In-depth

Dynamic Financial Analysis

Understanding Risk and Value Creation in Insurance

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the next Re generation

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Foreword

DFA – a concept and buzzword energizing actuaries and other insurance professionals in the 1990s! The general hope then was that such models would accurately describe the complexity of the risky environment in which insurance and reinsurance companies operate. After the first few years, however, expectations began to recede: people realized it would be a Herculean task to consider all influences deemed relevant.

In recent years, however, the pendulum has begun to swing back: financial and actuarial competencies are increasingly converging, and the power of today's computers enables even highly complex simulations in a reasonable amount of time.

DFA finally comes to reality, and expectations about what it can do have become much more realistic. Dynamic financial analysis is no longer conceived of as a black box, nor its answers as the ultimate truth. Instead it is viewed as a means of gaining insight and understanding, of reducing uncertainty and mastering complexity.

Today, DFA is becoming what it should be: a support for management for making informed decisions, not a decision maker itself. We should take it for what it is: a flight simulator – not an autopilot!

Enjoy your flight!

Hans Peter Boller

Chief Actuarial Officer

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Introduction

The changing business environment in non-life insurance and reinsurance has raised the need for new quantitative methods to analyze the impact of various types of strategic decisions on a company's bottom line. Dynamic Financial Analysis («DFA») has become popular among practitioners as a means of addressing these new requirements. It is a systematic approach based on large-scale computer simulations for the integrated financial modeling of non-life insurance and reinsurance companies aimed at assessing the risks and the benefits associated with strategic decisions. DFA allows decision makers to understand and quantify the impact and interplay of the various risks that their company is exposed to, and – ultimately – to make better informed strategic decisions. In this brochure, we provide an overview and assessment of the state of the industry related to DFA. We investigate the DFA value proposition, we explain its elements and we explore its potential and limitations.

1. Definition of DFA

Dynamic Financial Analysis («DFA») is a systematic approach based on large-scale computer simulations for the integrated financial modeling of non-life insurance and reinsurance companies aimed at assessing the risks and benefits associated with strategic decisions.

The most important characteristic of DFA is that it takes an integrated, holistic view – contrary to classic financial or actuarial analysis, where different aspects of one company are considered in isolation. Specifically, DFA models the reactions of the company in response to a large number of interrelated risk factors including both underwriting risks – usually from several different lines of business – and asset risks. In order to account for the long time horizons that are typical in insurance and reinsurance, DFA enables dynamic projections to be made for several future time periods, where one time period is usually one year, but can also be one quarter. DFA models normally reflect the full financial structure of the modeled company, including the impact of accounting and tax structures. Thus, DFA allows projections of the company's balance sheet and profit-and-loss account («P&L») to be made. Technically, DFA is a platform which integrates various models and techniques from finance and actuarial science into one multivariate dynamic simulation model. Given the complexity and the long time horizons of such a model, it is no longer possible to make analytical evaluations. Therefore, DFA is based on stochastic simulation (also called «Monte Carlo»), where large numbers of random scenarios are generated, the reaction of the company to each is evaluated, and the resulting outcomes are then analyzed statistically. Section 3 gives an in-depth description of the different elements required for a DFA.

With this set-up, DFA provides insight into the sources of value creation or destruction in the company and the impact of external risk factors, as well as internal strategic decisions, on the bottom line of the company, i.e. on its financial statements. The most important virtue of DFA is that it enables one to gain insight into various kinds of dependencies that affect the company, which would be hard to grasp without the holistic approach. Thus, DFA is a tool for integrated enterprise risk management and strategic decision support. In other words, DFA is a kind of flight simulator for decision makers of insurance and reinsurance companies that allows them to investigate the potential impact of their decisions while still on safe ground. Specifically, DFA addresses issues such as capital management, investment strategies, reinsurance strategies and strategic asset-liability management. Section 2 describes the problem space that gave rise to the genesis of DFA, and Section 4 provides more information on the uses of DFA.

The term DFA is mainly used in non-life insurance. In life insurance, techniques of this kind are usually termed «ALM» (for Asset Liability Management), although they are used for a wider range of applications – including the ones stated above. Similar methods are used in banking, where they are often referred to as «Balance Sheet Management».

DFA grew in the late 1990s out of practical needs rather than academic research. The main driving force behind the genesis and development of DFA was, and still is, the related research committee of the Casualty Actuarial Society (CAS). Their website[1] provides a variety of background materials on the topic, in particular a comprehensive and easy-to-read handbook [10] describing the value proposition and the basic concepts of DFA. A fully worked-out didactic example of a DFA, with emphasis on the underlying quantitative problems, is given in [18], whereas [21] describes the development and implementation of a large-scale DFA decision support system for a company. In [9], the authors describe comprehensively all modeling elements needed for setting up a DFA system, with the main emphasis on the underwriting side; complementary information can be found in [3].

[1] URL: http://www.casact.org/research/dfa/index.html

2. Value Proposition of DFA

The aim of this section is to describe the developments in the insurance and reinsurance market that gave rise to the genesis of DFA. For a long time – up until the 1980s or 1990s, depending on the country – insurance business used to be a fairly quiet area, characterized by little strategic flexibility and innovation. Regulations heavily constrained the types of risk insurers could assume, and the way they had to do business. Relatively simple products were predominant, each addressing a specific type of risk. Underwriting and investment were separated, both within the insurance companies themselves, and in the products they offered to their clients. In this rather static environment, there was no particular need for sophisticated analytics: actuarial analysis was carried out on the underwriting side – without linkage to the investment side of the company, which was analyzed separately. Reinsurance, as the only means of managing underwriting risks, was acquired locally for each line of business, whereas there were separate hedging activities for financial risks. Basically, quantitative analysis amounted to modeling a group of isolated silos, without taking a holistic view.

However, insurance is no longer a quiet area. Regulations were loosened and gave more strategic flexibility to insurers, leading to new types of complicated products and fierce competition in the market. The traditional boundaries between banking and insurance became increasingly blurred, and many companies developed into integrated financial services providers through mergers and acquisitions. Moreover, the risk landscape was also changing, due to demographic, social and political changes, and due to new types of insured risks or changes in the characteristics of already-insured risks (e.g. liability). The boom in the financial markets in the late 1990s also affected insurers. On the one hand, it opened up opportunities on the investment side, while on the other, insurers themselves faced shareholders that became more attentive and demanding. Achieving a sufficient return on capital provided by the investors was suddenly of paramount importance in order to avoid a capital drain into more profitable market segments. A detailed account of these developments, including case studies on some of their victims, can be found in [5].

As a consequence of these developments, insurers have to select their strategies in such a way that they have a favorable impact on the company's bottom line, and not only relative to some isolated aspect of their business. Diversification opportunities and offsetting effects between different lines of business or between underwriting risks and financial risks have to be exploited. This is the domain of a new discipline in finance, namely Integrated or Enterprise Risk Management (see [6]). Clearly, this new approach to risk management and decision-making calls for corresponding tools and methods that permit an integrated and holistic quantitative analysis of the company relative to all relevant risk factors and their interrelations. In non-life insurance, the term «DFA» was coined for tools and methods that emerged in response to these new requirements. On a technical level, Monte Carlo simulation was selected because it is basically the only means that allows one to deal with the long time horizons present in insurance, and with the combination of models for a large number of interacting risk factors.

3. Elements of DFA

This section provides a description of the methods and tools that are necessary for carrying out DFA. The structure referred to here is generic in that it does not describe specifically any one of the DFA tools available in the market, but it identifies all those elements that are typical in any DFA. DFA is a software-intensive activity – it relies on complex software tools and extensive computing power. However, we should not reduce DFA to its pure software aspects. Fully-fledged and operational, DFA is a combination of software, methods, concepts, processes and skills. Skilled people are the most critical ingredient in carrying out the analysis. In Figure 1 we show a schematic structure of a generic DFA system with its typical components and relations.

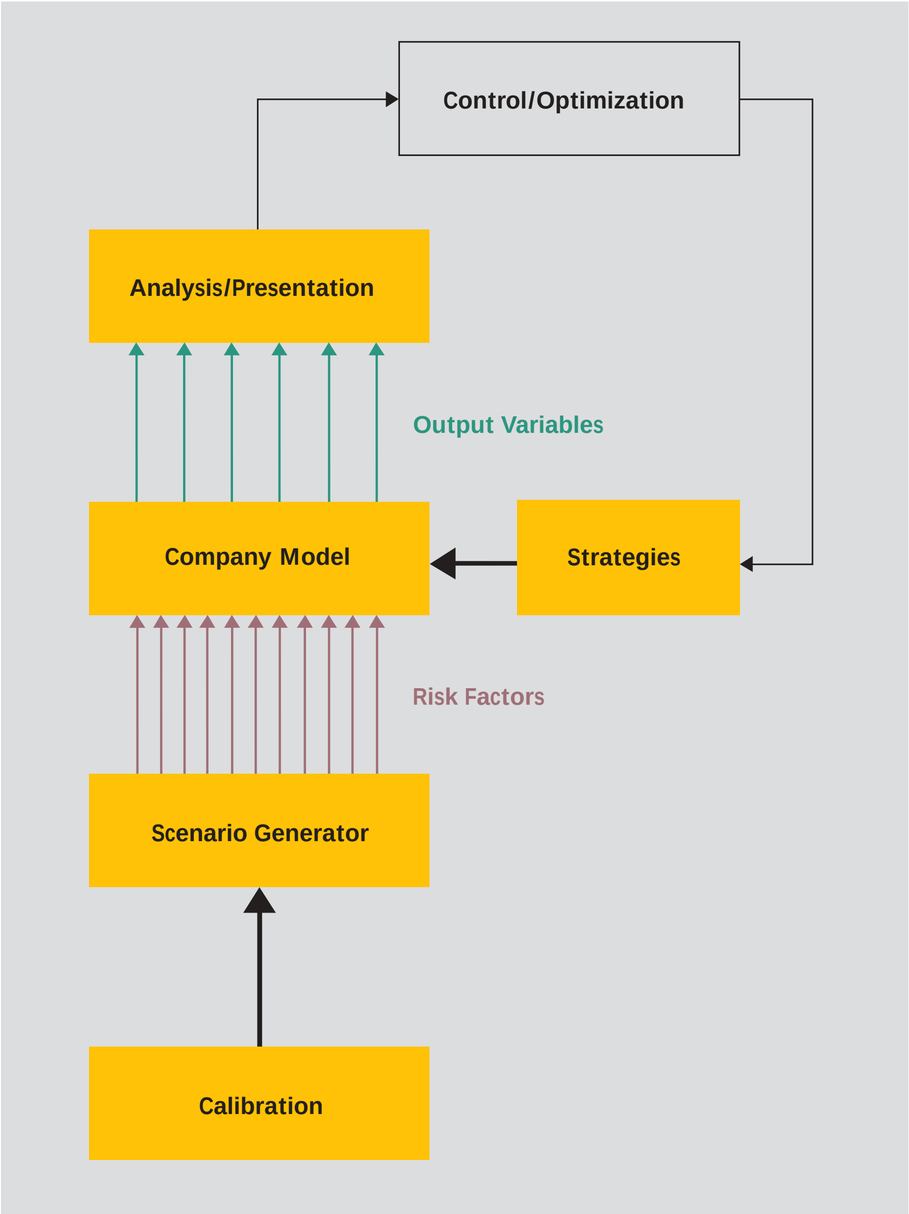
The *scenario generator* comprises stochastic models for the risk factors affecting a company. Risk factors typically include economic risks (e.g. inflation), underwriting risks (e.g. motor liability claims), asset risks (e.g. stock market returns) and business risks (e.g. underwriting cycles). The output of the scenario generator is a large number of Monte Carlo scenarios for the joint behavior of all modeled risk factors over the full time range of the study, representing possible future «states-of-nature» (where «nature» is interpreted in a wide sense). *Calibration* means the process of finding suitable parameters for the models to produce sensible scenarios; it is an integral part of any DFA. If the Monte Carlo scenarios were replaced by a small set of constructed scenarios, the DFA study would be equivalent to classical scenario testing of business plans.

Each one of the scenarios is then fed into the *company model* or *model office* that models the reaction of the company based on the behavior of the risk factors, as suggested by the scenarios. The company model reflects the internal financial and operating structure of the company, including features such as the consolidation of the various lines of business, the effects of reinsurance contracts on the risk assumed, or the structure of the investment portfolio of the company, not neglecting features such as accounting and taxation.

Each company model comprises a number of parameters under the control of management, such as investment portfolio weights or reinsurance retentions. A set of values for these parameters corresponds to a strategy, and DFA is a means for comparing the effectiveness of different strategies under the projected future course of events. The output of a DFA study consists of the results of the application of the company model, parameterized with a strategy, on each of the generated scenarios. So each risk scenario fed into the company model is mapped onto one result scenario, which can also be multivariate, going up to full pro-forma balance sheets.

Given the Monte Carlo set-up, there is a large number of output values, so that sophisticated *analysis and presentation* facilities become necessary for extracting information from the output: these can consist of statistical analysis (e.g. empirical moment and quantile computations), graphical methods (e.g. empirical distributions), or drill-down analysis, where input scenarios that gave rise to particularly bad results are identified and studied. The results can then be used to readjust the strategy for the *optimization* of the target values of the company. The rest of this section considers the different elements and related problems in somewhat greater detail.

Figure 1 Schematic overview of the elements of DFA



3.1 Scenario Generator and Calibration

Given the holistic point of view of DFA, the scenario generator has to contain stochastic models for a large number of risk factors belonging to different groups; the table below gives an overview of risk factors typically included (in parentheses: optional variables in more sophisticated systems).

Economic	Claims	Investment	Business
per economy:	per LOB:	gov't bonds	U/W cycles
■ inflation	■ attritional losses	stocks	(reinsurance cycles)
■ interest rates	■ large losses	real estate	(operational risks)
	■ loss development		(etc.)
(exchange rates)	across LOBs	(corporate bonds)	
(credit spreads)	■ CAT losses	(ABSs)	
(GDP)		(ILSs)	
(wage levels)	(reserve uncertainty)	(etc.)	
(etc.)	(etc.)		

The scenario generator has to satisfy a number of particular requirements: first of all, it does not only have to produce scenarios for each individual risk factor, but must also allow, specify and account for dependencies between the risk factors (contemporaneous dependencies) and dependencies over time (intertemporal dependencies). Neglecting these dependencies means underestimating the risks since the model would suggest diversification opportunities where, in fact, none are present. Moreover, the scenarios should not only reproduce the «usual» behavior of the risk factors, but they should also sufficiently account for their extreme individual and joint outcomes.

For individual risk factors, many possible models from actuarial science, finance and economics are available and can be reused for DFA scenario generation. For underwriting risks, the models used for pricing and reserving can be reused relatively directly (see [9] for a comprehensive survey). Attritional losses are usually modeled through loss ratios per line of business, whereas large losses are usually modeled through frequency-severity set-ups, mainly in order to be able to reflect properly the impact of non-proportional reinsurance. Catastrophe (CAT) modeling is special in that one CAT event usually affects several lines of business. CAT modeling can also be done through stochastic models (see [8]), but – for the perils covered by them – it is also fairly commonplace to rely on scenario output from special CAT models such as CATrader®[2], RiskLink®[3] or EQEcat®[4]. As DFA is used for simulating business projected over several years, it is important to model not only the incurred losses but also the development of the losses over time – particularly their payout patterns, given the cashflow-driven nature of the company models. Standard actuarial loss reserving techniques are normally used for this task (see [18] for a fully worked-out example). [23] provides full details on modeling loss reserves, including stochastic payout patterns that allow for the incorporation of specific reserving uncertainty that is not covered by the classical techniques.

Among the economic and financial risk factors, the most important ones are interest rates. There exists a large number of possible models from the realm of finance for modeling single interest rates or – preferably – full yield curves, be it risk-free or risky ones; the same is true for models of inflation, credit spreads or equities. Comprehensive references on these topics include [3] and [17]. However, some care must be taken: most of these models were developed with tasks other than simulation in mind, namely the valuation of derivatives. Thus, the structure of these models is often driven by mathematical convenience (easy valuation formulae for derivatives) which often goes at the expense of good statistical properties. The same is true for many econometric models (e.g. for inflation) which tend to be optimized for explaining the «usual» behavior of the variables while neglecting the more «extreme» events. In view of the difficulties caused by the composition of existing models for economic variables and invested assets, efforts have been made to develop integrated economic and asset scenario generators that respond to the particular requirements of DFA in terms of statistical behavior, dependencies and long-term stability. The basics of such economic models and their integration, along with the Wilkie model as the most classical example, are described in [9]. [20] provides a survey and comparison of several integrated economic models (including the ones by Wilkie, Cairns and Smith) and pointers to further references. Besides these publicized models, there are also several proprietary models by vendors of actuarial and financial software (e.g. B & W Deloitte[5], Barrie & Hibbert[6], SS & C[7] or Tillinghast[8]).

Besides the underwriting risks and the basic economic risk factors of inflation, (government) interest rates and equities, sophisticated DFA scenario generators may contain models for various further risk factors. In international set-ups, foreign exchange rates have to be incorporated, and an additional challenge is to let the model also reflect the international dependencies. Additional risk factors for one economy may include Gross Domestic Product (GDP) or specific relevant types of inflation such as wage or medical inflation. Increasingly important are models for credit defaults and credit spreads – which must, of course, properly reflect the dependencies on other economic variables. This, subsequently, allows one to model investments such as asset-backed securities and corporate bonds that are extremely important to insurers (see [3]). The modeling of operational risks (see [6], which also provides a very general overview and classification of all risks affecting financial companies), which are a current area of concern in banking regulation, is not yet very widespread in DFA. An important problem specific to insurance and reinsurance is the presence of underwriting cycles (hard and soft markets), which have a non-negligible business impact on the long time horizons considered by DFA. These cycles and their origins and dependencies are not very well understood and are very difficult to model (see [12] for a survey of the current state of knowledge).

The real challenge of DFA scenario generation lies in the composition of the component models into an integrated model, i.e. in the modeling of dependencies across as many outcomes as possible. These dependencies are ubiquitous in the risk factors affecting an insurance company. Think, for example, of the well-known fact that the number of car accidents tends to rise with increasing GDP. Moreover, many of those dependencies are non-linear in nature because of, for instance, market elasticities. A particular challenge in this context is the adequate assessment of the impact of extreme events, when the historically observable dependency becomes much stronger and risk factors appear much more interrelated (the so-called tail dependency). Different approaches for dependency modeling are pursued, namely:

- Deterministic modeling by postulating functional relations between various risk factors, e.g. mixture models or regression-type models (see [9] or [17]).

- Statistical modeling of dependencies, with linear correlation being the most popular concept. However, linear correlation has some serious limitations when extreme values are important (see [11] for a related study, possible modeling approaches and pointers to further readings).

An important aspect of the scenario generator is its calibration, the attribution of values to the parameters of the stochastic model. A particular challenge in this context is that there are usually only few data points for estimating and determining a large number of parameters in a high-dimensional space. This can obviously result in substantial parameter uncertainty. Parsimony and transparency are, therefore, crucial requirements for models used in DFA scenario generation. In any case, calibration, which also includes back-testing of the calibrated model, must be an integral part of any DFA study. Even though most DFA practitioners do not have to deal with it explicitly, as they rely on commercially available DFA software packages or components, it should not be forgotten that, in the end, generating Monte Carlo scenarios for a large number of dependent risk factors over several time periods also poses some non-trivial numerical problems. The most elementary example is to have a random number generator that is able to produce thousands, if not millions, of independent and identically distributed random variables (indeed a non-trivial issue in view of the sometimes poor performance of some popular random number generators). The technicalities of Monte Carlo methods are comprehensively described in [13].

Moreover, it is fundamentally difficult to make judgments on the plausibility of scenarios for the expanded time horizons often present in DFA studies. Fitting a stochastic model either to historical or current market data implies the assumption that history or current expectations are a reliable prediction for the future. While this may be true for short time horizons, it is definitely questionable for time horizons as long as five to 20 years, which are quite commonplace in insurance. There are regime switches or other hitherto inexperienced events that are not reflected by historical data or current market expectations. Past examples include asbestos liabilities or the events of September 11th, 2001. An interesting case study on the issue is [4], whereas [22] explores very generally the limitations of risk management based on stochastic models and argues that the latter must be complemented with some judgmental crisis scenarios.

[2] URL: http://www.air-boston.com
[3] URL: http://www.rms.com
[4] URL: http://www.eqecat.com
[5] URL: http://www.timbuk1.co.uk
[6] URL: http://www.barrhibb.com
[7] URL: http://www.ssctech.com
[8] URL: http://www.towers.com

3.2 Company and Strategy Modeling

Whereas the scenarios describe possible future courses of events in the world surrounding the modeled company, the company model itself reflects the reaction of the company in response to the scenario. The task of the company model is to consolidate different inputs into the company, i.e. to reflect its internal operating structure, including insurance activities, investment activities, and also the impact of reinsurance.

Company models can be relatively simple, such as the ones in [18] or [9] which basically consolidate in a purely technical way the outcome of the various risks. However, the goal of DFA is to make projections for the bottom line of the company. Therefore, practical DFA company models tend to be highly complex. In particular, they also incorporate the effects of regulation, accounting, and taxation, since these issues have an important impact on the behavior and financial results of insurance companies. However, these latter issues are extremely hard to model in a formal way, so that model uncertainty emanates from the company model. Examples of detailed models for US property-casualty insurers are described in [16] and [8]. In general, even relatively simple company models are already so complicated that they no longer represent mathematically tractable mappings of the input variables on the output variables, which precludes the use of formal optimization techniques such as dynamic programming. This distinguishes practical DFA models from the technically more sophisticated dynamic optimization models coming from the realm of operations research (see [19]). Figure 2 on page 14/15 shows an extract of a practical DFA company model, combining components that provide the scenario input, components that model the aggregation and consolidation of the different losses, components that model the in-force reinsurance programs, and components that aggregate the results into the company's overall results. It should be borne in mind that each component contains, moreover, a number of parameters such as reinsurance retentions and limits. The partial model shown in Figure 2 (see page 14/15) represents just one line of business of one company; the full model would then contain several other lines of business, plus the entire investment side of the company, and the top level structure consolidating everything into the balance sheet. This gives us a good idea of the actual complexity of real-world DFA models.

Company models used in DFA are usually very cash flow-oriented. They try to imitate the cash flows of the company or, more specifically, its technical and financial accounting structures. Alternatively, it would be conceivable to structure a company model along the lines of economic value creation. The problem with this approach, however, is that this issue is not very well understood in insurance (see [14] for a survey of the current state of the knowledge).

The modeling of the strategies (i.e. the parameters of the company model that are under the control of management) is usually done in a non-adaptive way, that is, as deterministic values over time. However, a DFA study usually involves several time periods of substantial length (one year, say) and it is not realistic to assume that management will not adapt its strategy if the underlying risk factors develop dramatically in a particular scenario.

For the reasons stated, the plausibility and accuracy of DFA outputs on a balance sheet level are often doubted, and the true benefit of a DFA study is seen rather in the insights gained from the analytical efforts of setting up a comprehensive model of the company and the relevant risk factors.

Figure 3 Extract of pro-forma projected balance sheets

t_0

	1Q2003	4Q2002	3Q2002	2Q2002	1Q2002
Earned Premium Income	1 061.4	1 713.3	1 653.2	787.0	694.4
Losses Incurred	–881.4	–1 415.3	–1 277.6	–647.9	–819.4
Total U/W Expense					
Underwriting Resu					
Invested Assets					
Total Other Assets					
Technical Reserves					
Total Other Liabilit					
Liabilities					
Total Equity & Liabi					
ROE					
Solvency Ratio					
Reserve Ratio					
Asset Leverage					

$t_0+\Delta t$

	1Q2004	4Q2003	3Q2003	2Q2003	1Q2003
Earned Premium Income	1 125.1	1 816.1	1 752.4	834.2	730.8
Losses Incurred	–934.3	–1 500.2	–1 354.3	–686.8	–868.6
Total U/W Expense					
Underwriting Resu					
Invested Assets					
Total Other Assets					
Technical Reserves					
Total Other Liabilit					
Liabilities					
Total Equity & Liabi					
ROE					
Solvency Ratio					
Reserve Ratio					
Asset Leverage					

$t_0+2\Delta t$

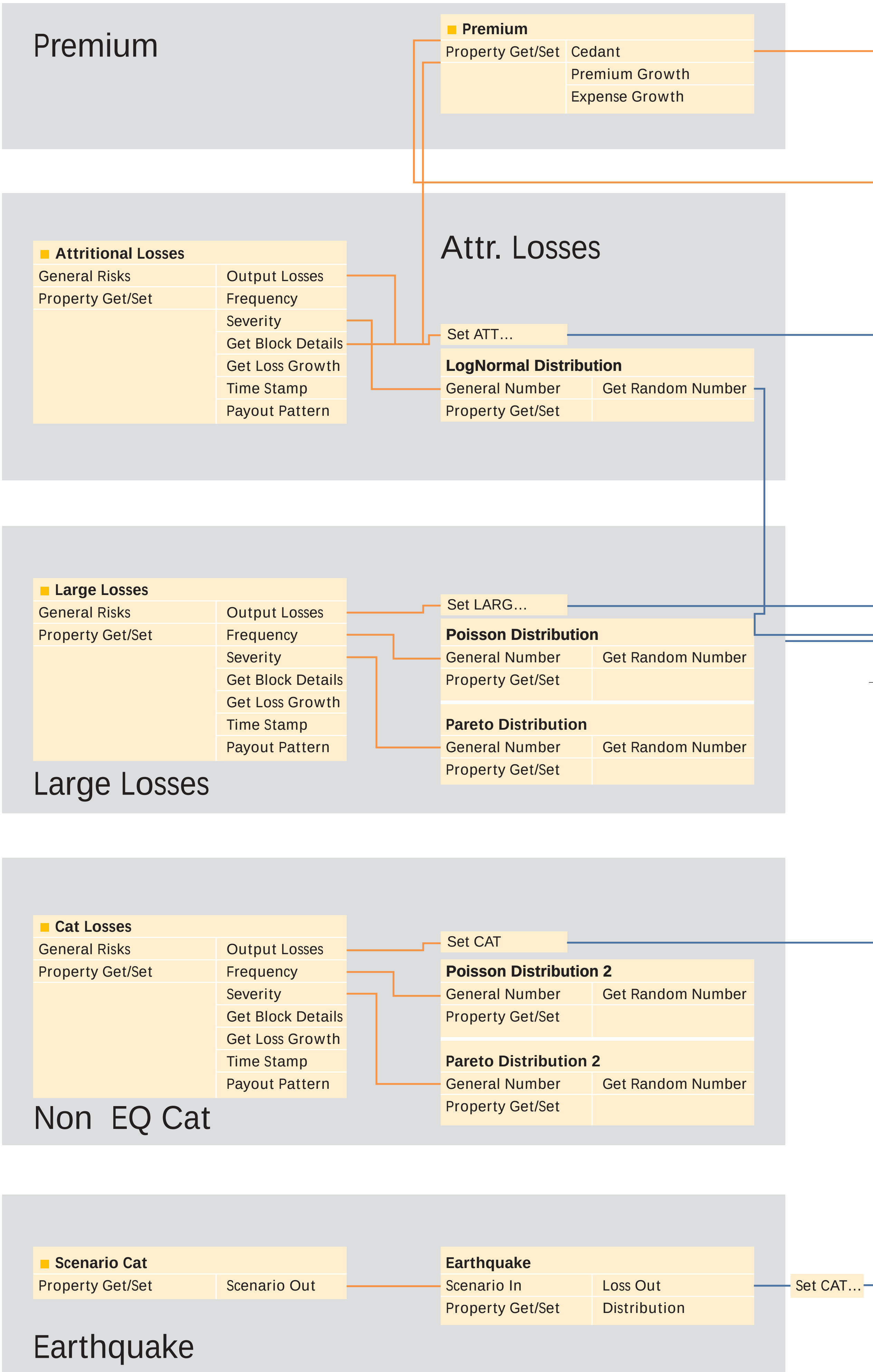
	1Q2005	4Q2004	3Q2004	2Q2004	1Q2004
Earned Premium Income	1 192.6	1 925.1	1 857.5	884.3	774.6
Losses Incurred	–990.3	–1 590.2	–1 435.5	–728.0	–920.7
Total U/W Expense					
Underwriting Resu					
Invested Assets					
Total Other Assets					
Technical Reserves					
Total Other Liabilit					
Liabilities					
Total Equity & Liabi					
ROE					
Solvency Ratio					
Reserve Ratio					
Asset Leverage					

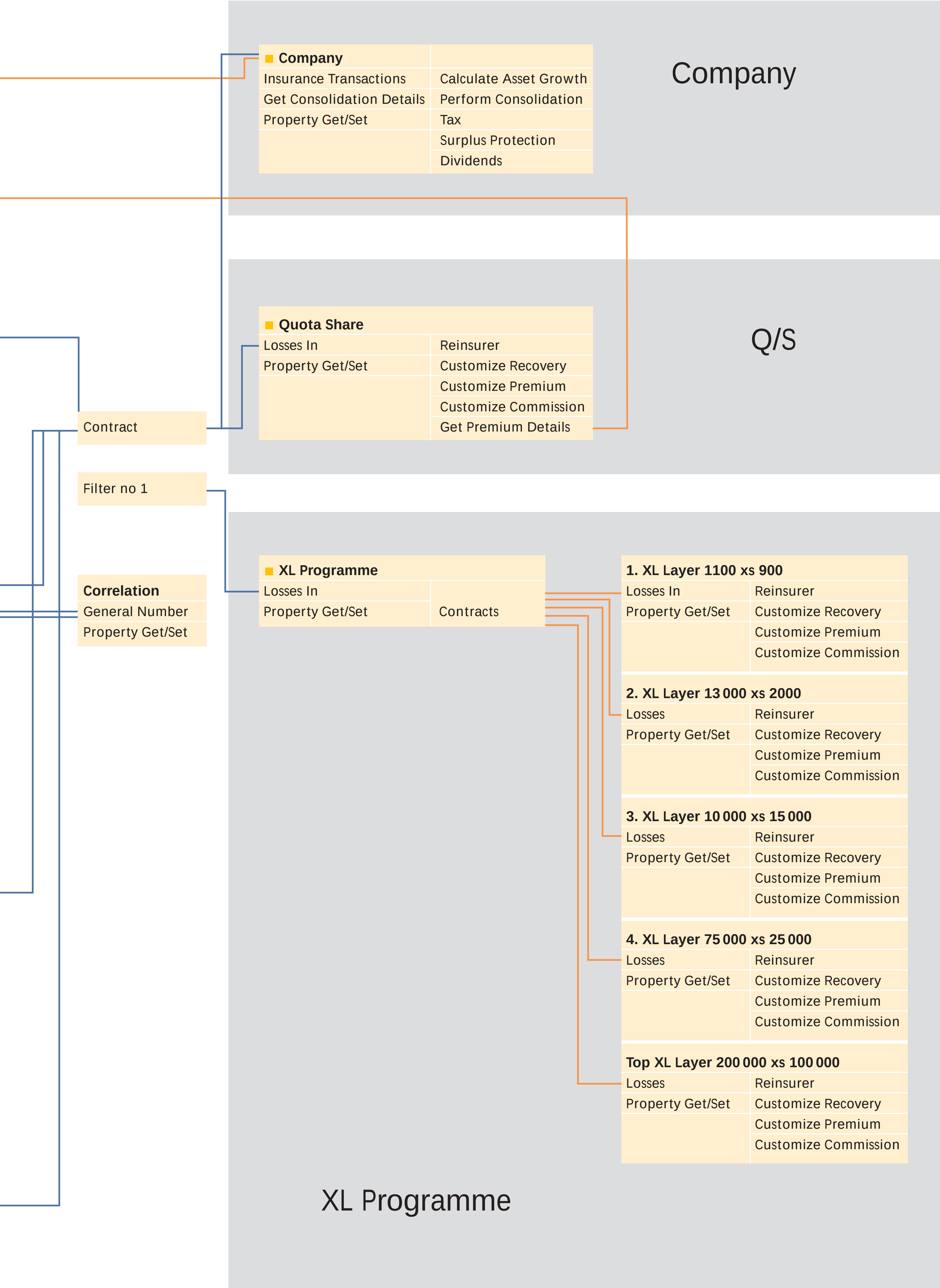
$t_0+3\Delta t$

	1Q2006	4Q2005	3Q2005	2Q2005	1Q2005
Earned Premium Income	1 264.1	2 040.6	1 969.0	937.3	821.1
Losses Incurred	–1 049.8	–1 685.6	–1 521.6	–771.7	–975.9
Total U/W Expenses	–222.2	–310.1	–295.0	–623.9	–100.3
Underwriting Results	–7.9	44.8	152.3	–458.2	–255.1
Invested Assets	8 249.2	6 951.5	6 475.1	6 248.8	6 134.6
Total Other Assets	2 714.2	2788.8	1 825.9	1 920.5	2 295.9
Technical Reserves	6 899.8	6 615.1	6 558.7	6 336.7	6 236.3
Total Other Liabilities	2 277.2	937.0	1 322.1	832.3	882.1
Liabilities	9 177.0	9 403.9	7 880.8	7 169.0	7 118.3
Total Equity & Liabilities	1 786.4	336.3	420.2	1 003.3	1 312.1
ROE	0.2	0.2	0.2	0.1	0.1
Solvency Ratio	1.2	1.0	1.1	1.0	1.0
Reserve Ratio	3.3	3.9	3.4	3.4	4.0
Asset Leverage	4.2	4.4	3.9	4.0	3.6

$\Delta t = 1$ year

Figure 2 Diagram of a part of a DFA company model




Company
Company
Insurance Transactions
Get Consolidation Details
Property Get/Set
Calculate Asset Growth
Perform Consolidation
Tax
Surplus Protection
Dividends
Q/S
Quota Share
Losses In
Property Get/Set
Reinsurer
Customize Recovery
Customize Premium
Customize Commission
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Contract
Filter no 1
Correlation
General Number
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Property Get/Set
Contracts
1. XL Layer 1100 xs 900
Losses In
Property Get/Set
Reinsurer
Customize Recovery
Customize Premium
Customize Commission
2. XL Layer 13 000 xs 2000
Losses
Property Get/Set
Reinsurer
Customize Recovery
Customize Premium
Customize Commission
3. XL Layer 10 000 xs 15 000
Losses
Property Get/Set
Reinsurer
Customize Recovery
Customize Premium
Customize Commission
4. XL Layer 75 000 xs 25 000
Losses
Property Get/Set
Reinsurer
Customize Recovery
Customize Premium
Customize Commission
Top XL Layer 200 000 xs 100 000
Losses
Property Get/Set
Reinsurer
Customize Recovery
Customize Premium
Customize Commission
XL Programme

3.3 Analysis and Presentation

The output of a DFA simulation consists of a large number of random replicates (possible results) for several output variables and for several future time points (see Figure 3 to get an idea), which implies the need for sophisticated analysis and presentation techniques in order to be able to draw sensible conclusions from the results.

The first step in the analysis procedure consists of selecting a number of sensible output variables, where the term «sensible» is always relative to the goals of the study. Typical examples include earnings before or after interest and tax, or the level of shareholders' equity. Besides such economic target variables, it may be sensible to compute at the same time certain regulatory values, e.g. the IRIS ratios in North America (see [8]), by which one can assess whether a strategy is consistent with in-force regulations. More information on the selection of target variables is given in [10].

Once the target variables are selected, there still remains the task of analyzing the large number of random replicates: suppose that Y is one of the target variables, e.g. shareholders' equity, then, the DFA simulation provides us with random replicates $y_1, \dots y_N$, where N is typically high.

The most common approach is to use statistical analysis techniques. The most general one is to analyze the full empirical distribution of the variable, i.e. to compute and plot

$$\hat{F}_Y(y) = \frac{1}{N}\sum_{k=1}^{N} 1(y_k \le y)$$

Figure 4 shows an example, together with some of the measures discussed below. For comparison and for making decisions, it is more desirable to characterize the result distribution by some particular numbers, that is, by values characterizing the average level and the variability (the riskiness) of the variable. For the average value, one can compute the empirical mean:

$$\hat{\mu}(Y) = \frac{1}{N}\sum_{k=1}^{N} y_k$$

For measuring the riskiness, the choice is less obvious. The most classical measure is the empirical standard deviation:

$$\hat{\sigma}(Y) = \left(\frac{1}{N-1}\sum_{k=1}^{N}(y_k - \hat{\mu})^2\right)^{\frac{1}{2}}$$

The standard deviation is a double-sided risk measure – it takes into account equally deviations to the upside as well as to the downside. In risk management, however, one is more interested in the potential downside of the target variable. A very popular measure for downside risk is the *Value-at-Risk (VaR)*, which is simply the p-quantile for the distribution of Y for some probability $0 < p < 1$. It is easily computed as

$$\widehat{VaR}_p(Y) = \min\left\{ y_{(k)} : \frac{k}{N} > p \right\}$$

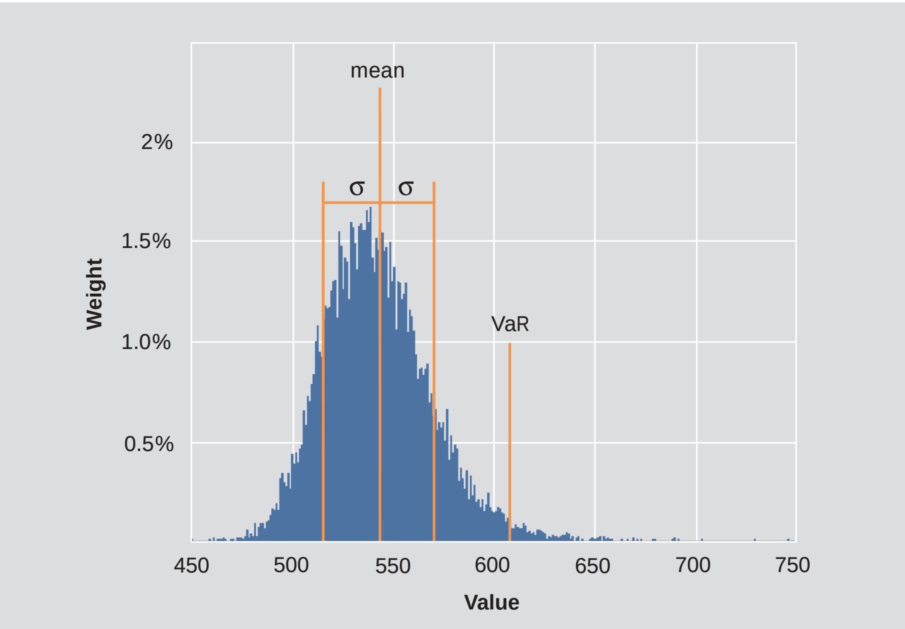
where $y_{(k)}$ is the k-th order statistic of $y_1, \dots, y_N$. Popular risk measures from the realm of actuarial science include, for example, Expected Policyholder Deficit, twisted means or Wang and Esscher Transforms (see [10] and [9] for more details). Another downside risk measure, extending the already introduced VaR, is the *TailVaR*, defined as

$$TailVaR_p(Y) = \mathrm{E}\left(Y \mid Y \ge VaR_p(Y)\right)$$

which is the expectation of Y given that Y is beyond the VaR-threshold, and which can be computed very easily by averaging over all replicates beyond VaR. The particular advantage of TailVaR is that – contrary to most other risk measures including VaR and standard deviation – it belongs to the class of *Coherent Risk Measures* (see [1] for full details). In particular, we have that

$$TailVaR_p(Y+Z) \le TailVaR_p(Y) + TailVaR_p(Z)$$

Figure 4 A P&L distribution and some measures of risk and reward



i.e. diversification benefits are accounted for. This aggregation property is particularly desirable if one analyzes a multi-line company, and one wants to put the results of the single lines of business in relation with the overall result. Another popular approach, particularly for reporting to the senior management, is to compute probabilities that the target variables exceed certain thresholds, e.g. for bankruptcy; such probabilities are easily computed by

$$\hat{p} = \frac{1}{N} \sum_{k=1}^{N} 1(y_k \geq y_{threshold})$$

In a multi-period set-up, measures of risk and reward are usually computed either for each time period $t_0 + n\Delta t$ individually, or only for the terminal time T (see Figure 5). An important caveat to be accounted for in this set-up is that the target variable may temporally assume values that correspond to a disruption of the ordinary course of business, e.g. ruin or regulatory intervention (see again Figure 5). Such degenerate trajectories have to be accounted for in suitable ways, otherwise the terminal results may no longer be realistic.

By repeating the simulation and computing the target values for several different strategies one can compare these strategies in terms of their risks and rewards, determine ranges of feasible and attainable results and, finally, select the best among the feasible strategies. Figure 6 shows such a comparison, conceptually very similar to risk-return analysis in classical portfolio theory. It is, however, important to note that DFA does not normally allow for the use of formal optimization techniques (such as convex optimization), since the structure of the model is too irregular. Rather, the optimization consists of educated guesses about potentially better strategies, and the subsequent evaluation of them through new simulation runs. Such repeated simulation runs with different strategy settings (or with different calibrations of the scenario generator) are often used for exploring the sensitivities of the business to strategy changes or to changes in the environment, i.e. for exploring relative rather than absolute impacts in order to see whether strategic actions do actually have a substantial leverage.

An alternative to this statistical type of analysis is drill-down. This consists of identifying particularly interesting (in whatever sense) output values y_k, to identify the input scenarios x_k that gave rise to them, and then to analyze the characteristics of these input scenarios. This type of analysis requires the storage of massive amounts of data, and doing sensible analysis on the usually high-dimensional input scenarios is not simple.

More information on analysis and presentation can be found in the related chapter of [10], or, for techniques more closely related to financial economics, in [7].

Figure 5 Evolution of expected surplus and expected shortfall over time

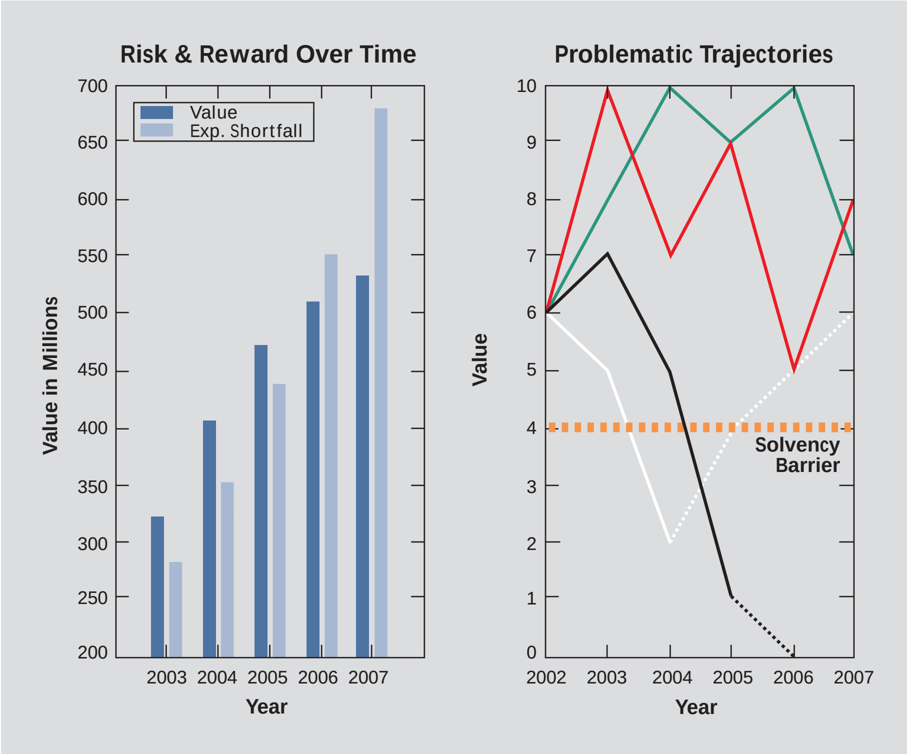
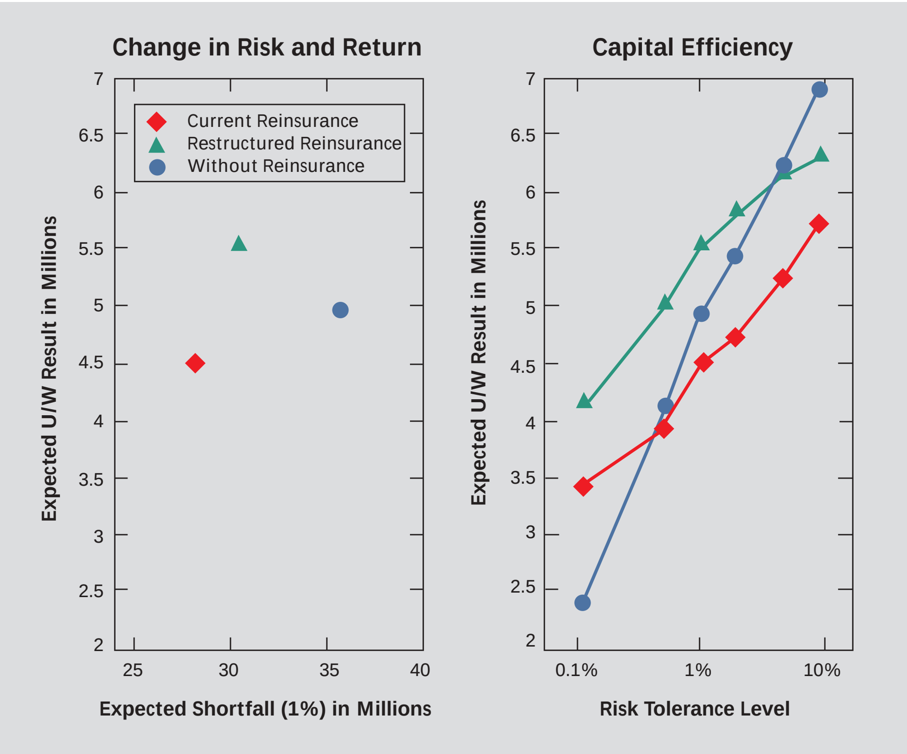


Figure 6 Evaluations of risk vs. return



There are a number of companies in the market that offer software packages or components for DFA, usually in conjunction with related consulting services (recall from the beginning of this section that DFA is not only a software package, but rather a combination of software, processes and skills). In general, one can distinguish between two types of DFA software packages:

1. Flexible, modular environments that can be adapted relatively quickly to different company structures, and that are mainly used for addressing dedicated problems, usually the structuring of complex reinsurance programs or other deals.

2. Large-scale software systems that model a company in great detail and that are used for internal risk management and strategic planning purposes on a regular basis, usually in close connection with other business systems.

Examples for the first kind of DFA software include Igloo® by Paratus Consulting[9] and Remetrica® II by Benfield Group[10]. Examples for the second kind of DFA systems include Finesse 2000® by SS&C[11], the general insurance version of Prophet by B&W Deloitte[12], TAS P/C® by Tillinghast[13] or DFA by DFA Capital Management Inc[14]. Dynamo[15] is a freeware DFA software based on Excel. It belongs to the second type of DFA software and is actually the practical implementation of [8]. An example of a DFA system for rating agency purposes is [2]. Moreover, some companies have proprietary DFA systems that they offer to customers in conjunction with their consulting and brokerage services, examples including Guy Carpenter[16] and AON[17].

[9] URL: http://www.paratusconsulting.com
[10] URL: http://www.benfieldgreig.com
[11] URL: http://www.ssctech.com
[12] URL: http://www.bw-deloitte.com
[13] URL: http://www.towers.com
[14] URL: http://www.dfa.com
[15] URL: http://www.pinnacleactuaries.com
[16] URL: http://www.guycarp.com
[17] URL: http://www.aon.com

4. Uses of DFA

In general, DFA is used to determine how an insurer might fare under a range of future possible environmental conditions and strategies. Here, environmental conditions are topics that are not under the control of management, whereas strategies are topics that are under the control of management. Typical strategy elements whose impact is explored by DFA studies include:

Business mix:
relative and absolute volumes in different lines of business, premium and commission levels, etc.

Reinsurance:
structures per line of business and on the entire account, including contract types, dependencies between contracts, parameters (quotas, deductibles, limits, reinstatements, etc.), cost of reinsurance.

Asset allocation:
normally only on a strategic level; allocation of the company's assets to the different investment asset classes, overall or per currency; portfolio re-balancing strategies.

Capital:
level and structure of the company's capital; equity and debt of all kinds, including dividend payments for equity, coupon schedules and values, redemption and embedded options for debt, allocation of capital to lines of business, return on capital.

The environmental conditions that DFA can investigate include all those that the scenario generator can model; c.f. Section 3. The generators are usually calibrated to the best estimates of future behavior of the risk factors, but one can also use conscious miscalibrations in order to investigate the company's sensitivity to unforeseen changes. More specifically, the analysis capabilities of DFA include:

Profitability:
this can be analyzed on a cash flow basis or on a return-on-capital basis. DFA allows one to measure profitability per line of business or for the entire company.

Solvency:
DFA allows one to measure the solvency and the liquidity of the company or parts of it, be it on an economic or statutory basis. DFA can serve as an early warning tool for future solvency and liquidity gaps.

Compliance:
A DFA company model can implement regulatory or statutory standards and mechanisms. In this way, the compliance of the company with regulations, or the likelihood of regulatory interventions, can be assessed. Besides legal ones, the standards of rating agencies are increasingly important to insurers.

Sensitivity:
One of the most important virtues of DFA is that it allows one to explore the company's reaction to a change in strategy (or also a change in environmental conditions) relative to the situation where the current strategy pertains also to the future.

Dependency:
Probably the most important benefit of DFA is that it allows one to discover and analyze dependencies of all kinds that are hard to grasp without a holistic modeling and analysis tool. A very typical application here is to analyze the interplay of assets and liabilities, i.e. the strategic asset/liability management («ALM»).

These analytical capabilities can then be used for a number of specific tasks, either on a permanent basis or for one-time dedicated studies of special issues. If a company has set up a DFA model, it can recalibrate and rerun it on a regular basis, quarterly or yearly, in order to evaluate the in-force strategy and possible improvements to this strategy. In this way, DFA can be an important part of the company's business planning and enterprise risk management set-up. On the other hand, DFA studies can also be made on a one-time basis if strategic decisions of great significance are to be made. Examples of such decisions include mergers and acquisitions, entry into or exit from a business, thorough rebalancing of reinsurance structures or investment portfolios, or capital market transactions. Basically, DFA can be used for assessing any strategic issues that affect the company as a whole. However, the exact purpose of the study has some drawbacks regarding the required structure, degree of refinement or time horizon of the DFA study (particularly the company model and the scenario generator).

The main users of DFA are insurance and reinsurance companies themselves. They normally use DFA models on a permanent basis as a part of their risk management and planning process; [21] describes such a system. DFA systems in this context are usually of substantial complexity, and only their continued use justifies the substantial costs and efforts of their construction. Other types of users are consulting companies and brokers who use dedicated – usually less complex – DFA studies for special tasks, such as the structuring of large and complicated deals. An emerging class of users are regulatory bodies and rating agencies who normally set up relatively simple models that are general enough to fit into a broad range of insurance companies and that allow them to regulate or rate in a quantitatively more sophisticated, transparent and standardized way (see [2]). A detailed account of the most important uses and users of DFA is given in [10], and some new perspectives are outlined in [15].

5. Assessment and Outlook

In view of developments in the insurance markets as outlined in Section 2, the approach taken by DFA is undoubtedly appropriate. DFA is a means of addressing those topics that really matter in the modern insurance world, particularly the management of risk capital and its structure, the analysis of overall profitability and solvency, cost-efficient integrated risk management aimed at optimal bottom line impact, and the addressing of regulatory, tax and rating agency issues. Moreover, DFA takes a sensible point of view in addressing these topics, namely a holistic one that makes no artificial separation of aspects that actually belong together.

The genesis of DFA was driven by the industry rather than academia. The downside of this very market-driven development is that many features of the DFA systems in use lack a certain scientific soundness: modeling elements that work well each one for itself are composed in an often ad-hoc manner, the model risk is high because of the large number of modeled variables, and company models are structured along the lines of accounting rather than economic value creation. So, even though DFA fundamentally does the right things, there is still considerable space and need for improvement in the way DFA does these things.

We conclude this presentation by outlining some DFA-related trends for the near and mid-term future. We expect, overall, that company-level effectiveness will remain the main yardstick for managerial decisions in the future. Though integrated risk management is still a vision rather than a reality, the trend in this direction will certainly prevail. Technically, Monte Carlo methods have become ubiquitous in quantitative analysis, and will remain so, since they are easy to implement and handle, and they allow for an easy combination of models. The easy availability of ever more computing power will make DFA even less computationally demanding in the future. We also expect models to become more sophisticated in several ways:

In the future the focus will be on economic value creation rather than simply mimicking the cash flow structures of the company. However, substantial fundamental research still needs to be done in this area (see [14]). A crucial point will be to incorporate managerial flexibility into the models in order to make projections more realistic. Currently, there is a wide gap between DFA-type models as described here and dynamic programming models aimed at similar goals (as described in [19]). In future, a certain convergence of these two approaches can be expected. For DFA, this means that models will have to become more simple. In scenario generation, the proper modeling of dependencies and extreme values (individual as well as joint ones) will be an important issue.

In general, the DFA approach has the potential of becoming the state of the industry for risk management and strategic decision support, but it will only exhaust this potential if the shortcomings discussed here are overcome in the foreseeable future.

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Encyclopedia of Actuarial Science

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