The advanced measurement approach for banks

Jan Lubbe[1] and Flippie Snyman[2]

Introduction

The Basel II Framework gives banks four options that they can use to calculate regulatory capital for operational risk. Each of these options requires an underlying risk measurement and management system, with increasing complexity and more refined capital calculations as one moves from the most basic to the most advanced approaches.

The most sophisticated and complex option under Basel II is the advanced measurement approach (AMA). This approach allows a bank to calculate its regulatory capital charge using internal models, based on internal risk variables and profiles, and not on exposure proxies such as gross income. This is the only risk-sensitive approach for operational risk allowed and described in Basel II.

Rationale for adopting the AMA

FirstRand decided on the AMA not only because of the capital savings that could be obtained, but also to achieve world-class, sophisticated risk management using state-of-the-art technology and techniques. The use of an AMA requires the implementation of various risk management processes, subprojects and measurement components that support good, accurate risk measurement, management and reporting.

Definition of operational risk

Operational risk is the risk of loss resulting from inadequate and failed internal processes, people or systems or from external events. This definition includes legal risk, but excludes strategic and reputational risk.

AMA risk management and measurement tools

Various risk measurement tools and supporting projects had to be put in place in order for FirstRand to follow an AMA. Fundamental AMA tools include internal loss data, external loss data, risk scenarios and business environment and internal control factors, which are addressed through risk and control self-assessments and key risk indicators.

1 Firstrand Banking Group, Enterprise Risk Management, Corner Fredman Drive and Rivonia Road, Sandton, 2196, South Africa. E-mail: jlubbe@firstrandbank.co.za.

2 Firstrand Banking Group, Enterprise Risk Management, Corner Fredman Drive and Rivonia Road, Sandton, 2196, South Africa. E-mail: flippie.snyman@firstrand.co.za.

Loss data (internal and external), key risk indicators (KRIs), risk and control self-assessment (RCSA) and scenarios are used extensively in the risk identification and management process. However, only risk scenarios and internal loss data are used in the capital calculation and allocation process. For capital purposes, all the other measurement tools are used to inform risk scenarios. External data can also be used as direct input into the capital calculation, but only after extensive development has been done (eg on selection, scaling and methodology).

Benefits of the advanced measurement approach

One of the most visible effects of implementing an advanced approach for operational risk management is the positive impact on reputation and perception by stakeholders. More sophisticated and advanced risk management certainly sends a clear message of solid and sound risk management to shareholders, clients, rating agencies and the market. This reassurance is extremely important and gives comfort to stakeholders, especially in times of economic turbulence and uncertainty.

The use of internal models to calculate capital requirements under the AMA may also lead to a reduction in regulatory and economic capital. Capital is based on risk exposures and not on income levels as is the case for the more basic approaches.

The most significant benefit, however, is that implementation of the AMA leads to improved risk management processes and more sophisticated risk measurement mechanisms. In many cases advanced risk measurement techniques (such as risk scenarios and the use of external data) were put in place earlier than originally anticipated to facilitate the successful implementation of an AMA system. Better-quality risk management ultimately protects the bank's value and the interests of stakeholders.

The AMA implementation has also resulted in improved relationships between deployed risk managers and centralised (Group function) risk specialists. Deployed risk managers had to take on extensive responsibility for the implementation of all operational risk measurement and management components in their business units. Guidance, frameworks and policies for these implementations were developed by centralised risk specialists, and therefore close cooperation between Group functions and business risk managers was required.

Lessons learnt

The implementation of an advanced measurement approach for operational risk was a challenging project and various valuable lessons were learnt. These lessons can be related to processes and systems, projects, regulatory aspects and quantification.

Processes and systems

Since internal loss data is a primary AMA component and a direct input into the capital model, the importance of data quality cannot be stressed enough. Internal data are used for risk management and reporting, regulatory returns and various other reports to the regulator, for submission to external data consortia and in the capital model.

It also became evident that the linking and alignment of all risk measurement and management tools are essential for effective risk monitoring and management. Tools cannot be viewed in isolation, but should be integrated to allow risk managers and business management to get a holistic view of their risk profile and exposures.

Operational risk measurement and management tools, for example, scenario analysis and key risk indicators, may be extremely useful in other risk types. The aim is to achieve an optimal balance between operational risk-specific tools and generic risk management tools, whereby tools are used across various risk types, but still address risk-type specific needs.

Risk management applications (support systems) and methodologies should be used in harmony, and evolution should take place in the right chronological order. Information technology (IT) systems should not determine or drive methodologies. Methodologies and manual implementation should reach a certain level of maturity before they are migrated onto a suitable IT platform.

Projects

Since operational risk management (specifically the AMA) is a very new science, it is easy to underestimate the scope of the project and the amount of effort and expertise required. Extensive subject knowledge and resources are required for the successful implementation of such an advanced risk management system.

Therefore, risk managers (in central teams and business units) should have an in-depth understanding of both the business they operate in and risk management. In over 200 business units, we have very diverse quality and skills levels among our human resources, which poses challenges for uniform implementation. To address some of these challenges, it is important to identify potential skills shortages early in order to allow for rectification without delaying implementation.

Strategic planning of a project of this size and complexity is extremely important. In the initial planning process, special attention must be given to estimating workloads, setting priorities, anticipating methodologies, implementing solutions and foreseeing the impact on business units.

Regulatory aspects

Regulatory interaction proved to be very beneficial for all participants. On-site visits and correspondence provided a channel for knowledge sharing between the bank and the regulator. As far as general correspondence is concerned, banks should be proactive in their communication and always give honest feedback and high-quality assessments. Requests from the regulator should be treated with great urgency and priority.

Quantification

The quantification and modelling of operational risk are very specialised subject fields and require people with the appropriate qualifications, skills and experience. External reviewers of models should also have extensive experience and appropriate credentials to validate such complex models and be well recognized in the industry as experts and thought leaders.

Quantification of operational risk

Quantification of operational risk for capital calculation purposes is a complex process, and a series of advanced statistical techniques are used. Since the scope of modelling is extensive, only key steps will be discussed.

Data used and classification

Internal loss data and risk scenarios are the two inputs into the capital calculation model. Loss data are historically suffered losses, while risk scenarios are prospective risk exposure estimates. Each risk scenario is quantified by experts who specify loss amounts at specific probability (or frequency) levels. Loss data and risk scenarios are classified in a matrix, where the vertical axis is typically business lines, while risk classes are depicted on the horizontal axis.

Data and extreme value theory analysis

Internal loss data exploration and analysis are an essential step in the overall modelling process and need to be performed before analytical modelling of available internal loss data can be performed.

Tabular and graphical data analysis provides the modeller with an indication of data completeness, spread, classification, patterns, breaks and possible compatibility with certain analytical model families. Typical tools that are utilised are summary tables, regulatory data matrices, multidimensional histograms and empirical distribution representations.

More formalised statistical tests are used to determine which family of distributions may be a possible fit for the data over various logical segments (specific reference is made here to light-tailed and fat-tailed theoretical distributions). These tests also help to determine the most appropriate truncation points and thresholds for modelling data in a single cell.

Some of the graphical plots that are used to determine the applicability of using extreme value theory (and light-tailed vs heavy-tailed distributions in general) are mean excess plots, Hill estimator plots, HKKP-Hill plots, DEdH plots, tail plots and stability parameter plots.

These plots help to determine whether the data show light-tailed or heavy-tailed behaviour or both (in different segments), whether certain data segments can be modelled using the empirical distribution and what the possible thresholds for modelling might be, and therefore whether one dataset or cell needs to be divided into and modelled across multiple segments.

The basic data and extreme value theory analysis also assists in determining the point at which risk scenarios should be incorporated into the models. This is typically done at a point where observations are very scarce and business areas are exposed to high severity events. It is important to note that scenarios are incorporated at a threshold that corresponds to an identified modelling segment for a specific cell, or from an additional threshold created specifically to facilitate the incorporation of risk scenarios into the capital model.

Once the thresholds have been determined, as well as the type of distributions that may be applicable, analytical modelling of the underlying loss data and scenarios can be performed.

Modelling of internal loss data

In segments where light-tailed behaviour is observed, the beta, chi-square, exponential, gamma, inverse Gaussian, log normal, normal, Weibull and Rayleigh distributions are usually considered for severity modelling. In segments where heavy-tailed behaviour is observed, the Burr, Cauchy, F-, generalised Pareto, generalised extreme value, log gamma, log logistic, Pareto and Student's *t*-distributions are tested for severity modelling.

Any of five methods of distribution fitting can be used, and in many cases more than one method is applied for a specific distribution, since they may yield different results. The methods used include the maximum likelihood estimation, least squares method, probability-weighted least squares method, robust least squares method and the method of moments (for frequency models only).

Once a series of fits have been performed, various non-graphical goodness of fit (GOF) measures are used to evaluate the accuracy and appropriateness of each fit. The most commonly used tests are Kolmogorov-Smirnov, Cramer von Mises, Anderson-Darling, analysis of fit differences, evaluation PP, evaluation QQ, chi-square tests and mean square error estimates.

A number of graphical representations are also used to supplement the GOF measures. These include probability-differences plots, probability-probability (PP) plots and quantile-quantile (QQ) plots. For QQ plots, linear scale QQ plots, logarithmic scale QQ plots, relative error plots (for specific quantiles) and absolute error plots (for specific quantiles) are evaluated.

Based on all the graphical and non-graphical GOF measures, a decision is made on the most suitable severity distribution for the data segment under consideration for a specific cell.

When performing frequency modelling for a segment where a corresponding severity model exists, tests are performed for the geometric, negative binomial and Poisson distributions. The same graphical and non-graphical GOF measures are evaluated for frequency distributions as for severity distributions in order to find the most appropriate and accurate frequency fit for a specific segment in a particular data cell under consideration. However, as a general assumption, the Poisson distribution is used for frequency modelling. While this assumption is well supported by research and literature, the Poisson distribution is also chosen to ensure consistency across all cells and segments, and to enable the integration of internal data and scenario models.

Modelling of risk scenarios

Each individual risk scenario should be quantified (loss estimates) at various probability/frequency levels. In addition, experts also provide an annual loss frequency for each scenario. This information is used to construct an empirical severity cumulative distribution function for each scenario, which consequently can be modelled with an analytical distribution. For frequency modelling, the annual frequency estimate is assigned as the mean parameter of the Poisson distribution. As discussed, each risk scenario is modelled individually.

Scenarios are consequently aggregated per cell in the classification matrix using Monte Carlo simulation with a high number of iterations. The result is an empirical dataset that contains all possible annual permutations and combinations of scenario realisations. For each cell, this empirical distribution is incorporated into the model from a specified threshold.

Since each point in the empirical distribution represents a combination of losses from various scenarios (annualised), a frequency distribution of Poisson (1) is associated with each empirical severity set. This mean parameter may be adjusted for threshold values. In cases where internal data are also present in the specific cell segment where scenarios will be incorporated, the internal data frequency distribution is set equal to the scenario frequency distribution. This is to ensure stability during simulation.

This frequency setting or equalisation determines the value of the threshold from where scenarios are incorporated. The threshold is chosen so that the annual frequency of internal data above the threshold is equal to 1 (or a slightly smaller parameter should adjustment for threshold value be necessary).

Independent simulation and aggregation

Before starting the simulation process, a decision needs to be made on the weights that will be assigned to internal loss data models and scenario models, respectively, during the simulation process for each segment in each cell. These weights determine the percentage of random values that are drawn from loss data models and risk scenario models. The weights are individually specified for each segment in each cell where both an internal loss data model and a risk scenario model were constructed. The weighting of the two input data type models is subjective and is determined by a predefined list of factors.

Multiple segment severity distributions can be used to introduce scenario analysis into the simulation above specific thresholds. Several thresholds, and hence segments in a specific cell, can be defined in order to specify the weight of internal loss models and scenario models per segment, as described earlier. In many cases it makes sense to assign a higher weight in the simulation to scenarios in higher value segments (tails) where internal data are scarcer or less reliable.

The process followed for simulation with multiple segments containing internal loss models and scenario models is the same as when only internal losses are used, except for the added complexity of mixing internal loss distributions and scenario distributions.

Monte Carlo simulation is performed simultaneously across all segments and distributions within a specific cell. For each simulation iteration the total losses across all segments are added up to arrive at an annual aggregate loss for the specific iteration. A large number of iterations are performed to construct a dense annual aggregate loss distribution for each cell. Value-at-risk (VAR) at the 99.9th percentile is calculated for each cell to arrive at the regulatory capital charge for a specific cell. For the calculation of the Group's (and each business line's) capital charge, all applicable cells' 99.9th percentile values-at-risk are added together. This equates to assuming full dependence between all cells and business lines.

Simulation taking correlation into account

Since the data are classified in a matrix, it is possible that inherent correlations are present between the individual internal loss datasets. These correlations can be taken into account during aggregation (simulation) to derive a diversified economic capital charge under Pillar 2 of the Basel II Framework.

Correlation is estimated based on internal data only. Consequently, the calculated correlation is applied to the whole cell and it is then implicitly assumed that the scenarios also pertaining to these cells have the same correlation characteristics and structures.

The copula calculation and simulation are performed in two steps. First, the aggregate loss distribution for each cell is generated in an independent process with several segments, including internal loss data models and scenario-based models. Second, the empirical distributions resulting from the simulation process are provided with the desired dependencies, tail properties and other distributional properties using copulas.

Copulas are used to model correlation structures. Gaussian and Student's *t* copulas require a correlation matrix for the simulation process and a tail parameter for the Student's *t* copula, in order to define the inter-cell dependencies and other distributional properties. A rank correlation matrix is calculated using event dates of the fitted data; therefore, it is only possible to calculate correlation parameters for the cells populated with empirical data (observed internal loss data).

The process followed to construct copulas and create multivariate distributions with marginal distributions correlated via copulas can be summarised in a few steps. The Gaussian copula is used as an example.

1. Generate/construct an empirical aggregate loss distribution for each cell utilising an independent Monte Carlo simulation procedure.

2. Generate independent normal random numbers (X), which are correlated through the rank correlation matrix, obtaining X^*.

3. Calculate the normal cumulative probabilities $\varphi(X^*)$ in order to recover the arguments of $C_\rho^{Ga}(u)$; and

4. Finally, determine the x_i (ie the loss of division/loss event type i) by inverting the marginal distributions F_i: $x_i = F_i^{-1}(u_i)$.

By iterating this process and summing up the x_i losses each time, we trace the whole integrated distribution for each cell and for the Group. Sampling is performed simultaneously across all cells, taking correlation structures into account. The Group's annual aggregate loss distribution will therefore inherently contain all underlying dependencies and correlation structures.

Calculating the VAR at the 99.9th percentile of the annual loss distribution will therefore yield a diversified operational risk capital charge number for the Group, where correlation has been taken into account.

Using insurance as mitigation agent

Insurance can be used as a mitigation instrument when calculating operational risk capital requirements. Insurance is applied to losses generated during the Monte Carlo simulation process. In the case of independent simulation, insurance is applied to losses as they are generated from various distributions. When correlation is taken into account, insurance is applied to losses generated after dependence structures are modelled. However, the principles of insurance application for independent and correlated losses are the same.

In order to incorporate the effect of insurance, available insurance policies and coverage clauses need to be mapped to the modelling structure, ie business lines and Basel II loss-event type combinations. This is quite a large project that needs to be conducted before insurance data are in a format usable for the capital model.

In addition to the policy and clause mapping to each cell, various insurance properties need to be parameterised for each cell, including maximum coverage, deductible and an indication whether cover is global or per event. It is also important for information on all applicable policies' compliance with Basel II minimum standards to be available. This includes parameters that will be used in haircut (discount) parameter calculations.

All of the above-mentioned parameterised insurance characteristics are consequently applied during the simulation process to each simulated loss in order to arrive at a mitigated aggregate loss distribution where insurance has been taken into account.

Capital allocation

After calculating the Group's total capital charge, the extent to which each business line and loss-event type combination contributes to the overall operational risk profile is estimated. This information will enable risk managers to focus efforts on and prioritise the mitigation of operational risk. In the case of independent simulation, each business line's capital charge is simply the sum of the VAR numbers at the 99.9th percentile across all loss event types.

Where an annual aggregate loss distribution has been constructed for the Group taking correlation structures into account, total capital is allocated based on the marginal contribution of each division/loss-event type combination's unexpected loss (UL) to the Group's unexpected loss. This is done on the principle of marginal UL contribution to the overall risk profile. The normalised contribution of each cell's UL to the Group's UL is also referred to as residual operational risk.

A very important property of this capital allocation methodology is that the sum of the allocated capital numbers equals the total calculated Group capital. Statistical (theoretical) allocations are only made down to business line level in the Group – allocations to lower levels in the organisation are done utilising subjectively compiled risk scorecards.

Conclusion

The implementation of an advanced measurement approach for operational risk was a very big project of extensive scope that involved all business areas in the Group. Many benefits can be associated with this project and lessons were learnt that will be extremely useful for future projects and implementations. The importance and value of advanced risk management practices and measurement cannot be overestimated: they play a critical role in protecting the bank's value.

References

Annis, C (2007): "Goodness-of-fit tests for statistical distributions", Statistical Engineering (www.statisticalengineering.com).

Basel Committee on Banking Supervision (2003): *Sound practices for the management and supervision of operational risk*, Basel, February.

——— (2006): *International convergence of capital measurement and capital standards – a revised framework – comprehensive version*, Basel, June.

Baud, Nicolas, Antoine Frachot and Thierry Roncalli (2002): "Internal data, external data and consortium data for operational risk measurement: how to pool data properly?", Groupe de Recherche Opérationnelle, Crédit Lyonnais, June.

Bazzarello, David, Bert Crielaard, Fabio Piacenza and Aldo Soprano (2007): "Modelling insurance mitigation on operational risk capital", Unicredit Group.

Committee of European Banking Supervisors (2006): Guidelines on the implementation, validation and assessment of advanced measurement (AMA) and internal ratings-based (IRB) approaches.

de Fontnouvelle, Patrick, Eric Rosengren and John Jordan (2004): "Implications of alternative operational risk modelling techniques", Federal Reserve Bank of Boston, June.

Marsaglia, George and John Marsaglia (2004): "Evaluating the Anderson-Darling distribution", *Journal of Statistical Software*, vol 9, no 2, February.

Mildenhall, Stephen (2006): "Correlation and aggregate loss distributions with an emphasis on the Iman-Conover method", Casualty Actuarial Society (CAS) Research Working Party on Correlation and Dependencies Among All Risk Sources, CAS *Forum*, Winter.

Morone, Marco, Anna Cornaglia and Giulio Mignola (2007): "Economic capital assessment via copulas: aggregation and allocation of different risk types", www.defaultrisk.com/pp_model160.htm.

Moscadelli, Marco (2004): "The modelling of operational risk: experience with the analysis of the data collected by the Basel Committee", Bank of Italy Economic Research Department, *Temi di discussione* (Economic Working Papers), no 517, July.

Perkins, Peter and Tom Lane (2003): "Monte Carlo simulation in MATLAB using copulas", MATLAB *News & Notes*, The Mathworks, November.

Press, William, Brian Flannery, Saul Teukolsky, and William Vetterling (1992): *Numerical recipes in C: the art of scientific computing*, Cambridge University Press.

Rebonato, R and P Jaeckel (1999): “The most general methodology to create a valid correlation matrix for risk management and option pricing purposes”, Quantitative Research Centre of the NatWest Group, 19 October.