

ABSTRACT

The mean-variance (MV) efficient portfolios (Markowitz, 1952) are obtained by searching for portfolios that attain the global minimum variance at a given level of expected return. However, MV efficient portfolios may not yield superior result due to the fact that the distribution of returns to financial assets is not normal but skewed. Past studies proved that investors whose utility can be approximated by the third-order Taylor's series expansion exhibit preference for positive skewness. This preference implies that portfolio selections should consider the mean-variance-skewness (MVS) model. However, studies on implications of skewness preference on portfolio selection are very limited due to computation difficulty.

To overcome this difficulty, this study proposes the use of multi-objective evolutionary algorithms (MOEAs) that are applied in the field of engineering for solving the multi-objective MVS portfolio optimization problem. The superiority of this method is its ability to generate a set of MVS efficient portfolios within a single run of algorithm. The non-dominated sorting genetic algorithm II (NSGA-II), the improved strength Pareto evolutionary algorithm II (SPEA-II), and the compressed objective genetic algorithm II (COGA-II) were applied. The MVS efficient surface was graphically plotted in the three-dimension MVS space.

The analysis started with an application to the stock market. Using the annualized weekly and monthly rates of return of 16 emerging market indices, expected returns of the MVS efficient portfolios are found to be smaller for those with larger skewness, at a given value

of standard deviation. The results suggest that investors have to sacrifice expected return for skewness. At a given value of expected return, the standard deviation decreases for MVS efficient portfolios with smaller skewness. Investors have to expose themselves to a larger return dispersion in order to increase the probability of gaining extreme expected returns.

This study develops a single-period model that allows for heterogeneous degree of risk aversion and skewness preference to investigate the impact of skewness preference on the efficient portfolio choice. Applying the returns of 29 component securities of Dow Jones Industrial Average index (DJIA), it was found that investors with greater skewness preference are willing to accept lower expected returns for a portfolio with higher skewness. In addition, investors with greater skewness preference are willing to accept larger return dispersion in exchange for a flatter right tail of the return distribution. The results explain why investors hold underdiversified portfolios. Investment allocations tend to concentrate on a small number of securities when the degree of skewness preference increases for a fixed level of degree of risk aversion.

The MVS analysis is extended to solve the electricity allocation problem in the electricity market, where the number of trading choices is considerably small. The electricity spot prices of nine pricing zones in the Pennsylvania-New Jersey-Maryland (PJM) market were utilized. To prevent excessive under-diversification, the MVS model is modified (MVS-D) by incorporating an additional objective to increase the number of trading choices included in the portfolio solutions. COGA-II, designed for handling an optimization problem with many objectives, have good optimization performance, particularly for the MVS-D model.

While the MVS efficient portfolios are found in the efficient set of MVS-D model, the MVS strategy provides better results than the MV model to a generation company.

ABSTRAK

Portfolio efisien min-varian (MV) diperolehi dengan mencari portfolio yang mencapai varian minimum global bagi suatu tahap pulangan dijangka. Walau bagaimanapun, portfolio efisien MV mungkin tidak memberi hasil terbaik kerana taburan pulangan kepada aset kewangan adalah tidak normal tetapi pencong. Kajian lepas menunjukkan pelabur yang utilitinya boleh dianggarkan oleh perkembangan Taylor peringkat ketiga mempunyai keutamaan untuk kepencongan positif. Implikasi keutamaan ini adalah pemilihan portfolio harus mempertimbangkan model min-varian-kepencongan (MVS). Walau bagaimanapun, kajian implikasi keutamaan kepencongan terhadap pemilihan portfolio adalah sangat terhad disebabkan kesukaran komputasi.

Untuk mengatasi kesukaran ini, kajian ini mencadangkan penggunaan *multi-objective evolutionary algorithms* (MOEAs) dari bidang kejuruteraan untuk menyelesaikan masalah multi-objektif pengoptimuman portfolio MVS. Kaedah ini mempunyai keupayaan untuk menjana satu set portfolio efisien MVS dalam larian tunggal algoritma. *Non-dominated sorting genetic algorithm II* (NSGA-II), *improved strength Pareto evolutionary algorithm II* (SPEA-II), dan *compressed objective genetic algorithm II* (COGA-II) telah digunakan. Permukaan efisien MVS diplot secara grafik dalam ruang MVS tiga-dimensi.

Analisis dimulakan dengan aplikasi untuk pasaran stok. Dengan kadar pulangan tahunan bagi indeks mingguan dan bulanan untuk 16 pasaran membangun, didapati bahawa pulangan dijangka portfolio efisien MVS adalah lebih kecil untuk portfolio dengan kepencongan yang lebih besar pada nilai sisihan piawai tertentu. Ini bermakna pelabur

perlu mengorbankan pulangan dijangka untuk kepencongan. Pada nilai pulangan dijangka tertentu, sisihan piawai menurun bagi portfolio efisien MVS dengan kepencongan yang lebih kecil. Pelabur perlu mendedahkan diri mereka kepada pulangan yang lebih tertabur untuk meningkatkan kebarangkalian mendapat pulangan dijangka ekstrem.

Kajian ini membina satu model tempoh tunggal dengan darjah pengelakan risiko dan keutamaan kepencongan yang heterogenous untuk menyiasat kesan keutamaan kepencongan kepada pemilihan portfolio yang efisien. Daripada kadar pulangan untuk 29 sekuriti komponen indeks *Dow Jones Industrial Average* (DJIA), keputusan menunjukkan bahawa pelabur dengan keutamaan kepencongan lebih tinggi bersedia untuk menerima pulangan dijangka yang lebih rendah untuk portfolio yang besar kepencongannya. Selain itu, pelabur dengan keutamaan kepencongan lebih tinggi bersedia untuk menerima pulangan yang lebih tertabur supaya dapat ekor kanan taburan pulangan yang lebih mendatar. Keputusan memberi penjelasan mengapa pelabur memegang portfolio kurang dipelbagaikan. Peruntukan pelaburan cenderung untuk menumpu pada sebilangan sekuriti yang kecil apabila tahap keutamaan kepencongan meningkat pada tahap penghindaran risiko yang tertentu.

Analisis MVS dilanjutkan untuk menyelesaikan masalah peruntukan elektrik di pasaran elektrik, di mana bilangan pilihan dagangan adalah lebih kecil. Harga elektrik spot untuk sembilan zon harga dalam pasaran *Pennsylvania-New Jersey-Maryland* (PJM) digunakan. Untuk mengelakkan kurang kepelbagaian yang berlebihan, model MVS diubahsuai (MVS-D) dengan memasukkan objektif tambahan untuk meningkatkan bilangan pilihan dagangan dalam penyelesaian. COGA-II, yang direka untuk menangani masalah pengoptimuman

dengan banyak objektif, memberikan keputusan yang baik, terutama untuk model MVS-D. Sementara portfolio efisien MVS adalah dirangkumi dalam set efisien MVS-D, strategi MVS memberikan keputusan yang lebih baik daripada model MV kepada syarikat penjana.

ACKNOWLEDGEMENTS

First and foremost, I would like to express my sincere gratitude to my supervisor Professor Dr. Goh Kim Leng for his continuous support, enthusiasm, patience, and encouragement since the first day I came to University of Malaya. His guidance and advice helped me throughout the entire process of research and writing of this thesis. Thanks are also due to his mercy and kindness since he has treated me not only as a student, but also as one of his friends. Apart from academic work, he shared with me lots of unforgettable experiences, and brought me to enjoyable trips, and delicious dinners. This makes me realize how lucky am I having him as my supervisor and mentor for my PhD study.

I am deeply indebted to my home institution, Faculty of Management and Tourism, Burapha University, Thailand for granting me a scholarship for my PhD study. Special thanks to my colleague in Department of Finance for taking care of my duties and visiting me during my period of study. I would like to thank Dr. Kittipong Boonlong for sharing with me his knowledge on the optimization techniques.

I would like to express my appreciation to all the faculty and staff members of Faculty of Economics and Administration for their assistance and support during my study period. Thanks are also due to the members of the Evaluation Committee for their valuable comments and suggestions on this thesis in several occasions namely, proposal defence, candidature defence, and final presentation. I also would like to thank my fellow colleagues and friends who have kindly advised, encouraged, and assisted me during my PhD study.

Lastly, I would like to thank my family for all their love and encouragement. Thanks to my parents who nurtured me with love and supported me in all my pursuits. Thanks to my brother for taking care of our parents when I was away from home.

TABLE OF CONTENTS

ABSTRACT	iii
ABSTRAK	vi
ACKNOWLEDGEMENTS	ix
TABLE OF CONTENTS	x
LIST OF FIGURES	xiv
LIST OF TABLES	xvi
LIST OF ABBREVIATIONS	xix

CHAPTER 1 INTRODUCTION

1.1	Background	1
1.2	Why Skewness Preference Matters?	3
1.3	Impact of Skewness Preference on Portfolio Choice	6
1.4	The Application of MVS Analysis in Electricity Market	8
1.5	Research Questions	10
1.6	Research Objectives	10
1.7	Organization of The Thesis	11

CHAPTER 2 LITERATURE REVIEW

2.1	Introduction	12
2.2	Skewness Preference Theory	12
2.2.1	Expected Utility Theory	13
2.2.2	Expected Utility and Mean-variance Analysis	14
2.2.3	Skewness Preference in Expected Utility Model	18
2.2.4	Skewness Preference and Decision to Gamble	24
2.2.5	Skewness Preference and Pricing Implication	25

2.3	Skewness Preference and Decision on Portfolio Choice	29
2.4	Causes of Skewness in Stock Prices	32
2.5	Asset Allocation Problem in the Electricity Market	34
2.5.1	Trading Environment	35
2.5.2	Studies on the Generation Asset Allocation Problem	37
2.6	Solving the MVS Portfolio Optimization Problem	39
2.6.1	The Existing Approaches	40
2.6.2	Shortcomings of the Existing Approaches	44
2.6.3	Multi-objective Evolutionary Algorithms (MOEAs)	45
2.6.4	Application of MOEAs for Solving Portfolio Optimization Problem	47
2.7	Research Gaps	50
2.7.1	MVS Efficient Portfolios in Multi-dimension Moment Space	50
2.7.2	Skewness Preference and Portfolio Choice	52
2.7.3	MVS Analysis for Solving an Electricity Allocation Problem	54

CHAPTER 3 METHODOLOGY

3.1	Introduction	57
3.2	Conceptual Framework	57
3.3	The Proposed Technique	60
3.3.1	The Multi-objective Optimization Framework	60
3.3.2	Multi-dimension Search Space	61
3.3.3	Determination of Non-dominated Solutions (Efficient Solutions)	62
3.4	Portfolio Selection with Skewness Preference	65
3.4.1	The Optimization Problem	66
3.4.2	Data	67
3.4.3	Procedure	67
3.5	The Impact of Skewness Preference on Portfolio Choice	71
3.5.1	The Model	72
3.5.2	The Optimization Problem	76
3.5.3	Data	76

3.5.4	Procedure	77
3.6	Electricity Allocation Problem	80
3.6.1	The Optimization Problem	80
3.6.2	Data	82
3.6.3	Procedure	83
3.6.4	The Setting of the Numerical Case Studies	88
3.6.5	Optimization Method and Setting	90

CHAPTER 4 PORTFOLIO SELECTION WITH SKEWNESS PREFERENCE: EVIDENCE FROM THE EMERGING STOCK MARKETS

4.1	Introduction	94
4.2	Summary Statistics and the Normality Test Results	95
4.3	MVS Efficient Portfolios and the Efficient Surface	101
4.4	Risk-return Characteristics of MVS Efficient Portfolios	107
4.4.1	Risk-return Characteristics for Fixed Standard Deviation	109
4.4.2	Risk-return Characteristics for Fixed Expected Return	115
4.5	Concluding Remarks	122

CHAPTER 5 THE IMPACT OF SKEWNESS PREFERENCE ON EFFICIENT PORTFOLIO CHOICES

5.1	Introduction	125
5.2	Summary Statistics and the Normality Test Results	126
5.3	MVS Efficient Portfolios and the Efficient Surface	131
5.4	The Impact of Skewness Preference on Portfolio Choice	132
5.4.1	Sorting of Efficient Portfolio Choices	132
5.4.2	Portfolio Choices for the Different Degree of Skewness Preference	136
5.5	Concluding Remarks	144

CHAPTER 6 MVS ANALYSIS FOR SOLVING AN ELECTRICITY ALLOCATION PROBLEM

6.1	Introduction	147
6.2	Summary Statistics and the Normality Test Results	148
6.3	Results and Discussions	151
6.3.1	Comparison of the Implemented MOEAs	151
6.3.2	Optimal Electricity Allocation	159
6.4	Concluding Remarks	164

CHAPTER 7 CONCLUSION

7.1	Introduction	166
7.2	Summary of Findings	167
7.3	Implications of the Study	171
7.4	Contributions of the Study	175
7.5	Limitations of the Study and Direction for Future Research	177

REFERENCES	179
------------	-----

APPENDICES

APPENDIX A	MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM	200
APPENDIX B	SUPPLEMENTARY INFORMATION FOR CHAPTER 4	228
APPENDIX C	SUPPLEMENTARY INFORMATION FOR CHAPTER 5	261

LIST OF PUBLICATIONS AND PAPERS PRESENTED	320
---	-----

LIST OF FIGURES

Figure 3.1	Mapping between Solution Space and Objective Space	63
Figure 4.1	The MVS Efficient Solutions from NSGA-II (Weekly Data)	102
Figure 4.2	The MVS Efficient Solutions from SPEA-II (Weekly Data)	103
Figure 4.3	Comparative Results of the Implemented Algorithms (Weekly Data)	104
Figure 4.4	The MVS Efficient Solutions from NSGA-II (Monthly Data)	105
Figure 4.5	The MVS Efficient Solutions from SPEA-II (Monthly Data)	106
Figure 4.6	Comparative Results of the Implemented Algorithms (Monthly Data)	107
Figure 4.7	Comparative Results of Different Investment Horizons	108
Figure 4.8	Impact of Skewness on MV Efficiency - Weekly	119
Figure 4.9	Impact of Skewness on MV Efficiency - Monthly	120
Figure 5.1	The MVS Efficient Solutions from a Universe of DJIA Listed Securities	132
Figure 5.2	Portfolio Choices for Different Degree of Risk-aversion and Skewness Preference	143
Figure 6.1	Mean M_1 versus Number of Generated Solutions of Case Study 1 and 2 for MVS-POP (3 Optimized Objectives)	156
Figure 6.2	Mean M_1 versus Number of Generated Solutions of Case Study 1 and 2 for MVS-D-POP (4 Optimized Objectives)	156
Figure 6.3	Mean HV versus Number of Generated Solutions of Case Study 1 and 2 for MVS-POP (3 Optimized Objectives)	157
Figure 6.4	Mean HV versus Number of Generated Solutions of Case Study 1 and 2 for MVS-D-POP (4 Optimized Objectives)	157

Figure 6.5	Mean <i>CRA</i> versus Number of Generated Solutions of Case Study 1 and 2 for MVS-POP (3 Optimized Objectives)	158
Figure 6.6	Mean <i>CRA</i> versus Number of Generated Solutions of Case Study 1 and 2 for MVS-D-POP (4 Optimized Objectives)	158
Figure 6.7	Pareto Fronts of Case Study 1 using COGA-II for Optimization Problem of (a) MVS and (b) MVS-D	160
Figure 6.8	Pareto Fronts of Case Study 2 using COGA-II for Optimization Problem of (a) MVS and (b) MVS-D	160
Figure 6.9	Comparison of Pareto Fronts of MVS and MVS-D Efficient Portfolios Generated by COGA-II	161
Figure 6.10	Box Plot of the Allocation Proportions of the MVS and MVS-D Efficient Portfolios Obtained from COGA-II for Case Study 1	163

LIST OF TABLES

Table 3.1	Parameter Setting for the NSGA-II and SPEA-II	70
Table 3.2	The List of Securities for Analysis on the Impact of Skewness Preference	77
Table 3.3	Parameter Setting for the SPEA-II	79
Table 3.4	Parameter Setting for the NSGA-II, SPEA-II, and COGA-II for Solving the Numerical Case Studies of Prob. 1 and Prob. 2	93
Table 4.1	Summary Statistics and the Normality Test Results of the Annualized Weekly Rate of Returns for Sixteen Emerging Markets	97
Table 4.2	Summary Statistics and the Normality Test Results of the Annualized Monthly Rate of Returns for Sixteen Emerging Markets	98
Table 4.3	The Return Matrix R and Variance-covariance Matrix A of the Annualized Weekly Rate of Returns for Sixteen Emerging Markets	99
Table 4.4	The Return Matrix R and Variance-covariance Matrix A of the Annualized Monthly Rate of Returns for Sixteen Emerging Markets	100
Table 4.5	The MVS Efficient Portfolios of Weekly Investment Horizon with SD Value of 1.00, 1.10, and 1.20	112
Table 4.6	The MVS Efficient Portfolios of Monthly Investment Horizon with SD Value of 1.00, 1.10, and 1.20	114
Table 4.7	The MVS Efficient Portfolios of Weekly Investment Horizon with Expected Return Value of 28.0 Percent	116
Table 4.8	The MVS Efficient Portfolios of Monthly Investment Horizon with Expected Return Value of 28.0 Percent	117

Table 5.1	Summary Statistics and the Normality Test Results of the Monthly Annualized Rate of Returns of 29 Securities Listed in the DJIA	127
Table 5.2	The Return Matrix \mathbf{R} and Variance-covariance Matrix $\mathbf{\Lambda}$ of 29 Securities listed in the DJIA	128
Table 5.3	The Average Expected Return, SD, and Skewness of MVS Efficient Portfolios Sorted into Quintiles by the Level of Expected Return	133
Table 5.4	The Average Expected Return, SD, Skewness, and Portfolio Holding of MVS Efficient Portfolios Sorted into Quintiles by the Value of Skewness	135
Table 5.5	The Average Expected Return, SD, Skewness, and Portfolio of MVS Efficient Portfolios Sorted into Quintiles by Portfolio Holding	136
Table 5.6	The Summary Statistics of Portfolio Choices that Maximize the Expected Utility for Given Values of Absolute Risk Aversion (A) and Degree of Skewness Preference (P)	139
Table 5.7	The Composition of Efficient Portfolio Choices that Maximized the Expected Utility at a Given Value of Absolute Risk Aversion (A) and Degree of Skewness Preference (P)	140
Table 6.1	Summary Statistics and the Normality Test Results of the Historical Daily Electricity Spot Prices of Nine Pricing Zones	149
Table 6.2	The Return Matrix \mathbf{R} of the Nine Trading Choices for the Two Case Studies	150
Table 6.3	The Variance-covariance Matrix $\mathbf{\Lambda}$ of the Nine Trading Choices	150
Table 6.4	The Skewness-coskewness Matrix $\mathbf{\Omega}$ of the Nine Trading Choices	150
Table 6.5	Mean and Standard Deviation (SD) of Running Time (Seconds)	152

Table 6.6	Mean and Standard Deviation (SD) of M_1	152
Table 6.7	Mean and Standard Deviation (SD) of HV	154
Table 6.8	Mean and Standard Deviation (SD) of CRA	154
Table 6.9	Selected MVS and MVS-D Efficient Portfolios	162

LIST OF ABBREVIATIONS

2D	Two-dimension
3D	Three-dimension
CAISO	California Independent System Operator
CAPM	Capital Asset Pricing Model
CE	Certainty Equivalent
COGA-II	Compressed Objective Genetic Algorithm II
CRA	Contribution Ratio to Artificial True Pareto
DJIA	Dow Jones Industrial Average index
DM	Decision Maker
DRA	Downside Risk Aversion
EP	Evolutionary Programming
ES	Expected Shortfall
GA	Genetic Algorithms
GARCH	Generalized Autoregressive Conditional Heteroscedastic
Genco	Generation Company
GMM	Generalized Method of Moments
HML	High (Book-to-Market Ratio) Minus Low
HV	Hypervolume
ISO	Independent System Operator
LHS	Left Hand Side
LMP	Locational Marginal Pricing
LP	Linear Programming
M_1	Average Distance to the True Pareto-optimal Front
MADS	Mean-absolute deviation-skewness
MCP	Market Clearing Price
MOEA	Multi-objective Evolutionary Algorithms
MOGA	multi-objective Genetic Algorithm
MOOP	Multi-objective Optimization Problem
MSCI	Morgan Stanley Capital International

MV	Mean-variance
MV-POP	Mean-variance Portfolio Optimization Problem
MVS	Mean-variance-skewness
MVS-POP	Mean-variance-skewness Portfolio Optimization Problem
NPGA	Niched Pareto Genetic Algorithm
NSGA	Non-dominated Sorting Genetic Algorithm
NSGA-II	Non-dominated Sorting Genetic Algorithm II
NYSE	New York Stock Exchange
OTC	Over-the-counter
PAES	Pareto-archive Evolution Strategy
PESA	Pareto Envelope-based Selection Algorithm
PGP	Polynomial Goal Programming
PJM	Pennsylvania-New Jersey-Maryland market
Prob. 1	Problem 1
Prob. 2	Problem 2
QP	Quadratic Programming
RHS	Right Hand Side
S&P 500	Standard & Poor's
S&P/ASX 300	Australian Securities Exchange from Standard & Poor's
SBX	Simulated Binary Crossover
SD	Standard Deviation
SMB	Small (Market Capitalization) Minus Big
SPEA	Strength Pareto Evolutionary Algorithm
SPEA-II	Improved Strength Pareto Evolutionary Algorithm
VaR	Value at Risk