000 ([123] p. 97)

Figure 4.2.1: Modelling Methods of OR [123]

The technical Expert Input of the OR modelling methods in Figure 4.2.1 above uses essentially qualitative assessment and process mapping for possible OR applications, described in Sections 3.2.1 and 7.1. On the other hand, the techniques of Modelling and Data Analysis use more quantitative approaches. In banking the most discussed methods for calculating OR are ([123] p. 97):

1. The factor-derived or indicator-based quantification models.
2. The statistical / actuarial or simulation based quantification models.
3. The loss-scenario / qualitative assessment models.
The complexity of the OR requires that models and techniques are used in combination [107], [123], [187]. But, the aggregation of the different OR components must ensure consistency of the various models. Otherwise an aggregation of the OR from different models might end up comparing apples with oranges\textsuperscript{49}.

1. The factor-derived / indicator based models that apply causal factors for OR calculation have been investigated by D. Hoffman (1998) [177]. Even if these models tend to have some drawbacks, Basel II [112] proposed similar indicator-based quantifications methods, BIA and SA, for OR quantification and ORR calculation in banks, described in Sections 3.2.2.1 and 3.2.2.2.

Indeed, the Basel II method is a simplified factor / causal theory model, and it has not yet been verified that there is linearity between the OR levels and the businesses. Furthermore, there are other important drawbacks of the BIS causal theory models that can lead to faulty approximations of the OR. For instance, [123] points out that if there is high context dependency between many OR elements it can be critical to determine the level of the qualitative OR aspects. But, Basel II [112] has yet to take into consideration some of these questions. For example, it has successively found key new OR indicators for different processes and qualitative aspects of OR, in order to make it more meaningful. Another problem with indicator based models is that they can raise the OR, if banks use them for lowering control related costs. On the other hand, if fee income is lowered to save capital in regulated banking activities, these activities could be forced out of banking, thereby favouring unregulated financial actors, which in turn could result in increased systemic risk in markets\textsuperscript{50}. According to [123], these indicator based methods might be useful in top-down frameworks\textsuperscript{51}, when low and high frequency events are of interest. However, this thesis does not investigate these OR explanatory variables further.

2. The statistical / actuarial or simulation based quantification models use actual loss data for OR calculation. Here frequencies and severities of operational losses are constructed in statistical probability distributions. But, initially financial OR

\textsuperscript{49} See Sections 2.4 and 10.1.
\textsuperscript{50} See Footnote 3.
\textsuperscript{51} See Sections 3.2.2 and 5.3
Chapter 4  ORM as System Processes

data must be captured and accumulated from loss events over different business lines and types for five to ten years to complete OR databases. Thereafter, these databases may be used for modelling future internal ORs and external loss events.\(^{52}\)

The statistical quantification models, described in Chapter 7, are very common in the OR literature. They can generate a loss distribution for each OR category or sub-category and they can also be reduced to individual business lines. Moreover, interdependencies among OR elements can be calculated. These statistical models are generally known among market and credit risk specialists in financial institutions [1], [26]. But, because of the lack of historical OR data it is not yet possible to do any back-testing or validation of the correctness of the OR distribution generated. Moreover, OR is high context dependent, specifically of changes in the environment, with the consequence that the whole simulation approach must be reviewed. Another drawback of this approach is that it is very complex and expensive to implement. However, ([123], p. 100) points out that there are four OR advantages of the simulation method:

- Quantitative support after validation with enough internal data.
- Consistent with those for market and credit risks.
- The model would generate VaR and OR measures.
- Allow bottom-up calculation of the OR.

3. The loss-scenario / qualitative assessment models state a subjective loss estimate for OR calculation. In Basel II this loss estimate is calculated for a one year holding period with 99.9% confidence level and is the result of key managers’ experience and expertise [112]. Chapter 5 discusses weaker assessment forms, where OR elements and levels are mapped and/or check listed. Recently, interest in OR qualitative assessment models has increased because of its context dependency. Sections 8.1, 9.1.3 and 10.1 investigate how qualitative assessment can be transformed into quantification. Such a method of evaluating the OR could involve four core elements [123]:

\(^{52}\) See Sections 3.2.1 and Chapter 9.
• Qualitative mapping principle of each business line and event types of the OR, shown in Figures 3.2.1.1 and 3.2.1.2.

• Grading risk priority assessment for severity, probability and holding period, described in Chapter 5 and Sections 8.1.2, 9.1.3 and 10.1.

• Grading strategic management for increasing businesses, described in Section 5.2.

• Grading transformed into an OR level expressed in monetary terms, described in Sections 8.1.2 and 9.1.3.

The Uncertainty Module of the framework, described in Sections 8.1.2 and 9.1.3, is in line with these loss-scenario / qualitative assessment models. An advantage of these methods is that they increase the transparency of the causal factors of change in the OR and make it easier for the management to predict the level of potential losses. For instance, root causes can be assessed and scenario analyses related to potential future environments. But, specifically these methods are not so good for ORR calculation because of the subjective judgment of experts.

The Basel II’s methods have now opened up the possibility of a new framework for larger international banks. After satisfying some qualifying criteria, these banks can choose the AMAs to calculate their own ORR based on their risk profiles and risk management methodology. However, these qualitative and quantitative standards for the use of the AMAs are minimal, which gives the banks the possibility of developing innovative OR frameworks. The Committee has announced that it intends to review the developments of OR approaches continuously. Hopefully, in the future this could be a way of solving the drawbacks mentioned above, when banks have got more data and experiences from their ORM approaches. The use of AMAs has also opened up possibilities for the banks to use methods 2 and 3 mentioned above, as well as for a systemic-holistic approach to ORM, not seen explicitly before in banking institutions.

Accordingly, Basel II has proposed three different ORM models for calculation a bank’s ORR. Today it seems that BIA and SA, described in Sections 3.2.2.1 and 3.2.2.2, with their use of risk control indicators (RCIs) are preferred to more complex models like the AMAs, described in Section 3.2.2.3. Even if these RCIs can help to effectively control or reduce partial OR in absolute value, they are not suitable for an active overall ORM. However, a combination of qualitative and quantitative methods
seems to be the best way of managing OR. Therefore, until more reliable databases are obtained, it is better to use such methods that capture the change of the OR and facilitate the prediction of the potential losses. But, this will only give a pragmatically acceptable ORM approach until a reliable database is available. A suitable active overall ORM and the lowest limit for the supervisor’s ORR may be possible to attain after collection of the operational events in a database over the next five to ten years. Such information used in a systemic perspective might be more useful and reliable for the ORM and the calculation of the ORR than the analytic approach. This will be further discussed in the next part of this thesis.

Basel II views ORM as a task of identifying all processes at risk and measuring the risk involved. This is a valid view, but looking at the ORM task from a systemic perspective gives a complementary picture. This does not mean that the analytic (bottom-up) view is false or irrelevant; it is merely not a complete picture. This is not a critique of Basel II per se; it is a comprehensive effort towards a regulatory ORM approach. But, for banks to encompass this in their operations there is a need for implementation guidance that takes the whole organisation into account. While it is important to be regulation compliant, implementation must aim at being efficient for the bank’s own use in terms of ORM processes. These two requirements are not in conflict to any large extent, but they do not coincide. In particular, the maturity levels among the risk measurement techniques are diverging, with techniques such as VaR being well investigated and others such as scorecards being less rigorous and less precisely defined. The conclusion of this survey of Basel II (AMAs) from a systems perspective is that these latter areas in particular need to be further investigated. The next paragraphs in this section give an overview of what is discussed in the following chapters, which also include this thesis’ proposed SAFOR model.

Section 3.2 shows how tentative rules for modelling OR in the banking industry have developed during the last five years. Besides that, this Chapter 4 describes how the Committee periodically guides banks in their modelling process by publishing Sound Practices for Management and Supervision of Operational Risk [170]. These guidelines are meant to serve as an additional incentive for banking institutions to incorporate transparency and sound conceptualisation into their ORM processes [111]. Furthermore, Figure 4.1 shows how the ORM should be evaluated in progress

53 See Section 5.3.
relative to objectives. The Committee points out that the results should be clearly reported and necessary decisions should be made daily. Below, four key areas will emerge, which correspond to the Chapters 5-8 in this thesis.

Chapter 5 and Section 9.1.1 investigate OR identification and classification against the Committee’s temporary definition of the OR. As mentioned before, the chosen methods for capital allocation in Basel II is the bottom-up model. But, before identifying OR it is necessary to define it. This thesis follows the approach taken by the BIS for individual banks, where OR is defined as the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events [112]. The definition focuses on the causes of OR, also called risk factors. Thereafter, in identifying OR it is enough to identify the risk factors that are the most important for maintaining material products, activities, processes and systems54. By doing so, it is possible to set priorities for ORM, including contingency measures for extreme events. This assessment can be made by internal and/or external operational experts of the systems. An environmental scan55 may also be useful for identifying the uncertainty of the changes in risk factors outside a bank’s systems.

BIS [170] lays down 7 principles for the development of an appropriate risk management environment. It is pointed out that in a changing external market, the methodology used for ORM must be supported by sound corporate governance, internal controls, policies and procedures, OR identifications and assessments, reports, appropriate strategies, and robust contingency plans [112], shown in Figure 4.1. It is mentioned above that once the frequency and severity of operational events have been registered in OR databases over the next five to ten years, it may be possible to use parts of this information for estimation of the future OR in different systems. But, until then, operations experts must give their opinions about the potential impact and frequency of events, used for the qualitative analysis, described in Sections 5.1, 8.1 and 9.1.5. In this rapidly changing world new forward looking OR tools and processes are being developed all the time. Some of these tools and processes are described in the following chapters of this thesis. Chapter 9 presents the thesis framework for the SAFOR model, while Section 10.1 describes a process used to assess and manage OR in a large international bank.

54 See Section 10.1.
55 See [110], Chapter 8 The Environmental Scanning Process.
Accordingly, the proposal in this thesis is to use a whole systemic\textsuperscript{56} approach to ORM in a bank. Such an approach will provide a different and more effective alternative than when each OR object of a bank’s system is separately investigated. However, up to now the OR in banking institutions seems to be based more on qualitative approaches rather than on hard data, while attention to the systemic aspect of the OR in the whole banking system seems to come from central banks. In the future, with operational events databases providing a more empirical basis, OR quantitative method may be used both in an individual bank and perhaps also in the banking system as a whole. But, this latter question is not further investigated in this thesis.

Specifically, changes in the international banking environment need more complex ORM for handling new banking activities and geographically unknown markets, sometimes far away from the head office. Consequently, rapid globalisation and the technological advances have shifted the composition of the OR and increased the complexity of the ORM. As mentioned, traditional approaches to ORM have mainly relied on qualitative and not aggregated approaches. However, through advances in the quantitative modelling of credit and market risks [1], [3], [26], larger international banks are now trying to develop quantitative models for integrating the OR in their worldwide ORM. Chapter 7 and Section 9.1.4 investigate how these VaR and CVaR models must be reliably constructed, to be able to supplement some qualitative approaches for measuring and managing OR in the future.

In terms of the methodology that is proposed in this thesis, the model for ORM in a bank’s systems involves identifying, assessing, monitoring, controlling and mitigating OR\textsuperscript{57}. This methodology is recommended in many recent publications, including those of the BIS [112], [170], [188], [190]. Moreover, since there is uncertainty about the distribution of different risk factors, the valuation of risky projects is further explored in Chapters 6 and 8, and Sections 9.1.3 and 9.1.5.

Accordingly, a systemic approach to ORM implies that banks should formulate, search, explain and interpret accurate information related to OR in their systems.

\textsuperscript{56} Systemic or soft systems thinking are when facts are treated as problems (the epistemological entity) and are solved by systemic methods [125]. The view of a problem as a whole is called a systemic approach in the systems science.

Systematic or hard systems thinking (engineering) is when facts are treated as existing systems (the ontological entity) and is solved by systematic methods. Soft systems and hard systems thinking can be seen as complements to each other [125], [178] (see systemic risk, Footnote 3).

\textsuperscript{57} See Figure 4.1 and Sections 9.1.2 and 9.2.
analysis. After collection of a bank’s OR information processes the modeller may use management information systems (MIS) to provide the management quickly with decision making criteria for monitoring and controlling the OR. By using data from the database a proactive management can then be established, where OR changes can be monitored in order to assess the new OR effect on the loss distribution and to forecast future changes. However, MIS can also be used to identify and develop early warning indicators of future operational problems [170], [188].

In the systemic approach each object of a bank’s systems has options for preventing or mitigating risk. Furthermore, it is important to test the contingency and business continuity plans for ensuring the bank’s survival. Here scorecards can be a help to identify possible risks and to mitigate them. Chapters 6 and 8, and Sections 9.1.5 and 9.3 investigate these problems and how to make acceptable decisions. As a consequence of the confidentiality in the banking system and the lack of availability of material, Chapter 10 uses a bank application of an advanced OR model as validation of the SAFOR. Chapter 11 concludes the thesis and gives some ideas for further research.
Part II
5 OR Identification and Classification

The proposal of a new Basle Capital Accord, Basel II, described in Section 3.2, is a result of an ongoing dialogue between the Committee and the financial market participants on how to identify measure and manage OR in banks. During this development of ORM in banks the Committee has also tried to borrow ideas from leading industry practice. One question that has been under extensive discussion is the various possible definitions of OR. Accordingly, in October, 2002, the Committee provided the following, temporary definition of OR: *The risk of loss resulting from inadequate or failed internal processes, people and systems or from external events, and therefore includes legal risk but not strategic, reputational and systemic risks* [112]. Legal risk is the risk of loss that occurs if the bank has not followed laws, ethical standards and contractual obligations, including litigation due to the bank’s activities. This definition of OR breaks down the OR event into four causes, i.e., people, processes, systems and external events. Section 3.2.1 describes the Committee’s tentative rules for modelling OR and the OR data collection exercise in banking institutions. The Committee also listed some typical event and failure types of OR, shown in Figure 3.2.1.1 and Table 5.1.
### Table 5.1: Types of Operational Failure Risks [112]

| 1. **People risk:** management failure, organisational structure or other human failures, which may be exacerbated by poor training, inadequate controls, poor staffing resources, or other factors. | • Incompetence  
• Fraud  
• Attrition |
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>2. <strong>Process risk:</strong> breakdown in established processes, failure to follow processes or inadequate process mapping within business lines.</td>
<td></td>
</tr>
</tbody>
</table>
| A. Model risk | • Model/methodology error  
• Mark-to-model error \(^{58}\) |
| B. Transaction risk | • Execution error  
• Product complexity  
• Booking error  
• Settlement error  
• Documentation/contract risk |
| C. Operational control risk | • Exceeding limits  
• Security risks  
• Volume risk |
| 3. **Systems risk:** disruption and outright system failures in both internal and outsourced operations. | • System failure  
• Programming error  
• Information risk  
• Telecommunications failure |
| 4. **External event risk:** natural disasters, terrorism, and vandalism. |  |

---

\(^{58}\) Mark-to-model valuation is used for estimating the fair value of a transaction, position, asset, or portfolio. It can be estimated by building a price model or by a combination of traded instruments or products and may also incorporate operational and other contractual constraints. Moreover, the model can be internally designed or obtained through a vendor (http://www.riskcenter.com/pdf/5819.pdf) (see Section 5.4).
It can be noted from Table 5.1 above that some risks can be difficult to quantify (e.g., incompetence) whereas others are more easily adapted for quantification (e.g., execution error).

5.1 OR Categorisation

Categorisation of OR starts with a risk analysis, which aims to investigate what kind and degree of control is needed for establishing a decision process. This analysis calls for some means of prioritising the risks categories, described in Sections 3.2.2, 9.4 and 10.1. There are several proposals of the same kind of metrics or variants thereof, frequently used in the risk literature [112], [130], [190]. But, in the following two sections the main source of information presented is from the paper *Security Issues in Internet E-Commerce* by the Sherwood Associates Ltd (1999) [106]. In this model the different values are expressed in non-monetary metrics for threat, impact and vulnerability. However, it can be very difficult to measure the size of the threat. Therefore, a way of solving this problem may be to ask if a threat exists or not (a binary decision). If it does, then the methodology is to establish the impact by using the well-known three-point scale as follows [106]:

- **Severe impact (high).** A risk so severe that the business will *not survive*.
- **Significant impact (medium).** A significant risk for the business, but it *will survive*.
- **Minor impact (low).** A normal risk in *ordinary business life*.

Thereafter, a detailed vulnerability analysis is performed that shows the necessary controls for the severe and significant impacts. Vulnerability is established by the use of a three-level model:

- **High vulnerability.** The systems show substantial weaknesses with severe or significant impacts. *The control must be improved.*
- **Medium vulnerability.** The systems show some weaknesses with severe or significant impacts. *The control can and should be improved.*
- **Low vulnerability.** There is no problem with the operation of the systems. *No additional control is needed.*

A three-level model is a combination of the business impact and the vulnerability. Such a model shows the risk calibration in a $3 \times 3$ matrix, shown in Figure 5.1.1
below. Table 5.1.1 explains the risk priorities between the risk categories A, B, C and D.

<table>
<thead>
<tr>
<th>Vulnerability</th>
<th>Business Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>A</td>
</tr>
<tr>
<td>Medium</td>
<td>B</td>
</tr>
<tr>
<td>Low</td>
<td>C</td>
</tr>
</tbody>
</table>

Figure 5.1.1: Risk Categories ([106] p. 12)

Table 5.1.1: Risk Categories ([106] p. 13)

<table>
<thead>
<tr>
<th>Risk Category</th>
<th>Risk Priority</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Immediate corrective actions are required either to reduce the vulnerability or to reduce the impact level, or both. These risks are of the highest priority to address.</td>
</tr>
<tr>
<td>B</td>
<td>Appropriate corrective actions should be planned and executed so as to reduce the vulnerability, or the impact level.</td>
</tr>
<tr>
<td>C</td>
<td>These risks are acceptable, because either the vulnerability is at its lowest possible, or impact is minor, but they should be monitored to ensure that they do not creep back into B category.</td>
</tr>
<tr>
<td>D</td>
<td>No action needed.</td>
</tr>
</tbody>
</table>

Naturally, there are criticisms against these risk level models, which are not compatible with any well-established principle, such as the principle of maximising the expected utility (PMEU) [130], discussed in Section 8.1. There are several problems with this kind of approximation of scales that is primarily ordinal in their nature, when they are aggregated. Furthermore, even if this is disregarded, the granulation is far too low and it is difficult to discriminate between the risks. Therefore, a more elaborated approach is needed for the purposes in this work. This
thesis suggests a decision theoretical risk model approach such as [129], described in Sections 8.1.2, 9.1.3 and 9.1.5.

5.2 Strategic Aspects

As soon as the ORs are defined and comprehended, the security architecture must be formulated for analysing the vulnerabilities in the systems and appropriate controls applied. Normally, the whole security architecture must be introduced to ensure that everything in the business works together and operate correctly both in the short term tactical and in the long run strategic approaches, described in Chapter 4. However, there are still organisations, which believe that it is enough to implement only a few technical security controls. But, such an approach will not be successful [106], [180].

![Figure 5.2.1: The Relationship between the SABSA Layers ([106] p. 14)]

It is a well-known concept in the IT security literature to visualise the architecture as a series of layers. In Figure 5.2.1, SABSA [106] has chosen a six-layer IT security model to show the process of defining the whole security architecture. This model should be approached from the top layer and down through the left five layers. As seen in Figure 5.2.1 the Security Management affects all of the other layers. Since IT security is one of the key areas of OR, this is an interesting example of an ORM security architecture for use in controlling and mitigating OR efficiently. While Table 5.2.1 below discusses issues particular to cryptography, analogous reasoning can be applied to other, neighbouring areas as well.
Table 5.2.1: The Six Layers of the SABSA Model ([106] p. 15)

<table>
<thead>
<tr>
<th>Layer</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contextual Architecture</td>
<td>The business requirements for security, including the risk analysis, but also the requirements for usability, cost, flexibility, scalability, time to market, etc.</td>
</tr>
<tr>
<td>Conceptual Architecture</td>
<td>The major strategic approaches to be used, such as the role of the network, the use of end-to-end security, the deployment of PKI (public key infrastructure), the approach to monitoring and audit, defining responsibilities and liabilities, etc.</td>
</tr>
<tr>
<td>Logical Architecture</td>
<td>The logical security services, such as entity authentication, access control, transaction integrity, service availability, confidentiality, accountability, non-repudiation, trust broker service, etc.</td>
</tr>
<tr>
<td>Physical Architecture</td>
<td>The security mechanisms, such as encryption, digital signatures, digital certificates, and authentication protocols, and so on, as well as their physical implementation and the configuration of physical components such as servers, firewalls and clients.</td>
</tr>
<tr>
<td>Component Architecture</td>
<td>Actual products and technologies that will be deployed to build the solution, such as cryptographic software packages, smart cards, CA (Certification Authority) systems, etc.</td>
</tr>
<tr>
<td>Operational Architecture</td>
<td>The way in which the security services will be operated, monitored, maintained and supported throughout their operational lifetime.</td>
</tr>
</tbody>
</table>

More detailed exploration of how these layers are used in an actual implementation can be found in J. Sherwood [106] and in Information Technology Security Evaluation Criteria, ITSEC [180].

5.3 Top-Down vs. Bottom-Up Models

O’Brien et al. [114] have investigated another approach to OR. They state that there are two categories of complete models of the OR: top-down and bottom-up. The top-down approaches attempt to allocate the business unit level risk down to the businesses, where loss or earnings volatility data are integrated independently of the actual workflow. One well-known, top-down approach is the Capital Asset Pricing Model (CAPM) often used as benchmark of other similar institutions. In this model large operational failures lead to movements in CAPM inputs, e.g., equity prices, betas and debt leverage. Although, CAPM-based models are easy to implement, they
only supply an overview of an enterprise-wide OR capital. Therefore, top-down models do not fit well for capital allocation in business processes. Consequently, Section 3.2 points out that Basel II [112] has chosen the bottom-up methods for the proposed OR capital allocation in banking.

The second way of categorising OR is through bottom-up models. Here, the principles for business line mapping are the same for OR, market risk and credit risk. Moreover, risk is estimated through actual causal relationships between failures and given losses. This makes the bottom-up model appropriate for business improvement but difficult to implement [114]. Furthermore, to find a firm’s risk profile it is necessary to analyse the loss events in individual business lines and, thereafter, try to identify and quantify each type of risk at that level, as shown in Figure 3.2.1.1. The frequencies and controls of the loss events are then estimated, wherever they may occur. Thereafter, the severities of the potential losses are estimated, after taking into consideration insurance and any other risk transfers, discussed in Chapter 4.

Another simpler implementation of a bottom-up model might be to calculate ORR over a year (chosen horizon), and then sum up the resulting operational VaR, also called CVaR, for each different type of loss event. VaR and CVaR are further investigated in Chapter 7 and Sections 9.1.4 and 10.1. By using statistical/actuarial methods in this approach, a more sophisticated implementation could be reached that modelled both event frequency and severity as probability distributions.

To handle inflation, the methods mentioned should also scale losses into a time-independent unit. Moreover, frequency and severity should be modelled separately and then put together, whereby causes and loss effects will be better drill-down [114]. Thereby, through triggered thresholds, it will be easier to implement dynamic control processes in the workflow and observe the effects of those, described in Sections 8.1.2 and 9.4.

5.4 Model Risk

Model risk may be a result if the data are of poor quality or if the model has poor precision and/or validity. Therefore, like a total loss distribution due to mishandled transaction events model risk must be considered and calculated. Accordingly, this calculation should include events that might be errors in market data, missing relevant trade attributes and life cycle events characterised in terms of canonical events [114].
The proposed technique here is *Dollar-unit sampling* for sampling the portfolio periodically, where the frequencies of errors, as well as the severity are assessed. With this method big transaction will be emphasised without ignoring the small ones. Furthermore, the sampled transactions are checked and, if necessary, corrected and revalued. The severity of the model error is estimated during comparison of the sampled result against the original valuation of a specific transaction. Total model error is then reached by extrapolating of these results from the sample. In practice the model parameters are highly uncertain, i.e., the model risk tends to be huge, potentially hiding the optimal decisions from any specific model\(^{59}\). However, this thesis is not going to analyse model risk specifically.

### 5.5 Estimation Risk

Estimation risk in the financial industry can be found in default rates, recovery rates and assets correlations. Therefore, if a sensitivity analysis is applied to the systems, it may seem that the result is robust in many factors. But, the maximum losses estimated are always critical. Especially, since estimation errors in these cases have a significant impact on the derived VaR and CVaR \(^{107}\) (see Chapter 7 and Section 10.1).

As an example, J.R. Horst et al. (2000) \(^{122}\) proposed an adjustment in Markowitz’ mean-variance portfolio weights \(^{9}\) to incorporate uncertainty, depending on the fact that, in general, estimated expected mean returns are used. Their adjustment implies that instead of the actual risk-aversion a higher pseudo risk-aversion should be adopted. They claim that the difference between these two aversions depends on different factors, as for instance, the sample size, the number of assets, and the mean-variance frontier \(^{122}\). For their statement, they refer to their adjustments to international G5\(^{60}\) country portfolios, which show that the adjustments are nontrivial

\(^{59}\) See also mark-to-model, Footnote 58 and Section 9.1.1.

\(^{60}\) The dataset includes monthly returns on stock indices for the G5 countries as well as monthly returns on three emerging market indices. The data for the G5 countries are for the period January 1974 until December 1998 and for the emerging markets for the period January 1989 until December 1998. The G5 stock indices are the MSCI indices for the US, France, Germany, Japan, and the United Kingdom. The emerging market indices are the indices for Latin America, Southeast Asia, and the Middle East/Europe. These indices are from the Emerging Markets Data Base (EMDB) of the International Finance Corporation (IFC). The indices for the emerging markets are the IFC Investable indices and therefore they represent stock portfolios that are obtainable for U.S. investors. All data are from Datastream and all returns are monthly unhedged U.S. Dollar returns \(^{122}\).
and that seem to be more accentuated when new markets are added. However, this thesis is not going to analyse estimation risk specifically.
6 Valuing Risky Projects

As pointed out in Chapter 1, the purpose of the proposed OR framework is mainly based around the causes of the loss in mitigating the OR, which means that we have taken the same regulatory approach as Basel II. However, Section 4.1 mentions that managers can also want to do an economic cost analysis for discovering the consequences of the loss. Therefore, the SAFOR2 module in Section 9 has been split into two sub-modules; The Uncertainty Module and The Decision Module. In uncertain situations when the consequences might be serious and the probability of catastrophic events is low a consequence analysis in The Uncertainty Module is recommended, discussed in Sections 8.1.2 and 9.1.3. This module handles the qualitative sorting function. On the other hand, The Decision Module handles the quantitative sorting function and includes causal models that provide the mathematical framework for predicting potential losses. These models are usually based on Bayesian networks.

In this chapter a short overview of how to value risky project from a systems perspective is given. Section 6.1 starts with the investigation of the general meaning and problems behind Bayesian inference and belief networks as background information. Section 6.2 investigates the conditions for coherent decision analysis in incomplete markets.

6.1 Bayesian Inference and Belief Networks

One of the subtasks of this thesis is to investigate whether decision analysis and interval predictions could be used in connection with VaR and CVaR to compute OR for an internal, advanced measurement approach. This section gives a short survey of the meaning and problems behind Bayesian inference and belief networks mainly in accordance with [99] and [100].

6.1.1 Decision Analysis

Probability theory and utility theory are two quantitative theories used in decision analysis, where observations are combined to find an optimal decision. Furthermore, decision analysis rests on the axioms of rational choice and its foundations are qualitative. With rational choice is meant that a person can model a decision problem,
including necessary options, relevant factors and quantification of uncertainty and preferences. But, the end choice, a rational decision, is often not easy. Therefore, in uncertain situations the decision analysis may only give insight into the problem, but not lead to any rational decision. There are many variants of probabilistic models based on directed acyclic graphs (DAGs), often used in cognitive science and artificial intelligence (AI) and known as Bayesian networks. These networks are also called belief networks or causal networks [99]. A lot of interesting inference algorithms and implementations for probabilistic reasoning in Bayesian networks with discrete variables have been proposed during the last fifteen years (see [23], [93], [94], [95]).

Belief networks use probability theory for managing uncertainty, and the interactions among the various sources of uncertainty in the belief networks are presented in an intuitive graphical visualisation. These are constituted through a set of variables (vertices or nodes), a graphical structure that connects these variables, and a set of conditional probability distributions (edges or arcs) between the different knowledge components. Furthermore, if there is no arc between two variables, this indicates conditional independence and implies that there are no conditions in which the probability of one of the variables depends directly upon the state of the other.

A probability model consists of elements (variables), where each element can take a set of different values that are mutually exclusive and exhaustive, which implies that no important distinctions are shared between the states, and that the states each variable can take must cover all possibilities for the variable. Many models can only handle discrete variables with a limited number of conditions.

After meaningful relationships and known evidence are established in the model the probabilities of the outcomes can be performed, also called inference or model evaluation. Evidence can be recent events or observations (information), which an end user applies to a Bayesian model. Then, through computations the probabilities of all the other connected variables are updated and, thereafter, the inference shows the new levels of belief in (or probabilities of) all possible outcomes, prior coded by the modeller. Before any evidence is known these earlier beliefs are known as prior probabilities, whilst beliefs after known evidence is applied are known as posterior probabilities. There are various assessments methods for the probability estimates in the model, but all have the same goal of specifying the distribution correctly and at
the same time minimising the required probabilities (see [98], [99], [121]), also discussed in SAFOR2, Section 9.1.3.

### 6.1.2 Utility

A necessary element of all decision problems is preference, explicitly or implicitly expressed as utility, also discussed in Section 8.1.2. Often an objective quantity, such as financial gain or factory output, can be used for establishing the preference. But, there will be complications, when decision problems comprise quantities without numerical measure, such as customer satisfaction. Also the attributes price and quality can cause problems in reflecting the decision maker’s risk preferences, even if a numerical measure of an outcome is available.

In decision theory the utility function maps the possible outcomes of a decision process in attributes on a set of real numbers. However, utility has no zero point and no meaningful scale. Consequently, since utility is subjective the choice may differ between various decision makers facing the same problem because of their different utility functions. Furthermore, the determination of a person’s utility function is known as utility elicitation, and the variables measuring this utility are always continuous. Accordingly, multi-attribute utility variables are continuous and specify a function by which the values of their parents are combined\(^6\). However, in graphical influence diagrams the variables usually have discrete parents and take a finite number of values (see below).

### 6.1.3 Influence Diagrams

A decision tree may be modelled as both decision tree and influence diagram, where each form has its advantages and drawbacks. But, it is possible to create a more comprehensive and understandable decision approach by using both approaches, discussed in Sections 1.4, 3.2.2 and 10.1.

Influence diagrams (or relevance diagrams) represent the structures of the decision problems by using DAGs [101] and are Bayesian networks with utility and decision functions. The utility functions quantify the cost or benefit connected with the set of outcomes/states and the decision functions model alternative actions. Influence diagrams can use a smaller number of nodes for showing the same decisions and

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\(^6\) See Sections 6.2 and 9.1.3, the Uncertainty Module.
events in the model, and therefore may be useful for creating an overview of a complex decision problem for presentation to another person.

However, there are also drawbacks associated with influence diagrams. For instance, due to the abstraction, it may be difficult to see the connection between an embedded event or decision node and its many outcomes. Moreover, the dimension of time in the decision problem can be difficult to infer (see Value nodes below).

Contrary to influence diagrams, decision trees show all possible decision options and chance events in the model. In this events and decisions are shown chronologically, from left to right, as they occur in time. Moreover, all options, including the values and probabilities associated with them, are shown in the model structure.

There are variations in the details of the modelling components for these approaches, but the semantics are similar and the expressive power is also similar. Many of these models have been implemented in various packages. A detailed demonstration of one particular model is to be found in [100].

### 6.2 Decision Analysis in Complete and Incomplete Markets

Decision analytical tools have been used for a variety of domains, but it has not been straightforward to combine them with financial theory and this will be discussed in this section.

Smith and Nau (1995) [10] and Copeland et al. (1990) [24] state that if market opportunities and a utility function for time and risk preferences are included in the decision tree approach, the financial options approach and the decision tree analysis will be consistent in complete markets. The assumption about complete markets in real options literature can be found in [33], [34], [35], [38].

Smith and Nau (1995) [10] present some attempts to model general properties of standard methods of decision analysis for valuing risky projects in complete markets. They claim that the only deviation from the option pricing theory is that they explicitly use the beliefs of a single market participant, called the *firm* instead of its owners. This *one mind* assumption is consistent with the decision analysis approach, where a corporate utility function operates at the request of the top management, according to ([31] p. 299), [40], [41]. This means that the modeller works with both
the firm's top officers and the firm's appointed experts for assessing the probabilities of the relevant uncertainties, also shown in the related case in Section 10.1.

The asymmetric assessment tree-based method, mentioned in Section 6.1, can be illustrated in sets of probabilities organised as a decision tree. For the definitions and the varying assumptions and information requirements behind such a framework we refer to [10], [24], [36], [37].

Moreover, it is well-known that economic theory uses money as a medium of measurement and exchange and that the arbitrage principle characterises rationality at the market level. This economic rationality is a result of deliberated optimisation by individual agents, where no-arbitrage is said to be synonymous with subjective expected utility maximisation. This approach can also be used to facilitate reconciliation between the concepts of equilibrium behaviour in games and markets (see below). Furthermore, in economic systems risk-neutral probability distributions have a central role. With risk-neutral probability distributions are meant the products of the probabilities and marginal utilities.

Accordingly, if there is a project and the manager wants to maximise the project's value, the option pricing and decision analysis approaches are consistent in the sense that they give the same optimal project management strategies. This is the case in spite of the inputs and outputs of the two analyses having different approaches.

Consequently, Smith and Nau (1995) [10] point out that both the option pricing and decision analysis approaches prescribe the firm to state the possible cash flows of the project as well as the possible values of the securities over time. Moreover, the states each variable can take must cover all possibilities for the variable, and all necessary project strategies must be considered.

However, when the decision analysis is used the firm must also specify probabilities and a utility function for the future cash flows. An additional output of this input from the decision analysis is that the firm gets information of the optimal strategy for investing in securities. Consequently, it has been shown in [10] that when markets are complete investment decisions can be made exclusively on the basis of the market information, while financing decisions must use subjective beliefs and preferences.

Moreover, Modigliani and Miller (1958) [41] claim that the firm’s financing decisions are irrelevant from the owners point of view since they can, through securities
transactions, replicate or negate the financing decisions. However, when markets are incomplete both the investment and financing decisions can use subjective preferences and beliefs. Even if Smith and Nau (1995) [10] have tried to solve this problem too, this thesis investigates newer valuation approaches for coherent decision analyses in incomplete markets, discussed in Sections 8.1, 9.1.3, 9.1.5 and 9.3.

A decision analysis like that in this section could be a useful strategic help in handling the ORs. But, in incomplete markets the model evaluation will be much more complicated.

Cerny and Hodges (1999) [22] investigate whether coherent risk measures and arbitrage bounds could be equivalent. However, the price calculations in practice, including transaction costs, have shown that there are differences between arbitrage valuation and utility maximisation (or equilibrium theory) [70], [71], [72]. Jaschke and Küchler (2000) [18] propose a new generic valuation theory, which seems to minimise these differences. El Karoui and Quenez (1992) [19], and Jouini and Kallal (1995a, b) [20], [21] have, with the use of super-hedging and arbitrage pricing, explained the valuation bounds in incomplete markets. Later on, Jaschke (1998) [77] has further developed this technique. Thereafter, Cerny and Hodges (1999) [22] have used no-arbitrage pricing theories for showing how arbitrage bounds can be generalised to good-deal bounds, also discussed in Section 9.1.5. Besides these, risk measures like VaR, described in Chapter 7, have been developed. Since, even VaR has weaknesses, the question of what is the necessary conditions for an economically sensible risk measure, cannot be answered by this measure. More recently, Artzner et al. (1999) [4] give an answer to these questions in their paper Coherent Measures of Risk, also described in Chapters 7 and 8. They show that coherent risk measures have the same mathematical structure as good-deal bounds, but start from different viewpoints. Moreover, arbitrage valuation for deriving price bounds does not need any estimation of probabilities and personal preferences. According to Brown et al. (1998) [63], these arbitrage bounds are robust with regard to model misspecification, also mentioned in Section 5.4. But, Hodges and Neuberger; (1989) [64] claim that it is better to use single agent utility maximisation, which derives much sharper (closer)
valuation bounds in realistic settings with transaction costs\textsuperscript{62}.

\textsuperscript{62} These aspects are incorporated in the SAFOR2 model, Section 9.1.2 and in Chapter 8.
Chapter 7 VaR and CVaR

7 VaR and CVaR

As mentioned in Section 1.5, VaR analysis is commonly used for group-wide and business risk analysis in financial markets. However, this chapter looks into the general conditions of VaR and CVaR to achieve greater integration for an advanced, strategic OR model across all business units. Employing GST, these financial VaR and CVaR investigations are used as templates for modelling this OR system. But, there is still considerable work remaining in integrating certain OR issues into a market risk-type VaR assessment, like that mentioned in Section 9.1.4.

VaR and CVaR are two risk measures often used. However, even if VaR is a commonly used risk measure, it has drawbacks. The most important weaknesses are the lack of sub-additivity\(^{63}\), the difficulties of optimising VaR in scenarios, and also that it is non-convex, has non-smooth density and has multiple local extrema. Compared to VaR, the recently developed CVaR has much more interesting properties. CVaR is also called Mean Excess Loss, Mean Shortfall, or Tail VaR\(^{7}\), \(^{105}\). Artzner et al. (1999)\(^{4}\) have shown that CVaR is sub-additive and convex and thereby a more substantial risk measure than VaR. In addition, Rockafellar and Uryasev (1999)\(^{6}\) have shown that it is possible to optimise CVaR with use of linear programming (LP) and non-smooth algorithms. These properties of the CVaR make it possible to optimise CVaR in scenarios with very large numbers of instruments. They have also shown that CVaR can be minimised with the result that VaR can attain near optimal solutions. For normal distribution VaR and CVaR are equivalent, which means that they coincide and thereby provide for the same optimal portfolio.

Both CVaR and Markowitz’ mean-variance approach\(^{9}\), are useable approaches in return-risk analyses. Also CVaR can be constrained to find the maximal return of a portfolio\(^{8}\). But, instead of constraining the variance, it is possible to detail changing confidence levels and several CVaR constraints simultaneously\(^{64}\)\(^{7}\), like that described in Section 8.1.2. Therefore, CVaR can provide the management with a...

\(^{63}\) Lack of sub-additivity is when the VaR of a portfolio with two instruments may be greater than the sum of the individual VaR of these two instruments\(^{18}\).

\(^{64}\) It has been shown in several case studies that risk optimisation with CVaR performance function and constraints can be done for large portfolios and a large number of scenarios with relatively small computational resources. For instance, in\(^{7}\) a problem that has 1,000 instruments and 20,000 scenarios has been optimised on a 300 MHz PC in less than one minute using the CPLEX LP solver.
flexible and powerful risk management tool. Furthermore, CVaR together with VaR are useful for estimating risks in various areas such as OR.65

Indeed, there are still need for more research to estimate a portfolio’s VaR and CVaR, both as risk concepts and decision variables. However, this chapter refers only to the evaluations of the potential role of VaR and CVaR as decision variables that have recently been published in a series of articles [6], [8], [42], [60], [85]. One of the outturns of these investigations is to represent the solution of the VaR problem as a fix-point of CVaR problems using the results of the relations between VaR and CVaR. For more details we refer to [60].

7.1 Stripping and Mapping Methods

The regulation behind the use of the VaR and the OR in the financial industry calls for stripping and mapping methods of financial instruments and in the supervisor's guidelines details are given of how this can be done [1], [26], [27], [28], [29], [30], [112]. However, these methods are not investigated in this thesis, but reference is made to further information in [1], [26] and [112]. The Basel II [112] states that the business line mapping of the OR must follow the same definitions of the business line as for other risk categories, e.g., market risk, described in Sections 3.2.1 and 5.1. Consequently, the following sections of this chapter only investigate those VaR and CVaR general decision conditions that have been found important for the calculation of the OR.

7.2 Optimal Portfolios with VaR Constraints

VaR is an important risk management tool used by larger international financial organisations as well as for their supervision. A lot of research has been carried out during the last ten years on improvement of this risk measure [1], [3], [26], [43], [44], [45], [46], [47]. For instance, Gaivoroski and Pflug (1999) [42] investigate how optimal portfolios and constraints on VaR can be satisfied simultaneously. Since this goes beyond normal estimation of VaR, they raise the following questions:

65 See Sections 7.5.1 and 10.1.
• **Suppose acceptable VaR with given fixed boundary.** With a given set of securities, the following question will be how to find the portfolio that simultaneously gives maximal yield and satisfy the VaR constraints.

• **Suppose movements in market conditions.** The following question here will be which portfolio strategy could rebalance the portfolio within a given boundary for VaR and simultaneously maximise the yield of the sequence of portfolios.

For solving these problems they used and developed algorithmic tools derived from stochastic optimisation and considered in machine learning. They use VaR in their approach instead of a variance approach similar to Markovitz’ theory [9]. Moreover, there are several algorithmic tools provided for computing such portfolios, which allow realistic cases to be obtained.

### 7.2.1 Parametric VaR with Constrained Optimal Portfolios

Even if minimising VaR is a simpler problem than maximising expected yield, minimising VaR can still be difficult. However, minimising VaR gives a guaranteed conservative estimate on attainable VaR, which obtains a local minimum and therefore in itself represents an important result. However, earlier it has been shown that if there are different portfolios with simultaneously the same maximum expected yield and minimum VaR, these problems belong to a general class of stochastic optimisation problems [48], [49].

Gaivoroski and Pflug (1999) [42] claim that the solution of how to find a portfolio $\mathbf{x}$ with maximum expected yield and constraints on parametric VaR is obtained by solving a succession of the problem to find portfolio $\mathbf{x}$, which also minimises VaR subject to constraints on expected yield.

Consequently, in the thesis’ framework, when parametric VaR calculation is used and the analysis of finding portfolio $\mathbf{x}$, which minimises VaR subject to constraints on expected yield will be solved, Gaivoroski and Pflug (1999) [42] recommend beginning with estimating sensitivities of the VaR for a given portfolio with different positions. In ([42] p. 6-7) it is also shown how the gradient of VaR can be used for constructing numerical procedures to find portfolio $\mathbf{x}$, which minimises parametric VaR subject to constraints on expected yield.
7.2.2 Historical VaR with Constrained Optimal Portfolios

Section 7.2.1 above applies a parametric approach to VaR. In that approach historical data were first adopted about risk factors $v$ for getting their probabilistic distribution. Thereafter, its density was used for computing parametric VaR with constrained optimal portfolios. In this section, however, historical VaR optimal portfolios are calculated from a historical sample for the distribution of the risk factors [42].

If a scenario is known, it follows that its VaR is the difference between the expected and the actual yield. Gaivoroski and Pflug (1999) ([42] p. 8) suggest that an arbitrary fraction $c$ of all scenarios should be satisfied by constraint $N(c)$. Therefore, they must formulate how to find the optimal portfolio that satisfies historical VaR constrained.

Normally, if it is possible to satisfy the constraint for all scenarios, this could be solved by using LP. However, if only a random sample of constraints is satisfied, the solution will be much more problematic. Gaivoroski and Pflug (1999) [42] claim that this depends on the fact that their defined feasible set becomes non-convex and may even be disjoint.

Gaivoroski and Pflug (1999) [42] claim that it is usually necessary to approximate historical VaR solutions to find portfolio $x$ which maximises expected yield iteratively. This is done by a sequence of LP problems, which leads to some general algorithmic tools, developed by ([42] p. 10).

7.3 CVaR for Continuous Loss Distributions

The VaR can be calculated and at the same time the CVaR minimised by introduction of a new function, and this can be applied to analytical or scenario based optimisation algorithms [6]. With a fixed number of scenarios there will only be an LP or non-smooth optimisation problem, which allow optimisation of portfolios with many instruments [6], [88], [89]. It is interesting to note that the proposed methodology by Rockafellar and Uryasev (1999) [6] is useful for the optimising of portfolios by many different actors, who evaluate risks. That means that this is a general method, which can be used on any problems involving optimisation of percentiles.

Consequently, the risk measure CVaR is related to the risk measure VaR. Figure 7.5.1.1 below shows that CVaR is either greater than VaR or equal, and, moreover, that the minimisation of the CVaR automatically leads to minimisation of the VaR.
These important statements depend on a new algorithm presented in [6], which can calculate VaR and minimises CVaR simultaneously. Moreover, Rockafellar and Uryasev (1999) [6] claim that this is a non-smooth stochastic optimisation problem, solved by using general stochastic optimisation approaches, in accordance with [51] and [53]. But, they claim that if there are finite numbers of scenarios LP techniques can also be applied. Accordingly, the CVaR can be used in various areas, e.g., it can be used for evaluation of the ORs.

Furthermore, in mathematical terms, \( \alpha \)-VaR represents the \( \alpha \)-quantile of a loss distribution. The probability that a loss exceeds \( \alpha \)-VaR is therefore equal to 1–\( \alpha \). Moreover, \( \alpha \)-CVaR is the expected value of \((1–\alpha)\cdot100\) percent of the highest losses, shown in Figure 7.5.1.1. Usually, in practise, three values of coefficient \( \alpha \) are used, \( \alpha = 0.90 \), \( \alpha = 0.95 \), and \( \alpha = 0.99 \). These approaches are investigated in [6].

7.4 Portfolio Optimisation with CVaR Objective and Constraints

Two basic requirements lie behind the recent developments of the portfolio optimisation [8]:

- Appropriate modelling of utility functions, risks, and constraints\(^{66}\).
- Efficiency, which here means that a lot of instruments and scenarios can be handled with the use of LP rather than quadratic programming in accordance with Markowitz [9]. Moreover, recently developed highly efficient tools are to be found in [55], [56] and [57].

As mentioned in Section 7.3 above, LP can be applied to CVaR optimisation. Furthermore, the approaches for CVaR minimisation and CVaR optimisation with constraints have also been investigated by Uryasev (2000) [7]. However, Palmquist and Uryasev (1999) [8] extend the CVaR minimisation approach further in this section. Here, they claim that the approach in [6] can be applied to portfolio optimisation with CVaR constraint instead of minimising CVaR. They formulate a general theorem that starts from various equal values of the efficient frontier with convex risk functions, which are well-known for mean-regret and mean-variance performance functions (see, e.g., [55], [58]). However, Palmquist and Uryasev (1999)

\(^{66}\) See Sections 6.1.2, 8.1, 9.1.3 and 9.1.5.
[8] claim that this statement also holds for other convex risk functions, including CVaR. Moreover, they used an auxiliary variable for the formulation of a new theorem that could reduce CVaR constraints to a much simpler convex problem. Note that convexity eliminates the possibility of a local minimum [8]. Rockafellar and Uryasev (1999) [6] also describe that with VaR optimisation the auxiliary variable is set automatically. This statement helps to solve the maximising return problem with CVaR constraint significantly, since CVaR is defined as a mean loss exceeding VaR. Finally, Palmquist and Uryasev (1999) [8] point out that when the scenarios are bounded and there is a linear loss function, it is enough to use this loss function together with a set of linear constraints instead of the CVaR function. The problem can then be solved using ordinary LP techniques.

Accordingly, Section 7.3 above investigates minimisation of CVaR with minimum expected return [6]. But the normal case is to maximise returns with no large risks, like Palmquist and Uryasev (1999) [8] in this section. They show that the optimisation problem can be formulated in three general equal values with the same efficient frontier. Moreover, they claim that discretisation and linearisation can be used for obtaining a range of possibilities (for further details see [8]).

### 7.5 Properties and Comparison between VaR and CVaR

Rockafellar and Uryasev (1999) [6] suggest that \( CVaR \) is equal to the conditional expectation of a random cost variable \( Y \), given that \( Y \geq \text{VaR}_\alpha \), i.e.,

\[
CVaR_\alpha(Y) = \mathbb{E}(Y|Y \geq \text{VaR}_\alpha(Y)),
\]

which is the usual definition of \( CVaR_\alpha \).

However, Pflug shows in [60] some further properties of VaR and CVaR and studies the relation between these two measures of risk. Each of these measures represents risks as one number. In his investigation he formulated risk measures in terms of preference structures induced by dominance relations, according to Fishburn (1980) [61]. Moreover, Artzner et al. (1999) [4] introduce a new coherent risk measure. They claim that this coherent risk measure is translation-invariant; sub-additive; convex w.r.t. portfolio positions; positively homogeneous and monotonic w.r.t. first order stochastic dominance, also described in Section 6.2. In this sense \( CVaR_\alpha \) is shown to
be coherent. Furthermore, $\text{VaR}_\alpha$ is not convex and, therefore, not coherent. But, VaR is comonotone\(^{67}\) additive in accordance with [60] and [62].

### 7.5.1 Relations between VaR and CVaR

Section 7.3 points out that VaR is a quantile, an $\alpha$-percentile of the loss distribution, while CVaR is a conditional tail expectation and, therefore, they measure different properties of the distribution. The two values coincide only if the tail is cut off, shown in Figure 7.5.1.1 below.

**VaR, CVaR**

![Image of Frequency and Loss](image-url)

**Figure 7.5.1.1: Frequency and Loss [105]**

Pflug [60] presents a detailed study of how a portfolio can be optimised with given VaR and CVaR. One of the most important results from this investigation is that the CVaR-optimisation problem shows that every local optimum is global, which makes the CVaR risk measure superior compared to the VaR risk measure [60].

Furthermore, Pflug [60] studies a fix-point formulation of the VaR optimisation problem, which shows that since the CVaR optimisation is much simpler in structure

\(^{67}\)With comonotonic or monotonic means that two functions have the same type of monotonicity. Since perfect correlation is too restrictive because it holds only for random variables with linear relationships ($Y = aX + b$ with $a > 0$) a generalisation of perfect correlation – which is an important concept of comonotonicity – has been introduced by Yaari (1987) [181] and Schmeidler (1986) [182]. This approach has been very important for the development of the decision theory under uncertainty [60] (see Sections 8.1.1 and 8.1.2).
than the VaR, it is desirable to solve the VaR optimisation by a sequence of CVaR optimisation problems. Therefore, Pflug claims that the VaR optimisation can be solved by reformulating this problem as a fix point of solutions of linear optimisation problems.

7.6 CVaR for General Loss Distributions with Discontinuities

α-CVaR is a coherent risk measure, which is a big advantage over most other applicable risk measures. Furthermore, [85] suggest that CVaR can be utilised in risk management, where several probability thresholds can be handled in an optimisation model.

Since CVaR is the most important OR measure in our VaR and CVaR Measurement Module, SAFOR3 in Chapter 9, most of the following discussion in Section 7.6 is devoted to this risk measure.

7.6.1 Background

CVaR can also be derived for discrete loss distributions [85]. This is of particular importance in applications based on scenarios or finite sampling of random variables. Moreover, Rockafellar and Uryasev (2001) [85] make up the most important properties of the CVaR and the VaR. This is based on the result mentioned in Section 7.5 [60], where CVaR is coherent and can estimate risks exceeding VaR, and on the information of [6], described in Section 7.3, which, for instance, implies that CVaR provides optimisation shortcuts through LP techniques. Several case studies about these problems are presented in [6], [60], and [85].

Consequently, CVaR has computational advantages over VaR, which has stimulated further development of the CVaR methodology, discussed in Sections 7.3, 7.4 and 7.5 above. But, only continuous loss distributions are treated there, and distributions are assumed to have smooth density and to be consistent with the mean-variance approach. Acerbi et al. (2002) [104] claim that for normal loss distributions optimal variance and CVaR portfolios coincide. Furthermore, Uryasev [105] claims that CVaR for continuous loss distributions often coincides with conditional EL exceeding VaR. But, for non-continuous as well as for continuous distributions CVaR may differ from this. Moreover, Acerbi et al. (2002) [86] have proved other properties of CVaR, as for instance asymptotic convergence of sample estimates to CVaR.
It is a well-known fact that when there is an uncertain optimisation situation, loss distributions with discontinuities are often present. Ermoliev et al. (1988) [87] were the first to show that discrete probabilities are common in scenario models and finite sampling of random variables. As mentioned above, at the same confidence level, CVaR for continuous loss distribution is either greater than VaR or equal, which is shown in Figure 7.5.1.1 and Section 7.3 [6]. But, for discontinuous loss distributions Rockafellar and Uryasev (2001) [85] point out that the definition of the CVaR is more difficult. Therefore, they designate CVaR in their paper by $CVaR^+$ (also called Mean Excess Loss and Expected Shortfall) and $CVaR^-$ (also called Tail VaR), with the meaning upper and lower CVaR, also discussed in Sections 7.6.2, 8.1 and 9.1.4, where CVaR can differ from either of those quantities. $CVaR^+$ is EL that strictly exceed VaR and $CVaR^-$ is EL that is equal to or exceed VaR. Furthermore, they state that on the same standing generally $CVaR^- \leq CVaR \leq CVaR^+$, shown in Figure 7.6.1.1, below. However, this statement only holds when there is no jump at the VaR threshold. When a jump does occur, which is the normal case in a scenario, both the inequalities can be strict.

$$\text{VaR} \leq CVaR^- \leq CVaR \leq CVaR^+$$

![Diagram of VaR, CVaR^-, and CVaR^+ relationships](image_url)

**Figure 7.6.1.1**: CVaR is Convex, but VaR, CVaR^- and CVaR^+ may be Non-Convex, Inequalities are Valid [105]
To sum up, this section explains the general definitions of CVaR with the help of the arguments in Section 7.5 [60] above. Moreover, in accordance with [4] CVaR is a coherent risk measure, whereas $CVaR^+$ and $CVaR^-$ are not [189]. Furthermore, Rockafellar and Uryasev (2001) [85] suggest that CVaR also is a weighted average of VaR and $CVaR^-$, where this weight depends on portfolio $x$ (the decision vector). However, they point out that neither VaR nor $CVaR^+$ is coherent due to the fact that CVaR splits the atom of probability at the VaR value, when one exists. Moreover, Uryasev investigates the three following CVaR discrete distribution problems in [105].

- $\alpha$ does not split atoms: $VaR < CVaR^- < CVaR = CVaR^+$;
- $\alpha$ splits the atom: $VaR < CVaR^- < CVaR < CVaR^+$;
- $\alpha$ splits the last atom: $VaR = CVaR^- = CVaR$.

Furthermore, Rockafellar and Uryasev (2001) [85] claim that, no matter what the choice of the portfolio $x$, an appropriate confidence level specification that depends on a finite, discrete distribution of the random vector $y$ can guarantee that $CVaR = CVaR^+$. Furthermore, they prove that with a confidence level close to $1$, $CVaR, CVaR^-$ and $VaR$ have equality maximum loss, also independently of $x$.

### 7.6.2 VaR and CVaR – Concluding Characteristics

There are some conditions for the risk measures VaR and CVaR as possible decision variables for calculating quantitative, advanced ORs. Here, $\alpha$-CVaR is the most important coherent risk measure proposed [85]. Consequently, the minimisation of the mean of the $\alpha$-tail distribution is one way of utilising CVaR in risk management [9]. Another way is to shape the risk in the optimisation model by handling several probability thresholds, also described in Section 10.1.

We assume that the reader has some knowledge about the concept of VaR [1], [3], [26]. However, the strength of VaR is that it can be applied to any financial instrument, be expressed in the same unit of measure and can include an estimate of future events. Accordingly, VaR can provide valuable information when used

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68 See also Section 6.2.
69 See SAFOR3 in Section 9.1.4.
correctly, but in the wrong hands it can cause big problems. As mentioned before, there also are weaknesses with VaR. For instance, like most quantile-based variables, VaR is affected by large statistical errors, in particular when the chosen probability level is very small. Moreover, the computation of the VaR is also a problem since VaR cannot be split into separate sub-computations due to the non-additivity, that is, by position and by risk variable. Also there is a criticism against VaR in that it comes too late for helping against an unwanted event. The reason for that depends on the common habit of calibrating future scenarios on past market data when calculating VaR. It is well-known that VaR calculation in practise must choose a specified level of confidence for selection of the set of worst cases under consideration and a time horizon over which the estimates of future Profit & Loss (P&L) are made. From this point of view Acerbi et al. (2001) [189] discuss a VaR example with a probability of 5% and a time horizon of 7 days, an definition of the VaR often used, as follows:

- **VaR is the minimum potential loss that a portfolio can suffer in the 5% worst cases in 7 days.** This is a correct version, but is seldom used because it sounds odd and maybe embarrassing.

- **VaR is the maximum potential loss that a portfolio can suffer in the 95% best cases in 7 days.** This is a more politically correct version. Here, in other words, VaR is a sort of best of worst cases scenario and it therefore systematically underestimates the potential losses associated with the specified level of probability.

The connections between VaR and CVaR have been formalised in [6], [60], [85] and [105], where $\alpha$–VaR is the $\alpha$–percentile of a loss distribution. Furthermore, Rockafellar and Uryasev (2001) [85] describe CVaR as follows: CVaR is the mean of the $\alpha$–tail distribution $\psi_{\alpha}$, where $\psi$ is the cumulative distribution of losses and $\psi_{\alpha}$ is $\alpha$–tail distribution, which equals to zero for losses below VaR, and equals to $(\psi - \alpha)/(1-\alpha)$ for losses exceeding or equal to VaR. Specifically, they point out that CVaR has stable statistical estimates with integral characteristics compared to VaR. Furthermore, with the use of several CVaR constraints with different confidence levels $\alpha$ in different intervals a loss distribution can be modelled.
7.6.3 Maximal Loss and Excess over Threshold

Extreme losses on the tails of the distribution are a well-known problem in financial risk management. There are two approaches for handling these problems often discussed in literature, the generalised extreme value (GEV) distribution using the maximal and minimal values in a sample, and the excesses over a predefined threshold, also called peaks over a threshold (POT)\(^{70}\), using the GPD. Both models are defined in terms of the underlying random variables. However, only when the sample size is large, is the classical maximum likelihood estimation approach applicable to fit the parameters of the GPD model. Therefore, exceptional events, such as POT with very low frequency, must be calculated using special estimation procedures [96], [97]. King (2001) [103] has advocated a useful application in the measurement of the ORs\(^{71}\).

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\(^{70}\) A POT model is a combination of GPD approach for loss impact and a Poisson process for frequency [190].

\(^{71}\) See Section 10.1 and Figure 10.1.2.
8 Interval Forecasts

One of the purposes of this chapter is to investigate whether VaR and CVaR interval predictions as a measurement of uncertainty can be applied to OR calculation for an internal, advanced measurement approach in a bank. The conditions for VaR and CVaR have already been investigated in Chapter 7.

First, Section 8.1 investigates different interval approaches, including the proposed risk analysis method Damage Evaluation and Effective Prevention (DEEP), described in Section 8.1.2. Then, Section 8.2 describes what Peter F. Christoffersen (1997) [11] means by a good interval forecast, and how such a forecast might be tested. However, there is not yet any complete theory that can be used for evaluating interval forecasts. One of the problems is the implicit assumed homoskedastic errors commonly used in the literature even when the situation is obvious violated. Such situations must therefore be tested for correct unconditional coverage. However, a macroeconomic summary of professional interval time series forecasts has been presented by Croushore (1993) [12]. Moreover, when higher-order moment dynamics are present, discussed in Section 8.1.1, it is very important that the framework for conditional interval forecast evaluation is built consistently. But, the research in economic forecasting has, until recently, mainly been applied to produce and evaluate point forecasts (like VaR), which are of first-order importance. These point forecasts are relatively easy to compute and understand, but they only describe one possible outcome, which normally is not satisfactory to the user. Chapter 7 above also noted these problems in connection with VaR and CVaR.

Consequently, as discretisation and linearisation can be used for obtaining a range of possibilities in accordance with [8], interval forecasts can indicate a more suitable approach for better planning, e.g., for getting a range of hypothetical sales conditions, also mentioned in Section 7.4. Even if there is a large literature of how to calculate

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72 Definition: *Homoskedastic* is an adjective describing a statistical model in which the errors are drawn from the same distribution for all values of the independent variables. This is a strong assumption, and includes in particular the assumption in a linear regression. *Heteroskedastic* is an adjective describing a data sample or data-generating process in which the errors are drawn from different distributions for different values of the independent variables. (An example is that variance of income across individuals is systematically higher for higher income individuals.)

73 See, e.g., Sections 7.1, 7.2, 7.5.1 and 8.2.1.2.
interval predictions [13], there are still problems about how to evaluate these approaches, described in Section 8.1 below.

Section 8.2 shows some of the evaluation problems in connection with VaR, which are investigated by Christoffersen (1997) [11]. He starts his investigation from the classical paper of the dynamic interval forecasts around point predictions by Engle (1982) [14]. But the problems with higher-order dynamics that may have correct unconditional coverage on average and still have clustered incorrect conditional coverage in any given period are not solved. Chatfield (1993) [13] has stressed that model error is a more common source of poor interval forecasting than estimation error, mentioned in Sections 5.4 and 5.5. Christoffersen [11] claims that the criterion for the tests and the tests of this criterion are free from model error, like that approach taken by Diebold and Mariano (1995) [15], and that it should be seen as a formal framework, which is in line with the ideas suggested by Granger, White and Kamstra (1989) [16].

Furthermore, the methods used in Section 8.2 are applied to a VaR interval forecast that is provided by J.P. Morgan (1995) [3], with their one-sided interval forecasts of portfolio returns, also discussed in Section 9.1.5. These forecasts procedures were first evaluated by Lopez (1996) [17].

### 8.1 Approaches to Impreciseness

In classical utility theory, determination of the best course of action can be made through distinguishing estimations of precise and additive probabilities and utilities. There is a common objection to utility theory that people are not capable of providing the inputs that are necessary for this theory [76], e.g., most people cannot distinguish between probabilities within wide intervals [131]. Also a utility-based ideal decision-maker who commonly bases his analysis on human assessments has difficulties when using induced preference functions [132].

Another problem with classical decision theory in general is that it aggregates background information too hard, which may result in loss of information. In real life, imprecisely specified probabilities and utilities are often important in risk and decision analyses, where it is necessary to find an acceptable trade-off between efficient evaluation and quality of information. Therefore, several imprecise
probability approaches have been suggested over the years, mentioned in Section 8.1.1 below.

### 8.1.1 Imprecise Probabilities

#### Interval-valued

Ellsberg (1961) [133] was one of the first that considered the decision theoretical effects of abandoning precise probabilities. But he did not object to the use of the PMEU. Instead, he suggested a classification of choice situations that comprise immeasurable uncertainty with numerical imprecise information. Moreover, only qualitative data are proposed in [134] to be used for imprecise values. This is, however, too restrictive in many cases ([193] Paper III).

A common method for modelling imprecise or partially ordered probabilities in a risk analysis is to consider the events as interval-valued instead of precise probabilities. Interval-valued or non-additive probabilities have been thoroughly investigated during the last 50 years or so, see Smith (1961) [139], Hodges and Lehmann (1952) [160], Hurwicz (1951) [161], Wald (1950) [162], Kyburg (1961) [163], Walley (1991) [169], Danielson and Ekenberg (1998) [164], Weichselberger and Pöhlman (1990) [142], Malmnäs (1994) [149], and Ekenberg et al. (2001) [152].

Some less significant approaches have been based on logic, see Nilsson (1986) [146] and Wilson (1999) [159]. Even approaches based on possibility theory have been proposed, Dubois (1988) [153] and Cooman (1997) [154].

In this context, it is important that interval and imprecise probability methods can also be used for back-calculation, which is difficult or impossible to do with standard probabilistic and Monte Carlo-methods [172].

#### Belief Functions

An early approach to express probabilities in terms of intervals, such as that in [135], [136] and [137], is taken by Dempster [140], where a framework for modelling upper and lower probabilities is investigated. This was further developed by Shafer in [141], where the concept of basic probability assignments was introduced also. Belief functions are, as mentioned above, a special type of coherent lower probability, evidence theory and belief functions. As well as for Dempster and Shafer, Denneberg
Shafer (1976) [141] supplied a representation of belief for quantifying subjective judgments as an alternative to the classical Bayesian approach. Every belief relation of belief functions corresponds to relations of sets of probability functions, which under certain conditions will be convex, Dempster [140], Kyburg [173]. However, with respect to pure interval representation Weichselberger et al. [142] find the Dempster-Shafer theory for quantifying subjective judgments unnecessarily restrictive.

**Sets of Probability Measures**

Another and related interval-valued approach is to represent the impreciseness as sets of probability measures, Good (1962) [138], Levi (1974) [147], Levi (1980) [148]. For instance, Good (1962) ([138] p. 322) represents the uncertainty by closed, convex sets of probability distributions, while Levi [148] takes a more pragmatic perspective in his use of convex sets of probabilities in his investigation of an agent’s language. Walley (1998) [121]) shows that sets of probability measures generate upper and lower previsions, also called upper and lower envelopes. Here, an interval of measures is also claimed to be a special type of set of probability measures.

**Hierarchical Models**

Interval approaches are sometimes perceived to be too limited for modelling uncertainty. Other approaches have therefore been introduced to better represent various possible strengths of beliefs. Such representations are usually referred to as hierarchical models and are, for instance, useful for representing situations when the belief is not uniform over a probability or utility interval. Gärdenfors and Sahlin (1982) [150], Gärdenfors and Sahlin (1983) [167], and Ekenberg and Thorbiörnson (2001) [168] use modelling distributions over interval assertions. It has been shown that any consistent hierarchical model is equivalent to a model for second-order uncertainty about the beliefs of a Bayesian economic agent [172].

**Multi-Criteria Decision Aids**

For extending the decision making, multi-criteria decision models have been developed that include interval approaches, e.g., Salo et al. (1995) [143] extended the
analytical hierarchy process (AHP) method [144]. The knowledge-based interactive system ARIADNE [145] uses the same sort of models for imprecise estimates. However, with overlapping intervals this system cannot discriminate between alternatives in the evaluation process ([193] Paper III).

General approaches for evaluating imprecise decision situations, which include probabilities and utilities, also belong to these multi-criteria models. Danielson (1997) [68] investigates these, described in Section 8.1.2 below.

### 8.1.2 Damage Evaluation and Effective Prevention

PMEU seems to be a *reasonably rational* concept74, but one of the main problems is that this principle demands too much of the decision-maker. On the other hand, the various approaches described in the previous sections are less focused on computational aspects, which, particularly in real-life cases involving imprecision, can be severe. A risk analytical approach addressing these issues is suggested in [128] and [193].

The approach is a computational framework (DEEP) for solving the problem with vague information in risk management. DEEP is a general risk analysis method that extends the evaluative phases, compared with other earlier risk analysis approaches. It includes the whole chain of the identification-valuation-action in risk management. However, in uncertain situation when the consequences might be serious and the probability of catastrophic events is low the PMEU cannot be used. Therefore, when evaluating information from consequence analysis in DEEP, the expected cost of an incident with vague background information is expressed using deliberately imprecise interval statements. The evaluation process in DEEP can also exclude acceptable risks from further evaluation with the aid of threshold levels. Furthermore, in DEEP the stability of the results are studied through a sensitivity analysis, where the probabilities and costs are altered. If the result of the evaluation then changes it is interesting to see where this occurs, since this can indicates where input data are critical. By studying those closer, it can lead to better use of the resources for analyses. Thus, proportional contractions of intervals can be seen as an automated sensitivity analysis [68], [129], [193], also mentioned in Sections 9.3 and 10.2. This

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74 Utility is described in Section 6.1.2.
interval approach is therefore particularly well-suited for the Uncertainty Module of the SAFOR2 framework, see Section 9.1.3.

8.2 Evaluation of Interval Forecasts

This section deals with a symmetric out-of-sample interval forecast of a given time series and the aim is to define a general criterion for good interval forecast, and outlines tests of the forecasting methodology that can be applied without any hypothesis about the underlying conditional distribution [11]. After the out-of-sample forecasts are investigated the indicator variable is defined, which shows that it is possible to introduce a general criterion of how to test for symmetric interval forecasts. After this definition, [11] suggests that it is possible to test interval forecasts without any distributional assumptions about the process under consideration. However, distributional assumptions are sometimes important, specifically in VaR applications, where the portfolio changes over time and the underlying returns series are non-stationary by construction. Furthermore, time-varying co-variances and option risk approximations are often causes of misspecification in VaR forecasts [1], [11].

In [11] tests for conditional efficiency with respect to the empty information set are carried out. This corresponds to the standard evaluation of the interval forecasts, where the nominal coverage is compared to the true coverage, proposed by, e.g., Baillie and Bollerslev (1992) [78] and McNees (1995) [79]. However, authors like [11] claim that in the presence of higher-order dynamics, this unconditional hypothesis is not enough, and why it is important that the conditional efficiency of the sequence even is tested under these circumstances.

VaR is a forecast application, where the intervals are called one-sided or open [17], [80]. When the one-sided terms are appropriately defined, they are similar to the two-sided intervals, also discussed in Section 9.1.5 [11]. Moreover, if a given sequence of interval forecasts is constructed, the hypothesis for the sequence of interval forecasts can then be tested with the intention of getting a feeling of the difference between actual and correct conditional coverages ([11], p. 6).
8.2.1 Testing the Conditional Coverage Hypothesis

This section specifies a likelihood ratio (LR) test for correct unconditional coverage, independence, and conditional coverage, which is a combination of unconditional coverage and independence tests [11].

8.2.1.1 The LR Test of Unconditional Coverage

Christoffersen [11] considers that the indicator sequence is built on a given interval forecast. Then he tests for the unconditional coverage and starts his test with the hypothesis that the sum of the indicator sequence is equal to the coverage probability \( E[I_t] = p \). This hypothesis has to be tested against the alternative \( E[I_t] \neq p \), given independence, in accordance with [79], [80]. Furthermore, a test should be done for unconditional coverage by formulating a standard likelihood ratio test. But, Christoffersen claims that there are problems in time-dependent states if the zeros and ones come clustered together, which depends on the fact that only the total number of ones have a meaning. However, he points out that when dynamics are present in higher-order moments it is necessary to test both for correct unconditional coverage as well as for correct conditional coverage, which calls for testing of both the independent assumption and the joint test of independence and correct coverage (see below).

8.2.1.2 The LR Test of Independence

This section tests the hypothesis of the independent assumption of the conditional coverage, mentioned above. This process is done by using a first-order binary Markov indicator chain, and an approximate likelihood function, conditioned on the first observation everywhere, which is standard [81]. Thereafter, the log-likelihood function is maximised (ML) and the parameters are solved (see [11] p. 7).

Furthermore, according to Hoel (1954) [82], the standard result is that the LR test of independence is asymptotically distributed as a \( \chi^2 \) with \( (s - 1)^2 \) degrees of freedom. Christoffersen [11] shows that this is as a binary sequence, so \( s = 2 \). But, as mentioned above, this test only tests the independence part of the hypothesis, not the true coverage \( p \). However, testing for independence, \( LR_{\text{ind}} \), is an interesting test of the dynamics in an interval forecast. Moreover, this \( LR_{\text{ind}} \) test is even practicable for
testing the region forecasts in the multivariate case, described in Section 8.2.2.1. In the next section the ultimately test for a correct conditional coverage is discussed [11].

8.2.1.3 Joint Test of Independence and Coverage
The unconditional coverage test and the test of the independence, described in Sections 8.2.1.1 and 8.2.1.2, are in this section combined to form a complete test of conditional coverage. These are done by testing the null hypothesis of the unconditional coverage test against the alternative of the independence test (see Appendix [11]). Therefore, it is necessary to find the LR test distribution of the conditional coverage (see [11] p. 9).

Furthermore, it is shown that if the first observation is ignored the three LR tests for conditional coverage, unconditional coverage and independence are numerically related by the following identity,

\[ LR_{cc} = LR_{uc} + LR_{ind}. \]

Accordingly, Christoffersen [11] points out that this approach carries through joint testing of randomness and correct coverage at the same time as the individual hypotheses as subcomponents are retained.

8.2.2 Extensions to the Conditional Coverage Testing
The following three sections give a short overview of the extensions to the basic framework above (For more details see ([11] p. 9 – 18)).

8.2.2.1 The Multivariate Case
There are no conceptual difficulties in extending the testing procedures mentioned above to the evaluation of multivariate forecasts. Christoffersen [11] shows that the testing procedure for the univariate case can be used even for testing a multivariate case. But, these region forecasts can in practise sometimes bring about problems related to computing and interpretation. Therefore, Bonferroni’s method that allows for separate tests of independence and coverage are often used for constructing these joint region forecasts. From the evaluation point of view Christoffersen claims that it is better to test independence and coverage separately, since there are often incorrect conditions in coverage. Alternatively, the LR\textsubscript{ind} test can be useful. However,
Christoffersen [11] points out that if the coverage is rejected because it is too large, it is no reason to reject a Bonferroni region forecast in the $LR_{cc}$ test.

### 8.2.2.2 Testing for Asymmetries in the Tail Probabilities
Tests that fall outside predicted symmetric interval in upper or lower tail of a symmetric conditional distribution are not critical. But, if each tail individually is calibrated, or there is an asymmetric interval, Christoffersen ([11] p. 10) shows that it is necessary to generalise this.

Furthermore, the three LR tests can also be used here in the asymmetric case for the tests of the $LR_{uc}$, the $LR_{ind}$, and the $LR_{cc}$.

### 8.2.2.3 Test of Interval Forecast Efficiency
This section starts with the use of the tests above, where an interval forecast is supposed to be rejected. The question then is how to find the cause of this rejection. In the tests above, the independence of the future indicator variable was only tested with respect to its past values [11]. But, the interval forecasts can also be tested if a realisation is obtained outside the predicted interval. This could happen if the realisation is associated with certain values of other variables or with combinations of these (see ([11] p. 11) for a binary regression framework).

Moreover, Christoffersen [11] claims that the test of interval forecast efficiency with respect to the information set can be considered a joint test of independence (slopes equal zeros), and correct unconditional coverage (the constant term equals the probability $p$). With such a methodology an inference process can be applied to the interval forecast. For instance, a positive coefficient can indicate that the corresponding regressor is not applied efficiently in the approach.

Furthermore, Christoffersen [11] suggests that under the null hypothesis that the current interval forecast estimates are efficient with respect to the information set, but that the error term will be homoskedastic, which indicates that standard inference procedures apply. Christoffersen also points out that another alternative approach to this regression framework is presented by Hansen (1982) [83].
Part III
9 The Thesis’ Framework

9.1 The SAFOR Model

GST is the main underlying method in this thesis; both for identification and classification of the OR systems\textsuperscript{75} and for connecting the interdisciplinary OR applications\textsuperscript{76} to produce the SAFOR. The GST focus is on the parts of the organisation and their interrelations, connecting the parts into a whole, where the same concepts and definition of an organisation are used independent of the branch of science, to integrate all scientific knowledge through analogies or isomorphisms \textsuperscript{[110]}. Therefore, even if VaR, CVaR, and other computational models use different methods\textsuperscript{77}, they can be connected in a dynamic systemic-holistic ORM framework that is constantly changing, moving, and evolving. Theoretically, such an ORM framework is built on the conception of the firm as a system\textsuperscript{78}, where the OR exposures are a subsystem, providing a more effective alternative to each OR objects being investigated separately.

A Systemic Approach to ORM

The purpose of this thesis is to construct and present an implementation framework for ORs\textsuperscript{79}. Thereby, we hope to attain greater efficiency in making more informed decisions about future process failures and for developing solutions. A systemic approach to ORM is used, which is meant as a reference point that could be adapted and improved individually. Using a systemic approach for implementation of this model means using analogies or isomorphisms\textsuperscript{80} between systems in accordance with GST. GST claims that experiences of a known system can stand as a template for modelling another system behaviour and life cycle\textsuperscript{81} of the organisation in question. Therefore, even though only banks are studied in this thesis, the SAFOR model might

\textsuperscript{75} See Chapter 5.
\textsuperscript{76} See Chapters 6 – 8.
\textsuperscript{77} See Chapters 6, 7 and 8.
\textsuperscript{78} See Chapter 2.
\textsuperscript{79} The texts in Sections 9.1, 10.1 and 10.2 were previously published as “An Implementational Framework for Operational Risks in Banks” by The Journal of Operational Risk (2007) ([183])
\textsuperscript{80} See Footnote 22.
\textsuperscript{81} A system life cycle might include the phases and activities associated with the analysis, acquisition, design, development, test, integration, operation, maintenance, and modification of the system (en.wikipedia.org).
be appropriate for other similar applications outside the banking sector. What is meant by a systemic approach was investigated in Chapter 2, where the various systems approaches used in the construction of a systemic approach are illustrated in Figure 2.3.1. A systemic approach begins with the general and proceeds to the specific, i.e., from left (GST) to right (Systems Engineering) in Figure 2.3.1. How ORM can be seen as system processes was further investigated in Chapter 4. In this later chapter, Figure 4.1 is a construction of how the Basel II proposal for ORM in banking, described in Chapter 3, might be illustrated as a systemic approach.

However, applying a systemic approach to ORM means that it is necessary to have a methodology for conceptualising and operationalising it. This approach can begin with the identification of the systems characteristics, which should also include some knowledge of the systems history and origin. Using a systemic approach to ORM consists of two phases: the knowledge and realisation of the GST, and the implementation. But knowledge and realisation of the GST demand awareness of the systemic approach, model building, and simulation. Therefore, it is important that the designer has an adequate knowledge of the whole system in focus before an elaborated knowledge of the parts can be obtained. Then a well-built information model will help to understand reality with use of experimentation. The implementation and the use of an ORM framework are not only expected, but mandatory to qualify a banking institute for the Committee’s lowest possible capital requirement [112].

Furthermore, in GST growth is a necessary condition for survival, as in any other system, and control is a necessary condition for balancing growth. Also, the system environment is beyond the system control, but exercises at the same time significant influence on the system performance, which means that the system growth and control capacity must be in balance with the environment. It is also important that the system results in a comprehension of the whole company’s structure without overlapping, which means that a system must be investigated as a whole and can never be broken down into parts and analysed. Therefore, the designer should begin with the general and the risk manager should only go a little bit further than what has been interpreted as satisfactory up to now. Moreover, in GST modelling processes are used for analysing an organisation as an open-organic system under constant change. After an overall conceptualisation of the planned system, including its relation to the
whole organisation and its environment, different calculating techniques can be used for recommended quantified outcomes.

A systemic approach must include many modelling attempts, arranged in an abstract hierarchy. The goal or division of interest defines the hierarchy, which is an organisation with nesting smaller subsystems constituting a complex whole. Subsystems\(^{82}\) can work parallel or in series \cite{110}. A system can also be characterised by its subsystems, which each has the potential to influence the whole. This means that the subsystems must be investigated within the context of the whole\(^{83}\).

The important implications of GST for this work are that an organisation, such as a bank, should be seen as a system, interacting with other systems through its boundaries. In order for this system to function efficiently, it needs to implement control structures, for example for giving feedback. While this is not new to organisational efforts, the feedback in an OR setting should be considered on two levels. The first level is the most immediate, with feedback more or less automatically given when something goes wrong or is clearly less optimal than desired. This is, to a large extent, already present in most well-functioning banking institutions of today. The other level, feedback through a deliberation filter (such as a formal decision), is not as well covered. This thesis considers deliberation feedback through investigating models for decision making under conditions of uncertainty and looking at suitable input data from OR measurements.

**Research Strategies**

There are various attempts to define risk and uncertainty in literature both for descriptive and explanatory research strategies. We focus on OR measures, where the research strategy is explanatory as well as descriptive. Since the thesis mainly rests on literature studies the strategy is, from this point of view, explanatory, but it is also descriptive, since the SAFOR model describes a systemic approach. Such an approach includes formulating, searching, explaining, and interpreting accurate information related to OR in the systems analysis including the fact that each object in the systems has options for preventing or mitigating risk. Moreover, the systemic approach is an

\(^{82}\) see Figure 2.2.1.

\(^{83}\) See Figure 2.5.1.
epistemology or meta-science used for communication and control between sciences. However, the systemic approach requires the project leader to understand the relationship and co-operations between different areas as well as to have knowledge of both corporate and financial risk management. That is the reason why the start is an investigation, based on literature studies, of the different SAFOR modules, which are then synthesised in this chapter into the suggested SAFOR model, Figure 9.1.1 below, for a comprehensive ORM implementation.

In the last fifteen years, ORs have been shown to be an important reason for high finance disasters. In addition, there has been uncertainty about the definitions and managing of these ORs in the financial industry. Probabilistic models for strategic decision-making and ORs in the financial industry have not until recently been presented in the literature, in a similar way to those for the core business risks; market risk and credit risk. Today, in the international financial industry, a quantitative, probabilistic approach, VaR, is commonly used for core business risks, while strategic decision-making and ORs are still under development and have not yet been proven in practical terms. The trend is now to use the traditional qualitative OR approaches together with new monitoring methods for making more informed decisions about future process failings and for developing solutions. The qualitative methodologies and tools are used to identify, assess, and mitigate the level of OR for choosing the right management strategies. But, we propose that such a system should be constructed by using the systemic-holistic approach, described in Chapter 2 and shown in Figure 4.1.

As mentioned before, the banking sector has been chosen for study for two main reasons. Firstly, national regulatory supervisors (e.g., Finansinspektionen in Sweden) have established common practices for how banks should consider OR, and secondly because there is work in progress among banks to find more globally acceptable standards in line with Basel II, described in Sections 3.2 and 9.1.2. A further motivational factor for studying the banking sector is that the author has worked in one of the four big banks in Sweden for 30 years, and was mainly responsible for

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84 See Footnote 33 and Sections 1.4.4.1 and 2.4.
85 See Chapters 5-8.
86 As an example, SAS OpRisk Solution was introduced in 2005, including OpRisk Monitor, OpRisk VaR, and OpRisk Global Data, mentioned in Section 1.3.
industrial world-wide credit risks, which at that time also included ORs. However, an investigation of the OR in banking is a more difficult task than the investigation of other types of risk management, such as credit and market risk management [1]. The development of ORM in banking is described in Chapter 3. Due to the confidentiality in the banking system, which results in a lack of material, it has not been possible to present any case study of the SAFOR processes. Instead, Section 10.1 discusses the application of an advanced OR model in banking by Ebernöther et al. (2001) [107]. This application has been chosen for discussion, since it is mainly in line with Basel II’s tentative quantitative standards for OR, the AMAs87, and provides information for a systems analysis.

**The Modules of SAFOR**

As mentioned above, this thesis treats ORM from a systemic perspective. As a result of applying this perspective, some problem areas must be identified. Therefore, in the preceding chapters, those areas are covered and recent, important findings in the literature are discussed. The synthesis of all these findings is a suggested framework for OR implementation. It is named SAFOR (Systemic Approach Framework for Operational Risk) and pronounced *safer*. The rationale for constructing this framework is to compile what is derived from an investigation based on a systemic-holistic perspective into a collection of modules for the aid of implementing efficient ORM.

The systemic approach shown in Figures 2.3.1 and 2.5.1 is applied to the SAFOR modules in Figure 9.1.1 below. SAFOR is an abstraction of the real phenomenon including factors essential for understanding them. Real phenomenon is an orderly summary of those features of the physical and/or social world that affect the behaviour of the ORM in general, and banking in particularly.

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87 See Section 3.2.2.3.
Figure 9.1.1 shows the modules of SAFOR, consisting of 4 main modules and 2 sub-modules, whose functionalities are described in the following sections of this chapter.

Considering the classical ORM Generation Process at a high level, the mapping of the SAFOR parts to the thesis chapters are as follows:

- Identification of OR (Chapter 5)
- Classification of OR (Chapter 5)
- Measurement of OR (Chapter 7)
- Valuation of OR (Chapter 6)
- Scenarios / Prediction of OR (Chapter 8)
- Decision / Control of OR (Chapter 8)

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88 See Figure 4.1.1 in Chapter 4.
Like Yngström’s Systemic-Holistic Model\textsuperscript{89} [125], these different SAFOR modules may be viewed as an epistemology (a theory of knowledge) or a meta-science\textsuperscript{90} used for communication between sciences, and which at the same time decide criteria for control. These are done by using the systemic approach of \textit{being in control of its inflows, throughflows (processes), and outflows of matter, energy, data, and information, over a specific period of time}. With that view it is possible to look at SAFOR in combination with Figures 2.5.1 and 4.1 as a whole system as well as its details.

We mean that a combination of observations from these three systemic-holistic approaches, applied with some transformation between them, might encapsulate the complex reality in banking better than using each approach separately. The problem can thereby be seen from different viewpoints, which might help to throw more light on the real situation ([198] p. 5).

Whole systems can be looked at as whole living systems, which can change, move, and evolve, like nature, an economy, a family, a company, a community, or an organisation. This view includes all the factors involved, including the relation between them, and where their effects are looked at as a whole. For constructing whole systems, it is necessary to use both scientific approaches and intuition, and therefore, holism includes both philosophical and conceptual assumptions. However, there is as yet, no consensus of what whole systems deal with. However, whole systems are time invariant and non-linear by nature, and they may aggregate to meta-systems (the system environment and context), as mentioned above. As shown in Figure 2.5.1 the context includes the geographical space expressed as \textit{local, national} or \textit{international}, and time bound system point. Whole systems also have a life cycle and may disintegrate into new systems [125], [126].

\section*{9.1.1 SAFOR1 – The OR Identification and Classification Module}

\textbf{Definition of OR}

An advanced ORM in banking requires a framework to identify, assess, monitor, and control/mitigate exposures like that shown in Figure 4.1. But, a definition of OR is important to any OR framework. The most common definition in literature is:

\textsuperscript{89} See Section 2.5, and Footnote 56.  
\textsuperscript{90} See Footnote 32.
Operational risk is the direct or indirect loss resulting from inadequate or failed internal processes, people and systems, or from external events [112], [114], [117], [123], [187]. This definition includes legal risk but not strategic, reputational and systemic (financial) risks⁹¹.

For quantification of regular capital in banking, Basel II has adopted this definition, but excluded indirect losses. Moreover, Basel II breaks down the OR event into four causes; people, processes, systems, and external events⁹². The reason for the elimination of indirect risks is that they are very difficult to measure, due to the risk of double counting⁹³. But, for internal management purposes, indirect exposures such as service, reputation, and business interruption should also be considered within the ORM.

**Measurement of OR**

The OR modelling process is necessary but not sufficient. There also is a need for measurement. One way of measuring is quantification, which begins when a need occurs for a measurement of the changes in the state of system elements. But quantification is only one way of measuring. Another way is known as the qualitative approach, which is also a meaningful measurement and, under certain conditions, as useful as the quantitative one. However, the measurement process operates on a particular level, where the systems analyst becomes a measurer⁹⁴. Before he/she starts the work the measurer must answer the following questions:

1. In what language should the results be expressed (language)?
2. To what objects and in what environments will the results apply (specification)?
3. How can the results be used (standardisation)?
4. How are the reliability of the results assessed and how is their use evaluated (accuracy and control)?

A comprehensive set of risk categories helps organise the process and create a common language across the organisation. But even if there is still no industry standard, many firms have adopted definitions with categories of OR events⁹⁵. The

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⁹¹ See Footnote 3.
⁹² See Table 5.1.
⁹³ See Section 9.1.2.
⁹⁴ See Figure 2.3.1.
⁹⁵ See Chapter 5.
definitions proposed for the banking industry by the Committee are shown in Figure 3.2.1.1 in Section 3. But a common risk language across business areas and tools is crucial. For instance, the actual implementations of approaches and tools may differ across business areas, but if the results can be aggregated and compared through the whole organisation, the process will be much more reliable.

The measurement process might end in a mathematical model that could be translated into a computer implementation, like that described below in Sections 9.1.3, SAFOR2, and 9.1.4, SAFOR3. However, the analyst must first compare the outcome of different phases of the process with the goals and expectations formulated in the conceptualisation. Here, computer simulation can be used for performing this comparison. This analysis may lead to reconceptualisation or to remeasurement and quantification or both. It also is important to note that the systems scientist proceeds from conceptualisation to computerisation and not vice versa.

**Mapping of OR**

Consequently, the result of OR identification and classification is a risk map that gives details of which risks apply to any one business, process or organisational unit and to what degree. Degree is often defined as frequency and severity, rated either qualitatively (high, medium, low) or on a quantitative scale. However, in risk identification the monitoring of the external environment and industry trends should also be included.

An organisation (but not objects, as mentioned above) is here seen as a system embedded in a specific environment. Therefore, a systemic approach to risk in an organisation includes all activities in it, and also comprises components such as consumers, competitors, government, and the public, due to the system being studied. There are different approaches if the outcomes are quantitative or qualitative. Quantitative outcomes demand a model that includes the major components of the problem, while qualitative outcomes can be measured in terms of probability, which means that different techniques are used for different problems. Therefore, a well-structured problem must first be ascertained with quantified variables specified objectives and established appropriate algorithms for numerical solutions. If there are

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96 See Figure 3.2.1.1.

97 See Chapter 5, Figure 4.1, Sections 9.4 and 10.1.
no useful algorithms, heuristic tools can be used for solving a poorly structured problem.

Systems methodology points to the causes of uncertainty in systems behaviour mostly through changes in the external environment. Moreover, the initial state of the organisation-environment interactive system should be known in order to be able to predict the final state of the system. Therefore, an important managerial task is to predict future changes in the external environment and to decide how this impact should be incorporated into the management strategic plan. Consequently, information about the environment is necessary for minimising uncertainty about the future consequences of today’s decisions and actions. This can be aided by a systems-oriented approach, where the manager should scan the external environment continually for incorporating potential impacts into the strategic plan.

**Modelling of OR**

Regarding the modelling of OR in banking institutions, it is still a process in progress. Today, the trend in the banking industry is towards a bottom-up model. This approach models the real workflows wherever possible. However, it is hard work to find a consistent VaR and capital allocation methodology with this approach. Furthermore, quantification is not enough for a reliable ORM. It is only a step towards better management. But, the greatest gains regarding modelling OR might be in the improvement of the firm’s core workflows.

Two categories of complete models of OR are discussed in the literature: top-down and bottom-up. The top-down approaches try to allocate the business unit level risk down to the businesses, independently of the actual workflows. A well-known top-down framework is the *Capital Asset Pricing Model* (CAPM), which is often used as benchmark against comparable institutions. In such a model larger operational failures lead to movements in CAPM inputs, as for instance *equity prices, betas, debt leverage and benchmark equity prices*. However, although these CAPM models are easy to implement they only can supply an overview of a firm-wide OR capital. Therefore, top-down models do not fit well for capital allocation in business activities.

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98 See Section 3.2.1 and Figure 3.2.1.1.
processes. This is the reason why Basel II [112] has chosen bottom-up methods for the proposed OR capital allocation in banking\textsuperscript{99}.

Bottom-up models categorise OR failures and given OR losses through the actual causal relationships between them. This OR categorisation makes the bottom-up approach appropriate for process improvement. However, it is difficult to implement [114]. In order to establish a firm’s risk profile the loss events in individual business lines must be analysed and then each type of risk at that level must be identified and quantified. In banking, the principles for business line mapping are the same for OR, market risk, and credit risk. Thereafter, the frequencies and controls of the loss events are estimated, as well as the severities of the potential losses after considering insurance and any other risk transfers\textsuperscript{100}.

There is a simpler bottom-up model for calculating ORR over a year (chosen horizon). Since OR formally is the UL to some confidence level, which is related to the standard deviation for the total operational loss distribution, the resulting operational VaR, also called CVaR, for each different type of loss event, can be totalled up\textsuperscript{101}. This statistical/actuarial method results in a more sophisticated implementation, where event frequency as well as severity can be modelled in probability distributions\textsuperscript{102}. In this case O’Brien et al. (1999) [114] point out that it is possible in the analysis to choose \textit{the granularity of the unit of workflow} pragmatically. They also claim that the methods mentioned must scale losses into a time-independent unit, according to inflation. Moreover, frequency and severity should be modelled separately and then summed to arrive at \textit{better drill-down into causes and effects of losses}. Thereafter, by using triggered thresholds, it will be easier to implement dynamic control processes into the workflow and to observe the following effects\textsuperscript{103}.

Since, there are both pros and cons of top-down and bottom-up approaches, discussed in Section 5.3; some firms have attempted to create hybrid models. This is also seen in the market, where new models are appearing, e.g., PricewaterhouseCooper’s OpVaR or Net Risk’s RiskOps. These approaches try to integrate a bottom-up model

\textsuperscript{99} See Section 3.2.
\textsuperscript{100} See Chapter 4.
\textsuperscript{101} See Chapter 7 and Sections 9.1.4 and 10.1.
\textsuperscript{102} See Chapters 4 and 7 and Section 10.1.
\textsuperscript{103} See Sections 8.1.2 and 9.4, LDA.
or a hybrid model with external loss event datasets (see Section 9.4).

**Security Architecture**

After definition and comprehension of the ORs in an organisation the security architecture has to be formulated. This architecture is then used for analysing the vulnerabilities in the system and for applying appropriate controls to ensure that everything in the business works together and operates correctly both tactically, in the short term, and strategically in the long run, described in Section 5.2.

In IT security literature, it is common to visualise the architecture as a series of layers. Here the SABSA’s [106] six-layer IT security model is chosen for the process of defining the whole security architecture in Figure 5.2.1. This model should be approached from the top layer and down through the left five layers.

However, the right hand Security Management affects all of the other layers. This IT security approach can stand as a template for the key areas of OR that need to be integrated into the ORM processing in order to control and mitigate OR efficiently. Specifically, Table 5.2.1 includes issues particular to cryptography. Analogous reasoning can be applied to other and neighbouring areas as well104.

**Strategic Risk**

The overall business strategy concerns *what the business is*, while the OR categories concern *how the business operates*, which generally means the day to day operations of the firm. Basel II suggests a qualitative standard for constructing OR into processes like pricing and paying decisions and it points out that the OR should be used as *an integral part of its overall business strategy*, after appropriate insurance is taken into account ([112] p.120). It also demands that the banks should build up historical loss databases, even if all indirect losses or opportunity costs do not have to be covered by ORR. However, there are still some important questions that must be answered. How to distinguish a loss event from a normal cost, e.g., at what point or threshold does the normal cost get to be a loss event? How to distinguish an operational loss already taken into account by market risk or credit risk? Furthermore, OR can be divided into business or strategic risks105 and internal risks. Strategic risks depend on external

104 A more detailed description how these layers are used in an actual implementation can be found in J. Sherwood [106] and in Information Technology Security Evaluation Criteria, ITSEC [180].

105 See Section 5.2, and Footnote 3.
factors that fail to attain expected returns, e.g., depend on changes in political, regulatory, and legal environment or in competition. Basel II points out that strategic risk is best modelled by using scenario analysis. On the other hand, internal risks can depend on suffering of losses or non-payment of earnings due to failures in internal processes, people and systems [112], [114].

Figure 4.1 demonstrates the Committee’s demand for a strategy that includes the responsibility, involvement and admission of the ORM approach being taken by the senior managements and the board of the directors, where the governance model includes the roles, authority levels and accountabilities of each organisational part [112], [190]. However, monitoring and reporting of risks must be independent of the decisions made to control the risk. Otherwise, many market traders could act in the same way, and thereby cause systemic risk. One way of solving this problem could be to give continuous reports to senior management for quickly managing the risk control strategies.

Consequently, Basel II points out that in a changing external market, the methodology used for ORM in banking must be supported by sound corporate governance, internal controls, policies and procedures, OR identifications and assessments, reports, appropriate strategies, and robust contingency plans [112]. The systemic approach to ORM presented in Figure 4.1 rests on these Basel II statements. After the frequency and severity of operational events have been registered in OR databases for five to ten years, parts of this information might be useful for estimation of the future OR in different systems. But until objective data are assessable, scenario analyses derived from expert opinions about the potential impact and frequency of events related to a potential bad future environment should be used for the qualitative analysis [112].

9.1.2 Basel II / SAFOR Compliance

This section looks into and compares the proposed OR standards (qualitative and quantitative) and criteria for use of the AMAs with the SAFOR model. The measurement methodologies described in Sections 3.2.2 are a synopsis of the proposed ORM in banking industry [112]. The aim of the analysis in this section is to find out if Basel II is compliant with a systemic approach framework for OR.

106 See Footnote 3.
107 See Sections 5.1, 8.1 and 9.1.5.
108 See Section 3.2.1, Basel II [112].
 Basel II determines the structural formula for AMAs. Therefore, a detailed framework is used for classifying and aggregating losses across banks. For instance, these operational losses must be classified in terms of a matrix, which comprises 8 standard business lines and 7 loss event categories with 20 sub-cATEGORIES\(^\text{109}\). Basel II includes also, what it calls; decision trees to determine event categorisation\(^\text{110}\). The effects of these events are shown in Table 9.1.2.1 below.

**Table 9.1.2.1: OR Events and Effects (Basel II) [112]**

<table>
<thead>
<tr>
<th>Events</th>
<th>Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internal fraud</td>
<td>Legal cost/settlement</td>
</tr>
<tr>
<td>External fraud</td>
<td>Regulatory/compliance</td>
</tr>
<tr>
<td>Employment practices/workplace safety</td>
<td>Restitution</td>
</tr>
<tr>
<td>Clients, products and business practices</td>
<td>Loss of recourse</td>
</tr>
<tr>
<td>Damage to physical assets</td>
<td>Write-downs</td>
</tr>
<tr>
<td>Business disruption and systems failures</td>
<td>Loss of physical asset</td>
</tr>
<tr>
<td>Execution, delivery and process management</td>
<td></td>
</tr>
</tbody>
</table>

These 7 types of OR may then be categorised in terms of frequency and severity. Banks that want to use AMAs to quantify the ORR must measure it for each type in each of the following 8 standard business lines (the same as for the calculations of the market and credit risks), shown in Table 9.1.2.2 below.

\(^{109}\) See Figure 3.2.1.1.  
\(^{110}\) See Figure 3.2.1.2.
Table 9.1.2.2: Standard Business Lines in Banking [112]

<table>
<thead>
<tr>
<th>Business Lines</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Corporate Finance</td>
</tr>
<tr>
<td>2. Trading and Sales</td>
</tr>
<tr>
<td>3. Retail Banking</td>
</tr>
<tr>
<td>4. Commercial Banking</td>
</tr>
<tr>
<td>5. Payment and Settlement</td>
</tr>
<tr>
<td>6. Agency Service</td>
</tr>
<tr>
<td>7. Asset Management</td>
</tr>
<tr>
<td>8. Retail Brokerage</td>
</tr>
</tbody>
</table>

Depending on the bank’s operations, there can be up to 56 separate ORR estimates to obtain a total ORR for the bank. The risks may then be categorised for business impact and vulnerability in a $3 \times 3$ matrix [106], also called the three-level risk model.

**Comments:** As mentioned before, Basel II has taken a bottom-up approach to the risk analysis\(^{111}\). This approach tries to distribute the business unit level risk down to the businesses, where loss or earnings volatility data are integrated independently of the actual workflow and, at the same time, try to remove the parts due to market and credit risk. Furthermore, the start is a mapping of the workflows in which failure may occur, in each of the eight business lines, mentioned above. In estimating risk, the bottom-up approaches use real causal relations between failures and their loss results, which make them sensitive to process improvement. But, implementation may be hard. Then, at every place in the organisation where operational failures can occur, frequency of loss events (the number of loss events during a certain time period) are estimated, taking into account appropriate controls. Thereafter, the severity of the potential losses (the impact of the event in terms of financial loss) is accounted for with the inclusion of any risk transfers, e.g., insurance [112], [114], [187].

Operational Risk Data Collection Exercise – 2002 [113] in banking institutions includes *risk maps*, which indicate typical EL frequency and expected severity for each risk type/line of the business. However, these factors are often very general and are, therefore, not always appropriate. For instance, it is pointed out in [113] that *employment practices, workplace safety, and damage to physical assets can have been classified as low/medium frequency and low severity*. This would not be applicable if a bank has operations in a geographically sensitive

\(^{111}\) See Sections 5.3.
location. Another example is that business disruptions and systems failure may not be a low impact risk in e-banking. Furthermore, risks that have high EL but relative low UL, like credit card fraud and some human risks should already be covered by the general provisions of the business. Therefore, if EL is priced in a proper way, it will have little influence on the ORR. On the other hand, if high ULs are likely to have substantial impact on the ORR, these medium-frequency and medium-severity risks must be in focus for measuring ORR [113], [190].

BIS (2003) [192] presents a discussion of how a loss aggregation method might be used across different risk types within a bank and between banking institutions for reaching a total loss distribution of a whole bank. But until more reliable methods have been developed, exposure indicators like number of employees or total assets are meant to solve this problem partly [112]. These indicators can also be used for investigating how historical loss experiences are associated with the current activities of the bank. Then, banks and supervisors can use these loss experiences to determine separate frequency and severity distributions of the OR [112].

- As mentioned before ORR does not include strategic risks when calculating for ORRs. But, as indicated in the 10 principles [113], the Committee expects directors’ as well as senior management’s involvement. This is applicable to all aspects of the strategy of the OR framework, and it is one of the prerequisites for the approval of the AMAs.

**Comments:** Consequently, Basel II does not state any details of how the AMAs and the ORR should be created. The banks are free to use their own internal approach to OR. But, in the qualifying general criteria, Basel II says, among other things, that the bank must have a risk management system that is conceptually sound and is implemented with integrity [112]. Section 5.2 investigates how to use a strategic aspect in implementing the security architecture to find the vulnerabilities of the whole business systems and the controls needed to counter those drawbacks [114].

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112 See Sections 3.2.1 and Chapter 4.
113 See Section 3.2.2, three general qualifying criteria for the SA and the AMAs, and seven qualitative standards for the AMAs.
114 These are shown in Figure 5.2.1 and Table 5.2.1.
The aim of categorising OR is to find the different OR types and how much control is needed for the management decision process. Therefore, some methods of setting priorities must be adopted for establishing the threat, the impact and the vulnerability. One way of doing this is described in Sections 5.1 and shown in the three-level model of the risk categories, Figure 5.1.1 and Table 5.1.1.

The three-level models, which handle the qualitative sorting function, express the different values in non-monetary terms. Variants of these risk level models are also frequently used in other circumstances\(^\text{115}\).

**Comments:** Even if an ordinary risk analyst knows the difference between disastrous, unacceptable, and acceptable risks without using any decision tools, there still is a problem in deciding the order and extent of the reduction needs of different unacceptable risks. However, in [130] it is demonstrated that the risk level model has weakness when compared to the expected utility model\(^\text{116}\). A major problem with only using such a risk level model is that the intervals are too wide, with no discrimination within them. Therefore, an interval decision model is suggested that is more general and includes maximum and minimum intervals for evaluation of different estimations. This technique is described in Section 8.1.2 \([128],[129],[193]\) and will be used in the Uncertainty Module, the sub-module of SAFOR2, to extend the risk level model, mentioned in Section 5.1.

For current loss reports banks have to gather OR data in databases, which in the future may cover OR information, going back 10 years. However, in the beginning, there can be a risk that this data gathered may involve a selection bias that will remain until more substantial databases on OR become available. Therefore, in the meanwhile, internal data might be supplemented by pooling of banking loss data, expert opinion, scorecards, and/or benchmarking to find an available loss distribution to support a bank’s OR approach. Such pooling of data are already well-known in credit risk management, specifically for very rare, large losses (exceptional losses) \([112],[187],[192]\). However, exceptional OR losses are often bank specific, and therefore pooling in these circumstances is of little use. In addition to the short period over which OR data have been gathered, there is also a confidentiality problem, which makes OR data hard to come by.

\(^{115}\) See also Sections 9.1.3 and 10.1.

\(^{116}\) See Section 6.1.2.
When risk is modelled, it is also important to avoid the risk being double counted or omitted. This can, for instance, be the case when insurance is used for risk mitigation. But, with an OR framework, like this SAFOR, where the target is to synthesise various aspects of risk and mitigate the risk around the loss causes, these problems should be diminished or avoided\textsuperscript{117}. However, a loss can depend on more than one cause. In banking, the two main categories of the core business risk are market risk and credit risk. These risks depend on the management’s decisions, while ORs depend on the implementation of those decisions, or on external factors. For example, loss of reputation can result from a systems failure or from failure to observe regulatory requirement. Here, a risk of double counting exists if reputational risk, systems risk and regulatory risk are each taken as a separate category. Elimination of double counting is thus primary to a comprehensive ORM approach. This requires that the OR processes are seen from a systemic perspective. Only then can double counting be detected at an early stage of the modelling exercise.

9.1.3 SAFOR\textsuperscript{2} – The Valuing Risky Projects Module

\textit{Bayesian Networks}

Section 6.1 starts with the investigation of the general meaning and problems behind Bayesian inference and belief networks as background information. The conclusion of this investigation is that Bayesian networks can manage uncertainty and that the interactions between the various sources of uncertainty in the networks can be presented in an intuitive causal interpretation of dependence. Such a causal approach can be used in ORM for describing the causes and effects of the operational losses. As described in Section 6.1, by a causal network is meant a set of variables and a graphical structure that connects these variables through a set of directed conditional probability links between them \textsuperscript{[99]}.

Bayesian networks are used for quantifying uncertain interactions among random variables for determining the impact of the observations. On the other hand, influence diagrams are used for quantifying a decision maker's decision options and preferences for determining the optimal policy. It is, therefore, important that the decision maker clearly models both the actual problem and the expected decision. But, the combination of the elements into an optimal decision can be a hard task. However,\textsuperscript{117} See Chapter 1.
this can be done in a model (e.g., Monte Carlo simulation) where the expected value (or expected utility) of each decision alternative is computed. These problems are investigated in Chapters 7 and 8, and in Section 9.1.4. Then, after considerable sensitivity analyses the best choice should be reached.

A firm’s subjective probabilities and its utility function for estimating time and risk preferences are normally used in the traditional decision analysis. Smith and Nau (1995) [10] have formalised this approach. However, the value of the project is often defined subjectively in terms of the firm's breakeven buying price or breakeven selling price (the latter also called the certainty equivalent), but in general, these two breakeven prices are not equal, according to Raiffa (1968) ([39] p.89-91). Therefore, an appropriate definition of the value will depend on whether the firm is buying or selling the project (see Walley (1991) [169] for further investigation of this problem).

**Coherent Risk Measures**

Thereafter, Section 6.2 investigates the conditions for coherent decision analyses in incomplete markets. In this section the observation that the usual coherent risk measure is somewhat generic the portfolio optimisation problem is also discussed (see [18] for more details). Furthermore, the price calculations in practice, including transaction costs, have shown that there are differences between arbitrage valuation and utility maximisation (or equilibrium theory). A somewhat new generic valuation theory is therefore presented, which claims that for pricing in practice bounds can be set that are sharp enough. This means that the bounds work for any cash stream spaces, and since they work in (possibly infinitely-dimensional) linear spaces they are also mathematically general (see further details in Jaschke and Küchler (2000) [18]).

The conclusion of the investigation in Section 6.2 is that the coherent risk measure in [4] is a generally applicable concept, and, therefore acceptable for the OR analyses in this thesis. There are, however, many widely used risk measures, like VaR\(^{118}\) and LPM (lower partial moment), which are not coherent, and therefore have several drawbacks. However, the recently developed CVaR is coherent\(^{119}\). Furthermore, coherent risk measures can be generalised and they are easy to bring together with the theories of arbitrage and utility maximisation. However, there still remain many open

\(^{118}\) See Sections 7.5 and 9.1.4.

\(^{119}\) See Chapter 7.
questions regarding the coherent concept, the valuation bounds, and the portfolio optimisation problem [18].

**Lower and Upper Preventions**

Walley (1998) [121] states that risky projects are priced in the financial trading markets as lower and upper previsions (expectations). However, this statement has been criticised for being unreasonable and sometimes misleading. In some applications this can lead to loss of information [128]. Furthermore, it has been pointed out that this way of modelling uncertainty is not general enough for determining upper and lower previsions and conditional probabilities uniquely\(^{120}\). But upper and lower previsions are easy to understand and to use in the decision process. However, the problem is that they only produce a partial ordering of the possible actions. This is similar to interval decision analysis, where the result can be several possible actions. Note that these imprecise probabilities differ from the well-known Bayesian analysis, which uses separate assessments of precise (additive) probabilities and utilities for constructing a coherent (complete) preference ordering of actions\(^{121}\).

Section 8.1.2 describes how to handle the problem with the principle of maximising the expected utility (PMEU). This principle should be augmented by other criteria when the potential impact is low-frequency; high-severity events\(^{122}\). For instance, when the consequences might be serious and the probability of catastrophic events is low, we recommend in the Uncertainty Module the use of the computational framework DEEP for solving the problem with vague information in risk management.

**The Uncertainty Module and the Decision Module**

The Valuing Risky Projects Module\(^{123}\), described in this section, is divided in two sub-modules, the Uncertainty Module and the Decision Module. The Uncertainty Module and interval forecasts are closely related to an interval approach [129], [193]. The idea behind the Uncertainty Module that handles a qualitative sorting function is described in Section 8.1.2. Moreover, the Uncertainty Module is in line with the loss-scenario/qualitative assessment models described in Section 4.2. These methods have

\(^{120}\) See Sections 8.1.2 and 9.3.

\(^{121}\) See Sections 6.2 and 9.3.

\(^{122}\) See Sections 3.2.2.2 and 5.1.

\(^{123}\) See Figure 9.1.1.
the advantages that they increase the transparency of the change of OR and facilitate ORM. But, because of the subjective expert judgments they are not appropriate for calculating the ORR [123].

The Decision Module handles the quantitative sorting function, which includes causal models, usually based on Bayesian networks that provide the mathematical framework for predicting potential losses\(^{124}\). However, Basel II points out that qualitative and quantitative OR approaches in combination seem to be the most promising methods [107], [112], [114], [123], [126].

Moreover, a goal in ORM is to be able to predict potential losses and to act on them before it is too late. Causal models provide the mathematical framework for this type of analysis, usually based on Bayesian networks or discriminating analysis\(^{125}\). These models take the history of risk drivers, risk indicators and loss events\(^{126}\) and develop the associated multivariate distributions\(^{127}\). They can determine which factor or factors have the highest association with losses (risks). As the causal factors change, the model can help predict potential losses. Therefore, the model can be used to assess root causes and perform scenario analyses\(^{128}\) relating to potential future environments. But, the causal model requires many data points, collected over five to ten years, for it to be useful. Moreover, there are for instance high-frequency categories of risk that are practicable only in operations departments. Some experiences have also shown mixed success with causal models, e.g., when correlations between losses and underlying variables are very low, or even contrary to expectation [107]. There are many different Bayesian networks for modelling multivariate distribution. Therefore, a correct network modelling of the OR calls for specification of both the institution and the management role. Nevertheless, there are advantages in using Bayesian networks for ORM in finance.

- Bayesian networks have many applications that can be useful for modelling distributions of ORs or key risk indicators, which influence ORs. As mentioned

\(^{124}\) See Section 6.1.1.
\(^{125}\) See Sections 6.1 and 8.1.
\(^{126}\) See Sections 1.3, 2.1, 3.2, 4.1 and 4.2.
\(^{127}\) See Section 8.2.2.1.
\(^{128}\) See Section 3.2.
earlier, conditional probabilities might also be based on scorecard and/or historical data from the activity of the firm\(^{129}\).

- With the use of key risk indicators and trigger levels in a Bayesian network the effectiveness of the risk control can be evaluated.

- Bayesian networks may include a method for decision making within a scenario analysis framework, which relies on both internal loss data, and relevant expert opinions and industry data. This is important, since reasoning with ORs is often scenario based, where computational models yield prediction intervals, within which losses are described.

Consequently, specific questions can be answered through a carefully and compliant scenario analysis. Therefore, Bayesian network modelling is a key SAFOR tool. But it is important to note that the risk handling does not end there. The actions for the desired risk levels must also be taken. Moreover, there may be a finite number of scenarios (typically a small number), which must use specific discriminating principle and methods and processes for its application\(^{130}\), mentioned above. This application will be handled in the sub-module Uncertainty Module in SAFOR2.

Furthermore, as also mentioned above, Bayesian networks use probability theory for managing uncertainty. But, frequency and severity/impact are often considered as random OR variables. In the Bayesian analysis this problem can be solved through letting the number of events \(N\) be estimated by a volume indicator, e.g., gross income and/or the targets for the next year, and then multiply \(N\) by the probability of a loss event \(p\). This expresses the expected frequency \(Np\). And, the probability-impact diagram in finance is often solved by using risk maps\(^{131}\). Then the management can reduce the frequency and/or the impact risks so that they lie within an acceptable level [124], [190].

As already pointed out, a major problem with the Bayesian approach is that the intervals are too wide, with no discrimination within them. Therefore, we propose the use of the Uncertainty Module, shown in Figure 9.1.1, to extend the risk level model. And, from the survey of how to model imprecise probabilities in Section 8.1.1, the conclusion is that there are still many unanswered questions. However, in this thesis,

\(^{129}\) See Sections 3.2, 4.2 and 10.1.

\(^{130}\) See Section 8.1.2.

\(^{131}\) See Sections 3.2 and 9.1.1.
the interval approach for imprecise probabilities together with the risk analysis method DEEP\textsuperscript{132} is suggested for the efficient evaluation of decision situations [129], [193].

**Scorecard Data and Scenario Analyses in Basel II**

According to the AMAs (Basel II)\textsuperscript{133}, banks are allowed to quantify their ORR using a loss distribution model that needs historical data based on actual loss experience of at least three years (preferably five years). But these data are difficult to obtain. Therefore, banks can supplement their internal data with internal scorecard data based on risk owners or other expert opinions. Scorecard data can also be offered from reliable external sources, e.g., public data warehouses. These reliable external sources may also be acceptable for the ORR model under Basel II. Sometimes this external information together with internal loss event data give a better indication of future loss experience than when only internal data are used [107], [112], [190]. Consequently, it is allowed to use scorecard data in the AMAs. But it is prescribed that both expected frequency and expected severity must be assessed quantitatively from scores. However, the scores themselves may be purely qualitative. Solving this problem can be done by specifying a range of expected frequencies. Thereafter, for fixing the exact point in this range scenario analysis should be used and compared with loss experience data. Moreover, in validating the scorecard, internal data, if possible, should be used and otherwise external data. There are pros and cons with using scorecards. The scores themselves are subjective, and they are often mapped in a subjective way into monetary loss amounts. This involves human risks of inadequate decisions and management processes. But, despite limitations using scorecards to OR can be practical for identifying risks and controls. For instance, the calculation of the ORR can start early with scorecards before reliable internal and external databases are in operation.

**9.1.4 SAFOR3 – The VaR and CVaR Measurement Module**

This section investigates the general conditions of the VaR and the CVaR to achieve greater integration for an advanced, strategic OR model across all business units in a bank. As already shown in the Licentiate Thesis [1], market risk VaR (and now also

\textsuperscript{132} See Section 8.1.2.
\textsuperscript{133} See Section 3.2.2.
credit risk VaR) analysis is commonly driven for group-wide and business risk analysis in larger international financial institutions. Chapter 7 states some of the properties of the VaR and the CVaR and makes a comparison between them. But, there is still considerable work under way to integrate certain OR issues into market risk type VaR and CVaR assessments.

However, the bottom-up OR model proposed by Basel II is an advanced model, which takes overall earnings into account and at the same time tries to remove ORs that are already included in market risk or credit risk\textsuperscript{134}. These models also involve mapping of the workflows, where failure may occur\textsuperscript{135}.

One of the ORRs discussed by Basel II [112] is the *VaR at significance α* (typically $0.001 \leq \alpha \leq 0.0025$ for OR losses) for next year’s operational loss variable. But, no stand on this question is taken in this thesis. Instead, The VaR and CVaR Measurement Module (SAFOR3) investigates how useful these instruments might be for investigating OR loss data. It is already known that these quantitative modelling techniques are important for banks that want to use the AMAs.

But, there are methodological problems\textsuperscript{136} when trying to calculate ORR for quantifiable ORs. A reliable OR database will consist of realisations of random variables exceeding a predefined threshold for data collection. However, Embrecht et al [117], [118] point out that it is not realistic to estimate the VaR at this low significance level $\alpha$, and that no risk theory, including extreme value theory (EVT), will be able to present any scientifically sensible estimate at this level\textsuperscript{137}. Instead, they show that within quantitatively well-defined sub-categories of OR data with some sort of underlying repetitions, EVT might be used for low tail levels, based on an out-of-sample tail fit of the loss distribution [117]. Thereafter, a conditional loss distribution function, like CVaR, for the OR categories in question might be estimated from these tail models. This method has been used in a bank, described in Section 10.1 [107].

Chapter 7 discusses VaR and CVaR. One conclusion is that VaR is often used in banking in spite of its sometimes weak properties. For instance, if the frequency distributions are not normal VaR is not sub-additivity, which means that a portfolio

\textsuperscript{134} See Sections 5.3 and 9.1.1.
\textsuperscript{135} See Section 3.2.1.
\textsuperscript{136} See Section 9.1.3.
\textsuperscript{137} See Sections 4.2 and 8.1.1.
VaR may be increased by diversification in that portfolio\textsuperscript{138} [1], [26]. VaR is also difficult to optimise, when scenarios are used in calculation. In this case, VaR is non-convex, has non-smooth density and has multiple local extrema [60]. However, the percentile risk measure, CVaR, does not have these drawbacks.

For continuous loss distributions, CVaR is equal to the conditional expectation beyond VaR, and for distributions in general, \textit{CVaR is the weighted average of the VaR and the conditional expectation beyond VaR} [85]. As shown in Section 7.6, CVaR is coherent and can be used for measuring OR from any asymmetric and discontinuous loss distribution with discrete probabilities. Moreover, in several case studies CVaR has been proved to be an appropriate portfolio risk measure\textsuperscript{139}.

Consequently, as soon as OR identification, classification, and measurement have been investigated enough, the severity, frequency and aggregated distributions could be estimated. Then, calculating and calibrating ORR should be done in five steps [190]:

- \textit{Make a consistent data qualification for modelling}. Basel II has proposed definitions for a bottom-up approach, where the capital requirement is calculated at the intersection of a business line and event type\textsuperscript{140}. Automated tools that allow for \textit{slicing and dicing} can be a help in this process.

- \textit{Model severity}. When a loss occurs, the question will arise how to approximate the probabilities of the potential amount of the loss. One approach that could be used is to level out the irregularities in the raw experience data\textsuperscript{141}.

However, C. Alexander [102], [190] proposes the use of maximum likelihood estimation (MLE) technique to fit several different types of distributions and to use statistical tests to evaluate how well the different distributions fit the data\textsuperscript{142}. These techniques are used in the referred case in Section 10.1. Moreover, if there is not enough loss data, further information about these data can, as mentioned before, be collected from public sources or from similar financial institutions.

\textsuperscript{138} The whole is more than the sum of its parts – a well-known synergistic principle. The whole VaR for two instruments are greater than the sum of these two individual VaR (see Chapter 2).

\textsuperscript{139} See Sections 7.6 and 10.1.

\textsuperscript{140} See Figure 3.2.1.1.

\textsuperscript{141} See Figure 5.1.1.

\textsuperscript{142} See Sections 7.6.3 and 8.2.2.
Chapter 9 The SAFO Model

- **Model frequency.** There is a de facto standard to assume that the frequency of losses follows a Poisson distribution with a given density [107], [114], [190]. This distribution is the average frequency of events that have occurred over a particular holding period, e.g., one year. A negative binomial distribution can also be a choice for frequency modelling of OR events.

- **Monte Carlo simulation.** A simulation across the frequency and severity distribution will produce a total distribution of the selected data, e.g., an event type within a business line over a specified time horizon.

From this information a mean annual loss and an annual loss at a particular confidence level can be calculated. Then, the difference between these two numbers will indicate the necessary capital to protect the business line from the estimated event type. This calculation is repeated for every event type within each business line. Moreover, if all of the modelled cells are included into a combined simulation model, an aggregated total loss distribution for the entire financial institution is obtained.

Event types are here assumed to be independent of each other, which means that each event type is simulated for each business line. However, the total VaR distribution of the institution will incorporate diversification benefits, which means that the worst loss will not always happen simultaneously in each business line for every event type. Moreover, if there are correlations between business lines and/or event types copulas can be used.

- **Validating results.** Each modelled risk should be compared with actual historical experience to find out if it is reasonable, i.e., if the risk process is sound.

One of the goals of the thesis is to investigate if interval predictions as a measurement of uncertainty could be used in connection with VaR and CVaR to compute OR for an internal, advanced measurement approach in a bank. Therefore, it is assumed here that data are available for the methodology adopted. Then, Sections 8.2 and 9.1.5 analyse

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143 See Section 10.1.
144 See Figure 3.2.1.1.
145 See Figure 4.1.1
146 See Section 10.1.
147 Copulas are a tool for modelling dependence between random variables. It is an expression for a multivariate distribution in terms of the marginal distributions ([190] p. 168).
how different tests might be useful to find out if a given interval forecast is to be considered good or acceptable.

The conclusion of the investigation in Section 7.3 is that it is possible to minimise CVaR formally for effective continuous loss distributions by the use of linear programming and non-smooth optimisation techniques [6]. Because CVaR dominates VaR, it has been shown that CVaR always minimises the VaR. Moreover, the minimum VaR and minimum CVaR are equivalent when the Profit/Loss distribution is normally distributed. However, there are still possibilities for improving these approaches, for example one approach possibility is to find out optimal portfolios with VaR constraints, shown in Section 7.2 [42]. Furthermore, CVaR for general loss distributions with discontinuities is investigated in Section 7.6 [85].

The approach for portfolio optimisation in Section 7.3 is extended in Section 7.4 [8] to an analysis that calculates VaR and optimises CVaR simultaneously. There it is shown that different optimisation formulations can be used for risk-return optimisation problems with convex constraints. This is also true for CVaR optimisation problem. In a case study it is shown that the optimisation algorithm is stable and efficient and that the portfolio optimisation with CVaR constraints might give rise to new and interesting investment strategies [8].

Section 7.5 analyses how to optimise a portfolio, when the risk variable VaR is incorporated into the optimisation problem. The problem is, however, that \( \text{VaR}_\alpha \) is not coherent, since it is not convex and does not satisfy a sub-additivity property, but is comonotone\(^ {148} \) additive. But, Pflug (2000) [60] shows that the VaR optimisation problem can be reformulated as a fix-point problem of solutions of linear optimisation problems, which could lead to a feasible solution strategy.

On the other hand, CVaR is a coherent measure of risk according to Artzner et al. (1999) [4], who call a risk measure coherent, if it is \textit{translation-invariant}, \textit{convex}, \textit{positively homogeneous} \textit{and} \textit{monotonic} \textit{w.r.t. first order stochastic dominance}. Furthermore, Section 7.5 provides a general exposition of coherence and discusses several additional desirable properties of CVaR. It is also shown that every local optimum is global in the CVaR approach, which makes the CVaR risk measure superior compared to the VaR risk measure [60].

\(^{148}\) See Footnote 67.
Therefore, CVaR as a coherent risk measure is often recommended as an alternative to VaR. Moreover, in a dynamic setting it is always possible to transform a CVaR limit into an equivalent VaR limit, and conversely.

To sum up, contrary to VaR, CVaR is a convex, sub-additive and coherent risk measure. But, CVaR and VaR can be used together, and CVaR can be applied in non-symmetric return-loss distributions, where a portfolio can be calculated with a specified return and a minimal CVaR, as well as a portfolio with maximal return with a constrained CVaR. Furthermore, several CVaR constraints can be specified simultaneously with various confidence levels and CVaR can provide optimisation shortcuts, which, through LP techniques make CVaR calculations feasible [6], [60], [85]. However, CVaR only measures OR, estimation or model risks\textsuperscript{149}, but not financial risk [18].

In practice, standard VaR [1], [3], [26] is widely used in international financial institutions. The calculation of the VaR is usually based on a single probability measure $P$, estimated from historical data. A simple example may illustrate the difference between VaR and CVaR. Suppose, e.g., that 100000 simulations of the risk factors at the risk horizon are used to generate a P&L distribution and consider the 1000 losses that are simulated. Then, the 1% VaR is the smallest of these 1000 losses and the 1% CVaR is the average of these 1000 losses. This shows that CVaR will always be at least as great as VaR, but that CVaR will usually be greater [6], [60], [85], [190].

Furthermore, the main conclusion of the analysis in Section 7.6 is that it is also possible to use CVaR for general loss distributions with discontinuities [85], which is very important in application based on scenarios and finite sampling of random variables. The bank application described in Section 10.1 shows that CVaR can be used in a bank for controlling ORs. Moreover, in problem optimisation under uncertainty, CVaR can be applied to both the objective and to the constraints or to each of them.

Under these circumstances, the convexity of the CVaR is a big advantage over the VaR. Section 7.6.2 sums up the characteristics of VaR and CVaR and shows the relation between them in some example and figures.

\textsuperscript{149} See Sections 5.4 and 5.5.
Chapter 9 The SAFOR Model

9.1.5 SAFOR4 – The Interval Forecasts Evaluation Module

Chapter 8 highlights some scientists, who have investigated how to design efficient evaluation and decision-making situations. This chapter includes an overview of how different interval approaches and tests have been investigated by different scientists to find out if an investigated interval forecast could be considered good or acceptable. First, Section 8.1.1 gives an overview of the classical decision theory of imprecise probability statements in terms of different alternative modelling methods. Then, Section 8.1.2 shortly describes the DEEP risk method devised by Danielson et al. (1999) [129] and the used theory behind their framework. They use, for instance, hierarchical models, such as second-order probability theory, to describe how impreciseness can be modelled and evaluated using belief distributions. It is this DEEP method we recommend have to be used in the Uncertainty Module in SAFOR2\textsuperscript{150}. Finally, the following Section 8.2 investigates in more detail how an interval forecast could be tested in different ways for being considered good. A general efficiency criterion is then established. By using a simple Monte Carlo experiment for showing how important it is to distinguish between conditional and unconditional coverage, Christoffersen (1997) [11] tests a particular real-life VaR interval forecast with the help of J.P. Morgan’s\textsuperscript{151} daily financial time series [1], [3] (for further details see [11]).

A VaR setup is restricted to the lower tail of the distribution of a one-sided interval forecast. Therefore, in volatility dynamics a VaR test for conditional coverage can result in important loss of information. Another problem with VaR for risk management in general is that it is difficult to investigate the relevance of variance dynamics.

The conclusion of the different tests is that if volatility is forecastable in ten or fifteen trading days, this prognosis approach is practicable for risk management. But, for longer horizons the volatility is not an effective prediction method. Consequently, if the risk horizon is more than ten or fifteen trading days, management should show more interest in modelling the extreme tails of return densities. Like other scientists, Christoffersen (1997) [11] claims that recent advances in EVT\textsuperscript{152}, which requires

\textsuperscript{150} See Section 9.1.3.
\textsuperscript{151} J.P.Morgan is a leader in investment banking, asset management, private equity, custody and transaction services, middle market financial services, and e-finance.
\textsuperscript{152} See P. Embrechts et al. (December 10, 2002) [117].
independent and identically distributed observations, have shown that EVT has the potential to facilitate this task\textsuperscript{153}. Therefore, Christoffersen et al. (1998)\textsuperscript{[84]} point out that EVT is an alternative for improving long-horizon risk management modelling of extreme events. This is normally the case when we talk about OR.

However, in order to make decisions using data from different sources, it must be possible to aggregate the data. At the same time, the uncertainties inherent in the measurements need to be taken into account. Using interval methods, this is viable, even considering information as diverse as CVaR intervals and scorecard data.

9.1.6 Connection of the SAFOR Modules into a Whole

Thus, when using GST to produce this systemic-holistic framework, SAFOR, we connect identified parts into one whole; parts which may be much more detailed at each instance, but which together constitute the whole - and for a specialist acts as a mind-map of how details on various levels interact and helps the human mind to overlook ORs in changing, moving and evolving landscapes. The specialist with this mind-map may him/herself work at a very detailed level at times, but will always be able to re-connect to the wholeness in his/her mind/decision.

9.2 Implementations

In practise there are banks that have already started to develop their own ORM approaches. They try to implement a comprehensive ORM process by modelling loss distributions using VaR parametric approaches, like those used for calculating market risk\textsuperscript{154}.

Under the AMAs, banks are allowed to use their own internal OR measurement systems for deciding the regulatory ORR. These internal measurement systems must, however, use the qualitative and the quantitative criteria in accordance with the AMAs\textsuperscript{155}. In principle, these criteria are in line with the systemic approach described in Chapter 2. Moreover, Basel II expects that the banking institutions will continue the evolution of their OR approaches but points out that a bank must be able to demonstrate how it includes potentially severe tail loss events in its ORR calculation.

\begin{footnotesize}
\begin{itemize}
\item \textsuperscript{153} See Sections 9.1.4 and 10.1.
\item \textsuperscript{154} See Sections 7.2.1 and 9.1.4.
\item \textsuperscript{155} See Section 3.2.2.
\end{itemize}
\end{footnotesize}
[113]. Severe tail loss events do not mean catastrophic events, which are not included in the regulation. Furthermore, a bank must always be able to convince the supervisor that its ORR calculation *meets a soundness standard comparable to one year holding period and a 99.9 percent confidence interval*. Basel II is also reviewing how the OR approaches progress in different banks and also in theory and hopes to find a reliable ORM framework for banking by the end of 2006 [113]. In 2005 Basel II extended the time for banks under the AMAs to the end of 2007.

Consequently, the banks under the AMAs can use a systemic implementation approach to ORM in such a way as has been described in Chapter 2. Such a systemic approach is also proposed in the SAFOR model in the beginning of the Section 9.1.

### 9.3 Bayesian Inference

Walley (1991) [169] points out that there are three basic probability principles, *avoiding sure loss, coherence and natural extension*, for formalising that different assessments cohere (fit together). These principles are used for producing inferences (natural extension) and conclusions, and for validating the consistency of a proposed model. Moreover, Walley claims that qualitative judgments (or a mixture of qualitative and quantitative judgments) can produce upper and lower previsions (expectations). Furthermore, he suggests that acceptable transactions have no positive linear combination, which means that there will be a certain loss. Therefore, he states that only *coherent* lower previsions *avoid sure loss*. However, Walley argues that for generalisation of the standard axiom of countable additivity there are, indeed, cases where the definitions of coherence and avoiding sure loss may be strengthen (see [179] and [121] for further details).

Section 8.1 shows that over the years several scientists have proposed and studied different types of imprecise prior probabilities, though Walley (1998) [121] states that there are few investigations made for specific models of imprecise sampling. However, there are some new suggestions of imprecise probabilities in this field, presented after 1998156, among which the CVaR and interval risk analysis are the most important in the SAFOR framework.

Bayesian inference has been criticised specifically for the problem that it is not

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156 See Sections 7.6, 8.1.1, 8.1.2, 9.1.3 and 10.1.
possible to choose the order of several prior distributions. However, there are means to use both data as probability and non-data information as prior distribution in order to resolve this statistical measurement problem to a certain extent [25]. But, as mentioned before, indicators (key risk or early warning indicators) are also useful for the prediction of the OR. They could indicate future possible ORs, which, for instance, might be that when a business grows too rapidly, problems arise in connection with introduction of new products, and systems break down\textsuperscript{157} [112]. It also is important to establish quantitative data such as self-assessment scoring or results objectively. Scorecards\textsuperscript{158} could be used for changing qualitative data into quantitative with relative OR ranking. Bayesian inference that utilises self-assessment results often develops increasing levels of sophistication of risk management, which in turn might result in a reduction of ORR [107], [112], [117], [123]. It is well-know that Bayesian inference accepts some degree of subjectivity in only choosing the prior distribution. But, checking the process of choosing the prior distribution in banks by internal auditors and supervisors may warrant transparency.

Consequently, choosing prior distributions mean that ORs for all activities, processes and systems must be identified and assessed. Therefore, this consideration itself is a process of great significance for ORM as well as for measuring\textsuperscript{159}. Senior management has to confirm the prior distribution before the Committee gives approval to it. This greatly improves the senior manager’s recognition of OR, and contributes to enhancing ORM and the control principle.

Anyway, the first thing banks have to do is to collect loss events in a robust loss database. Therefore, Basel II has proposed that the banks record specified OR data systematically in different business lines across the bank\textsuperscript{160}. This must be done in a correct and consistent way in all banks to facilitate any bank’s opportunity to monitor OR in the future [124]. However, there is still a need for further development of how to understand and measure OR, and how to validate different methods. As already mentioned, the measuring techniques in this thesis include the necessary data requirements (SAFOR1) as well as the robustness of estimation techniques (SAFOR2 and SAFOR3) and the validation methods that might be goodness-of-fit (acceptable).

\textsuperscript{157} See Sections 3.2, 4.2 and 10.1.
\textsuperscript{158}See Sections 4.2, 9.1.3 and 10.1.
\textsuperscript{159}See Section 9.1.1, SAFOR1.
\textsuperscript{160}See Chapter 3 and Figure 3.2.1.1.
tests and interval estimation (SAFOR4). This is a main aim of the SAFOR framework.

The conclusion of this investigation is that Bayesian inference is important for measuring OR in banking industry and probably also in larger, industrial organisations, which already use VaR calculation for their market risk.

9.4 Software Packages for Measuring and Managing OR

The preceding chapters show that in practice it is very arduous to aggregate OR. For financial analysts it is well-known that OR is a harder work and quite different to market and credit risks. In practice there are many questions about how to choose between different ORM tools. This choice must also be consistent with the bank’s and the regulator’s goals. However, most vendors do not provide complete ORM capabilities; even if they often imply that their systems can do everything.\textsuperscript{161}

Up to now there has been a tendency to offer more quantitative historical databases.\textsuperscript{162} Moreover, [171] points out that the OR software market must be more consolidated. In the future whole systems must be able to combine necessary OR tools for monitoring risk indicators, processes and different solutions for qualification and quantification of OR\textsuperscript{163}. But, there are also opinions that full-service ORM systems will not be found in the market. There seems to be a tendency in the market for vendors only to tackle some aspects of the OR. Furthermore, the products offered often strengthen the monitoring or the ORM of a particular type of bank system, or are specialist modelling tools [171].

Indeed, there is a well-known financial bottom-up internal measurement model, called the loss-distribution approach (LDA), which larger international banks can use partly for assessing and managing their ORs. In accordance with Basel II \cite{112} the LDA definition of the OR must be consistent and applicable to all elements of the systems. Even LDA breaks down the OR event into four risk factors/causes, i.e., people, processes, systems, and external events.\textsuperscript{164} Risks are then assessed as potential operational events with regard to their risk factors, likelihood and frequency.\cite{113}.

\textsuperscript{161} See Chapter 5.
\textsuperscript{162} See Section 9.1.1.
\textsuperscript{163} See Chapter 4.
\textsuperscript{164} See Table 5.1.
The statistical / actuarial or simulation based quantification models\textsuperscript{165} are used in LDA for the calculation of the ORR. These quantitative models are aimed to supplement qualitative OR approaches. In accordance with Basel II, LDA defines the loss-distribution, after internal controls and risk mitigations, as the relationship between causes and consequences \[188\].

Therefore, the implementation of the methodology for measuring OR in banks is an LDA, proposed by the Committee \[113\], \[188\], \[190\]. This approach uses three components of risk, the range of outcomes from a single risk factor, the likelihood (or probability) of each of those outcomes and the frequency of occurrence of this risk factor during, e.g., one year. An overall OR profile for a bank is then calculated in the following way. Firstly, the range and the likelihood are captured in a loss-severity distribution (LSD) and then, the third component in a frequency distribution\textsuperscript{166}. Secondly, these two new distributions are combined in a complete risk profile of the chosen risk factor. But, there are problems of how to combine these two distributions to obtain a reliable loss distribution\textsuperscript{167}. A numerical method such as a Monte Carlo simulation might be useful for the combination of the LSD and the frequency distribution\textsuperscript{168}. And finally, the overall OR for the bank is aggregated across all risk factors, which is based on the assumption of perfect dependency among risk types. But, as mentioned before, there are many experts who criticise this assumption as unrealistic.

Moreover, the Committee points out that it is permitted to use the qualitative scorecard risk approach to find low, medium or high likelihoods to problems in a banks operations and activities and low, medium or high rating of the consequences\textsuperscript{169}. This approach aims at guarantying that every point of the distribution falls within acceptable risk levels. Furthermore, even if the consequences of the scorecard approach are uncertain, it might be a complementary way of aggregating all the information captured in a bank’s loss distribution.

\textsuperscript{165} See Section 4.2, and Chapter 7.
\textsuperscript{166} See Section 9.2.
\textsuperscript{167} See Section 5.3.
\textsuperscript{168} See Section 9.1.4.
\textsuperscript{169} See Sections 5.1, 9.4 and 10.1.
Chapter 9  The SAFOR Model

However, many OR practitioners try to integrate their OR approaches with established systems, which are in use at their firms, and which already have scalability and methods for information collection and distribution\textsuperscript{170} [171].

\textsuperscript{170} See Section 3.2.1.
10 Validation of SAFOR

10.1 Quantification of OR

OR data have been hard to come by in this thesis, due to the confidentiality in the banking system. Therefore, we have not done our own case study of the SAFOR processes presented in this thesis. Instead, this Section 10.1 investigates an application of an advanced OR model, which is a result of the ongoing Basel II discussions for the OR regulation of the banking industry\(^{171}\). However, in this thesis the proposed ORR is not investigated, though this is not of importance for the thesis, since a bank must show for the supervisor that its internal advanced ORM approach is sound, and if this approach is accepted it can also be used for the calculation of the ORR. The application referred to below can however be looked upon as a validation of the SAFOR processes.

Ebnöther et al. (2001) \cite{107} investigate a detailed OR model, in which they use a production unit of a bank and its workflow processes for constructing a comprehensive self-assessment based on six risk factors. Their analysis also includes measurement of independent risk factors as well as dependent, where they use techniques from EVT\(^{172}\). This modelling exercise is shown to be relevant for the implementation of the ORM processes. The conclusion of the investigation in \cite{107} is that dependence of the frequency among the risk factors changes the independency results only slightly. On the other hand, dependence of the severity changes the independency results significantly.

The investigation shows that fraud is the most important risk factor and that 10% of all processes\(^{173}\) contribute 98% to the VaR, which is very important information for lowering the costs of defining and maintaining ORM processes. Moreover, a sensitivity analysis shows that this information is rather robust under stress testing.

Ebnöther et al. (2001) \cite{107} state that modelling OR production activities of a bank can be compared to a bank account process, which includes opening an account.

\(^{171}\) See Section 3.2.
\(^{172}\) See Sections 9.1.3, 9.1.4 and 9.1.5.
\(^{173}\) 103 production processes are used in the data sample but only 11 have been necessary for estimating the risk figures at a 90 percent level of accuracy. Furthermore, 6 risk factors were considered in the analysis, but only 2 of them seem to be important \cite{107}.
payment services from this account and all kinds of processing of this account. These activities are then considered as time ordering processes, which can be described and managed. For instance, a bank’s Production unit can be classified into pure management production processes and controlling. This statement has a certain resemblance to the systemic approach to ORM described in Figure 4.1. Furthermore, Ebnöther et al. (2001) [107] highlight the basic structure by using (time) directed graphs for the mathematical model\textsuperscript{174}, used for connecting the risk information.

For instance, if each node is designed for a machine or a person, errors can occur in the processing. These errors have a cause (a risk factor such as fraud, systems failure, etc.) at a node and a random input effect of the cause (action) $R$ on the performance of the process, which will lead to a random output performance (outgoing edges). Then, the main objective is to model the associated link between effects and causes. However, the prime interest in ORM is to investigate how causes, through the underlying risk factors, impact losses at individual edges. Ebnöther et al. (2001) [107] use a probabilistic approach, where a loss distribution $P_{(k,k_{out})}$ is associated with each edge, and which leads to the global loss distribution $P_R$ for the whole graph or process. They call this the operations risk distribution, which is defined for all OR losses. But, for OR distribution they consider only OR losses exceeding a given threshold, shown in Figure 10.1.1 below.

\textsuperscript{174} See Section 6.1.
Consequently, Basel II defines OR modelling in Section 3.2.1 as operations loss distribution that includes all OR losses. However, in practice banks already have efficient systems for small losses and no further modelling for these losses is needed. Therefore, Ebnöther et al. (2001) [107] propose a separation between operations and ORs like that shown in Figure 10.1.1 above, and they also suggest a new definition for large ORs with low intensity and high severity:

*Operational risk for a set of product processes are those operations risks associated with these processes which can be quantified and presented on a directed graph and which exceed a given threshold value.*

In consequence of this definition the analysis in [107] can be concentrated on well-defined processes that only show losses exceeding a given minimal, present value. Furthermore, graph theory for calculating OR in banking is suitable due to its standardised and stable processes. And, since only a fraction of the processes needs to be defined for measuring an accurate OR, the cost for this measuring can be significantly reduced by the use of thresholds. Section 3.2 investigates how the Committee handles this question. However, Basel II has not yet definitively defined the word *loss*, but its demand is that the banks shall build up historical loss databases even though not all indirect losses or opportunity costs have to be covered by capital.
requirement. Thereafter, banks must show for the supervisor how they distinguish between a loss event and a normal cost, i.e., at what point or threshold does the normal cost get to be a loss event. They must also show how they distinguish operational losses already taken into account, e.g., by market and credit risks (see Sections 3.2 and 7.6.3).

As mentioned above, it is necessary to have a meaningful definition of the risk as well as current databases and technology for the modelling of an advanced OR framework. But, until reliable databases are developed, expert knowledge (i.e., self-assessment) can be used in the applications in accordance with Basel II. The risk of each production process in [107] is therefore valued in standardised questionnaire forms by respective process owner. Then the experts were asked to make a choice between different real life situations to avoid people applying the mathematical laws of probability incorrectly (i.e., create their own laws) [116]. Consequently, Ebnöther et al. (2001) [107] state that it is important to have a database that is build on expert opinions. This database must be designed such that the most important and prominent biases are avoided and that a sensitivity analysis can be done. The following classes used in the case are LOW, MEDIUM or HIGH\(^{175}\). Moreover, for the severity self-assessment processes maximum and minimum possible losses are estimated. Then, two models are investigated, one independent of the risk factors and the other dependent on them. These can be compared with our Uncertainty Module and Interval Forecasts Evaluation Module described in Sections 8.1.2, 9.1.3, 9.1.4 and 9.1.5.

**Model 1 (Independence of the Risk Factors)**

In the independent quantitative approach to OR, data are first generated through simulation from expert knowledge. Thereafter, the distribution for heavy losses is modelled and estimated using EVT\(^{176}\). Then, the key risk figures, VaR and CVaR, are calculated. And finally, a sensitivity analysis is carried out. Furthermore, the analysis in [107] starts by considering a business unit of a bank with some production processes \(\Gamma_i\). Moreover, for any process six risk factors are assumed, which might lead to the following malfunctions: **systems failure, external catastrophes, theft, fraud, error and temporary loss of staff.**

\(^{175}\) See Sections 5.1, 9.4, and Figure 5.1.1.

\(^{176}\) See Sections 9.1.4 and 9.1.5.
Consequently, Model 1 assumes that all risk factors are independent. Then, two risk processes, the stochastic time of a loss event occurrence and the stochastic loss amount (the severity) of an event expressed in a given currency, are simulated to generate the data.

Ebnöther et al. (2001) [107] simulate the total first years loss 1000 times. Then, they simulate the tail of the heavy loss distribution. Thereafter, a threshold \( u \) is chosen, which only takes care of losses exceeding a given minimal, present value. Moreover, to get a feeling for this distribution in the heavy-loss region, they use the simulated data for plotting the empirical estimate for 1 year \( e_1(u) = E(S(l) - u|S(l) \geq u) \). They call this function the mean-excess function\(^{177}\), and suggest that this is a useful measure of their OR. Furthermore, Embrechts, P., Klüppelberg, C., and Mikosh, T. (1997) [118] have shown that EVT for typically heavy tailed distributions like Pareto distributions, \( e_1(u) \) is a linearly increasing function.

Moreover, even if Monte Carlo simulation can simulate as much data as are wanted, EVT offers some more refinement over empirical quantile estimation, e.g., VaR. This method can, for instance, be used whenever sufficient real loss data become available, and is useful when the tail of loss distribution must be smoothed, but it is also useful for the modelling of extremes in light tailed situations\(^{178}\). There are several examples of the use of EVT within risk management that can be found in [117], [118].

After the various processes are defined, Ebnöther et al. (2001) [107] ask the experts for estimates on the loss-range mixture distribution of the severity variable. Thereafter, under the independence assumptions, they simulate the losses \( S(t) \). Thereby, they use the model independent EVT\(^{179}\) approach to obtain a tail fit. They point out that they have sufficiently many observations on \( S(t) \) for the use of this procedure. Furthermore, they use the POT method based on a GPD model, described in Section 7.6.3, that allows the construction of a tail fit like that in Figure 10.1.2 below with a certain threshold \( u \) (for details of the method, see [117]).

\(^{177}\)CVaR\(^{\dagger}\) (upper CVaR) = expected losses strictly exceeding VaR (also called Mean Excess Loss and Expected Shortfall) [105]. See Figure 7.6.1.1 and Sections 7.6.2, 7.6.3 and 9.1.4.

\(^{178}\) The theoretical motivation for using the GPD is here the Pickands-Balkema-de Haan Theorem [118].

\(^{179}\) The software used, EVIS (Extreme Values In S-Plus) was developed by Alexander McNeil and can be downloaded via http://www.math.ethz.ch/~mcneil [107], [117].
Figure 10.1.2 is a comparison between empirical data of 1000 simulations (see *A Bank Application* below) and a GPD (fitted by the maximum likelihood method with threshold $u = \text{VaR}(90\%)$ of the possible loss) [107].

The data behind Figure 10.1.2 above and the resulting OR measures are explained and discussed in detail in *A Bank Application* below in this section.

**Model 2 (Dependence of the Risk Factors)**

Model 2 introduces dependence though an independent shock model. This approach is developed by Lindskog and McNeil (2001) [119], where applications to credit risk modelling are specifically discussed. Accordingly, modelling dependence is based on the assumption that all losses are connected with a series of underlying and independent shock processes, which may be the reason for losses of several different risk factors. In the Model 2 approach Ebnöther et al. (2001) [107] assume that among risk factors, the following are dependencies: systems failures, external catastrophes, and temporary loss of staff. The other three risk factors theft, fraud, and human error are still independent.

Therefore, dependencies are first modelled with the assumption that when an event realisation (e.g. an earthquake) strikes a process, it also affects all other processes. In the next step the systems are ordered in three hierarchies classes...
LOW/MEDIUM/HIGH\textsuperscript{180}. They are classified as LOW, MEDIUM or HIGH if the self-assessment probabilities of a failure at the same time are rated low, medium or high. Finally, three states 1, 2 and 3 are defined as meaning that if 1 is realised all systems in the three hierarchy classes fail. But, if 2 is realised, failure only occurs in the MEDIUM and HIGH systems and if 3 is realised failure only occurs in the HIGH system. However, it is important that the frequencies of the states 1, 2, 3 are consistent with the frequency of the self-assessment and the defined dependency structure in individual system. The objective behind this modelling of dependencies is that failure in the more important systems (host systems) should be avoided. But, if such a host system does fail, systems which depend on it will also fail (see Silvan Ebnöther et al. (2001) [107] for details of the mathematical model). In Model 2, two different random states can be used, the stochastic time of an event realisation and the stochastic loss (severity). For instance, it is possible with this model to calculate correlations if either frequencies or severities are dependent (see Lindskog and McNeil (2001) [119] for further details of this model).

**A Bank Application**

In this application, Ebnöther et al. (2001) [107] describe how they used the above mentioned approaches on 103 production processes at Zurich Kantonalbank. They also used six risk factors (systems failure, external catastrophes, theft, fraud, error and temporary loss of staff) for self-assessment of the probability and severity of losses. The values presented are not real because of the confidentiality, but their relative magnitudes are real. Their calculations are based on 1000 simulations. In Table 10.1.1 below results for Model 1 are shown.

\textsuperscript{180} See Sections 5.1, 9.1.1 and 9.4.
Table 10.1.1: Data for Model 1 [107]

<table>
<thead>
<tr>
<th></th>
<th>$\alpha = 90%$</th>
<th>$\alpha = 95%$</th>
<th>$\alpha = 99%$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$VaR_\alpha$</td>
<td>$CVaR_\alpha$</td>
<td>$VaR_\alpha$</td>
</tr>
<tr>
<td>Empirical</td>
<td>208</td>
<td>288</td>
<td>264</td>
</tr>
<tr>
<td>$u = 100; \ # \ 386$</td>
<td>268</td>
<td>340</td>
<td>324</td>
</tr>
<tr>
<td>$u = 208; \ # \ 100$</td>
<td>268</td>
<td>340</td>
<td>324</td>
</tr>
</tbody>
</table>

In the Table 10.1.1: Empirical shows the results derived from 1000 simulations for the Beta-mixture model. The line ($u = 100; \ # \ 386$) shows that the empirical data are based on a threshold of $u = 100$ and that 386 observations out of the 1000 are above this level. Similarly for ($u = 208; \ # \ 100$) [107].

Consequently, Table 10.1.1 and Figure 10.1.2 show that the POT model seems to be a reasonable tail fit for both the thresholds $u = 100$ and $u = 208$. For further information on the loss tail behaviour and the statistical uncertainty see P. Embrechts (2000) [120]. Moreover, Table 10.1.1 shows that, given a threshold, the VaR and the CVaR on 1 percent level are between twice and four times the threshold value. Ebnöther et al. (2001) [107] suggest that such estimates may be used in the premium calculation of OR insurance. However, future insurance to cover OR will also depend on potentially asymmetric information and how reasonably the insurance premium will be interpreted.

To find out what fraction of the 103 processes significantly contributes to the risk exposure, the total VaR contribution of the most important 10 processes is considered. These 10 processes lead to a VaR of 98% in Table 10.1.1. Therefore, risk management needs to be defined only for these processes and thereby the cost of managing OR is significantly reduced.

Thereafter, the relative contribution of each single process on the 95%-VaR level is calculated to evaluate the importance of a portfolio setup. The sum of these individual contributions is thereafter compared with the joint VaR of all 103 processes. The empirical VaR on the 95% level in Table 10.1.1 is shown to be 1:4 times smaller than the sum over all single VaR contributions. This is interpreted as the result of a

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181 Basel II states under Insurance (see Section 3.2.1. above) that there is a risk that insurance can be used to cover certain operational risk exposures. For instance insurance can be used to externalise the risk of potentially low frequency, high severity losses. [112].
significant diversification effect. Hence, Ebnöther et al. (2001) [107] claim that OR measurement and management must also pay close attention to the current portfolio.

The next step in the analysis is to compare the results above with the results from Model 2, where the frequencies of systems failures, external catastrophes and temporary loss of staff are dependent, but the percentage of events over the threshold is maintained. This analysis shows that the dependence of the three risk factors only slightly changes the capital at risk of the independence Model 1, which at first seems surprising. In fact, it is because the dominant risk factor is fraud\textsuperscript{182} and this factor is assumed to be independent in Model 2. Instead, if it is assumed that the fraud frequencies are dependent, there will be an increase by 15 to 20 percent of the risk quantities, which in turn means that if all risk factors are temporally dependent, the impact on risk does not seem to be very high [107]\textsuperscript{183}.

In addition, sensitivity analyses for Model 1 are issued and the result is summarised in Table 10.1.2 below.

\textsuperscript{182} In the data set, fraud contributes with 89\%, system failure with 2\%, external catastrophes with 3\% and error with 5\% to OR [107].

\textsuperscript{183} See also Section 8.1.2.
Table 10.1.2: Sensitivity Analysis for Model 1 [107]

<table>
<thead>
<tr>
<th>Empirical VaR from stress test</th>
</tr>
</thead>
<tbody>
<tr>
<td>$VaR_\alpha$</td>
</tr>
<tr>
<td>$\alpha = 95%$</td>
</tr>
<tr>
<td>$\alpha = 99%$</td>
</tr>
<tr>
<td>Original situation (see Table 10.1.1)</td>
</tr>
<tr>
<td>Only the 15 processes with the largest possible severities</td>
</tr>
<tr>
<td>Underestimating maximum loss by 20% in all processes</td>
</tr>
<tr>
<td>Overestimating maximum loss by 20% in all processes</td>
</tr>
<tr>
<td>Systems failure is more probable than the experts assume</td>
</tr>
<tr>
<td>Loss from systems failure is twice as high as assumed</td>
</tr>
<tr>
<td>Loss from fraud is twice as high as assumed</td>
</tr>
</tbody>
</table>

In the Table 10.1.2: Sensitivity analysis for Model 1 with case $u = 100$ in Table 10.1.1 and 1000 simulations (for more details see [107]).

From Table 10.1.2 it is seen that misjudgements about losses due to underestimation of the probability of systems failure and fraud are sensitive to the experts’ self-assessment. Consequently, fraud and systems failure are in this case the most important risk factors, which is in line with the result of the dependency analysis.

[107] then analyse the robustness of the above five sensitivity analyses on the total 95 % VaR level. Processes that vary less than 0.01 percent in their mean and standard deviation are not taken into consideration. This investigation shows that 25 of the 103 processes have a sensitivity of not less than 0.01 percent in the mean and the standard deviation. This means that the sensitivity analysis shows that the contribution to the VaR comes from the most significant number of processes, which remains almost invariant and small compared to all processes [107].

However, another more important sensitivity analysis considers the estimate of the maximum potential loss an event can cause in a process. Here it is assumed that the self-assessment of this worst event is not feasible and the upper bound loss information is therefore missing. Instead, to find a reasonable fit Ebnöther et al. (2001) [107] use a Pareto distribution in the calculations for Model 1. They find that a reasonable threshold is at $u = 4000$, and the corresponding estimate for VaR 99% is 7899, which is 20 times larger than the VaR 99% for the Beta approach. This
difference demonstrates the important point that statistical models should be used very carefully when information is missing, since they can cause unrealistic results\(^{184}\).

Consequently, there will be problems in deciding potential worst losses, since they can never be managed and the risk cannot be mitigated. Therefore, Ebnöther et al. (2001) [107] propose that one solution to this problem is to use a mixture of a Beta and a Gamma distribution. They draw 1000 events from a Beta distribution, interpreted as an uncertain self-assessment. These points are then used for fitting a Gamma distribution, thereby maintaining reasonable properties in the low severity region, but there is still no guarantee that losses may not become arbitrary large. However, the results in Table 10.1.3 below confirm that this model leads to reasonable results for both the VaR and the CVaR.

Table 10.1.3: Data for Model 1 with a Mixture of a Beta and a Gamma Distribution for the Severity [107]

<table>
<thead>
<tr>
<th></th>
<th>(\alpha = 90%)</th>
<th>(\alpha = 95%)</th>
<th>(\alpha = 99%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(VaR_\alpha)</td>
<td>(CVaR_\alpha)</td>
<td>(VaR_\alpha)</td>
</tr>
<tr>
<td>Empirical</td>
<td>217 307</td>
<td>277 368</td>
<td>408 593</td>
</tr>
<tr>
<td>(u = 217); # 100</td>
<td>217 326</td>
<td>276 388</td>
<td>427 551</td>
</tr>
</tbody>
</table>

In the Table 10.1.3: Empirical is the results derived from 1000 simulations for the Beta-Gamma mixture model, where \(u = 217\); \# 100 is estimated from a POT model with a threshold of \(u = 217\), and where 100 observations of the 1000 are above this level [107].

To sum up, if the number of observations above the threshold is kept the same in both the Beta-Gamma model and the original Model 1\(^{185}\), the VaR values are only slightly larger when losses can be arbitrarily high. But, on the other hand, the CVaR values are, for high \(\alpha\)-values, about 20 percent larger in the Beta-Gamma model than in Model 1. This means that the critical value seems to be almost unchanged but some very high losses occur, which shift the mean value of CVaR significantly upwards [107].

\(^{184}\) See Sections 5.4 and 5.5.
\(^{185}\) 100 in Tables 10.1.1, and 10.1.3.
10.2 A Bank Application and SAFOR – Concluding Characteristics

Section 10.1 shows how an advanced OR implementation in a bank could be managed and how quantification of OR, adapted to business units, is feasible if data exist and the problem is modelled with appropriate tools. This application seems to be in line with the tentative quantitative standards for the AMAs in Basel II. We also compare it with the SAFOR model. Like SAFOR, The OR Identification and Classification Module, described in Section 9.1.1, the bank application points out the importance of having well-defined objects or processes for the quantification of the OR and the ORM. The difference between the application and SAFOR is that we investigate the structure of the OR framework in detail from a systemic-holistic point of view. The application only points out that a reliable structure is necessary for quantifying OR in a firm. However, it shows that only the most important objects or processes need to be defined. Thereby, the OR costs can be decreased and, at the same time, the results will be sufficiently precise.

The application shows that self-assessment data are useful for applying a sensitivity analysis. Even if its results appear to be robust in many areas of assessment, there are problems with the maximum losses estimation. For instance, that sort of error has a significant impact on the derived VaR and CVaR. Moreover, the application shows that besides extensive simulations, EVT can also be used for obtaining OR measures. In SAFOR4, The Interval Forecasts Evaluation Module, it is pointed out that EVT is an alternative for improving long-horizon risk management modelling of extreme events, which are often the focus in discussion of OR. Since data have been hard to come by, it has not been possible to study the use of EVT for OR measures in a bank such as that in the application. Therefore, we look upon its result as a partial validation of the measurement technique proposed in SAFOR3, but without prediction intervals as CVaR⁺ and CVaR⁻.

Moreover, the application indicates that temporal dependence of the events has a negligible impact on the results. It is pointed out in SAFOR3 that there is a de facto standard of assuming that the frequency of losses follows a Poisson distribution with a

186 See Section 5.4.
187 See Figures 2.2.1 and 2.5.1.
188 See Sections 5.5 and 9.1.4, SAFOR3, The VaR and CVaR Measurement Module.
189 See Section 9.1.4 and Figure 7.6.1.1.
given density. If a Poisson model is not appropriate a negative binomial distribution can be the choice instead. Accordingly, the proposal in the application is to model the stochastic time events realisations through a Poisson process, which can usually be considered independent of the severities, shown in Section 10.1, \textit{Model 1}. This Model 1 is used and described in detail in the application above, which can also be seen as a validation of the statements in SAFOR3 about frequency modelling of OR events.

Indeed, it is said that the model considered in the application can be extended in various directions. For instance, it is proposed that all processes need to be modelled and all pieces catenated\textsuperscript{190} using graph theory for defining the total bank activities\textsuperscript{191}. This will lead to a comprehensive risk exposure for all the activities\textsuperscript{192}. Silvan Ebnöther et al. (2001) [107] suggest that their modelling exercise described in Section 10.1 is relevant for implementation of an ORM framework in banking. Both Ebnöther et al. [107] and Basel II propose that the task of ORM is to identify all the processes at risk in measuring the total risk involved. Of cause, this is a valid view, but in the SAFOR framework we look at the ORM task from a systemic-holistic perspective that gives a complementary picture. A holistic treatment of the problem emphasises the environment and the ongoing administration of the system in the implementation. Therefore, in the SAFOR model we propose implementational guidelines that take the whole bank’s organisation, including its environment, into account. This means that a systemic-holistic approach may avoid a large fraction of the operational mistakes and errors that have their origin in the design of the systems, e.g., people, machines, plant/environment and management. Moreover, to preserve the bank’s safety and security, overall systems effectiveness must result in an efficiently operating control.

Specifically, in the related bank application above an investigation like that described in SAFOR2, The Valuing Risk Projects Module, in Section 9.1.3 is missing. This module is further divided in two sub-modules, the Uncertainty Module and the Decision Module. The Uncertainty Module provides the qualitative sorting function. In our approach this module and interval forecasts are closely related to an interval approach described in Section 8.1.2. The Decision Module provides the quantitative sorting function described in Section 6.1.1. It is also stated in the bank application and

\textsuperscript{190} Catenary is in mathematics a plane curve whose shape is that of a flexible cable suspended from two level points and acted upon by no external force except its own weight. Galileo described the catenary as a proper curve for an arch equilibrium (http://en.wikipedia.org/wiki/Catenary).

\textsuperscript{191} See Section 3.2.

\textsuperscript{192} See Chapter 4 and Section 9.1, the SAFOR model.
in Basel II that for grasping all ORs in a bank both qualitative and quantitative approaches must be used.

However, the SAFOR framework not only considers and discusses the OR models, but it also includes a method for decision making. This is important, since reasoning about OR is often scenario based. And, for each scenario, VaR and CVaR, or other computational models yield OR prediction intervals. Therefore, a decision must be made, which takes into consideration what sort of actions have to be taken to reach reasonable OR levels. However, for a small number of scenarios, there has to be a discriminating principle and methods and processes for its approach. The proposed discriminating intervals framework DEEP in SAFOR2 and SAFOR4 is of a higher degree of confidence than the risk level model proposed in the bank application and in Basel II. These latter risk level models only serve as a first approximation of a decision situation, while the proposed interval decision model in SAFOR2 and SAFOR4 increases the transparency of the change of OR and facilitates a proactive ORM.

Consequently, the application shows that the technique holds as validation of the SAFOR modules, but contrary to SAFOR the application has no discriminating interval method for decision making, nor does it say much about of how to find and control correct data.

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193 See Sections 8.1.2, 9.1.3 and 9.1.5
194 See Figure 5.1.1.
11 Concluding Remarks and Further Research

It is shown in the case study (a bank application) at Zurich Kantonalbank in Section 10.1 [107] that if the workflow processes are well-defined for a production line in a bank, OR can undoubtedly be defined and modelled. As mentioned above, the OR in the application is calculated on a comprehensive self-assessment for six independent and dependent risk factors, respectively, with use of techniques from EVT. It is also noted that the OR distribution in the application, seems to be in line with the tentative quantitative standards defined by Basel II for the AMAs in Section 3.2.2.3. However, Basel II does not specify any OR approach or distributional assumptions to generate the ORR. It relies on the continuing evolution of analytical approaches for OR. But, a bank must be able to present for its supervisor how its own OR calculation meets a standard of soundness, expressed in one year holding period and 99.9 percent confidence interval [112]. Furthermore, one of the conclusions of this investigation is that the value added of quantitative ORM for banks is that they can obtain better control of large losses with low frequency and high severity. Moreover, distinguishing between large and small losses in banking is not a problem, since in practice an efficient organisation for small losses already exists, so no further modelling for small losses is needed at all. Therefore, the approach used in the application seems to be relevant for implementation of an advanced ORM framework in banking, resulting in significantly reduced costs for OR measuring. In the preceding Section 10.2 a comparison was made of some characteristics between the bank application and the SAFOR model and, specifically, that were omitted in the application.

In a comprehensive ORM framework an expertly based database must be designed so that the most important and prominent biases are avoided. First thereafter, a sensitivity analysis can be done. But, it is important that the experts estimate the severity self-assessment maximum and minimum possible losses in respective processes. This is investigated in SAFOR4195, where PMEU is suggested as the basis for the evaluation models. There are, as mentioned before, the risk level models complemented with discrimination intervals for handling the qualitative sorting function described in the Uncertainty Module in SAFOR2, in Sections 8.1.2 and

195 See Sections 8.1 and 9.1.5.
9.1.5. This evaluation is shown in intervals, which are expressed in risk managers’ maximum and minimum forecast losses. Such intervals will then be compared and investigated against real outcomes. Using intervals in this way can improve the evaluation process, since the expected utility model is better-founded than the risk level model described in Section 5.1. The proposed severity self-assessment data in the bank application to the experts with estimated maximum and minimum possible losses in their respective processes\textsuperscript{196} is in line with the proposed Uncertainty Module\textsuperscript{197}. Thereafter, the main difference between SAFOR\textsubscript{2} and the bank application lies in the evaluation approach.

Accordingly, the conclusion of this OR analysis is that it is necessary to have a consistent, co-ordinated and global framework for ORM. That framework is called SAFOR in this thesis, which means that ORM is treated from a systemic-holistic perspective and therefore covers several different areas (see Figure 2.5.1). Moreover, when OR processes are seen from a systemic perspective the risk for double counting can be detected much earlier. Specifically, this is the case when the OR level is mitigated. Basel II and other investigators have all stressed the same fact that different processes have to be connected together in a whole view of the company's ORs, useable for risk professionals, senior managers and the members of the board \textsuperscript{[107],[112],[190].}

It has been pointed out that managing the whole enterprise risk is a complicated task. It is, for instance, necessary to be familiar with probability theory, which is not something typical of a corporate risk manager. However, in OR investigations knowledge of both corporate and financial risk management are important. Therefore, an OR framework must be able to consolidate responsibility and keep all different risks together and under control. All the statements about OR are general. They are true in banking, but they also are true for any other organisation. Note that SAFOR\textsubscript{1} and SAFOR\textsubscript{2} are not based on any sophisticated theory of economic behaviour, since it relays only on interpreting in a special way. Even if Basel II and some other investigators agree with these OR statements, we have not found any implementational guidance other than the SAFOR model that takes all aspects of the organisation into account. Moreover, in investigating OR in banks, we have not found

\textsuperscript{196} See Section 10.1.
\textsuperscript{197} See Section 9.1.3, SAFOR \textsubscript{2}.
any complete decision and evaluation processes such as those described in SAFOR2 and SAFOR4.

We propose that a proper ORM approach must include a systemic perspective and qualified decision and evaluation processes. Furthermore, ORM in a bank, like in other organisations, must be an ongoing process of identifying risks, determining probability and severity of impact and providing solutions to mitigate the risks. Moreover, firms must further develop their learning to base uncertain decisions on the best information available at any given time. It also is necessary that they test how systems behave under various conditions and how they can get help to find out appropriate consequences and probabilities. Also, good project management practices and iterative development techniques are important aids to use early as possible in the development of the life cycle. Here, our proposed interval risk analysis method DEEP, described in Section 8.1.2, can be of great help.

Consequently, statistical measurement approach and scenario analysis are the two main methods used in banking for an advanced measurement OR approach. For consistency in risk-handling in larger international banks, it is necessary that the OR statistical measurement approach is performed to the same standard as for market risk and credit risk. On the other hand, in scenario analysis the inputs are derived from expert opinions, all available internal loss data, and relevant examples from industry. Therefore, scenario analysis tends to be less objective than a statistical measurement approach.

To sum up, the general conditions for using these measures in the thesis’ framework have been specifically investigated. It is important to be aware of the pros and cons when using these measures, even if not all these qualifications are explicitly demonstrated in the SAFOR model. However, the general conclusion of this investigation is that we propose a systemic-holistic approach to OR, where both the technical and non-technical aspects are taken into consideration, combined in a coherent system\textsuperscript{198}. Such an approach includes both the ontological (physics and mathematics) methodology and the epistemological methodology that emphasises an open, living approach to open dynamic research objects\textsuperscript{199}. Another conclusion of the investigation is that Bayesian inference, which can treat both statistical measurement

\textsuperscript{198} See Figure 2.5.1.
\textsuperscript{199} See Section 2.4 and 2.5.
approach as well as scenario analysis is exceedingly effective for controlling OR in larger international banks and probably also in other large international industrial organisations, which already use VaR calculation for their market risk\textsuperscript{200}.

### 11.1 Banking Regulations

An important instrument of banking regulation, which is used in most countries, is the direct supervision of banks. In such a case, banking system is monitored by regular on-site examinations\textsuperscript{201} and enforced by regulations such as capital adequacy. In recent years supervisors have increased their attention to assessing directly the risk management process of the bank. Moreover, there is a large literature dealing critically with capital adequacy. How capital adequacy works in a system with many heterogeneous banks is, however, an interesting question. For instance, if capital adequacy does not contribute to the safety and soundness of a single institution it can hardly contribute to the prevention of systemic risk, which risks the breakdown of the whole financial system. But, this question is not discussed further in this thesis.

#### 11.1.1 Advanced Measurement Approaches (AMAs) for OR

Basel II is currently working on new rules to include OR within capital adequacy and for new OR guidelines relating to market and credit risks in banking institutions. Within this framework, banks can choose to calculate their own required regulatory capital based on their own risk profiles and risk management methodology. But, this includes the selection of a more advanced approach from the proposed menu in line with their risk profiles. Moreover, Basel II has given some qualitative and quantitative standards for banks that wish to use the AMAs, described in Section 3.2.2.3. The most important standards are pointed out to demonstrate how a systemic approach might be included in this framework\textsuperscript{202}.

In general, Basel II points out that any OR measurement system must include the use of *internal data, external data, scenario analysis and factors reflecting the business environment and internal control systems*. Furthermore, the OR framework should be

\textsuperscript{200} See Section 9.3.
\textsuperscript{201} On-site examination provides the opportunity to examine at first hand how an institution is managed and controlled. It is particularly useful for assessing assets quality and the adequacy of internal controls.
\textsuperscript{202} See Chapter 2, Section 4.2 and Figure 4.2.
internally consistent and double counting of qualitative assessments or risk mitigants already taken care of, must be avoided [112].

Consequently, even if Basel II points out that the OR measurement has to follow some key features, banks are free to choose their own rules for generating ORR as long as they can show that their OR framework is capable of managing potentially severe tail loss events in its ORR calculation. Moreover, a bank must present for its supervisor how its OR calculation meets a standard of soundness of one year holding period and 99.9 percent confidence interval. But, banks are allowed to make further progress in their development of the analytical OR framework. This is the reason why the SAFOR model is proposed here to incorporate the calculations for comparisons.

11.1.2 Data Availability
An advanced OR modelling is not possible given current databases and technology even if a meaningful definition of the risk were to be provided by Basel II. Despite that, it is felt that by the study in the preceding chapters and the conclusions drawn from this, the thesis’ aim of developing a framework for systems properties of the OR, especially OR for banking institutions has been achieved. Furthermore, an analysis of whether decision analysis or interval predictions could be used in connection with VaR and CVaR to compute OR in banking institutions has been made. The conclusion of these analyses is that Bayesian inference to ORM will be the most important issue for calculating an advanced OR in banking industry. But there are still a lot of problems that have to be solved in the future. For instance, there are still problems in understanding and measuring OR as well as in the robustness of estimation techniques, and how to validate different methods.

11.1.3 Other Industries
The concern here has primarily been with OR in banks. The topic of OR is so vast that a focus on a specific sector was necessary. But the methodology described, i.e., studying approaches to OR in some sector and having that as a guiding principle in finding current weaknesses, is applicable to a wider set of sectors. Large active international industrial companies also have ORs arising from financial transactions,

203 See Sections 6.1, 8.1, 9.1.3, 9.3 and 10.1.
204 See Section 9.3.
IT systems, human error, and miscalculations. The set of risks, while differing from those of banks, are not totally dissimilar. Thus, the systemic approach to identifying and discussing improvement to OR practises should, with modifications, be applicable to those other sectors. It constitutes a very interesting avenue for further research to try and apply the approach of this thesis to other sectors.

It has been a purpose of this thesis to point out that the entire set of OR procedures could be used by large international industrial organisations, which already use VaR calculations for their market risk. The conclusion from the investigation in this thesis is that these industrial organisations could also manage their ORs in the same way as proposed here for the banking industry.

### 11.2 Systemic Approach to Banking Supervision and Risk Assessment in the Future

Specifically, during the last ten years risk management in banking has been considerably improved. These improvements have been very much a consequence of a more volatile and dynamic financial environment, followed by demands from regulators for new risk management standards on banks [111], [112], [113], [124].

The arguments for these risk improvements have often been that an improved risk management in banking might reduce potential systemic risk and thereby reduce the risk of a breakdown of the whole financial system. However, the supervisory focus on individual institutions is not yet designed appropriately to achieve these goals. Indeed, for handling systemic risk, a risk approach of the entire banking system must go beyond the individual institution’s own perspective.

In banking a lot of reciprocal exposures exist, which makes it problematic to calculate an OR for the entire financial systems. Furthermore, risks in an individual bank that are embedded in the whole banking system may easily be hidden. Accordingly, there can be a lot of mutual correlated risks between banks, without a bank noticing them. Thereby, an individual bank’s actual risk exposure might be quite substantial compared to its risk exposure in the entire financial system [127].

Therefore, instead of looking at individual banks, a total risk assessment approach for the whole banking system must be assessed appropriately. Such a risk assessment requires that the majority of systemic risk factors and the complex network of
interbank transactions are simultaneously taken into account. Thereafter, a method might be designed for applying detailed data collected at a central bank\textsuperscript{205}. In spite of different attempts to conceptualise these problems, they have not yet been solved satisfactorily [127], [188], [190]. Accordingly, the question is how long will it take for there to be enough data, readable and available to the supervisors and to the central banks for a risk calculation of the banking system as a whole to be undertaken.

However, we have investigated an ORM framework with a purely regulatory purpose, which means that the framework is based around the loss cause to mitigate the risk. But, there can be other reasons for OR modelling, e. g., an economic cost analysis in different areas of the business. With such a target the framework would be based around the loss consequence. Moreover, when choosing methodology managers must also ascertain if data are available.

Indeed, taking a GST approach to all aggregated banking risks (market risk, credit risk, OR, and so on) in the whole banking system could be a method of managing systemic risk in the future\textsuperscript{206}. In writing this thesis, it has been possible to structure and compile knowledge in an adequate and processable way using GST principles. Therefore, under these circumstances we specifically recommend the holistic approach to risk, described in Sections 2.4 and 2.5\textsuperscript{207} [109], [125], where the epistemological methodology emphasises an open approach with reasoning processes, weaker evidence for observations and predictions, and the consequence of unique event. The aim of the framework should be to find the real risk in the whole financial system. Moreover, in such a framework it is relatively easy to ask what if questions and to develop a useful stress testing model. This model might be like the SAFOR2 module that through a risk analysis method can evaluate uncertain situations when the consequences might be serious and the probability of catastrophic events is low\textsuperscript{208}. Since SAFOR2 is not based on any sophisticated theory of economic behaviour, but only relies on interpreting in a special way, it is also easy to validate.

Consequently, it seems possible now to start a learning system that can already use available data for thinking about the stability of the whole banking system, without

\textsuperscript{205} See Section 3.2.
\textsuperscript{206} See Footnote 3.
\textsuperscript{207} See Figure 2.5.1.
\textsuperscript{208} See Section 8.1.2.
waiting until reporting systems are complete. The regulators have already had an aggregated risk exposure of the banking system over some years\textsuperscript{209}. Therefore, theoretical and practical discussions on how to reform the reporting systems have started and how a whole systemic approach to banking supervision could proceed. As mentioned above, the use of GST, as in the SAFOR model, might also be a practicable method for supervision and risk assessment in the banking system. While the results are not inductively generalisable, they are indicative of the possibilities offered by GST in assessing complex phenomena like ORs in the banking system and highlighting problems that could have been harder to detect with other approaches.

\textsuperscript{209} See Section 3.2.
<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>AHP</td>
<td>Analytical Hierarchy Process</td>
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<td>AI</td>
<td>Artificial Intelligence</td>
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<td>AMAs</td>
<td>Advanced Measurement Approaches</td>
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<tr>
<td>ARIADNE</td>
<td>A knowledge-based interactive system for planning and decision support</td>
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<td>Basel II</td>
<td>Basle Committee on Banking Supervision, New Basle Accord</td>
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<td>BIA</td>
<td>Basic Indicator Approach</td>
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<td>BIS</td>
<td>Bank for International Settlements</td>
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<td>CAPM</td>
<td>Capital Asset Pricing Model</td>
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<td>CaR</td>
<td>Capital at Risk</td>
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<td>CVaR</td>
<td>Conditional Value at Risk</td>
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<td>CVaR⁺</td>
<td>(‘upper CVaR’) = expected losses strictly exceeding VaR (also called Mean Excess Loss and Expected Shortfall).</td>
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<td>CVaR⁻</td>
<td>(‘lower CVaR’) = expected losses weakly exceeding VaR, i.e., expected losses, which are equal to or exceed VaR (also called Tail VaR).</td>
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<tr>
<td>DAGs</td>
<td>Directed Acyclic Graphs</td>
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<td>DEEP</td>
<td>Damage Evaluation and Effective Prevention</td>
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<td>EL</td>
<td>Expected Loss</td>
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<td>ERM</td>
<td>Enterprise Risk Management</td>
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<td>EVT</td>
<td>Extreme Value Theory</td>
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<td>GBR</td>
<td>Generalised Bayes’ Rule</td>
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<td>GEV</td>
<td>Generalised extreme value</td>
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<td>GLST</td>
<td>General Living Systems Theory</td>
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<td>GPD</td>
<td>Generalised Pareto Distribution</td>
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<td>GST</td>
<td>General Systems Theory</td>
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<td>Information Systems</td>
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<td>Information Technology</td>
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<td>Loss-Distribution Approach</td>
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<td>LP</td>
<td>Linear Programming</td>
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<td>LR</td>
<td>Likelihood Ratio</td>
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<td>Loss-Severity Distribution</td>
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<td>LTCM</td>
<td>Long-Term Capital Management</td>
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<td>Management Information Systems</td>
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<td>ML</td>
<td>Maximised log-likelihood</td>
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<td>NPV</td>
<td>Net Present Value</td>
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<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>OR</td>
<td>Operational Risk</td>
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<td>ORM</td>
<td>Operational Risk Management</td>
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<td>ORR</td>
<td>Regulatory Operational Risk Capital Requirement</td>
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<td>PKI</td>
<td>Public Key Infrastructure</td>
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<tr>
<td>P&amp;L</td>
<td>Profit &amp; Loss</td>
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<td>PMEU</td>
<td>The Principle of Maximising the Expected Utility</td>
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<td>POT</td>
<td>Peaks over a threshold</td>
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<td>QIS 2</td>
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<td>QIS 3</td>
<td>Third Quantitative Impact Survey, 2002</td>
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<td>RCI</td>
<td>Risk Control Indicator</td>
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<td>SA</td>
<td>Standard Approach</td>
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<td>Sherwood Associates Business Architecture</td>
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<td>Systemic Approach Framework for Operational Risk</td>
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<td>Unexpected Loss</td>
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<td>VaR</td>
<td>Value at Risk</td>
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</table>
References


Volume 1, General Market Risk of Dept Instruments, 2nd edition
Volume 2, Standardised Approach Audits
Volume 3, Evaluation of Value at Risk-Models
Volume 4, Provisions for Option Risks
Volume 5, Stress Testing
Volume 6, Other Risks Associated with the Trading Book


http://cepa.newschool.edu/het/essays/sequence/completing.htm


http://www-ccrma.standford.edu/~jos/mdft.pdf/


References


http://www.bis.org/publ/bcbs96.pdf


http://www.financewise.com/publ/edit/riskm/oprisk/op-soft00.htm
References


References


http://pespmc1.vub.ac.be/PRMAT.html