A NEW PRACTICAL APPROACH TO ASSET LIABILITY MANAGEMENT FOR BASEL III AND SOLVENCY II

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ABSTRACT

A new practical approach to Asset Liability Management (ALM) is proposed, which combines Monte Carlo Simulation, Optimisation and Six Sigma Define, Measure, Analyse, Improve, Control (DMAIC) methodology. This new method determines an optimally diversified minimal variance investment portfolio, which gains a desired range of return with minimal financial risk. Simulation and optimisation are conventionally applied to find the optimal portfolio to provide the required return. In addition, the Six Sigma DMAIC methodology is used to measure and improve the portfolio management process in order to establish the optimally diversified portfolio. Applying Six Sigma DMAIC to the portfolio management process is an improvement in comparison with conventional stochastic ALM risk models. It offers financial institutions internal model options for Basel III and Solvency II, which can help them to reduce their capital requirements and Value-at-Risk (VaR) providing for higher business capabilities and increasing their competitive position, which is their ultimate objective.

Keywords: Asset Liability Management; Portfolio Optimisation – Minimal Variance; Monte Carlo Simulation; Six Sigma DMAIC; Basel III; Solvency II.

1. INTRODUCTION

Basel III is a comprehensive set of reform measures, developed by the Basel Committee on Banking Supervision, to strengthen the regulation, supervision and risk management of the banking sector. These measures aim to: i) improve the banking sector's ability to absorb shocks arising from financial and economic stress, whatever the source; ii) improve risk management and governance; and iii) strengthen banks' transparency and disclosures (Atkinson and Blundell-Wignall 2010; BCBS 2010a; BCBS 2010b; BCBS 2011; BIS 2011; Cosimano and Hakura 2011).

Solvency II is designed to introduce a harmonised insurance regulatory regime across European Union (EU) that will protect policyholders and minimise market disruption. The regulation sets stronger requirements for capital adequacy, risk management and disclosure. Primarily this concerns the amount of capital that EU insurance companies must hold to reduce the risk of insolvency. Solvency II is an EU Directive, which needs to be approved by the European Parliament, and will be scheduled to come into effect on 1 January 2014 once it is approved (Cruz 2009; Bourdeau 2009; GDV 2005; SST 2004).

The economic capital of financial institutions is one major aspect of Basel III and Solvency II. According to a research by Mercer Oliver Wyman, the impact of the Asset Liability Management (ALM) risk, i.e. Market Risk, on the economic capital of banking and insurance companies is 64%. This is by far the largest impact compared to other quantifiable risk factors, e.g. 27% Operational Risk, 5% Credit Risk, and 4% Insurance Risk. Consequently, this paper will focus on ALM.

ALM has originated from the duration analysis proposed by Macaulay and Redington (Macaulay 1938; Redington 1952). Subsequently, ALM has evolved in a powerful and integrated tool for analysis of assets and liabilities in order to value not only the interest rate risk but the liquidity risk, solvency risk, firm strategies and asset allocation as well (Bloomsbury 2012).

The new regulation requirements introduced by Basel III and Solvency II focus on the solvency risk in order to impose a required amount of equity value on the base of the risk associated to the investments of asset portfolio. The banking and insurance industry are responding to these requirements by developing internal models based essentially on the Value-at-Risk (VaR), parametric (GARCH, EGARCH) and simulation (Monte Carlo) models, extended to Conditional Valueat-Risk (CVaR) and Copulas.

Some financial institutions extended the analysis to the cash flows by using a stress testing to generate different scenarios. In this case it is possible to analyse how the cash flows can evolve to study a strategy to hedge the risk exposure.

The financial institutions with greater equity value have the possibility to invest in riskier assets focussed on the portfolio insurance. The basic idea is to construct a Put option on the value of asset portfolio by taking a long position on the risky assets and on the default-free bonds such that their weight will be rebalanced dynamically, which will replicate the value of a portfolio of risky assets with a protective Put option.

The frontier of Asset and Liability Management is based on stochastic optimisation and simulation models that involve an asset allocation approach by considering the liabilities side as well.

Another major aspect of Basel III and Solvency II is Financial Risk Management. Jorion, in his book for financial risk management, presented the utilisation of Monte Carlo Simulation for options' valuation and VaR calculation. He also generally elaborated on Optimal Hedging applying Optimal Hedge Ratio, i.e. the minimal variance hedge ratio. In addition, he specifically described the application of Optimal Hedging in two important cases such as Duration Hedging and Beta Hedging (Jorion2011).

Advanced Financial Risk models involve optimisation of investment portfolios. The problem of asset allocation for portfolio optimisation was solved by Markowitz in the 1950's. Markowitz applied his meanvariance method in order to determine the minimum variance portfolio that yields a desired expected return (Markowitz 1952; Markowitz 1987).

Also, advanced Financial Risk models are stochastic and use Monte Carlo Simulation. A comprehensive elaboration on general applications of Monte Carlo Simulation in Finance was published by Glasserman (2004). Specifically, an internal Monte Carlo Simulation model for Solvency II (i.e. an ALM – Market Risk simulation model) was presented by Bourdeau (Bourdeau 2009).

Today, Six Sigma is recognized across industries as a standard means to accomplish process and quality improvements in order to meet customer requirements and achieve higher customer satisfaction. One of the principal Six Sigma methodologies is Define, Measure, Analyse, Improve, Control (DMAIC). Six Sigma applications in finace at introductory level were published by Stamatis (Stamatis 2003).

This paper presents a new practical approach to the ALM risk models for Basel III and Solvency II, i.e. the Optimisation-Simulation-DMAIC method. The new Optimisation, method combines Monte Carlo Simulation, and Six Sigma DMAIC methodology. It determines an optimally diversified minimal variance investment portfolio, which gains a desired range of return with minimal financial risk. Optimisation and Simulation are conventionally applied to find the minimal variance portfolio to provide the required return. In addition, the Six Sigma DMAIC methodology is used to measure and improve the portfolio management process in order to establish the optimally diversified portfolio.

Applying Six Sigma DMAIC to the portfolio management process is an improvement in comparison with the conventional stochastic optimisation and simulation ALM risk models. It offers financial institutions internal model options for Basel III and Solvency II, which can help them to reduce their capital requirements and VaR providing for higher business capabilities and increasing their competitive position, which is their ultimate objective.

In order to facilitate this presentation, a very simple ALM risk model is used to demonstrate the method. Only the practical aspects of the ALM risk modelling are discussed. MicrosoftTM Excel® and PalisadeTM @RISK® and RISKOptimizer® were used in the demonstration experiments.

1.1. Related Work

1.1.1. ALM

Mitra and Schwaiger edited a book which brings together state-of-the-art quantitative decision models for asset and liability management in respect of pension funds, insurance companies and banks. It takes into account new regulations and industry risks, covering new accounting standards for pension funds, Solvency II implementation for insurance companies and Basel II accord for banks (Mitra and Schwaiger 2011).

In addition, Adam published a comprehensive guide to Asset and Liability Management from a quantitative perspective with economic explanations. He presented advanced ALM stochastic models for Solvency II and Basel II & III using optimisation and simulation methodologies (Adam 2007).

1.1.2. Six Sigma

Hayler and Nichols showed how financial giants such as American Express, Bank of America, and Wachovia have applied Six Sigma, Lean, and Process Management to their service-based operations by providing specific, real-world examples and offering step-by-step solutions (Hayler and Nichols 2006).

Also, Tarantino and Cernauskas provided an operational risk framework by using proven qualitycontrol methods such as Six Sigma and Total Quality Management (TQM) in financial risk management to forestall major risk management failures (Tarantino and Cernauskas 2009).

2. ALM BY USING THE OPTIMISATION-SIMULATION-DMAIC METHOD

The following sections demonstrate the new method's procedure step-by-step for ALM Risk modelling. Actual financial market data are used in the presentation.

2.1. Problem Statement

The following is a simplified problem statement for the demonstrated ALM risk model.

Determine the optimally diversified minimum variance investment portfolio that yields a desired expected annual return to cover the liabilities. The model should allow the financial institution to reduce their capital requirements and VaR providing for higher business capabilities and increasing their competitive position. The model should help the company to achieve their ultimate objective.

2.2. Calculating Compounded Monthly Return

The monthly returns of four stocks are available for a period of seven years, i.e. 1990-1996 (Table 1). Note that the data for the period July/1990- June/1996 are not shown.

Month	Stock1	Stock2	Stock3	Stock4	
Jan/1990	0.048	-0.01	-0.06	-0.01	
Feb/1990	0.066	0.096	0.037	0.038	
Mar/1990	0.022	0.022	0.12	0.015	
Apr/1990	0.027	-0.04	-0.02	-0.04	
May/1990	0.112	0.116	0.123	0.075	
Jun/1990	-0.02	-0.02	-0.04	-0.01	
Jul/1996	0.086	-0.07	-0.12	-0.02	
Aug/1996	0.067	0.026	0.146	0.018	
Sep/1996	0.089	-0.03	-0.04	0.092	
Oct/1996	0.036	0.117	0.049	0.039	

Table 1: Monthly Return (MR)

The Compounded Monthly Return (*CMR*) is calculated for each month and each stock from the given stock Monthly Return (*MR*) using the following formula (Table 2):

CMR = ln (1 + MR)

Table 2: Compounded Monthly Return (CMR)

Month	CMR1	CMR2	CMR3	CMR4
Jan/1990	0.047	-0.01	-0.06	-0.01
Feb/1990	0.063	0.092	0.036	0.038
Mar/1990	0.021	0.022	0.113	0.015
Apr/1990	0.027	-0.04	-0.02	-0.04
May/1990	0.106	0.11	0.116	0.073
Jun/1990	-0.02	-0.02	-0.04	-0.01
Jul/1996	0.082	-0.07	-0.13	-0.02
Aug/1996	0.065	0.026	0.136	0.018
Sep/1996	0.085	-0.03	-0.04	0.088
Oct/1996	0.036	0.111	0.048	0.038

2.3. Fitting Distributions to Compounded Monthly Return

For the Monte Carlo method, we need the distribution of the compounded monthly return for each stock. Thus, for each stock, we determine the best fit distribution based on the Chi-Square measure. For example, the best fit distribution for the compounded monthly return of Stock 4 (i.e. CMR4) is the normal distribution, with Mean Return of 0.6% and Standard Deviation of 4.7%, presented in Figure 1.



2.4. Finding Compounded Monthly Return Correlations

The compounded monthly returns of the stocks are correlated. We need to find the correlation to allow the Monte Carlo method to generate correlated random values for the compounded monthly returns. The correlation matrix is presented in Table 3.

Table 3: Correlation Matrix

	CMR1	CMR2	CMR3	CMR4
CRM 1	1	0.263	0.038	0.0868
CRM2	0.263	1	0.244	0.0895
CRM3	0.038	0.244	1	0.095
CRM4	0.087	0.089	0.095	1

2.5. Generating Compounded Monthly Return

The Compounded Monthly Return (*CMR*) is randomly generated for each stock from the best fit distribution considering the correlations. The following distribution functions of the PalisadeTM @RISK® are used:

CMR1=RiskLogistic(0.0091429,0.044596))

CMR2=RiskLognorm(1.1261,0.077433,Shift(-1.1203))

CMR3= RiskWeibull(6.9531,0.46395, Shift(-0.42581))

CMR4= RiskNormal(0.0060531,0.047225)

The correlation is applied by using the "*RiskCorrmat*" function of the PalisadeTM @RISK®.

2.6. Calculating Compounded Annual Return by Stock

The Compounded Annual Return (CAR) is calculated for each stock from the respective Compounded Monthly Return (CMR), using the following formula:

CAR = 12 * CMR

2.7. Calculating Expected Annual Mean Return on the Portfolio

The expected annual mean return on the portfolio (EAPR-Mean) is calculated from the asset allocation weights vector (Weights-V) and the vector of compounded annual returns of stocks (CAR-V) by using the following Excel® formula:

EAR-Mean = SumProduct(Weights-V, CAR-V)

2.8. Calculating Variance, Standard Deviation and VaR of the Portfolio

The variance, standard deviation and VaR (VaR is calculated at Confidence Level of 99.95%) of the portfolio are calculated from the distribution of the expected annual mean return of the portfolio (*EAR-Mean*) by using the following PalisadeTM @RISK® functions:

Variance = RiskVariance(EAR-Mean)

Standard-Deviation = *RiskStdDev*(*EAR-Mean*)

VaR = *RiskPercentile*(*EAR-Mean*,0.005)

2.8.1. Portfolio Simulation and Optimisation

PalisadeTM RISKOptimizer® is used to solve the portfolio simulation and optimisation problem. That is to find the minimal variance portfolio of investments, which yields sufficient return to cover the liabilities. Thus, the aim of the simulation and optimisation model is to minimise the variance of the portfolio subject to the following specific constraints:

- The expected portfolio return is at least 9%, which is sufficient to cover the liabilities;
- All the money is invested, i.e. 100% of the available funds is invested; and
- No short selling is allowed so all the fractions of the capital placed in each stock should be non-negative.

The model should also calculate the Standard Deviation and VaR of the portfolio.

2.8.2. Measuring Performance of the Portfolio

PalisadeTM @RISK® has Six Sigma capabilities, thus it is used to simulate the optimal portfolio found above and calculate the Six Sigma metrics from the simulation distribution in order to measure the performance of the optimal portfolio. For this purpose the following Six Sigma parameters are specified:

- Lower Specified Limit (LSL) of the expected portfolio return is 5%;
- Target Value (TV) of the expected portfolio return is 9%;
- Upper Specified Limit (USL) of the expected portfolio return is 15%;

The simulation model calculates the following Six Sigma process capability metrics to measure the performance of the investment process: i) Process Capability (Cp); Probability of Non-Compliance (PNC); and Sigma Level (σ L). The following PalisadeTM @RISK® functions are used:

 $\sigma L = RiskSigmaLevel(EAR-Mean)$

2.8.3. Sensitivity Analysis of the Portfolio

The next step is to calculate (quantify) the impact of the investment in every stock to the portfolio mean return, by using the sensitivity analysis features of PalisadeTM @RISK®. This calculation is stochastic and it is based on the statistics of the simulation distribution.

From the calculated correlation coefficients, the stock on which the portfolio return is most dependent can be determined. In addition, the calculated regression mapped values show how the portfolio mean return is changed in terms of Standard Deviation, if the return of a particular stock is changed by one Standard Deviation.

The sensitivity analysis is used in order to determine how to improve the performance of the investment process, i.e. which stocks should be hedged to reduce the financial risk of the portfolio.

2.8.4. Simulating the Hedged Portfolio

Six Sigma Simulation is used again to simulate and measure the performance of the hedged portfolio. The Six Sigma parameters specified for this simulation are the same as in Sec. 2.8.2. Also, the model calculates the Six Sigma process capability metrics to measure the performance of the investment process as presented in Sec. 2.8.2.

2.8.5. Comparing Results and Quantifying Improvements

The final step is to compare the simulation results of the initial optimal portfolio with the hedged portfolio and quantify the improvements from three aspects, portfolio return, financial risk and investment process capability.

To quantify the improvements, the following results are compared: i) Expected Annual Return – Mean (*EAR- Mean*) for portfolio return; ii) Variance, Standard Deviation and Value-at-Risk (VaR) for financial risk; and iii) Process Capability (Cp), Probability of Non-Compliance (PNC), and Sigma Level (σ L) for investment process capability.

3. RESULTS AND DISCUSSION

3.1. Portfolio Simulation and Optimisation

The optimal portfolio found by the simulation and optimisation model has the following investment fractions: 28.6% in Stock 1; 0.7% in Stock 2; 28.5% in Stock 3; and 42.2% in Stock 4. The Portfolio Return

was 9% with Variance of 22.9%, Standard Deviation of 47.8% and VaR of -19.7%.

The probability distribution of this optimal portfolio is given in Figure 2.



The confidence levels were the following. The probability that the portfolio return will be below zero (0%), i.e. negative, is 41.7%. There is a 38.5% probability that the return will be in the range of 0%-50%, and 19.8% probability that the return will be greater than 50%.

3.2. Measuring the Portfolio Performance

The performance of the optimal portfolio found above was measured with a Six Sigma simulation model. It should be noted that the optimal portfolio found above is simulated; thus, the investment fractions for this simulation model are the same, i.e.: 28.6% in Stock 1; 0.7% in Stock 2; 28.5% in Stock 3; and 42.2% in Stock 4. The following Six Sigma parameters were specified: i) LSL = 5%; ii) TV = 9%; iii) USL = 15%.

The Portfolio Return was 9%, Variance 22.9%, Standard Deviation 47.8% and VaR -23%. These figures suggest that the financial risk for the optimal portfolio is significant.

The probability distribution of the optimal portfolio Six Sigma simulation is shown in Figure 3.



The confidence levels were as follows. The probability that the portfolio return will be below 5% (i.e. below LSL) is 46%. There is an 8.9% probability that the return will be in the range of 5%-15% (i.e.

within the desired target range), and 45.1% probability that the return will be greater than 15% (i.e. above USL).

The Six Sigma metrics (i.e. the investment process capability metrics) of the optimal portfolio is shown in Table 4.

It is easy to draw the conclusion by using the Six Sigma *Probability of Non-Compliance (PNC)* metric of the process. The PNC metric determines the total probability that the portfolio return distribution will deviate from the desired specified limits. The PNC equals 0.9112, which is an extremely high probability.

Also, Cp and Sigma Level are very low, i.e. 0.0348 and 0.1115, which indicates a poor performance.

Table 4: Investment Process Six Sigma Metrics

Process	Ср	PNC	Sigma
			Level
Optimal			
Portfolio	0.0348	0.9112	0.1115

The significant financial risk and the poor performance of the optimal portfolio presented above strongly suggest that this portfolio is not acceptable. Therefore, the portfolio should be improved by hedging for example.

3.3. Sensitivity Analysis

The sensitivity analysis was used in order to determine how to improve the performance of the investment process, i.e. how to hedge the portfolio.

The correlation sensitivity graph is given in Figure 4. The graph shows that the portfolio return is most dependent on the return of Stock 4 with a correlation coefficient of 0.77. The other three stocks, i.e. Stock 3, Stock 2 and Stock 1, are less influential with correlation coefficients of 0.49, 0.46 and 0.43 respectively.



The regression sensitivity graph is given in Figure 5. This graph shows how the portfolio mean return is changed in terms of Standard Deviation, if the return of a particular stock is changed by one Standard Deviation.

Therefore, this graph shows that if Stock 4 return is changed by one Standard Deviation, the portfolio return will be changed by 0.313 Standard Deviations (i.e. the regression mapped value is 0.313 for Stock 4). Again, the other three stocks, i.e. Stock 3, Stock 1 and Stock 2, are less influential as their regression mapped values are 0.163, 0.141 and 0.108 respectively.



Figure 5: Regression Mapped Values Sensitivity

The conclusions of this sensitivity analysis suggested that the portfolio can be hedged for example if Stock 4 is replaced with an option of Stock 4.

3.4. Option 4 Return Data and Distribution

A part of the market data for Option 4 (i.e. an option of Stock 4) are shown in Table 5, i.e. the Monthly Return (MR) and the calculated Compounded Monthly Return (CMR) of the option. The Average CMR is 0.61% and the yearly return is 7.28%.

Table 5: Option 4 MR and CMR

Month	MR	CMR
Jan/1990	0	0
Feb/1990	0.038	0.038
Mar/1990	0.015	0.015
Apr/1990	0	0
Jul/1996	0	-0
Aug/1996	0.018	0.018
Sep/1996	0.092	0.088
Oct/1996	0.039	0.038

The best fit distribution to Option 4 CMR is shown on Figure 6.



3.5. The Hedged Portfolio Simulation

The performance of the hedged portfolio was measured with a Six Sigma simulation model. It should be noted that the Stock 4 was replaced with Option 4 (i.e. an option on Stock 4); thus, the investment fractions for this simulation model are: 28.6% in Stock 1; 0.7% in Stock 2; 28.5% in Stock 3; and 42.2% in Option 4.

The same Six Sigma parameters were specified: i) LSL = 5%; ii) TV = 9%; iii) USL = 15%.

The Portfolio Return was 9%, Variance 14.6%, Standard Deviation 38.3% and VaR -0.45%. These figures suggest that the financial risk was considerably reduced.

The probability distribution of the hedged portfolio Six Sigma simulation is shown in Figure 7. The confidence levels were as follows. The probability that the portfolio return will be below 5% (i.e. below LSL) is 44.4%. There is an 10.9% probability that the return will be in the range of 5%-15% (i.e. within the desired target range), and 44.7% probability that the return will be greater than 15% (i.e. above USL).



The Six Sigma metrics (i.e. the investment process capability metrics) of the hedged portfolio is shown in Table 6.

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Process	Ср	PNC	Sigma Level	
Hedged Portfolio	0.2176	0.5294	0.6289	

Table 6: Hedged Portfolio Six Sigma Metrics

Compared with the initial optimal portfolio performance, PNC was reduced from 0.9112 to 0.5294, Cp was increased from 0.0348 to 0.2176 and Sigma Level was increased from 0.1115 to 0.6289. Therefore, an important improvement was achieved with the hedged portfolio.

3.6. Sensitivity Analysis

This sensitivity analysis can be used in order to determine how to further improve the performance of the investment process, i.e. how to further hedge the portfolio. The correlation graph (Figure 8), shows that the portfolio return is most dependent on the return of Stock 1 with a correlation coefficient of 0.72. The other two stocks and Option 4, i.e. Stock 3, Stock 2 and Option 4, are less influential with correlation coefficients of 0.67, 0.35 and 0.0 9 respectively.



Figure 8: Hedged Portfolio Correlation Sensitivity

The regression sensitivity graph is given in Figure 9. This graph shows that if Stock 1 return is changed by one Standard Deviation, the portfolio return will be changed by 0.277 Standard Deviations (the regression mapped value is 0.277 for Stock 1). Again, the other two stocks and Option 4, i.e. Stock 3, Stock 2 and Option 4, are less influential as their regression mapped values are 0.251, 0.0065 and 0.0308 respectively.



Figure 9: Hedged Portfolio Regression Mapped Values Sensitivity

The conclusions of this sensitivity analysis suggested that the hedged portfolio can be further improved (hedged) if Stock 1 is replaced with an option of Stock 1 for example.

It should be noted that this method is iterative and can be iteratively applied until an optimally diversified portfolio is established. Only the first iteration is presented in the paper.

3.7. The Method's First Iteration Results

The results of the first iteration of the method are presented and compared in this section. Table 7 shows the Mean Return, Variance, Standard Deviation and VaR of the initial optimal portfolio and the hedged optimal portfolio.

The hedged optimal portfolio was significantly better than the initial optimal portfolio. The mean return is 9% for initial and hedged portfolio but the financial risk was considerably reduced by the hedged portfolio, i.e. i) Variance was reduced from 22.88% to 14.67%; ii) Standard Deviation was reduced from 47.84% to 38.30%; and iii) Value-at-Risk was reduced from 23.04% to only 0.45%.

Table 7: The Method's First Iteration Results

Table 7. The Method's Physi heration Results				
Portfolio	Mean	Variance	Standard	VaR
	Return		Deviation	
Initial	0.0900	0.2288	0.4784	-0.2304
Hedged	0.0900	0.1467	0.3830	-0.0045

The Six Sigma metrics of the first iteration is given in Table 8. The Six Sigma metrics for the hedged portfolio was also significantly improved. PNC was reduced from 0.9112 to 0.5294, Cp was increased from 0.0348 to 0.2176 and Sigma Level was increased from 0.1115 to 0.6289.

Table 8: The First Iteration Six Sigma Metrics

Process	Ср	PNC	Sigma Level
Initial			
Portfolio	0.0348	0.9112	0.1115
Hedged			
Portfolio	0.2176	0.5294	0.6289

3.8. The Optimisation-Simulation-DMAIC Method versus the Related Work

A simple comparison of the Optimisation-Simulation-DMAIC method, i.e. the new practical approach to ALM proposed in this paper, with the related work summarized in Sec. 1.1 is as follows.

3.8.1. ALM

The ALM models presented by Mitra and Schwaiger (Mitra and Schwaiger 2011) are advanced stochastic optimisation and simulation models. The ALM models published by Adam are also advanced stochastic models using optimisation and simulation (Adam 2007).

The presented Optimisation-Simulation-DMAIC model is by nature an advanced stochastic model applying optimisation and simulation, which is like the models presented in the related work. In contrast, the Optimisation-Simulation-DMAIC model uses Six Sigma DMAIC to measure and improve the portfolio management process in order to establish an optimally diversified (hedged) portfolio, which is an advantage.

3.8.2. Six Sigma

Hayler and Nichols presented applications of Six Sigma tools, e.g. Lean Six Sigma, to the financial service-based operations, which is related to the operational risk (Hayler and Nichols 2006). The work of Tarantino and Cernauskas is also related to the operational risk as they created an operational risk framework by applying Six Sigma to improve the financial risk management process from operational point of view in general (Tarantino and Cernauskas 2009).

On the contrary, the Optimisation-Simulation-DMAIC model uses Six Sigma DMAIC in order to establish an optimally diversified (hedged) portfolio. This is a new concept as DMAIC is dynamically applied to specifically reduce the ALM Market Risk in an on-going investment portfolio management process.

4. CONCLUSION

This paper proposed a new practical and stochastic method, i.e. the Optimisation-Simulation-DMAIC method, for ALM risk modelling under Solvency II and Basel III. The method combines Optimisation, Monte Carlo Simulation and Six Sigma DMAIC methodologies in order to dynamically manage the financial ALM risk (i.e. the market risk) in an on-going investment portfolio management process. The new method applies the Markowitz's Mean-Variance and Monte Carlo Simulation methodologies in order to determine, by using stochastic calculation, the minimum variance portfolio that yields a desired expected return. In addition, the new method uses Six Sigma DMAIC to measure and improve the portfolio management process in order to establish an optimally diversified (hedged) portfolio.

Consequently, the synergy of the Optimisation, Monte Carlo Simulation and Six Sigma DMAIC methodologies, which are used by the method, provides for a significant advantage compared to the conventional ALM models.

This new Optimisation-Simulation-DMAIC method can help the financial institutions to develop or improve their Basel III and Solvency II internal risk models in order to reduce their capital requirements and VaR. Reducing the capital requirements and VaR will ultimately provide the insurance companies and banks with higher business capabilities, which will increase their competitive position on the market. Moreover, the proposed method can significantly assist the financial institutions to achieve their business objectives.

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Vojo has a very strong background in Mathematics, Operations Research, Modeling and Simulation, Risk & Decision Analysis, Six Sigma and Software Engineering, and a proven track record of delivered solutions applying these methodologies in practice. He is also a specialist in Business Systems Analysis & Design (Banking & Insurance) and has delivered major business solutions across several organizations. He has received several formal awards and published a number of written works, including a couple of textbooks. Vojo has also been featured as a guest speaker at several prominent conferences internationally.