

# TOWARDS FORMAL ONTOLOGIES FOR TECHNOLOGY RISK MEASUREMENT IN THE BANKING INDUSTRY

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## ABSTRACT

*Formal ontologies are well suited for embodying different types of domain knowledge and they provide reasoning capabilities to various applications. Our paper proposes a basic approach for applying ontologies to risk measurement in today's banking industry. This industry is constantly driven by international capital regulation like the new Basel Capital Accord (Basel II) which requires substantial management and understanding of operational risk. Therefore, we elaborate on an ontology-based application which can be employed for the formalization of operational risk and used for subsequent measurement. Hereby, we focus on technology-dependent risk which is a subcategory of operational risk. The paper proposes a formal representation in Description Logic based on the Web Ontology Language (OWL). Further, we discuss the application of the Unified Modeling Language (UML) as graphical notation for visualizing the domain knowledge. The overall architecture embraces a simulation environment which measures technology risk in proprietary trading. Finally, we discuss practical considerations and demonstrate the benefits of this approach.*

**Keywords:** Domain Ontology, Risk Management,  
Risk Measurement, Operational Risk, Technology Risk, Basel II.

(\*) The views presented in this paper are those of the authors and do thereby not necessarily represent those of Ernst & Young AG.

# 1. INTRODUCTION

Today, the most prevalent ontology application areas in industrial context refer to the Semantic Web. Along with the emergence of the Semantic Web new potential applications for formal ontologies are revealed. Until recently, formal ontologies have been playing a subordinate role in the banking industry. However, we argue that they are capable of solving domain specific problems like supporting the measurement of operational risks. The following paper proposes a formal ontology which allows to model a subcategory of operational risk, namely technology-dependent risk. This formal representation then serves as the architectural backbone for a simulation environment which measures technology-dependent operational risk.

The **measurement of risks** has always been regarded as a core challenge for financial institutions [8], particularly when operating in a volatile business setting. Consequently, the intermediation and transformation of risks marks a central activity throughout this industry [14]. Since the banking industry is of great importance to overall economical stability, the consequences of losses stemming from potential bankruptcies may not be underestimated. Herein lies the foundation for introducing regulatory rules on international scope ([3], [9]). Accordingly, the Basel Committee has revealed the first capital adequacy framework in 1988 [5]. It was firstly targeted at the management of credit risks and was expanded to market risk in 1996 [4]. In response to the downfall of the Barings Bank in 1995, the category of operational risk also slid into public attention. The next generation capital accord ([6], [7]) therefore regulates operational risk along with market and credit risk. From 2007 on credit institutions will be required to provide net worth for their operational risk. In the Basel II Accord “*operational risk is defined as the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events [...]*” [7]. As a consequence, system risk measurement will be demanded on a regulatory basis in the near future. In order to avoid misconceptions, we refer to the more general term technology risk instead of system risk.

Since it is not possible to cover all aspects in risk management simultaneously, the concepts presented here are narrowed down to one financial area, namely **proprietary trading**. This constraint helps to reduce the complexity of the underlying example. We choose proprietary trading because of the high dependence on technology in this domain. It comprises all trading activities which are carried out on the firm's account and not on the accounts of its clients. In the terminology of the Basel business lines proprietary trading corresponds to “Trading and Sales” [7].

The main purpose of this paper can best be described as proving the applicability of formal ontologies in the banking industry. A “technology risk ontology” is developed in order to explicitly capture technology-dependent risks in credit institutions. In order to find an appropriate solution which meets the above regulatory requirements, this paper analyzes why a formal representation of domain knowledge is favorable. By adopting formal ontologies to this application area, we intend to utilize two advantages:

Firstly, when formalizing domain knowledge, a deeper understanding of technology risk is promoted. It increases the risk managers' awareness of the systematic interdependencies. Moreover, understanding the risks one is exposed to can be regarded as integral part of the Basel requirements [7].

Secondly, a formal representation in some logical language simplifies consistency checking of the captured domain knowledge. Further, it enables to perform reasoning on terminological and individual knowledge respectively. Since the ontology is intended for reuse, we build upon the Semantic Web framework [25] and make use of the **Web Ontology Language (OWL)** [24], which is based on Description Logic. A suitable graphical representation plays a vital role in risk modeling. Here, the **Unified Modeling Language (UML)** [22] is a widely accepted industry standard for domain modeling. Because its limited consistency checking ability, recent research has proposed to combine

the strengths of UML with those of formal ontology languages [11] [21]. These considerations serve as a starting point for further investigation on how such a mapping can reap its benefits in real-world applications. Though a proprietary mapping from UML to OWL is investigated, we do not cover a transformation approach.

The paper is structured as follows. The subsequent paragraph illustrates the system environment by example and describes the system architecture as a whole. The third paragraph introduces the technology risk ontology. Finally, we demonstrate the integration into an overall risk simulation and measurement environment and discuss the results to date.

## 2. SYSTEM ENVIRONMENT

Prior to suggesting an initial system environment which will be used for technology risk measurement, we give a short example of the problem domain in question. Figure 1 shows a simplified proprietary trading environment in which the following process elements may be exposed to risks:

- front office (e.g. pricing, trading)
- back office (e.g. conformation, settlement)
- controlling (e.g. risk or performance measurement)
- accounting (e.g. balancing, reporting)

The above process starts with the extrinsic decision to trade on own account. Inside the bank the trade is processed from the front office to accounting which finally delivers the reporting statement. Interaction with external elements happens through the usage of market data and the execution of the order. In this environment we will first model and then measure the inherent technology-dependent risk by using simulation. To quote a concrete example for such technology risk, one could imagine a power outage resulting in a failure of the front office system. This leads to financial losses due to delayed trading. Alternatively, one could consider an incompleteness of the accounting system with an incorrect reporting statement as consequence.

For being able to capture, formalize and measure technology-dependent risks, we identify a general system architecture which can be broken down into two main parts as depicted in figure 2. The architecture is functionally divided into a risk measurement subsystem and a risk modeling subsystem. The risk measurement system inherits the technology risk ontology and represents the individual knowledge. The knowledge base embodies the corporate system structure and binds it to risk factor assessments. A particular technology risk model then serves as input data to risk simulation. Hereby, the usage of the Web Ontology Language (OWL) greatly simplifies serialization and exchange of domain knowledge. The knowledge base can be easily manipulated using an OWL API and processed for simulation purposes. Moreover, the risk measurement part can be extended to enable reasoning. Instance reasoning is required to check for inconsistencies in the domain model. Above all, reasoning may be used to reveal interrelations between systems and thus provide expert support.

The second subsystem manages the graphical representation of technology risk models. This turns out to be a crucial feature when it comes to the communication of risk assessments to stakeholders in the risk management process. One possibility is the employment of a widely-used graphical representation format which is suitable for modeling system structures and affiliated risk assessments. These requirements are fully met by the UML standard. Models compliant to the UML metamodel can be encoded in the XML Metadata Exchange (XMI) format and transformed into a knowledge representation format. In our case, the integration of risk assessments that have been modeled with the UML require the definition of a one-way transformation from UML object diagrams into a OWL knowledge bases. Hereby, the advantages of a well accepted graphical standard and a formal representation can be combined.

The Unified Modeling Language definition is organized into four meta levels [20] which differ from the OWL language structure. Although transformations between UML and OWL are ambiguous, there is ongoing work in defining a common Ontology Definition Metamodel [21]. Most often UML classes are related to OWL classes though the semantics remain subtle [23]. Previous work focuses on transforming UML class models into OWL DL ontologies or related representation formats ([2], [11], [12]). We think that a transformation of UML objects into OWL individuals is equally important because this type of knowledge is likely to change. Hence, in our architecture a UML Profile is specified in order to develop an appropriate transformation.

The transformation output is checked for consistency and then processed by the risk simulation environment which returns the results. The risk simulation environment may optionally enrich the knowledge base with simulation results in a later stage. This data can then be analyzed by applying logical rules and reasoning. This part represents an extension of the core architecture which is intended to assure overall maintainability of the system.

### 3. AN ONTOLOGY FOR TECHNOLOGY RISK MANAGEMENT

Understanding the actual risk environment is regarded as a prerequisite for an effective management of operational technology risk. Since there is a large variety in the scope of risk definitions concerning technology we propose to further subdivide the Basel system risk definition to derive our technology risk ontology:

- IT related risks directly result from failures that effect for example the availability, integrity or confidentiality of IT Components. IT Components comprise hardware, software, network or infrastructure entities.
- System related risks affect complex entities of technology, such as an entire trading system. The systems in our model are composed of single IT components. Systems can interact with other systems, although the properties affected are far more high level. Examples of risk factors are the completeness, correctness or timeliness of a system.

This short description of the technology risk domain is substantiated into a formal ontology as visualized below using a UML compliant graphical notation. Because both UML/OWL classes and UML associations/OWL properties do not share the same semantics [23], proprietary UML stereotypes are introduced by defining a custom UML profile. By using the UML extension mechanism we are able to significantly simplify the definition of an UML to OWL transformation which will be realized in our future prototypical implementation.

At the beginning, a taxonomy is created defining the class Component as superclass to SystemComponent and ITComponent. The class hierarchy contains SystemRiskFactor and ITRiskFactor as subclasses of RiskFactor. This hierarchy is then subdivided according to the diagram. The class hierarchy is subsequently extended to describe the concepts of stochastic distribution and risk factor weights. Figure 3 shows both three IT risk factors and three system risk factors. Each of the factors is additionally assigned a stochastic distribution, which is not included in the diagram.

As shown in figure 4, a number of object properties is specified in order to capture and restrain the dependencies between SystemComponent and ITComponent as well as among system components. In other words, systems can either depend on IT components or on other systems. Here, the object properties are represented in the UML language by defining association stereotypes.

To give an idea of how the according knowledge base for risk measurement and simulation is created, we add system and IT component instances (see figure 5). Interdependencies are modeled using object properties and stereotyped UML associations respectively. Then risk factors are attached and tagged with risk estimation values.

The example above describes a front office system which is composed of a server and a network connection, possibly to external markets. Those can fail with respect to availability or confidentiality. The front office delivers data to the back office system, which is mainly based on a database that possibly suffers from violated integrity. On the system layer the timeliness of the front office and the completeness of the back office system are essential.

Overall it can be considered as utterly essential for risk measurement to cover as many of such relations between technology-dependent risks as possible.

#### 4. RISK MEASUREMENT USING THE ONTOLOGY

Despite of being a relatively new research area there already exists a large number of approaches to operational risk measurement ([1], [10], [15]). Most approaches do not deal with a specific subcategory of operational risk but target at process, human-error, system and external risk. The spectrum reaches from basic qualitative models relying on expert interviews to complex quantitative approaches based upon loss databases or stochastic processes. A detailed comparison of existing measurement models is beyond the scope of this paper. Without loss of generality, we follow a partial model which focuses on functional dependencies in process, respectively technology dependent risks ([17], [18]). In the underlying model component properties depend on stochastic processes and dependencies among them:

- To model the dependencies among risk events a functional correlation approach was introduced. This tags the status of a risk element as simply up or down – depending on the state of other risk elements and on a noise factor  $\eta$  [17]:

$$h(t) = \vartheta - \sum \omega n(t) + \eta$$

The value of  $h$  represents the initial support of the element, whereby the states of the needed systems and the noise  $\eta$  is subtracted from an initial value  $\vartheta$ .

- The stochastic character is then expanded by adding risk factors to the model [19]. The status of the operational risk assets (in this case technology components) now depends on other systems as well as affecting risk factors [18].
- Combining the weighted risk factors  $r$  with the above noise factor the following dependency results in:

$$h = \vartheta - \sum \omega n(t) - \sum \alpha r - \eta$$

The state is calculated using for example a step function to map the value of  $h$  to either up or down [16]:

$$n(t + \Delta t) = \Theta(h)$$

At this the relationships of systems and IT components as well as between systems themselves are used to combine the independent risk factors towards measurable technology defaults. For the simulation framework itself the instance data is read from the knowledge base and further processed in the stochastic model. There the IT risk factors (as for example availability) map to the term  $\alpha r$ . Common frequency distributions for modeling the risk events (the values) of the factor are the Poisson or the negative binomial distribution ([1], [13], [17]).

The system risk factors are interpreted as the elements  $h$  and calculated using the above formulas using Gaussian noise. The transformation of the components states' into the resulting costs and losses is not discussed here.

## 5. RESULTS

Currently, our proposed concept involves the initial technology risk ontology and a risk simulation environment which is based on an exemplary knowledge base. For the ongoing ontology development we used both UML as graphical notation and OWL for knowledge representation. Hereby, we discuss the preliminary results from different viewpoints.

By using formal ontologies as the architectural basis of our risk measurement framework, we are able to realize not only technical benefits. First of all, the approach offers a precise and formal way to model risk assets and their dependencies in the banking domain. This serves as the foundation for a sound simulation environment. Furthermore, distributed ontologies can be used to build an extensible knowledge space for technology-dependent risk, either inside the bank or even among separate financial institutions.

Apart from mere implementation aspects the usage of ontologies fosters a deeper understanding of the domain in the way that the relevant knowledge is made explicit. This will simplify and partially automate the validation of risk assessments.

The main reason for working with ontologies that are serialized in OWL instead of plain XML lies in the exploitation of reasoning capabilities. Most important, the usage of formal ontologies makes it possible not only to perform consistency checks but also to reason on the knowledge base data using logical rules. In addition with the integration of simulation results, a risk manager can execute deductive queries in order to disclose interrelations that would remain undetected otherwise. Moreover, the usage of Semantic Web standards simplifies the integration from different knowledge sources. This advantage applies to the Semantic Web infrastructure as well.

A possible disadvantage of using formal ontologies in the area of operational risk management is a potential increase in the complexity of the underlying model. Whilst it is not to be considered as an issue concerning the implementation it can impact the comprehensiveness in communication towards upper management.

The idea of using UML as graphical notation for the modeling of technology risk by domain experts should be further evaluated. Since the UML is a widely-accepted standard for representing of domain knowledge, dependencies between operational risks might be more easily communicated to stakeholders. The definition of an appropriate UML profile and a UML to OWL transformation would make it possible to comfortably check the correctness of technology risk models and further process them within the risk simulation framework. However, the feasibility of this approach remains to be demonstrated.

## 6. CONCLUSION

In this paper, we demonstrated that formal ontologies and affiliated Semantic Web technologies are highly suitable for representing technology-related domain knowledge in the banking industry. This statement is constituted by introducing ontologies to a promising application area which is currently shaped by the international Basel II Accord. By focusing on technology risk management in proprietary trading, we were able to develop an integrated system environment that uses risk simulation in order to simulate potential operational losses. The suggested findings build the foundation for the future prototypical implementation.

The integration of UML-based and ontology-oriented domain modeling represents a vital part of the CollaBaWue research project<sup>1</sup>. This project closely involves semantic web technologies for investigating collaborative, component-based software development within the financial service provider

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<sup>1</sup> see also <http://www.collabawue.de>

domain. This way, the suggested approach can be broadened to other types of domain knowledge and address different business cases. In parallel to the ontology-dependent domain modeling a full implementation of the sketched quantitative simulation approach is ongoing as well.

There are several potential extension points to the identified system architecture. It may be integrated into a full risk management environment which includes integrated support for identification, measurement, controlling and monitoring of operational risk. In terms of ontology development, we believe that an extension of the technology risk ontology's scope is feasible, e.g. by including project risk measurement. Furthermore, the approach can be broadened to related businesses like the insurance industry which is due to respond to the Solvency II framework.

The next steps will include the full implementation of an extensible risk simulation framework which employs OWL for the representation of domain knowledge. At a subsequent stage of the implementation it is intended to transfer simulation results back into the knowledge base. In this case, the critical issue for searching the best strategy which reduces technology-dependent risk can be reasoned using logical rules. Altogether we think that formal ontologies might impact the development of operational risk management systems in the financial service industry.

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## 9. FIGURES

Fig. 1 : Application scenario for the occurrence of technology risks in proprietary trading.

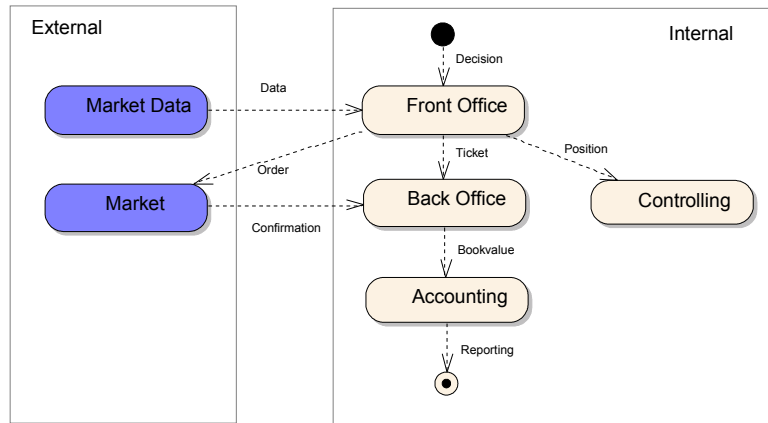


Fig. 2 : Proposed architecture for an ontology-based risk simulation and measurement system.

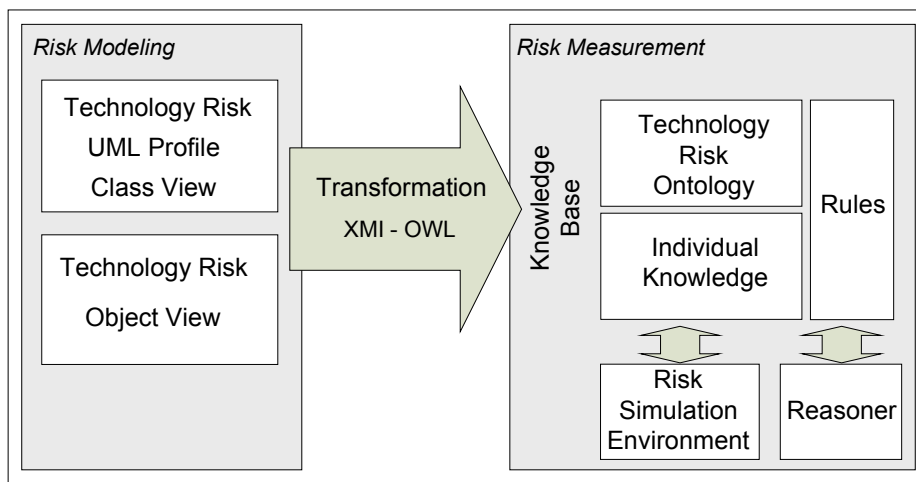


Fig. 3 : Class hierarchy of the technology risk ontology as UML class view.

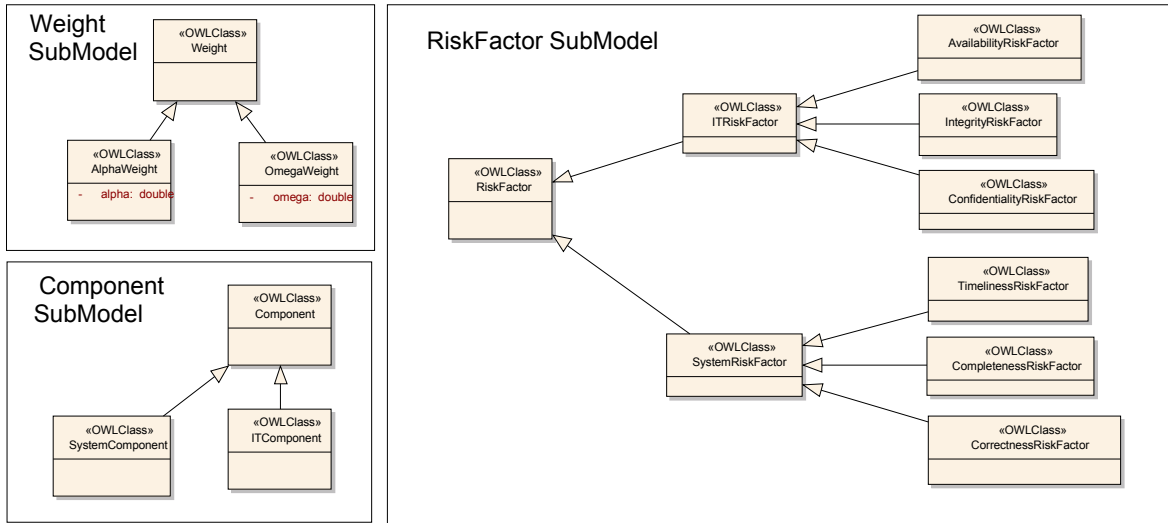


Fig. 4 : Object properties of the technology risk ontology.

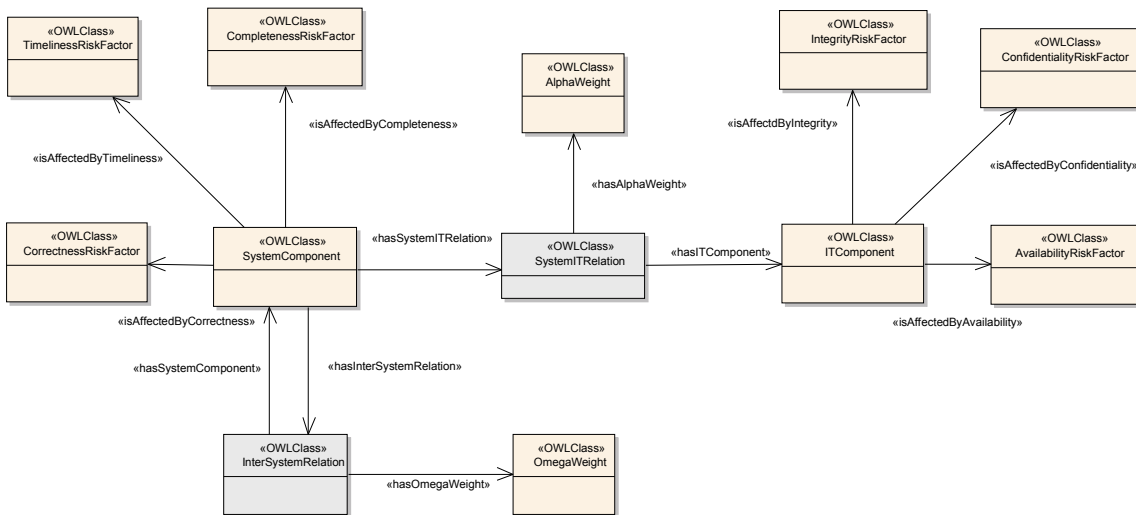


Fig. 5 Exemplary instance model visualized in UML object view.

