RC24534 (C0804-008) April 14, 2008
Mathematics

IBM Research Report

Harnessing Uncertainty: The Future of Risk Analytics

Bonnie Ray, Chid Apte, Kevin McAuliffe, Lea Deleris
IBM Research Division
Thomas J. Watson Research Center
P.O. Box 218
Yorktown Heights, NY 10598

Eric Cope
IBM Research GmbH
Zurich Research Laboratory
8803 Rüschlikon, Switzerland

Research Division
Almaden - Austin - Beijing - Cambridge - Haifa - India - T. J. Watson - Tokyo - Zurich

Harnessing Uncertainty: The Future of Risk Analytics
Point of View Paper

Bonnie Ray, Chid Apte, Kevin McAuliffe, Lea Deleris
IBM T.J. Watson Research Center, Yorktown Heights, NY
Eric Cope
IBM Zurich Research Lab, Zurich, Switzerland

Executive Summary

The increasingly complex and global nature of enterprises and of their activities, i.e. global supply chains, cross-border financial activity, services outsourcing etc., is accompanied by increasing levels of economic uncertainty, greater regulatory controls, and higher dependence on information technologies to conduct business. The combined effect of these factors is an increased exposure to events having the potential to severely impact operations of an enterprise, as well as the operations of enterprises with which they interact. At the same time, greater visibility to such factors can provide opportunity to use the uncertainty for strategic gain. This potential for both risk exposure and risk opportunity highlights the importance of a systematic and integrated approach to risk management. While myriad risk modeling methods and tools exist today, current methods do not fully address the challenges arising in developing end-to-end, integrated risk management systems which span risk data collection and management, development of flexible, scaleable risk models that can capture dependencies across multiple systems, and risk information presentation and interaction for ongoing, dynamic decision support. The purpose of this paper is to outline IBM Research's point of view on integrated risk management, delineating existing risk analytics capabilities and presenting strategic initiatives to address outstanding scientific challenges.

1. Introduction

Incomplete knowledge or uncertainty about the outcome of events is a business reality. This uncertainty is what we define as *Risk*, i.e., the possibility that an event will occur and affect, either adversely or, in some cases, beneficially, the achievement of objectives. Although it is impossible to control all events, e.g. the occurrence of a natural disaster, an enterprise *can* attempt to harness available information to intelligently plan for the uncertainty, i.e., use the information to better understand the nature of the risk and the expected outcome of different risk response strategies and to make decisions accordingly to conform to a specified risk tolerance.

We define a *risk event* as "an incident or occurrence from internal or external sources that affects an entity's achievement of objectives." While risk typically has a negative connotation, we also use the term to denote potentially positive outcomes of events that represent opportunities to create value for an organization, through impacting the ability of an organization to execute its strategy and achieve its objectives and performance goals. Possible responses to risk include avoiding activities that have large uncertainty in their outcome, balancing different levels of risk across a portfolio of activities, exploiting the risk, reducing risks through use of internal controls and processes, and sharing or transferring risks to another entity through the use of outsourcing agreements or insurance policies. We define the term *Risk Analytics* for the use of mathematical methods and tools to address the broad range of risk-related activities performed by an enterprise.

While analytic approaches to risk modeling and management have been in use for years, they typically have been developed to address narrowly defined problems in specific fields or risks of specific types, i.e., taking a silo approach to risk analysis. For example, financial institutions have developed extremely sophisticated mathematical models to characterize and manage risks to their business due to fluctuations in financial markets, or Market risks [9], while researchers in the medical field use mathematical models for human health risk assessment, such as exposure assessment, pharmacokinetic modeling, and dose-response modeling [3]. In the engineering field, the use of mathematical models to characterize the reliability and safety of complex systems, such as nuclear reactors, has a long history, and produced the well-know Failure Mode and Effects Analysis (FMEA) approach to risk modeling. See, e.g., [15]. The books [2] and [11] both provide good introductions to the general field of risk analysis. Recently, the field of Enterprise Risk Management [6, 16] has developed, focused on providing a holistic way to characterize and quantify risks to an organization. However, standardized methods and tools to implement such a holistic approach are still in their infancy.

Given the existence of a large body of research in the area of risk analytics, why should we now be interested in another look at risk management methods and tools? One compelling reason is that with increasing globalization, enterprises more and more resemble complex networks, with nodes in the network dependent not only on other nodes or units within the same organization, but also nodes in other enterprises, such as distant suppliers, financial institutions, and governments.. In a system with such interdependencies, the occurrence of a risk event has ever widening consequences, both within and across enterprises. Witness the impact of the subprime lending crisis, currently affecting the US economy and markets worldwide, or the potential worldwide economic and health implications of an avian flu outbreak. From a business perspective, the events in one market, e.g. political instability in India, can potentially impact the financial results of an entire globally integrated enterprise. Enterprises also face the challenges of being increasingly subjected to various regulations (Sarbanes-Oxley Act, HIPAA, Basel II, GAAP, etc.) and are being held accountable for meeting the high expectations set by the boards, investors, regulators and other stakeholders. Significant losses caused by inadequate risk management and controls have plagued the financial industry over the past decade with a significant increase in the number of firms involved in large failures over the past few years. A recent meeting of the National Academy of Sciences brought together well-known experts in a variety of risk management areas to discuss new directions for understanding such systemic business risks. See [12] for details of their discussions and findings.

Additionally, some risks impact multiple enterprises, and there is a need for coordination of risk response efforts so as to maximize the global good. Take the example of supply chain management--from an operational perspective, having a small number of suppliers providing huge amounts of a product results in economies of scale, potentially increasing efficiency. However, such efficiencies may also lead to increased risks, if something happens to one of the suppliers. Additionally, complex networks of suppliers, customers and third party service providers as well as large interdependencies among multiple firms exist, making inter-organizational coordination another source of risk. Even reputation risks, such as finding lead paint use in a toy company's products, may have impact spread beyond a single enterprise and require coordination of efforts to respond and recovery from the risk event. To illustrate the intricacies of current supply chains and their associated risk, consider the case of toy maker Mattel, who repeatedly made the headlines during the summer 2007 for a recall of toys containing significant amount of lead in the paint. In one specific case, the culprit seems to be a sub-sub-contractor that decided to use paint from a non-authorized third-party supplier[1].

As mentioned previously, deep analytical methods to address pieces of the risk management puzzle are well-developed. However, comprehensive, end-to-end management of risk on the scale required by the previous examples remains a major challenge. For example, even as data availability continues to grow, data reliability may actually decrease, creating risks from business decisions based on that data. Also, different data and risk quantification methods may be required to assess , e.g., IT security risks and reputation risks, but there must be a way to combine the risk information to create an integrated assessment of risk at the enterprise level. Today, enterprises lack practical frameworks for assessing such risks in a holistic fashion. In order to effectively harness risk and make risk management a core competency, effective methods must be in place for:

- gathering and managing risk-relevant data, including assessment of data uncertainty,
- building mathematical models involving thousands of uncertainties and complex interdependencies between events, upon which risk mitigation and response plans can be developed, and
- interacting effectively with the parameters and results of risk models, e.g. via dashboards, scenario analysis, etc..

Additionally, effective policies must be in place to govern the lifecycle of the risk data, models, and interaction methods.

Figure 1 shows a picture of a risk quantification framework for addressing the first three key tasks mentioned above, data management, mathematical modeling, and user interaction. The building of a flexible framework to address these tasks in an integrated fashion requires significant investment in new research and technology, both to address challenging scientific issues within each layer, as well as to achieve effective interactions between the layers. IBM Research is currently developing a prototype risk analytics composition framework to validate the integrated risk management framework idea. Along with other tasks, creation of the framework will involve:

---

[1] Chen, S-C. J. (2007), "Analysis: Mattel recall, a blow to Hong Kong's 'Toy King'," Channel News Asia, http://www.channelnewsasia.com/stories/analysis/view/295398/1/.html, August 22, 2007.

1. Creation of a repository for data that will support creation of models for risk quantification and management,

2. Enhancement of business process modeling tools with risk metrics, enhanced modeling and simulation capabilities, and integrated optimization to design and produce business process artifacts that incorporate risk measures, and

3. Integration of these business artifacts into a services oriented architecture (SOA) framework with a portal based channel for visualizing and interacting with the results of the risk analysis.

Our goal is to demonstrate a system that includes tools and run time capability for composition of data capture and normalization services, aggregation of risk models, and visualization to enable users to integrate various risk data sources, risk models and risk data presentations. Such a standardized, flexible, integrated risk management system provides *global* visibility on risks to an organization as well as consistency in risk estimation across the organization. A consistent and global risk management system in turn can provide the following benefits:

- Greater insight into key risk drivers and indicators,
- Increases in operational efficiency,
- Service improvements and higher customer satisfaction,
- Decreased risk exposures, and
- Improved strategic decision making.

The essential elements of each layer are discussed in more detail in following sections.

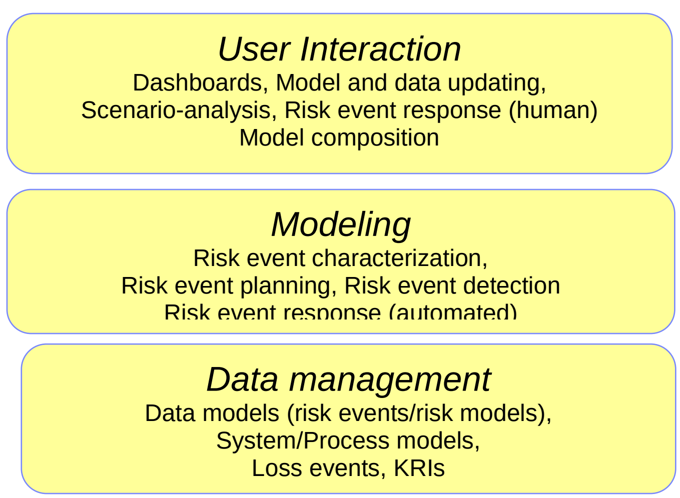

Figure 1: Risk Quantification Framework

Section 2: Risk Data Management

It is often useful for enterprises to consider categories of risks as a starting point in initial assessment of their risks. For example, Table 1 summarizes various types of risks facing an organization, with examples in each category.

While many different risk taxonomies like that shown in Table 1 exist[2], a key point in effective and on-going risk management within an organization is the ability to use meta-models for managing risk data, allowing easy updating of risk taxonomies and easier coordination of risks across multiple enterprises. In this sense, management of risk data is a particular instance of an organization's overall enterprise information management strategy, which may be standards and open platform-based and include data services, metadata management and ability to reconcile data semantics for integrating data from various sources. Different enterprises will also balance risk factors differently, even though the underlying taxonomy may be the same. An effective risk data management strategy will allow for such differences.

Additionally, integrated risk management for an organization requires a way to operationalize the semantic depiction of the enterprise characterized in part by risks, processes, entities, and the interdependencies among them. The operational aspects of the risk-oriented depiction can then be used to interact with *Governance, Risk and Compliance (GRC)* related applications as well as *Business Performance Management (BPM)* related applications and solutions, such IBM's Websphere Business Monitor[3].

High Level Risk Category	Definition	Examples
Market Risk	Losses due to fluctuations in demand and supply, competitors, and other exogenous economic forces	Market fluctuations, interest rates, currency fluctuations
Credit Risk	Losses due to the inability of counterparties to deliver on a contract	Loan defaults, customer concentration
Operations Risk	Losses due to failed or inadequate internal processes, systems, resources	Information Technology availability, Data integrity, Employee fraud, regulatory compliance, sourcing, project overruns
Environment Risk	Losses due to external events	Competitor actions, Geo-political issues, Natural Disasters
Strategic Risk	Losses due to strategic business	Business model, business

[2] See, for example, http://www.knowledgeleader.com/KnowledgeLeader/Content.nsf/Web+Content/MethodologiesModelsBusinessRiskModel!OpenDocument

[3] http://www-306.ibm.com/software/integration/wbimonitor.

	decisions	portfolio, organization structure
Reputation Risk	Losses due to damages to and perceptions of an organization by outside parties, such as key constituencies or stakeholders	Image and branding, Stakeholder relations

Table 1: Example Risk Taxonomy

Understanding the sources of risk, their dependencies and relationships, as well as their business impacts, is a daunting challenge. IBM is addressing this challenge, in part, through use of business process models as an organizing structure for thinking about risks. For example, an effective means of identifying and managing risk-relevant information is to decompose an organization from a functional point of view, by first identifying the business processes that contribute to the key performance metrics of interest to the organization, such as cost, service delay, quality, and liability. Common dependencies and vulnerabilities among these processes can then be identified by mapping the vital resources supporting each activity in the business process. These resources may include people, materials, capital equipment and infrastructure, and IT systems. For each resource and business process activity, one may catalogue the various possible failure modes and root causes of failure. Once this process is complete, one can then trace the chain of dependencies linking each root cause to its overall impacts on business performance, through its resulting effects on resources, activities, and processes, assuming a tree structure of dependencies.

This approach creates a layered view of the organization, as shown in Figure 2. At the bottom, the resource layer, are the IT systems, low-level processes, and human resource elements that are required for the business to function. Above this layer are the business processes that are supported by these underlying resources. At the top, risk can be viewed from the point of view of individual business lines or the enterprise as a whole. Failure events and root causes of failures are considered as they affect the lowest layer (the resources), and the effects traced as they propagate out to total impacts at the process, business line, and enterprise levels. Although the benefits of pursuing such a cause-to-effect approach to risk management are high in comparison with more high-level approaches to predicting impacts of loss events, the method calls for much greater effort in collecting and organizing the necessary information . Using a method such as IBM's Component Business Model[4] allows an enterprise to determine key services of a company and understand the risk associated with those services first.

[4] http://www-03.ibm.com/solutions/sap/doc/content/resource/thought/1671826130.html

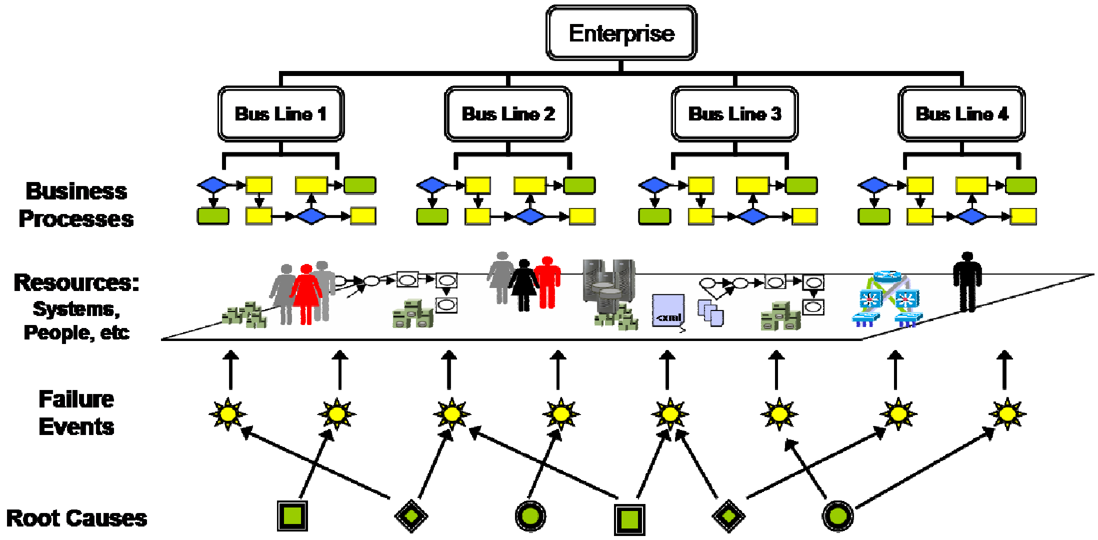

Figure 2: A layered view of the enterprise that maps key resources supporting business processes, and the causes of failures affecting these resources

The massive scale and often dynamic nature of this risk data dictates that computational technologies be fast, flexible, and capable of operating at multiple levels of abstraction. Data of different types often must be synthesized into a single model that permits an emphasis on underlying data meaning. For instance, integration of unstructured information, such as text collected from Web blogs and chat room discussions indicative of the perception of an enterprise must be integrated with structured enterprise data to quantify the impact of such discussion on the reputation of the enterprise. Standardized ways of managing risk model meta-data and specifying model linkages are also required, so that risk models can easily be associated to risk data and connected to provide an integrated view of an organization's risks.

IBM is leveraging its considerable expertise and assets for business process management[5], information management[6], and IT security & risk management[7] to address management of risk data, including loss event data, risk model input/outputs, system and process models, key risk indicators, etc. The recent acquisition of Cognos Incorporated, a leader in business intelligence systems, will also contribute to IBM's leadership in risk data management and reporting.

Section 3: Risk Modeling

Given risk-relevant information, methods are required to quantify and manage risks across an organization. Methods and models are needed for:

- *Risk quantification*, i.e., characterization of the probability of a risk event and its

[5] http://www-306.ibm.com/software/info1/websphere/index.jsp?tab=products/businessint
[6] http://www-306.ibm.com/software/data/
[7] http://www-306.ibm.com/software/tivoli/solutions/security/

potential impact,
- *Risk monitoring and detection*, i.e., identifying whether a risk event has occurred, and
- *Risk management*, i.e., designing an optimal set of actions to take so as to achieve a specified risk objective prior to a risk occurrence, or to respond effectively after a risk event occurs.

Risk models are typically domain specific, but can be broadly categorized as follows.

1. **Statistical and machine learning models,** used to discover key risk indicators and characterize likelihood and impact of risks based on historical data;
2. **Simulation models**, which are (usually) data-driven representations of a system facilitated by sampling from specified probability distributions.
3. **Stochastic optimization models**, where at least one of the variables involves uncertainty, and is assumed to follow a particular probability distribution;

Here, we provide some examples of practical experiences in risk model development and deployment at IBM Research, including applications in project risk management, operational and IT risk management, natural disaster and pandemic risk management, supply chain risk management, data and security risk management, reputation risk management, and product lifecycle risk management. We then describe some of the identified open challenges in the area of risk modeling.

Section 3.1 Recent risk analysis projects at IBM Research

- **Models to characterize event likelihood**: Floods, hurricanes, earthquakes, and power outages can produce rare, but devastating effects on an organization's operations. Estimating the likelihood of such occurrences leading to a crisis is a critical part of failure analysis. IBM Research has produced statistical models for estimating these frequencies, based on data collected from its Business Continuity and Recovery Services unit, comprising tens of thousands of customer-years of exposure, as well as geographical data on thousands of disaster phenomena. These models make use of non-traditional statistical distributions that allow for higher probability of event occurrences in the "tail" of the distribution than would be expected under using a Normal distribution. The result is a highly sophisticated prediction engine for assessing the need for specialized backup and recovery services [8]. In another example, IBM Research has developed statistical algorithms for proactively identifying projects having a high likelihood of missing planned profit targets, based on matching a project's key attributes over time to those exhibited by failed projects in the past. Technologies such as IBM's Parallel Machine Learning (PML) toolkit[8] enable such predictive models to be applied to large data sets by distributing the required computations to computing nodes in a parallel fashion.
- **Models to characterize event impact:** Loss data is often subject to significant reporting biases, and if external data is to be used in a risk analysis, one must be careful to ensure that this data is reliably similar to one's own, or to scale the data appropriately in order to make it more comparable. A source of reporting bias often occurs because

[8] http://awhub.sanjose.ibm.com/tech/pml

large losses are more likely to attract attention than small losses, which can often go undiscovered (or simply undisclosed). Therefore, there may appear to be proportionally more large losses in a database than occur in reality, making them appear to be much more likely than they actually are. Statistical models for loss discovery probability according to loss size can reduce this type of bias. IBM has developed specialized methods for assessing the compatibility of external loss data, or data from disparate business lines or reporting periods. In particular, data mining techniques for discovering similarities and patterns among loss event data have been developed, as well as statistical learning methods for appropriately scaling such data.

- **Models to link risk events to risk impacts and select among sets of competing risk mitigation actions to minimize risk impact, subject to constraints:** High-level organizational views, such as business process models, provide a useful organizing structure for linking risk events to the activities they impact, allowing for aggregation of risk exposures along different dimensions. IBM Research has developed a highly sophisticated, process-oriented risk quantification tool for determining optimal risk mitigation strategies. Using advanced algorithms that efficiently compute the distribution of total impacts at the business line and enterprise level based on the associated frequencies and severities, loss distributions can be assessed, in particular enabling the evaluation of value at risk (VaR). In addition, various possible risk countermeasures to be assessed based on their effects on the impact distributions. Combined with a cost assessment, the computed benefits may form the basis of a comparison of various risk mitigation strategies in terms of return on investment. See [5] for additional information. With respect to project risk management, stochastic optimization methods have been developed to adaptively modify a project's schedule of tasks so as to minimize chances of falling behind the schedule.

Additionally, IBM Research is actively working to address specific challenges associated with integrated risk quantification as they arise in practice. For example, IBM recently focused on understanding and quantifying risks associated with the supply chain for a product known as System X servers. IBM's product supply chains span multiple geographies and cover a complex network of suppliers, manufacturing sites, and shippers. Following the example of [7], *probabilistic risk analysis* was used to provide a comprehensive and unified perspective on risk factors affecting the supply chain: from frequent operational problems to catastrophic events, and from local delays to industry-wide phenomena. An approach based on the use of Bayesian networks, or *influence diagrams*, was used for quantification of identified supply chain risks. The combined map of business processes, resources, and risk causes and factors became the basis of the Bayesian network model. See Figure 3 for an example. The reference [2] provides additional background on probabilistic risk analysis and Bayesian networks.

The network model was generated based on numerous extensive interviews. By assigning quantities to each element in the network, one can evaluate the distribution of overall system performance, measured in terms of cost and order-to-delivery time. The study used a combination of publicly available data, expert knowledge, and internal incident tracking databases to supply the required numbers to the model. The causal network model provided a blueprint for a simulation model to identify the most important sources of risk in terms of impact, key points of failure within the chain, and the total distribution of performance. Once validated against observed performance statistics, the model of the “as-is” supply chain can then be altered to determine the effects of desired changes in supply chain operation, allowing one to assess the effects of risk mitigation strategies and countermeasures, or the effects of supply chain redesigns. Such a model provides a powerful tool for supply chain managers and executives to directly measure the total costs and benefits of making changes to the existing operations, and thus explicitly take risk factors into account when making strategic and tactical decisions.

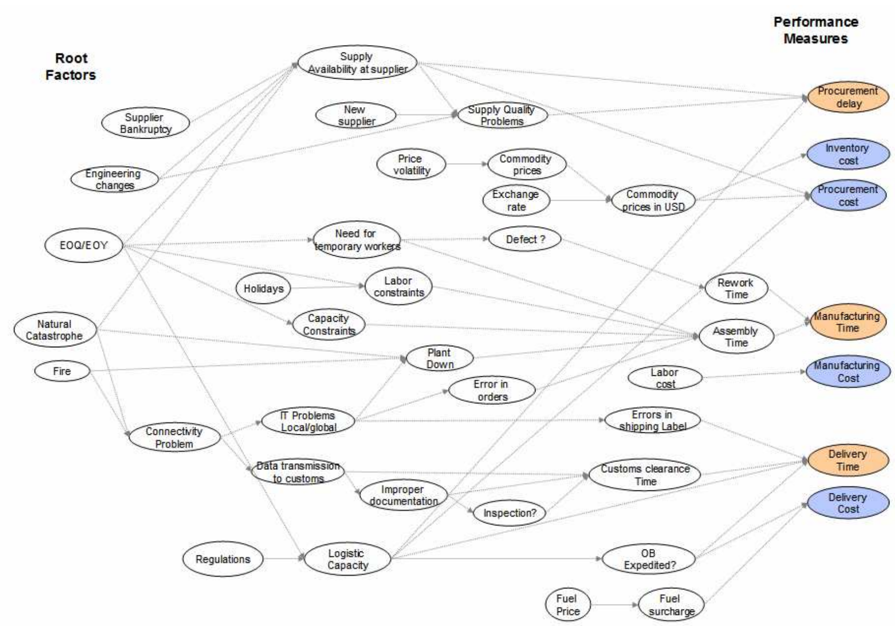

Figure 3: Example of influence diagrams, illustrating root causes of risk and how they may impact supply chain performance

Section 3.2: Risk Science Challenges Identified

In the course of the work described in the previous section, several challenging research issues were identified, motivating IBM Research to further scientific advances in risk analytics. These include

- **Risk network modeling, including automated discovery and/or expert elicitation of risk network structure, risk network sensitivity analysis, etc.**: Specification of comprehensive risk networks such as those described in the supply chain analysis is extremely time-consuming, requiring information collected from multiple experts combined with data-based network evidence. We are examining how networks can be discovered automatically through business process information, and combined with information collected from experts. We are also looking at ways to combine information from multiple, competing models and examine the sensitivity of the risk assessments to the risk network structure.
- **Methods for characterizing multiple, interdependent heavy-tailed events.**

In risk analysis, a key concept is understanding not simply the average loss that may be incurred if a risk event happens, but rather the probability of incurring a huge loss, i.e. understanding the behavior of the loss distribution in its tail region. While much is known about modeling multivariate dependent events that occur following a Normal distribution, complex networks of dependent entities give rise to events whose distributions follow a power law distribution, or have heavier tails than normal tails. New techniques to model multivariate extremes, such as those discussed in [13] or those based on the theory of L-moments[9], pioneered by IBM Researcher Jonathan R Hosking, are fundamental to advancing the state-of-the art in risk modeling. Techniques such as Quantile Regression, which looks at building models to explain the percentile value of a variable as a function of covariates rather than the average value, are also important in building accurate models reflecting the tail behavior of, e.g., a risk loss distribution.

- **Computational methods for large-scale simulations, addressing systems-of-systems issues and simulation of rare events.** Systems-of-systems are large scale concurrent and distributed systems that are comprised of complex systems, i.e. systems characterized by having a large number of dimensions, nonlinear or nonexistent models, strong interactions, unknown or inherently random parameters, time delays in the dynamical structure, etc . Modeling risks within and across enterprises, such as in supply chain risk management, will ultimately consist of analysis of such systems of complex systems, allowing for dependencies amongst the risks represented in the different models, and addressing issues created by modeling at different levels or scales. Initial strides have been made to address these issues in the context of a Pandemic Business Impact Modeler [4], a tool in which systems dynamics simulation and optimization models are run in sequence to model the business and financial impact of a global pandemic on an organization. Models included an epidemiological (SEIR) model, infrastructure model, economic model, behavioral model, supply chain model and financial model. However, closer integration between simulations of small-scale behavior, such as that of individual decision makers, and the large-scale aggregate behavior of the system are needed. The challenge is to build realistic links between the small-scale behavior at the level of individual agents and the larges scale aggregate behavior of the system. Additionally, approaches are needed to account for potential dependencies across risk events represented in the different models. Since many risk events by nature occur only rarely, methods are needed to efficiently generate observation paths to provide information about the impact of the rare event [10]. IBM's expertise in developing computationally efficient mathematical algorithms and work on parallel implementations of linear algebra and mathematical optimization algorithms, as well as work in complex systems, can be leveraged to address these issues.
- **Advanced stochastic optimization methods:** Fundamental advances in stochastic optimization methods are required to address decision making under uncertainty, which is the essence of risk management. For instance, risk response and coordination may require *multi-stage stochastic optimization* techniques, such as used in [1]. Stochastic methods, e.g., stochastic dynamic programs, optimal stochastic control, are needed to optimize and control the various forms of risk dynamics over time. IBM is

[9] http://www.research.ibm.com/people/h/hosking/lmoments.html

researching new methods, such as Markov Chain Monte Carlo methods, to address such complex stochastic optimization methods. Other applications require *hierarchical* or *multilevel* optimization, i.e., efficiently solving subproblems at different levels and aggregating information across different levels. An example application requiring this type of optimization is the design of a robust maintenance plan for a set of dependent oil platforms. The problem involves modeling preventive maintenance, inspection and corrective maintenance activities and simulating their combined effect on planned and unplanned downtime, identifying the most important contributors to unplanned shutdown risk, and creating optimal maintenance plans for each platform and for the set of platforms as a whole. Similar issues arise in maintenance of any complex network of resources, such as IT resources or utility grids and arise in other capital intensive industries such as steel or micro-processor industries.

- **Quantification methods for emergent types of risk:** To provide an enterprise-wide approach to risk management, quantification methods for risks not typically considered, such as security risks and data quality risks, must be developed. For example, IT security risk quantification models may require use of advanced data mining algorithms to model user behavior, combined with techniques from adversarial risk management to assess and combat attempts by intelligent entities to selectively alter a user environment. Emergent risks related to energy availability and costs, as well as environmental regulations, may also require new methods and tools for management.
- **Application of financial risk management strategies to manage other types of business risk:** The use of real options and other advanced mathematical methods for managing risks in the financial industry provide a rich background and framework for understanding and hedging risks in other domains, such as IT project management, workforce management, and supply chain management. IBM Research is exploiting its strong business services domain knowledge together with its mathematical sciences expertise to modify and extend financial risk management methods so as to be applicable in other domains. An example is the management of software applications over their lifecycle. Analytic components to address risks arising in specific areas of the lifecycle, e.g. development risks, data integrity risks, etc., are being developed, exploring new techniques for risk and value quantification in heretofore unexplored areas, such as valuation for software projects during their execution.

Each of the areas described above requires significant investment in research and technology, and all of the items listed are not expected to be relevant for all risk management applications. Development of a risk model composition framework will allow “assembly” of risk analytics into a risk management system customized to address the particular needs of an organization. In fact, how to do this assembly from a methodological standpoint is an open research question in itself.

Section 4: Risk Interaction and Response

The top layer of the integrated risk management framework includes capabilities for users to “interact” with the risk management system to manage enterprise risks on an ongoing basis, where the term "interaction" covers various tasks users might do. While some of these tasks, such as summary reporting and visualization of key risk indicators, drill down into root causes of risks, etc. are typical of any business intelligence system, others, such as composition of risk models or initiation of actions in response to a risk event, are unique to risk management and require new methods and tools to address.

An example is the population of Bayesian risk models based on solicitation of expert opinion, such as in the supply chain risk modeling work described in Section 3. In another recent project for a major pharmaceutical company [14], IBM Research developed a Bayesian network model to characterize and evaluate the risks to its drug manufacturing process. A requirement of Bayesian network modeling is the ability to specify the probability distributions associated with each node in the network. For a realistic business process, such a network might consist of thousands of possible nodes, few of which may have data available with which to construct a probability distribution empirically. Instead, probability information is typically elicited from discussions with experts. To collect the necessary information in a feasible way, IBM Research developed a web-based tool to collect information from experts based on roles, i.e., each node in the network was associated with a particular expert role, and experts were presented questionnaires for eliciting risk information containing only questions relevant their role. Additionally, methods were implemented to automatically calibrate rating scales across multiple experts and to aggregate information elicited from multiple experts for the same node.

The ability to examine sets of risk scenarios using “what-if” analysis provides another example in which users of a risk quantification system can benefit from interactive technologies. Human-Computer Interaction (HCI) research, focused on behavioral, aesthetic, and value-sensitive aspects of the design of interactive systems, is one of the most extensive research areas at IBM. This expertise is relevant to address the challenges of providing intuitive ways for users to link disparate risk models together, and initiate actions based on observed risk events.

Finally, new research may be required to develop insightful ways to visualize risks, particularly when there are multiple sets of possibly interdependent risks, and taking into account how different people perceive risk, as the psychological factors that can exacerbate and mitigate risk perceptions impact how risk information is presented to a user.

Section 5: Risk Governance: Putting it All Together

While methods for data management, modeling, and interaction are each necessary to the development of a comprehensive risk management framework, however, they are not sufficient.. To create a sustainable risk management practice, methods for governing the enterprise risk management process must be in place. Risk management cannot be static. It is essential to develop processes to understand and manage the evolving role of risks within the organization. For instance,

- What risks are fundamental to the enterprises strategy? How does the relationship among risks change?
- What/who will determine when risk models need to be updated?

- Can dynamic adaptation of changes in input-output relationships be implemented on an automated ongoing basis or will they require periodic assessment by humans?
- Who will decide when an event should no longer be considered a risk or new events need to be added to the risk catalog?
- How shall errors in risk models and risk data quality issues be corrected and/or controlled?

Procedures governing these decisions are what we call *Risk Lifecycle Management* or *Risk Governance*. We distinguish this concept from the concept of modeling of single risk as it impacts a project or product over the product/project lifecycle, which we refer to as Product (Project) Lifecycle Management. We also distinguish it from the concept of modeling the changing impact of a risk event over time, e.g. impact of the initial, direct loss event, followed by potential legal, reputational, or other impacts. These temporal aspects of risk management can be addressed at the risk modeling stage.

Figure 4 shows the integrated risk framework of Figure 1, but wrapped in circular arrows to indicate the ongoing nature of the risk management process.

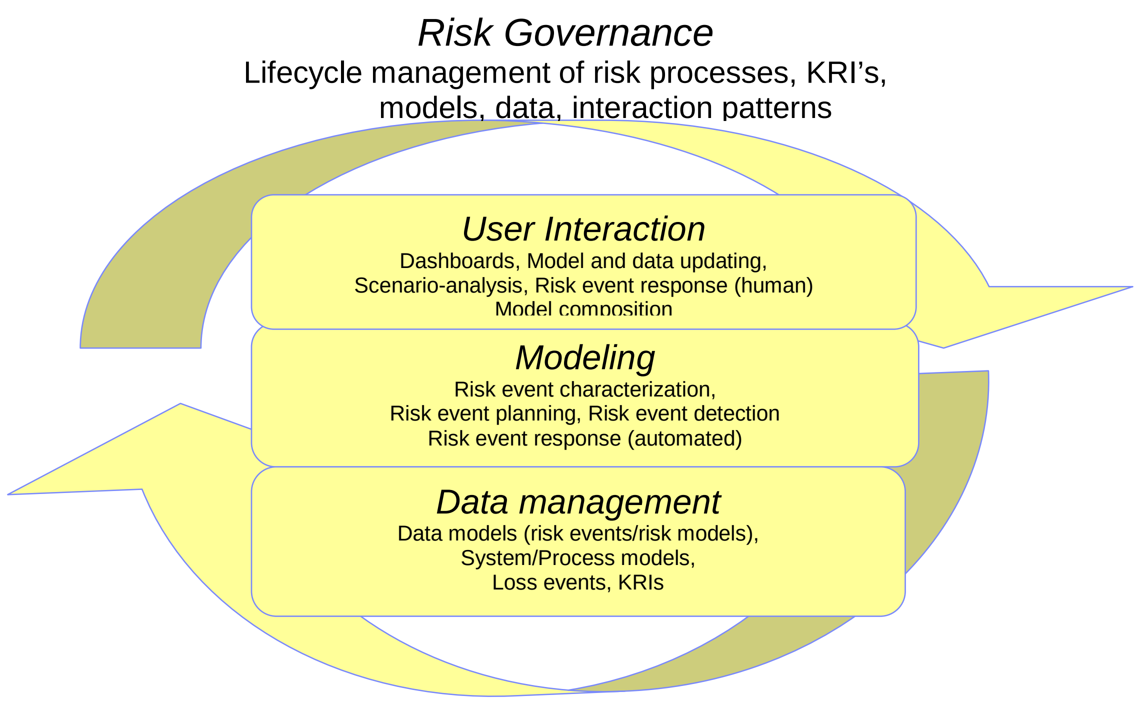

Figure 4: Integrated Risk Management Governance

The development of a practical risk governance structure requires new research to address issues such as construction of risk models that dynamically incorporate information via data assimilation and machine learning. Ultimately, the value of a model depends on the major challenge of validation against "ground truth". As discussed in Section 4 on Risk

Interactions, feedbacks between mathematical, computational, and application-domain analyses are vital to real-world insight.

Section 6: Collaborative Research and Development to Advance Methods for Integrated Risk Management

From the preceding discussion, it becomes obvious that risk analytics is inherently cross-disciplinary in its nature. For instance, academic work related to risk is currently carried out, in part, by faculty housed in departments of Statistics and Probability, Finance, Civil and Environmental Engineering, and Operations Research, including academic focus areas of Optimization, Simulation, and Decision Sciences (both in schools of business and schools of engineering). Additionally, risk studies related to information technology issues are becoming popular with faculty housed in departments of Management Information Systems and Computer Science, for example looking at secure data access and business architectures for risk and compliance, and research related to risk perception and cognition may be housed in departments of Psychology.

The development of an integrated risk management framework can provide a unifying principle with which to bring together the various academic, government, and industrial research threads and foster collaboration within the research community. Collaboration is needed, for example, to enable sharing risk data (both raw and processed). Pooling of risk data is crucial for collecting statistically significant amounts of data for building proper predictive models, while sharing modeling tools enables benchmarking and rapid advances of the predictive models for the risk. IBM is accelerating such collaborations through providing support for university faculty to do joint work with IBM Research, running focused summer institutes for graduate students to work on risk-related topics, and organizing and supporting mini-symposia on Risk Analytics Science for invitees from business, academia, and government. Additionally, IBM will establish and maintain an open source library of risk models that can be used freely by academia, government, and business community, similar to the COIN-OR library for optimization models[11]. This will provide an outlet for collaborative work.

IBM already has a number of university collaborations focused on research and development of models to better understand and manage, e.g., supply chain risk. In particular, two projects focus on using simulation, one for the purpose of determining at a high level how structural characteristics of the supply chain affect its responsiveness to disruption, the second involved a distributed simulation environment (for a distributed global supply chain) designed for real-time decision support on a global level to meet customer orders at lower cost. IBM has also been involved in designing a multi-criteria optimization model to incorporate risk in global sourcing decisions by developing mathematical models to manage supplier risk.

With respect to data security risk, IBM Research is part of a consortium consisting of several universities and government agencies focused on developing the foundational

[11] http://www.coin-or.org/].

technologies for utilizing dynamic trust and risk assessments in information management decisions. Such policies, when used in addition to static policies, can add flexibility and adaptability to information management decision-making in military missions in highly dynamic coalition environments.

From the industry perspective, IBM Research is providing analytic capability for the Operational Riskdata eXchange (ORX) Association. ORX is a consortium of over 35 international banks which have pooled their loss data in a common database in order to better understand and estimate their individual risk exposures. IBM Research's role is to develop statistical methods and models for the purposes of comparing and scaling loss data from the various banks, so that, for example, smaller regional banks can benefit from the loss data from large international banks to better understand their own risk exposures.

Beyond these examples, IBM Research is actively seeking new collaborative opportunities with academia, industry, and government agencies to advance risk analytics work across organizational boundaries. The intellectual capital generated from these collaborations is providing input for IBM's on-going development of cutting edge methods and tools for use in helping enterprises better manage risks throughout their organizations.

Section 7: Summary

Developing methods and tools to provide a comprehensive, yet practical, integrated risk management practice both within an organization and across organizations is challenging. These problems are hard, and there is no "one-size-fits-all" method for solving them. However, IBM is making significant strides in innovation to provide a flexible framework and a set of quantitative and analytical tools for evaluating risk both within an organization and across organizations, while bringing significant research resources to address outstanding scientific challenges. Such a framework and tool set will provide organizations the capability to manage risk as a business fundamental, creating opportunities to bring significant new value to the enterprise.

References

1. Ahmed, S., G.R. Parija, A.J. King: (2003). A multi-stage stochastic integer programming approach for capacity planning under uncertainty. *Journal of Global Optimization*, 26(1), 3-24.
2. Bedford, T., and R. Cooke (2001). *Probabilistic Risk Analysis: Foundations and Methods*. Cambridge University Press.
3. Crawford-Brown, D. (2001). *Mathematical Methods of Environmental Risk Modeling*, Springer.
4. Chen-Ritzo, C., An, L., Buckley, S., Chowdhary, P., Ervolina, T., Lamba, N., Lee, Y., Subramanian, D. 2007, "Pandemic Business Impact Modeler" *Proceedings of the 2007 INFORMS Simulation Society Research Workshop*, Fontainebleau, France.
5. Cheng, F., D. Gamarnik, N. Jengte, W. Min and B. Ramachandran (2007). Modeling operational risks in business processes, *Journal of Operational Risk*, 2(2), 1—26.

6. *COSO: Enterprise Risk Management - Integrated Framework*. *Executive Summary*. Committee of Sponsoring Organizations of the Threadway Commission, (2004)
7. Deleris, L.A., and Erhun, F. (2007), "Risk Management In A Supply Network: A Case Study Based On Engineering Risk Analysis Concepts," in *Handbook of Production Planning*. Edited by K. Kempf, P. Keskinocak, and R. Uzsoy, Kluwer International Series in Operations Research and Management Science, Kluwer Academic Publishers (To appear).
8. Garmarnik, D., J. Hosking, W.F. Kane, T. Li, I. Yashchin. *Method and apparatus for risk assessment for a disaster recovery process*, United States Patent 20050027571.
9. Gleason, T. (2000). *Risk: The New Management Imperative in Finance*. Bloomberg Press.
10. Juneja, S. and P. Shahabuddin (2006). Rare Event Simulation Techniques: An Introduction and Recent Advances. *Handbook on Simulation.* Chapter 11. Elsevier. Editors: Shane Henderson and Barry Nelson, 291-350.
11. McNeil, A. J., R. Frey, and P. Embrechts (2005). *Quantitative Risk Management: Concepts, Techniques, and Tools.* Princeton University Press.
12. New Directions for Understanding Systemic Risk: A Report on a Conference Cosponsored by the Federal Reserve Bank of New York and the National Academy of Sciences (http://www.nap.edu/catalog/11914.html)
13. Nolan, J.P. (2007). *Stable Distributions - Models for Heavy Tailed Data*. Birkhauser, Boston (in progress, Chapter 1 online at http://academic2.american.edu/~/jpnolan/stable/chap1.pdf).
14. Pratsini, E. and Dean D. (2005). Regulatory compliance of pharmaceutical supply chains, *ERCIM News* No. 60, Special Issue on Biomedical Informatics.
15. Stamatis, D. H.,(2003). *Failure Mode and Effect Analysis: FMEA from Theory to Execution*, 2nd ed., ASQ Quality Press.
16. Walker, P., Shenkir, W.G. and Barton, T.L. (2002). *Enterprise Risk Management: Pulling it All Together,* Institute of International Auditors.