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AN ECONOMIC ANALYSIS OF SERVICE-ORIENTED INFRASTRUCTURES FOR RISK/RETURN MANAGEMENT

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AN ECONOMIC ANALYSIS OF SERVICE-ORIENTED INFRASTRUCTURES FOR RISK/RETURN MANAGEMENT

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Abstract

Risk/return management has not only evolved as one of the key success factors for enterprises especially in the financial services industry, but is in the times of the financial crisis crucial for the survival of a company. It demands powerful and at the same time flexible computational resources making it an almost ideal application for service-oriented computing concepts. An essential characteristic of service-oriented infrastructures is that computational resources can be accessed on demand and paid per use. Taking the estimation of covariances for a portfolio of risky investment objects as an example, we propose quantification for the economic value of fast risk/return management calculations. Our model analyzes the influence factors on the optimal computing capacity dedicated to these calculations and reveals interesting insights in how far the optimal computing capacity depends on market parameters. Our main result is that more volatile markets require a lower computing capacity as the optimal computing capacity depends positively on changes of the market risk but negatively on the risk itself.

Keywords: Risk/Return Management; Service-Oriented Infrastructures; Grid Computing.

1 INTRODUCTION

Risk/return management is crucial for today's enterprises in order to thrive and even to survive in a market environment that can be characterized by tight competition and global integration of markets. This is more than ever emphasized by the problems arising from the current crisis on the financial markets. Especially in the financial services industry, already strict rules and regulations – that nevertheless have not prevented the crisis – are expected to be much more tightened as generally decided by the G20 meeting in April 2009. Consequently, very sophisticated and resource intensive methods for risk/return quantification and aggregation have to be in place. Innovative approaches of distributed computing like grid computing, cluster computing or service-oriented architectures (SOA) are en vogue in academia as well as in practice, offering potentially suitable infrastructures for the corresponding complex calculations. We will speak of service-oriented infrastructures (SOI) in this context as an instance of (the abstract principle of) SOA where (mostly resource-intensive) distributed services are made available transparently over a grid network. Up to now the intellectual treatment of SOI is usually technically oriented and most often neglecting the necessary economic aspects. Even though these aspects are addressed in general by approaches like for instance “grid economics” or “utility computing”, the reflection on benefits and cost still constitutes a widely unresolved issue for specific application domains. We are therefore striving to narrow the gap between the technical capabilities of service-oriented computing and its economical application in risk/return management.

One basic task in risk/return management is the frequent estimation of the risk exposure associated with a portfolio of investment objects (e.g. securities). Today, enterprises mostly calculate their risk exposure during fixed time intervals like e.g. several days. With the possibly huge amount of computing capacity a SOI based on grid technologies offers (embracing resources of the whole enterprise or even of external resource providers), calculations can be accelerated dramatically (Middlemiss 2004). Nevertheless, economic models quantifying the business value of a more frequent recalculation of the risk exposure are not available yet. Thus, the question arises, what is the optimal amount of computing capacity that should be allocated to risk quantification, considering benefits as well as cost? We will deliver a solution to this problem in the form of an optimization model.

Concerning risk/return management¹, we restrict our considerations to publications addressing risk forecasting and in particular the estimation of covariance matrices. Huther (2003, pp. 111), or Faisst and Buhl (2005, pp. 408) for example describe the use of covariances for a comprehensive enterprise-wide risk/return management. Other publications are dealing with the question of how covariances can be empirically estimated or forecasted by analyzing historical data. In fact forecasting is “one of the important problems in finance” (Elton and Gruber 1972) and consequently there are a lot of publications already covering the question of how many and which historic quotations should be used to determine a suitable risk forecast. To give an impression about applicable techniques we refer to Engle (1982), Kupiec (1995) and Hull and White (1998). Alexander (1996, pp. 233) provides an overview of the corresponding methods used in volatility and correlation forecasting. Recent approaches to volatility forecasting like conditional autoregressive Value-at-Risk (CAVaR) models are presented in Taylor (2005). Although it is widely known that the corresponding calculations are very resource and time intensive, there is to the best of our knowledge so far no publication dealing with the specific problem of quantifying the economic value of a frequent (re)calculation of risk.

Grid computing can be regarded as an infrastructure technology enabling the virtualization of physical resources. Available definitions for the term grid computing are mostly of descriptive nature and provide little more than certain essential characteristics (see e.g. Foster 2002; Foster et al. 2001, 2002;

¹Whereas literature most often focuses on either side separately, we will rather speak of risk/return management emphasizing an integrated view because risk management can only unfold its potential in combination with the management of the corresponding return.

Foster and Kesselman 1998). However, various proponents have agreed with Foster and Kesselman (1998) that “a computational grid is a hardware and software infrastructure that provides dependable, consistent, pervasive and inexpensive access to high-end computational capabilities”. Recently, an evolution towards SOA can be observed (Longworth 2004). Grid technologies are one possibility to realize a SOA consisting of so called “grid services”. Grid services are based on specific web service standards, like the specifications (Open Grid Services Architecture) and (Web Services Resource Framework). They extend web services insofar as they imply the dynamic, yet for the user transparent, allocation of (physical) resources to services by a grid middleware and therefore are especially suited to fulfil resource intensive tasks. There is an extensive literature on service-oriented computing or grid computing in general (see for instance Berman 2005; Foster and Kesselman 1998; Silva 2006; Singh and Huhns 2004). Some publications even consider the application of these technologies for portfolio management, derivatives pricing or other areas of financial risk management (Brownlees et al. 2006; Crespo et al. 2006; Schumacher et al. 2006). However, these approaches describe how grid technologies can be applied, but do not quantify the resulting business value. In the context of grid computing also resource allocation mechanisms have been widely discussed—most often under the term “grid economics”. We refer to Regev and Nisan (1998), Buyya et al. (2000), Nabrzyski et al. (2003) and Wolski et al. (2004) which provide an overview of this area. They most often dwell either on the question which principles are appropriate to resource management or on technical and architectural issues connected with the development of resource management systems. Accordingly, in most of the existing approaches demand for computational resources is merely an external factor whereas in our approach it is subject to optimization.

In this context an important characteristic of SOI based on grid technologies is the on-demand access to distributed resources. When resources stem from an external provider this concept is often labelled utility computing, meaning that resources can be consumed and priced as easy as for instance electricity or water. Utility computing has been subject to research as well. Bhargava and Sundaresan (2004) analyze pay-as-you-go pricing scenarios where providers guarantee computing capacity, but users do not make a commitment towards actual use. Our paper to some extent continues the ideas of Bhargava and Sundaresan (2004). However, we take the perspective of a service user and present a rationale for decisions on computing capacity in the context of risk/return management.

2 RISK/RETURN MANAGEMENT

The term “risk” is used heterogeneously in general speaking as well as in academic circles. Therefore we feel that it is appropriate to begin with a definition of risk before we describe the various requirements and objectives of risk/return management applications. While in the economic literature risk is often generically explained as the “possibility of missing a planned outcome” we will follow a more finance-related approach. From this point of view we define with Schröck (2001, p. 24) risk as “the deviation of a financial value from the expected value”. A positive deviation is often in general speaking referred to as “chance” while a negative deviation is characterized as “danger”. Because of this two-sided perception of risk, variance or standard deviation of a risky value are suitable and well accepted measures of risk. We will use the standard deviation of historical portfolio returns as the risk measure later in this text. Synonymously we will speak of the volatility of a portfolio and define it as the “annualized standard deviation of percentage change in daily price” (Spremann 2003, pp. 154).

Enterprises are investing capital into investment objects in order to generate cash inflows and subsequently to increase the return of the invested capital. Typically risk-averse management is making risky investments hoping to achieve an excess return over the risk-free rate. There is a general connection between risk and return of an investment object: higher return is systematically associated with higher risk. This connection is theoretically explained by economic models like the CAPM (the “Capital Asset Pricing Model” was originally developed by Sharpe (1964), Lintner (1965) and Mossin (1966)) and empirically evaluated later on (an overview of relevant empirical studies can be found e.g. in Copeland and Weston (1988, pp. 212)). Following the argumentation of Wilson (1996, pp. 194) it is

therefore crucial for the survival and success of an enterprise to be able to allocate the available capital to the right combination of investment objects, taking into account their specific contributions to the overall risk and return. Investment objects in this context are not restricted to securities. Almost all business transactions are associated with uncertainty and thus contribute to an enterprises overall risk exposure. Thus in the spirit of an enterprise-wide risk/return management all investments an enterprise is engaged in, like credit decisions or even customers or projects can be seen as components of the enterprise's overall investment portfolio, having a return and a variance (as a measure of risk).

One major goal of risk/return management in this context is the prevention of bankruptcy by restricting potential losses resulting from risky investment objects. The increasing importance of this goal is emphasized by the current crisis on the financial markets. A growing number of rules and regulations require enterprises to hold a part of their available capital to back their risky investments (Jackson et al. 1998, pp. 8). This share of the available capital then makes less or no contribution to the overall earnings. By management decisions these restrictions are broken down along the organizational hierarchies into guidelines on business unit or departmental level. We are assuming in the following text that those guidelines are essentially representing limits for the maximum risk a department, business unit and consequently an enterprise is willing (or able) to take.

In order to evaluate whether an enterprise or department complies with a given risk limit, it is necessary to calculate the current risk exposure frequently. For simplifying means, we concentrate on one fundamental instrument in this paper: The covariance approach. This constitutes a basic principle in finance and forms the foundation for many risk/return management applications ranging from Markowitz portfolio optimization to Value-at-Risk (VaR) calculations. In our context covariances are used for determining the overall risk position of an enterprise taking into account diversification effects that exist between the investment objects. Nevertheless, the proposed methods are also applicable to other risk measures as long as they take dependencies between single investment objects into account.

Following the covariance approach, we can represent risky investment objects by random variables. Typically historical data are used in order to derive a distribution for a random variable² and calculate the distribution parameters. It is worth mentioning that considering the portfolio risk and return merely on an aggregated level is not satisfactory because all information is lost about the risk attributable to a single investment object. It is crucial to separate the portfolio and decompose it into data per investment object, i.e. to calculate the covariances. Only then the enterprise can perform economically rational investment decisions on different aggregation levels. With σ_i^2 and Cov_{ij} denoting variance and covariance of investment objects respectively we can determine the overall risk of a portfolio σ_p^2 , consisting of $n \gg 0$ investment objects (numbered from 1 to n), as³

$$\sigma_p^2 = \sum_{i=1}^n \sigma_i^2 + \sum_{i=1}^n \sum_{j=1, j \neq i}^n Cov_{ij} = \sum_{i=1}^n \sum_{j=1}^n Cov_{ij}$$

The so defined matrix of all covariances is called *covariance matrix*. An important characteristic of covariances is that $Cov_{ij} = Cov_{ji}$. This makes the matrix symmetric and thus not all of its values have to be calculated. The total number of covariance calculations necessary is given by $n(n+1)/2$.

3 A VALUATION MODEL FOR FAST RISK QUANTIFICATION

We consider an enterprise which has access to (and is possibly engaged in) a set of risky investment objects as well as to a risk-free investment alternative. It is frequently (re)calculating its overall risk position by estimating the covariance matrix of its portfolio. Our main hypothesis for the valuation of

² A thorough overview and discussion of the statistical analysis of financial data can be found in Shiryayev (1999) pp. 314.

³ As we analyze the complete investment objects and not parts or quantities of investment objects (e.g. stocks), this formula contains no weights.

benefits is: the faster risk/return management calculations can be executed the higher will be the return of the enterprise because given risk limits can better be exploited.

Since the enterprise is acting in an uncertain and dynamic environment its risk position is changing willingly (by investment decisions) or unwillingly (by “movement” of the markets). Because the estimation of risk cannot be accomplished in real-time the covariances at hand are always significantly outdated. We are in the following recurring to the fact that the enterprise is adjusting its risk position to a value somewhere below a certain threshold thus constituting a “safety margin”. In the regulatory context this is often called “haircut”, like in Basel Committee on Banking Supervision (2004). The financial crisis made clear, that – depending on the assets invested in – a high safety margin is necessary to account for changes of parameters, especially in liquidity. It is doing so by using the capital allocation between the risky investment objects and the risk-free alternative for balancing their overall risk position. It is important to understand that our model is not addressing the evaluation of the efficient set of investment objects or portfolio optimization (both require covariances), but the aggregation and management of the risk position of an enterprise. Whenever covariances are available the safety margin can be adjusted immediately in a way that the resulting (and over time changing) overall risk position of the enterprise does not exceed the given risk limit at any time. Hence, the faster covariances are available, the smaller the safety margin can be. We will use this effect to quantify the benefits of fast covariance estimations depending on the time needed for the completion of one covariance matrix.

3.1 Model Setting and Basic Assumptions

The time interval under consideration consists of equidistant periods such that $t=0$ denotes the beginning of the current period. We shall write for example σ_t to indicate the value of a model parameter at the end of period t . Correspondingly (dis)investment decisions take effect only at the end of each period. If not mentioned otherwise all variables assume real values, i.e. values $\in \mathfrak{R}$.

The enterprise is equipped with a total capital of $K>0$ which is always completely allocated to the risky portfolio and/or the risk-free alternative. We denote the risky portion of K with $x \geq 0$ and furthermore use x for risk adjustment. T indicates the length of the calculation time frame, $T \in \mathfrak{N} \setminus 0$ with \mathfrak{N} as the set of natural numbers. At the end of each time frame we choose x in a way that the risk limit is “probably” not exceeded during the next time frame. We will formulate more precisely what is meant by “probably” later on. Future returns of the portfolio are modelled as independent random variables. Their probability distribution for each period can be characterized by mean and standard deviation. This implies that the investment objects can be marked to market, i.e. there is a price attached to them. We additionally need a set of assumptions for the deductions following thereafter.

Assumption 1 *The enterprise is generally risk-averse and striving for efficient combinations of investment objects. Investment objects are perfectly divisible and traded on a no-frictions market.*⁴

Assumption 2 *The risky part of the enterprise’s capital yields the expected return μ , the risk-free investment pays the time-invariant risk-free interest rate i , which is equal to the borrowing rate.*⁵ *We always have $\mu > i > 0$.*

Assumption 2 is made in the spirit of the model of (Modigliani and Miller 1958) where enterprises and investors can borrow or place money at will for a risk-free rate, but expect a premium for taking the risk associated with the investment in risky assets. With the so defined parameters and x as decision

⁴In the sense of the “Portfolio Selection” theory (Markowitz, 1971) investors are trying to achieve the highest possible return on their investment for a given risk. They are acting under perfect trading conditions, i.e. no arbitrage, no transaction cost, strong information efficiency etc.

⁵The equality of lending and borrowing rate is assumed for sake of simplicity and justifies the case $x > I$, where the enterprise is actually borrowing money for making risky investments.

variable we can determine the overall expected return $\mu^U(x)$ and risk $\sigma_i^U(x)$ of the enterprise according to common rules of statistics as

$$\mu^U(x) = x\mu + (1-x)i = i + x(\mu - i) \text{ and } \sigma_i^U(x) = x\sigma_i. \quad (1)$$

The overall risk of the enterprise is expressed by the portfolio risk (the enterprise is the weighted “sum” of its investment objects) and thus changes over time driven by the varying σ_i . Note that due to our focus on changing risk we do not regard a changing $\mu^U(x)$ over time (which would result in an index t as in $\sigma_i^U(x)$). As we see, with ascending x the overall returns as well as the overall risk of the enterprise are both increasing. On the one side the enterprise certainly strives for the highest possible return, on the other side a limitation exists for x from the given risk limit.

It is common practice to use some variation of a random walk for the price movement on security and commodity markets. This approach goes ultimately back to Louis Bachelier (1900) who compared the stock market with a “drunkards walk”). Although controversially discussed, it was picked up more than half a century later by Mandelbrot (1963, 1972) and Fama (1965) among others. Following this theory of random walks historical (e.g. daily or weekly) portfolio returns can be used for estimating mean μ and standard deviation σ_i of future portfolio returns. It is important to understand that in our model the standard deviation is possibly changing in each period (indicated by its index t).

Assumption 3 *The initial calculation of covariances starts in $t=0$ and is finished after T periods. Each new covariance calculation begins in the finishing period of the previous covariance calculation.*

According to assumption 3, whenever a covariance matrix is completed, the input data used for its calculation are T periods old. We can immediately determine the portfolio risk by summing up the covariances in the matrix. This can then be used for a risk adjustment decision as well as for portfolio optimization. The moment before the next matrix is finished the input data used for risk calculations are already $2T$ periods outdated. Therefore the uncertainty interval that has to be taken into account spans $2T$ periods: in the worst case the risk has been going up over $2T$ periods before the enterprise realizes that it is exceeding the maximum risk it is willing (or able) to take (see figure 1). Without loss of generality we will concentrate our analysis on the first covariance matrix calculation and the corresponding adjustment decision, therefore focussing on the time interval $[0; 2T]$. During this time the portfolio risk is fluctuating in a non-predictable way.

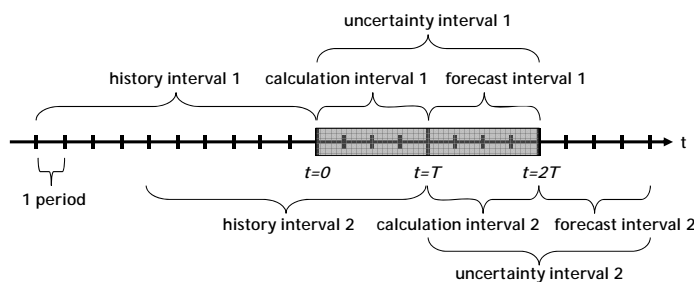


Figure 1. *Period Model and Relevant Time Intervals.*

3.2 The Risk-at-Risk Approach

We will now dwell on the portfolio risk at time t , denoted as σ_t , modelling it as a random variable. This relates to a phenomenon known from the behavior of stock market prices called *heteroscedasticity* (see e.g. Spremann 2003, pp. 152). In analogy to the periodical returns we write

Assumption 4 *The σ_t are normally distributed.*

This distribution assumption can (and would in practice) be relaxed by approximating the distribution of the σ_t delivered by the calculated sequence of standard deviations. Arranged in increasing order one

can easily deduce the quantiles needed in our model. Nevertheless, for reasons of simplicity and without significantly changing the general result we assume σ_t to be normally distributed here.

We will again focus on two distribution parameters: Our notation for the (strictly positive) mean will be μ_σ , for the standard deviation σ_σ (both tagged with an σ indicating the fact that the distribution applies to the portfolio *risk*), thus $\sigma_t \sim N(\mu_\sigma; \sigma_\sigma)$ with N short for the normal distribution.

The distribution parameters in our model can again be estimated using historical data. For example, the standard deviation of the portfolio risk can be taken as an estimate for the expected portfolio risk μ_σ and thus as the starting point for the random walk of σ_t . In order to maximize x in equation (1) under the given constraints we have to consider the uncertainty interval $[0; 2T]$. Because of assumption 4 the standard deviation of the expected portfolio risk after $2T$ periods is (as a sum of normally distributed random variables) again normally distributed according to $N(\mu_\sigma; \sigma_\sigma \sqrt{2T})$. As a consequence for the overall risk of the enterprise we have $\sigma_t^U(x) \sim N(x\mu_\sigma; x\sigma_\sigma \sqrt{2T})$.

In order to rephrase the fuzzy formulation “the risk limit is probably not exceeded” we will follow an approach comparable to the VaR for quantifying portfolio risk. We speak of a Risk-at-Risk over a holding period and a confidence level α , $0 < \alpha < 1$ and think of it as the standard deviation $\bar{\sigma}$ which is exceeded within the holding period only with the (small) probability of $(1-\alpha)$. With $\Phi(x)$ denoting the standardized normal distribution function, we know for the distribution of $\sigma_t^U(x)$ over $2T$ periods that

$$P(\sigma_t^U(x) \leq \bar{\sigma}) = \Phi\left(\frac{\bar{\sigma} - x\mu_\sigma}{x\sigma_\sigma \sqrt{2T}}\right).$$

At the same time we require in the spirit of the Risk-at-Risk approach the probability given above to be greater than or equal to the confidence level α , i.e.

$$P(\sigma_t^U(x) \leq \bar{\sigma}) \geq \alpha \quad \text{for } t = 2T \tag{2}$$

In the marginal case both sides of the equation are equal and we can therefore state—with q_α as the (onesided) α -quantile of the standardized normal distribution—that

$$\frac{\bar{\sigma} - x\mu_\sigma}{x\sigma_\sigma \sqrt{2T}} = q_\alpha \Leftrightarrow x = \frac{\bar{\sigma}}{q_\alpha \sigma_\sigma \sqrt{2T} + \mu_\sigma} \tag{3}$$

x gives us the portion of risk-free and risky investment objects in a way that equation (2) holds. We can calculate the overall expected earnings of the enterprise, given this capital allocation, as

$$B(x) = \mu^U(x) \cdot K = (i + x(\mu - i)) \cdot K$$

Obviously $B(x)$ represents only expected, calculatory (and not real) earnings because the returns are not fully cash-flow effective and the earnings themselves subject to interpretation. We will neglect the adjectives “expected” and “calculatory” and speak of earnings or, more generally, of benefits.

By inserting x from equation (3) into $\mu^U(x)$ from equation (1) we find for the benefits (with the number of periods needed for the completion of one covariance matrix as the independent variable)

$$B(T) = \left(i + \frac{\bar{\sigma}(\mu - i)}{q_\alpha \sigma_\sigma \sqrt{2T} - \mu_\sigma} \right) \cdot K \tag{4}$$

Considering equation (4) an enterprise could maximize its benefit by minimizing the time T that is needed to calculate a covariance matrix. Yet there is a trade-off between the benefits and the cost, i.e. cost caused by the infrastructure that is necessary to compute the calculations.

4 SERVICE-ORIENTED INFRASTRUCTURES FOR RISK QUANTIFICATION

From a SOI point of view the risk calculation can be regarded as a service providing its user transparently with up-to-date risk information for the relevant investment universe. In this section we derive the relationship between the computing capacity (i.e. cost) allocated to risk quantification and the time needed for the computation.

4.1 Computing Capacity for Risk Quantification

We denote with z the computing capacity necessary for estimating one covariance matrix in exactly T periods. We use CPUs as a measure for computing capacity and are aware of the fact that this means a one-dimensional view on matters as other determinants of system performance are ignored. We denote with w the workload—measured in CPU hours—for estimating one covariance. Applying a simple moving average technique with a rolling sample of historical data (Elton and Gruber 1972, pp. 409) we get unbiased estimators of the expected value and (co)variances for every point in time.

Assumption 5 *The same workload w is necessary for estimating variances and covariances.⁶ Furthermore every covariance is estimated from scratch, i.e. no intermediate results are used.⁷*

Assumption 6 *The length of the calculation time frame T depends solely on the time needed for the computation, neglecting e.g. latency or transmission times. Correspondingly the only cost relevant is cost for computation which occurs in the form of a (internal or external) factor price per CPU hour over a given time.*

Note that for the calculation of covariance matrices on a SOI it is convenient that the computations can be distributed on several nodes and executed in parallel, as all pairwise covariances can be calculated independently from each other. Thus efficiency losses are considerably low.

We can now deduce the computing capacity $z(T)$ (workload per time) that is required in every period over T periods. We already know that for n investment objects $n(n+1)/2$ covariances have to be calculated. Multiplied with the workload per covariance this determines the total number of CPU hours needed. This in turn—divided by the calculation time frame—leads to the functional relationship

$$z(T) = \left(\frac{n(n+1)w}{2T} \right) \Leftrightarrow T(z) = \left(\frac{n(n+1)w}{2z} \right) \quad (5)$$

Given n investment objects and a computing capacity of z CPUs, the covariance matrix will be completed after $T(z)$ periods.⁸ This constitutes an important parameter of the covariance estimation service since it describes the economic value that should be attributed to the consumption of capacity for covariance estimation. By inserting (5) into equation (4) and neglecting the mean risk compared to the standard deviation of the risk⁹ we quantify the benefits as

⁶Variance estimation requires only one historical time series, so its intrinsic workload is smaller than the workload for covariance estimation. Nevertheless, this effect can be neglected since for n variances there are $n(n-1)/2$ covariances in a given covariance matrix. With n sufficiently large the variances have merely no effect on the number of calculations (e.g. with $n=201$, the number of variances is only 1% of the number of covariances to be calculated).

⁷This could be considered awkward for the simple moving average procedure but is a realistic approach for more sophisticated methods.

⁸Here as well as for the optimal $T(z^*)$ later in this text the outcome is assumed real-valued. In reality and in order to fit it to the discrete-time period model one has to check the neighboring integer values to obtain the discrete optimum.

⁹The exact quantification would lead to a strictly increasing and concave benefit function B , as well. It would nevertheless be tedious to continue in our analysis with the exact expression. In order to avoid writing overhead we deliberately simplify our objective function by neglecting the mean risk, which is a numerically justifiable approximation in our context.

$$B(z) = a + 2b\sqrt{z} \quad \text{with } a := iK > 0, \quad b := \frac{\bar{\sigma}(\mu - i)K}{2q_\alpha \sigma_\sigma \sqrt{n(n+1)w}} > 0, \quad B'(z) = \frac{b}{\sqrt{z}} > 0, \quad B''(z) = -\frac{b}{2\sqrt{z}^3} < 0. \quad (6)$$

$B(z)$ is a strictly increasing and concave function.

4.2 Optimizing Computing Capacity on a Service-Oriented Infrastructure

In this paper we abstract from a specific SOI framework or technological implementation, but only consider the essential characteristics of such an infrastructure: A service user can consume exactly the amount of resources needed and is charged by the service provider on a pay-per-use basis. Thereby, it makes no difference whether resources stem from internal sources like enterprise-owned desktop computers and servers that are connected via a grid network or from an external provider. In the case of allocating the (limited) resources of an internal SOI, the enterprise faces opportunity cost that may be taken as a usage price. For external resources a price per unit of computing capacity is set by the provider. The price can be changing depending on the contract and service level agreement used. For example resources could be more expensive when delivered fail-safe during peak times while covering basic load on a lower service level might be cheaper (Bhargava and Sundaresan 2004, p. 203).

In an external provisioning scenario we assume a straightforward cost function using a factor price p (measured in e.g. \$ per workload over a period). Using equation (6) our cost function $C(z)$ and our objective function $Z(z)$ then are defined as

$$C(z) := pz, \quad Z(z) := B(z) - C(z) = a + 2b\sqrt{z} - pz.$$

Note that—as it is generally the case for the parameters in our model— $C(z)$ describes the cost per period and $B(z)$ the benefits per period depending on the capacity used per period for the completion of the covariance matrix over T periods. As the difference of a strictly concave benefit function and a linear cost function, $Z(z)$ is again a strictly concave function. The first derivative $Z'(z) = b/\sqrt{z} - p$ features its only null at $b^2/p^2 > 0$. Due to the strict concavity of $Z(z)$ and with respect to equation (6) the only maximum of $Z(z)$ is at

$$z^* = \frac{b^2}{p^2} = \frac{\bar{\sigma}^2(\mu - i)^2 K^2}{4q_\alpha^2 \sigma_\sigma^2 n(n+1)wp^2}. \quad (7)$$

On a short-term, iterative basis this result can be used to allocate resources of an external provider to risk/return management services. It is possible to examine in detail how input parameters affect z^* . For example the more capital the enterprise has to its disposal the more (in absolute terms) it will invest into risky investment objects. Higher risk exposure in turn increases the importance of risk/return management which is correctly reflected by the positive sign of $\partial z^*/\partial K$. The same argumentation holds when the enterprise faces a higher risk limit $\bar{\sigma}$. In this case it should allocate more capacity to risk/return management applications, which is consistently leading to an increasing z^* . Eventually when the risk premium $(\mu - i)$ rises (due to higher μ and/or lower i) investing into risky objects becomes more attractive, resulting in a larger share of risky capital. In order to manage the consequently more voluminous portfolio our model suggests that additional capacity should be allocated. In the denominator of equation (7) we have the parameter w determining the CPU hours needed for one covariance estimation. Increasing w generates higher cost. This in turn leads to less capacity allocation in the optimal case, reflecting the known trade off between accuracy and speed of risk/return management calculations. The behavior of z^* depending on the confidence level α is quite surprising. Theoretically q_α could grow infinitely (with increasing confidence level α) leading to an infinitesimal small z^* . This is the case because in our model the only way to account for a higher confidence level is a larger safety margin. This causes diminishing benefits and therefore a decreasing z^* in the optimum. Another interesting and to some extent counter-intuitive result is produced in combination with the parameter σ_σ . One would possibly expect that with increasing volatility of the portfolio risk the optimal capacity allocation increases which is actually not true. Basically, for a given risk limit $\bar{\sigma}$ a higher volatility of the portfolio risk can be leveraged by faster risk calculations (so that the enterprise

can still get close to the risk limit without hazardously exceeding it during the uncertainty interval). Going back to Bachelier's proposition the benefits of fast covariance calculations are of order $1/\sqrt{T}$. On the other side, the cost are depending on T in a reciprocal ($1/T$) fashion. As a consequence for higher volatility of the portfolio risk the cost are increasing more quickly than the benefits, leading ultimately to an increasing T^* and decreasing z^* , respectively.¹⁰

Figure 2 shows a numerical example of the described optimization. All values are per hour and were in parts estimated from intraday data of the German stock index DAX. The example pictures a company with capital of $K=50$ million \$ and $n=200,000$ investment objects. The company tries to hold a risk limit of $\bar{\sigma}=0.1\%$ with a confidence level $\alpha=99\%$. It can realize a risk free return $i=0.0008\%$ and a risky expected return $\mu=0.001\%$. The workload per covariance is assumed $w=2,5\cdot 10^{-10}$ CPU hours, the price per CPU $p=2\$$. It features an optimum at 72 CPUs.

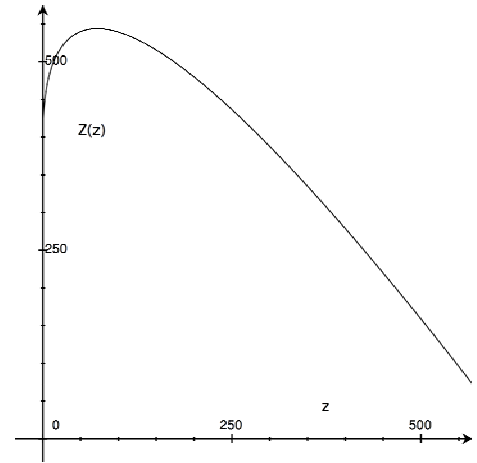


Figure 2 Numerical Example for $B(z)$.

Besides this straight forward linear cost function, especially in an internal provisioning scenario, more complex cost structures may apply. For instance, in a scenario where a high number of services are competing for a limited number of resources, opportunity cost may not increase proportionally, because ever more services with increasing opportunity cost are suppressed. After all, it becomes clear, that a detailed analysis of cost structures along with the knowledge of the concrete utility function of a service not only delivers the opportunity to allocate resources on-demand. The analysis also supports design decisions concerning for instance the questions whether external or internal provision or a mixture of both is preferable, whether or not the service should be deployed doing risk calculations in the background and whether an existing SOI is sufficient or should be enlarged due to an already high utilization rate resulting in high opportunity cost.

5 LIMITATIONS OF THE MODEL AND CONCLUSION

In this paper we demonstrated how the economic value that can be derived from risk/return management calculations can be measured considering an enterprise that has to decide on the amount of capital it wants to reserve to cover potential losses resulting from a risky investment portfolio. Several assumptions (e.g. regarding the distribution of the expected portfolio risk) were necessary to achieve an analytical solution.

Using the covariance approach as an example we moreover developed an optimization model that delivers the optimal amount of computing capacity that should be allocated to risk calculations at a time. In doing so we restricted our analysis to one well-defined risk/return management problem. Although covariances are fundamental and widely used in financial applications we thereby covered only one element of numerous risk/return management methods and algorithms. Other approaches and applications for SOI concepts (like for instance Monte-Carlo simulations which also have a very high parallelization potential) have to be examined as well. In fact, most of the basic principles introduced in this paper can be adapted to other scenarios in more sophisticated and complex surroundings.

Putting it all together a SOI is especially advantageous when market parameters determining the benefits of risk calculations are highly volatile as could be observed during the crisis since July 2007

¹⁰Such a situation could be observed e.g. during a "regime switch" between two volatility clusters where a time interval with relatively low volatility switches into an interval with higher volatility or vice versa.

resulting in varying demand for computing capacity. With a SOI, resources can be reallocated at any time to reach an economic optimum. As discussed, not only benefits but also (opportunity) cost may vary depending on the total demand for capacity. For example, during “quiet times” risk calculations may be computed more frequently generating added value out of readily available excess capacity even if benefits are comparably small. One caveat not mentioned in this paper is information security. As information on investment objects may be sensitive business data, spreading the calculations over the company or even over service providers may not be desired. Implementing a system as described would therefore require additional security mechanisms and persuasion of the management.

After all, this paper is a contribution to understand the application of service-oriented infrastructures in the specific domain of risk/return management. Although a validation of our findings based on real-world data is still subject to further research, in our point of view, such a systematic and economic analysis is a requirement as a first step for the further development of the new concepts like service-oriented computing or utility computing.

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