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RISK MANAGEMENT OF A P/C INSURANCE COMPANY SCENARIO GENERATION, SIMULATION AND OPTIMIZATION

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ABSTRACT

A large conglomerate such as a property/casualty insurance firm in this case, can be divided along business boundaries. This division might be along commercial lines, homeowner lines and perhaps across countries. An insurance firm's capital can be interpreted as a buffer that protects the company from insolvency and its inability to pay policyholder losses. Rare events have been simulated over the two divisions of an insurance firm. Different risk measures like conditional value at risk (CVaR) have been implemented into the optimization model. Decomposition methods will be applied in the context of decentralized decision making of a multi-divisional firm.

1 INTRODUCTION

In the context of risk management, the primary decision variables entail three elements – asset and liability decisions, under a range of stochastic scenario system. The insurance arena has several advantages. The scenarios have been well vetted and are employed on a routine basis for important decisions such as pricing hurricane insurance; there are several leading companies supplying these scenarios of losses (RMS, AIR, EQECAT, see SwissRe (2002) for further discussion); and the loss distributions are highly skewed – extremely large losses possible with minute probabilities discussed in Berger, Mulvey and Nish (1998). Large global insurance companies can be analyzed via decentralized optimization to reduce the enterprise risks and to improve the company's portfolio of businesses. The topic of integrated risk management has several names, depending upon the application:

1. Asset and Liability Management in banks and pension plans,
2. Enterprise Risk Management for non-financial companies,
3. Dynamic Financial Analysis called DFA for insurance companies.

See Laster and Thorlacius (2000), Lowe and Stanard (1996), Mango and Mulvey (2000), Cariño et al. (1994), Mulvey et al. (2000) for applications of DFA. Also, see Boender (1997), Consigli and Dempster (1998) for applications in other financial domains. The insurance portfolio manager and the underwriter require sophisticated analytical tools to achieve enterprise goals. For example, the insurance portfolio manager needs to understand the effects of adding an additional account to the business line.

A developed decision support system, called SmartWriter answers these questions for one application area, the catastrophe property business. SmartWriter employs data from earthquake and hurricane modeling systems to show the effects of adding a new account or subtracting an existing account from the current portfolio. In addition, SmartWriter optimizes the portfolio composition to produce a portfolio meeting user-specified characteristics. See references Berger et al. (1998) for details (Also see Wallace (2001) for generating scenarios over a stochastic programming tree and Boender (1997), Kouwenberg (2001) and Cariño and Ziemba (1998) for different scenario-generation methods).

In the light of Berger et al. (1998), insurance companies can also be analyzed within the DFA context to reduce the enterprise risks and to improve the company's businesses. The insurance portfolio manager and underwriter require sophisticated analytical tools to assist decision-making.

The insurance portfolio manager needs to understand the effects of adding an additional account to the business line. In addition, there are many other issues the manager must address, such as: (1) Should an existing account be renewed and, if so, at what price? (2) Where are the best areas to expand the current portfolio? (3) How can two books of business be merged profitably?

The developed decision support system, called SmartWriter answers these questions for one application area, the catastrophe property business. SmartWriter employs data from earthquake and hurricane modeling systems to show the effects of adding a new account or subtracting an existing account from the current portfolio. In addition, SmartWriter optimizes the portfolio composition to produce a portfolio meeting user-specified characteristics.

Suppose there is a portfolio of insurance liabilities. As an example, Berger et al. (1998) consider a portfolio of commercial businesses insured against earthquakes in California by St. Paul, a large property and casualty insurance company. A potential new piece of business is presented to the portfolio manager, who must decide whether to write the account or reject it. Of course, some negotiating with the insurance broker who presents the account is possible, so the portfolio manager would also like to know the required premium to meet a profitability hurdle. Before analyzing the incremental business, there is a need to define a profitability measure for the existing portfolio. Two measures are return on allocated capital and expected utility (see Bell (1995) for an example). Their comparison is summarized in Table 1. Table 2 displays the analysis.

Table 1: Compare Allocated Capital & Exp. Utility

	Advantages	Disadvantages
Allocated Capital	-Easy to explain	-Extra work to sort discrete distributions
	-Returns have intuitive meaning	-Limited points on loss distribution
Expected Utility	-Handle entire loss distribution at once	-Hard to determine utility function
	-Convex math program	-Results not intuitive

Table 2: New Account Analysis, Numbers ($000)

	Current Portfolio	New Account	Combined
Premium	$98	$3,800	$4,780
Expenses	$294	$1,140	$1,434
Expected Cat Loss	$71	$615	$686
Expected Profit	$615	$2,045	$2,660
Loss at 99^{th}%= $F^{-1}(0.99)$	$5,200	$14,300	$18,100
Capital Required	$4,200	$11,600	$14,700
Return on Capital (ROC)	14.6%	17.6%	18.1%
Return on Marginal (ROMAC)	19.8%		

There is a SmartWriter analysis (Table 2) of an account recently offered to St. Paul's commercial property business. The SmartWriter output is divided into three columns. The first column is the new account as a stand-alone business. The expected income for the account, after taking expenses and expected catastrophe losses from the premium, is $615,000. The new account requires $4,200,000 in capital based on the 1-in-100 year loss of $5,200,000. This yields a return of 14.6%, which is below our hurdle rate of 15%.

The second column contains data on the portfolio as it stands today, and the final column is the portfolio performance if the new account were added. The capital requirement for the combined portfolio is less than the sum of the new account and current portfolio capital: This indicates that the new account will diversify the business to some extent. Two additional items help quantify this diversification. The return on marginally allocated capital (ROMAC) for the new account is 19.8%, which means that the marginal return for adding the account divided by the marginal capital is significantly over the hurdle rate. The second item is the increase in the return on capital (ROC) for the portfolio from 17.6% to 18.1% if the account is added. For these reasons, the account was considered a good prospect, even though on a stand-alone basis it was slightly below the hurdle rate.

For a portfolio of large commercial accounts, the optimizer could locate the five accounts most in need of repricing, or the subset of the current portfolio that maximizes return. For a homeowners portfolio, the book of business is managed less on a home-by-home basis and more on a zip code, county, or state level; the optimizer can focus on which counties to expand market penetration and which zip codes to reduce premium volume.

The variables and the objective function are defined as follows. Define the following sets:

{1, 2, … N} – set of accounts in the portfolio

{1, 2, … S} – set of loss scenarios.

Define the following input parameters:

p_i = premium for account i

e_i = non-catastrophe expense for account i

l_{is} = loss (in dollars) for account i in scenario s

π_s = probability of scenario s

ρ = discount factor.

Define the following decision variables:

x_i, i=1,…,N – amount of account i in the portfolio.

The objective is to maximize expected return on capital

$$\text{Max} \frac{\sum_{s=1,S}\sum_{i=1,N} \Pi_s (x_i \; (p_i \; - \; e_i \; - \; l_{is}))}{\left(\rho F^{-1}(0.99) - \sum_{i=1,N} x_i (p_i - e_i)\right)} \tag{1}$$

where $F^{-1}(0.99)$ is calculated from the revised loss distribution $x_i{*}l_{is}$. Correlations are implicitly captured in the analysis. Since the entire loss distribution is calculated for the objective function, the correlation among accounts will affect the return on capital.

The following constraints can be added to the model. An account can either be in the portfolio or out of the portfolio so we add a binary constraint $x_i \in \{0,1\}$.If one or more properties must be retained, then $x_i = 1$.

The total premium for the portfolio must exceed a specified level, MinPrem:

$$\sum_{i=1,N} x_i p_i \geq \text{MinPrem}. \tag{2}$$

The expected income on the portfolio cannot be reduced past a specified level, MinInc:

$$\sum_{i=1,N} \left(x_i \left(p_i - e_i - l_{is} \right) \right) \geq \text{MinInc}. \tag{3}$$

Below is the SmartWriter output for a California earthquake portfolio with 173 accounts (Berger et al. (1998)). The results are from an actual company data, but the numbers have been disguised to protect client confidentiality. The optimizer recommended the removal of 16 accounts from the portfolio. Table 3 shows summary information before and after the optimization for the portfolio as a whole.

On the whole, this was a profitable book of business, but there were a small number of relatively poorly performing accounts. Not only did these accounts have a poor expected return, but also they had a severe effect in the tail of the distribution. Expected income only decreased by \$100,000 (3%), but the loss at the 99^{th} percentile decreased by over \$15M. Return on capital jumped from 14.7% to 37.5%. We have seen this with other books of business as well: a small percentage of accounts represent a large portion of the tail of the loss distribution.

Table 3: Portfolio Before-After Optimization

	Portfolio Today	Optimized Portfolio
Number of accounts	173	157
Premium	\$5,600	\$5,200
Expenses	\$1,700	\$1,600
Expected Cat Loss	\$500	\$300
Expected Income	\$3,400	\$3,300
Loss at 99%=$F^{-1}(0.99)$	\$28,600	\$12,900
Capital Required	\$23,200	\$8,800
Return on Capital(ROC)	14.7%	37.5%

Ideally, the portfolio manager should reprice these accounts upon renewal instead of terminating them. Although market conditions will determine the extent to which this is feasible, SmartWriter provides output on all the accounts targeted by the optimizer. Table 4 contains information for one of these accounts.

Table 4: Acc.Targeted for Removal/Repricing

	Account A
Premium	\$20
Expenses	\$6
Expected Cat Loss	\$12
Expected Profit	\$2
Loss at 99^{th}%=$F^{-1}(0.99)$	\$780
Capital Required	\$740
Return on Capital (ROC)	0.3%
Return on Marginal (ROMAC)	0.4%
Premium needed to meet 15% ROC hurdle	\$150
Premium needed to meet 15% ROMAC hurdle	\$145

For this example, the premium needed to meet the stand-alone return on capital hurdle of 15% is \$150,000, much greater than the current premium of \$20,000. Repricing is most likely not an option for this account, but for examples where the current ROC is closer to the hurdle rate, repricing can be viable.

While applying the SmartWriter analysis, we have in mind that multi-normal distributions cannot be used, even as crude approximations, and the risk adjusted return on capital (RAROC) methods will have problems with estimating the rare events across the divisions. The scenario set approach should improve decision-making; this hypothesis should also be tested.

We will mention a two-divisional optimization model of a p/c insurance company where both divisions are simulated over the same scenario set generated by the SmartWriter.

The large-scale optimization literature (Baumol et al. 1964, Bradley et al. 1977, Dantzig and Wolfe 1961) will be applied to maintain the privacy of the information within the specific divisions and to increase the profit of the whole company by watching out the performance of the divisions simulated over the same batch of scenarios.

First, we will discuss the need of decentralization and the advantages and drawbacks of DFA and DQA algorithms.

Next, we will introduced the centralized model and the multi-divisional optimization model to which the decentralized algorithms will be applied throughout our research.

Lastly, we will refer two the implementation of the conditional value at risk (CVaR) to the optimization model as a coherent risk measure(Artzner et al. 1999).

2 DFA, DQA AND DECENTRALIZED OPTIMIZATION

Dynamic financial analysis (DFA) provides a tool to analyze various business strategies and risk/return structures within enterprise-wide planning systems. DFA aims at maximizing the shareholder value and tracking the free cash flow over the time.

Leading insurance and reinsurance companies have begun applying DFA, in order to increase profitability, reduce enterprise risks, and identify the optimal capital structure of the firm.

DFA process should analyze the financial status of an insurance enterprise, namely the ability of the firm's capital and earnings path to adequately support its future operations in light of stochastic external factors affecting the enterprise.

A DFA model should combine the asset/liability structure of the enterprise and dynamic optimization of the strategies together with the headquarter decisions. A DFA system consists of three major elements: a stochastic scenario generator (also see Wallace (2001) for generating scenarios over a stochastic programming tree and see Boender (1997) and Kouwenberg (2001) for different scenario-generation methods), a multi-period simulator and an optimization module displayed in Figure 1.

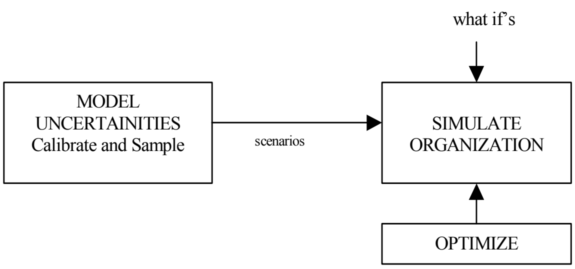

Figure 1: Optimization Module is One of the Major Components of the DFA System.

Linking the assets and liabilities in a consistent fashion requires modeling the driving factors. The factor models are well placed to support DFA displayed in Figure 2.

DFA is described further in Mulvey, Pauling, Britt and Morrin (2003). We discuss the scenario tree in Figure 3.

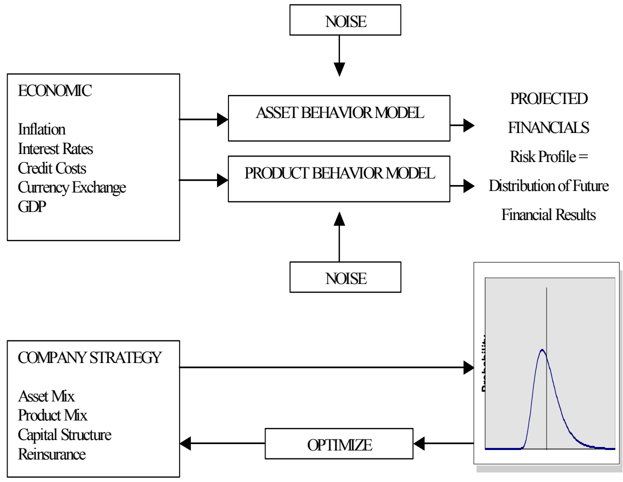

Figure 2: DFA Factor Models

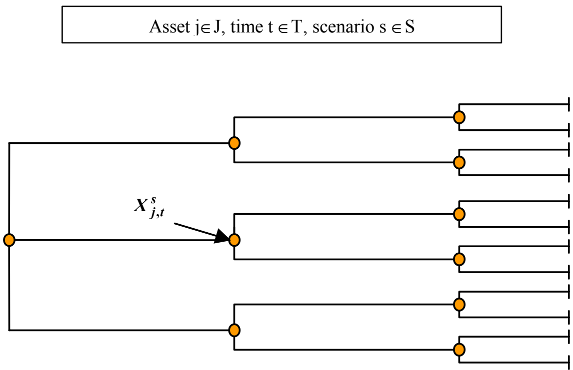

Figure 3: Scenario Tree

Considering these external dynamic factors the scenario tree is built up. A fundamental issue in the area of stochastic programming is the selection of the scenario set. Figure 4 visualizes the centralized DFA model of a large-scale enterprise:

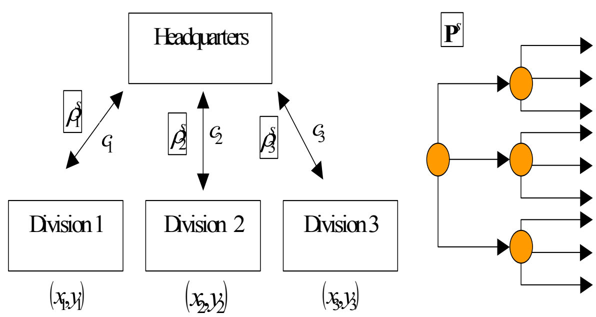

Figure 4: Centralized DFA Scheme

Many alternative large-scale algorithms have been developed and tested for computational efficiency. However, the standard risk management approach employs capital allocation concepts. Thus the first research task will be to adapt the optimization algorithms for managing a large decentralized organization. Previous work on decomposition, for example, involves solving stochastic programs(Birge and Louveaux 1997, Dantzig and Infanger 1993). But again, these approaches have not formed the basis for decentralized decision-making under uncertainty within large financial organizations. Three of the leading optimization approaches (Dantzig-Wolfe, Benders decomposition, and augmented Lagrangian methods (Bertsekas 1982) such as the DQA algorithm) will be evaluated on several dimensions.

The DW method is compatible with common practice as dictated by the aforementioned capital allocation procedure. However, this method must be adapted for the multi-scenario formulation (for risk management). We call the resulting algorithm – state price coordination in order to emphasize the nature of the information that is transmitted across the organization. The process goes as follows: the headquarters sends out capital to each division based on a rough estimate of the division's projected risks. (Actual capital may be transferred in certain cases such as legal entities (private companies), or the capital is a device for protecting the organization. In addition, the headquarters must transmit the state prices for each scenario.

For instance, we will study their acceptance by senior management and other decision makers in the organization. As most current methods rely on capital allocation, we must be able to project the state prices onto this fundamental mechanism and extend it, if the algorithms are to be accepted in a practical context.

In addition, we will research the convergence properties of the decentralized algorithms under a variety of risk measures. There is no general agreement regarding a proper definition of risks; many alternative metrics have been proposed and compared. See Artzner et al. (1999) for a sample. In some cases, the corresponding optimization model will result in a non-convex optimization problem, such as Value at Risk.

3 RISK MANAGEMENT IN INSURANCE ARENA

The risk management can be implemented in a centralized fashion where the optimization takes the company as a single entity into consideration. However the need for coordination across divisional boundaries in order to improve the efficiency of large financial organizations suggests a planning in the division level. So that the optimization model is consistent with current managerial procedures, we will divide the model into subproblems along divisional structures. Figure 5 displays the coordination among headquarters and divisions.

Importantly, all of the divisions are given the same set of scenarios. A two division model has been proposed in Mulvey and Erkan (2003a) where the optimization solution consists of the optimal capital allocation to the divi-

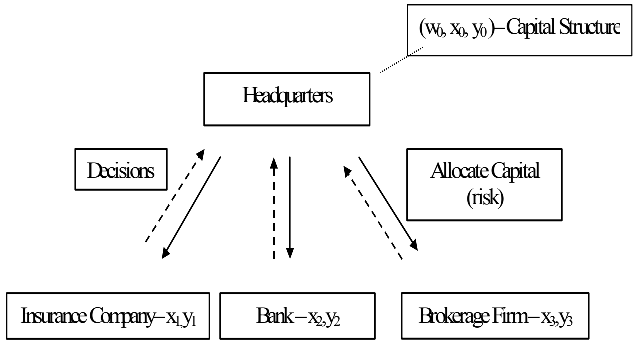

Figure 5: Coordination Among Headquarters and Divisions - The Headquarters Decide on the Capital allocation and the asset-liability management of the company

sions and the optimal investment strategies of the two divisions so that after the investment horizon, the whole company is better off.

In Mulvey and Erkan (2003a), we interpret the problem as a utility maximization of the certainty equivalent for an insurance firm with two divisions. There are 216 accounts to invest and 50,000 scenarios for uncertain losses associated with each account. The loss data for each account is generated by the SmartWriter. There are two levels of decision-making – headquarter and division. The centralized decision-making model allows only the headquarters to decide on the accounts to be invested and on the leverage. This large-scale convex programming problem is solved and analyzed numerically by using the software LOQO.

The whole firm is modeled as a single entity as follows. The maximization of the expected utility of ending capital forms the objective function in the convex programming formulation of the centralized model (4). Definitional constraints set up the initial capital and the ending capital in terms of borrowings and investments.

$$
\begin{aligned}
&\text{Maximize} \quad \sum_s \Pi_s * z_s - f_1 * \exp(-f_2 * \sum_s \Pi_s * z_s) \\
&\text{subject to:} \\
&x - w - \sum_a p_a * y_a = c \\
&z_s = (1+r) * x - (1+b) * w - \sum_a l_a^s * y_a \qquad \forall s \in \text{scen} \\
&x \le k * c \\
&0 \le w \le f * c \\
&0 \le y_a \le 1 \qquad \forall a \in \text{acc}
\end{aligned} \tag{4}
$$

The objective function in (4) maximizes the utility from the certainty equivalent of the capital at the end of the investment horizon with respect to the losses in each scenario. The first constraint equates the initial asset to the sum of the amount borrowed and the return of the investments at the beginning of the time period. The second batch of constraints imply that the ending capital is calculated by subtracting the amount borrowed with the interest on it and the losses with respect to each scenario from the initial asset together with the return on it. We also have the constraint setting the asset-capital ratio to k. Other than that, we limit the amount to borrow by a factor f times the initial capital we start with.

The last constraint sets the bounds to the fraction we can invest in each account. However in the decentralized optimization, the initial capital of the firm will be allocated to each of the divisions and being the capital allocation a variable itself allows defining the initial assets as two distinct variables for each division.

Moreover the divisions will invest into the accounts mutually exclusively. Each division can only invest in a certain number of accounts. It is totally the division's decisions how much in which account to invest and how much to borrow. In that manner each division can decide on its own strategies and the capital allocation should not exceed the initial capital of the firm.

Proceeding with the decentralization at the division level (5) , the objective function is still the maximization of the utility of the certainty equivalent. Different from the centralized model, we define seperate variables for the initial asset, amount borrowed, ending capital with respect to the scenarios and fractions invested in each account regarding to both divisions.

The first couple of constraints define the initial assets in terms of amount borrowed and revenues from accounts according to the fractions invested. The second couple of constraints calculate the ending capital by taking the account losses with respect to the scenarios into account. The amount borrowed cannot exceed k multiple of capital allocated to that division.

The capital allocation should adapt to the initial capital the company starts with. We have the upper and lower bounds for the amount borrowed in total and the fractions invested in each account. In the convex programming formulation of the decentralized model each division decides on its own asset-liability management by watching out the complicating resource constraints.

The capital allocation is one of major outputs of the decentralized model (see Mulvey and Erkan (2003a) for convergence and numerical experimentation). The decomposition will be utilized to simulate the divisions through the same set of scenarios and to come up with better capital allocation and risk management consequences. That is a stochastic simulation where we consider all of the 50,000 scenarios in the earthquake context. The losses in this area display highly skewed distributions with enormous consequences. Thus, multi-normal distributions cannot be used, even as crude approximations, and the RAROC methods will have problems with estimating the rare events across the divisions.

$$
\begin{aligned}
&\text{Maximize } \sum_s \Pi_s (z_s^1 + z_s^2) - f_1 \exp(-f_2 \sum_s \Pi_s (z_s^1 + z_s^2)) \\
&\text{subject to:} \\
&x_1 = w_1 + c_1 + \sum_{a_1 \in Acc_1} p_{a_1} y_{a_1}^1 \\
&x_2 = w_2 + c_2 + \sum_{a_2 \in Acc_2} p_{a_2} y_{a_2}^2 \\
&z_s^1 = (1+r)x_1 - (1+b)w_1 - \sum_{a_1 \in Acc_1} l_{a_1}^s y_{a_1}^1 \quad \forall s \in \text{scen} \\
&z_s^2 = (1+r)x_2 - (1+b)w_2 - \sum_{a_2 \in Acc_2} l_{a_2}^s y_{a_2}^2 \quad \forall s \in \text{scen} \\
&x_1 \le k * c_1 \\
&x_2 \le k * c_2 \\
&c_1 + c_2 = c \\
&0 \le w_1 + w_2 \le f * c \\
&0 \le y_{a_1}^1 \le 1 \qquad \forall a_1 \in acc_1 \qquad (5) \\
&0 \le y_{a_2}^2 \le 1 \qquad \forall a_2 \in acc_2 \\
&0 \le w_1 \\
&0 \le w_2
\end{aligned}
$$

4 OPTIMIZATION USING CVAR AS A COHERENT RISK MEASURE

CVaR is a risk measure with significant advantages compared to VaR and is an excellent tool for risk management (see Rockafellar and Uryasev (2000) and also Rockafellar and Uryasev (2001)). It has a parallel in Expected Policyholder Deficit or EPD that uses expected loss as its base, expressing the target deficit as a percentage of expected loss. The paper by Mango and Mulvey (2002) discusses the merits and weaknesses of different risk measures.

Similar measures as CVaR have been analyzed earlier in the stochastic programming literature, although not in financial mathematics context. The reader interested in other applications of optimization techniques in finance area can find relevant papers in Ziemba and Mulvey (1998).

Artzner et al. (1999) presents and justifies a set of four desirable properties for measures of risk, and calls the measures satisfying these constraints "coherent". Especially the sub-additivity property of CVaR makes this risk measure indispensable for decentralized risk management involving multiple divisions and headquarters. CVaR is considered as a more consistent measure than VaR. CVaR supplements the information provided by VaR and calculates the quantity of the excess loss. Since CVaR is greater than or equal to VaR, portfolios with a low CVaR also have a low VaR. Under quite general conditions, CVaR is a convex function with respect to positions (see Rockafellar and Uryasev (2000)), allowing the construction of efficient optimization algorithms.

In particular, it has been shown in Rockafellar and Uryasev (2000) that CVaR can be minimized using linear programming (LP) techniques. A simple description of the approach for minimization of CVaR and the optimization problems with CVaR constraints can be found in Uryasev (2000).

The optimization problem with CVaR constraint for the insurance company is formulated below:

$$
\begin{aligned}
&\text{Maximize} \quad \sum_s \Pi_s (z_s^1 + z_s^2) \\
&\text{subject to:} \\
&\zeta + \upsilon \sum_s q_s \le B \\
&\upsilon = \frac{1}{((1-\alpha)ns)} \qquad ns := \text{ total number of scenarios} \\
&q_s \ge -(z_s^1 + z_s^2) - \zeta \\
&q_s \ge 0 \qquad \forall s \in \text{scen} \\
&x_1 = w_1 + c_1 + \sum_{a_1 \in Acc_1} p_{a_1} y_{a_1}^1 \\
&x_2 = w_2 + c_2 + \sum_{a_2 \in Acc_2} p_{a_2} y_{a_2}^2 \\
&z_s^1 = (1+r)x_1 - (1+b)w_1 - \sum_{a_1 \in Acc_1} l_{a_1}^s y_{a_1}^1 \quad \forall s \in \text{scen} \\
&z_s^2 = (1+r)x_2 - (1+b)w_2 - \sum_{a_2 \in Acc_2} l_{a_2}^s y_{a_2}^2 \quad \forall s \in \text{scen} \\
&x_1 \le k * c_1 \\
&x_2 \le k * c_2 \\
&c_1 + c_2 = c \\
&0 \le w_1 + w_2 \le f * c \\
&0 \le y_{a_1}^1 \le 1 \qquad \forall a_1 \in acc_1 \\
&0 \le y_{a_2}^2 \le 1 \qquad \forall a_2 \in acc_2 \\
&0 \le w_1 \\
&0 \le w_2
\end{aligned}
\tag{6}
$$

In the optimization model (6), B designates the maximum tolerance set for the CVaR constraint. The optimization model is solved for different upper bounds on CVaR. By solving the model, we find the optimal investment strategy, the optimal capital allocation, corresponding VaR, which equals to the optimal ζ^*, and the CVaR.

See Mulvey and Erkan (2003b) for the efficient frontiers similar to return-variance analysis and the results.

5 FUTURE WORK

The decentralized model will provide guidance among asset and liability managers (who invest their portion of the overall portfolio). The state prices depict the enterprise risks on a scenario-by-scenario basis. We will currently extending the research to the application of decomposition methods on our multi-divisional optimization model for which the state prices will act as scenario dependent parameters in the objective of divisions optimization.

REFERENCES

Artzner, P., F. Delbean, J. Eber and D. Heath. 1999. Coherent Measures Of Risk. *Mathematical Finance* 9(3): 203-228.

Baumol, W. J. Fabian and T. Fabian. Sep. 1964. Decomposition, pricing for decentralization and external economies. *Management Science* Vol. 11 Issue 1: 1–32.

Bell, D. 1995. Risk, return, and utility. *Management Science* 41: 23-30.

Bertsekas, D. P. 1982. *Constrained Optimization and Lagrange Multiplier Methods.* Academic Press.

Berger, A. J., J. M. Mulvey and K. Nish. Summer 1998. A portfolio management system for catastrophe property liabilities. Casualty Actuarial Society Forum, 1-14.

Birge, J.R. and F. Louveaux. 1997. *Introduction to Stochastic Programming.* Springer-Verlag. New York.

Boender, G. C. E. 1997. A hybrid simulation/optimization scenario model for asset liability management. *European Journal of Operations Research* 99: 126-135.

Bradley, S. P., A. C. Hax and T. L. Magnanti. 1977. *Applied mathematical programming*. Addison-Wesley.

Cariño, Kent T., D. Myers, C. Stacy, M. Sylvanus, A. Turner, K. Watanabe and W. Ziemba. 1994. The Russell-Yasuda Kasai model: an asset liability model for a Japanese insurance company using multi-stage stochastic programming. *Interfaces* 24: 29-49.

Cariño, D.R. and W. T. Ziemba. 1998. Formulation of the Russell-Yasuda Kasai financial planning model. *Operations Research.*

Consigli, G. and M.A.H. Dempster. 1998. Dynamic stochastic programming for asset-liability management. *Annals of Operations Research* 81: 131-161.

Dantzig, G. and G. Infanger. 1993. Multi-Stage stochastic linear programs for portfolio optimization. *Annals of Operations Research* 45: 59-76.

Dantzig, G. B. and P. Wolfe. Oct. 1961. The decomposition algorithm for linear programming. *Econometrica* 29, No. 4.

Kouwenberg, R. 2001. Scenario generation and stochastic programming models for asset liability management. *European Journal of Operations Research* 134: 279-292.

Laster, D. and E. Thorlacius. 2000. Asset-liability management for insurers. *Swiss Re Sigma* 6.

Lowe, S.P. and J. Stanard. 1996. An integrated dynamic financial analysis and decision support system for a property catastrophe reinsurer. CAS Seminar on Dynamic Financial Analysis, Spring CAS Forum.

Mango, D. and J. Mulvey. Summer 2000. Capital adequacy and allocation using dynamic financial analysis. Casualty Actuarial Society Forum.

Mulvey, J. M. and H. G. Erkan. to appear, 2003. Decentralized risk management for global P/C insurance companies. *Handbook on Finance.*

Mulvey, J. M. and H. G. Erkan. submitted, 2003. Applying CVaR for decentralized risk management of financial companies. *Journal of Banking and Finance*.

Mulvey, J. M., B. Pauling, S. Britt and F. Morrin. to appear, 2003. Dynamic financial analysis for multinational insurance companies. *Handbook on Finance*.

Rockafellar R. T. and S. Uryasev. 2000. Optimization of conditional value-at-risk. *Journal of Risk* 2: 21-41.

Rockafellar R. T. and S. Uryasev. 2001. Conditional value-at-risk for general loss distributions. Research Report 2001-5, ISE Depart., University of Florida.

Swiss Re. 2002. Natural catastrophes and man-made disasters in 2001: man-made losses take on a new dimension. *Sigma*, No.1.

Uryasev, S. Feb. 2000. Conditional value-at-risk: optimization algorithms and applications. *Financial Engineering News* 14, 1-5.

Vanderbei, R. B. Optimization and applications website at Princeton University. Available via <www.orfe.princeton.edu/~loqo> [accessed July 1, 2003].

Wallace S. Feb. 2001. Generating scenario trees for multistage problems. *Management Science*, 295-307.

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