An electronic financial system adviser for investors: the case of Saudi Arabia

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Abstract

Financial markets, particularly capital and stock markets, play an important role in mobilizing and canalising the idle savings of individuals and institutions to the investment options where they are really required for productive purposes. The prediction of stock prices and returns is carried out in order to enhance the quality of investment decisions in stock markets, but it is considered to be tricky and complicates tasks as these prices behave in a random fashion and vary with time. Owing to the potential of returns and inherent risk factors in stock market returns. Various stock market prediction models and decision support systems such as Capital asset pricing model, the arbitrage pricing theory of Ross, the inter-temporal capital asset pricing model of Merton ,Fama and French five-factor model, and zero beta model to provide investors with an optimal forecast of stock prices and returns. In this research thesis, a stock market prediction model consisting of two parts is presented and discussed. The first is the three factors of the Fama and French model (FF) at the micro level to forecast the return of the portfolios on the Saudi Arabian Stock Exchange (SASE) and the second is a Value Based Management (VBM) model of decision-making. The latter is based on the expectations of shareholders and portfolio investors about taking investment decisions, and on the behaviour of stock prices using an accurate modern nonlinear technique in forecasting, known as Artificial Neural Networks (ANN).

This study examined monthly data relating to common stocks from the listed companies of the Saudi Arabian Stock Exchange from January 2007 to December 2011. The stock returns were predicted using the linear form of asset pricing models (capital asset pricing model as well as Fama and French three factor model). In addition, non-linear models were also estimated by using various artificial neural network techniques, and adaptive neural fuzzy inference systems. Six portfolios of stock predictors are combined using: average, weighted average, and genetic algorithm optimized weighted average. Moreover, value-based management models were applied to the investment decision-making process in combination with stock prediction model results for both the shareholders' perspective and the share prices' perspective. The results from this study indicate that the ANN technique can be used to predict stock portfolio returns; the investment decisions and the behaviour of stock prices, optimized by the genetic algorithm weighted average, provided better results in terms of error and prediction accuracy compared to the simple linear form of stock price prediction models. The Fama and French model of stock prediction is better suited to Saudi Arabian Stock Exchange investment activities in comparison to the conventional capital assets pricing model. Moreover, the multi-stage type1 model, which is a combination of Fama and French predicted stock returns and a value-based management model, gives more accurate results for the stock market decision-making process for investment or divestment decisions, as well as for observing variation in and the behaviour of stock prices on the Saudi stock market. Furthermore, the study also designed a graphic user interface in order to simplify the decision-making process based upon Fama and French and value-based management, which might help Saudi investors to make investment decisions quickly and with greater precision. Finally, the study also gives some practical implications for investors and regulators, along with proposing future research in this area.

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*Secondly I dedicate this work to the soul of my grandfather **Abdulaziz***

*Last but not the least; (also) I would like to thank my grandfather **Uthman** and my grandmother **Om Adel** and my parents **Adel** and **Salha** for giving birth to me at the first place and supporting me spiritually throughout my life. Finally, all thanks to relatives, friends and my best friend **Aiydh Alanazi**.*

Declaration

It is hereby declared that the thesis in focus is the author's own work and is submitted for the first time to the Post-Graduate Research Office. The study was originated, composed and reviewed by the mentioned author and supervisors in the department of Electronic and Computer Engineering, College of Engineering, Design and Physical Sciences, Brunel University London UK. All the information derived from other works has been properly referenced and acknowledged.

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Table of Contents

List of Figures

List of Tables

List of Abbreviations

AE	Average Ensemble
AMF	Arab Monetary Fund
ANFIS	Adaptive Neural Fuzzy Inference Systems
ANN	Artificial Neural Networks
B/H	Big size and high book to market value portfolio
B/L	Big size and low book to market value portfolio
B/M	Big size and medium book to market value portfolio
CAPM	Capital Asset Pricing Model
CM	Commerce ministry
CMA	Capital Market Authority
FF	Fama-French three factor model
GA	Genetic Algorithm
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
GUI	Graphical User Interface
HAC	Time Series Heteroskedasticity Auto correlation
HML	high minus low
IC	Invested Capital
Kd	cost of debt
Kp	cost of preferred stock
Ks	the cost of equity
LR	liner Regression
MC	Market Capitalization
MFNE	ministry of Finance and National Economy
MR	market returns
Multi type 1	VBM and FF model
Multi type 2	VBM and CAPM
New CF	Cascade-Forward Network
New DTDNN	Distributed Time Delay Neural Network
New ELM	Elman Neural Networks
New FF	Feed forward Neural Networks
New FFTD	Feed Forward Input Time-Delay Back Propagation Network
New FIT	Fitting Networks
New RB	Radial Basis Function Network
NOPLAT	Net Operating Profit less Adjusted Taxes
R_{act}	Actual Return of Investments
R_{exp}	Expected Investment Return
R_{req}	Required return on invested capital
RHB	Portfolio returns for companies with high Book-to-Market level and big group
RHS	Portfolio return for companies with high Book-to-Market level and small group
RLB	Portfolio return for companies with low Book-to-Market level and big group
RLS	Portfolio return for companies with low Book-to-Market level and small group

RMB	Portfolio return for companies with medium Book-to-Market level and big group
RMS	Portfolio return for companies with medium Book-to-Market level and small group.
RMS	root mean squared
ROIC	Return on Invested Capital
S/H	Small size and high book to market value portfolio
S/L	Small size and low book to market value portfolio
S/M	Small size and medium book to market value portfolio
SAMA	Saudi Arabian Monetary Agency
SH	Shareholder
SMB	small minus big
SP	Share price
SSME	Saudi stock market exchange.
T	corporate tax rate
Tadawul	Saudi Stock Exchange
TASI	Tadawul All Share Index, the general share price index of the Saudi stock market
VBM	Value Based Management Model
VST	Value of Shares Traded
WA	Weighted Average
WACC	Weighted Average Cost of Capital
Wd	weight of debt
Wp	weight of preferred stock
Ws	weight of equity

List of Publications

Journals:

[1] A. Aldaarmi and M Abbod, "A data model for processing financial market and news data in electronic financial System for investors with non- financial expertises: the case of Saudi Arabia". International Journal of Sciences: Basic and Applied Research (IJSBAR), Volume 15, No 2, pp 192-208, 2014.

[2] A. Aldaarmi, M. Abbod and H. Salameh 'Implement Fama and French and Capital Asset Pricing Models in Saudi Arabia Stock Exchange' Journal of Applied Business Research (JABR) Volume 3 , No 3 , pp 953-968, 2015.

Conferences:

[3] A. Aldaarmi and M Abbod, "A Data Driven Model for Predicting the Financial Market Prices for Investors with Non Financial Experts: The Case of Saudi Arabia". 1st International Conference on Systems Informatics, Modelling and Simulation, (SIMS2014) 29 April - 1 May 2014, Sheffield, UK.

[4] A. Aldaarmi, "A data model for processing financial market and news data in electronic financial System for investors with non- financial expertises: the case of Saudi Arabia", 6th Annual Student Research Conference 24-26 June, Brunel University, College of Engineering, Design and physical sciences London, UK 2013.

Posters:

[5] A. Aldaarmi," Implement Fama and French and CAPM Pricing Models in Saudi Arabia Stock Exchange (Tadwal)".poster 7th Saudi student conference, Edinburgh, UK, 2014.

[6] A. Aldaarmi,"Value Based Management VBM Expectation Model in Saudi Arabia Stock Exchange",poster Graduate school conference, Brunel University London , UK, 2014.

CHAPTER 1

Introduction

1.1 Introduction

Financial markets are considered a significant ingredient of a better financial system in any country, as the role of financial markets in the economic development of a country cannot be ignored. Financial markets, particularly capital and stock markets, play an important role in mobilizing and canalising the idle savings of individuals and institutions to the investment options where they are really required for productive purposes. This efficient allocation of savings to the real sector and businesses depends heavily on the efficiency of stock markets in pricing various stocks being listed at the stock exchange. Different classical and modern financial theories highlighted that certain inherent factors in stocks (such as sources of risk) are responsible for returns on individual stocks on the stock market (Rao and Radjeswari, 2000). Hence some researchers in finance literature have proposed different models to accurately forecast the stock prices and returns, which better enable an investor to make appropriate profits on his investments in capital markets (Al-Zubi and Salameh, 2009).

The prediction of stock prices and returns is normally considered to be tricky and complicates task as these prices behave in a random fashion and vary with time (Tay and Cao, 2002; Zhou and Sornette, 2005). Owing to the potential of returns and inherent risk factors in stock market returns, researchers have proposed various stock market prediction models and decision support systems to provide investors with an optimal forecast of stock prices and returns. These include most notably the Capital Asset Pricing Model (CAPM) and the Fama and French three-factor model, which have been validated using time series analysis techniques (such as “mixed auto regression moving average [ARMA]” as well as multiple regression models (Kendall, 1990). However, the prevalence of complexity in stock market prices made intelligent prediction paradigms highly significant, as well as forecasting stock prices using the conventional prediction models of CAPM and Fama and French (Huang et al., 2004; Wichard et al., 2004).

The stock pricing model was initially proposed by Markowitz in 1952 and was followed by many other proposed models to predict the stock market prices and investigate the relationship between excess returns on stock portfolios and market portfolios. Most popular among all of them, CAPM was based upon the work of Sharpe (1964) and Lintner (1965). CAPM is one of the oldest and most conventional models used by various researchers to explain the cross-sectional variation in stock market returns behaviour. As noted by Fama and French (2004), CAPM is still popular even forty years after its introduction in different financial applications, such as evaluation of managed portfolios' performance, as well as the cost of capital estimations by firms, and the identification of over and undervalued securities in any stock market. CAPM argues that just one factor (risk-adjusted excess market returns) explains the variations in the required rate of returns on a particular stock. The basic underlying assumption of the capital asset pricing model is its linear function of a security's returns and the relative risk of the market. A major implication of this model is that the relative risk of the security (β) is alone sufficient to explain the variability of its expected returns. Al-Zubi and Salameh (2009) have stated that the capital asset pricing model helps all the countries in the world to enhance the savings of firms and to accept the challenge of rivalry between firms in the corporate sector of the economy, as this model is helpful in accurately forecasting stock prices in most of the world's stock exchanges.

However, Fama and French (1992) provided empirical evidence that covariance of market and portfolio returns (a fundamental factor of CAPM) does not explain the variations in excess returns on portfolio which makes the CAPM less reliable. Keeping in view this poor and less reliable performance of CAPM, they developed another prediction model, later known as the Fama and French three-factor model, by introducing two more determining factors of portfolio returns. The three factors which explain the cross-sectional variation in stock returns are "excess market returns, the difference between the excess return on a portfolio of small stocks and the excess return on a portfolio of big stocks (SMB, small minus big); and the difference between the excess return on a portfolio of high-book-to-market stocks and the excess return on a portfolio of low-book-to-market stocks (HML, high minus low)".

The two additional factors introduced by Fama and French (1992) to the traditional model of CAPM are more capable of explaining the variations in stock returns over time and deal with anomalies inherent in the CAPM. As noted by Fama and French (1996), the three-factor Fama and French model soaks up many of the anomalies that have inundated CAPM and it explains most of the cross-sectional variations in average stock returns in the capital market. Their study further argued that the better predictive power of the Fama and French three-factor model suggests that this could be called an 'equilibrium pricing model' which is a modified and three-factor edition of the inter-temporal capital asset pricing model of Merton (1973) or the arbitrage pricing theory of Ross (1976). Chawarit (1996) also favours this argument of Fama and French (1996), as the arbitrage pricing theory of Ross better explains the stock market returns on the Thai stock market, compared to the conventional capital asset pricing model. This notion was further confirmed by Fama and French (1998), who stated that inclusion of the size and value factor in CAPM is useful and explains cross-sectional variations in stock returns in many of the stock markets around the globe.

While comparing CAPM and the three-factor model, Fama and French (2004) stated that although CAPM is an attractive stock price prediction model which offers "powerful and intuitively pleasing" predictions to estimate risk-return relationships, empirical support negates its prediction power. For instance, CAPM assumes that stock risk should be measured in comparison to a "comprehensive market portfolio" which is realistically not legitimate as this market portfolio might include not only traded financial assets (stocks and bonds) on the stock market but also human capital, real estate or consumer goods etc. Theoretically and empirically, the CAPM lacks real unbiased estimation of stock market returns in comparison to the three-factor model, not only in US capital markets but in the financial markets of the rest of the world.

As discussed earlier, the capital asset pricing model and the three factor model of Fama and French have been validated using time series analysis techniques of regression (Kendall, 1990), as both of these models assume that there is a linear relationship between stock returns and predicting factors of the model (i.e. excess market returns, size factor, value factor). However, several researchers have argued that relaxing the basic assumption of linearity in stock price prediction models may enhance the prediction accuracy, and this could be done by applying Artificial Neural Network (ANN) models as well as other fuzzy models, which are formulated to impersonate the organizational and knowledge acquisitions skills of the human brain (Bergerson and Wunsch, 1991; Sharda and Patil, 1992). Particularly, ANN models try to confine the nonlinearity, the different linking of various information points in the human brain, and its information network parallel structure (Haykin, 1998). These models estimate weights of coefficients by using an iterative process of sample input data and predict different output states and after that adjust the coefficient weights in order to enhance the robustness of estimated and actual return values. According to Cao et al. (2011), ANN models' training processes are helpful in accumulating, storing, and recognising samples of knowledge and then adjusting those samples of knowledge according to changes in the environment.

Along with the conventional methods of stock market forecasting, academic researchers have been using computer-based information systems to predict stock prices and indices in recent years with the development of the information technology era. Artificial neural networks are not only being successfully applied to stock price prediction in capital markets, but these techniques are also being used in different fields of management sciences such as marketing (Papatla et al., 2002), operations management (Kaparthi and Suresh, 1994), finance (Etheridge et al., 2000), economics (Hu et al., 1999), accounting (Lenard et al., 1995), and management information systems (Zhu et al., 2001). Empirically, ANN models have been found to outperform traditional quantitative forecasting models, such as regression analysis and discriminate analysis, on a consistent basis as reported by many earlier studies (Desai and Bharati 1998; Bhattacharyya and Pendharkar 1998; Jiang et al. 2000). More recently, other artificial intelligence methods such as genetic algorithms and adaptive neural fuzzy inference systems (ANFIS), in addition to ANN, are being utilized in estimating stock market returns in comparison to conventional linear quantitative regression techniques. However, very few studies have used these techniques and methodologies for stock price prediction in emerging markets (Cao et al., 2011), such as Saudi Arabia.

In order to analyse the investment activity in the financial markets, a relatively newer technique of value-based management is being used. The value-based management model focuses on the portfolio investors and actual/potential shareholders. The basic objective of applying this management model to stock market activities is to enhance and improvise the operational and strategic decision-making as a whole. In the words of Copeland et al. (2000), "a manager with value as a principle is as interested in the subtleties of the organizational behaviour, as in using the evaluation as a measure of performance and as a decision tool." The basic focus area of the value-based management model is the reason for the existence of corporations, and its ultimate goal is the maximisation of the wealth of the shareholders, while also considering the interests of all the stakeholders involved. Hence, the value-based management model focuses on four dimensions: Required Return on Invested Capital (Rreq), Expected Investment Return (Rexp), Actual Return of Investments (Ract) and Weighted Average Cost of Capital (WACC). Output generated from the stock returns prediction models of CAPM and Fama and French is used as the input for making decisions in the value-based management model.

1.2 Scope of the Study

The scope of the present thesis is limited to the analysis and application of stock price prediction models (i.e. CAPM and Fama and French) through different artificial neural network techniques and other computer-based artificial intelligence techniques (such as adaptive neural fuzzy inference systems and genetic algorithm etc.) in the Saudi Arabian Stock Exchange (SASE). In this regard, training will also be performed for neural network techniques for the investors and on the basis of the obtained results, the present study will apply a value-based management model to perform investment activity in SASE. Finally, an easy-to-use graphic user interface application will be designed which will help investors to purchase and sell the stocks on the basis of the best model chosen from the best prediction model and neural network techniques.

1.3 Aim and Objectives

The main aim of the present study is to predict the stock market returns, and based on that prediction, to make the investment decision to determine whether the predictive power of stock prices can be improved on the Saudi Arabian Stock Exchange (SASE) by using the various Artificial Neural Networks techniques (ANN). Therefore, this research develops an appropriate investment prediction model of an emerging stock market (Saudi Arabia) which has special features due to its religion, culture and tradition. In this regard, the CAPM and Fama and French three-factor pricing models are applied to check which one is more appropriate for use in Saudi Arabia. Moreover, this study explores the efficiency of the Saudi Arabian Stock Exchange by comparing the real return with the returns predicted using the CAPM and Fama and French prediction models. If the attempts to improve the prediction power of stock prices on the SASE using the ANN technique made the market inefficient, then there are two possibilities. This inefficiency may be due to the fact that it is an emerging market or there are market anomalies. Alternatively, the predicting power of stock returns in the SASE cannot be improved by using this specific technique (ANN). This is the first study that uses the same approach of Fama and French in measuring the dependent and independent variables. It will add evidence as to which of these risk factors affects the stock return.

In order to achieve the objectives of this study, the following objectives were set:

- Determining the accuracy of computer-based information systems based on artificial neural techniques in predicting stock prices movement for companies listed on the Saudi Arabian Stock Exchange;
- Specifying a model that may predict the stock return on SASE by applying the Fama and French (FF) three-factor model at the micro level and CAPM using ANN;
- Making a comparative analysis of predictive power of CAPM and Fama and French models to predict stock market returns;
- Validating whether the stock market returns prediction power of the CAPM and Fama and French models improves after the usage of computer-based ANN techniques; and
- Testing the Value Based Management (VBM) model of decision-making on the basis of expectations of shareholders and portfolio investors in SASE.

When we compare the Saudi stock market to the rest of the Arab world's stock markets, we see that it is the largest stock market in the region in terms of US$. In 2012, the market capitalization of the Saudi stock market was around 340 billion US$ whereas the average Arab world stock market capitalization was only 58 billion US$ for the participants of the Arab Monetary Fund Index (AMFI). The level of activity in the stock market is also greater in Saudi Arabia as compared to its Arab counterparts. As a result the Saudi stoke market needs more research to consider that as one of most important stock market in Arabic world. Therefore the aim and objective of this study is to investigate pricing models in this emerging market and build an investment model help investor to take correct designs because two price collapses (2006) and (2008) happen to this emerging market since its development.

1.4 Contributions to the Knowledge

The underlying research thesis is of significant value in its nature. It makes contribution to the existing body of knowledge in the field of financial markets, particularly stock returns prediction. Firstly, it applies the computer-based artificial neural techniques in training and testing for the investors in the emerging market of Saudi Arabia where capital markets are growing at a good pace. Moreover, it compares the most influential stock market prediction models (i.e. CAPM and Fama and French) and compares the returns obtained from both the models which are further used to investigate whether the stock market prediction power has been increased by the use of ANN techniques. Secondly, value-based management models are applied to the investment decision-making process in combination with stock prediction models results for both the shareholders' perspective and share prices' perspective. Moreover, it develops an easy-to-use graphic user interface of a computer application based on the best results achieved for the Saudi stock market investor which will be beneficial for small investors in forecasting stock prices, and thus help them in the decision-making process in the purchase or sale of stocks. Moreover, it is the first study which uses ANN techniques along with ANFIS for CAPM and Fama and French models in emerging markets, particularly Saudi Arabia. It is therefore expected that the present study will contribute significantly to the existing literature on financial markets and people who interesting in stock market such as universities, banks, National Economy ministry , Commerce ministry , Finance ministry ,Capital Market Authority (CMA) ,The Saudi Arabian Monetary Agency (SAMA),Investors, Saudi Arabia Stock Exchange , Mutual Funds , other PhD students and foreign investors.

1.5 Thesis Contents

The rest of the thesis has been organized as follows:

- Chapter two reviews the relevant literature on stock returns prediction models of the Capital Asset Pricing Models and Fama and French three-factor model, as well as value-based management and various computer-based techniques such as artificial neural networks, ANFIS, GA etc.

- Chapter three overviews the history of Saudi stock market development divided in three phases of preliminary stage, established stage and modernized phase, followed by different indicators of performance of the Saudi Arabian Stock Exchange.
- Chapter 4 presents the methodological framework in which the calculation of different dependent and independent study variables has been given and estimation equations have been formulated for methods used in the study.
- Chapters 5 and 6 present and discuss the results obtained by applying different techniques of model forecasting and multi-stage type 1 and 2 models, respectively.
- Lastly, chapter 7 summarizes the findings and proposes some future research directions.

CHAPTER 2

Literature Review

2.1 Introduction

Forecasting stock prices in capital markets is significant and of great interest because attractive benefits may be achieved by successful prediction of stock prices. However, this prediction is very difficult and highly complicated. During the last few years, prediction and forecasting of stock prices have remained an important issue in financial and capital market research. Sharp (1964), Ross and Roll (1975), Fama and French (1992) & (1993), Banz (1981), Danial and Titman (1997) and others have used and proposed various techniques in order to predict future stock prices in different capital markets and make investment decisions. Among the techniques used are conventional capital asset pricing model (CAPM) and an improved version of CAPM, the Fama and French three factor model. However, in recent years, academic researchers have started utilizing computer based information systems to predict stock prices. These information system based techniques involve the concept of neural networks. These neural network based information systems, named Artificial Neural Networks (ANN), are considered to be able to forecast and predict stock prices with great predictive power. Artificial Neural Networks are not only being successfully applied to stock price prediction in capital markets, but are also being used in other fields of management sciences such as marketing (Papatla, Zahedi, & Zekic-Susac, 2002), operations management (Kaparthi & Suresh, 1994), finance (Etheridge, Sriram, & Hsu, 2000), economics (Hu, Zhang, Jiang, & Patuwo, 1999), accounting (Lenard, Alam, & Madey, 1995), and management information systems (Zhu, Premkumar, Zhang, & Chu, 2001).

This section of the literature review on stock price prediction models is categorized mainly into three sections. The first deals with the comparison and analysis of predictive power or conventional capital asset pricing models, and the Fama & French three factors model for stock price forecasting. The second section deals with Artificial Intelligent techniques and their usage in stock price prediction as used in earlier research studies. Finally deals with Value-based management model. It is used to analyse investment activity and make decisions based upon that analysis.

2.2 Forecasting Price Modelling

Traditionally, stock market behaviour is forecasted using conventional methods such as capital asset pricing models and/or the Fama and French three factor model. Sharp (1964), Ross and Roll (1975), Fama and French (1992) & (1993), Banz (1981), Danial and Titman

(1997) and others have either used one of these models to predict stock market behaviour in isolation, or compared the predictive power of both models for forecasting accuracy and performance.

2.2.1 Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) is one of the oldest and most conventional models used by Sharp (1964), Ross and Roll (1975), Fama and French (1992) & (1993), Banz (1981), Danial and Titman (1997) and others to explain the cross-sectional variation in stock market behaviour. This model is proposed by Sharpe (1964) and Lintner (1965) in their separate studies. The basic underlying assumption of CAPM is the linear function of a security's returns and the relative risk of the market. A major implication of this model is that the relative risk of the security (β) is alone sufficient to explain the variability of all its expected returns.

Further, Hu (2007) argued that the cost of capital ca)n be measured and estimated using various models as authentic sources of estimation, while the best practice of previous historical studies has been estimated using the proxy of the premium factors. The study suggested a unique methodology for the estimation of the premium factors and Hu utilized several types of variables from the business cycle. He used trade strategy based on the sample results and concluded that his results were better than the maximum previous estimations where many researchers had used the general practices of the Fama and French three factor model in developing economies. This study found that the Fama and French model was better than CAPM when the results were interpreted in the short run. However, in the long run, the model of asset-pricing, in which researchers use an estimation method, was found to perform well from the perspective of firms in the corporate sector of a developing economy. At the end it is recommended that for the estimation of capital budgeting decisions in the corporate sector, for short term planning, the Fama and French three factor model is one of the best methods for business organisations.

Al-Zubi and Salameh (2009) have stated that the capital asset pricing model helps all the countries in the world to enhance the savings of firms and to accept the challenges of competition between firms in the corporate sector of the economies. The main purpose of their paper is to specifically analyse and predict the return on stock for industrial firms on the Amman Stock Exchange (ASE). The main objective is to implement this model in a developed economy so that the cross-sectional variations on the returns of stock can be verified and analysed in firms relevant to the industrial sector in the Amman Stock Exchange (ASE). The study used the new technique and method of Generalized Methods of Moments (GMM). By regressing these two models (Fama and French and CAPM), their output (results) indicated that the Fama and French model, with just two or three factors, showed variations which were found to be common as cross-sectional variations in the return of the stock, and did so comparatively better than CAPM.

2.2.2 Fama and French Model

Alternatively, the model proposed by Fama and French (1992, 1993) is a modified version of this capital asset pricing model which assumes that cross-sectional variation in the expected returns of a security is a function of three factors: market risk, size of the firm and its book-to-market ratio. This is known as the Fama and French three factor model of forecasting volatility in stock market behaviour. Many academic researchers and economists have applied these models to the US and non-US equity market and concluded that, in emerging economies, the returns on individual stocks are a decreasing function of its size and an increasing function of its book-to- market ratio (Barry, Goldreyer, Lockwood, & Rodriguez, 2002; Drew & Veeraraghavan, 2001; Fama & French, 1998).

Fama and French (1992) used two variables together to check the effect of the firm's size and the value of the book-to-market equity ratio. Their aim was to see how they would impact the variation by using the cross section in average returns on the stock of the various material which was kept in the different firms as inventory. They used the values of the β for the variables of relative risk of security, and another value for the variables of price to earnings ratios. On the other hand, when statistical analysis is done to check the effect of the variations in β, which are not related to the firm's size, and the association among the market value of the β, it is found that the average return on these variables are flat, when the value of the β is just used as an explanatory variable.

Fama and French (1993) also applied the Fama and French three factor model along with two additional risk and return factors which may forecast and explain the possible variation in stock and bonds returns. The additional factors included in the Fama and French three factor model are maturity and the market-related default risk of bonds. The results demonstrated that stock market related variables like book-to-market and firm size successfully forecasted the returns variations in the stock/equity portfolio. However, this Fama and French three factor model is successful in capturing the bond returns variation, except that this is only so for low graded firms which have a higher default risk. The final conclusion is that five factors are required, two in addition to the Fama and French three factor model, or four in addition to the traditional capital asset pricing model. These are essential for explaining the variation in capital market returns and for forecasting the capital market's behaviour.

Fama (1998) stated that market efficiency depends upon the survival of different challenges based on the literature of various authors on a long-term return basis on long-term unique methods. These results were consistent with the hypothesis related to efficiency, and found that such results are unique and traced rarely in the literature due to uncertainty. Such reactions are found that clear information regarding over reaction is common. Fama found that there is a total difference in market efficiency in long-term return unique patterns during under reaction events as well as after the events occur. He suggested that these are common results with respect to financial decisions taken over a long period of time, but that this is not true for short-term analysis of firms' investing patterns. The logic behind this is that during short-term analysis, financial behaviour cannot be treated in an efficient way to get the results. Fama concluded that the methodology is changed then it can the results mostly in long term anomalies in capital markets trends that they tend to not appear properly due to reasonable changes in the tools and techniques used.

China, as one of the major emerging economies, has also provided support for these conventional forecasting models. In the Shanghai and Shenzhen stock market, the random walk hypotheseis is applicable (Liu, Song, & Romilly, 1997), whereas a link between returns and lagged interests rates can also be found in foreign markets (Su & Fleisher, 1998). Drew et al. (2003) found that both the firm related factors of the Fama and French model (book-to-market ratio and firm size) have a negative impact on stock price variations, however many others have found a positive sign between stock price and book-to-market ratio. In this regard, Wang and Di Iorio (2007) used the data set of 1994-2002 and concluded that beta is not an important predictor of stock returns; however, the other two factors of the

Fama and French model have significant explanatory power in cross-sectional variation of stock returns. In addition, Wong et al. (2006) also found similar findings to the Fama and French model by adding two other variables of average returns in the preceeding six months, and floating equity. Moreover, Chen et al. (2007) provided evidence on data from 1998 to 2007 that there is a non-linea inverted U-shaped relationship between stock returns and book-to-market ratio for smaller firms.

Homsud et al. (2009) indicated the importance of the Fama and French three factor model in the stock exchange of Thailand for the five years from 2002 to 2007. The data of the 421 firms from the developed economy of Thailand were divided into six major groups, and these groups were labelled as follows: big high (BH), big medum (BM), big low (BL), small high (SH), small medum (SM), and small low (SL). B and S were taken to mean the mean size impact by measuring the trends of the capitalization of the market in all companies in this study. They found that the H, M and L values have significant impact on the measurement of the book- to-market values of firms in the developing economy of Thailand. Their research was able to add two significant variables of firms' specific factors (the firms' size and book-to-market value ratios) on the basis of the capital asset pricing model. This was done by following Fama and French model's explanation and inducing the risk factor and return on assets in the Thailand stock exchange in the BH, SH, BM, and SL groups in the mixed economy of Thailand. It was concluded that the Fama and French three factors model verified the variations, explaining risk factors in the form of the returns of the stock, which was found to be a better option compared to the traditional model of the capital asset pricing model in four groups (SH, BH, BM, SL).

Along with this, Hamid et al. (2012) investigated and evaluated the efficiency of the Fama and French three factors model by using the variable asset of pricing, and one other variable which is the expected returns on the portfolio for various corporate stocks in the financial corporate sector of Pakistan, using data on various firms from the Karachi stock exchange. In their research they used the various six firms having portfolios in their corporate sector by using multivariate regression analysis on the basis of the size and the book value to market value. They used the monthly data from the financial sectors, i.e. banks from developing economy of Pakistan, from 2006 to 2010. Results indicated that majority of firms in Pakistan which are using the Fama and French three factors model have a lot of variation in their returns.

Similarly, Bhatnagar and Ramlogan (2012) stated that the work done by Fama and French at various time periods using the three factor model helped firms to apply the CAPM theorem and it contained the capability to explain the returns on stock. This study used premium values for the calculation of the CAPM model used in the United State of America. Their work provided a special perspective from the previous work of Fama and French by using multiple regressions for the comparison of the performance and evaluation of CAPM done in the developed economy of the United Kingdom.

Recently, Eraslan (2013) checked the validity of the Fama and French three factor asset pricing model by analysing monthly data from the Istanbul Stock Exchange from the period 2003-2010. Using firm size, it was found that large firms have more excess of expected return on average, compared to small firms where both small and large firms have portfolios in their corporate structure and policies. Generally speaking, firms which have low book-to-market ratios in portfolio management perform much better than those firms which have higher book-to-market ratios. Further, it is reported that there is strong effect of the factor of risk on the portfolios of small firms, while large firms do not have a variation of portfolios, and medium sized firms have the strong impact on the Istanbul Stock Exchange. The book-to-market ratio factor is found to have significant impact on the portfolios of firms with high book-to-market ratios from the perspective of portfolio management. Shaker & Elgiziry (2014) compared the applicability of some of pricing models in the Egyptian stock market:, the Fama-French three factor model, the CAPM, the liquidity-augmented four factor model, the Cahart four factor model and the five factor model (liquidity and momentum-augmented Fama-French three factor model). The sample was divided into 6 portfolios sorted on book-to-market rate and size o. The results based on the GRS (1989) test show evidence that the Fama and French model is the best and the other models are rejected. From their side, Shams, Abshari, Kordlouie, Naghshineh & Gholipour (2014) studied the influence of information value about liquidity risk and risk of market on non-ordinary returns in the Fama and French three factor model at the Tehran Stock market. The results show that the impact of SMB and HML of the Fama-French three model factor was eliminated. Furthermore, corporate properties and the stock market are considered as market risk variables and liquidity risks. Also, outcomes show that the model is satisfactory. Finally, Khalafalla (2014) examined the power of the CAPM model, the arbitrage pricing theory APT, and the Fama and French three factor model on the Khartoum Stock market. Outcomes showed that volatility computed via TARCH shows the effect of bad news at the conditional is double that of good news; furthermore to the preference of generalized least squares over a covariate model as an estimation technique. Results are against the CAPM because the CAPM's prediction that the intercept must equal 0 has not been achieved, and its main assumption that the stock market is effective is violated. The APT presented no response to news from macroeconomic variables. However APT out-performed the CAPM and the Fama-French three factor model. However, there are not study that applies Fama and French three factor model or CAPM in Saudi Arabia stock market which is useful to attempt apply FF and CAPM models.

2.3 Artificial Intelligence (forecasting stock prices)

2.3.1 Artificial Neural Network

Alongside conventional methods of stock market forecasting, academic researchers have begun using computer based information systems to predict stock prices and indices in recent years with the development of the information technology era. These information systems are based on techniques involving the concept of neural networks such as Artificial Neural Networks (ANN), which are considered to be able to forecast and predict stock prices with great predictive power. The conventional methods of stock market forecasting, such as CAPM and the Fama-French three factor models, assume linearity between the stock prices and the predicting variables. However, Artificial Neural Networks relax the assumption of linearity and these techniques imitate the expert skills of human brains and knowledge-acquisition (Bergerson & Wunsch, 1991; Sharda & Patil, 1992). These ANN networks are based upon the non-linear strucutrue of the information network of human brains and the links between informational nodes (Haykin, 2010).

Research on the usage of ANNs to solve complex financial problems has taken place in recent years. In this regard, Chen et al. (2003) used a probabilistic neural network to predict the returns on the Taiwanese Stock Exchange index. The objective was to compare the forecast accuracy of the probabilistic neural network with that of conventional methods by using a linear technique of generalized methods of moments. The study reported that the probabilistic neural network had a better predictive power of stock market forecasts, compared to the linear generalized method of moments. Similarly, Diler (2003) also utilized various technical-based ANNs to predict the Istanbul Stock Market 100 Index returns. The study confirmed a 61% accuracy rate of prediction of the stock market index of the Istanbul Stock Exchange if the investors are using artificial neural networks to predict this value. On the same lines, Altay and Satman (2005) compared the forecasting performance of ANNs with ordinary least square for stock market behaviour forecasts of the same Turkish stock market. The results of this study also confirmed that ANN models predict the daily and monthly index values more accurately, however, these models failed to outperform the linear regression model.

Cao et al. (2011) investigated the forecasting capability of conventional forecasting models, such as the capital asset pricing model and the Fama and French three factor model, along with a three layer feedforward artificial neural network to predict the stock market behaviour of Chinese stock markets. The predictor variables used for both types of models were the same. However, the conventional models were run with an assumption of linearity. Contrary to expectations, no significant differences were found in the forecasting accuracy of conventional models and artificial neural network models. The results may be attributed to the emerging nature of Chinese capital markets. However, ANN models outperformed the traditional linear prediction models which are a clear indication of the usefulness of ANNs for stock market forecasting in emerging markets. Similarly, Kara et al. (2011) attempted to develop two prediction models for stock price movements and compared their performance in the daily Istanbul Stock Exchange National 100 Index. The models included support vector machines and artificial neural networks. Input variables were based upon 10 technical indicators of stock price volatility. The results found that the three layer feedforward artificial neural network outperformed the support vector machine models for stock market prediction.

Olatunji et al. (2013) presented an ANN based model for predicting the Saudi Arabian stock market. The proposed model was tested on three different companies selected as the major determinants of the Saudi stock market. The results indicated that the proposed ANN model predicts the next day closing price stock market value with a very low RMSE down to 1.8174, very low MAD down to 18.2835, very low MAPE down to 1.6476, and a very high correlation coefficient of up to 99.9% for the test set. On the other hand, Al-Zubi et al. (2010) applied the Fama and French model (with generalized method of moments) and ANN to predict the stock returns on the Amman Stock Exchange. The results documented that adding more variables to the Fama and French model improved its predictive power; however the same was not true for feed forward ANN. Hence it was concluded that feed forward artificial neural network based forecasting modes are proven to be less fruitful in forecasting stock returns on the Amman stock exchange which is an indicator of the stock market efficiency of Jordan.

Along with feed forward ANN, some researchers have used other types of ANNs. Huang et al. (2005) used a support vector machine to measure the financial variability in the Nikkei 225 Index of Japan. In order to evaluate the predictive power of the support vector machine, the performance of the Elman back propagation neural network model was compared to quadratic discriminant analysis and linear discriminate analysis. The experimental findings have concluded that support vector machines are successful in outperforming the other methods of forecasting. However, the proposed model, based upon the integration of the support vector machine and the Elman back propagation neural network model, has outperformed all other forecasting techniques. In addition, Naeini et al. (2010) used two kinds of neural networks, a feed forward multilayer perception (MLP) and an Elman recurrent network, to predict a company's stock value based on its stock share value history. The empirical findings indicated that multilayer perception neural networks are more capable of predicting stock market behaviour compared to both linear regression models and the Elman recurrent network. Moreover, the accuracy level of the Elman recurrent network model and the linear model were better than the multi-layer perception neural network model.

Hodnett and Hsieh (2012) evaluated the predicting capacity of ANNs in the selection of stocks for mutual funds. In doing so, the authors used two artificial neural network forecasting models namely "cascade – correlation algorithm of Fahlman and Lebiere (1990/1991)" which is embedded with "back propagation learning rule with extended Kalman filter" to predict the Dow Jones global equity returns. The results were in support of the capability of artificial neural networks to better forecast financial values and for use in active portfolio management. Moreover, the results of a risk-adjusted return performance matrix and fractile analysis evidenced that the Kalman filter rule trained model of an artificial neural network has a greater capacity to identify the outperformers in the global equity market compared to the back propagation learning rule trained model. However, there is not much significant difference between the performances of both artificial neural network models. The study further recommended the implication of the “extended Kalman filter rule” in training ANNs for financial data prediction.

Shen et al. (2011) applied a radial basis neural network forecasting model to train data and predict the market index of the Shanghai stock exchange. They used the “artificial fish swarm algorithm” to achieve the optimal radial basis function. Moreover, in order to increase the efficiency of the prediction process, AFSA – optimized mean -k clustering algorithm – is used in the learning process of radial basis function neural network forecasting. Then the study compares the ANN based forecasting model results (radial basis function optimized by AFSA, particle swarm optimization, and genetic algorithm) with the findings of autoregressive moving averages, support vector machine, and BP. The experimental results indicated that the radial basis function, which was optimized with AFSA, is much easier to use and provides much improved accuracy. All of the models combined that experimented in the study, including BIAS6 + MA5 +ASY4, were optimal with least level of errors.

Sutheebanjard and Premchaiswadi (2010) predicted the index movements of the stock exchange of Thailand. There are two stock markets operational in Thailand; “the market for alternative investment (MAI) and the stock exchange of Thailand (SET)”. Their study focused on the movements of the Stock Exchange of Thailand (SET), using back propagation neural network (BPNN) technology to forecast the index value of the Thailand Stock Exchange. By deploying the data of 124 trading days, the experiment was conducted to forecast the index value. There were two sub samples of the data i.e. 53 days for the training of the back propagation neural network (BPNN) and 71 days for the testing of this artificial neural network model. The findings reported that the back propagation neural network (BPNN) successfully predicted the Stock Exchange of Thailand Index with more than 98% accuracy. The back propagation neural network (BPNN) model also achieved less forecasting error when compared to the adaptive evolution strategy, but a higher prediction error when compared to the (1+1) evolution strategy.

With respect to time delay neural networks, Saad et al. (1998) compared three ANNs and evaluated their performance against the conventional method of stock market forecasting. The ANNs included a time delay neural network, a recurrent neural network, and a probabilistic neural network using conjugate inclined and multi-stream extended Kalman filter training for the time delay neural network and the recurrent neural network. The core objective of forecasting was to reduce the false alarms in the stock market, particularly with respect to options trading. The paper also discusses various forecasting analysis methods and performed these analyses based upon daily price data. The findings proved again that all the artificial neural network based forecasting models were capable of accurately forecasting the stock market behaviour on a convenient basis.

2.3.2 Adaptive Neural Fuzzy Inference Systems

The Fuzzy Inference System (FIS) is one of the most commonly used frameworks for obtaining the solutions to complex problems which use fuzzy reasoning, fuzzy if-then rules, and fuzzy set theory concepts. The Adaptive Neural Fuzzy Inference System is the integration of Artificial Neural Networks and Fuzzy Inference Systems, hence called Adaptive Neural Fuzzy Inference Systems (ANFIS) Jang (1992). Many earlier studies have used this integrated technique of ANFIS to solve complex financial problems such as prediction of stock prices in capital markets (Abraham, 2001, 2002; Abraham & Nath, 2001; Abraham, Nath, & Mahanti, 2001; Bouqata, Bensaid, Palliam, & Gomez Skarmeta, 2000; Lapedes & Farber, 1988; Pantazopoulos, Tsoukalas, & Houstis, 1997).

In this regards, Cheng et al. (2007) utilized Adaptive Neural Fuzzy Inference Systems and a Neuro-Fuzzy network to predict the stock prices for investors in the United States capital market. They concluded that ANFIS is very effective at forecasting capital markets and stock price behaviour in the US Stock Exchange. Similarly, Trinkle (2005) investigated stock price movements by applying ANFIS and neural networks to measure the excess returns for publicly listed companies on an annual basis. The core objective of the study was to compare and contrast the predictive power of these two neural network based models with Autoregressive Moving Average (ARIMA) model. The results indicated that the predictive power of ANFIS and ANNs is much greater than that of the ARIMA model, and ANFIS can predict stock returns with greater accuracy.

In the Malaysian capital market, Yunos et al., (2008) used a hybrid Neuro-Fuzzy along with Adaptive Neural Fuzzy Inference Systems for forecasting stock prices on a daily basis on the Kuala Lumpur Composite Index (KLCI). The study analysed the daily price data of KLCI. The results indicated that the indices are moving in an unstable manner which makes the prediction process relatively difficult. The Hybrid Neurofuzzy integrated with ANFIS is suggested to forecast the index behaviour on the KL capital market. Using four technical indicators for data analysis and two experiments, the study found that ANFIS is a better forecasting technique to predict the index prices on KL's capital markets, compared to ANNs.

The case study by Abbasi and Abouec (2008) designed a model to track trends in the stock price of an Iranian Corporation, the Iran Khodro Corporation, listed on the Tehran Stock Exchange. They applied ANFIS to predict the stock price movements of underlying stock. They use both short term and long term prediction models. In the long term, a neuro-fuzzy with dual membership functions and four independent variables (price to earnings ratio, dividend per share, stock volume and closing price) are used as an optimal model for measuring stock price fluctuations. Whereas in the short term, quarterly data was used to apply a neuro-fuzzy model with different membership functions in each quarter along with independent variables of stock volume, closing prices and price-to-earnings ratio. The findings of the research were twofold. It was reported that stock prices can be forecasted with fewer errors on the stock market of Iran using the ANFIS based prediction model. Secondly, the price movements of the Iran Khodro Corporation follow a non-linear behaviour on the Tehran Stock Exchange and the fuzzy models are also based upon non-linear concepts. So, stock prices can be predicted on the Tehran stock exchange using these fuzzy models, with more accuracy and less chances of estimation errors.

Similarly, Atsalakis and Valavanis (2009) used ANFIS to estimate stock prices, and concluded that Adaptive Neuro-Fuzzy Inference Systems are more capable of estimating the next day's stock price in capital markets. Boyacioglu and Avci (2010) also applied ANFIS to forecast stock prices and to explore whether an ANFIS algorithm could predict stock prices more accurately. Data from the Istanbul Stock Exchange index was obtained and ANFIS was applied on that data to predict the return on stock price index. In order to obtain the predictive results, three indices of the stock market and six macro-economic variables were used as input variables. The results indicated that the ANFIS model's predictive power and forecasting ability has an accuracy rate of 98.3% for a monthly return forecast of the Istanbul Stock Exchange National 100 Index. Hence, ANFIS can be used successfully as an alternative model for forecasting stock market behaviour and it can be proven as a valuable technique for practitioners and researchers in economics who are working in capital market forecasting.

With a different perspective, Giovanis (2011) explored the impact of interest rate fluctuations on the returns of common stocks of banking firms in Greece. Two alternative models for measuring this volatility had been applied by the research, namely Generalized Autoregressive Heteroskedasticity (GARCH) and ANFIS. The results suggested that interest rate fluctuations have not been found to significantly impact the stock price returns during the sample period using the GARCH model. However, when ANFIS was adopted, the results were based upon positive/negative effects along with trading rules which are not possible to obtain by applying conventional econometric models. Moreover, it was concluded that ANFIS is a better measure to forecast volatility in stock returns compared to the GARCH model for both of the sample periods used in the study.

Recently, Svalina (2013) applied an adaptive neuro-fuzzy inference system model to predict the closing prices of the Crobex Index of Zagreb Stock Exchange in Croatia. An individual fuzzy inference system was generated for each day by applying ANFIS, however separate fuzzy system subsets were used and input variables were created in a different way. The results suggested that ANFIS is a better technique to predict the index closing price of the Crobex Index of Zagreb Stock Exchange within its limits. The research studies on the ANFIS application suggested that it is a relatively better technique to forecast stock behaviour compared to conventional models of forecasting, as well as ANN techniques. However, there are not study that apply new techniques like Artificial Intelligence in Saudi Arabia stock market which is improve the obtain results with high accuracy .

2.3.3 Genetic Algorithm

Another information system based technique used in stock price forecasting is genetic algorithms (GA) which is an algorithm used for obtaining solutions to complex problems. These algorithms actually work in genetic operators through which the desired outcome is achieved by modifying the artificial structure population in an iterative manner. The application of these genetic algorithms is also being applied to solving financial problems, particularly stock market behaviour forecasts. In this regard, Kim and Han (2000) utilized a modified ANN along with GA to forecast the index value of the stock exchange. The results reported that the genetic algorithm approach is better compared to other conventional methods of stock market behaviour forecasting, as it can predict the index values with more accuracy and less volume of errors.

On the same lines, Kuo et al. (2001) developed a genetic algorithm along with a fuzzy neural network (GFNN) in order to measure the qualitative impact of the stock market. Moreover, ANN is used to integrate this effect with technical indexes. The data was obtained from the Taiwan Stock Exchange for this purpose on a case study basis to evaluate the effectiveness of this proposed artificial intelligence system. The results indicated that ANFIS, which considers both qualitative and quantitative factors, enhanced the performance of neural networks for buying-selling points and performance. The proposed GFNN uses fuzzy inferences based upon experts' knowledge and the qualitative factors of the stock market and hence is very useful in predicting stock market returns.

In addition, Grosan et al. (2005) used a genetic programming technique to forecast the NASDAQ-100 index of the NASDAQ stock market, as well as the S&P CNX Nifty stock index. This genetic algorithm technique was called Multi-Expression programming (MEP). The performance of this multi-expression programming algorithm was compared with an artificial network with the algorithm of Levenberg-Marquardt that supports vector machines, different boosting neural networks and the Takagi-Sugeno neuro-fuzzy inference system. The obtained results pointed out that multi-expression programming developed by the researchers is a new analytical technique to solve complex financial and stock market problems, and it is very promising in its nature. Moreover, the multi-expression programming technique also yields the lowest MAP values for both the stock indices of NASDAQ -100 and the S&P CNX Nifty index.

Recently, Abbasi et al. (2014) combined the fuzzy genetic algorithm and ANN techniques to predict the financial trends in the stock market index of the Tehran stock exchange. Initially, their study used a neural network to predict the market index. Afterwards, a genetic algorithm was used, based upon the output weights of the optimal neural network, to predict the index values. Consistent with the results of earlier studies which confirmed that non-linear models were superior to their counterparts, the present study also offered an integrated model of fuzzy genetic and neural networks. The empirical results also confirm the notion that this integrated model is superior in predicting the index value of the Tehran stock market. However, the study also pointed out that further investigation and research is required to find out more optimal models and solutions to complex financial problems such as forecasting stock market behaviour.

2.3.4 Hybrid Methods

Along with the above-discussed ANNs and its modified versions, researchers have also used some other related techniques based upon artificial intelligent information systems for predicting and forecasting stock market behaviour. Among these, Yamashita et al. (2005) applied a multi- branch artificial neural network (MBNN) to financial market applications. After investigating the predictive accuracy of the TOPIX index of the Tokyo Stock market using MBNN, the results evidenced that these multi-branch neural networks based on artificial intelligence might be more capable of generating greater generalization and representation, compared to simple conventional neural networks. Using the index value of TOPIX, multi-branch neural networks are better at predicting the next day TPOIX values. After various simulations were conducted to compare the multi-branch neural networks with other conventional neural networks, it was concluded that investors and economists can achieve a higher accuracy of forecasting with the proposed MBNN model.

Moreover, Afolabi and Olatoyosiuse (2007) used the “Kohonen Self Organising Map (SOM) and hybrid Kohonen SOM” prediction of stock prices. The empirical results demonstrated that the hybrid Kohonen self-organizing map (SOM) has greater predictive power for forecasting stock prices, compared to other techniques, performing with better accuracy and fewer errors. In addition to this, Chang and Liu (2008) also developed a Takagi – Sugeno – Kang type fuzzy rule based information system to predict the variation and deviation in the Taiwan Stock Exchange stock price values. The results also reported that this proposed model is capable of successfully predicting stock price variations with an accuracy rate of 97.6% on the Taiwan Stock Exchange and with an accuracy rate of 98.08% in MediaTek. Recently, Wei et al. (2014) argued that linear models are easier to understand and apply to predict stock market behaviour. On the contrary, non-linear artificial intelligence based neural network forecasting models are complex and hard to understand. Keeping in view this issue, they proposed a hybrid prediction model which uses a linear model and a moving average technical index (MATI) which further employs fuzzy logics (fuzzy inference systems) and a refined adaptive neural network. A ten year data set was utilized from the Taiwan stock market to verify the predictive ability of the proposed model on the criterion of root mean square error. The empirical results indicated that the proposed model is superior compared to other forecasting models such as Chen's model and Yu's model in terms of root mean square error.

2.4 Decision Making

2.4.1 Value-Based Management Model

Value-based management is a relatively newer methodology, and it is used to analyse investment activity and make decisions based upon that analysis. This model is based upon the expectation of portfolio investors and the firm's actual and potential shareholders. Value-based management aims *"to improve the process of making strategic and operational decisions in the organisation as a whole"*. Moreover, a cultural change of the organisation is the basic focus of this model. As is mentioned by Copeland et al. (2000), *"a manager with value as a principle is as interested in the subtleties of the organisational behaviour, as in using the evaluation as a measure of performance and as a decision tool*." Corporate and joint stock companies exist to fulfil the mutual benefits of all the stakeholders and to enhance the total value of firm. The role of management in these companies is to act as an agent of the shareholders to achieve this value enhancing objective, as this objective is really essential for the company. Value-based management focuses on four sections such as the required return on invested capital, expected investment return, actual return of investments, and weighted average cost of capital.

In this regard, Assaf and Araujo (2005) argued that value-based management practices of creating value for stakeholders can be applied to not-for-profit organisations, called "*The*

Third Sector." Using economic value added as a tool for value-based management and value creation for all stakeholders (not only shareholders) and the case study of a hospital, this study dealt with the adequacy of value-based management for the third sector and its ability to create societal value and to achieve the socio-economic goals of organisations. Copeland and Dolgoff (2006) emphasised the importance of expectation-based management as a tool to create value for the stakeholders by criticizing the already established performance measurement techniques. Expectation-based management is often used as a term for value-based management because both use the same tools and techniques as performance metrics. The authors defined expectation- based management as the difference between actual and expected economic profit, economic value added, both of which terms are used interchangeably by them. The study concluded that changes in expectations are highly correlated with returns to shareholders. This correlation is much stronger than the correlation of returns to shareholders with other measures such EVA growth, earnings growth or earnings etc. They argued that expectation-based management might help the management to refocus on corporate strategy, and help management by guiding them on how to communicate with potential investors and set internal performance and value creation parameters.

Grubisic (2007) conducted a survey of thirty top companies regarding the application of value-based management practices in different business segments. The results of the questionnaire survey indicated that the practices of value-based management are partially present in certain orbs of companies' operations; however, the companies are making great efforts to create value or concern about value management practices. Moreover, companies with a well-defined shareholder structure and institutional shareholder activism have greater impact on value-based management presence. The statistical results suggest that management focus and investment budget allocation can provide a quick overview about the value orientation of the company.

Moreover, Fourie (2010) tried to explore the applicability of value-based management performance metrics to measure the share price movements of the listed banking institutions of South Africa. At the first stage, linear regression models were applied to the individual share prices of sample banks in order to see whether the results of specified performance metrics of value-based management have any impact on share prices or not. In the second stage, pooled regression analysis was conducted to explore any possible differences in the combined integrated effect on share prices. Primarily, four performance metrics of value-based management were selected, namely: economic value added, economic profit, cash flow returns on investment and shareholder value analysis. The findings indicated that almost all of the value-based performance measures were not useful in determining the share price movements of selected sample banks, rather the price to earnings ratio and net operating profit after taxes predict the variations in share prices of banks in a more positive manner. The study suggested that although results are not favourable for value-based management and other techniques are more relevant to share price movements, firms should still concentrate on shareholders' value creation and should not ignore value-based management.

Furthermore, Sherstneva and Kostyhin (2012) focused on Russian companies which have initiated the use of value-based management in recent years. This paper is based upon the concept of expectation-based management given by Copeland and Dolgoff (2011). In their book they argued that there is little or no relationship between economic value added and returns to shareholders; however, expectation-based management has a strong relationship with the returns to shareholders. Sherstneva and Kostyhin (2012) stated that management is making investment/ disinvestment decisions or dividend payouts on the basis of expectation of shareholders (i.e. required rate of return) and hence these decisions will lead to either an increase or decrease in the share price of the stock, which will ultimately lead to enhanced economic value added. The proposed model of Sherstneva and Kostyhin (2012) is based upon the balance of four factors: WACC, (Ract), (Rexp) and (R_{req}) by shareholders and portfolio managers.

2.5 Summary

Capital Asset Pricing Model was the first ever technique introduced to forecast the expected returns of stock market securities in the early 1960s. However, this method of forecasting was modified by the notable work of Fama and French who introduced two additional factors into the traditional capital asset pricing model. This forecasting model became very popular under the name of 'Fama and French three factor model' and was heavily used in academic research, as well as by economists to predict and forecast stock market behaviour. Afterwards, with the development of the information technology era, several technology-based solutions to complex financial problems were introduced. One common technique with multiple variations is the usage of neural networks to forecast the capital market behaviour. These are artificial neural networks (ANN) which use different methods to forecast stock markets such as feed-forward network, Elman network, cascade-forward network, radial basis function, and back propagation networks etc. Along with these ANNs, the researchers also applied fuzzy logics such as adapted neural fuzzy inference system and genetic algorithms.

The empirical research on forecasting stock markets has proved that the Fama and French model was more successful in predicting the capital market securities' behaviour, compared to the simple capital asset pricing model which was considering only one factor (i.e. market risk) to explain the cross-sectional variation in expected returns on securities. The Fama and French three factor model is still commonly used today in capital market research. However, various researchers, discussed in the above literature review, have proved that artificial neural network based forecasting models are more capable of predicting and forecasting stock market behaviour, compared to conventional methods of capital asset pricing models, as well as the Fama and French three factor model. Hence the present study also focuses on the application of artificial neural network models to predict the stock market behaviour of the Saudi Stock Exchange (Tadawul). Based upon expectations and the required/expected rates of return from investment, managers may apply the value-based management model to make investment/disinvestment or dividend payout decisions, which will affect the share price and ultimately impact the economic value added of the business entity.

CHAPTER 3

Overview of the Saudi Stock Market

3.1 Introduction

In the current chapter of the study, the operational, structural and regulatory development of the stock market in Saudi Arabia will be reviewed with respect to the historical development stages from 1935 to the present date. This development is supported with facts and figures and interpretative statistical analysis regarding the Saudi Stock Market for the period of 1993 to 2012. The rest of this chapter is organized as follows: section two describes the Saudi Stock Market from a progressive historical perspective; section three discusses the performance of the Saudi Stock Market; Section four presents the rank of the Saudi Stock Market in the Arab world; and finally the last section provides a summary.

3.2 Saudi Stock Market: A Progressive Historical Perspective

If we explore the history of stock market operations in Saudi Arabia, 'Arab Automobiles' is considered to be the first ever Saudi joint stock company, and it commenced its operations in the mid-1930s (SAMA Annual Report, 1997). Hence, the present study categorizes the lifeline of the Saudi Stock Market into three main historical stages of development: operational, structural and regulatory. The first era includes the time period of its earlier development, which starts from its inception in 1935, and continues until 1982. In 1935, the stock market initiated its preliminary operations with the first ever publically listed joint stock company 'Arab Automobiles' and its shares were offered to the general public. This first era concludes in 1982, when a committee of Ministers consisting of the National Economy, Commerce , Finance and The Saudi Arabian Monetary Agency (SAMA) were charged with the responsibility of supervising the stock market operations of the first capital market of Saudi Arabia (SAMA Annual Report, 1997). This stage of development continues until 2002 in the new millennium, and is also known as the establishment stage of the Saudi Stock Market. It is characterized as a time period when the committee of ministers initiated regulation of stock market operations in a more sophisticated manner. This stage ended in 2002 when, under the Royal Decree # M / 30 dated 31 July 2003, the new Capital Market Law (CML) was issued. Finally, the third stage in the historical development of the Saudi capital market is 2003 to the current date, when the

Capital Market Authority began its operations to govern the stock market. The text below gives some important elements of each of these development periods.

3.2.1 The Preliminary Stage (1935 - 1982)

During the preliminary stage from 1935 to 1982, the Saudi government and regulatory authorities were least concerned with the development of the capital market in Saudi Arabia, which meant that the stock market of Saudi Arabia had a more primitive and informal nature. During this long phase of almost 50 years, two important factors can be identified which stalled the development of the stock market. First is the economic condition of Saudi Arabia which was experiencing its early development during this time period. The focus of the regulatory bodies and government of Saudi Arabia was on the development of the infrastructure for the country, the production of a skilled workforce, and efforts to enhance the living standards of the citizens of Saudi Arabia. This different focus delayed the development of the stock market. The second most important factor in this regard is that the country was blessed with a great deal of oil wealth within a very short span of time. The Saudi government, being the sole claimant of the ownership of these massive oil reserves, made available to the corporate sector many institutional channels of interest- free loans. Hence, the stock market was not the major source of finance for the corporate sector within Saudi Arabia, and stock market development was not a prioritized government activity (Molivor and Abbondante, 1980).

Researchers have also focused on this late development of the stock market in Saudi Arabia and have identified some important features of this early phase of stock market history. Abdeen and Shook (1984) argued that the proposed stock market was not backed by any single regulatory framework which could govern the stock market in an organized way. In its place were three legal government agents leading the stock market – the Ministry of Finance , the Ministry of National Economy, the Ministry of Commerce, and the Saudi Arabian Monetary Agency (SAMA). So the lack of an organized legal framework, and official policies to govern and regulate the activities of the stock market, led to its under-development in Saudi Arabia. In addition, shares were dealt in the stock market by unlicensed and unprofessional brokers which led to a less controlled share ownership.

Moreover, the founding and/or board members owned a greater fraction of companies' shares, and this disturbed the market equilibrium, allowing them to control the market in the way they wished, regardless of the best interest of the general public and common investors in the stock market. With a lack of awareness and knowledge about stock trading and the operations of the stock market, Saudi citizens were unable to trade and participate in the stock market as they did not have access to any rational investing approach or fundamental technical analysis (Abdeen and Shook, 1984, Al-Dukheil, 2002).

Along with these identified factors causing the slow development of the stock market in Saudi Arabia, the lack of investment opportunities and the small number of investment channels in domestic financial markets triggered speculative behaviour because of the excess cash available for investment by citizens (Abdeen and Shook, 1984). The lack of investment options and alternatives in the stock market discouraged the general public from participating in the stock market because there were only 14 joint stock companies listed on the Saudi stock market till 1975. However, the number of listed companies on the stock market increased to 38 in 1983 because of the massive oil reserve exploration in the 1970s, the Saudizaion program of the government under which foreign investment of foreign commercial banks in Saudi Arabia and privatization of government companies (Molivor and Abbondante, 1980, Abdeen and Shook, 1984).

3.2.2 The Established Stage (1984 - 2003)

In the 1970s, the Saudi government shifted its focus on the sole source of national income – oil wealth. The policy of 5-year development plans was adopted and the government tried to diversify the Saudi economy base. The initial three 5-year development plans of the government, starting from 1970, focused on improving the national infrastructure, developing a skilled workforce, and raising the living standards of citizens. After the third 5-year development plan, the government encouraged the private sector to contribute to the national economy, and foreign direct investment began by private-public ventures in 1986 (Niblock and Malik, 2007).

With this strategy of economic development, the Saudi capital market entered into the second phase of its development, classified as the established phase. Regularization and modernization had been the focus point of the government's policy of stock market development. In this phase, a three party alliance of legal agents was formed to govern and supervise the stock market in 1983. This three party governing body consisted of the Ministry of Finance and National Economy, the Ministry of Commerce, and the Saudi Arabian Monetary Agency. Among these three legal bodies, the initial public offering and the regulation of the joint stock companies in the Saudi capital market was the prime responsibility of the Ministry of Commerce. The Saudi Arabian Monetary Agency was charged with the responsibility of the daily operational activities of the stock market, and the supervision and regulation of the stock market. The Ministry of Finance and National Economy was the overall supervisory body for stock market development (Dukheil, 2002).

In this second phase of the stock market from 1983 to 2003, noteworthy development was witnessed in all aspects of the stock market, such as regulation, operations and market structure. According to the SAMA annual report of 1997, Ramady (2005), and Al-Dukheil (2002), some of the developments and progress included:

- Only twelve commercial banks were authorized to perform intermediation services and the maximum limit of the service charges was restricted to 1%.
- These twelve intermediaries set up a central "Saudi Share Registration Company (SSRC)" in 1984 for the registration of listed firms and to settle the share transactions. This body was moved to an automated system for stock market transactions in 1989.
- "The National Centre for Financial and Economic Information (NCFEI)" initiated in 1989 the general index of shares to estimate the stock market's performance. The index was named as the NCFEI index. This was initiated with the base value of 100 points based upon a value-weighted index with the initial date of 28th February 1985. One more stock market index, "Consulting Centre for Finance and Investment Index (CCFI)" was also formed in 1995 by a Riyadh-based private consultancy firm (Al-Dukheil, 2002).
- SAMA went for an electronic share information system (ESIS) in 1990 which enabled investors in different locations to trade in the stock market simultaneously. This gave the floorless market concept to the Saudi stock exchange.

- In the new millennium, the name of the electronic share information system (ESIS) was replaced with the "Tadawul All Share Index (TASI)" in October 2001. Contrary to ESIS, the TASI introduced a T + 0 (same day transaction settlement) with a comprehensive system of deposits, trading, and settlements. Online trading is an integral part of the Tadawul system, which is also capable of handling more e-trading and includes more financial instruments such as treasury bonds, investment companies' units, and corporate bonds and debentures. The operational structure was also enhanced and enlarged by introducing corporate announcements and financial information disclosures on the stock market website for the participants of the stock market (Tadawul Annual Report, 2002).
- Lastly, foreign investors were also allowed to participate in the Saudi stock exchange in 1997 which was restricted in the first phase of stock market for Saudi citizens

As the outcome of this regulatory transformation, the stock market of Saudi Arabia experienced significant development and growth compared to its previous era. Technology was adopted for the improvement of stock market operations and the regulatory regime was improved. However, there was still a lack of an independent authority to regulate the stock market (Al-Dukheil, 2002). The three party based governing system was not considered to be as successful as it should have been. That may have been because of a lack of communication between the three regulatory bodies. Moreover, the level of activity and participation by investors in the stock market was relatively lower (28.9% in 2002) as measured by the turnover of stock market (Al-Dukheil, 2002). Still there were only 68 joint stock companies listed on the stock market in 2002 which may be attributed to the weakness of the stock market development. The government, along with some big families, was the majority shareholder in the listed companies which left few free floating shares to be a part of stock market activity; another important reason for the slow development of the Saudi stock market (Niblock and Malik, 2007). In this era, there was less focus on the accountability and transparency in disclosures of financial information by the companies. The joint stock listed companies were required to report their earning results in every quarter; however, they were not penalized if they failed to do so (Niblock and Malik, 2007). Only a minimum of the required information was therefore disclosed, and there was no concept of voluntary disclosure in Saudi companies in this period. Inside trading was very common and the informed traders were moulding the market equilibrium in the direction they wished (Niblock and Malik, 2007). Finally, there was a lack of independent professional trading brokers as the trading intermediaries were only the twelve commercial banks in the Saudi stock market.

3.2.3 The Modernized Phase (2003 - date)

The government realized the weaknesses and flaws in the stock market development program as discussed above, therefore the 5-year plans of the Saudi government have continued to support the development of the stock market. The Royal Decree # M / 30 of 31st July, 2003 introduced the 'Capital Market Law' which initiated a new era of development in the history of the Saudi stock market. This phase was named as the modernized era of the stock market. Under this capital market law, the 'Capital Market Authority (CMA)' was formed in 2003. This is an autonomous governmental institution which regulates the stock market and reports directly to the honourable Saudi Prime Minister. It is the complete authoritative institute of the Saudi capital market and the enforcement agency of the CML (CMA Annual Report, 2009). The core functions of the Capital Market Authority, as described in the Capital Market Law and reported on the website of CMA, are defined in the following words:

- Regulate and develop the Exchange, seek to develop and improve the systems of entities trading in securities, and develop procedures that would reduce the risks related to securities transactions.
- Regulate the issuance of securities and monitor and deal securities.
- Regulate and monitor the works and activities of parties subject to the control and supervision of the Authority.
- Protect citizens and investors in securities from unfair and unsound practices or practices involving fraud, deceit, cheating, or manipulation.
- Seek to achieve fairness, efficiency, and transparency in securities transactions.
- Regulate and monitor the full disclosure of information regarding securities and their issuers, regulate and monitor the dealings of informed persons and major shareholders and investors, and determine information which participants in the market should provide and disclose to shareholders and the public.

- Regulate proxy and purchase requests and public offers of shares.

After its incorporation, the main function and focus of the CMA has remained on the development of the different facets of the Saudi stock market. One of these functions also includes the support, implementation and enforcement of a Saudi privatization program as a part of the diversification policy of the government with respect to the economic position of Saudi Arabia. Some of the significant improvements which have been observed in this third phase of stock market development are:

1. The establishment of the Saudi Stock Exchange (SSE) in 2007. The SSE was charged with the sole responsibility of conducting financial transactions in investment instruments based in the Kingdom. The SSE was called Tadawul and was an autonomous joint stock firm with a capital base of SR1200 million, owned by a “Public Investment Fund (PIF)”. Tadawul was formed to regulate and administer financial transactions trading, and to ensure a clean and transparent clearing of these transactions including depository services and information dissemination. The establishment of the SSE segregated the operational aspects of the stock market from the surveillance and supervisory functions, as emphasized in the targets of the Capital Market Law (CMA Annual Report, 2007).
2. The CMA also introduced monitoring criteria in order to ensure true/fair information dissemination and transparent quality disclosers. This requires a company with initial public offerings to issue a prospect containing hardcore information about the issuer of the security. Moreover, the CMA also ensures continuous information disclosures for all the stakeholders of the listed companies.
3. In order to avoid insider trading, the CMA reported information about the block holders of companies, holding more that 5% of the shares of a company, as well as trade restrictions for the board members and executives of the companies to participate in the stock market.
4. In order to settle trading conflicts, a resolution of securities disputes was adopted by CMA on 23rd January 2011.
5. A restructuring of the industrial sectors of the stock market was done by the CMA in April 2008, which formed the fifteen industrial sectors in the Saudi market and sixteen indices, compared to previous classification.

6. The Tadawul All Share Index was recalculated based on this new sectoral development and actual free float tradable shares, in order to better reflect the stock market changes (CMA Annual Report, 2008).
7. In order to liberalize the Saudi stock market:
   - All share values were split to SR10 from SR50 in April 2006 by CMA.
   - The GCC citizens were granted investor status in 2007 to increase the investor base of the Saudi stock market (Tadawul Annual Report, 2007).
   - From 2008, foreign citizens and investors were allowed to participate and trade in the Saudi stock market (CMA Annual Report, 2009).
8. The CMA introduced 110 independent professional brokers to facilitate stock market transactions in 2009, and banks were no longer authorized to perform trading intermediation services.
9. SUKUK and corporate bonds were introduced as trading securities for the very first time the Kingdom in June, 2009. This is a forward step in order to stock market development through financial engineering of tradable investment alternatives in the stock market of Saudi Arabia. This action enhanced the market depth of Saudi stock exchange and total worth of SUKUK and corporate bonds was estimated at SR 28 billion (US$7.45 billion) in 2010. The issuers of these debt instruments were SABIC and Saudi Electric Company.

In this most recent phase of stock market development in Saudi Arabia, the CMA has introduced many investment options and liberalized the financial market by increasing the accountability of listed companies, and creating and enhancing public awareness which has enhanced the investment culture in the Kingdom (Tadawul Annual Report, 2009). More than 1 million copies of an investment awareness information and educational campaign were distributed by the CMA in 2009. Medial training to report the accounting disclosures of financial information of listed companies was also one of the major contributions of the CMA to the Saudi stock market development. Furthermore, the CMA also welcomed university students in the Kingdom to familiarise them with the role of capital markets in the economic development of Saudi Arabia (CMA Annual Report, 2009).

3.3 Performance of Saudi Stock Market

Following the above review of the historical development of the Saudi stock market since its inception in 1935, the next section focuses on the financial facts of the stock market of Saudi Arabia (Tadawul). The data period for this analysis is 2007-2012, and it is based upon a time series review of the performance of the stock market. This section also compares the performance of different sectors of the stock market. Moreover, the performance of the Saudi stock market is compared with the regional stock markets of the Gulf and the Middle East, including North Africa. Lastly, the stock market activity of Tadawul is portrayed for the sample period.

3.3.1 Market Activity of the Saudi Stock Market

During the last three decades, the Saudi stock market has played its role in reducing the country's dependence on its massive oil reserves. Although it is one of the oldest stock markets in the Arab world, it is still very young compared to the world's major stock exchanges which were established in the nineteenth or early twentieth century, such as the New York Stock Exchange, the London Stock Exchange, and the Istanbul Stock Exchange etc. In this regard, Table 3.1 presents some of the summary figures about the stock market of Saudi Arabia. These facts and figures include the number of joint stock companies, quantity of traded shares, market canalization, turnover, and the Tadawul All Share Index for the period of 1985 to 2012.

As Table 3.1 shows, there were only 46 joint stock firms listed and trading in 1986. However, in 2012, the last year of analysis, this number has increased to 158 firms. Figure 3.1 below the table also depicts the listed companies' growth year by year in the Saudi Stock market. The annual growth rate in the listing of joint stock companies remained relatively low between the period of 1985 and 2005 and only 31 new companies were listed on the stock exchange during this period. In 2005, this total became 77 companies. Table 3.1 also reports that the number of listed companies decreased in 2002 because of the merger of different power/electricity companies in one company. The last few years have experienced a tremendous growth in the listing of companies on the stock market, and these listed companies almost doubled between 2005 and 2012. On average, the growth in the listing of companies for this period remained at 5% with respect to the initial listing.

Table 3.1: Key Indicators of Saudi Stock Market Activity.

Year	Total Firms	%	Shares Traded (Million SR)	%	Value of Shares Traded (Billion SR)	%	Transactions (Thousand)	%	Share Price Index (1985= 1000)	%
1985	na.	na.	4	na.	0.76	na.	7.84	na.	690.88	na.
1986	46	na.	5	25	0.83	9	10.83	38	646.03	-6
1987	51	11	12	140	1.69	104	23.27	115	780.64	21
1988	52	2	15	25	2.04	21	41.96	80	892	14
1989	54	4	15	0	3.36	65	110.03	162	1086.83	22
1990	57	6	17	13	4.4	31	85.3	-22	979.8	-10
1991	60	5	31	82	8.53	94	90.6	6	1765.24	80
1992	60	0	35	13	13.7	61	272.08	200	1888.65	7
1993	65	8	60	71	17.36	27	319.58	17	1793.3	-5
1994	68	5	152	153	24.87	43	357.18	12	1282.9	-28
1995	69	1	117	-23	23.23	-7	291.74	-18	1367.6	7
1996	70	1	138	18	25.4	9	283.76	-3	1531	12
1997	70	0	312	126	62.06	144	460.06	62	1957.8	28
1998	74	6	293	-6	51.51	-17	376.62	-18	1413.1	-28
1999	73	-1	528	80	56.58	10	438.23	16	2028.53	44
2000	75	3	555	5	65.29	15	498.14	14	2258.29	11
2001	76	1	692	25	83.6	28	605.04	21	2430.11	8
2002	68	-11	1736	151	133.79	60	1,033.67	71	2518.08	4
2003	70	3	5566	221	596.51	346	3,763.40	264	4437.58	76
2004	73	4	10298	85	1773.86	197	13,319.52	254	8206.23	85
2005	77	5	12281	19	4138.7	133	46,607.95	250	16712.64	104
2006	86	12	68515	458	5261.85	27	96,095.92	106	7933.29	-53
2007	111	29	57829	-16	2557.71	-51	65,665.50	-32	11038.66	39
2008	127	14	58727	2	1962.95	-23	52,135.93	-21	4802.99	-56
2009	135	6	56685	-3	1264.01	-36	36,458.33	-30	6121.76	27
2010	146	8	33007	-42	759.18	-40	19,536.14	-46	6620.75	8
2011	151	3	48263	46	1098.83	45	25,546.93	31	6417.73	-3
2012	158	5	82544	71	1929.31	76	42,105.04	65	6801.22	6

Source: SAMA Annual Report, 2012; and Tadawul Annual Report, 2002-2012.

Figures 3.1 and 3.2 below show the total annual number of listed companies and percentage growth in this listing for the period of 1985 to 2012, respectively. There was much less variation and volatility observed during this whole period (almost zero volatility) until suddenly there was a large jump. There has been a significant increase in last 5 years in the listing of companies which may be attributed to the CMA's efforts to development and transform the Saudi stock market. These efforts include foreign investment in the stock market and the conversion of savings of local citizens and expatriates to investment, which has enhanced the investment base of the Saudi stock market.

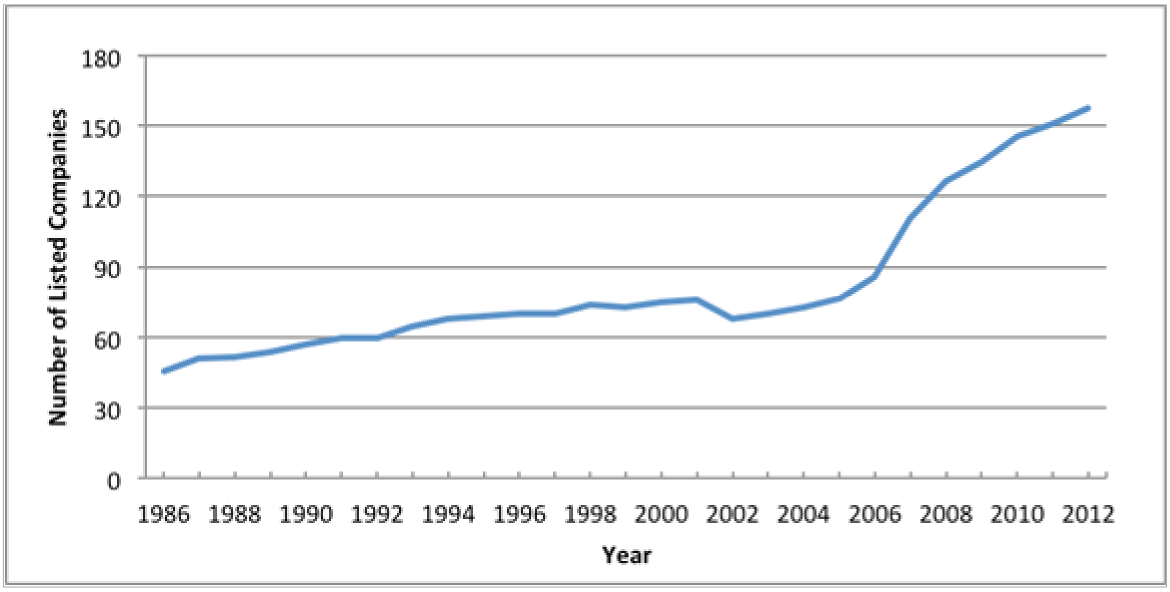


Figure 3.1: Annual Number of Listed Companies

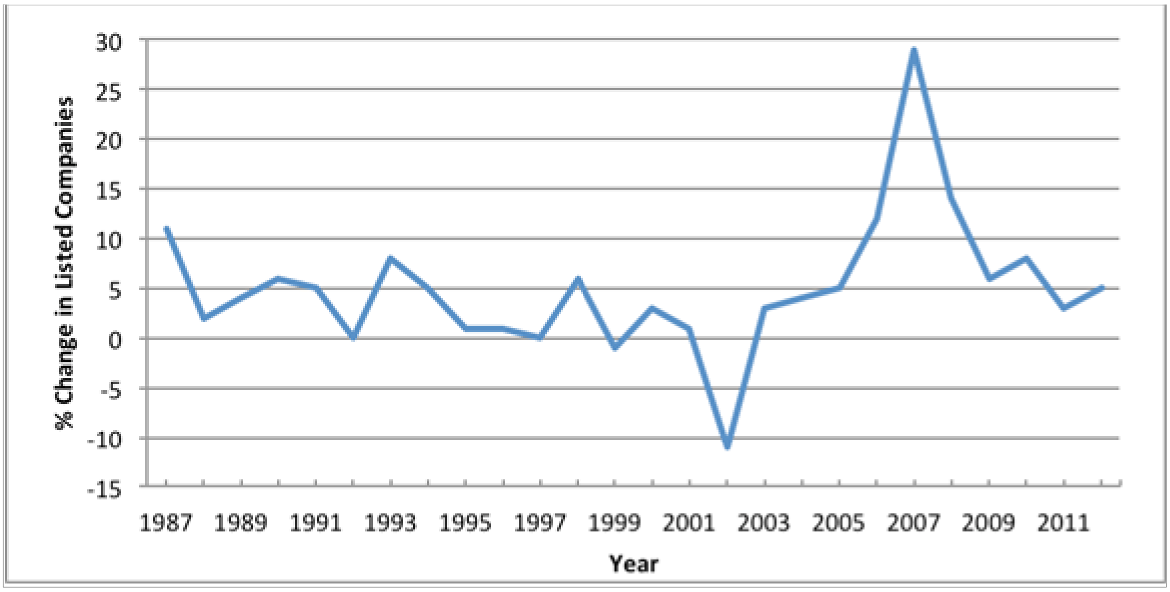


Figure 3.2: Annual Percentage Change in Number of Listed Companies

In addition to the increasing number of companies listed on the stock exchange of Saudi Arabia, other parts of stock market development have also shown a significant increase. For example, the number of traded shares on the stock exchange has increased. The quantity of shares traded on the Saudi stock market increased from 0.04 billion to 83 billion shares between 1985 and 2012. However, it is noteworthy that this movement is most significant in the last 7 years of the analysis. After the establishment of the Tadawul transaction mechanism in 2001, there was a significant increase in the quantity of shares traded, particularly between 2002 and 2006. This is because of the CMA's initiative of technology adoption in stock market operations and online floorless trading. There has been a great growth rate in the volume of shares traded between 2001 and 2006, approximately 64% per year (Figures 3.3 and 3.4).

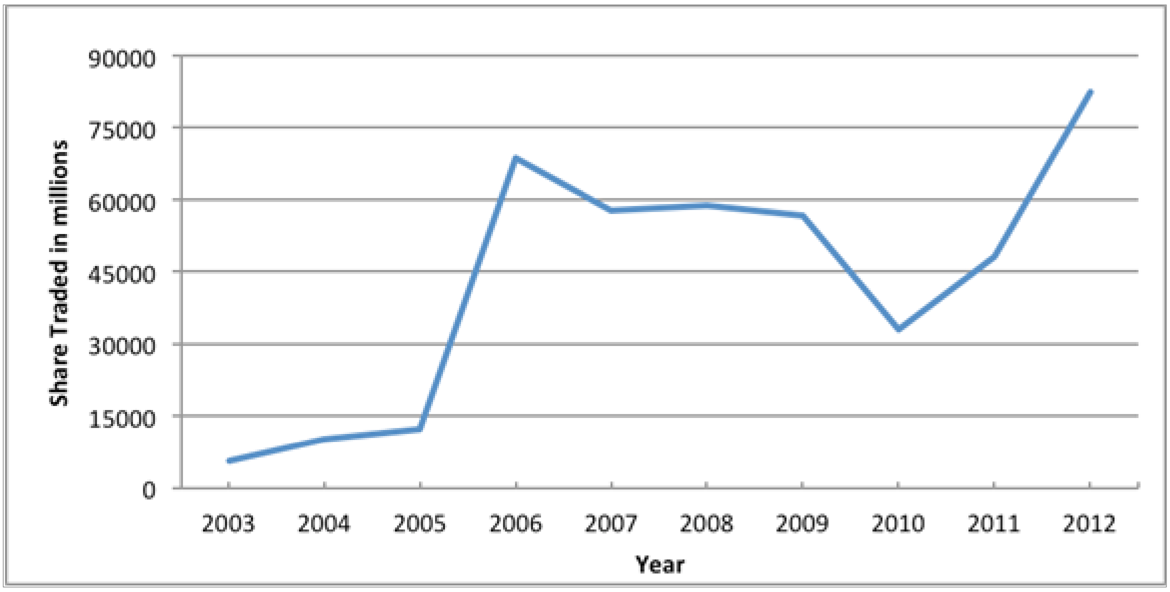


Figure 3.3: Annual Shares Traded

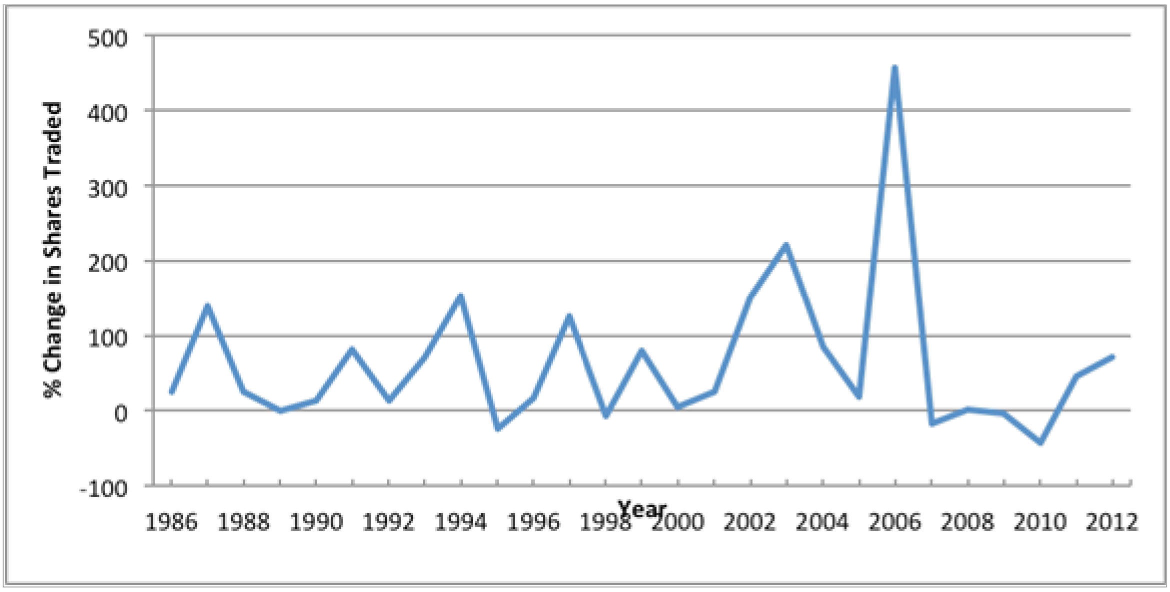


Figure 3.4: Annual Percentage Change in Shares Traded

The year 2006 is a special case where the share traded volume experienced an abnormal growth rate of 458% compared to the previous year. This was the time period when the CMA took the initiative to split the face value of shares from 50 to 10 Saudi Riyals in order to make them convenient investment options, particularly for small investments. However, in the financial crisis of the Saudi capital market in the last days of 2006 and 2008, turnover was reduced significantly and negative growth has been observed in 2007 by 16%, in 2009 by 3% and in 2010 by 43%. However, investors' confidence was restored in 2011 and 2012, and there was a positive trend and growth in share trading value which was 46% and 71% in 2011 and 2012, respectively.

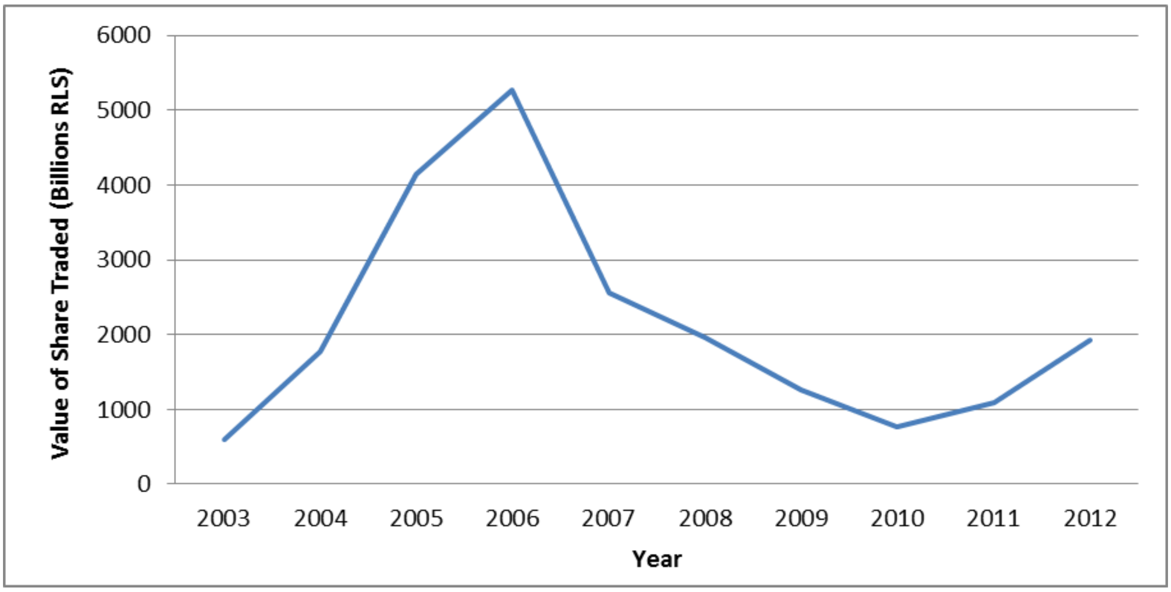


Figure 3.5: Annual Values of Shares Traded

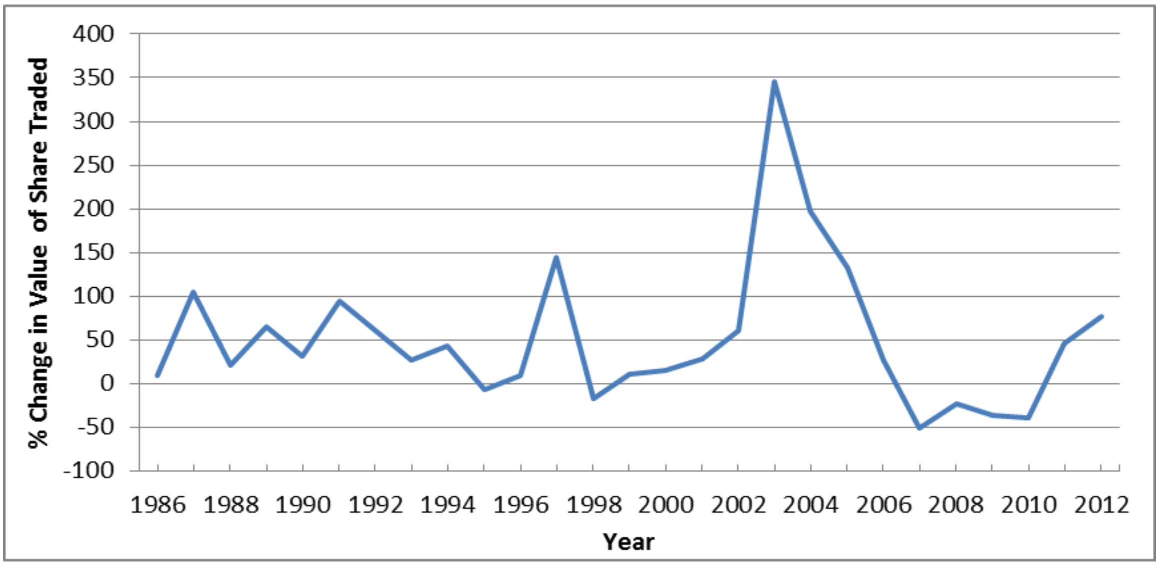


Figure 3.6: Annual Percentage Change in Values of Shares Traded

The facts reported in Table 3.1 and Figures 3.5 and 3.6 are based upon the value of shares traded in billion SR and the percentage change in this value from 1985 to 2012. It is predicted that the stock market of Saudi Arabia will be an active market with regard to share transactions and values traded. The share value traded has increased from 0.76 billion SR to 1930 billion SR during the study period of 1985 to 2012 (Table 3.1). The total number of financial transactions which were executed and completed increased from 0.784 million in 1985 to 96 million in 2006, depicting enhanced investor confidence. During the economic recession and downfall of the Saudi stock market in 2006 and 2008, a significant decline (around 30%) was observed in the value of shares traded and in the total number of transactions executed. This period can be considered as a failure in stock market development, however growth was renewed in 2011 and 2012 (Figure 3.7 and Figure 3.8).

There has been a constantly increasing trend in the share prices on Tadawul after the year 1986. This price increase was exceptional in the period between 2002 and 2006 (Figure 3.9). Table 3.1 shows that the lowest increase observed was 4% whereas during this period the growth rate peaked at 104% in 2005. During the period of 1985 to 2012, the Tadawul All Share Index decreased significantly 6 times. As shown in Figure 3.10, these time periods were 1986, 1990, 1994, 1998, 2006, and 2008.

During the year of 1986, the market index of TASI depreciated by six percent compared to the previous year, and then its growth remained positive at 19% per year for the next 3 years. The second Gulf war in 1990 caused the market index to decrease by 10%, however after the war, the index witnessed 80% growth but then decreased by 5% and 28% in 1993 and 1994, on average respectively. During the subsequent 3 years after 1994, the index improved due to the enhancement and development of the overall economy of the country with high GDP growth rates, increases in public expenditures, favourable balance of payments etc. (SAMA Annual Report, 1997). It can also be observed from the available data that the Saudi stock market was not affected by the Asian financial crisis immediately; rather there was an increase of 28% in the market index during 1997, the period of Asian financial crisis 1997. This is an indicator of the localization and immunity of the Saudi stock market from the effects of the international financial crisis (Figure 9).

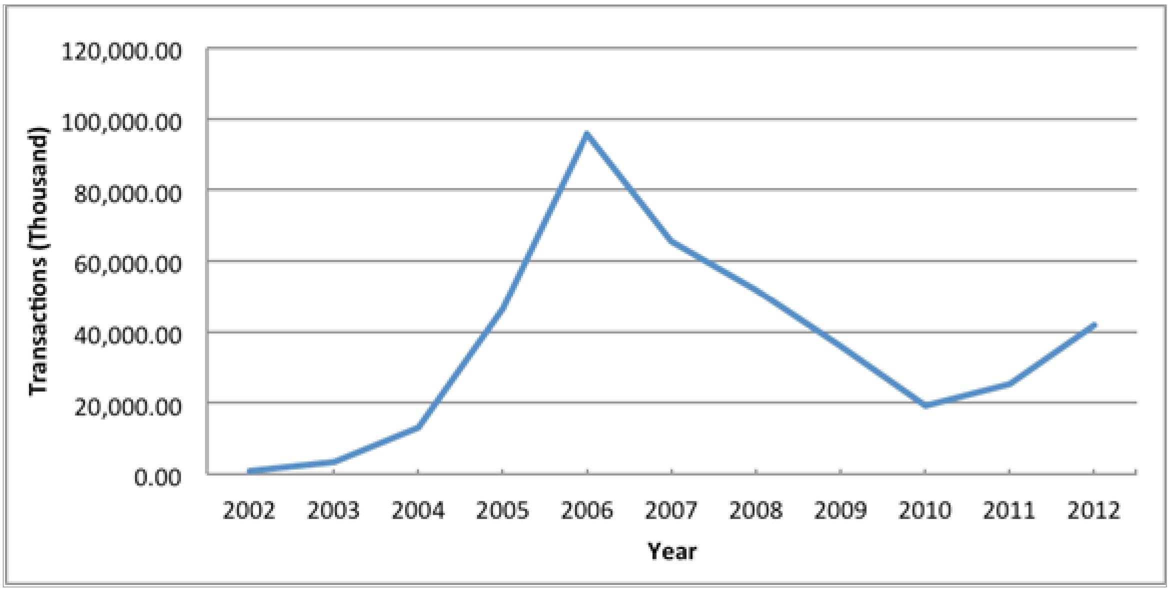


Figure 3.7: Annual Transactions

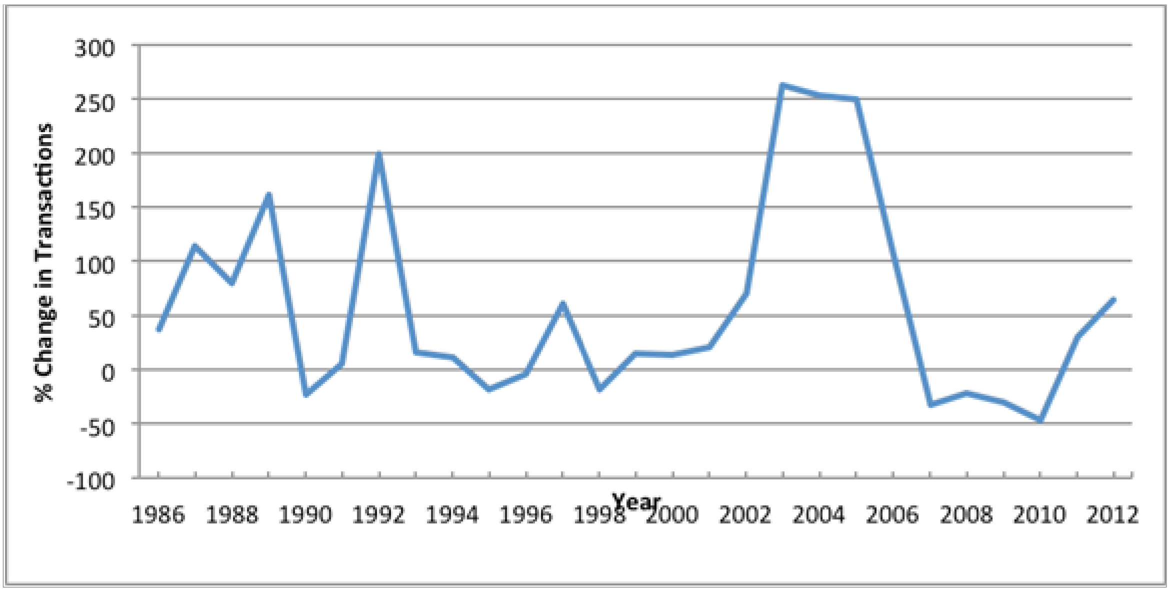


Figure 3.8: Annual Percentage Change in Transactions

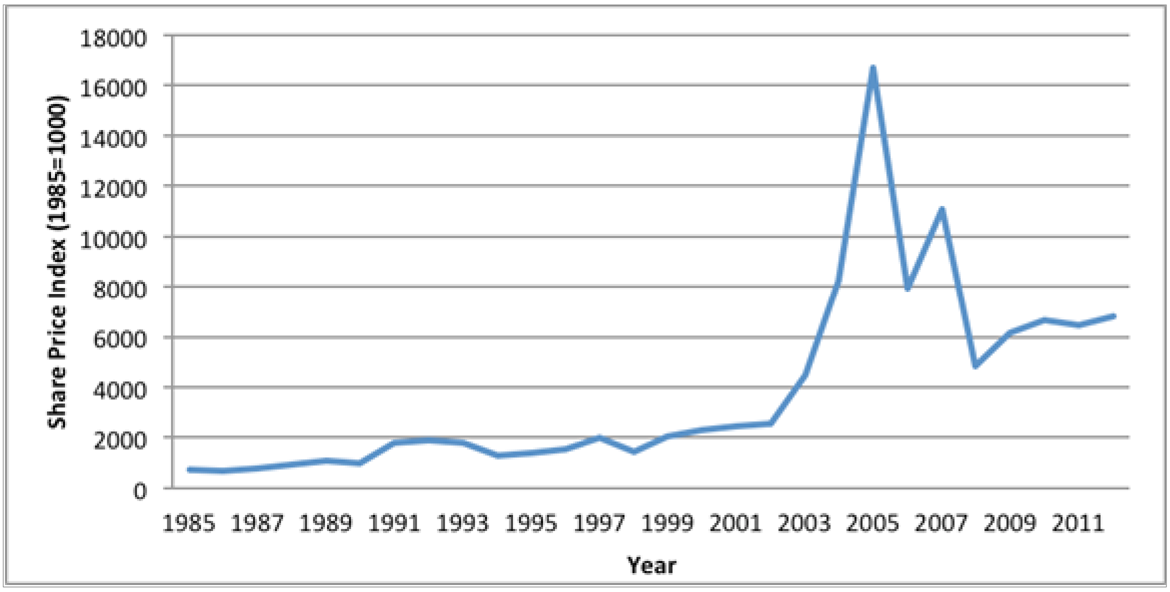


Figure 3.9: Tadawul All Share Index

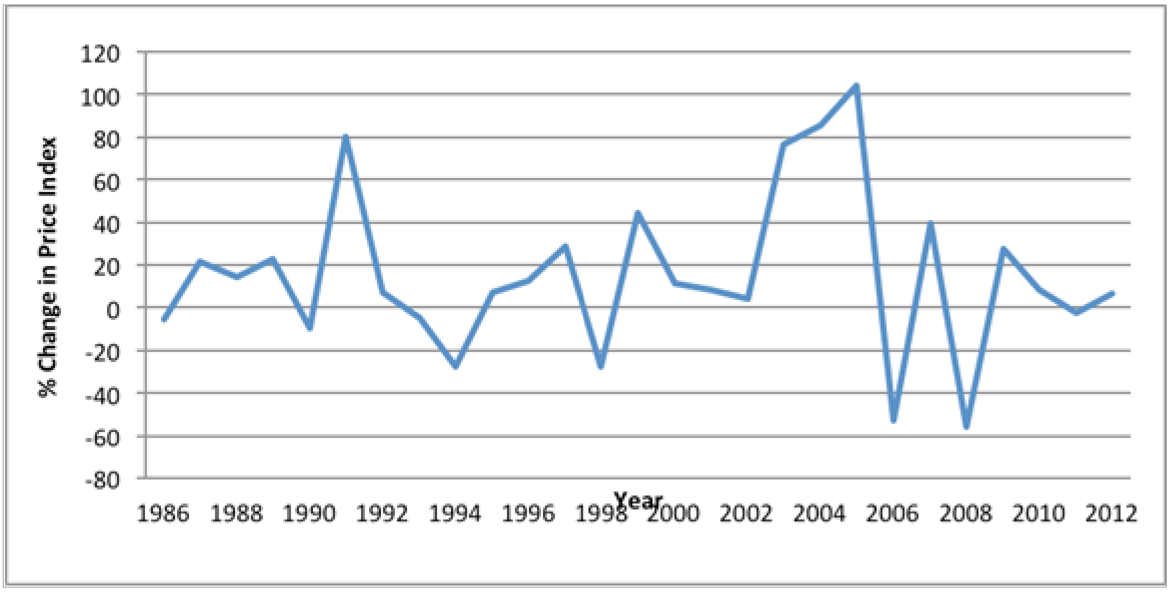


Figure 3.10: Annual Percentage Change in Market Return in TASI

In contrast to a loss in value of 28% in 1998, the market index of TASI continued to grow at a greater growth rate of 35% per year for the following 7 years. This growth rate was quite stable during the period of 2003 – 2005 at an average of 22% per annum, and then it experienced a tremendous growth of 88% per year afterwards (Figures 3.9 and 3.10). The annual report of the Saudi Arabia Monetary Agency (2006) described this development of the Saudi stock market as an outcome of many factors. These contributory factors include the role of structural reforms in reducing the dependency of the country on petro-dollars, the positive accounting performance of listed firms on the Saudi stock market which motivated investors to invest their savings in the stock market, stable oil prices globally, and an increase in the investor and investment base of the stock market. According to Al-Twaijry Abdulrahman (2007), the increased investor base enhanced the demand for more shares to be traded on the Saudi stock market, and this has played a major role in the stock market's development.

The highest closing point value of the market index of TASI was 20634.85 on 25th February, 2006. However, the end of 2006 also experienced the collapse of the Saudi stock market and TASI dropped to 12700 points approximately. This was more than a 60% decline in the index during that single year. Billions of riyals were withdrawn from the capital market due to this crisis and the total portfolio investment in the stock market declined by 39% to the level of 53 billion SR (SAMA Annual Report, 2007). As an outcome of this crisis, many investors lost their money on the stock market and experienced increased financial burdens.

During the year 2007, the stock market begun to recover its losses and the market index increased by 3106 points. This growth rate in the index value was 38.9%. In addition, the total investment base of the Saudi stock market increased by 25% to the level of 105 billion SR (SAMA Annual Report, 2008). The stock market suffered another financial crunch in 2008 and the index closed at its lowest value during the new millennium at 4803 points. This was a decrease of 56% compared to the previous year and the total investment base declined by 30 billion SR – approximately 30% negative growth (SAMA Annual Report, 2009). This financial crunch of 2008 has been attributed to the global financial crisis of the USA and the Western world, with the Saudi market participating as part of the world's financial markets. In the preceding years, the Saudi stock market recovered from its losses of the financial crises of 2006 and 2008; however, these crises really harmed the significant growth rate that the Saudi stock market was experiencing until the start of 2006 (Table 3.1, and Figures 3.9 and 3.10).

3.3.2 Size and Liquidity of the Saudi Stock Market

This study has utilized the following indicators to assess the maturity of the Saudi stock market; there are many measures of stock market size and liquidity in the literature, and there is no consensus on this:

1. Share Traded value to GDP
2. Share Traded Value to Market Capitalization
3. Market Capitalization to GDP

The market capitalization to GDP ratio is used to estimate the size of a stock market whereas the remaining two ratios are used to judge the stock market liquidity as used in the earlier literature on stock markets and financial markets (Levine and Zervos, 1996; Victor, 2006).

Table 3.2 and Figure 3.11 below report the size of the stock market of Saudi Arabia. The first ratio of market capitalization to GDP shows that this increased to 41% in 1993, compared to 18% in 1985. This growth rate has remained almost consistent until 2002. If we compare this ratio to the markets of the USA and other European counties, it seems to be relatively low because it is usually greater than in developed countries (Victor, 2006). This lower ratio can be justified by the argument that very few companies were added to the listing of the stock market of Saudi Arabia during the period of 1994 to 2002. This ratio greatly increased in 2003 when the market capitalization ratio jumped to a new peak value of 74%.

The new Capital Market Law introduced by the Saudi government in 2003 was the main cause of the increase in the size of the stock market. The new law and the new regulatory authority performed very well in enhancing the size of the Saudi stock market by enhancing the market base of investment, attracting new investors to the stock market, improving the operational efficiency and trading mechanism of the stock market, and introducing the central body for new securities registration etc. So, it can be observed that the stock market size as measured by this ratio increased by 110% in the next seven years with a significant jump of 208% in 2005.

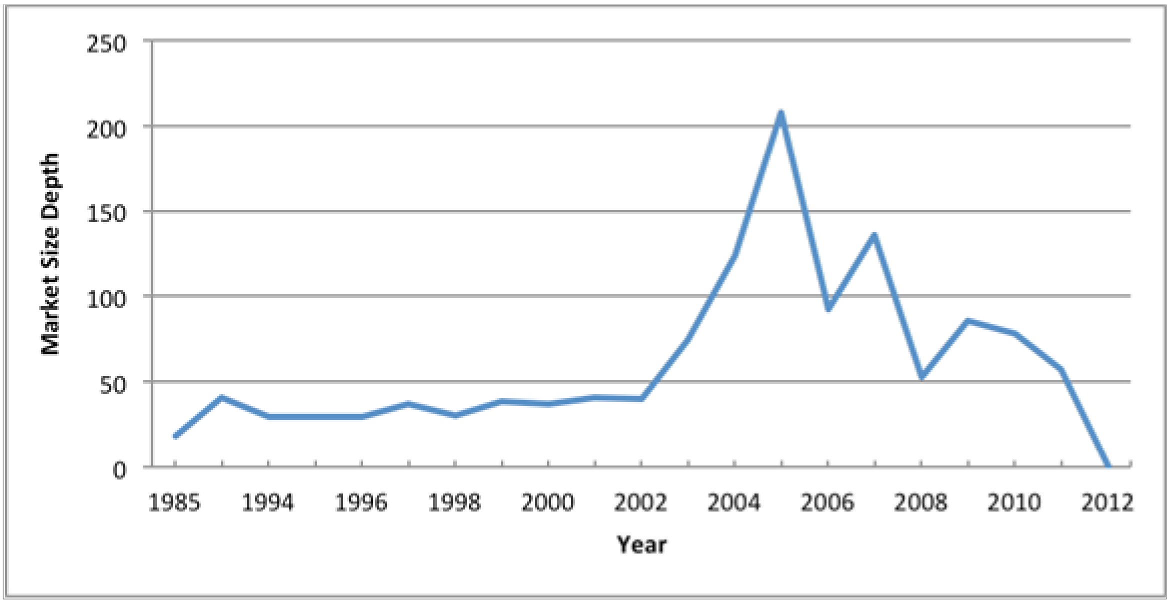


Figure 3.11: Market Liquidity (Depth): The ratio of market capitalization to gross domestic product (GDP) of the Saudi Stock Market, 1985 to 2012

Table 3.2: Market Size and Market Liquidity of the Saudi Stock Market, 1985-2012

year	Market Capitalization (MC) Billion RS	Value of Shares Traded (VST) Billion RS	GDP Billion RS	Market Size (depth) (MC/GDP)	Market Liquidity Ind (VST/MC)	Market Liquidity Ind (VST/GDP)
1985	67.00	0.76	372.41	17.99	1.13	0.20
1993	197.90	17.36	485.63	40.75	8.77	3.57
1994	145.10	24.87	494.77	29.33	17.14	5.03
1995	153.39	23.23	526.00	29.16	15.14	4.42
1996	171.98	25.40	581.87	29.56	14.77	4.37
1997	222.70	62.06	608.80	36.58	27.87	10.19
1998	159.91	51.51	536.64	29.80	32.21	9.60
1999	228.59	56.58	593.96	38.49	24.75	9.53
2000	254.46	65.29	697.01	36.51	25.66	9.37
2001	274.53	83.60	679.16	40.42	30.45	12.31
2002	280.73	133.79	699.68	40.12	47.66	19.12
2003	589.93	596.51	796.56	74.06	101.12	74.89
2004	1148.60	1773.86	929.95	123.51	154.44	190.75
2005	2438.20	4138.70	1172.40	207.97	169.74	353.01
2006	1225.86	5261.85	1324.56	92.55	429.24	397.25
2007	1946.35	2557.71	1430.77	136.04	131.41	178.76
2008	924.53	1962.95	1771.20	52.20	212.32	110.83
2009	1195.51	1264.01	1396.23	85.62	105.73	90.53
2010	1325.39	759.18	1695.03	78.19	57.28	44.79
2011	1270.84	1098.83	2221.77	57.20	86.46	49.46
2012	1400.34	1929.31	NA	NA	137.77	NA

Source: Tadawul Annual Statistical Report, 2002; 2012, and SAMA Annual Report, 2012.

The next ratio measures the stock market liquidity which is the value of share trading to the total market capitalization as well as to the GDP of the country, and the literature has suggested that a higher value indicates greater market efficiency and a lower exchange cost of financial transactions, because investors are trading more and more in the financial markets (Victor, 2006, Levine and Zervos 1996).

The values reported in Table 3.2 and the facts depicted in Figures 3.12 and 3.13 elaborate the stock market liquidity of the Saudi stock exchange. According to these values, the stock market of Saudi Arabia became more and more liquid after 2002. Since the highest value of the first indicator (VST/MC) was 48% and the highest value of the second indicator (VST/GDP) was 19%, we can interpret these ratios in the light of the earlier literature, and conclude that the stock market of Saudi Arabia is relatively less liquid and less efficient, as well as having higher costs of transactions during the analysis period 1985-2002 (Levine and Zervos, 1996).

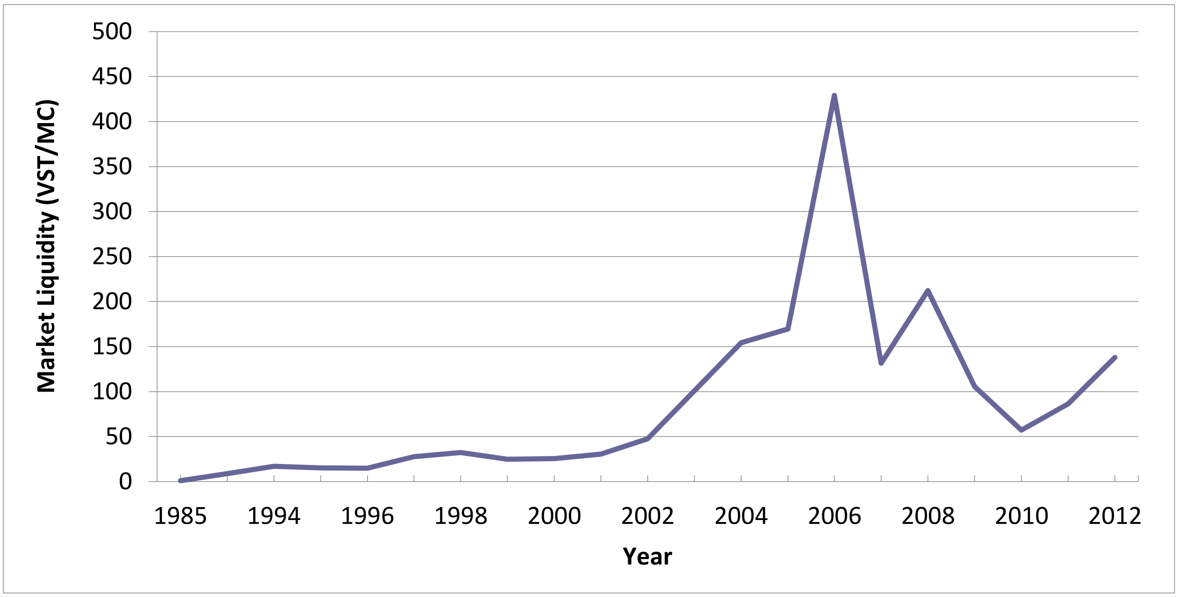


Figure 3.12: Market Liquidity (VST/MC) of the Saudi Stock Market, 1985 to 2012

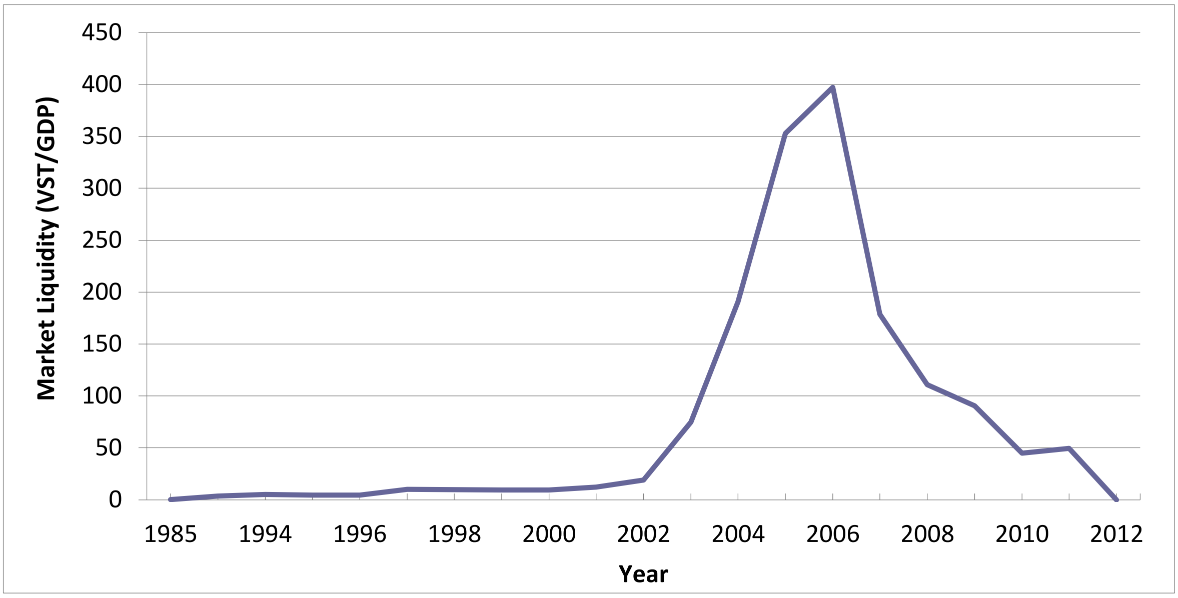


Figure 3.13: Market Liquidity in Terms of (VST /GDP) of the Saudi Stock Market, 1985 to 2012

The stock market of Saudi Arabia experienced higher liquidity during the period of 2003 to 2008 based upon the ratios of (VST/MC) and (VST/GDP). The average increase during this period was more than 200% in both of these years (Figures 3.12 and 3.13). This was the period of financial crunch in Saudi Arabia. In 2006, the market lost 53% of its value compared to 2005, whereas 56% of market capitalization was lost in 2008. Compared to 2007, the liquidity level of the Saudi stock market measured by the (VST/MC) indicator dropped by 50% in 2009, by 73% in 2010 to a level of 57%, then increased by 30% in 2011 to a level of 86%. Finally, it increased by 50% in 2012 to a level of 138% (Table 3.2).

3.3.3 Saudi Arabia Stock Market Sectors

The following section analyzes the industrial sectors of the Saudi stock market. There were a total of 8 business sectors in the capital market of Saudi Arabia in 2007. Among these, the business segment (which is also called the manufacturing sector) accounts for around 40% of the total market; the financial services (banks and others) constitute 30% of total market; and the remaining two big sectors (services and telecom) are 12% and 10%, respectively (Figure 3.14). The period from 2007 to 2012 witnessed a development in these classifications from 8 to 15. The percentage contribution of each business sector in 2012 is also represented in Figure 3.15.

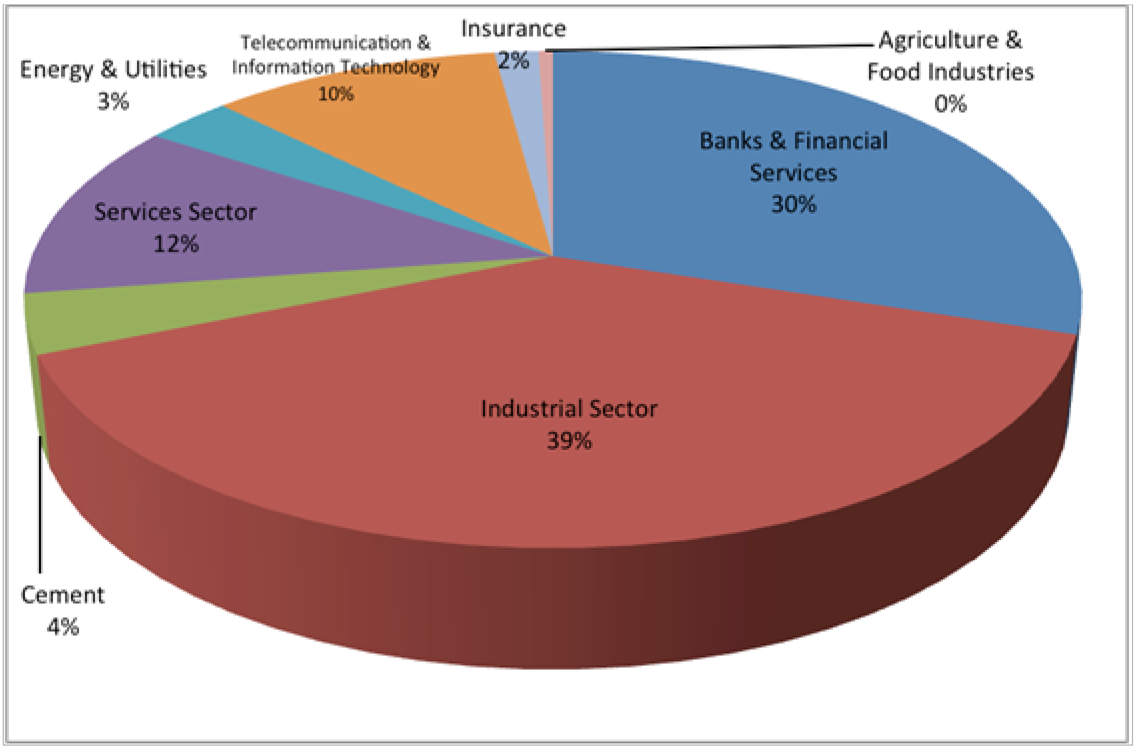


Figure 3.14: Percantage of Market Capitalization for each sector 2007
Source: Tadawul Annual Statistical Report 2008

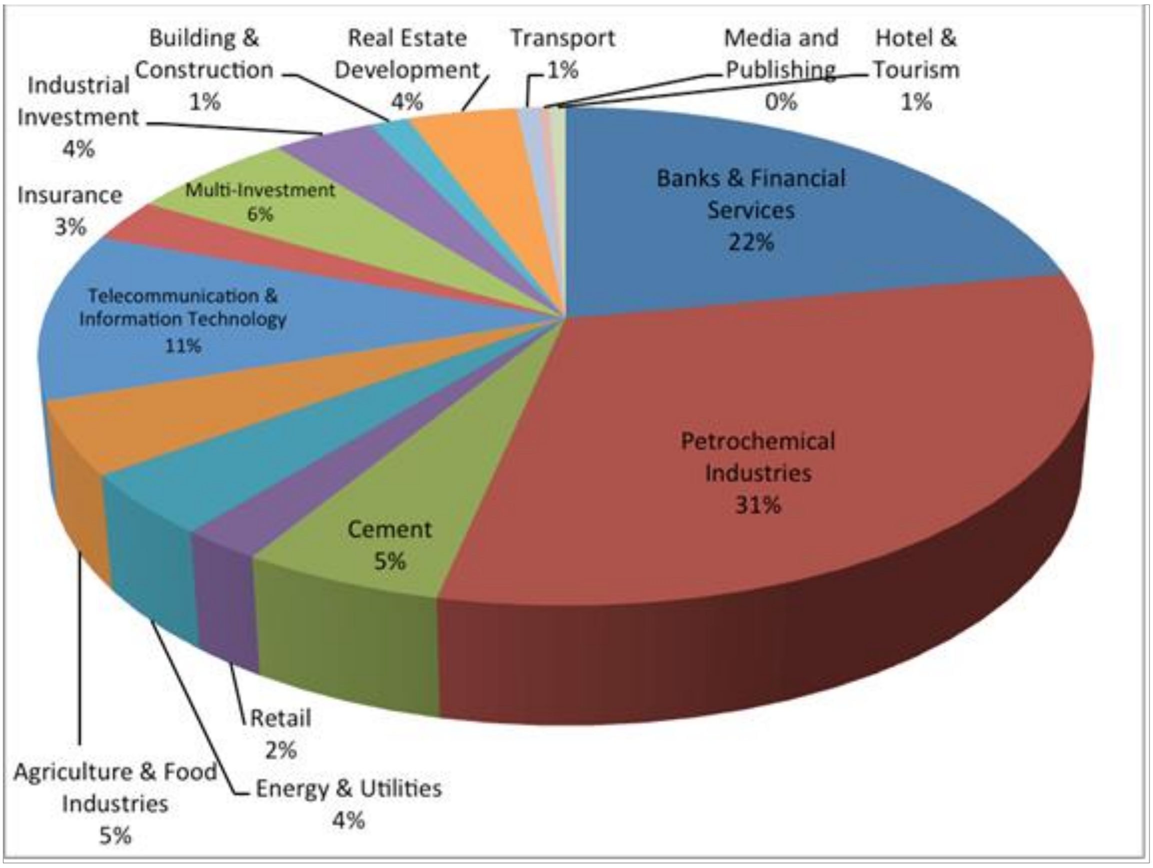


Figure 3.15: Percentage of Market Capitalization for each sector 2012
Source: Tadawul Annual Statistical Report 2008

Through the last five years, several improvements led to an increase in the number of sectors to fifteen sectors in 2008, the percentage of market capitalization of each sector in the end of 2012 was: Petrochemical Industries 31%; Banks and Financial services 22%; Telecommunication & Information Technology sector 11%; Agriculture & Food Industries 5%; Cement sector 5%; the other ten sectors – Energy & Utilities, Insurance, retail, Industrial Investment, Real Estate Development, Building & Construction, Hotel & Tourism, Transport, Media and Publishing and Multi-investment – 26% of the market (Figure 3.15).

3.4 Saudi Stock Market Rank in the Arab World

When we compare the Saudi stock market to the rest of the Arab world's stock markets, we see that it is the largest stock market in the region in terms of US$. In 2012, the market capitalization of the Saudi stock market was around 340 billion US$ whereas the average Arab world stock market capitalization was only US$ 58 billion for the participants of the Arab Monetary Fund Index (AMFI) (Table 3.3). The biggest stock market of the Arab region, the Saudi stock market, also constituted around 40% of the total market capitalization of the Arab world's stock markets in 2012 (Figure 3.16).

Table 3.3: Key Indicators of Arab World Share Markets, end of 2012

Capital Market	Market Capitalization (Million of Dollars)	% of Total	Value of Shares Traded (Million of Dollars)	No. of Listed Companies	Average Company Size (Million of Dollars)	GDP at Current Prices (Million of Dollars)	Market Depth	Turnover Ratio
S. Arabia	338873	39%	293000	150	2259.2	578.6	58.6	86.5
Kuwait	86295	10%	24494	216	399.5	172.8	49.9	28.4
Egypt	48679	6%	43715	214	227.5	231.1	21.1	89.8
Morocco	60092	7%	11116	76	790.7	100.3	59.9	18.5
Bahrain	16590	2%	279	49	338.6	26.5	62.6	1.7
Jordan	27210	3%	4023	247	110.2	30	90.8	14.8
Oman	26210	3%	2575	130	201.6	66	39.7	9.8
Tunisia	9648	1%	1169	57	169.3	46.6	20.7	12.1
Lebanon	10285	1%	516	25	411.4	42.5	24.2	5
A. Dhabi	71329	8%	6970	67	1064.6	363.8	19.6	9.8
Algeria	136	0%	2132.8	2	68	192.4	0.1	1568.2
Dubai	49033	6%	8736	62	790.9	363.8	13.5	17.8
Sudan	2695	0%	949	56	48.1	75.1	3.6	35.2
Qatar	125598	14%	22936	42	2990.4	194.3	64.7	18.3
Palestine	2782	0%	396	46	60.5	NA	NA	14.2
Total	875455	100%	423006.8	1439	9930.5	2483.8	529	1930.1
Average	58364		28200	96	662	177	38	26

Source: Quarterly Bulletin, Arab Monetary Fund, 2012.

The value of shares traded on the stock market of Saudi Arabia is far larger than on the rest of the stock markets of Arab world. The average share traded value of its stock market was US$ 293 billion in 2012 (Table 3.3) followed by the stock market of Egypt which has a size of US$ 44 billion (Figure 3.17).

The stock market of Saudi Arabia is ranked number 4 with regard to the number of listed companies. The highest listed companies in this region are in Jordon, Kuwait and Egypt (Figure 3.18). On the other hand, we can categorise the Saudi stock exchange as number 2 with respect to average company size. The average size of listed firms in the Saudi Stock market is US$ 2.3 billion whereas in Qatar it is US$ 3 billion. The average market capitalization is US$ 662 million/company in the AMFI countries (Table 3.3 and Figure 3.19). The data also indicates that the class of companies listed on the Saudi stock market is different from those countries in the AMFI.

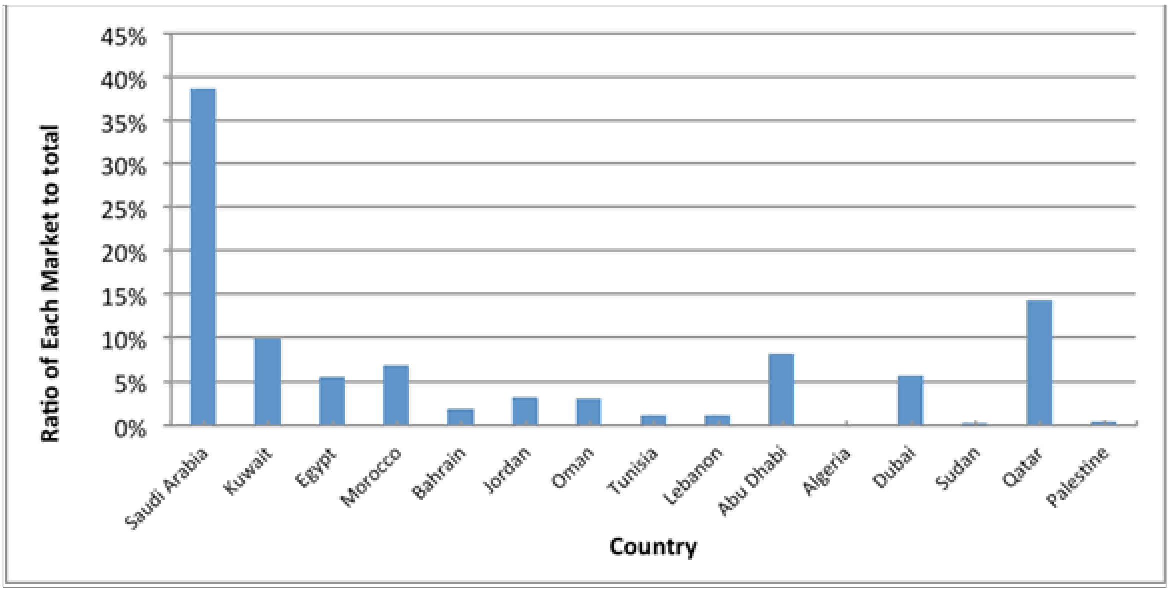


Figure 3.16: Ratio of each Country Market Capitalization to the total Markets

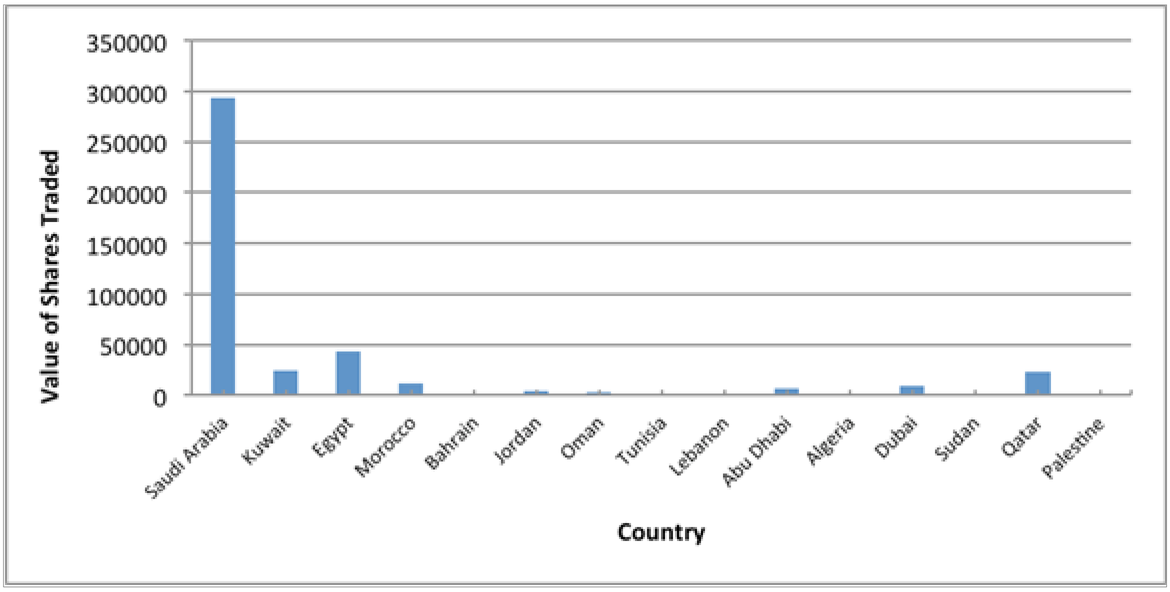


Figure 3.17: Value of Shares Traded for Each Country

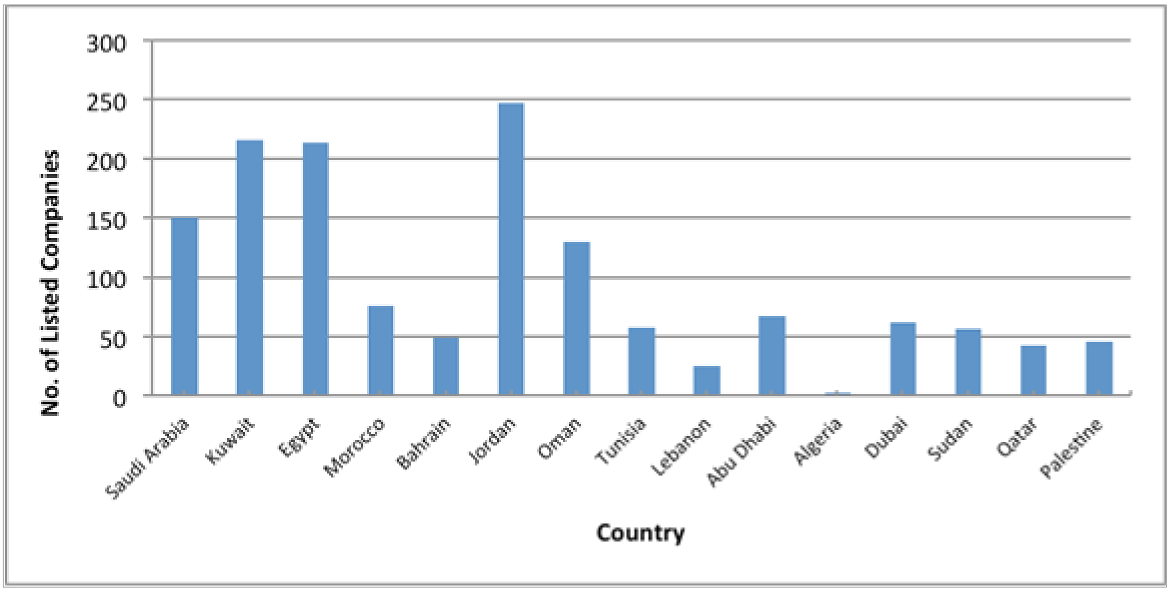


Figure 3.18: Number of Listed Companies in Each Country

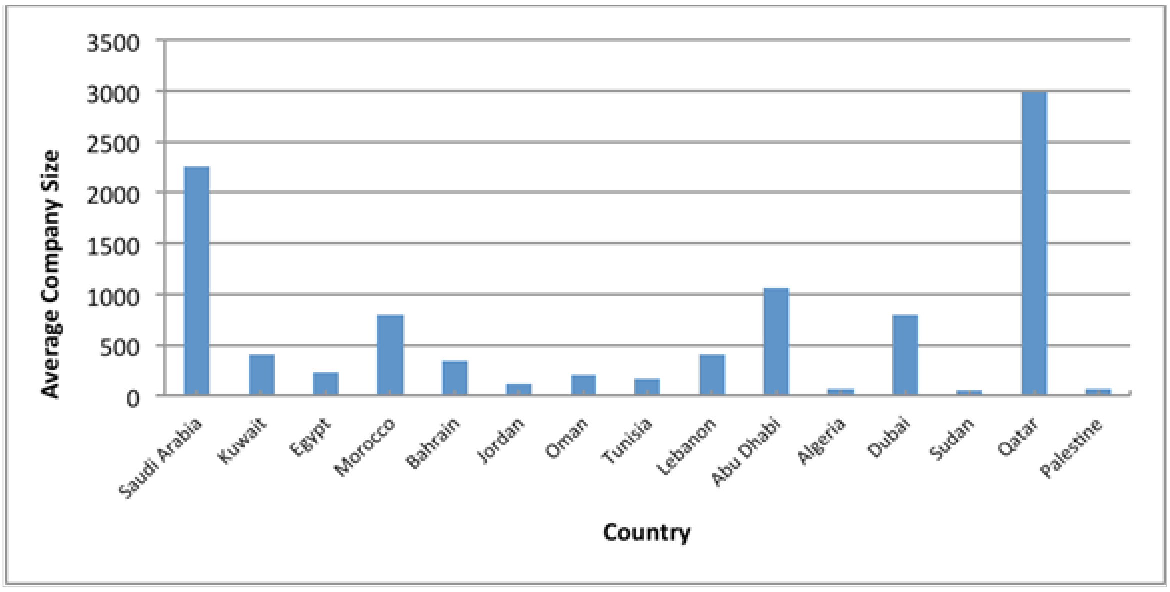


Figure 3.19: Average Company Size in Each Country

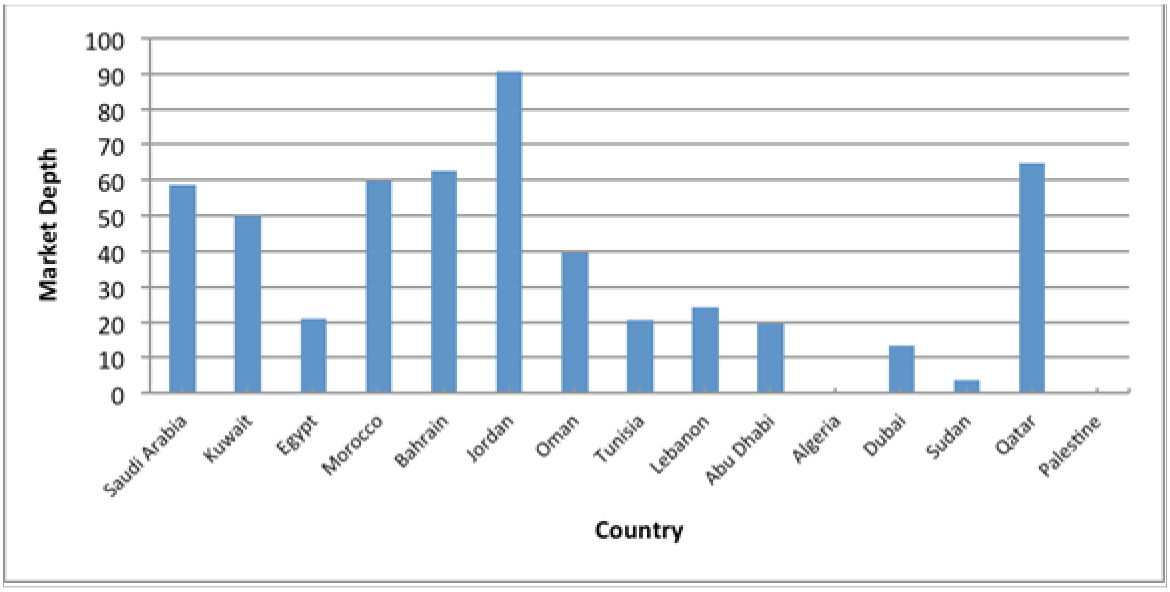


Figure 3.20: Market depth for each Country

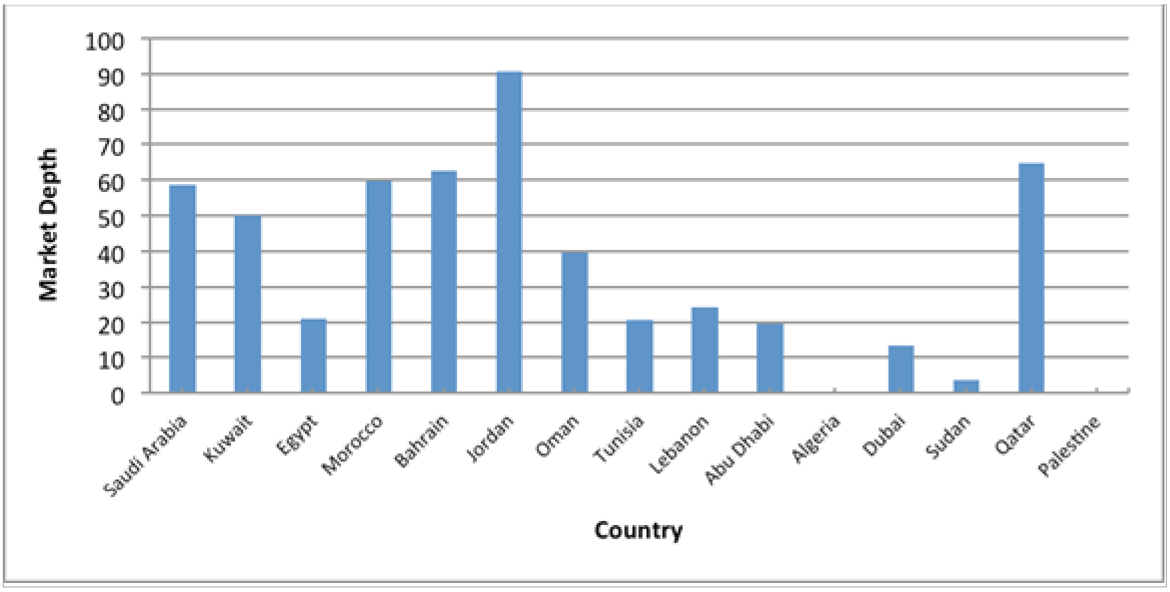


Figure 3.21: Turnover Ratio for each Country

The level of activity in the stock market is also greater in Saudi Arabia as compared to its Arab counterparts. The Saudi stock market is deeper compared to others, with 59% of GDP while the average of Arab countries is only 38% (Table 3.3 and Figure 3.20). This is also the most liquid market after Egypt, with a turnover ratio of 87% (Egypt is 89.8%) in 2012 (Table 3.3 and Figure 3.21).

3.5 Summary

In summary, it can be concluded that the stock market of Saudi Arabia experienced tremendous growth and major development during the period of 1985 to 2012. However, there are still fewer companies listed than on the international stock markets of developing and developed countries. The total size of the economy of Saudi Arabia is relatively large and the ratio of companies to the size of the economy is very small (Table 3.4). This number should be improved. This is also depicted in Figure 3.22 which portrays the percentages of company types against the total number of companies. It is clear that limited liability partnerships represent 80% of the total companies operational in Saudi Arabia.

Table 3.4: Existing Companies by Type of Capital, 2012

Type of company	Number	Capital (Million Riyals)
Joint-stock companies	5076	1707555.6
Limited liability partnerships	54294	280534.6
Joint-liability partnerships	5854	3927.2
Mixed liability partnerships	2767	9939.2
Mixed liability partnerships by shares	1	0.5
Total	67992	2001957.1

Source: SAMA Annual Report, 2012.

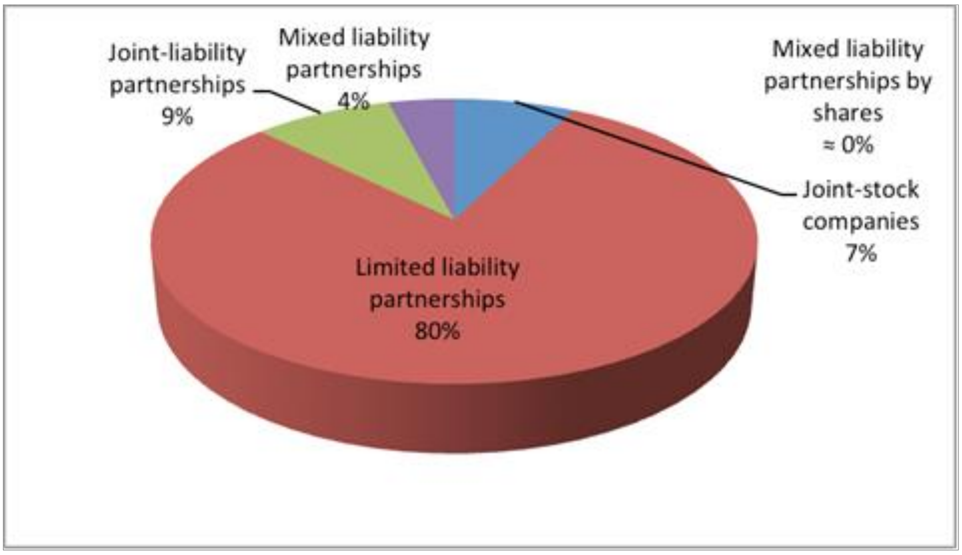


Figure 3.22: Percentage of number of each type of the companies to the total.

The second most significant area for improvement in the stock market of Saudi Arabia is the issue of free floating tradable shares in the market. As many of the shares are held by government or a small number of families, there are fewer shares available for trading on the stock market, which makes the stock market less liquid. Table 3.5 reports some facts and figures about these free floating shares compared to the total issued and paid up shares of listed companies. Out of the 42.3 billion shares issued, there were only 4.4 billion free-floating shares available for trade, or 9.6% of the issued shares. There are only 1% tradable shares in the insurance sector which makes this the most concentrated sector. The least concentrated and highly tradable sector is the multi-investment sector in which there are 24% free floating shares available for trade by the general public, followed by petrochemical industries, and the cement and banking sectors. Figure 3.23 shows the number of companies in each sector.

Table 3.5: Total Issued Shares and Free-Floating Shares in the Saudi Stock Market, end of 2012

No	Sector	Number of Companies	Issued Shares	Floating Shares	%
1	Banks & Financial Services	11	9,700,917,875	564,099,762	17.2
2	Petrochemical Industries	14	9,185,524,165	465,843,666	19.7
3	Cement	12	1,533,600,000	88,897,031	17.3
4	Retail	11	438,700,000	171,630,466	2.6
5	Energy & Utilities	2	4,241,593,815	38,102,861	0.89
6	Agriculture & Food Industries	16	1,383,708,930	247,169,236	5.6
7	Telecom. & Information Tech	5	4,037,600,000	420,791,975	9.6
8	Insurance	33	903,166,667	892,783,664	1.0
9	Multi-Investment	7	4,022,471,189	164,624,670	24.4
10	Industrial Investment	14	1,462,457,236	156,927,850	9.3
11	Building & Construction	15	799,922,979	139,784,489	5.7
12	Real Estate Development	8	3,733,516,240	893,019,120	4.2
13	Transport Sector	4	482,400,000	84,612,013	5.7
14	Media and Publishing	3	155,000,000	27,129,677	5.7
15	Hotel & Tourism	3	190,150,000	32,512,898	5.8
	Total	158	42,270,729,096	4,387,929,378	9.6

Source: Tadawul Quarterly Report November, 2012.

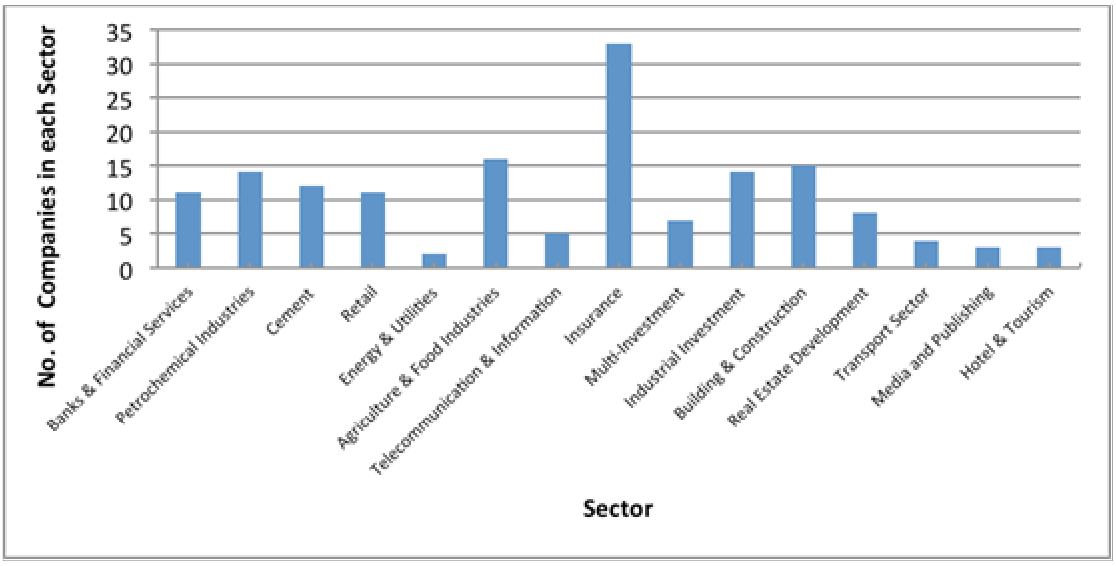


Figure 3.23: Number of Companies in Each Sector in Saudi Arab Market

Last but not least, the stock market of Saudi Arabia is not yet fully open to foreign portfolio investment. Foreign investors can only invest in mutual funds or Swap agreements. The level of investment by resident and non-resident foreign investors is less and that is the main reason for the low level of association of the Saudi stock market with the international financial markets of the world. Therefore, the Saudi stock market can offer global investors real market diversification benefits.

CHAPTER 4

Theoretical Framework

4.1 Introduction

This chapter describes in detail the logics and working of the frameworks that are used in the analysis. These are the tools that are used to implement the methodology in order to acquire the desired results. They are designed by renowned scientists and are implemented without any changes, with all of their advantages and drawbacks. Hence, these are treated as laws. The analysis involved in this study comprises several models and frameworks for testing the hypotheses, and the empirical validity of a standard mean-variance model that suggests a linear relationship between the covariance risk of risky assets and the return of assets. This chapter involves the description of several models that are implemented in sequence during the execution of the methodology. These include the Capital Asset Pricing Model (CAPM) introduced by Lintner (1966), Sharpe (1964), and Black (1972), Fama and French (1993), and the Value Based Management Model presented by Anthony (1965), and several types of artificial neural networks. Artificial neural networks are computer-based models that are inspired by the central nervous system of human beings, particularly the brain, and are also based on special types of logic, developed by different scientists, for finding solutions to various problems. These are generally shown in the form of connected graphs called neurons that take values from the user as input. It performs functions systematically on these inputs and gives an output value. These are widely used for solving problems that are difficult to solve using ordinary rules or programming techniques. Several types of neural networks have been used in this study and their functionality is discussed in this chapter. This chapter will discuss in detail neural networks with multilayer perceptron algorithm, the feed forward and back propagation techniques, monotonically increasing and decreasing functions, and curve fitting.

4.2 The Capital Asset Pricing Model and Fama and French model

The Capital Asset Pricing Model (CAPM) introduced by Lintner (1966), Sharpe (1964), and Black (1972) is considered to be a major tool in financial economics for investigating and explaining the connection between predictable risk and return.

$$R_i - R_f = \alpha i + \beta_i(R_m - R_f) + \varepsilon_i \qquad (4.1)$$

where:

R_i denotes the expected return on the its asset

R_f denotes the risk-free rate

R_m defines the expected return on the market portfolio

β_i measures the risk of market sensitivity parameter which is defined as the Cov (R_i-R_f, R_m-R_f)/Var(R_m-R_f), which measures the sensitivity of asset return to variability in market return.

The risk premium CAPM equation is defined by:

$$(R_i-R_f)= \beta_i (R_m -R_f) \qquad (4.2)$$

where:

(R_i-R_f) represents the excess return on asset i.

(R_m –R_f) represents the risk free excess return on the market portfolio.

The above equation represents the fact that for any asset the expected excess return is directly proportional to its beta.

The distribution of ex-post type from where the returns are received is ex-ante observed by the stakeholder. Multivariate normality shows that the above equation satisfies the assumptions of the Gauss-Markov regression. Hence, empirical testing by CAPM would be carried out with the following equation:

$$R_i=\lambda_0 + \lambda_1 \beta_1 +\varepsilon_i \qquad (4.3)$$

where:

λ_0 has been added to the equation as an intercept term

λ_1 shows the premium related to the beta risk

Another version of CAPM is used for the adequacy that holds when there are risk free assets. A zero beta portfolio is used, R_z. Hence, after involving the zero beta portfolio return, the CAPM equation becomes:

$$R_i-R_f = R_z + \beta_i(R_m-R_z) + \varepsilon_i \qquad (4.4)$$

The zero beta portfolios perform in a similar way as the risk-free rate of return in the Sharpe-Lintner model.

For testing the linearity of the relationship of risk and return, the quadratic equation of β_i can be written as the equation of the standard model as below:

$$R_i=\lambda_0 + \lambda_1 \beta_1 + \lambda_2 \beta_{2i} + \varepsilon i \quad (4.5)$$

For testing the hypothesis of the relationship between the residuals and the risks that show no effect on the expected asset return, the residual risk of assets are included as explanatory parameters:

$$R_i=\lambda_0 + \lambda_1 \beta_1 + \lambda_{2SD}(\varepsilon_i)+ \varepsilon_i \quad (4.6)$$

In the CAPM versions defined by Sharpe-Lintner and Black, market portfolios are the mean-variance efficient in the joint hypothesis. This shows that the expected return of all assets is described by the difference in market betas, and other variables may not be added to explain the expected return.

The CAPM model estimates the risk of assets by calculating the covariance of its return with all the invested wealth's return, which is called the market return. The expected return must be linearly related to the covariance of an asset with the market portfolio return, which is called beta risk. These are the major implications of the model. The association of a higher beta risk with a higher return is the principle of risk compensation. However, no or weak statistical relationship to support this association are identified as empirical evidence by Basu (1977), and Fama and French (1992). The poor empirical performance and static versions of CAPM are discussed by Lintner (1966), and further motivated the research on conditional testing of the asset pricing model (Harvey, 1989; Jagannathan and Wang, 1996). These tests allow risk, and the prices of risk, to vary with time under particular assumptions. This suggests using data from the real world, with certain assumptions which are closer to the real world. The behaviour of the investor in only one period is examined under unconditional CAPM, whereas in real world investment, decisions are taken over many time periods. The betas of assets, risk premium, and the expected return usually rely on the nature of available information in any particular time period and hence vary accordingly. The relative risk of a firm's cash flow is subject to fluctuations over the business cycles. It is also argued by

Jagannathan and Wang (1996) that to the same degree that business cycles are affected by taste and technology, the comparative share of multiple divisions of the economy fluctuates, causing variations in the betas of the firms in these divisions. Moreover, in times of recession, the financial influence of badly performing businesses may rise, compared to other businesses, causing their betas to increase. In times of deprivation, the risk premium is increased as stakeholders try to smooth out their consumption. Therefore, the risk premium should be high in equilibrium in order to make sure that stakeholders hold on to their portfolio of stocks. This implies that the conditioning information (instrument variables) should be associated with the future or current macro-economic scenario.

The empirical inadequacy of CAPM might be due to several apparently inexplicable situations in asset returns that have caused the use of screened and sorted portfolios of stocks to show the further risk factor in the standard model. Fama and French's (1993) three factor model, which requires a model of expected return, has been widely used in empirical research (Iqbal et al. 2010). Hence, due to the prominence of Fama and French (1992), the three factor model has been tested for its empirical performance as an asset pricing model in various studies. The standard CAPM model can be extended to Fama and French (1993) model by including variables, to test whether these variables can describe the expected returns that cannot be explained by CAPM. Firstly, the sensitivity, or betas of asset returns, to the firm's characteristic variables (book to market value and size), and market returns capturing the estimated variability, are added. Secondly, the variation of cross section in the expected returns is estimated and explained for the firm characteristic is added.

The series of papers by Fama and French (1992, 1993, 1995, 1996, 1998, and 2004) are the most noticeable work in its response. They presented a three-factor model which states that the expected return in the additional risk-free rate is described by the excess market return. The excess market return is defined by:

SMB= the return on portfolio of small stocks - return on portfolio of large stocks

HML= the return on portfolio of high book-to-market stocks - return on a portfolio of low book-to-market stocks.

SMB reflects the fact that all firms should expect sensitivity to several risk factors because of their comparatively inflexible nature and their minimum ability to captivate undesirable financial situations. HML reflects the fact that factors pose a higher risk exposure for 'value' stocks versus 'growth' stocks. This is logical because firms need to be approaching the minimum size if they want to accomplish an Initial Public Offering. If this is observed in the perspective of 'value' stock, it indicates that the public market value has fallen due to hard financial situations, or doubts related to future returns of profits.

The equation of Fama and French model is defined as:

$$R_i\text{-}R_f = \alpha_i + \beta_i\,(R_M\text{-}R_f) + \gamma_i\, R_{SMB} + \delta_i\, R_{HML} + \varepsilon_i \qquad (4.7)$$

where:

R_{SMB} is referred to as size premium

R_{HML} is referred to as value premium

β_i, γ_i,and δ_i show the slopes in the multiple regression equation. Therefore, one of the implication of this equation is that the intercept is zero for all assets $_i$ in the time-series regression.

Since Fama and French model is a multifactor model and represents the expected beta of the linear factor pricing model, it can be written as:

$$R_i = \alpha_i + \beta_{i\lambda m} + \gamma_{i\lambda s} + \delta_{i\lambda h} + \varepsilon_i \quad {}_i \in \{1, \ldots, N\}. \qquad (4.8)$$

By cross sectional regression of average returns on betas, the newly involved variables in the above equation can be estimated.

α_i is the intercept and λ_m, λ_s, and λ_h represent the slope in this relation of cross-section. Betas represent the unconditional sensitivities of the involved assets of the factors. Furthermore, the additional beta i.e. β_{ij}, for any j$\in$ {m, s, h}, can be seen as the rate of risk exposure to factor j of asset $_i$, so λ_j will indicate the price of risk exposure. Therefore, betas are described as the coefficients of multiple regression of the factors' return.

Fama and McBeth (1973) performed the classical CAPM on twenty portfolios of assets. The results of their study show statistically significant beta whose value remained small for several sub periods during the total studied time period. Fama and McBeth (1973) also validated the CAPM on all stocks during 1935 to 1968, whereas Tinic and West (1984) tested the same data for the period of 1935 to 1982 and found contrary evidence. They stated that the intercept of residual risk and asset return is much greater that the risk-free rate, and the residual risk has no effect on asset returns, therefore the CAPM may not hold.

CAPM was not valid with UK private sector data when investigated by Greene (1990). However, according to Sauer and Murphy (1992), the CAPM is the best model for describing the stock market data of Germany. The validity of CAPM could not be confirmed for the equity markets of the USA, Spain, France, Belgium, Canada, Japan, and UK (Hawawini, 1993).

4.2.1 CAPM Model and FF model

The equation of the CAPM model is given below:

$$R_i\text{-}R_f = \alpha_i + \beta_i(R_M\text{-}R_f)+ \varepsilon_i \qquad (4.9)$$

The equation of the Fama and French (1993) three factor model is given below:

$$R_i\text{-}R_f = \alpha i + \beta_i (R_M\text{-}R_f) + \gamma_i R_{SMB} + \delta_i R_{HML} + \varepsilon_i \qquad (4.10)$$

The dependent variable is:

R_i-R_f represents the weighted average return of all the firms in each portfolio of the six portfolios.

R_f : risk-free rate of return (there is none in Saudi Arabia).

The independent variables are:

1- Market Portfolio

This is defined as the sum over, or cumulative portfolio, of each individual stakeholder. Each lender has a corresponding borrower; they both cancel each other out. The entire wealth of the economy will be equal to the value of the aggregate risky portfolio (Bodie et al., 2002). The weighted average return of each stock present in the model is same as the market portfolio return (R_m-R_f) as described by Fama and French (1993).

2- Size effect

Size effect is the shared stock of smaller companies on averaged higher risk-adjusted returns as compared to the shared stock of larger companies (Banz, 1981). The difference between the return on the portfolios of small stocks and the return on the portfolios of big stocks is represented by R_{SMB} as described by Fama and French (1993), and can be written in the following equation:

$$R_{SMB} = (R_{SL}+R_{SM}+R_{SH}-R_{BL}-R_{BM}-R_{BH}) / 3. \quad (4.11)$$

3- Book-to-Market effect

Firms having poor prospects are judged and indicated by the market as having a high ratio of book-to-market equity, low stock prices, and higher expected stock returns, compared to firms with strong prospects (Banz, 1981). The difference between the return on the portfolios of high book-to-market stocks and the return on a portfolio of low-book-to-market stocks is defined by R_{HML}. According to Fama and French (1993), this can be shown in the equation as:

$$R_{HML} = (R_{SH} +R_{BH}-R_{SL}-R_{BL}) / 2. \quad (4.12)$$

4.2.2 Measurement of the Variables and Forming the Portfolios

4.2.2.1 Monthly Return

The monthly return is the function of the price of the stock in the current month and the price of the stock in the previous month and can be represented in the following equation:

$$R_t =(P_t - P_{t-1}) / P_{t-1} \quad (4.13)$$

4.2.2.2 Method of Forming the Dependent Variable Portfolios

All the companies of the Saudi Arabia Stock Exchange are considered in this study and the 50% breakpoint for size at year t is calculated. The sample stock on two size groups (B & S) was placed on the breakpoint. B is used for a big group and S was used for a small group. Two breakpoints at 30% and 70% for book-to-market at year t-1 for both groups were calculated. The sample companies are placed into three book-to-market groups for each size group. B/H denotes the above 50% breakpoint for size and above 70% breakpoint for book-to market, B/M denotes the above 50% breakpoint for size and between 30% and 70% breakpoints for book-to-market, B/L denotes above 50% breakpoint for size and below 30% breakpoint for book-to-market, S/L denotes below 50% breakpoint for size and below 30% breakpoint for book-to-market, S/M denotes below 50% breakpoint for size and between 30% and 70% breakpoints for book-to-market, and S/H denotes below 50% breakpoint for size and above 70% for book-to-market. Hence, six value weighted portfolios are formed (S/L, S/M, S/H, B/H, B/M, B/L,) in the study period by adopting the Fama and French methodology and applying the Tim Loughran considering the varied number of firms in each of the six portfolios.

4.2.2.3 Method of Forming the Independent Variable Portfolios

A similar technique was adopted for forming the independent factor portfolios. Breakpoints for book-to-market are 30%, whereas 70% and 50% breakpoints for size were considered. Hence the six value-weighted portfolios S/L, S/M, S/H, B/L, B/M, B/H, were formed with a varied number of firms in each portfolio. The SMB portfolio is calculated from these portfolio returns and is defined as $R_{SMB} = (R_{SL}+R_{SM}+R_{SH}-R_{BL}-R_{BM}-R_{BH})/3$. The HML portfolio returns are defined as $R_{HML} = (R_{SH} + R_{BH}-R_{SL}-R_{BL})/2$. Another value-weighted portfolio was created that contains all the firms in the portfolios and is denoted by Mkt. The six outputs in the FF and CAPM model are as follows:

RHB = Portfolio return for companies with high book-to-market level and big group.

RHS = Portfolio return for companies with high book-to-market level and small group.

RMB = Portfolio return for companies with medium book-to-market level and big group.

RMS = Portfolio return for companies with medium book-to-market level and small group.

RLB = Portfolio return for companies with low book-to-market level and big group.

RLS = Portfolio return for companies with low book-to-market level and small group.

4.3 Value-Based Management Model

Anthony (1965), described the management control framework as the procedure for ensuring the acquisition of resources, and their effective and efficient use, to achieve the objectives of the organization. This framework highlighted the differences of strategic planning, management, and operational control, thus restricting the possibility of managerial accounting responsibilities, while directing the prime consideration towards accounting information (Otley, 1999). The planning and control frameworks of management are expanded by contingency theories, by involving a few contingent or contextual factors affecting the whole company's control 'package' of non-accounting & accounting information structures, several control mechanisms, and organizational design (Otley, 1980). According to these theories, there is no system that is applicable universally for management accounting and control. The selection of suitable control and accounting techniques depends on the situation of the organization. Most contingent factors involve the external environment (including static vs. dynamic; simple vs. complex), the competitive mission and strategy (including innovation vs. low cost), observability and knowledge factors (including behaviour observability, the transformation process, and outcome observability etc.), technology (for example automation, job shop to mass production, and interdependencies of production), industry characteristics and business unit (for example diversification, regulation, structure of the firm, and size) (Fisher, 1995).

The Value-based Management Model is based on previous behaviours to provide a unified framework to manage and measure businesses, with the particular aim of creating bigger long- term value for investors (Black et al., 1998). These models differ from firm to firm and usually involve six basic steps. These are as follows:

1- Selection of specific objectives internally that may enhance the stakeholder value.
2- Choosing reliable organizational designs and strategies to achieve the selected objectives.
3- Identification of 'value drivers' or specific performance variables which make value in business subject to the strategies and design of the organization.
4- Setting targets, choosing methods for performance evaluation, and developing action plans established on the significances recognized during the phase of value driver analysis.

5- Evaluation of the action strategies and their execution by steering managerial & organizational performance measures.
6- Measuring the present rationality of the internal objectives, control systems, plans, and strategies of the organization in the perspective of achieved results, and modifying them as per requirements.

Like the frameworks of all other organizational designs, VBM has also a simple sequential framework with a concept of multifaceted simultaneous options, interdependencies, and response loops present within the execution process. Its organizational design structure is shown in Figure 4.1. It provides a valuable mechanism to categorize empirical work in this field of successive processes execution, and to measure the degree to which the new methods maintain the association between different processes. Specifically, this framework captures several connections highlighted by principal-agent models as discussed by Lambert (2001), contingency theories (see Baiman [1990]), and organizational design frameworks based on economic theories (Jensen 1998). The representative contingency and economic frameworks developed by Otley (1980) and Brickley et al. (1995) are given in Figures 4.2 and 4.3. Though the placement of variables and specified terminologies varies, each framework proposes that the control systems and managerial accounting should be seen as a single control package of the organization containing the performance evaluation and reward systems, the organizational objectives and strategies, and the choice of performance consequences for the activities each department performs. The VBM framework encompasses the new designs to point out the financial and non-financial value drivers of a specific firm, to reassess the objectives and strategies of the firm, and to provide a feedback loop involving the performance of the activities, and the control and design of the organization.

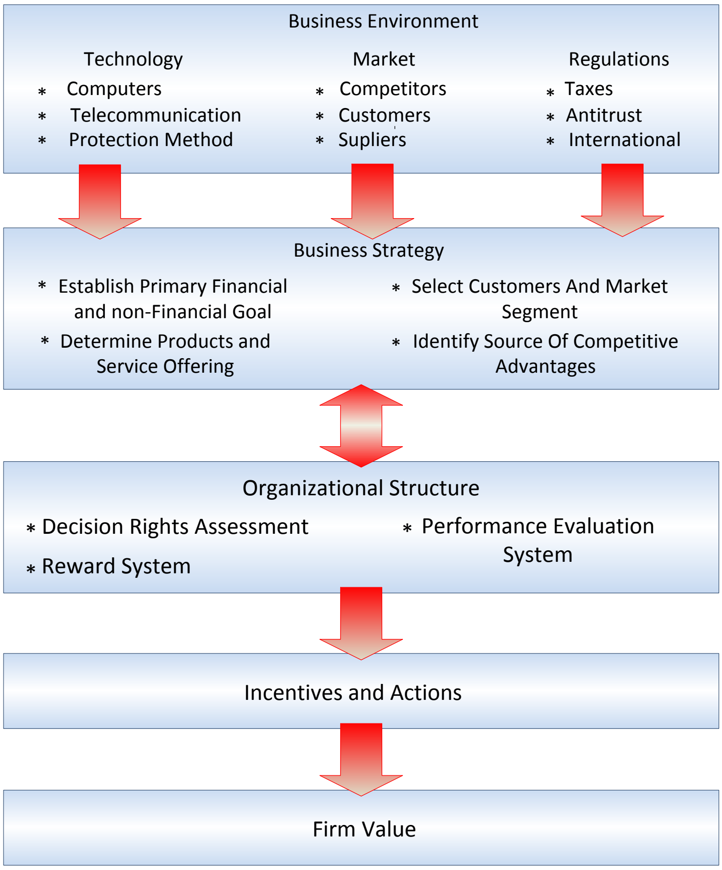


Figure 4.1: Organizational structure model

Figure 4.2: A typical VBM framework

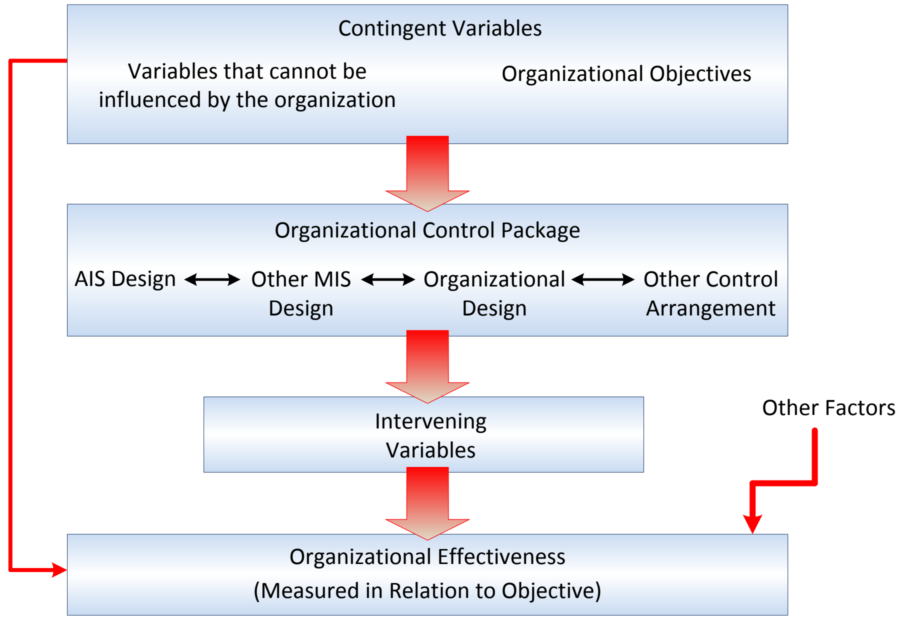


Figure 4.3: Contingency theory framework Otley (1980)

4.3.1 VBM Model

This is a decision-making model. The decisions are taken on the basis of expectations of shareholders and portfolio investors following the methodology of Sherstneva & Kostyhin (2012). The decision depends on the expectation of growth, on the fall or speculative fall of the stock price, and on the expectation of investment, disinvestment or dividend of the shareholder. In this study we used a balance of the following four indicators:

1- Weighted Average Cost of Capital (WACC) is a weighted cost from financing the capital of any company from its different resources (Equity, Debt, Preferred Stock etc.). It is defined as:

$$WACC = K_s \cdot W_s + K_d \cdot W_d \cdot (1 - T) + K_p \cdot W_p \qquad (4.14)$$

where: K_s = the cost of equity; W_s = weight of equity; K_d = cost of debt; W_d = weight of debt;

T = corporate tax rate; K_p = cost of preferred stock; W_p = weight of preferred stock.

2-Actual Return of Investments (R_{act}) is the real rate of return that is gained from holding an asset during a specific period of time.

To calculate R_{act} we can use ROIC

R_{act} = ROIC , where

ROIC = Return on Invested Capital

R_{act} = ROIC = NOPLAT / IC, where

NOPLAT = Net Operating Profit Less Adjusted Taxes; IC = Invested Capital.

3-Expected Investment Return (R_{exp}) is the mean value of the probability distribution of the return. For calculation of R_{exp}:

$R_{exp} = D/P_o+Q$

where :D = dividend; P_o = share price; Q =dividend growth.

4- Required return on invested capital (R_{req})

The required rate of return is the required return from the market to compensate the investor for the risk he faces from investing in this stock. The present study proposes using Fama and French Model formula and CAPM Model.

R_{req} = FF

FF = Fama and French Model $(R_i-R_f) = \alpha_i + \beta_i(R_M-R_f) + \gamma_i R_{SMB} + \delta_i R_{HML} + \varepsilon_i$ (4.15)

$$R_{req} = \alpha_i + \beta_i(R_M-R_f) + \gamma_i R_{SMB} + \delta_i R_{HML} + \varepsilon_i \qquad (4.16)$$

Where:

$(R_M - R_f)$ = Risk premium; R_m = the return rate of a market benchmark; R_f = the rate of return for a risk-free security; R_{SMB}= Size effect = $(R_{SL}+R_{SM}+R_{SH}-R_{BL}-R_{BM}-R_{BH})/3$;

R_{HML}= Book-to-Market effect = $(R_{SH} +R_{BH}-R_{SL}-R_{BL})/2$; β_i = beta of the company's shares.

R_{req} = CAPM

CAPM – Capital Asset Pricing Model

$$R_{req} = R_f + \beta_i *(R_m - R_f) \qquad (4.17)$$

where: R_f = the rate of return for a risk-free security; R_m = the return rate of a market benchmark; $(R_m - R_f)$ = risk premium; βi = beta of the company's shares.

Table 4.1: The model of decision-making on the basis of expectations of shareholders and portfolio investor

BALANCE OF INDICATORS							Increasing shareholders wealth carried out at the expense of:	Share price
WACC	<	R_{act}	>	R_{exp}	>	R_{req}	investments	growth
WACC	<	R_{act}	<	R_{exp}	<	R_{req}	disinvestment	fall
WACC	<	R_{act}	<	R_{exp}	>	R_{req}	investments	speculative fall
				R_{act}	>	R_{req}		
WACC	>	R_{act}	>	R_{exp}	>	R_{req}	dividends	growth
WACC	>	R_{act}	<	R_{exp}	<	R_{req}	disinvestment	fall
WACC	>	R_{act}	<	R_{exp}	>	R_{req}	dividends	fall
				R_{act}	>	R_{req}		

Table 4.1 shows that in the model of decision for the expectations of shareholder and portfolio investors, the decision will depend on the balance of four indicators. The expectation of the growth, fall or speculative fall of the stock price depends on the R actual and R expected:

Growth: If the actual or real return is bigger than the expected, we predict that the stock price will grow.

Fall: If the actual return is less than the expected return, we expect that the stock price will fall.

Speculative fall: If the expected return is more than the real return, but both of them are larger than the required return, the result will be a speculative fall.

The following three paragraphs show how the decision of invest, disinvest or dividend of the shareholder has been taken:

Disinvest: if the real return is bigger than the weighted average cost of capital (WACC), which encourages investing in this company, but still the expected & real return is less than the required return, this means that this portfolio will not compensate the investor for the risk he will exposed to. Therefore the result will be to disinvest.

Dividend: If the real rate of return is less than WACC, any money spent on this company's projects will not cover its cost of capital, so it is preferred to distribute the profit to the investors and let them invest their money in economically profitable companies, instead in investing it in losing projects. Therefore the result will be dividend.

Invest: If the real rate of return is bigger than WACC, any money spent on this company's projects will cover its cost of capital, so it is preferred to keep the money inside the company as a retained earning instead of distributing the profit to the investors, because this company is economically profitable. In addition, the real rate of return is bigger than the required return. Therefore the result will be to invest.

4.4 Hypothesizes

The following hypothesizes are tested using GMM Regressions Coefficients

CAPM Model Hypothesis

Hypothesis number 1

Ho: There is no significant effect of the market return on the portfolio return.

H1: There is a significant effect of the market return on the portfolio return.

The Fama and French Model Hypothesis

Hypothesis number 2

Ho: There is no significant effect of the market return on the portfolio return.

H1: There is a significant effect of the market return on the portfolio return.

Hypothesis number 3

Ho: There is no significant effect of the size on the portfolio return.

H1: There is a significant effect of the size on the portfolio return.

Hypothesis number 4

Ho: There is no significant effect of the book-to-market value on the portfolio return.

H1: There is a significant effect of the book-to-market value on the portfolio return.

4.5 Data Description

This study examined monthly data relating to common stocks in the listed companies of the Saudi Arabia Stock Exchange from January 2007 to December 2011. The data herein is collected from several sources. Monthly stock returns, size, book-to-market values and market returns are taken from the Saudi Arabia Stock Exchange. Over the study period (2007-2011) the researcher collected all available stock prices relating to all companies in the Saudi Arabia Stock Exchange. The number of observations during the study period was 60.

4.6 Artificial Neural Network Tools

Neural networks are the powerful tools used for forecasting of recent developments in artificial intelligence research. These involve non-linear models that may be used for mapping of past and future trends and time series data, and for revealing the hidden relationships and structures that govern them. The tools are used in several applied fields, for example economics, computer sciences, and medicine. They are used in the analysis of the relationships among financial and economic phenomena, generating time-series and optimization, and forecasting and filtration (Hamm and Brorsen, 2000). Neural networks are accepted as strong supporters of several investment banks, avant-grade portfolio managers, and trading firms. Several big banks like Morgan Stanley and Goldman Sachs have particular departments for the implementation of this tool. Similarly, Fidelity Investments has also been using these networks and gives recommendations based on the results of artificial neural networks. The fact that several of the world's largest companies are investing their valuable financial resources in neural networks is proof that these are significant tools for forecasting.

ANNs are electronic models based on a neural structure similar to the human brain. This modelling involves a less technical way of generating solutions, much as the brain does on the basis of experience. ANN is a non-linear self-adaptive data driven method. It takes vector ($y_j \ldots y_k$) as input and is a type of real function. The output is usually a function, mostly a sigmoid function i.e. tangent hyperbolic or logistic function. These types of functions (multilayer perceptron) consist of combinations of weighted sums of the functions parallel to the neurons. Cascade-forward and feedforward networks are particularly applicable in approximation functions when all inputs and outputs are known. The Neural network training parameters are:

- The initial weights and biases randomly between -1 and +1
- Training parameters learning rule Back-propagation
- Adaptive learning rate is 0.001
- Momentum constant is 0.9
- Acceptable mean-squared error is 0.001
- Performance function: mean square error (MSE)

There are several types of neural networks that work effectively and efficiently to execute the process of the research. Some of these are discussed below:

4.6.1 Feed-forward Neural Networks

Feedforward neural networks (FF networks) are the most widely and popularly used models in many applications. These networks are also known as 'multilayer perceptrons'. They involve hidden layers, input layers, and output layers. These networks begin with input layers, which are connected to a hidden layer or may be directly connected to the output layer. One hidden layer may be connected to another hidden layer or layers, or it may be connected to an output layer directly. The majority of such networks have only one hidden layer, although occasionally there exists neural networks that involve more than two hidden layers.

The input layer is channelled through which the pattern of the neural network is presented by the external environment. The output layer produces another pattern as soon as a pattern is presented to the input layer. This is the basic function that a neural network performs. The condition for which the neural network is trained should be represented clearly. At least one independent variable should be represented by every neuron that has an influence on the output. The input to these networks is always floating point numbers.

The output layer actually presents the forecasted pattern to the external environment. The path of the output layer can also be tracked back directly to the input layer. To classify items into groups, at least one output neuron is necessary for each group whose input values are to be assigned. A typical feedforward neural network with a single hidden layer is shown in Figure 4.4 below.

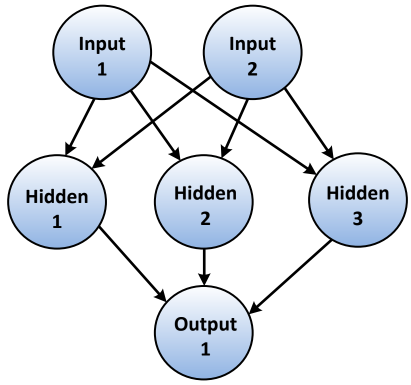


Figure 4.4: Feed forward neural network with single hidden layer

4.6.2 Elman Neural Networks

Elman (1990) presented the ‘Elman network’ which is a recurrent type of network used for dynamic system identification and financial prediction. The basic Elman network was only able to model first order dynamic systems by executing the back propagation algorithm; this process was later modified by Pham and Liu (1992). One output unit and one input unit are involved in an ‘Elman network’. Similar networks were presented by Robinson and Fallside (1987). By setting some variable values to zero, the neural networks presented by Robinson and Fallside (1987) and Elman (1990) show a similar structure. Figure 4.5 shows the Elman network which involves different units like input, hidden, and output units. In addition to these layers, it also consists of context units. The input and output layers interact with the external environment, whereas other units do not. The output unit sums the feed signals and has a linear unit function. Hidden units can involve either non-linear or linear activation functions. The context unit stores the previous processes of the activations of the hidden layer and supports the functions in one-step time delays. The feedforward processes are modifiable, whereas the recurrent processes are fixed. The Elman network is also called a partially recurrent network due to its feature of fixed recurrent connections.

At a particular instant *k*, the preceding processes of the hidden units *(at time = k-1)* and the input at *k* input are fed to the network. Now, the system executes its functions as a feed forward network and processes the inputs forward to generate the output. According to

Rumelhart and McClelland (1986), at this stage, the standard back propagation learning rule can be adopted for training the network. At the next step, activation of the hidden layers at time *k* are set back by the associations of recurrent processes towards the context layers, and are stored for the next step's execution *(time k+1)*. The activations of the hidden layers are unknown at the beginning of the execution process. Most of the time, they are set to one-half of their domain. Figure 4.5 of the Elman network shows the external input which is represented by *u(k)* and the output which is represented by *y(k)*. The input to the hidden layer at *i*th level is represented by *x(k)*. The subsequent *x(k)* is acquired from the next context layer.

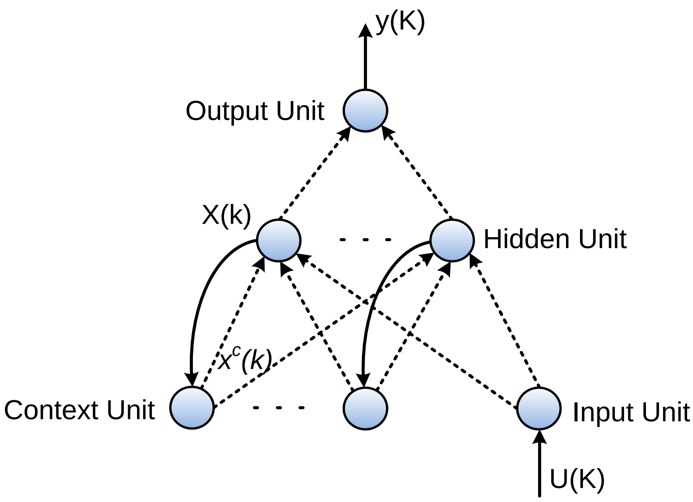


Figure 4.5: Elman network structure

4.6.3 Cascade-Forward Network

Cascade-Forward (CF) architecture is built by combining new neurons and developing their links with every input and hidden neuron. The weight of newly introduced neurons is fitted to reduce the outstanding error in the network. The newly added neurons increase the performance of the system. Hence, the usual cascade-correlation network supposes that all variables ($x_1,\ldots,x_m$) attributing to the processing data are pertinent to the problem of classification. A cascade neural network with m number of inputs and only one output neuron begins the execution without the hidden layers. The adjustable weights ($w_1,\ldots,w_m$) connect the output neurons to every input neuron. The standard sigmoid function f gives the output y of neurons in the network. Hence,

$$y = f(x; y) = \frac{1}{1+\exp\left(-w - \sum_i^m w_i\, x_i\right)} \qquad (4.18)$$

where:

w= (w_1,…,w_m) represents a mx1 weight vector, w_0 is the term representing error and is omitted,

x=(x_1,…,x_m) represents a mx1 input vector.

The new neurons are entered one by one into the network and each of them is linked to every *m* number of inputs and to the hidden layers. Only output layer is trained each time. For data processing and training, there are many algorithms and any one of them can be employed to acquire the output. These algorithms adjust their weights to minimize the residual error and then add and train the other new input neuron, while continuously minimizing the bias of the network. Cascade neural networks are widely accepted for data processing due to their several advantages. In this network there are no predefined structures. The network is built up automatically from the training data. It starts processing very fast because every neuron is trained separately from each other. There is also a disadvantage of these networks. They can be over fitted because of the presence of noise in the training data. An evolving cascade neural network is used to reduce the noise.

There are *p* numbers of inputs that continue to increase from one layer to another. The neuron is linked to two inputs at the first layer $(x_{i1},\ldots, x_{i2})$, $i_1 \neq i_2 \epsilon (1, m)$. x_{i1} is the input that has the minimum error. The newly added neuron at the second layer is linked with the input x_{i1} and also with the output of the previously executed neuron. Similarly, the third neuron would also be connected to the input x_{i1}. Hence each new neuron connected with the input continues to reduce the bias of the network and the output.

In the same manner, the new neuron at the r^{th} layer has input $p=r+1$. The output z_r of this new neuron for a logistic activation function can be shown as:

$$Z_r = f(u; w) = \frac{1}{1+\exp\,(-w - \sum_i^p u_i\, w_i)} \quad (4.19)$$

where:

r represents the total number of layers

u= (u_1,…,u_p) represents px1 input vector of the neuron added in the r^{th} layer

The cascade network for r=3 layers and m=4 inputs is shown in Figure 4.6 The squares in the figure show the synaptic links between the inputs *(x_1,..., x_4)*, two hidden neurons with two outputs z_1 and z_2 , and the output neuron.

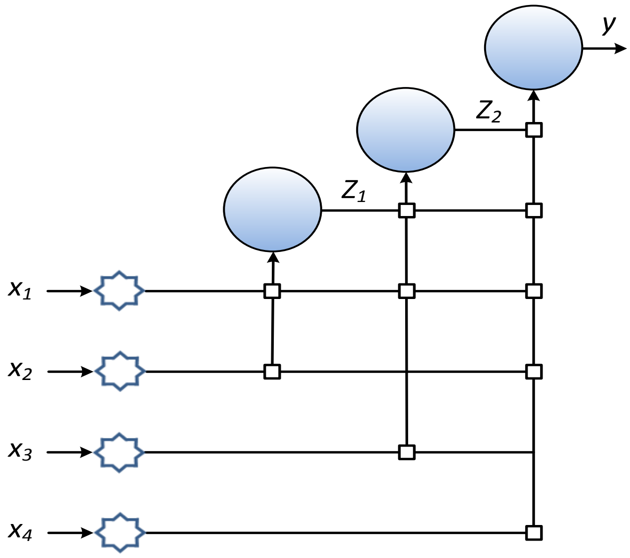


Figure 4.6: Cascade neural network for 4 inputs and 3 layers

The above diagram shows that the reduction in the bias of the output feature that is involved in connection with the previous feature can be easily estimated by simply following the above algorithm. The redundant, as well as the irrelevant, features are restricted to being involved in the resultant network if the output bias is evaluated by validating dataset. Hence, the selection criterion for the algorithm behaves as a regularity criterion *Cr*, which is calculated for any number of neurons that are not included in the fitting of the synaptic weights. The *Cr* values use the algorithm that involves the generalization ability of the neuron along with the other connections of the neuron. The value of the *Cr* continues to increase proportionally. The irrelevant connections of the *rth* neuron with other layers cannot be classified, hence the value of *Cr* is expected to be high.

4.6.4 Radial Basis Function Network

For a function y(x), a linear model takes the form:

$$y(x) = \sum_{j=1}^{m} w_j \, h_j \, (x) \qquad (4.20)$$

The function f of the model is represented as a linear combination of m fixed number of functions which are usually known as basic functions. A basis function involves a vector that consists of a linear arrangement of basis vectors. The ability of the function *f* to be flexible, its derivation only from the freedom to pick separate values for the weights, and its ability to fit into many different functions, makes it more reliable and easier to apply. The parameters contained by the basis function and the function itself are fixed, but in the case of change during the process, the model would be non-linear. Linear models are easier to process mathematically.

Any set of functions can be processed as the basis but it would be more useful if the function were differentiable. Classical statistics use several different types of basis function for different purposes, however the multilayer perceptron method involves logistic functions that are widely used in artificial neural networks of the form:

$$h(x) = \frac{1}{1+\exp\,(b^T x - b_0)} \qquad (4.21)$$

where *h(x)* is the hidden layer.

Another special class of functions is known as radial functions. Their response decreases or increases monotonically with changes in distance from the centre. The distance scale, the centre, and the precise shape of these functions are assumed to be the parameters involved in the model. If the function is linear, all parameters will be fixed.

A Gaussian function is a typical radial function if it takes the scalar as an input:

$$\mathrm{h(x)} = \exp\,(\,-(x-c)^2\,/r^2\,) \qquad (4.22)$$

Where: the radius *r* and the centre *c* are the parameters of the model. Figure 4.7 shows the Gaussian Radial Basis Function (RBF) with the radius *r* =1, and *c* =0.

This RBF (Gaussian) decreases monotonically as the distance from the centre. The multi-quadratic RBF with the input as a scalar is:

$$h(x) = \frac{\sqrt{r^2+(x-c)^2}}{r} \qquad (4.23)$$

h(x) increases monotonically as the distance from the centre (see Figure 4.7). RBFs such as Gaussian give a logical output near the centre and usually use the multi-quadric type radial basis functions that give global output and their response is finite.

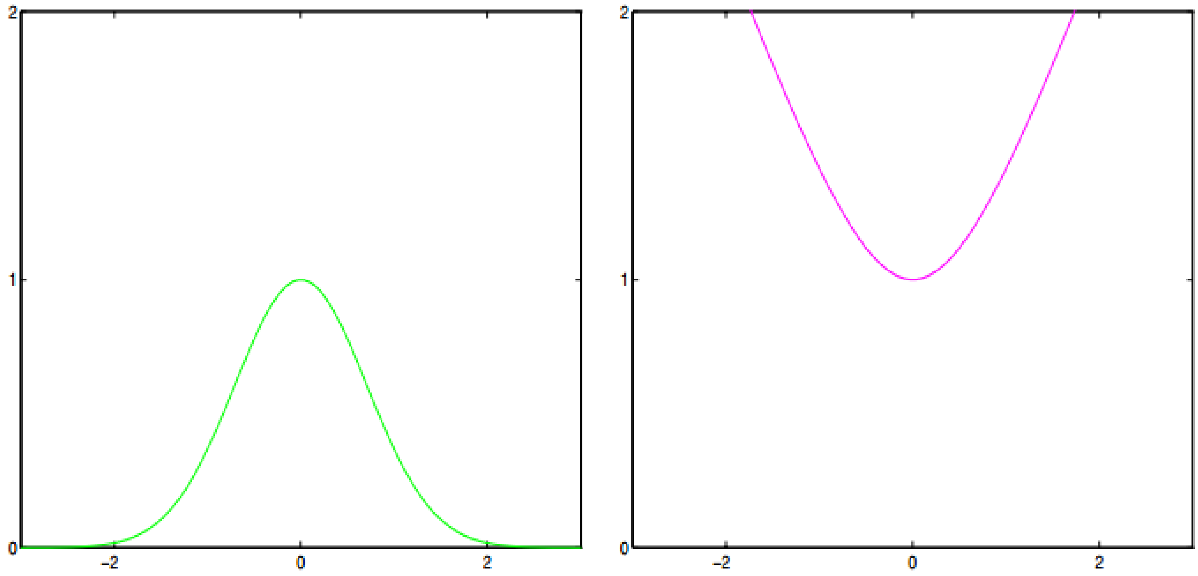


Figure 4.7: Gaussian Functions (left) and Radial Basis Functions (right)

RBFs are a class of functions and they can be used in any kind of nonlinear or linear model and any kind of multilayer or single layer network. Traditionally, RBF networks (Figure 4.8) are associated with the single layer radial function network as discussed by Broomhead and Lowe (1988).

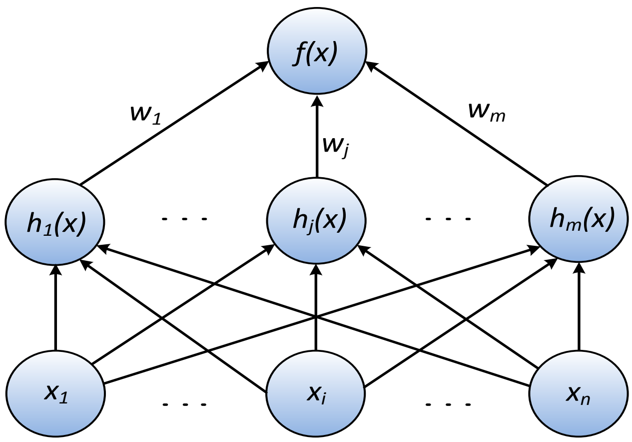


Figure 4.8: Radial Basis Function Network

All the n input vectors x are given to m number of basis functions. The outputs of these basis functions are combined linearly with the weights w*j* when *j*=1,…,m into the output of the network *y(x)*. The radial basis function network is non-linear if the basis function will change the size or move in the case of more than one hidden unit. Nonlinear optimization can also be used for the optimal subset of basis functions in forward selection and in ride regression for the regularization parameters. These RBFs networks make computation quicker, and analysis easier.

4.6.5 Fitting Networks

Fitting using neural networks (FIT) is assumed to be good by researchers and statisticians. A simple neural network can easily compute the fitting function of practical functions. ANN represents a simple to compute and is used for interpolation or curve fitting. Curve fitting is very simple for a 1-n-1 network. It consists of only one input, one linear output, and n number of nodes as shown in Figure 4.9:

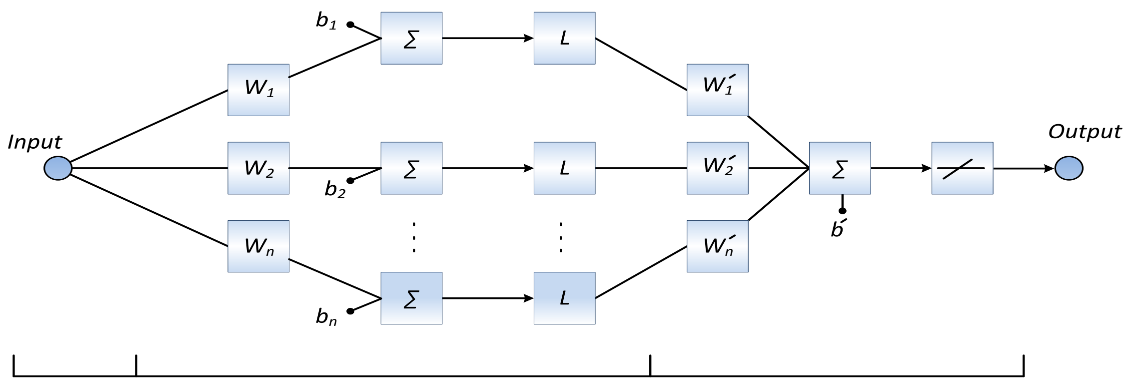


Figure 4.9: *n* hidden layers, 1 output layer

Back propagation networks are used to reduce the bias errors in the previous layers. It is a supervised data processing method for training a neural network involving feedforward propagation. Back propagation uses artificial neurons or nodes to transfer the function in the hidden layers that are differentiable. The Log-Sigmoid function is used and is denoted by 'L' and is shown in Figure 4.9. The values stored in the biases and weights describe the behaviour of the neural network and are denoted by b and W. The feedforward network used for fitting is described by the following equation:

$$a = Logsig\ (Wx\,(input) + b) \qquad (4.24)$$

where: the resultant vector is represented by a from the hidden nodes,

Logsig ( ) is the output = purelin (W'xa+b') is the log sigmoid function, W, W', and a are the vectors,

Purelin ( ) is represents the linear output of the function.

As the biases and weights (vectors) are trained suitably for the points of the data set, the fitting neural network will start to model the function and indefinitely describe the set of data points. The behaviour of the network would not be a specified equation. Hence, the network will remain free of restrictions of functions or polynomials and would be specified before processing. To store the final biases and weights, the volume of information needed is:

Numbers stored = nodes x 3+1

where 'nodes' defines the number of nodes in the hidden layer.

To train the network for fitting, an extensive amount of time is required. The behaviour will be closer to the points that are used in processing if more time is given. Below are the points that are followed to train the network for fitting the cure:

1-Training sample (data set points) is given to the neural network as input value.

2- Compare the output of the network with the expected output of the sample. Calculate the error of all the neuron's output.

3- Calculate the scaling factor and the output for each neuron, and explain by how much higher or lower the output should be adjusted to bring it closer to the expected output. This is known as the local error of the network.

4- The weights of each neuron should be adjusted to the local or lower error.

5- Allocate the neurons responsible for generating or increasing error at the preceding level, prioritizing with the higher responsibility neurons linked with the higher weights.

6- Repeat the procedure in the same manner.

4.6.6 Feed Forward Input Time-Delay Back Propagation Network

Satsri et al. (2007) used this model arrangement for the comparison that consists of a single layer and involves three levels:

1- The feedforward of the input neurons' pattern

2- Associated errors are back propagated

3- Weight adjustments

A multilayer perceptron has one input layer and one output layer of source nodes and neurons respectively, in a back propagation arrangement. These nodes are called computation nodes. It also comprises a hidden layer, as in all other types of neural networks, and it works in the same way. More often, the training of data is done by using a back propagation algorithm which has 2 important phases. The input signal is transmitted layer by layer through the network and all the free parameters are fixed during the forward phase. This phase completes while producing a signal of error.

$$E_i = d_i - y_i \qquad (4.25)$$

where:

d_i represents the expected response,

y_i represents the actual output generated in response to the input x_i by the network.

The error signal e_i is transmitted by the network in the backward direction during the second phase. Adjustments are made at this stage of the independent parameters to minimize the error e_i.

The back propagation technique is easy to implement and efficient in computational processes, and it has linear complexity in the synaptic weights. However, this algorithm has the limitations that it is slow and does not always converge, which generates issues, specifically when processing difficult learning tasks which require the use of sophisticated networks (Haykin et al., 2001). The iterations of the back propagation algorithm can be written in the following form (Demuth et al., 2008):

$$x_{k+1} = x_k - a_k g_k \qquad (4.26)$$

where:

a_k the rate of learning,

x_k is the vector of biases and weights,

g_k is the gradient.

The back propagation algorithm is typically concerned with an approximation of the arrangement without any dynamics, i.e. a static system. Time is another important aspect of learning in this algorithm. The time can be incorporated into the neural network's system explicitly or implicitly. The time 1 can be implicitly represented by a straightforward method in the static neural network i.e. to add a short term memory structure in the input layer. The resultant configuration is known as a focused time lagged feedforward network. The mechanism is shown in the Figures 4.10 - 4.12.

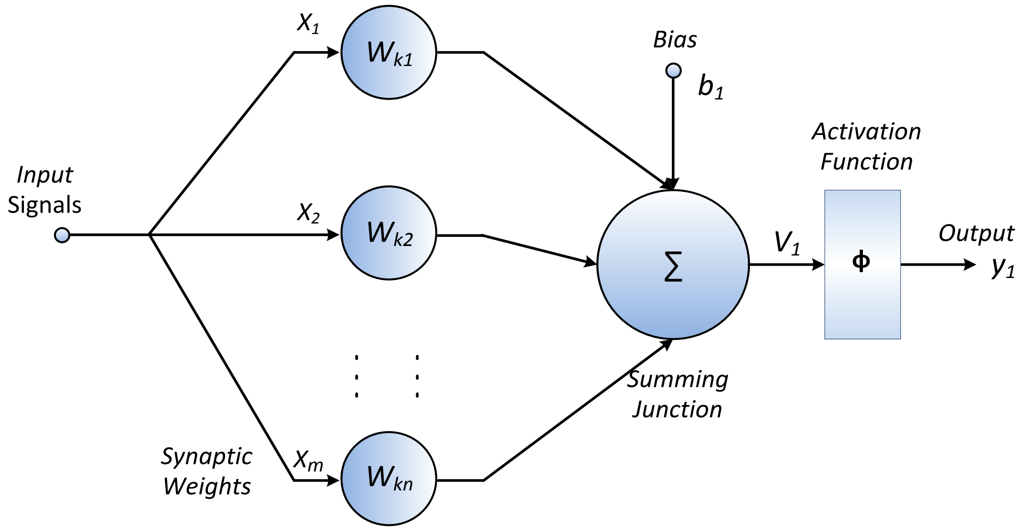


Figure 4.10: Artificial neural network

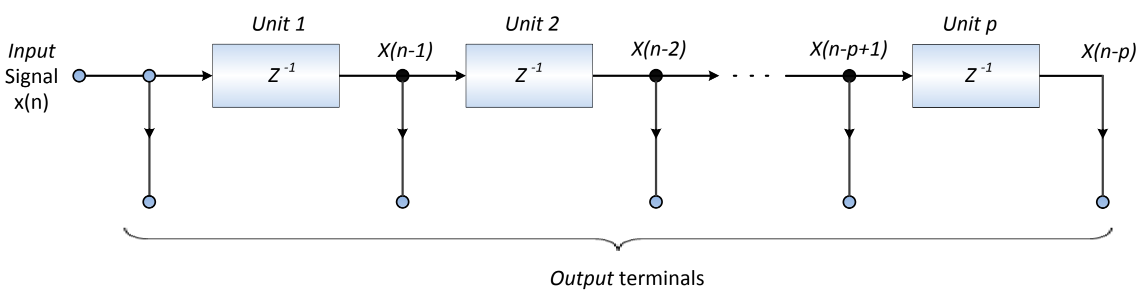


Figure 4.11: Order p ordinary tapped delay line memory

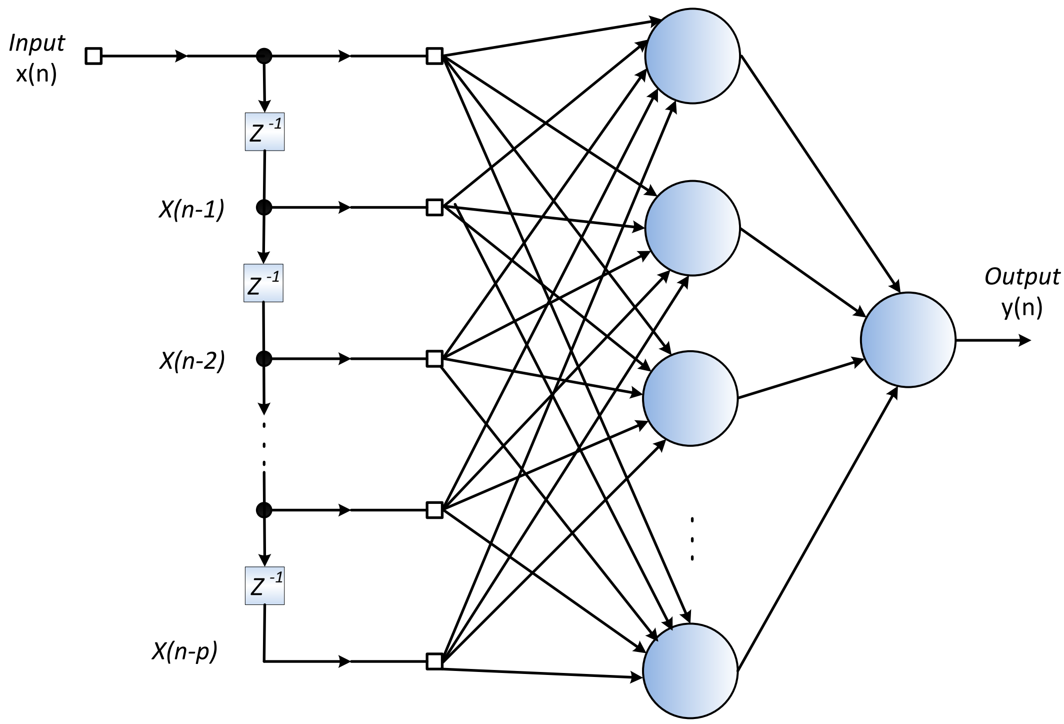


Figure 4.12: Focused time lagged feedforward network

The most widely used form of short term memory is the tapped delay line. Figure 4.11 shows *p* unit delays of time with *p*+1 terminal. It can be seen that it takes in one input and results in multiple output networks. Figure 4.12, which illustrates a focused time lagged feedforward network, shows a network employing a combination of tapped delay line. In Figures 4.11 & 4.12, the time delay is represented by z-1. The tapped delay line memory's time is fixed at *p*, whereas the resolution of the memory is fixed at 1, generating a depth resolution *p* as a constant. The focused time lagged feedforward network (TLFN) employs the tapped delay line memory, or gamma memory, that are restricted to dynamic procedures, in which the time is spread throughout the network at the synaptic level. The training of a TLFN is complex compared to the training of a focused TLFN. To train a focused TLFN, the ordinary back propagation algorithm can be used. The back propagation algorithm can be extended in the ordinary multilayer perceptron to cope with the replacement of the synaptic weight vector. The extension of the algorithm is known as the temporal back propagation algorithm (Wan 1994).

4.6.7 Distributed Time Delay Neural Network

The tapped delay line memory processes in the focused time delay neural network (TDNN) only at the input to the first layer of the static feedforward network. The tapped delay lines may be dispersed throughout the network system. The distributed time delay neural network was introduced for distinguishing the phoneme. At first, it was designed especially for the particular problem. The two-layer distributed TDNN is shown in Figure 4.13.

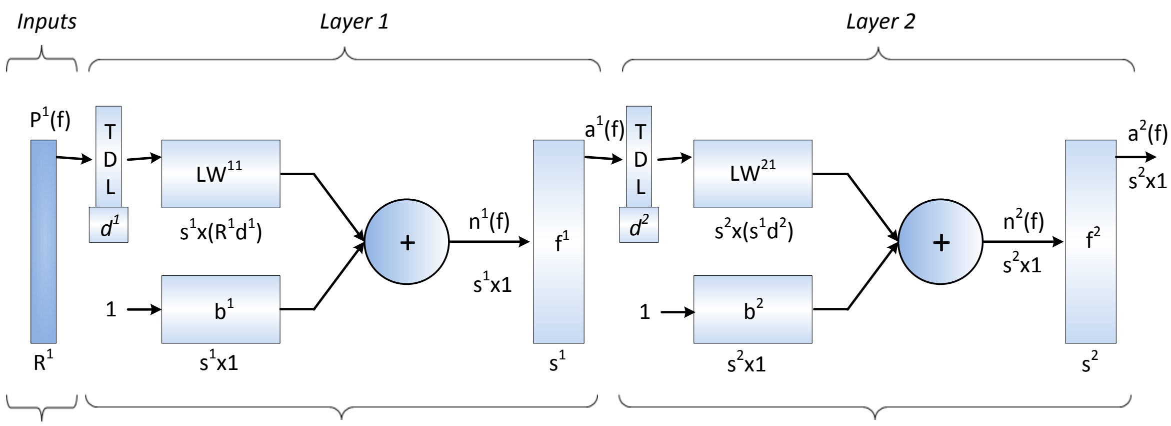


Figure 4.13: Distributed time delay two-layer neural network

This network usually tries to identify the input signal and its frequency content. The signal with one of two frequencies is shown in Figure 4.14:

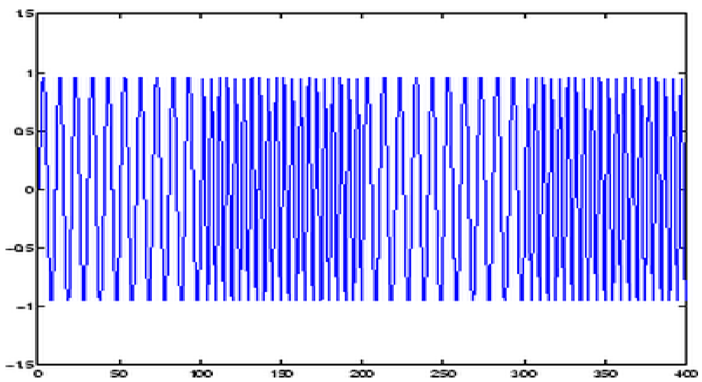


Figure 4.14: Frequency content of an input signal with one of two frequencies

4.7 Adaptive Neural Fuzzy Inference Systems

Zadeh (1965) introduced fuzzy logic to show and manipulate data and information involving several types of uncertainty. Linguistic variables are used in fuzzy rule-based systems to give reasons by utilizing a series of logics containing If-Then rules. These rules connect consequents and antecedents together. An antecedent with a specific degree of membership between 0 - 1 is a fuzzy clause. Multiple antecedents may be linked with OR and AND operators by fuzzy rules. All processes are executed and resolved simultaneously. There may be multiple parts of consequents that may be averaged into a single output/number of a fuzzy set (Negnevitsky, 2005). The process of mapping from a given input to an output through the fuzzy set of methods is called fuzzy inference and its system is shown in Figure 4.15:

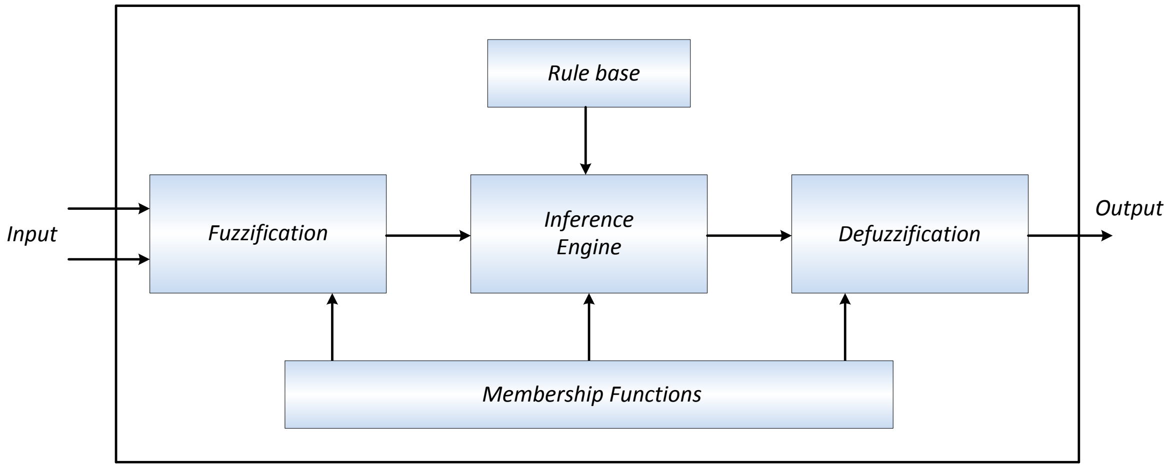


Figure 4.15: A typical system of fuzzy inference

The fuzzy inference system has five functions as shown in Figure 4.15. The fuzzification component transforms each crisp input variable into a membership grade which is typically based on the membership's functions. The fuzzy reasoning is processed in the inference component by the suitable fuzzy operators to acquire the fuzzy set. These fuzzy sets are further collected in the consequent variable. The fuzzy output variable is than transformed into a crisp resultant by employing the method of certain defuzzification, which occurs in the defuzzifiication component. Jang (1993) proposed the Adaptive Neuro-Fuzzy Inference System, and in 1993 he implemented a Sugeno fuzzy inference method. This Adaptive Neuro-

Fuzzy Inference System (ANFIS) consisted of a six layers feed-forward neural network and is shown in Figure 4.16.

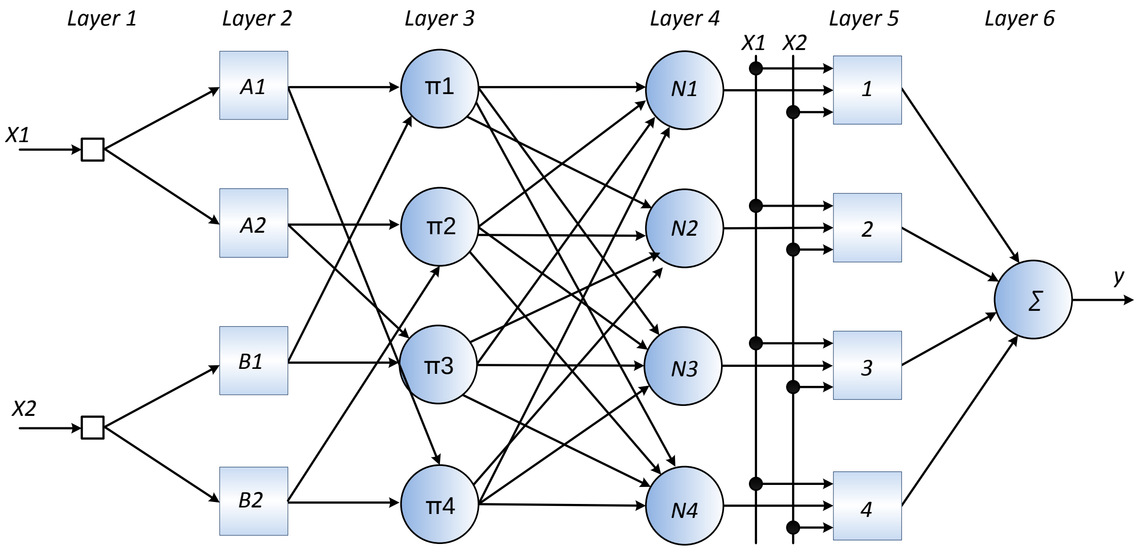


Figure 4.16: Six-layered feed-forward Adaptive Neuro-Fuzzy Inference Systems neural network (Jang, 1993)

The external crisp signals are passed through layer 1 to layer 2 and is called the fuzzification layer. This determines the membership grades for all inputs applied by the specified function of the fuzzy membership. Examples of such fuzzy membership functions include Gaussian curve and bell-shaped. The membership function can be shown in the form of the given equation:

$$\mu_{Ai}(x) = \frac{1}{1+[\left(\frac{x-ci}{ai}\right)^2]^{bi}} \qquad (4.27)$$

$$\mu_{Ai}(x) = exp\left\{-\left(\frac{x-ci}{ai}\right)^2\right\} \qquad (4.28)$$

where a_i, b_i, and c_i represent the parameters used in the membership function.

The 3rd layer computes the firing strength of the rule as a multiple of the membership grades of ANFIS, which is called the rule layer. In layer 4, each neuron receives input from the previous layers' neurons. This layer further computes the ratio of the sum of the firing strengths of all the rules, and the firing strength of a given rule. Layer 4 is known as 'normalized firing strengths'. The defuzzification layer is layer 5, and it yields the restrictions of the output part of the process. There is only one node in layer 6 that computes the final resultant, considering it to be the sum of all the input signals. The specifics of ANFIS are discussed in detail by Jang (1993) and Negnevitsky (2005).

$$O_{3,i} = w_i = \frac{w_i}{w_1 + w_2 + w_3 + w_4} \quad (4.29)$$

$$O_{4,i} = w_i f_i = w_i(p_i x + q_i y + r_i) \quad (4.30)$$

p, q, represent the set of parameters of layer 4 that may be identified by applying the Least Square Estimation method.

$$O_{5,i} = \sum_i w_j f_j \quad (4.31)$$

4.31 is the equation of layer 5 which represents the summation of the all input signals in the previous layers.

The training error can be reduced by applying the ANFIS and using the alternative algorithms. The least square algorithm and gradient descent algorithm are effective for finding the optimal parameters. This hybrid technique has the advantage of being very fast, and it reduces the dimensions of the search space of the back propagation technique commonly used in neural networks (Jang 1993).

4.8 Genetic Algorithm

Genetic algorithm (GA) was first described by Holland (1975). After that, a series of papers have been published by Srinivas and Patnaik (1994) and Beasley (1993). As its name suggests, it is inspired by the natural biological mechanism which says that stronger individuals are more likely to win in a competitive environment. The genetic algorithm engages the direct examples of natural evolution. It believes that an individual is the potential solution to the problem and it can be shown using a set of parameters. These parameters can be likened to the genes of a chromosome. The structure of a chromosome is like a string of binary values. The fitness value (i.e. a positive value) usually reflects the height of ‘goodness’ of the chromosome that is involved in problem solving. Such a value is very close to the objective value. A fitter chromosome has the tendency to yield good quality offspring through the genetic evolution process that indicates a good solution for the problem. The chromosomes can be set initially on a random basis and their population pool has to be installed in a specific application of the genetic algorithm. McFarlane and Glover (1990) have defined some guidelines to deal with the problems of the size of the population variation. The evolution process is the cycle of genetic operation. A consequent generation is produced from the current population's chromosomes through the process of evolution. The evolution process can only be successful if a group of chromosomes, usually known as a "mating pool" or "parents", pass through a particular routine of selection. The parental genes are recombined and mixed for the next generation's production of offspring. This process of evolution, or the manipulation of genes, is expected to give better chromosomes that can generate a large number of offspring. Therefore there is more chance to survive in the consequent population, following the survival of the best mechanism in nature. To understand this mechanism, the roulette wheel selection (Davies and Clarke, 1995) is the best suitable scheme for such a type of selection mechanism. The evolution cycle is repeated until the desired outcome is achieved, based on predefined criterion. The number of evolution cycles or computational runs, fitness values, and the aggregate of variation between the individuals of different generations can be set as a predefined criterion. Crossover and mutation are two fundamental operators which are required to facilitate the evolution cycle of the genetic algorithm. The selection criterion can also be considered as another operator. The operational procedure is shown in Figures 4.17 and 4.18 in a one point crossover mechanism:

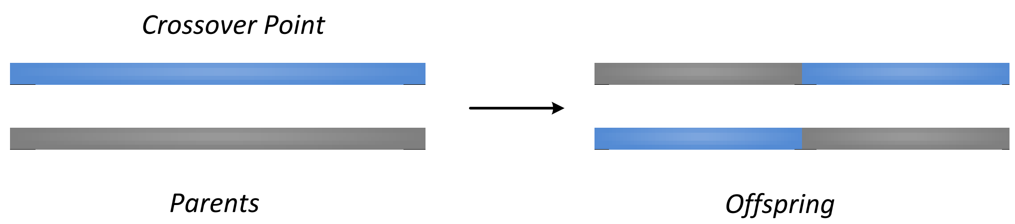


Figure 4.17: One-point crossover

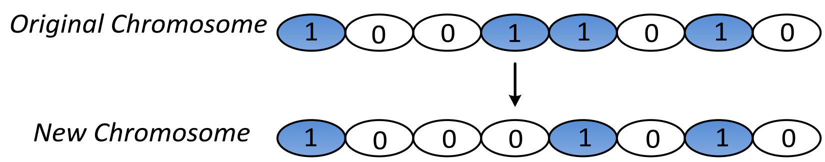


Figure 4.18: New chromosomes generated by original chromosomes with bit mutation on the fourth bit

The crossover point is set randomly as the cut-off point. The sharing of the two chromosomes has to be exchanged after this point to the right to create the offspring. *pc* represents the rate of operation which is a value between 0.6 to 1.0, and is the probability crossover. The process is applicable to every individual offspring for mutation after the crossover exercise. Each bit with a small probability *pm* typically less than 0.1 is given an alert randomly.

The control parameters *pm* and *pc* can be chosen for nonlinear optimization problems. Moreover, the settings of these control parameters depend on the characteristics of the objective function.

According to the roulette wheel parent selection, N represents the sum of the fitness of all population members, *n* represents the random number between 0 and total fitness N. The when process returns to the first population member whose fitness, added to the fitness of the preceding population members, is usually larger or equal to *n*.

4.9 Summary

The theoretical frameworks described in this chapter are used in the analysis of data sets in this research. These frameworks are scientifically designed to solve multiple problems in the real world and their structure and mechanism cannot be randomly modified. The neural network is the most widely used method which provides solutions to problems in multiple fields of study. The theories of these frameworks help to understand the mechanisms that execute the processes and achieve the required objectives. The authentication of these above-discussed mechanisms is obvious in the literature, and the scientific community widely accepts them in order to achieve a level of reliability in data analysis and results. The CAPM is used to explain the association between the predictable market return and risk in the field of economics. It involves linear methods. Since CAPM has the limitation of certain types of problem solving, the Fama and French (1993) model performs as an extension of CAPM and provides valuable additional information about the risks and returns of the market. This model is a three factor model and also describes the risk-free rate of return with the help of different mathematical formulae and logics. Both models have been used in several studies in the past, which highlighted the importance of their application. The VBM model ensures the effective and efficient use of the available firm's resources and highlights the differences between management, planning, and control of accounting. It also involves some contingency theories that affect the information structures and the organizational design. VBM is a theory-based model that describes the smooth execution of organizational processes. The neural networks are the most popular models, used in many applications. The feed forward neural network is based on a multilayer perceptron algorithm that involves the hidden, input, and output layers. The layers are interconnected and give the output after complex logical processing. The Elman network was presented by Elman (1990) and it involves the recurrent type of network logics that are used for identification and prediction of dynamic financial systems. It involves the back propagation algorithm and context unit functions to deal with the previous process of activations in layers to support time delays. The recurrent processes are fixed networks. The cascade-forward network is based on the connections built internally between all the layers. The new neurons are introduced in a chain in order to reduce the network bias error. This network is used for dealing with the problems of classification in the data sets. The radial basis function networks are based on the Gaussian functions and radial basis functions, involving linear and nonlinear models of multilayer or single layer networks. These networks are used for optimization of the finances of firms. The fitting networks are used to fit the linear regression curve fitting of n number of nodes. It is also based on the back propagation algorithm to reduce the model bias, and then it uses the supervised processing of data with feed forward propagation. The Log-Sigmoid functions are also used by this network to fit the curve. The Feed-Forward Input Time-Delay Back Propagation Network consists of a single layer and a feed forward algorithm as well as the back propagation algorithm. It is used for time delays during the logical processing of data sets involved in the study. This network uses several different types of algorithms at different stages for reducing the errors in the output. The distributed time delay neural network employs the static feed forward algorithm to process the data sets in which the dispersion occurs. It is used for distinguishing and identifying the frequency content of the signals or different practical problems. Adaptive neural fuzzy inference systems were introduced by Zadeh (1965) to manipulate data and information that involve probabilities. It uses fuzzy rules consisting of If-Then logics to solve the problems of economics. The genetic algorithm was introduced by Holland (1975) and proposes to find solutions to problems based on natural evolution processes. It involves the application of the roulette wheel selection for the operational procedures.

Chapter 5

Model Developments

5.1 Introduction

The present chapter of this thesis reports the model forecasting for the stock return predictions on the Saudi Arabian Stock Exchange, using the traditional Capital Asset Pricing Model (CAPM) along with the Fama and French (FF) three factor model. The popular Fama and French three factor model is based upon market returns, size and book to market. In order to boost the predictive power of stock prediction models, various Artificial Neural Network (ANN) models have been applied as well. For both CAPM and FF, forecasting has been done through a linear regression model, along with eight ANN models such as Cascade-Forward Network (CF), Elman Neural Networks (ELM), Feed Forward Input Time-Delay Back Propagation Network (FFTD), Feed forward Neural Network (FF), Distributed Time Delay Neural Network (DTDNN), Fitting Network (FIT), Radial Basis Function Network (RB) and Adaptive Neural Fuzzy Inference Systems (ANFIS). Along with this, the simple average and weighted average of all these ANN models, as well as a Genetic Algorithm (GA,) have also been used in this study as stock return prediction models for the Saudi Arabian Stock Exchange for the period of January 2007 to December 2011 using MATLAB software. The rest of this chapter is organized as follows: Section two describes the results of the forecasting FF model, while section three shows the results of the forecasting CAPM model. Section four provides comparisons between the FF and CAPM models, and finally the last section presents the summary.

5.2 Forecasting Fama-French three factor Model

According to Fama and French (1993) methodology using monthly data in each model is based upon 60 monthly observations from 2007 to 2011, and it is divided into training type for the first 48 observations, and testing type for the last 12 observations. The training type is the biggest type and is used by neural network to learn patterns present in the data. The testing type is used to evaluate the generalization ability of a supposedly trained network Jha (2007). This data was done in order to see the accuracy of the predictive power of ANN and other models in CAPM and FF. The root mean squared (RMS) is used to estimate the difference between the actual and predicted values for each of the six portfolios constructed for training and testing .The RMS is calculated as:

$$RMS = \frac{\sqrt{\sum_{i=1}^{N} (X - \hat{X})^2}}{N} \qquad (5.1)$$

where: N = the sample size, X = the actual values and $\widehat{X}$ = the predicted values.

All the numbers in the tables are the RMS measure (Standard deviation) and each number has two values (training and testing) for returns of each portfolio – RHB, RHS, RMB, RMS, RLB, and RLS. The Fama and French (FF) proposed three-factor model is used for forecasting the stock returns in individual securities and portfolios. This model is actually an extension of the traditional CAPM model, which only uses market returns to predict individual stock returns. The FF model also includes the size and value effect (book to market ratio) along with market returns in order to forecast stock returns for a security. The present study uses the FF three-factor model to predict stock returns in the Saudi Arabian Stock market. The method uses a linear model, various ANN models, average and weighted average of ANN models and a genetic algorithm to predict the stock returns for the six portfolios constructed, based upon size and book to market ratio.

5.2.1 Results of Linear Regression

Table 5.1 shows the explanation power (R2) ranges from 0.73 to 0.34 which means that the three-factor model explains more of the variations in stock return, but not all of them. This means that there are other variables which explain the dependent variable.

Table 5.1 R-squared for FF

FF	RHB	RHS	RMB	RMS	RLB	RLS
R-squared	0.472	0.339	0.434	0.702	0.731	0.703

Moreover, Table 5.2 shows that the null hypothesis can be rejected which implies that there is no significant effect of the market return variable (independent variable) on the big portfolios return as the P-value is less than 1% (1 - confidence level (99%)). This implies that the alternative hypothesis can be accepted which indicates that there is positive significant effect for the market value on the stock return for the big portfolios. While the coefficients of the market return (independent variable) are 0.98 and 0.61 and 0.76 big portfolios.

Furthermore, table 5.2 shows that the null hypothesis can be rejected which implies that there is no significant effect of the market return variable (independent variable) on the small portfolios return as the P-value is less than 1% (1 - confidence level (99%)). This implies that the alternative hypothesis can be accepted which indicates that there is positive significant effect for the market value on the stock return for the small portfolios. While the coefficients of the market return (independent variable) are 0.77 and 0.84 and 0.91 for the small portfolios. This means that the market return significantly affects the stock return in the six portfolios when regressed with the other two factors.

Table 5.2 shows the SMB size factor, the coefficients for big size high B/H, portfolio is significantly different than zero at 1 percent significant level but the coefficient for small size high S/H and small size Medium S/M and big size low B/L portfolios are significantly different than zero at 10 percent significant, finally coefficients of big size Medium B/M, small size Low S/L portfolios are not significantly different than zero. The coefficients are positive for all the portfolios except the big size high B/H and big size low B/L portfolio it's coefficient sign is negative.

For the SMB size factor; Table 5.2 show that the null hypothesis can be rejected which implies that there is no significant effect of the SMB size variable (independent variable) on the for big size high B/H portfolio returns as the P-value is less than 1% (1-confidence level (99%). This implies that the alternative hypothesis can be accepted which indicates that there is negative significant effect for the SMB size on the big size high B/H portfolio return for the small portfolios.

Furthermore Table 5.2 shows that for the SMB size factor the null hypothesis can be rejected which implies that there is no significant effect of the SMB size variable (independent variable) on the for small size high S/H and small size Medium S/M and big size low B/L portfolios returns as the P-value is less than 10% (1-confidence level (90%). This implies that the alternative hypothesis can be accepted which indicates that there is positive significant effect for the SMB size on the for small size high S/H and small size Medium S/M portfolios return and there is negative significant effect for the SMB size on big size low B/L portfolio return. Moreover, Table 5.2 shows that for the SMB size factor, the null hypothesis cannot be rejected which implies that there is no significant effect of the SMB size variable (independent variable) on the big size Medium B/M, and small size Low S/L portfolios returns as the P-value is more than 10% (1 - confidence level (90%)). This implies that there is no significant effect for the SMB size on the big size Medium B/M, and small size Low S/L portfolios returns. The coefficients are positive for all the portfolios except the big size high B/H and a big size low B/L portfolio it's coefficient sign is negative.

For HML book-to-market factor, Table 5.2 show that the null hypothesis can be rejected which implies that there is no significant effect of the HML book-to-market variable (independent variable) on the big size high B/H and small size high S/H portfolios returns as the P-value is less than 1% (1 - confidence level (99%)). This implies that the alternative hypothesis can be accepted which indicates that there is positive significant effect for the HML book-to-market on the big size high B/H and small size high S/H portfolios return.

Furthermore, Table 5.2 shows that for the HML book-to-market factor, the null hypothesis can be rejected which implies that there is no significant effect of the HML book-to-market variable (independent variable) on the for small size medium S/M portfolio returns as the P-value is less than 5% (1 - confidence level (95%)). This implies that the alternative hypothesis can be accepted which indicates that there is positive significant effect for the HML book-to-market on the small size medium S/M portfolio.

Finally, Table 5.2 shows that for the HML book-to-market factor, the null hypothesis cannot be rejected which implies that there is no significant effect of the HML book-to-market variable (independent variable) on the big size medium B/M and big size low B/L and small size low S/L portfolios return as the P-value is more than 10% (1 - confidence level (90%)). This implies that there is no significant effect for the HML book-to-market factor on the big size medium B/M and big size low B/L and small size low S/L portfolios return. So there is no absolute evidence that this variable affects the stock return.

Adding SMB and HML to the regression has an interesting effect on the market βs for stocks. It collapses the βs for stocks toward 1.0, low βs move up and high βs move down toward one. This behaviour is due to correlation between market and SMB or HML.

Table 5.2 Fama and French 1993 model Three Coefficients

Portfolios	Coefficients C(2) R_M	Prob.	Hypothesis	Coefficients C(3) R_{SMB}	Prob.	Hypothesis	Coefficients C(4) R_{HML}	Prob.	Hypothesis
RHB	0.982	0.000	Reject (Ho)	-0.373	0.0014	Reject (Ho)	0.770	0.0000	Reject (Ho)
RHS	0.778	0.000	Reject (Ho)	0.191	0.0779	Reject (Ho) at 10%	0.514	0.0018	Reject (Ho)
RMB	0.612	0.000	Reject (Ho)	0.038	0.7612	Accept (Ho)	0.171	0.1799	Accept (Ho)
RMS	0.842	0.000	Reject (Ho)	0.172	0.0834	Reject (Ho) at 10%	0.251	0.0159	Reject (Ho) at 5%
RLB	03762	0.000	Reject (Ho)	-0.256	0.0607	Reject (Ho) at 10%	-0.114	0.3511	Accept (Ho)
RLS	0.912	0.000	Reject (Ho)	0.058	0.6123	Accept (Ho)	-0.019	0.8657	Accept (Ho)

The intercept in the time series regression of returns should be indistinguishable from zero. Intercepts close to zero say that the regressions that use market return, SMB and HML to absorb common time series variation in returns do a good job in explaining the cross section of average stock returns. The result in Table 5.3 shows that some of the intercepts when regress three factor model are closer to zero than the intercepts for CAPM for three portfolios but not with a clear evidence because not all of them which means that using the three factor model market return, SMB and HML to absorb common time-series variation in returns does a better job in explaining the cross-section of average stocks returns.

Table 5.3: CAPM and Fama and French 1993 Intercepts

FF model	Coefficients C(1)	Prob.	CAPM model	Coefficients C(1)	Prob.
RHB	0.016209	0.5077	RHB	0.008081	0.8126
RHS	0.004754	0.8853	RHS	0.025829	0.4867
RMB	0.001554	0.9522	RMB	0.006519	0.8166
RMS	-0.001987	0.9101	RMS	0.009791	0.6062
RLB	0.017826	0.4280	RLB	0.007420	0.7615
RLS	0.002692	0.9182	RLS	0.002758	0.9154

The Fama and French three factor model tested the first 48 observations by conducting the Generalized Method of Moments (GMM) regression (Time Series Heteroskedasticity Autocorrelation [HAC]), to find the intercept and the coefficients for the six portfolios as Shown in Table 5.4.

The equation of the FF model is:

$$R_i\text{-}R_f = \alpha i + \beta_i(R_M - R_f) + \gamma_i R_{SMB} + \delta_i R_{HML} + \varepsilon_i \qquad (5.2)$$

Table 5.4 shows the coefficients and T-value and P-value for the six portfolios tested according to the FF Model:

- The intercept and the coefficients of big size and high book to market value portfolio. The following equation was used to calculate the 48 estimated returns for big size and high book to market value portfolio.

$$R_{HB} = 0.0246 + 0.9893\, R_M - 0.3447\, R_{SMB} + 0.8091\, R_{HML} \qquad (5.3)$$

- The intercept and the coefficients of small size and high book to market value portfolio. The following equation was used to calculate the 48 estimated returns for small size and high book to market value portfolio.

$$R_{HS} = -0.0093 + 0.8362\, R_M + 0.2037\, R_{SMB} + 0.496\, R_{HML} \qquad (5.4)$$

- The intercept and the coefficients of big size and medium book to market value portfolio. The following equation was used to calculate the 48 estimated returns for big size and medium book to market value portfolio.

$$R_{MB} = -0.0067 + 0.6084\, R_M + 0.0589\, R_{SMB} + 0.0329\, R_{HML} \qquad (5.5)$$

- The intercept and the coefficients of small size and medium book to market value portfolio. The following equation was used to calculate the 48 estimated returns for small size and medium book to market value portfolio.

$$R_{MS} = -0.0016 + 0.8507\, R_M + 0.1937\, R_{SMB} + 0.1831\, R_{HML} \qquad (5.6)$$

- The intercept and the coefficients of big size and low book to market value portfolio. The following equation was used to calculate the 48 estimated returns for big size and low book to market value portfolio.

$$R_{LB} = 0.0215 + 0.7927\, R_M - 0.1448\, R_{SMB} - 0.1441\, R_{HML} \qquad (5.7)$$

- The intercept and the coefficients of small size and low book to market value portfolio. The following equation was used to calculate the 48 estimated returns for small size and low book to market value portfolio.

$$R_{LS} = -0.0034 + 0.9689\ R_M + 0.147\ R_{SMB} - 0.1058\ R_{HML} \quad (5.8)$$

Moreover, the linear regression results are reported for the FF model and for all the portfolios in Table 5.5. The RMS values for RHB, RHS, RMB, RMS, RLB, and RLS for training are 0.3088, 0.2890, 0.2737, 0.1856, 0.2416, and 0.2223 (0.2294, 0.2940, 0.3032, 0.1179, 0.2220, and 0.2410 for testing), respectively. Figure 5.1 depicts the fact that the actual return values are located very far apart and spread unevenly from the prediction line in the training observations, as does Figure 5.2. The table of RMS values and both figures indicate that the predictive power of the linear model is very weak as the RMS values are high and the return points are located far away from the prediction line.

Table 5.4: Fama and French 1993 model 48 observation regression six portfolios coefficient

No	Model		Intercept & Coefficients β	T Value	P Value
1	R_{HB}=C(1)+C(2)*R_M+C(3)*R_{SMB}+C(4)*R_{HML}	αi	0.0246	0.840	0.405
		R_M β_i	0.9893	8.312	0.000
		R_{SMB} γ_i	-0.3447	-2.677	0.010
		R_{HML} δ_i	0.8091	4.852	0.000
2	R_{HS}=C(1)+C(2)*R_M+C(3)*R_{SMB}+C(4)*R_{HML}	αi	-0.0093	-0.281	0.779
		R_M β_i	0.8362	4.974	0.000
		R_{SMB} γ_i	0.2037	2.801	0.007
		R_{HML} δ_i	0.496	3.091	0.003
3	R_{MB}=C(1)+C(2)*R_M+C(3)*R_{SMB}+C(4)*R_{HML}	αi	-0.0067	-0.251	0.802
		R_M β_i	0.6084	4.289	0.000
		R_{SMB} γ_i	0.0589	0.591	0.557
		R_{HML} δ_i	0.0329	0.246	0.806
4	R_{MS}=C(1)+C(2)*R_M+C(3)*R_{SMB}+C(4)*R_{HML}	αi	-0.0016	-0.077	0.938
		R_M β_i	0.8507	8.325	0.000
		R_{SMB} γ_i	0.1937	1.773	0.083
		R_{HML} δ_i	0.1831	1.504	0.139
5	R_{LB}=C(1)+C(2)*R_M+C(3)*R_{SMB}+C(4)*R_{HML}	αi	0.0215	0.871	0.388
		R_M β_i	0.7927	6.016	0.000
		R_{SMB} γ_i	-0.1448	-1.033	0.307
		R_{HML} δ_i	-0.1441	-1.034	0.306
6	R_{LS}=C(1)+C(2)*R_M+C(3)*R_{SMB}+C(4)*R_{HML}	αi	-0.0034	-0.123	0.902
		R_M β_i	0.9689	7.894	0.000
		R_{SMB} γ_i	0.147	1.360	0.180
		R_{HML} δ_i	-0.1058	-0.680	0.500

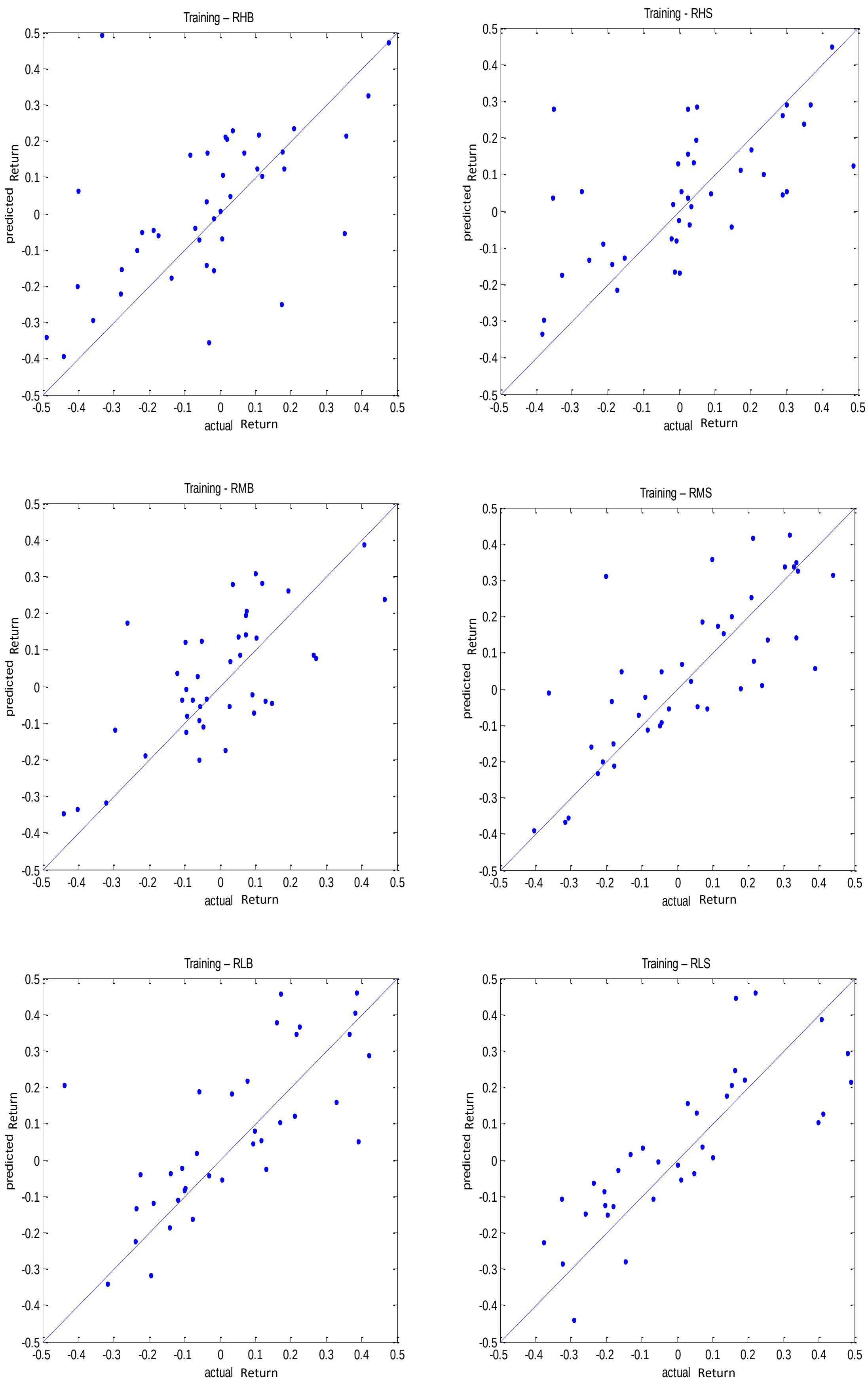


Figure 5.1: RMS Training results (FF model) using logistic regression technique (LR)

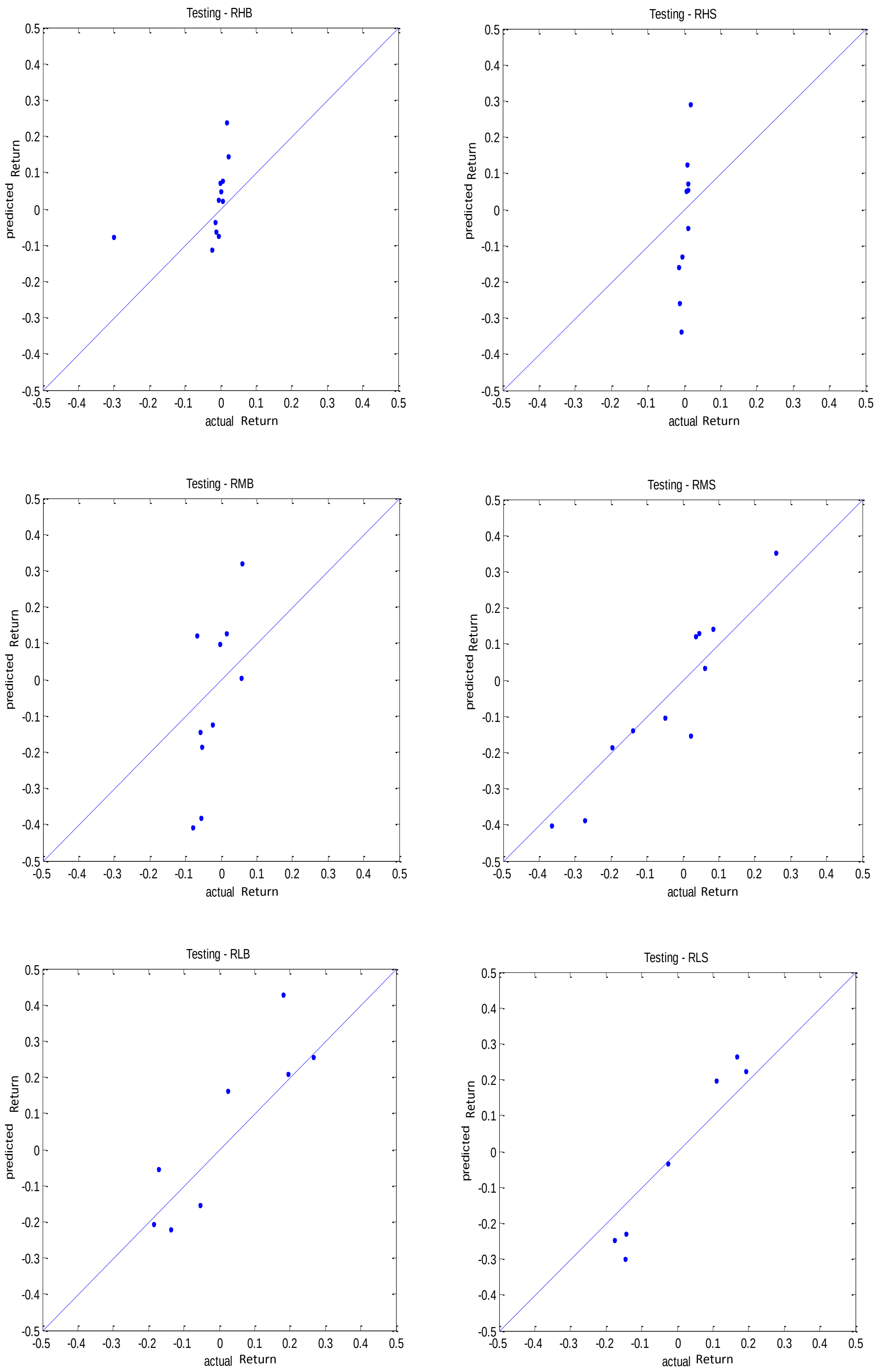


Figure 5.2: RMS Testing results (FF model) using logistic regression technique (LR)

Table 5.5: FF model RMS Training and Testing Results for Linear Regression

FF	RMS	RHB	RHS	RMB	RMS	RLB	RLS
LR	Train	0.3088	0.2890	0.2737	0.1856	0.2416	0.2223
	Test	0.2294	0.2940	0.3032	0.1179	0.2220	0.2410

5.2.2 Results of Artificial Neural Networks Model

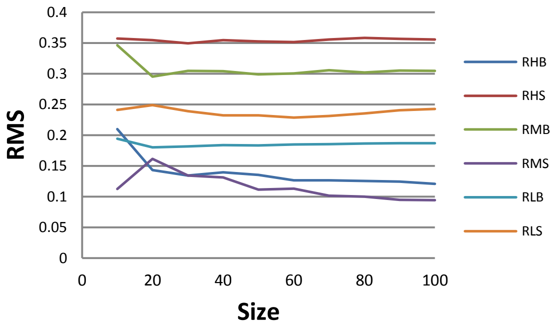
Just like the previous section, when ANN models have been used to forecast stock portfolio returns, the predictive power of these models is greater than that of the linear model. The ANN parameters and topology are illustrated in Table 5.6. Table 5.7 shows that the best results are produced by the ELM model for portfolios RHB, RHS, and RMB with error values of 0.3051, 0.2875, and 0.2584 for training (0.2001, 0.2810, and 0.2631 for testing), respectively. For RMS, the FFTD ANN model has predicted with fewer errors and more accuracy; the RMS values are 0.1296 for training and 0.1167 for testing. Moreover, RB is the best ANN model for the RLB portfolio and the DTDNN model is best for the RLS portfolio with error values of 0.2352 and 0.1818 for training (0.1760 and 0.2327 for testing), respectively. These error values are less than the linear model prediction results, which indicates that the ANN models have greater predictive power (when compared to the simple linear model) for predicting FF three factor portfolio returns on the Saudi Arabian Stock Market. The figures given in Appendix A also present quite a similar picture i.e. better and closer return points predicted by the ANN models when compared to the linear model where the actual return points are more dispersed. Figure 5.3 shows that the best size of the ANN ensemble is 30 in general for all methods of ANN.

Table 5.6: ANN Parameters and Topologies

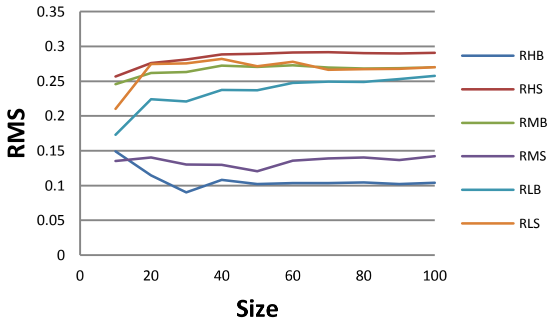
TYPE	Topology	Train/valid	Training epochs	Training function
CF	3-5-1	80/20	500	Levenberg-Marquardt
ELM	3-5-1	80/20	500	Gradient descent
FFTD	3-5-1	80/20	500	Levenberg-Marquardt
FF	3-5-1	80/20	500	Levenberg-Marquardt
DTDNN	3-5-1	80/20	500	Levenberg-Marquardt
FIT	3-5-1	80/20	500	Levenberg-Marquardt
RB	3-5-1	80/20	500	Radial Bases Functions

Table 5.7: FF model RMS Training and Testing Results for ANNs

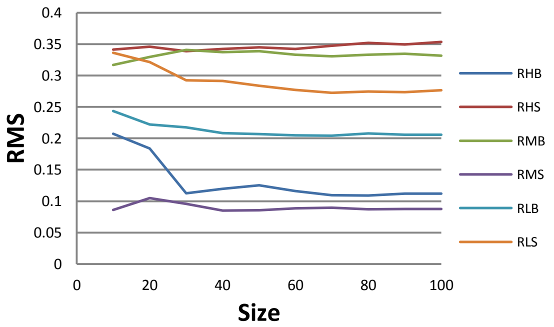
FF	RMS	RHB	RHS	RMB	RMS	RLB	RLS
CF	Train	0.2004	0.1693	0.1468	0.1205	0.1327	0.172
	Test	0.1123	0.3388	0.341	0.0957	0.2176	0.2925
ELM	Train	0.3051	0.2875	0.2584	0.2616	0.2668	0.3261
	Test	0.2001	0.281	0.2631	0.1301	0.2209	0.2756
FFTD	Train	0.2032	0.1932	0.1541	0.1296	0.1426	0.1683
	Test	0.1761	0.3579	0.3085	0.1167	0.2169	0.2457
FF	Train	0.216	0.1844	0.1545	0.1225	0.1503	0.1657
	Test	0.1342	0.3494	0.3047	0.1342	0.1817	0.2388
DTDNN	Train	0.2151	0.1894	0.1556	0.1293	0.1578	0.1818
	Test	0.1148	0.3314	0.3276	0.1201	0.1875	0.2327
FIT	Train	0.216	0.1844	0.1545	0.1225	0.1503	0.1657
	Test	0.1342	0.3494	0.3047	0.1342	0.1817	0.2388
RB	Train	0.2632	0.2681	0.2174	0.2154	0.2353	0.2419
	Test	0.2222	0.3532	0.3496	0.2231	0.1760	0.3186



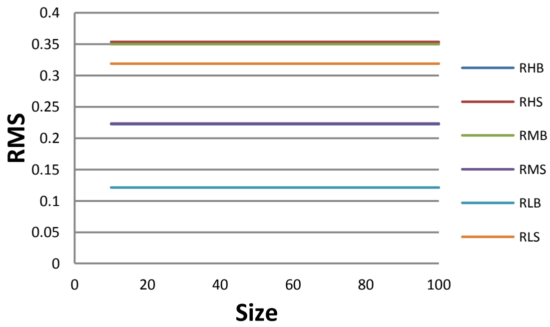
a). Feed-Forward Network (FF)



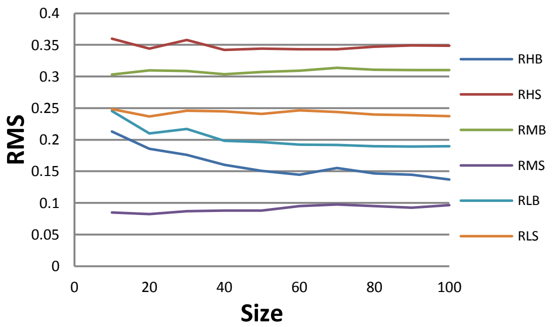
b) Elman Networks (ELM)



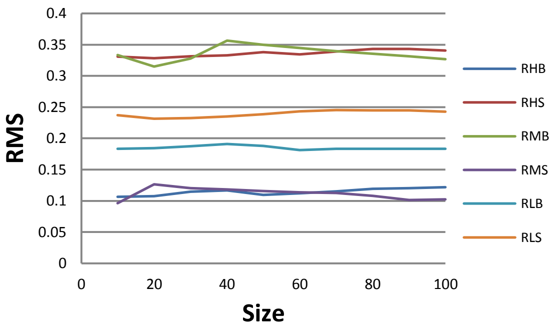
c) Cascade-Forward Network (CF)



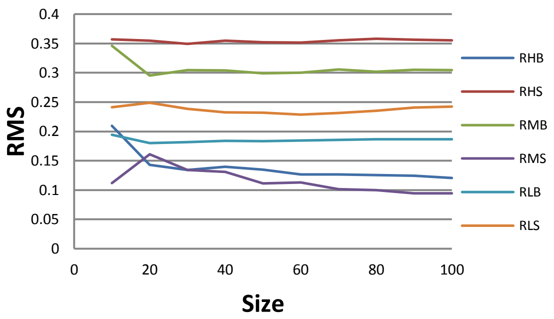
d) Radial Basis Networks (RB)



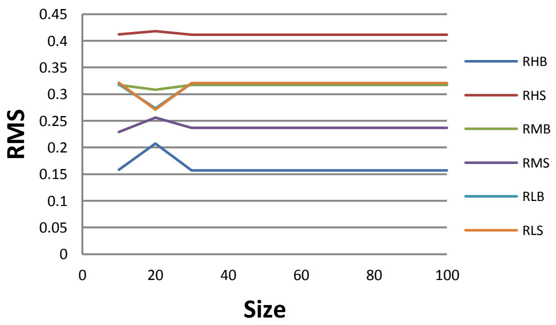
e) Feed- Forward Input Time-Delay Back Propagation Network (FFTD)



f) Distributed Time Delay Neural Network (DTDNN)



g) Fitting Network (FIT)



h) Adaptive Neural Fuzzy Inference Systems (ANFIS)

Figure 5.3: RMS results for different ensemble size of ANNs and ANFIS.

5.2.3 Results of Adaptive Neural Fuzzy Inference Systems Model

The setting of ANFIS is type of membership: Gaussian membership function and the number of fuzzy rules are shown in Table 5.8. Table 5.9 reports the RMS values of the adaptive neural fuzzy inference system (ANFIS) for our six portfolios. The error values for RHB, RHS, RMB, RMS, RLB, and RLS are 4.18E-06, 3.90E-06, 3.74E-06, 4.09E-06, 2.30E-06, 2.86E-06 for training (0.1571, 0.4113, 0.3173, 0.2367, 0.3201, and 0.3206 for testing), respectively. These values show that ANFIS has a weaker prediction power than those of the ANN models used earlier in the case of Fama and French. The actual values of stock return using ANFIS models have also been plotted and these figures are reported in Appendix A.

Table 5.8: Number of fuzzy rules

Portfolios	1	2	3	4	5	6	7	8	9	10
RHB	140	125	200	100	160	175	120	160	60	80
RHS	200	125	120	150	175	140	160	160	100	100
RMB	140	200	140	150	125	175	160	120	100	75
RMS	200	160	160	175	140	120	64	80	80	80
RLB	160	120	140	125	80	100	100	175	200	120
RLS	200	160	140	120	125	100	100	150	80	140

Table 5.9: FF model RMS Training and Testing Results for ANFIS

FF	RMS	RHB	RHS	RMB	RMS	RLB	RLS
ANFIS	Train	4.18E-06	3.90E-06	3.74E-06	4.09E-06	2.30E-06	2.86E-06
	Test	0.1571	0.4113	0.3173	0.2367	0.3201	0.3206

5.2.4 Ensembles Model

5.2.4.1 Results of Average Ensemble Model

Figure 5.4 shows the average method of all types of ANN and ANFIS. Moreover, the average of ANN models have also been used to predict FF stock returns for underlying portfolios. In Table 5.10 the results show that the average method is better than the individual model of ANN as well as the linear model. The error values for RHB, RHS, RMB, RMS, RLB, and RLS are 0.1875, 0.1723, 0.1417, 0.1219, 0.1382, and 0.1583 for training (0.1566, 0.1858, 0.2576, 0.1127, 0.1760, and 2250 for testing), respectively. These values are less than the best individual models of ANN tested before, showing that the average method is superior at predicting the stock portfolio returns in Saudi Arabia. Figures 5.5 and 5.6 also indicate that actual return points predicted by the average method are in a better and closer position to the prediction line, as compared to previously discussed prediction models.

The equation for the average is:

$$Average = \frac{\sum_{i=1}^{n} para(i)}{N} \qquad (5.9)$$

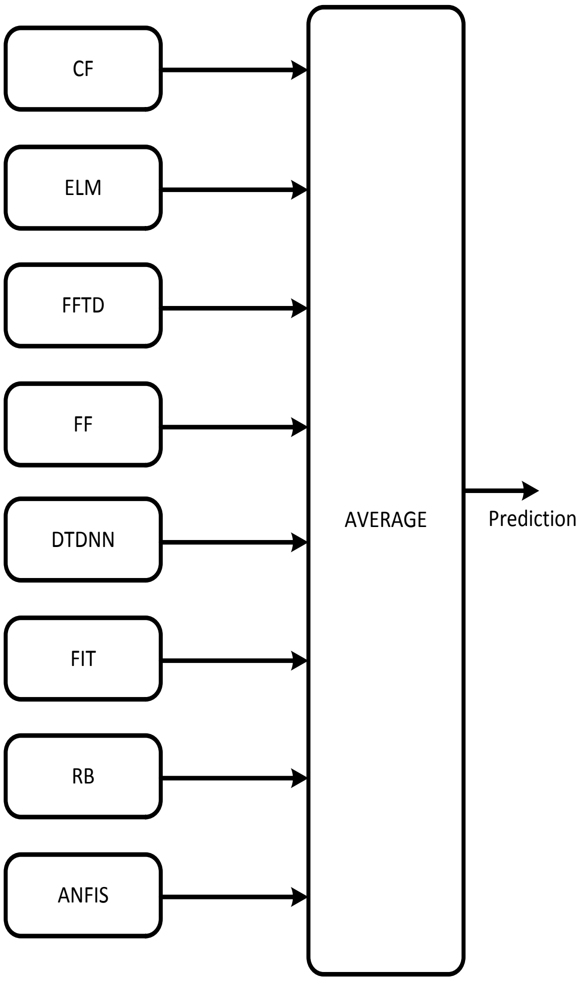


Figure 5.4: The average ensemble methods

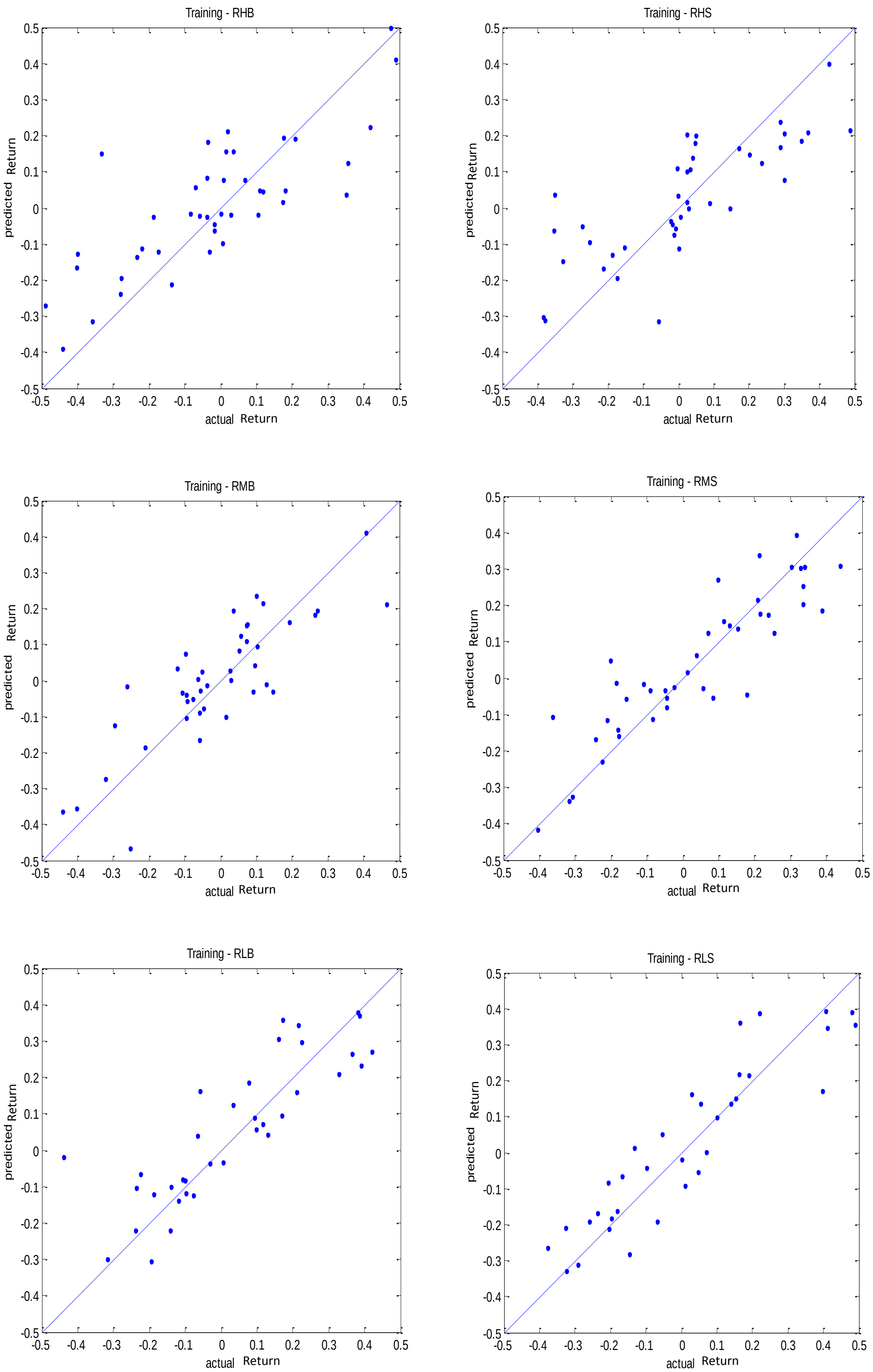


Figure 5.5: RMS Training results using (FF model) average technique

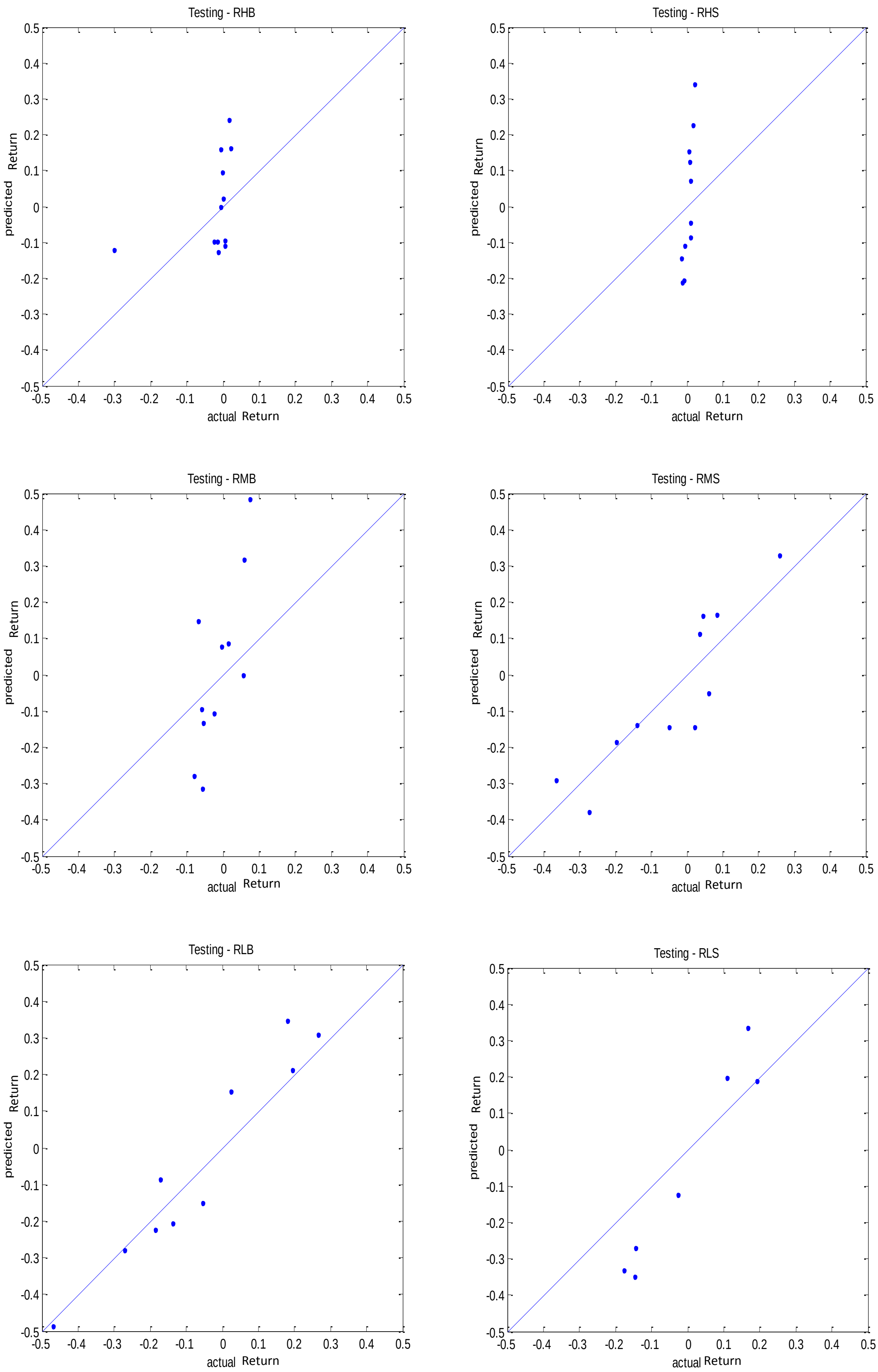


Figure 5.6: RMS Testing results using (FF model) Average technique

Table 5.10: FF model RMS Training and Testing Results for Average ensemble

FF	RMS	RHB	RHS	RMB	RMS	RLB	RLS
Average	Train	0.1875	0.1723	0.1417	0.1219	0.1382	0.1583
	Test	0.1566	0.1858	0.2576	0.1127	0.1760	0.2250

5.2.4.2 Results of Weighted Average Model

The weighted average method is even better than the simple average. The error values in Table 5.11 for RHB, RHS, RMB, RMS, RLB, and RLS are 0.1846, 0.1685, 0.1372, 0.1119, 0.1342, and 0.1573 for training (0.1253, 0.1554, 0.2446, 0.1027, 0.1625, and 0.2230 for testing), respectively. Figures 5.7 and 5.8 also indicate that the actual return points predicted by the weighted average are in a better and closer position to the prediction line, as compared to previously discussed prediction models. The weighted average was set in the training phase where the results were divided into 10 bins, and then the standard deviation was taken for each bin. Then the weights are set inversely to the standard deviation. The lower the deviation is, the higher the weight will be. The equations for the weighted average are:

$$Weighted\ average = \frac{\sum_{i=1}^{n} para(i)\ x\ W(i)}{\sum_{i=1}^{n} W(i)} \qquad (5.10)$$

$$W(i) = 1 - \overline{STD_i(bin)} \qquad (5.11)$$

where: STD_i is the standard deviation for *bin* ,the normalized values taken ($\overline{STD}$)

Table 5.11: FF model RMS Training and Testing Results for Weighted Average

FF	RMS	RHB	RHS	RMB	RMS	RLB	RLS
Weighted Average	Train	0.1846	0.1685	0.1372	0.1119	0.1342	0.1573
	Test	0.1253	0.1554	0.2446	0.1027	0.1625	0.2230

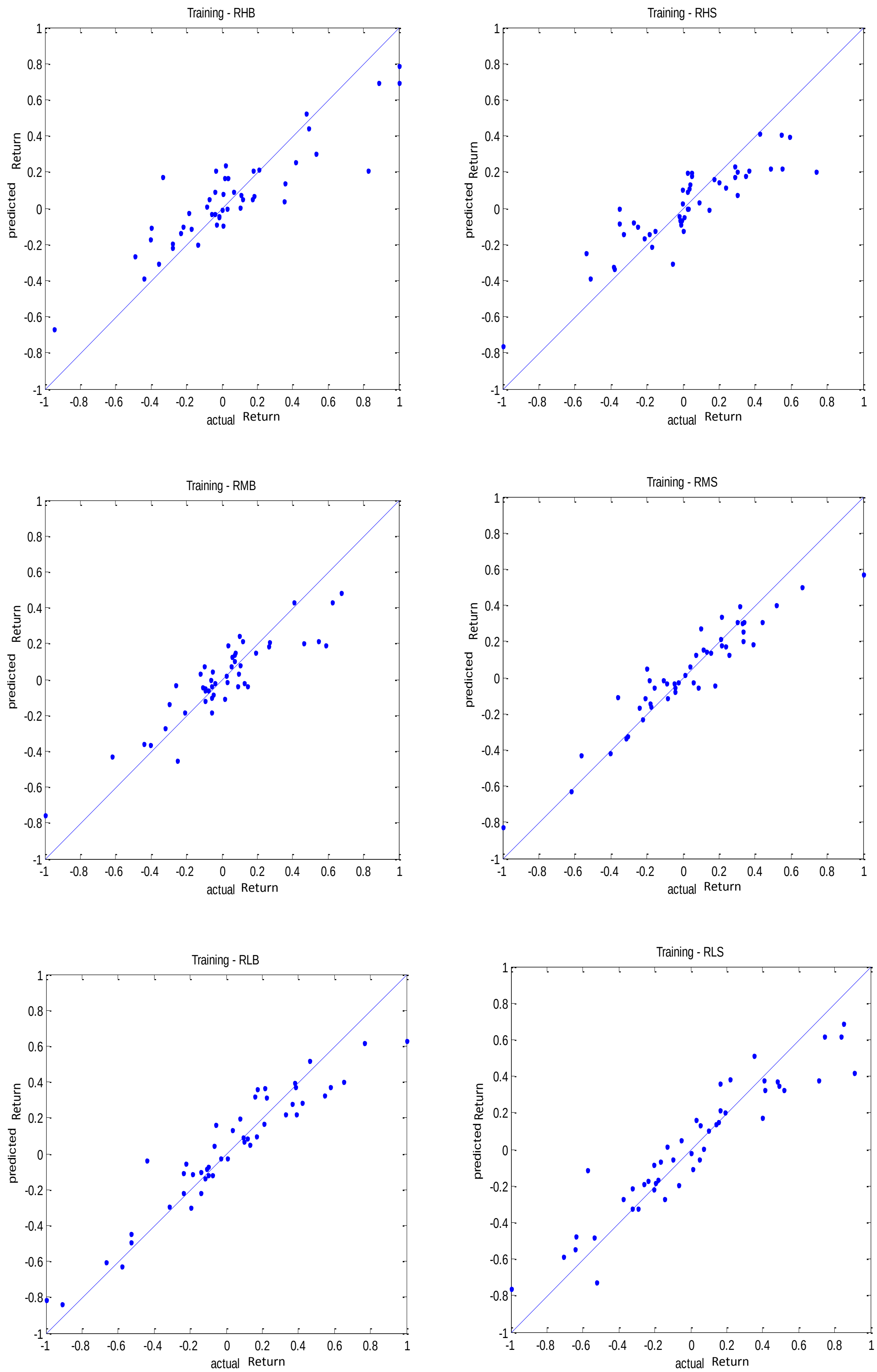


Figure 5.7: RMS Training results (FF model) using weighted average technique

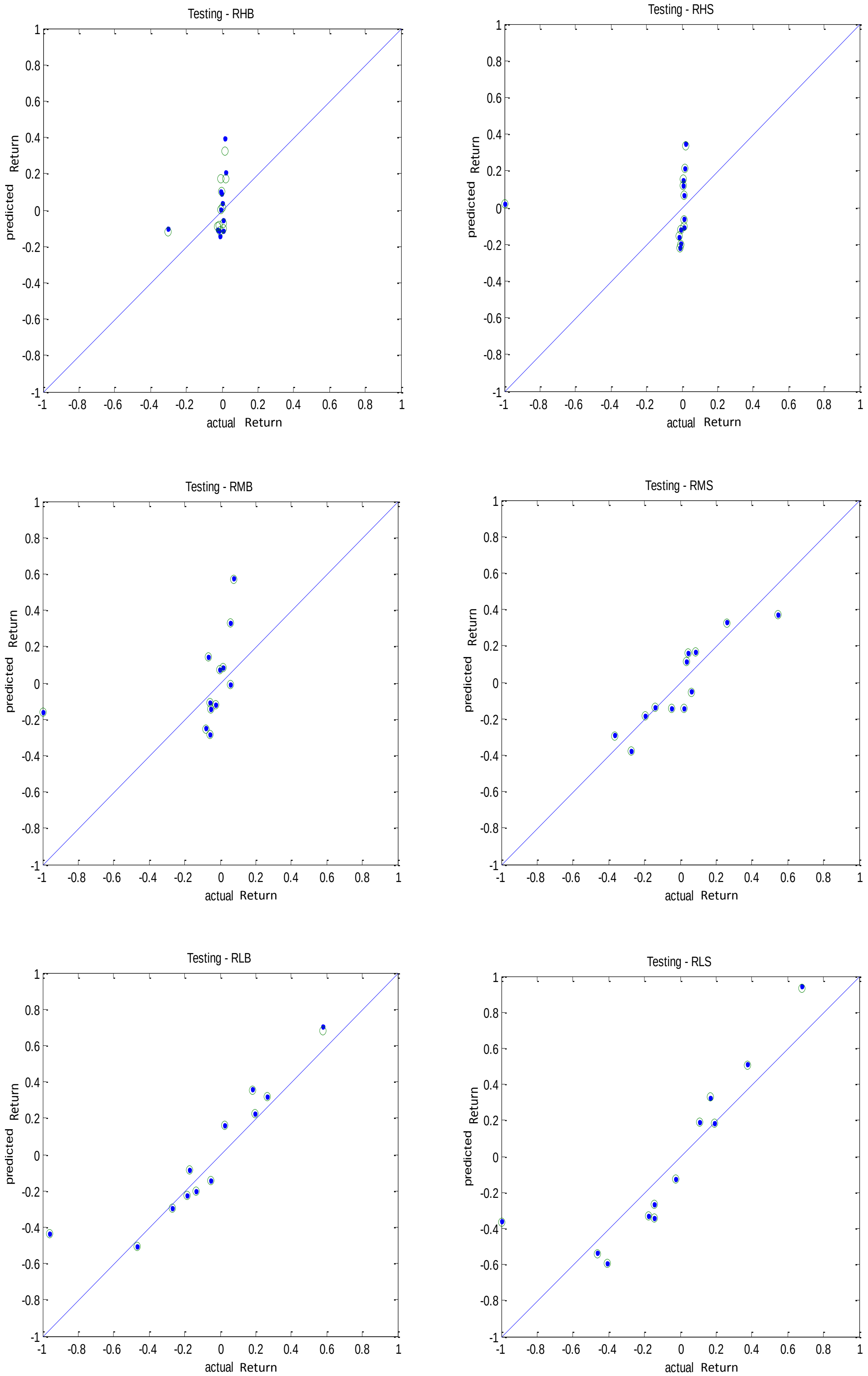


Figure 5.8: RMS Testing results (FF model) using weighted average technique

5.2.4.3 Results of GA Optimized Weighted Average Model

The settings of the GA: Population size 20, No. of generations 100, mutation rate 0.05 and crossover rate 0.08. Figure 5.9 shows the weighted average and GA methods. Finally, the FF returns are predicted using a genetic algorithm and the results are much better than in all of the models used so far. In Table 5.12 the RMS values for our stock portfolios of RHB, RHS, RMB, RMS, RLB, and RLS are 0.0218, 0.0546, 0.0298, 0.0520, 0.0634 and 0.0595 for training (0.1165, 0.1269, 0.2243, 0.0590, 0.1587, and 0.1885 for testing), respectively. These error values are the least out of all the ANN models, average methods, and the linear regression model, which indicate that GA is the best model to predict the stock portfolio returns on the Saudi Arabian Stock Exchange. Figures 5.10 and 5.11 depict the predicting values of all the portfolios for the GA model for training and testing, respectively. It is clear from the figures of the GA model that the actual return points are approximately located on the prediction line, indicating that there is a very small error in prediction and stock returns are forecasted with the highest accuracy. While predicting FF based stock returns, the genetic algorithm is expected to provide the best results and much more accurate predicted values.

Table 5.12: FF model RMS Training and Testing Results for GA

FF	RMS	RHB	RHS	RMB	RMS	RLB	RLS
GA	Train	0.0218	0.0546	0.0298	0.052	0.0634	0.0595
	Test	0.1165	0.1269	0.2243	0.059	0.1587	0.1885

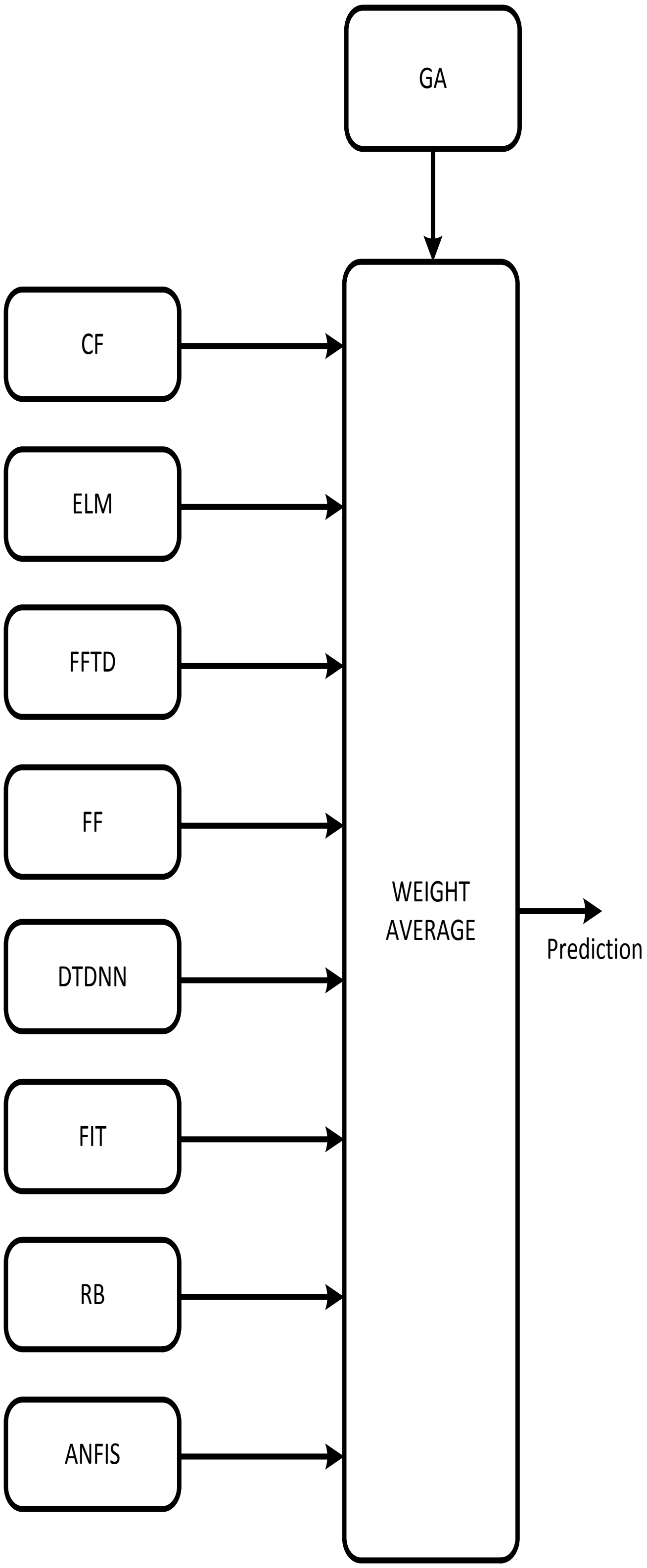


Figure 5.9: The weighted average and GA ensembles methods

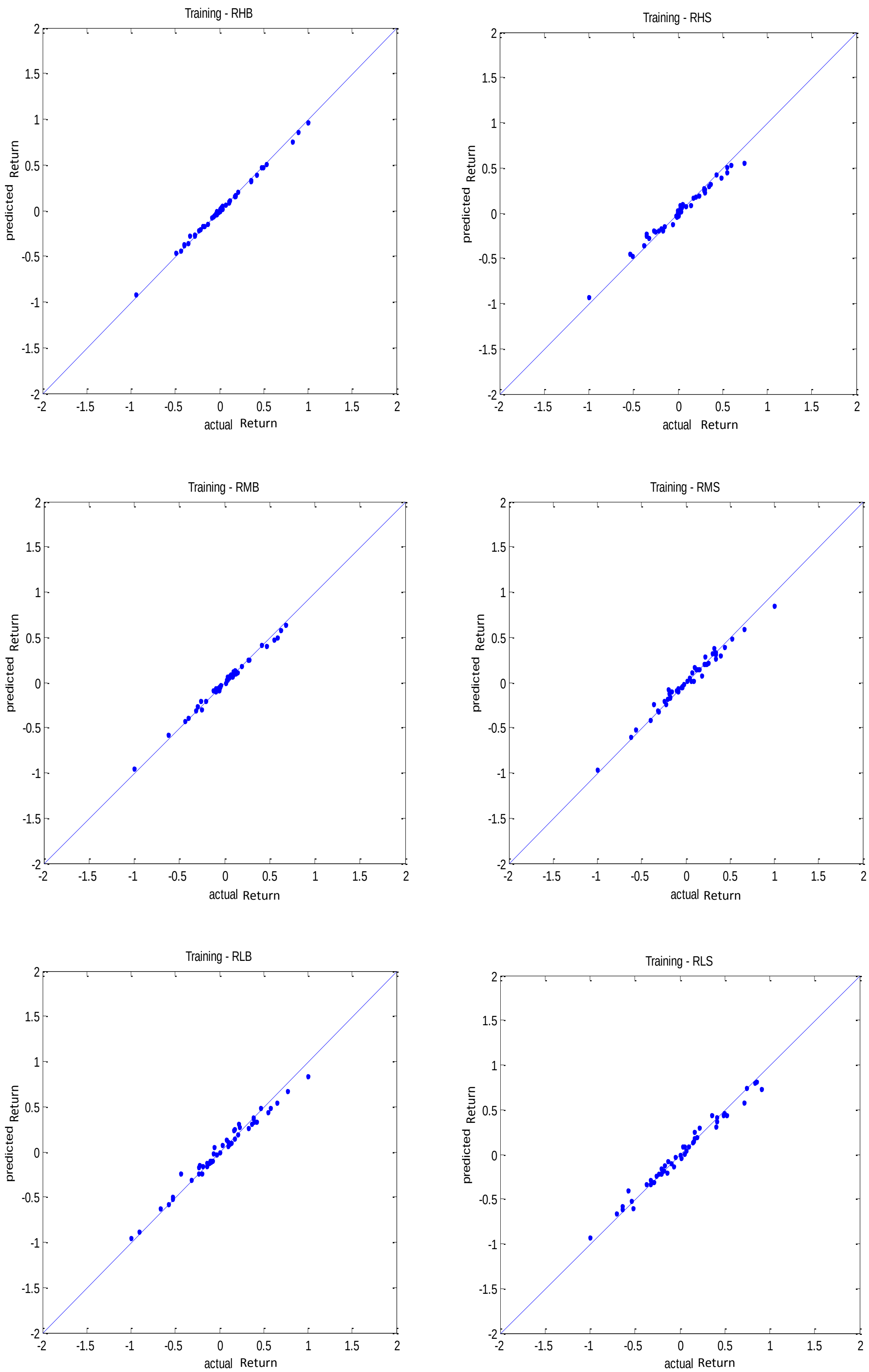


Figure 5.10: RMS Training results (FF model) using GA technique

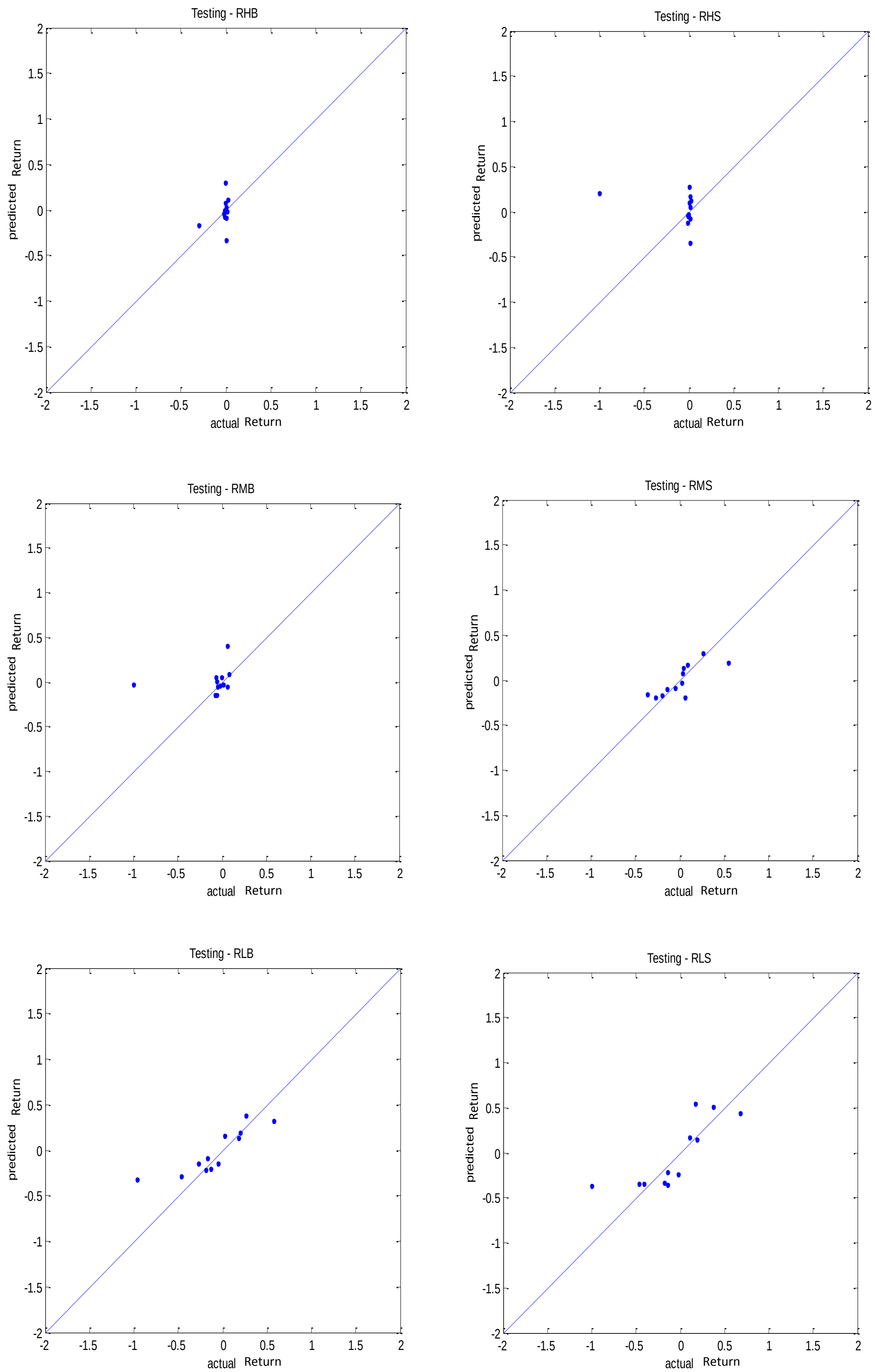


Figure 5.11: RMS Testing results (FF model) using GA technique

5.3 Forecasting Capital Asset Pricing Model

This section will report the RMS values of training and testing for all portfolio returns for CAPM, using the linear model, nonlinear ANN models, average of ANN, weighted average ANN, and GA.

5.3.1 Results of Linear Regression

In Table 5.13 the explanation power (R^2) ranges from 0.28 to 0.69 which means that the market return explains good a part of the variation in stock return, but not all of it. This means that there are other variables which explain the dependent variable.

Table 5.13 R-squared for CAPM

CAPM	RHB	RHS	RMB	RMS	RLB	RLS
R-squared	0.284	0.293	0.438	0.685	0.698	0.692

Furthermore, Table 5.14 shows that the null hypothesis can be rejected which implies there is no significant effect of the market return variable (independent variable) on the small and big portfolios return as the P-value is less than 1% (1 - confidence level (99%)). This implies that can be accepted the alternative hypothesis which indicates that there is positive significant effect for the market value on the stock return for the small and big portfolios. While the coefficients of the market return (independent variable) are 0.38 and 0.65 and 0.90 for the small portfolios. And the coefficients of the market return (independent variable) are 0.37 and 0.49 and 0.85 for the big portfolios.

Table 5.14: CAPM Model Coefficient

Portfolios	Coefficients C(2) R_M	Prob.	Hypothesis
RHB	0.369	0.0045	Reject Ho
RHS	0.380	0.0018	Reject Ho
RMB	0.498	0.0000	Reject Ho
RMS	0.646	0.0000	Reject Ho
RLB	0.854	0.0000	Reject Ho
RLS	0.909	0.0000	Reject Ho

The CAPM model is used to test the first 48 observations by conducting the Generalized Method of Moments GMM regression (Time Series Heteroskedasticity Autocorrelation [HAC]), to find the intercept and the coefficient for the six portfolios as Shown in Table 5.15. The equation of CAPM model:

$$R_i\text{-}R_f = \alpha_i + \beta_i (R_M - R_f) \qquad (5.12)$$

The six portfolios are as described below:

- The intercept and the coefficient of big size and high book to market value portfolio. The following equation was used to calculate the 48 estimated returns for big size and high book to market B/H value portfolio. $R_{HB} = 0.0204 + 0.5755\ RM$ (5.13)
- The intercept and the coefficient of small size and high book to market value portfolio. The following equation was used to calculate the 48 estimated returns for small size and high book to market value portfolio. $R_{HS} = 0.0185+0.4617\ R_M$ (5.14)
- The intercept and the coefficient of big size and medium book to market value portfolio. The following equation was used to calculate the 48 estimated returns for big size and medium book to market value portfolio. $R_{MB} = -0.0108 + 0.5683\ R_M$ (5.15)
- The intercept and the coefficient of small size and medium book to market value portfolio. The following equation was used to calculate the 48 estimated returns for small size and medium book to market value portfolio. $R_{MS} = 0.0081 + 0.7085\ R_M$ (5.16)
- The intercept and the coefficient of big size and low book to market value portfolio. The following equation was used to calculate the 48 estimated returns for big size and low book to market value portfolio.

  $$R_{LB} = 0.0148 + 0.9054\ R_M \qquad (5.17)$$
- The intercept and the coefficient of small size and low book to market value portfolio. The following equation was used to calculate the 48 estimated returns for small size and low book to market value portfolio.

  $$R_{LS} = 0.0044 + 0.9405\ R_M \qquad (5.18)$$

Further, the linear regression results have been reported for the CAPM model and for all the portfolios. In Table 5.16 the RMS values for RHB, RHS, RMB, RMS, RLB, and RLS for training are 0.3289, 0.3048, 0.2306, 0.2224, 0.2150, and 0.2438 (0.2522, 0.3200, 0.3086, 0.1191, 0.2402, and 0.2120 for testing), respectively. Figures 5.12 and 5.13 depict that the actual return values are located very far from the prediction line in both training and testing observations. Although this weak prediction is present in almost all figures of the linear model of training and testing. This spread is more in the case of RMS and RMB in both training and testing. The location of the return points in the cases of RMB, RMS, RLB, and RLS is relatively better than those of RHS and RHB, but we cannot say that the stock return prediction is fine.The table of RMS values and both figures indicate that the predictive power of the linear model is very weak as the RMS values are high and return points are located far away from prediction line.

Table 5.15: CAPM model 48 observation regression six portfolios coefficient

NO	Model	Intercept & Coefficients β		T Value	P Value
1	R_{HB}=C(1)+C(2)*R_M	αi	0.0204	0.549	0.585
		$R_M\ \beta_i$	0.5755	4.040	0.000
2	R_{HS}=C(1)+C(2)*R_M	αi	0.0185	0.472	0.638
		$R_M\ \beta_i$	0.4617	3.467	0.001
3	R_{MB}=C(1)+C(2)*R_M	αi	-0.0108	-0.411	0.682
		$R_M\ \beta_i$	0.5683	5.044	0.000
4	R_{MS}=C(1)+C(2)*R_M	αi	0.0081	0.356	0.723
		$R_M\ \beta_i$	0.7085	10.851	0.000
5	R_{LB}=C(1)+C(2)*R_M	αi	0.0148	0.573	0.569
		$R_M\ \beta_i$	0.9054	9.823	0.000
6	R_{LS}=C(1)+C(2)*R_M	αi	0.0044	0.169	0.865
		$R_M\ \beta_i$	0.9405	9.352	0.000

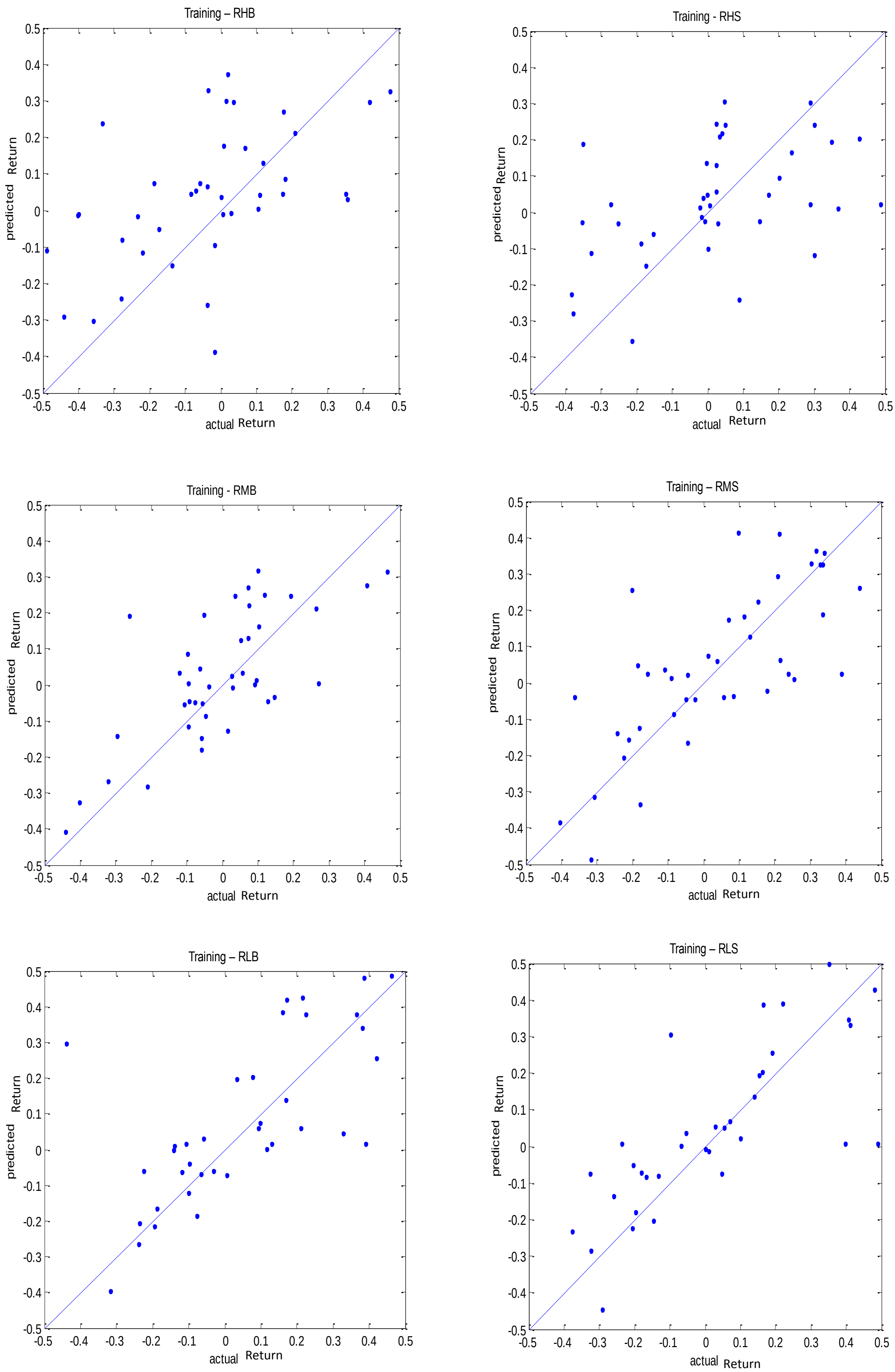


Figure 5.12: RMS Training results (CAPM model) using regression technique (LR)

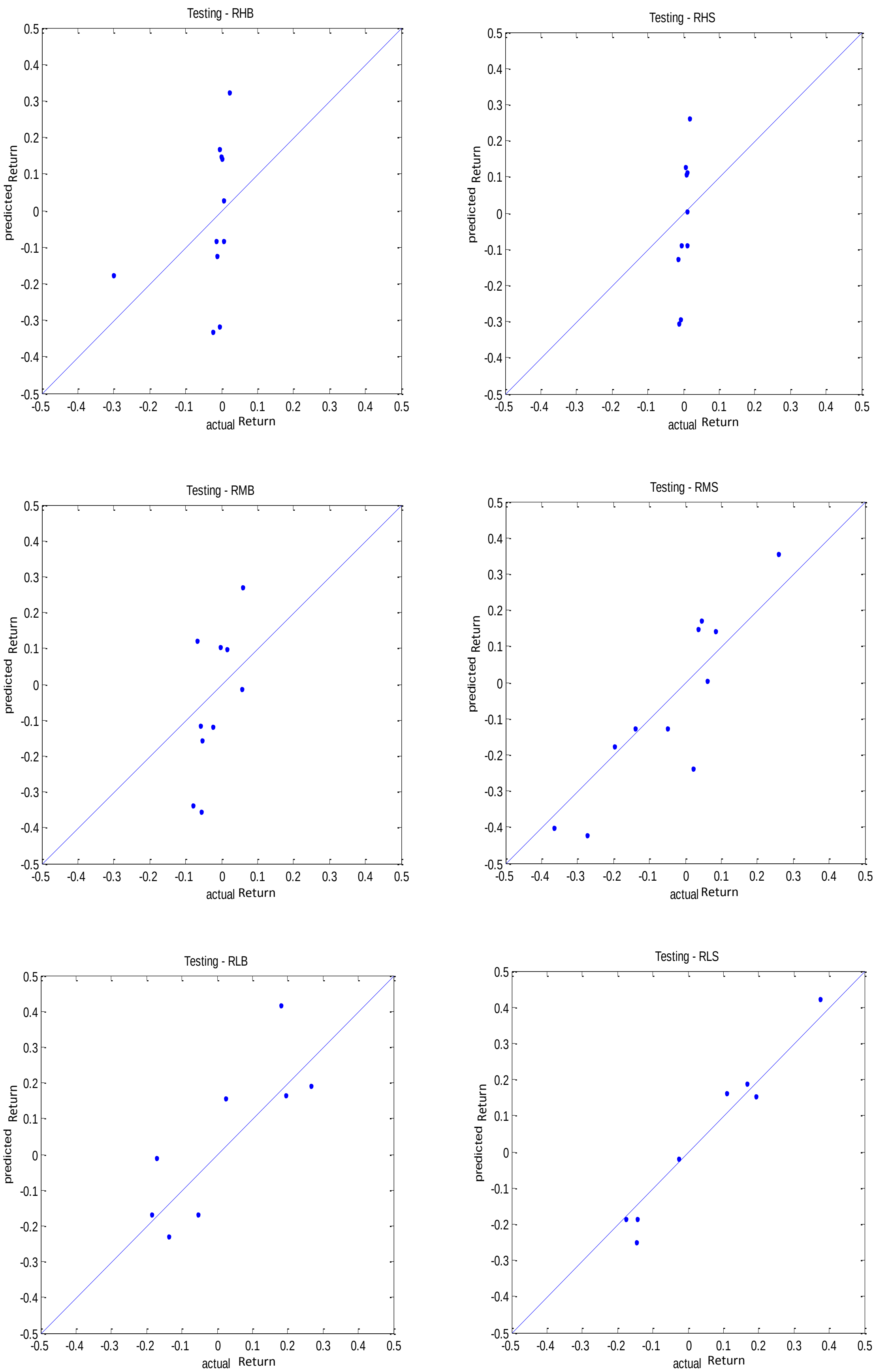


Figure 5.13: RMS Testing results (CAPM model) using regression technique (LR)

Table 5.16: CAPM model RMS Training and testing Results for LR

CAPM	RMS	RHB	RHS	RMB	RMS	RLB	RLS
LR	Train	0.3289	0.3048	0.2306	0.2224	0.2150	0.2438
	Test	0.2522	0.3200	0.3086	0.1191	0.2402	0.2120

5.3.2 Results of Artificial Neural Networks Model

After the linear regression model, different nonlinear ANN techniques were also used to predict the stock returns on the Saudi Arabian stock market. The ANN parameters and topology are illustrated in Table 5.17. Table 5.18 also reports the results of these portfolio stock returns of CAPM based upon these ANN techniques. It is clear from the table that the use of ANN techniques has improved the accuracy and predictive power of the CAPM return prediction. For the portfolio returns based upon high market to book ratio and big size (RHB), ELM has the lowest RMS which is 0.2520 for testing and 0.3173 for training. This is the best among all the ANN models. For the RHB stock portfolio, ELM has the highest predictive power by providing the least root mean square error which is only 0.2708 for training ANN and 0.2848 for testing ANN. Similarly, both the small and big stock portfolios with medium book to market ratio have been predicted more accurately with ELM techniques where RMS is 0.2212 and 0.2164 for training RMB and RMS; 0.3135 and 0.1190 for testing RMB and RMS, respectively. For low book to market ratio and big stock size, FFTD provides the best result with the RMS values of 0.2114 and 0.2351 for training and testing, respectively. Finally, RLS returns have been best predicted by the radial based artificial neural network with RMS of 0.2411 and 0.2068 for training and testing values, respectively. It is obvious from Table 5.18 that CAPM portfolio returns can better be predicted by ANN models, compared to the simple linear regression model. The actual values of stock returns using these ANN models have also been plotted and these figures are reported in Appendix B.

Table 5.17: ANN Parameters and Topologies

TYPE	Topology	Train/valid	Training epochs	Training function
CF	1-5-1	80/20	500	Levenberg-Marquardt
ELM	1-5-1	80/20	500	Gradient descent
FFTD	1-5-1	80/20	500	Levenberg-Marquardt
FF	1-5-1	80/20	500	Levenberg-Marquardt
DTDNN	1-5-1	80/20	500	Levenberg-Marquardt
FIT	1-5-1	80/20	500	Levenberg-Marquardt
RB	1-5-1	80/20	500	Radial Bases Functions

Table 5.18: CAPM model RMS Training and testing Results for ANNs

CAPM	RMS	RHB	RHS	RMB	RMS	RLB	RLS
CF	Train	0.2904	0.2554	0.1947	0.1965	0.2087	0.2401
	Test	0.2569	0.3164	0.3226	0.128	0.2363	0.2091
ELM	Train	0.3173	0.2708	0.2212	0.2164	0.2468	0.2691
	Test	0.2520	0.2847	0.3135	0.1190	0.2412	0.2321
FFTD	Train	0.2897	0.2553	0.1973	0.1897	0.2114	0.2393
	Test	0.2605	0.3109	0.3305	0.1213	0.2351	0.2097
FF	Train	0.2878	0.2596	0.1948	0.1975	0.2106	0.2421
	Test	0.2698	0.3219	0.3313	0.1404	0.2935	0.2208
DTDNN	Train	0.2904	0.2554	0.1947	0.1965	0.2087	0.2401
	Test	0.2569	0.3164	0.3226	0.1280	0.2363	0.2091
FIT	Train	0.2878	0.2596	0.1948	0.1975	0.2106	0.2421
	Test	0.2698	0.3219	0.3313	0.1404	0.2935	0.2208
RB	Train	0.2943	0.2567	0.2004	0.1967	0.2099	0.2411
	Test	0.2534	0.314	0.3339	0.1278	0.2493	0.2068

5.3.3 Results of Adaptive Neural Fuzzy Inference Systems Model

The settings of the ANFIS are: type of membership: Gaussian and number of fuzzy rules: 11. Table 5.19 reports the RMS values of the adaptive neural fuzzy inference system (ANFIS) for both training and testing. The RMS for ANFIS training is (0.1806, 0.2289, 0.1668, 0.1605, 0.1616, and 0.1906) and for testing are (0.9444, 0.6082, 0.6464, 0.2303, 0.3131, and 0.5551), respectively. These values are even higher than those of the ANN models which indicate that ANFIS provides less prediction accuracy in the case of the Saudi Arabian Stock Exchange. The actual values of stock return using ANFIS model has also been plotted and these figures are reported in Appendix B.

Table 5.19: CAPM model RMS Training and testing Results for ANFIS

CAPM	RMS	RHB	RHS	RMB	RMS	RLB	RLS
ANFIS	Train	0.1806	0.2289	0.1668	0.1605	0.1616	0.1906
	Test	0.9444	0.6082	0.6466	0.2303	0.3131	0.5551

5.3.4 Ensembles Model

5.3.4.1 Results of Average Ensemble Model

The present study not only used different ANN models to predict the stock returns based upon six CAPM portfolios, but also used the simple and weighted average of these ANN models. Table 5.20 also shows that the portfolio stock returns prediction improves when we use the average of ANN models instead of individual ANN models. The RMS for simple average training is (0.2840, 0.2431, 0.1838, 0.1793, 0.1920, and 0.2223) and for testing is (0.2418, 0.2214, 0.2944, 0.1109, 0.2346, and 0.2011). These RMS values are lower than the individual ANN models, which indicate that simple average provides best predicting CAPM stock returns, as well as the simple linear models. These results can also be verified by Figure 5.14 and 5.15 which show the actual returns with prediction line. The equation for the average is:

$$Average = \frac{\sum_{i=1}^{n} para(i)}{N} \qquad (5.19)$$

Table 5.20: CAPM model RMS Training and testing results for average

CAPM	RMS	RHB	RHS	RMB	RMS	RLB	RLS
Average	Train	0.2840	0.2431	0.1838	0.1793	0.1920	0.2223
	Test	0.2418	0.2214	0.2944	0.1109	0.2346	0.2011

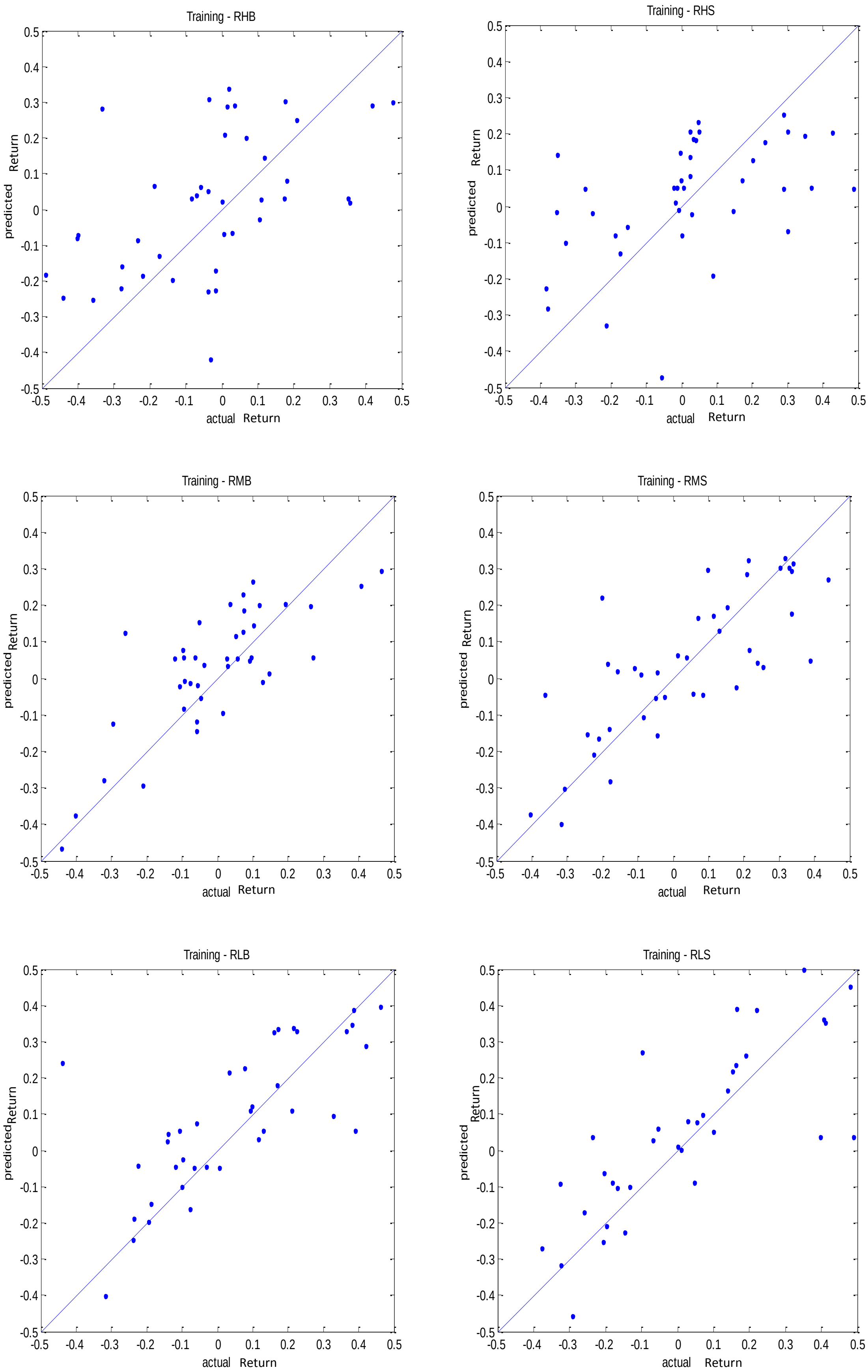


Figure 5.14: RMS Training results (CAPM model) using average technique

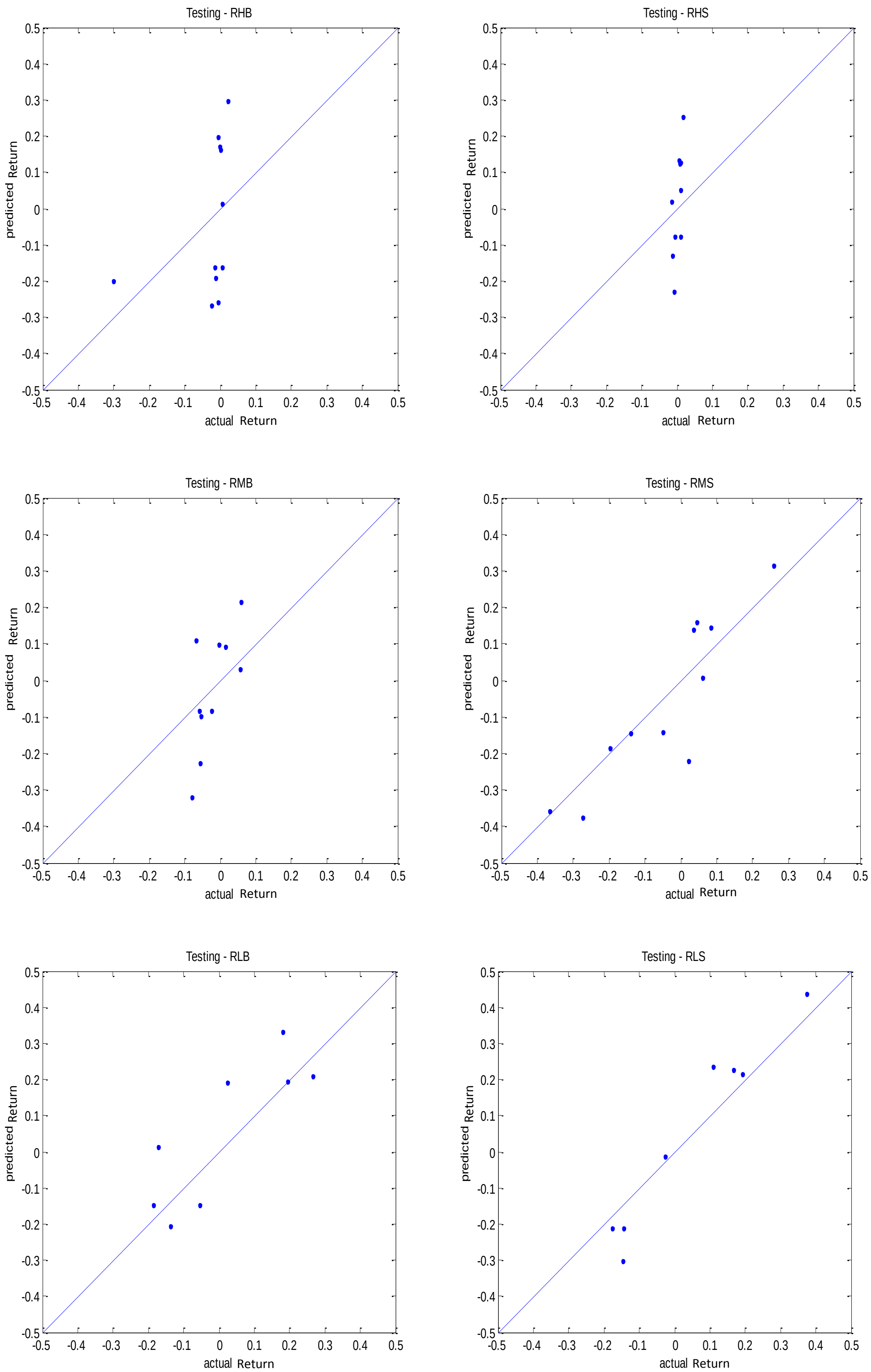


Figure 5.15: RMS Testing results (CAPM model) using average technique

5.3.4.2 Results of Weighted Average model

The accuracy level of prediction improves even more by using the weighted average instead of the simple average. In Table 5.21 the stock return prediction errors for RHB, RHS, RMB, RMS, RLB and RLS are (0.2737, 0.2425, 0.1825, 0.1757, 0.1820, and 0.2211) for weighted average training, and for testing they are (0.2282, 0.2209, 0.2910, 0.1064, 0.2251 and 0.1985). Figures 5.16 and 5.17 also show that the weighted average technique provides better results than ANN and average of ANN, particularly when predicting the stock returns of medium and low book to market ratios for small and big stocks (i.e. RMB, RMS, RLB, and RLS). However, there is still some divergence of returns from the prediction line in the case of the RHB and RHS portfolios, even in the case of the weighted average. Particularly when predicting the stock returns of medium and low book to market ratios for small and big stocks (i.e. RMB, RMS, RLB, and RLS). However, there is still some divergence of returns from the prediction line in the case of the RHB and RHS portfolios, even in the case of the weighted average. The equation of the weighted average is:

$$\text{Weighted average} = \frac{\sum_{i=1}^{n} \text{para}(i) \text{ x } W(i)}{\sum_{i=1}^{n} W(i)} \qquad (5.20)$$

$$W(i) = 1 - \overline{\text{STD}_i(\text{bin})} \qquad (5.21)$$

where :*STD_i* is the standard deviation for bin, the normalized values taken $(\overline{STD})$

Table 5.21: CAPM model RMS Training and Testing Results for Weighted Average

CAPM	RMS	RHB	RHS	RMB	RMS	RLB	RLS
Weighted Average	Train	0.2736	0.2425	0.1825	0.1757	0.1820	0.2211
	Test	0.2282	0.2209	0.2910	0.1064	0.2251	0.1985

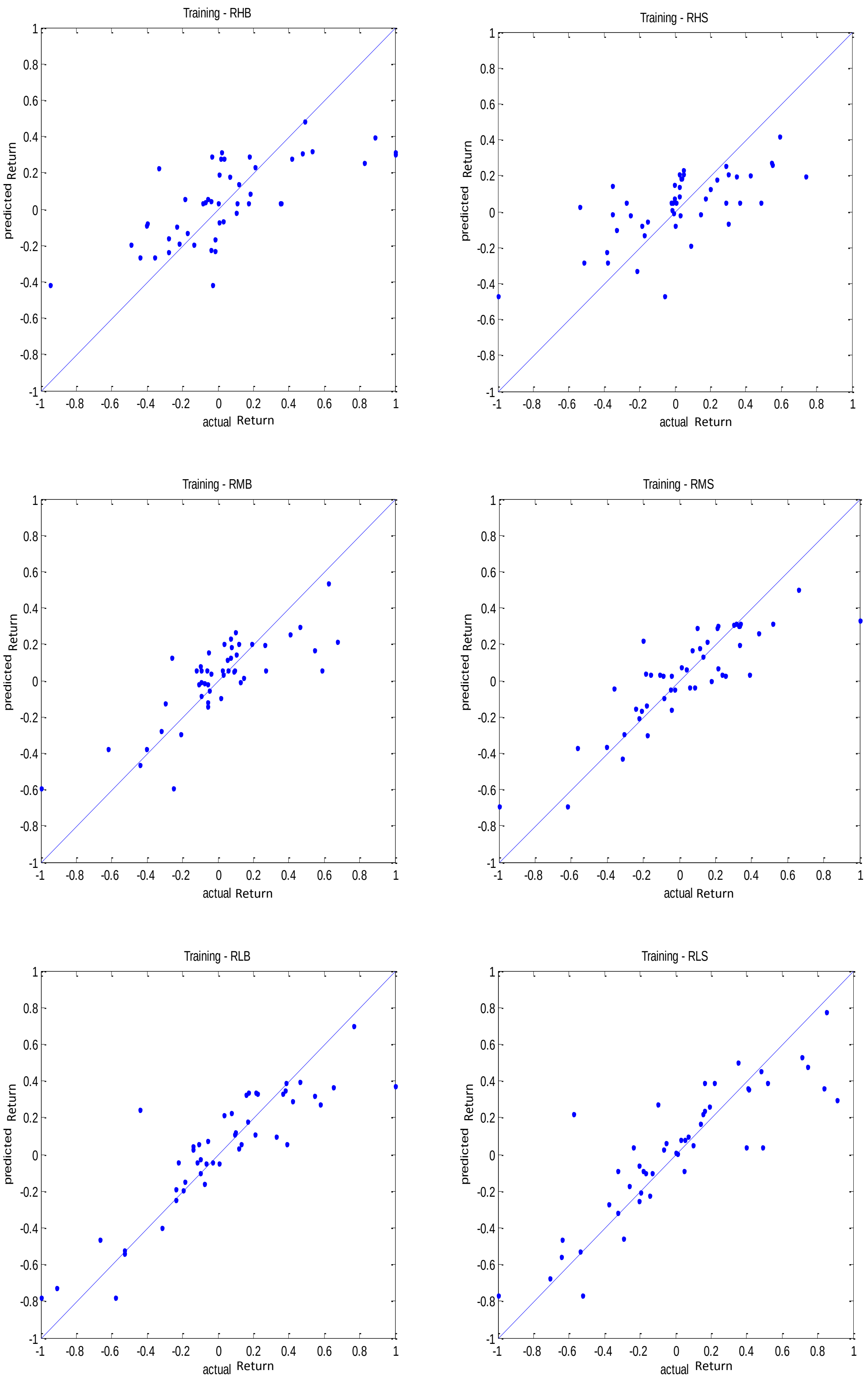


Figure 5.16: RMS Training results (CAPM) using weighted average technique

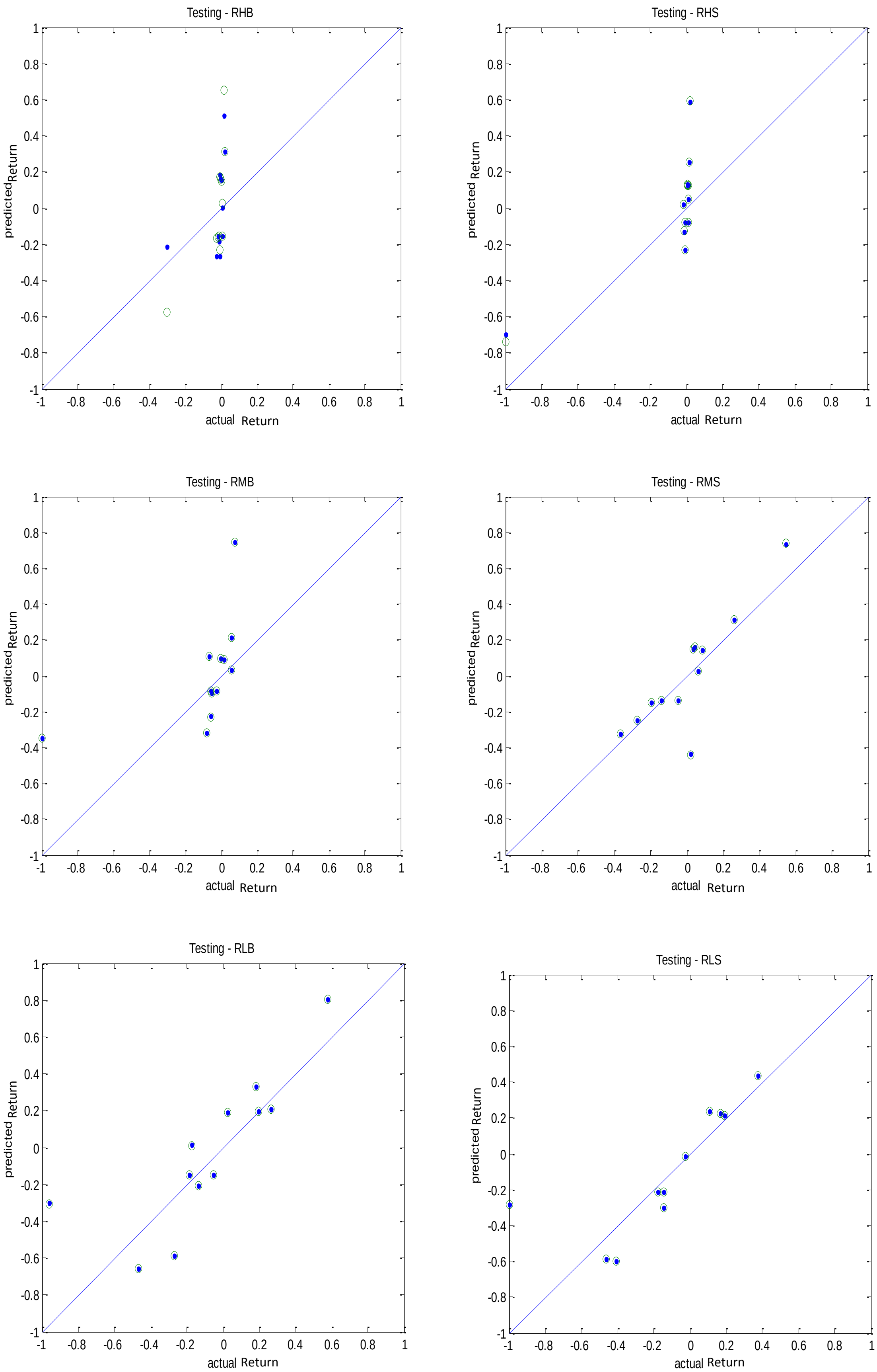


Figure 5.17: RMS Testing results (CAPM model) using weighted average technique

5.3.4.3 Results of GA Optimized Weighted Average model

Finally, the genetic algorithm has been used to predict the stock returns on the underlying six portfolios. The settings of the GA: Population size 20, No. of generations 100, mutation function 0.05 and crossover function 0.08. In Table 5.22 the results show that GA predicted the stock returns with the maximum accuracy where the RMS values for RHB, RHS, RMB, RMS, RLB, RLS training are 0.2620, 0.2325, 0.1538, 0.1285, 0.1737, and 0.1783, and for testing are (0.2206,0.2207,0.2905,0.0942,0.2158 and 0.1913) respectively. These RMS values are least among all the models used and discussed above for predicting stock returns on CAPM basis. Figures 5.18 and 5.19 for GA based returns prediction also indicate that the actual return points on these portfolios are much closer to the prediction line for all the stock portfolios.

Table 5.22: CAPM model RMS Training and testing Results for GA

CAPM	RMS	RHB	RHS	RMB	RMS	RLB	RLS
GA	Train	0.2620	0.2325	0.1538	0.1285	0.1737	0.1783
	Test	0.2206	0.2207	0.2905	0.0942	0.2158	0.1913

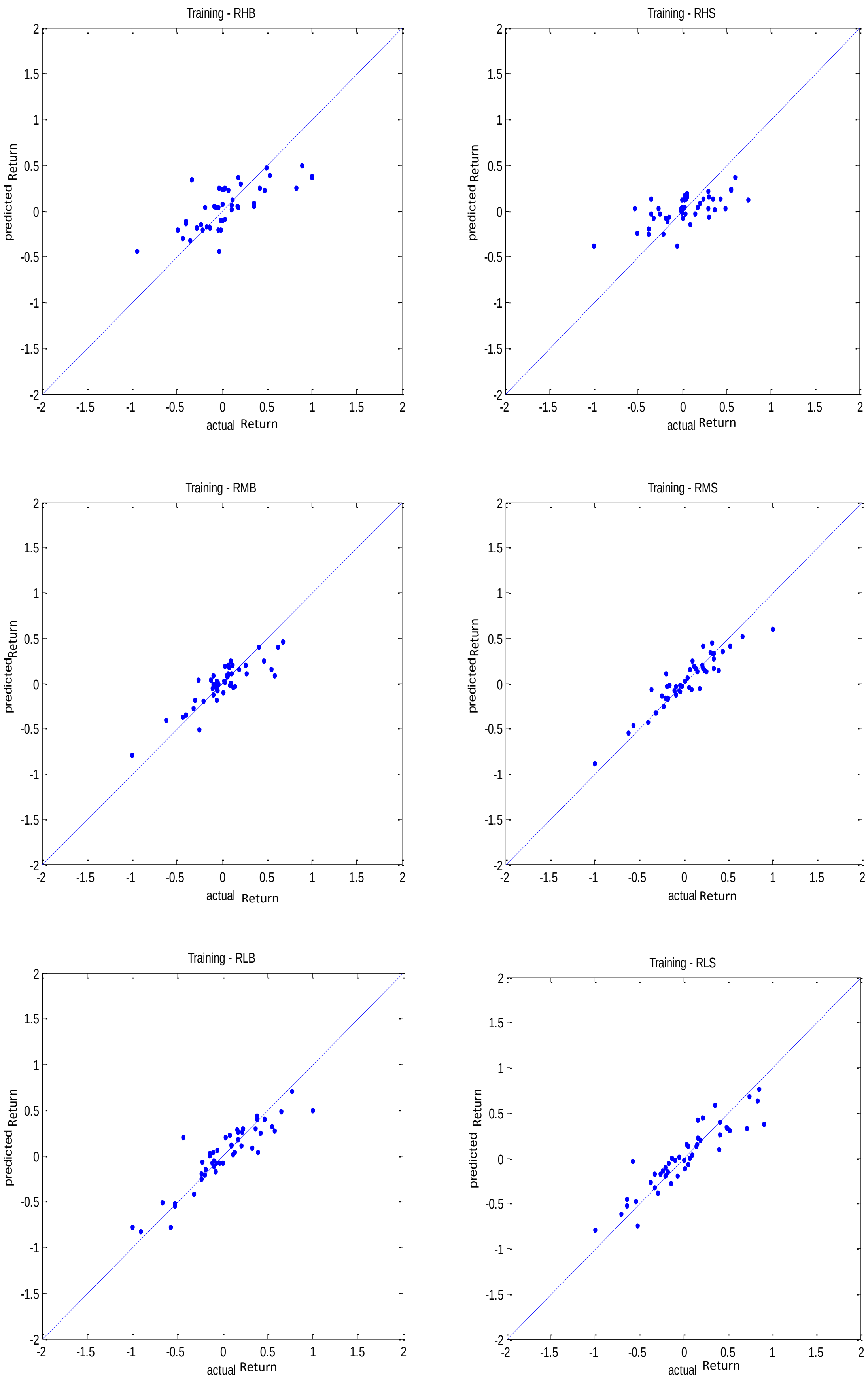


Figure 5.18: RMS Training results (CAPM model) using GA technique

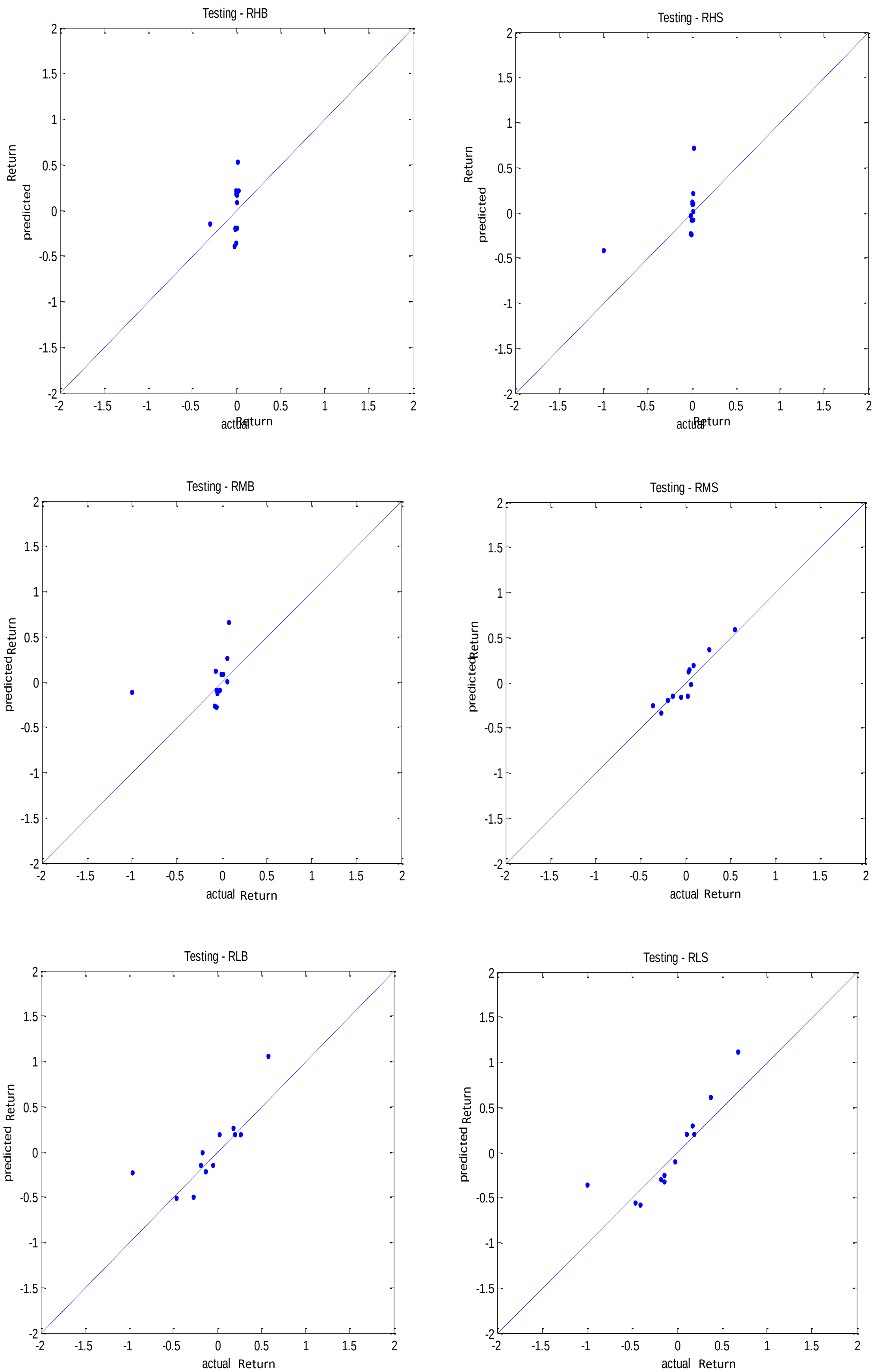


Figure 5.19: RMS Testing results (CAPM model) using GA technique

5.4 Comparison between CAPM and FF Models

While comparing the FF and CAPM model results of forecasting discussed above, it can be concluded that FF models the stock returns in a better way with less error and greater prediction accuracy. Moreover, the returns predicted using the FF model are plotted closer to the prediction line as compared to CAPM where the actual return points are located relatively far away from the main prediction line. In case of our sample of Saudi Arabian stock portfolios, the FF model is better than CAPM and it is preferred to CAPM when using the GA method as shown in Table 5.23. This difference might be attributed to the size effect in the market which causes CAPM to be less effective in the Saudi market. Just like many other markets, Saudi capital markets also support the fact that the FF model is superior to the traditional CAPM model.

Table 5.23: Results RMS for GA in FF model and CAPM Model

model	GA	RHB	RHS	RMB	RMS	RLB	RLS
FF	Train	0.0218	0.0546	0.0298	0.052	0.0634	0.0595
	Test	0.1165	0.1269	0.2243	0.059	0.1587	0.1885
CAPM	Train	0.2620	0.2325	0.1538	0.1285	0.1737	0.1783
	Test	0.2206	0.2207	0.2905	0.0942	0.2158	0.1913

5.5 Summary

Stock return prediction is an important phenomenon which has generated enormous research as well as different sophisticated methods and models to more accurately forecast stock returns because the accurate prediction of stock returns may yield attractive benefits. In this regard, the traditional CAPM and advanced Fama and French models utilize linear models as well as nonlinear ANN models along with fuzzy networks and a genetic algorithm. The present chapter reports the forecasted results based upon the linear model, various ANN techniques, and a genetic algorithm for stock returns of six portfolios constructed.

The results illustrate that for the CAPM model FF model explains good part of the variation in stock return, but not all of it which means that there are other variables to explain the dependent variable. But the FF model has more explanatory power than the CAPM. Also, the results show when applying the CAPM model for the six portfolios of the study that there is positive significant effect for the market value on the stock return for the small and big portfolios.

The results of FF model show that there is positive significant effect for the market value on the stock return for the small and big portfolios. For the size effect two of the big size portfolio has a negative significant effect for the size factor (which consistent with the theory upon the sign of the effect) while one of the big size portfolios has insignificant effect, while for the small portfolio also two portfolios of the small size portfolios has a positive significant effect for the size factor (which inconsistent with the theory upon the sign of the effect). Finally for the book to market effect, one of the big size portfolio has a positive significant effect for the book to market factor (which consistent with the theory upon the sign of the effect) while two of the big size portfolios has insignificant effect, while for the small portfolio also two portfolios of the small size portfolios has a positive significant effect for the book to market factor (which inconsistent with the theory upon the sign of the effect) while one portfolio of the book to market effect.

It can be summarized that the linear models provide the weakest prediction of stock returns both in the case of CAPM and Fama and French. However, when we used ANN models, the prediction power and accuracy tended to increase. This even gets better when the average and weighted average method is utilized instead of using the individual model of ANN. However, the genetic algorithm (GA) based upon FF can be considered as the best prediction model in the case of the Saudi Arabian Stock Market as it provides the best estimates of stock returns with the lowest prediction error as measured by RMS. After that, the weighted average method of ANN provides even better results and the simple average results are also good. So, GA is the best technique to provide Saudi Arabian Stock Market returns prediction, followed by the weighted average of ANN models, because it improves the level of predicting accuracy for stock market returns, investment decisions and the movement of future stock prices in the emerging market of Saudi Arabia.

CHAPTER 6

Multi-Stage Model

6.1 Introduction

This section of the current research presents the results of the multi-Stage model of value-based management for decision making in the stock exchange of Saudi Arabia. Using the Value-Based Management (VBM) model of decision making and the prediction of stock portfolio returns with the help of Artificial Neural Networks (ANN), expectations of shareholders and portfolio investors to take investment decisions, and the behaviour of stock prices, There are two multi-Stage models discussed in this chapter. The first is based upon the combination of traditional forecasting based upon the Fama and French (FF) model, and applies value-based management to the results obtained. This is based upon the shareholder perspective as well as the share price perspective. The shareholder perspective describes the decision making of shareholders that involves investment, dividend and disinvestment decisions. The share price perspective focuses on the movement of the share price in terms of growth, speculative fall and fall. The results are based upon training and testing observations as discussed in previous chapters. The second multi-Stage model is the combination of CAPM and value-based management which uses the same approach for training and testing observations for shareholder and share price perspectives for decision making. This chapter will discuss the multi-Stage Model in Section two then discuss the results of the multi-Stage type-1 model in Section three and Section four describes the result of the multi-Stage type-2 model. Section five makes comparisons between both models, and then presents the Graphical User Interface (GUI) using Matlab software. Lastly the final section presents the summary.

6.2 Multi-Stage Model

This study uses different types of models to execute the process and achieve the objectives. These are the Capital Asset Pricing Model (CAPM) or the Fama and French (FF) model, the Value-Based Management (VBM) model, the Multi-Stage type 1 (VBM and FF model), Multi-Stage type 2 (VBM and CAPM) model and Artificial Neural Networks.

A multi-Stage type model includes two different types: the first one includes the VBM and FF models and the second one the VBM and CAPM models. The first type is designed by combining the operations of VBM and FF models. Four basic steps are considered while computing the VBM model. This model design include the estimates of weighted average cost of capital (WACC), actual return of investment (Ract), expected investment return (Rexp), and required return on investment capital (Rreq). The required return on investment capital is basically the FF model integrated with the VBM model. Hence, the FF model is first used as a factor within the VBM model. Figure 6.1 below describes the mechanism of this model design:

The second type (VBM and CAPM model) is designed by combining the operations of the VBM and CAPM models. Four basic steps are considered while computing the VBM model. This model design include the estimates of weighted average cost of capital (WACC), actual return of investment (Ract), expected investment return (Rexp), and required return on investment capital (Rreq).The required return on investment capital is basically the CAPM model integrated with the VBM model. Hence, the CAPM model is used as a factor within the VBM model. Figure 6.2 below describes the mechanism of this model design.

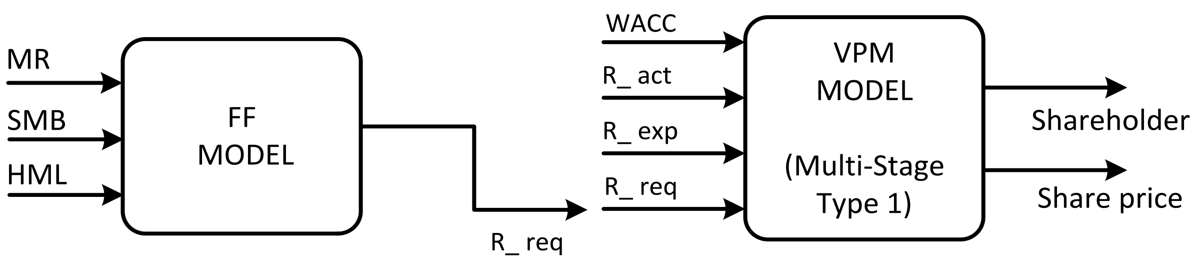


Figure 6.1: Multi-Stage type-1 VBM and FF model design

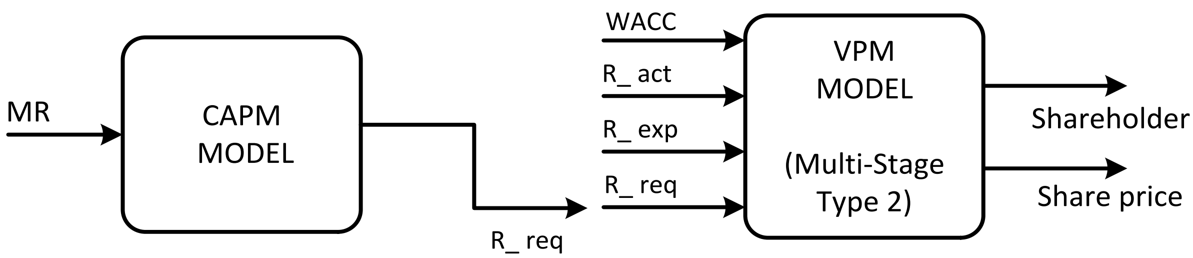


Figure 6.2: Multi-Stage type-2 VBM and CAPM model design

6.3 Forecasting Multi-Stage Type-1 Model

This section uses the multi-stage type-1 model which is based on the FF and VBM model for shareholder and share price as shown in Figure 6.3 Various ANN models, average and weighted average of ANN models, along with a genetic algorithm, are utilized to predict and make decisions with respect to shareholder and share price.

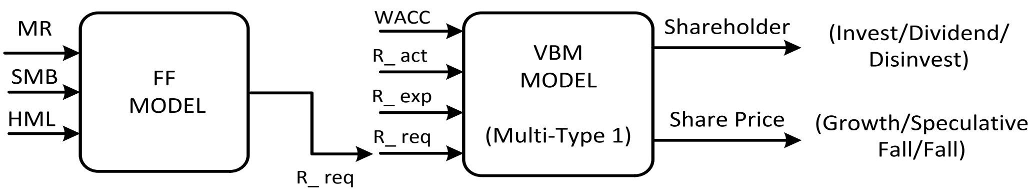


Figure 6.3: multi-Stage type-1 model

6.3.1 Results of Artificial Neural Networks Model

The ANN parameters and topology are illustrated in Table 6.1. Table 6.2 reports the RMS values for the shareholder perspective for multi-Stage type 1. When ANN models have been used to forecast stock returns, FFTD, RB, DTDNN, FF and FIT have proved to be the best prediction models for RHB, RHS, RMB, RMS, RLB, and RLS, respectively. The training values are 0.3479, 0.2846, 0.1524, 0.0926, 0.1434, and 0.1955 whereas the testing values are 0.2240, 0.2280, 0.1615, 0.0950, 0.1063 and 0.1050. There is no single model which is best for all portfolios; rather different models provide good results for different portfolios. On the basis of the figures given in Appendix C, which shows that the decision for shareholders is to invest and dividends, these decisions are predicted well. According the methodology that followed, the figures are divided into three parts: Part 1: between 0.5 and -0.5 which is means this area for Dividend. Part 2: Above 0.5 which means that this area for Invest. Part 3: below -0.5 which is means this area for disinvest. On the other hand, Table 6.3 discusses the RMS values for the share price perspective for multi-Stage type-1. Here also different ANN models are best for the stock prediction of different portfolios – FFTD, RB, FF & FIT, DTDNN, FFTD and FIT are best for RHB, RHS, RMB, RMS, RLB, and RLS, respectively. The best values of ANN RMS for training are 0.2463, 0.5275, 0.2766, 0.2311, 0.5970, and 0.9660, and for testing are 0.4250, 0.3698, 0.2895, 0.1863, 0.339, and 0.1839. Appendix D which shows the prediction results for share prices indicate that the expectations for share prices are growth and fall and speculative fall. According the methodology that followed, the figures are divided into three parts: Part 1: between 0.5 and -0.5 which is means this area for speculative fall. Part 2: above 0.5 which means that this area for growth. Part 3: below -0.5 which is means this area for fall.

Table 6.1: ANN Parameters and Topologies.

TYPE	Topology	Train/valid	Training epochs	Training function
CF	4-5-1	80/20	500	Levenberg-Marquardt
ELM	4-5-1	80/20	500	Gradient descent
FFTD	4-5-1	80/20	500	Levenberg-Marquardt
FF	4-5-1	80/20	500	Levenberg-Marquardt
DTDNN	4-5-1	80/20	500	Levenberg-Marquardt
FIT	4-5-1	80/20	500	Levenberg-Marquardt
RB	4-5-1	80/20	500	Radial Bases Functions

Table 6.2: Shareholder RMS Training and Testing Results for ANNs

Multi-Stage Type 1: Shareholder	RMS	RHB	RHS	RMB	RMS	RLB	RLS
CF	Train	0.2742	0.1646	0.2244	0.1552	0.2241	0.1998
	Test	0.2463	0.3837	0.2423	0.1607	0.2092	0.2066
ELM	Train	0.3801	0.2894	0.4208	0.3819	0.4785	0.3681
	Test	0.3903	0.2994	0.2536	0.2751	0.3129	0.277
FFTD	Train	0.3479	0.0978	0.2767	0.0503	0.0553	0.1229
	Test	0.2240	0.281	0.2048	0.1204	0.1084	0.1133
FF	Train	0.2493	0.0951	0.1521	0.0926	0.1600	0.1303
	Test	0.2684	0.325	0.1954	0.0950	0.1081	0.1096
DTDNN	Train	0.2998	0.2145	0.1524	0.2047	0.1434	0.0952
	Test	0.2929	0.2582	0.1615	0.1448	0.1063	0.1164
FIT	Train	0.3166	0.1444	0.1574	0.1349	0.0777	0.1955
	Test	0.315	0.2708	0.1716	0.1204	0.1108	0.1050
RB	Train	0.2581	0.2846	0.2596	0.3158	0.2632	0.3277
	Test	0.2293	0.228	0.2006	0.2075	0.1677	0.1512

Table 6.3: share price RMS Training and Testing Results for ANNs

Multi-Stage Type 1: Share price	RMS	RHB	RHS	RMB	RMS	RLB	RLS
CF	Train	0.3713	0.3915	0.3332	0.2847	0.2638	0.3396
	Test	0.4866	0.8388	0.5172	0.2855	0.3827	0.3559
ELM	Train	0.5148	0.574	0.5484	0.5244	0.5307	0.4886
	Test	0.6731	0.6107	0.5853	0.3977	0.4747	0.4198
FFTD	Train	0.2463	0.19	0.2805	0.1025	0.5970	0.1341
	Test	0.4250	0.4328	0.2736	0.1902	0.3390	0.0937
FF	Train	0.3085	0.2178	0.2766	0.2239	0.1389	0.1428
	Test	0.5582	0.5206	0.2895	0.2294	0.4113	0.1281
DTDNN	Train	0.3521	0.1288	0.3005	0.2311	0.1165	0.1258
	Test	0.5125	0.5272	0.294	0.1863	0.6820	0.1132
FIT	Train	0.4343	0.2178	0.2766	0.2239	0.1389	0.966
	Test	1.2367	0.5206	0.2895	0.2294	0.4113	0.1839
RB	Train	0.5911	0.5275	0.5528	0.4435	0.4776	0.5554
	Test	0.4264	0.3698	0.5566	0.4132	0.3190	0.7329

6.3.2 Results of Adaptive Neural Fuzzy Inference Systems Model

The settings of the ANFIS: Type of membership: Gaussian and number of fuzzy rules are 16, 24, 32, 24, 32, 24, 32, 128, 54 and 144. In Table 6.4 the training RMS values for the ANFIS technique for shareholder and share price are 0.1436, 0.0807, 0.0661, 0.0392, 0.0282, 0.0527 and testing values are 4.3760, 1.7610, 0.2686, 0.4391, 0.3636, and 1.4386. Similarly, for share prices Table 6.4 gives the RMS values as 0.1795, 0.1877, 0.1143, 0.1229, 0.0946, 0.1277 for training and 3.4501, 4.1106, 1.1875, 0.5161, 0.8476, 0.7584 for testing, in the case of all portfolios respectively. The figures in Appendices C and D indicate that invest, dividend and disinvest decisions are predicted with weak prediction accuracy, and there are expectations about growth, fall and speculative fall in share prices.

Table 6.4: shareholder & share price RMS Training and Testing Results for ANFIS

Multi-Stage Type 1:	RMS	RHB	RHS	RMB	RMS	RLB	RLS
Shareholder	Train	0.1436	0.0807	0.0661	0.0392	0.0282	0.0527
	Test	4.376	1.761	0.2686	0.4391	0.3636	1.4386
Share price	Train	0.1795	0.1877	0.1143	0.1229	0.0946	0.1277
	Test	3.4501	4.1106	1.1875	0.5161	0.8476	0.7584

6.3.3 Ensembled model

6.3.3.1 Results of Average Ensemble model

The average method has been used next which is the average of the ANN and ANIFS techniques. According to Table 6.5 which reports the results of the shareholder and share price, the RMS training values for the average method are 0.2525, 0.1334, 0.1629, 0.1102, 0.1289, and 0.1409 and for testing are 0.2205, 0.1834, 0.1585, 0.0939, 0.1040, and 0.1023, for all stock portfolios. Figures 6.4 and 6.5 indicate that investment; dividend and disinvestment decisions are predicted with relatively more accuracy if we use the average method, as compared to the individual ANN and ANFIS techniques. On the other hand, Table 6.5 points out that the RMS training values for predicting stock prices are 0.4083, 0.3642, 0.2954, 0.2233, 0.2508, 0.2491 and for testing are 0.4126, 0.3661, 0.2860, 0.1810, 0.2920, 0.1804 for all the portfolios of RHB, RHS, RMB, RMS, RLB, and RLS, respectively. Figures 6.6 and 6.7 also indicate that growth, fall and speculative fall expectations are there in Saudi Arabia market.

The equation for the average is:

$$\text{Average} = \frac{\sum_{i=1}^{n} \text{para(i)}}{\text{N}} \qquad (6.1)$$

Table 6.5: shareholder & share price RMS Training and Testing Results for Average Ensemble model

Multi-Stage Type 1:	RMS	RHB	RHS	RMB	RMS	RLB	RLS
Shareholder	Train	0.2525	0.1334	0.1629	0.1102	0.1289	0.1409
	Test	0.2205	0.1834	0.1585	0.0939	0.1040	0.1023
Share price	Train	0.4083	0.3642	0.2954	0.2233	0.2508	0.2491
	Test	0.4126	0.3661	0.2860	0.1810	0.292	0.1804

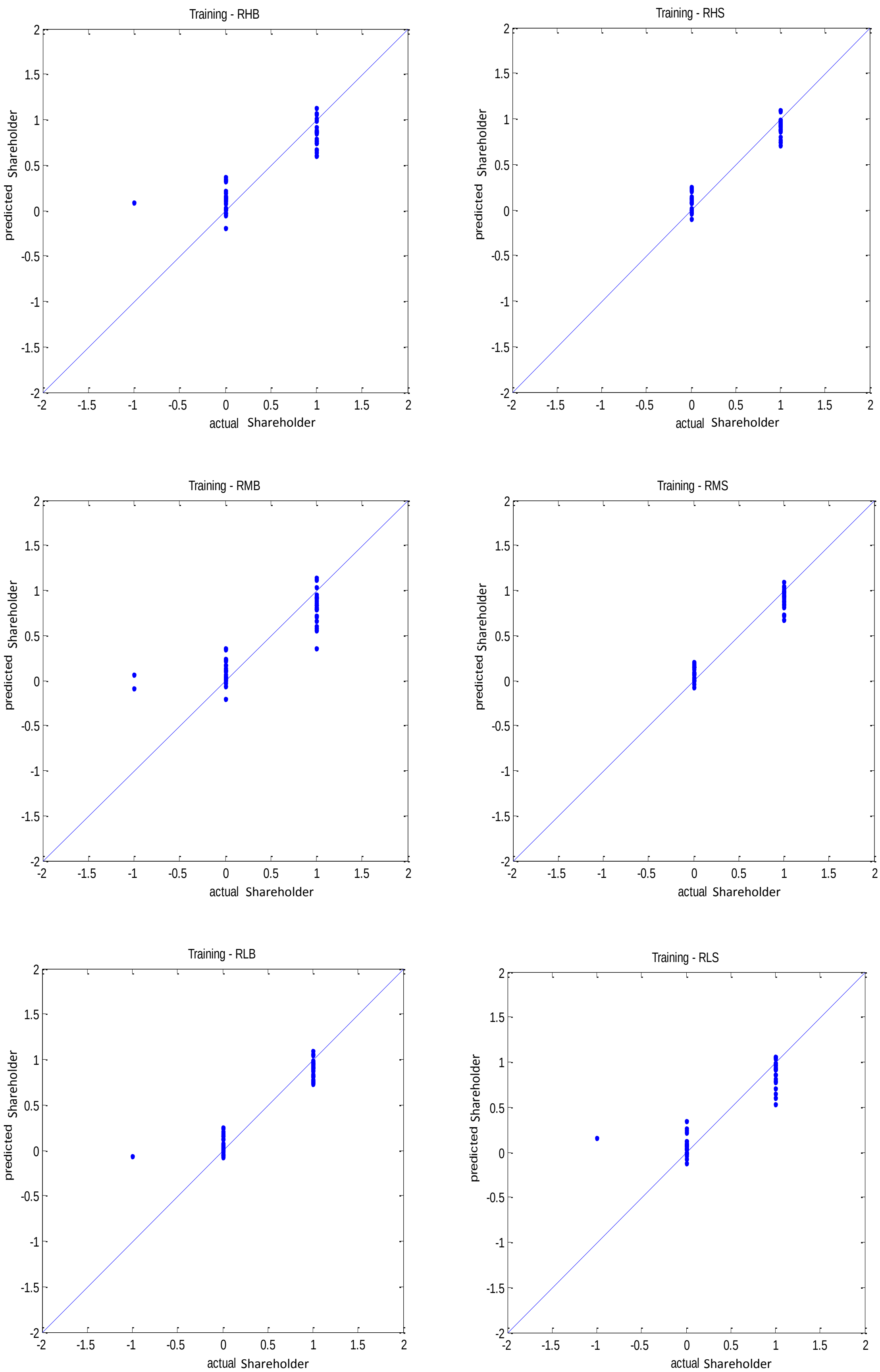


Figure 6.4: RMS Training results (multi-stage type 1 shareholder) using average technique

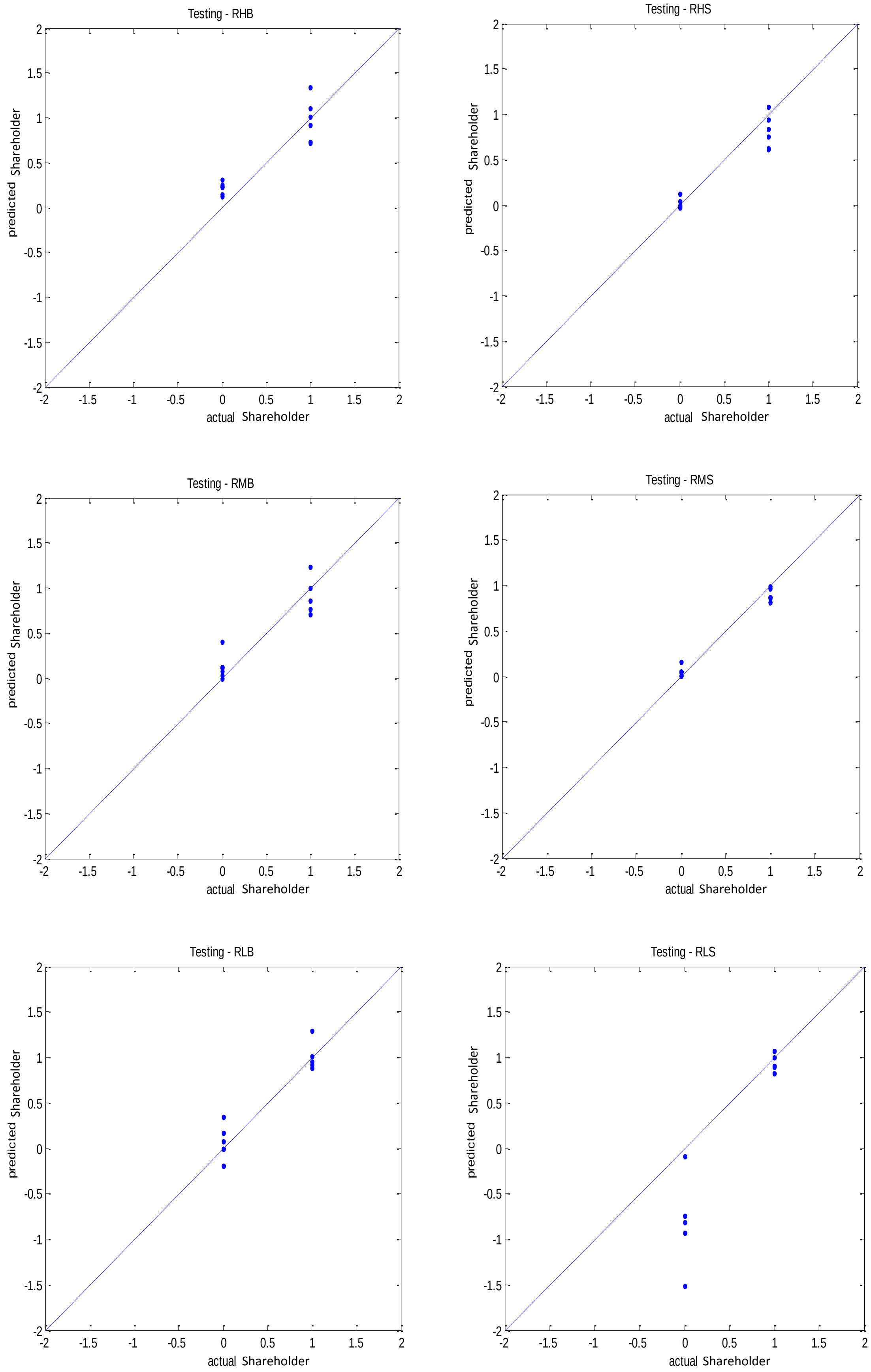


Figure 6.5: RMS Testing results (multi-stage type 1 shareholder) using average technique

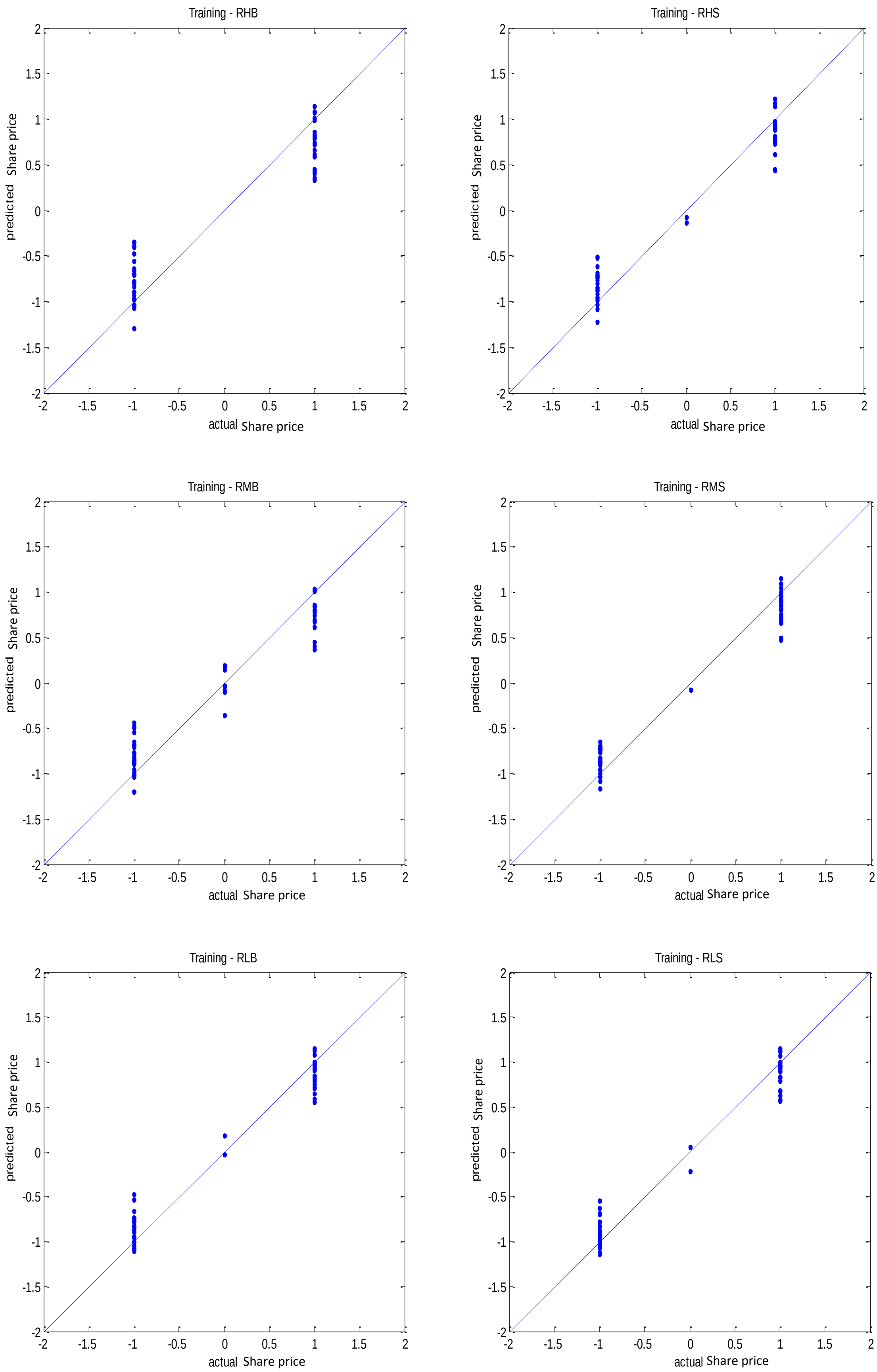


Figure 6.6: RMS Training results (multi-stage type 1 share price) using average technique

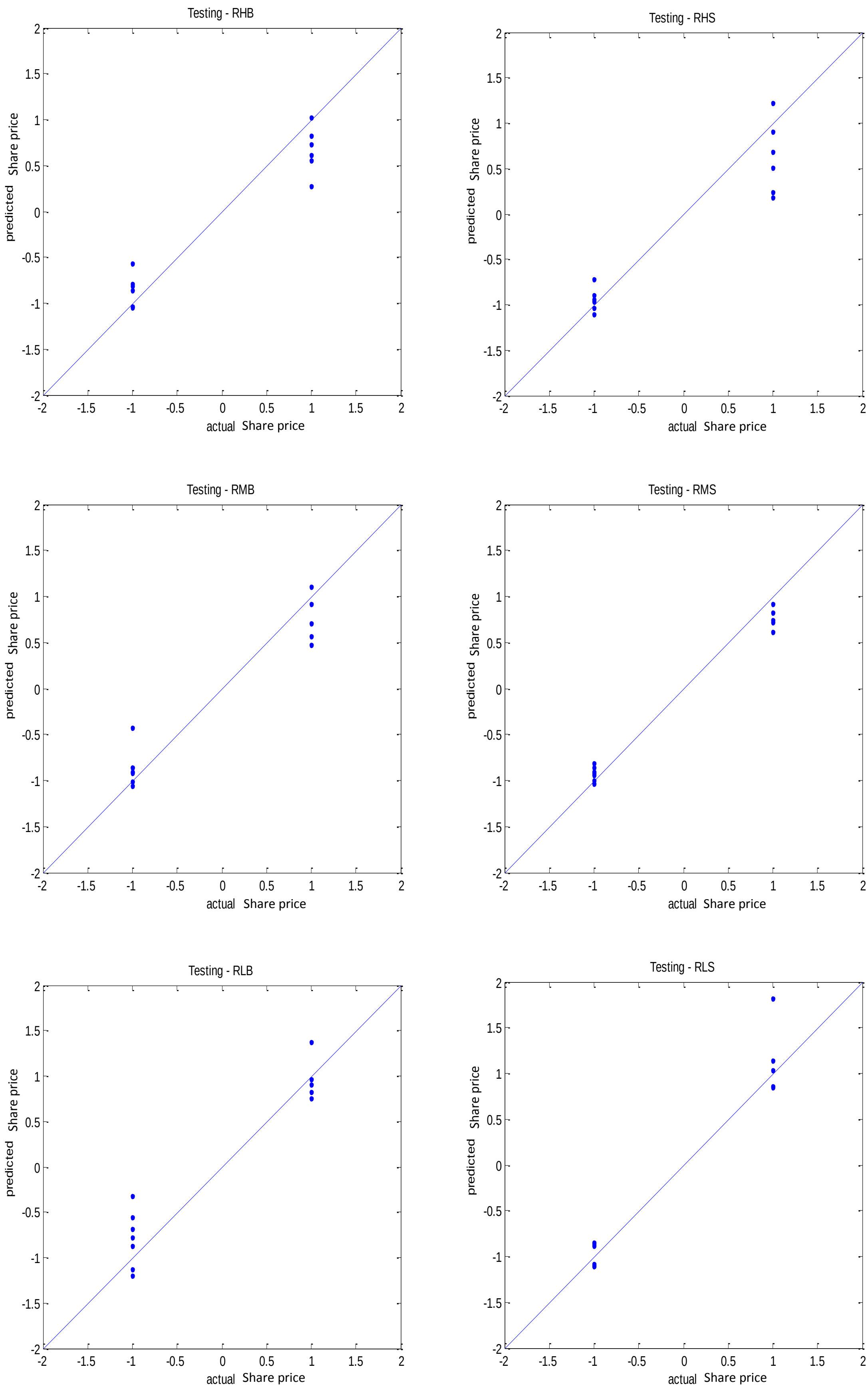


Figure 6.7: RMS Testing results (multi- stage type 1 share price) using average technique

6.3.3.2 Results of Weighted Average Model

The results of the weighted average method are much better than the simple average and individual ANN techniques in terms of prediction accuracy and error values. With respect to the shareholder perspective, in Table 6.6 the RMS values for training portfolios are 0.2402, 0.1330, 0.1629, 0.1060, 0.1289, and 0.1303 and for testing are 0.2196, 0.1770, 0.1395, 0.0919, 0.1033, and 0.1015. Figures 6.8 and 6.9 point out that there is much better prediction of investment and dividend decisions for shareholders. On the other hand, in Table 6.6 the training RMS values for the share price dimension are 0.3359, 0.2297, 0.2773, 0.2098, 0.2044, and 0.2030 and for testing are 0.3125, 0.3630, 0.2809, 0.1792, 0.2862, and 0.1799, respectively for all portfolios. Similarly, Figures 6.10 and 6.11 indicate that expectations for growth, fall and speculative fall are in share prices. However, these results are better than the simple average and individual ANN techniques because the prediction accuracy is much better in case of the weighted average method.

The equations for the weighted average are:

$$\text{Weighted average} = \frac{\sum_{i=1}^{n} \text{para(i) x W(i)}}{\sum_{i=1}^{n} \text{W(i)}} \qquad (6.2)$$

$$\text{W(i)} = 1 - \overline{\text{STD}_i\text{(bin)}} \qquad (6.3)$$

Where: STD_i is the standard deviation for *bin* , the normalized values taken (STD)

Table 6.6: shareholder & share price RMS Training and Testing Results for Weighted Average Model

Multi-Stage Type 1:	RMS	RHB	RHS	RMB	RMS	RLB	RLS
	Train	0.2402	0.133	0.1629	0.106	0.1289	0.1303
Shareholder	Test	0.2196	0.177	0.1395	0.0919	0.1033	0.1015
	Train	0.3359	0.2297	0.2773	0.2098	0.2044	0.203
Share price	Test	0.3125	0.3630	0.2809	0.1792	0.2862	0.1799

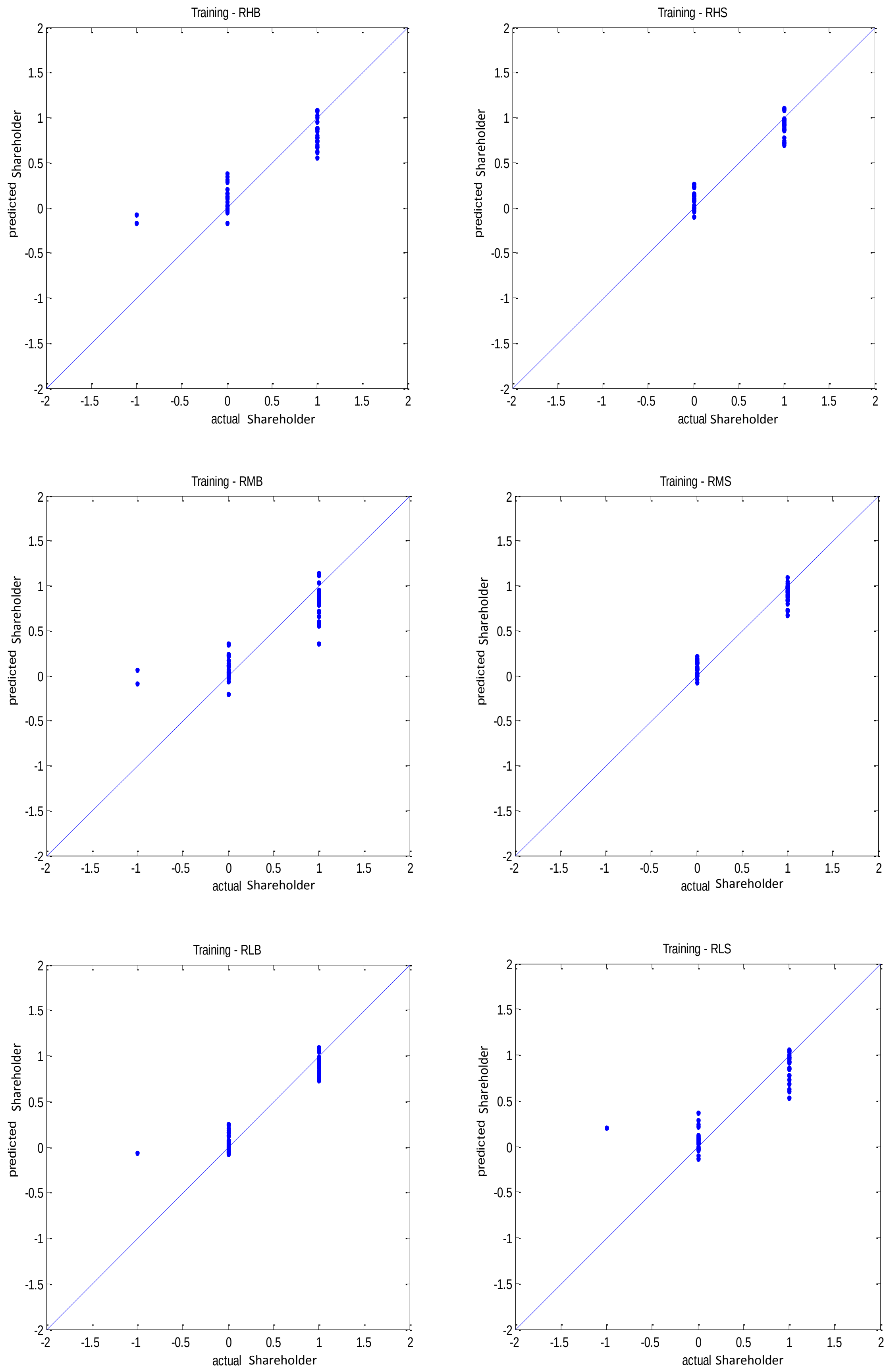


Figure 6.8: RMS Training results (multi-stage type 1 shareholder) using weighted average technique

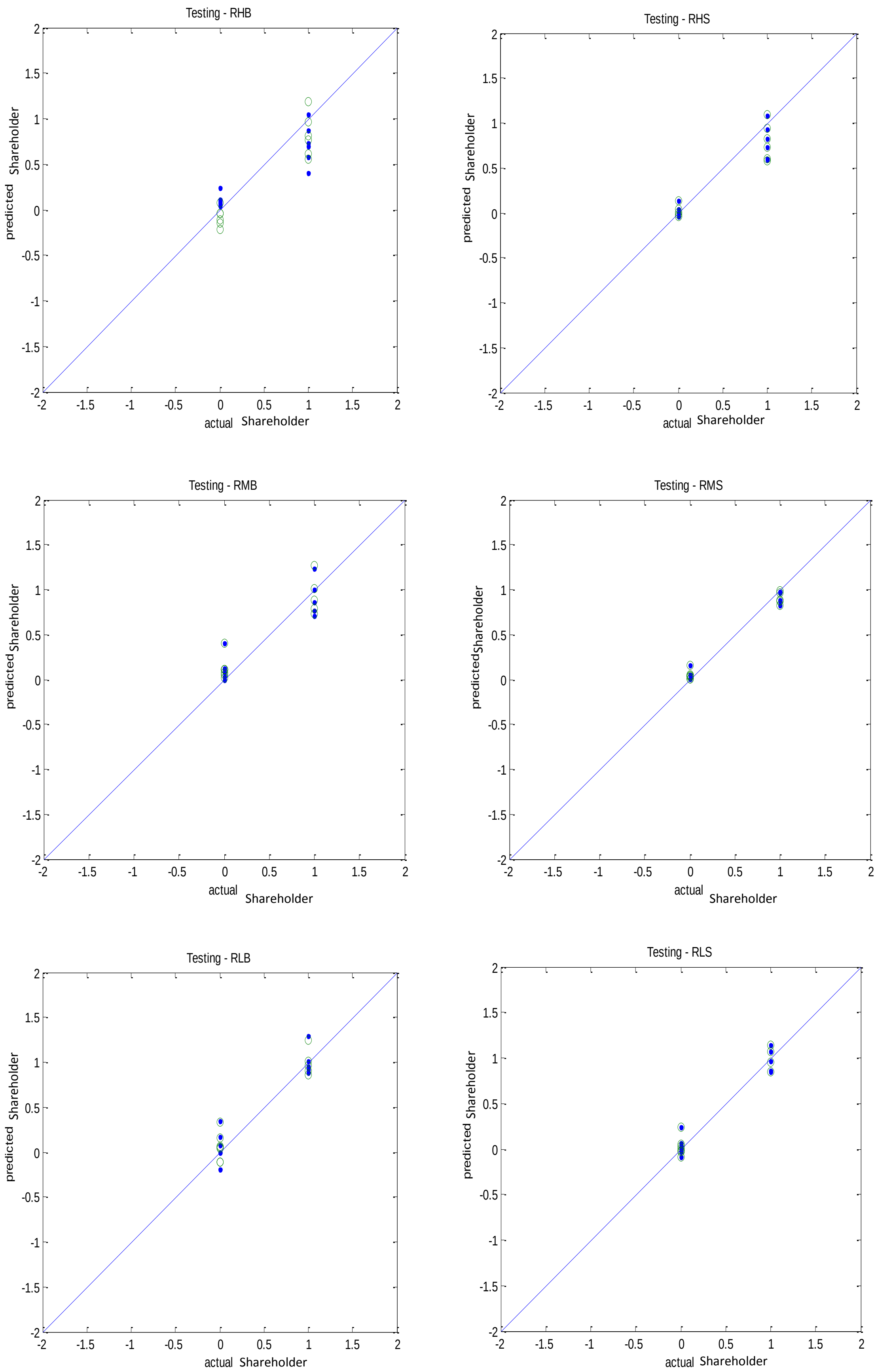


Figure 6.9: RMS Testing results (multi-stage type 1 shareholder) using weighted average technique

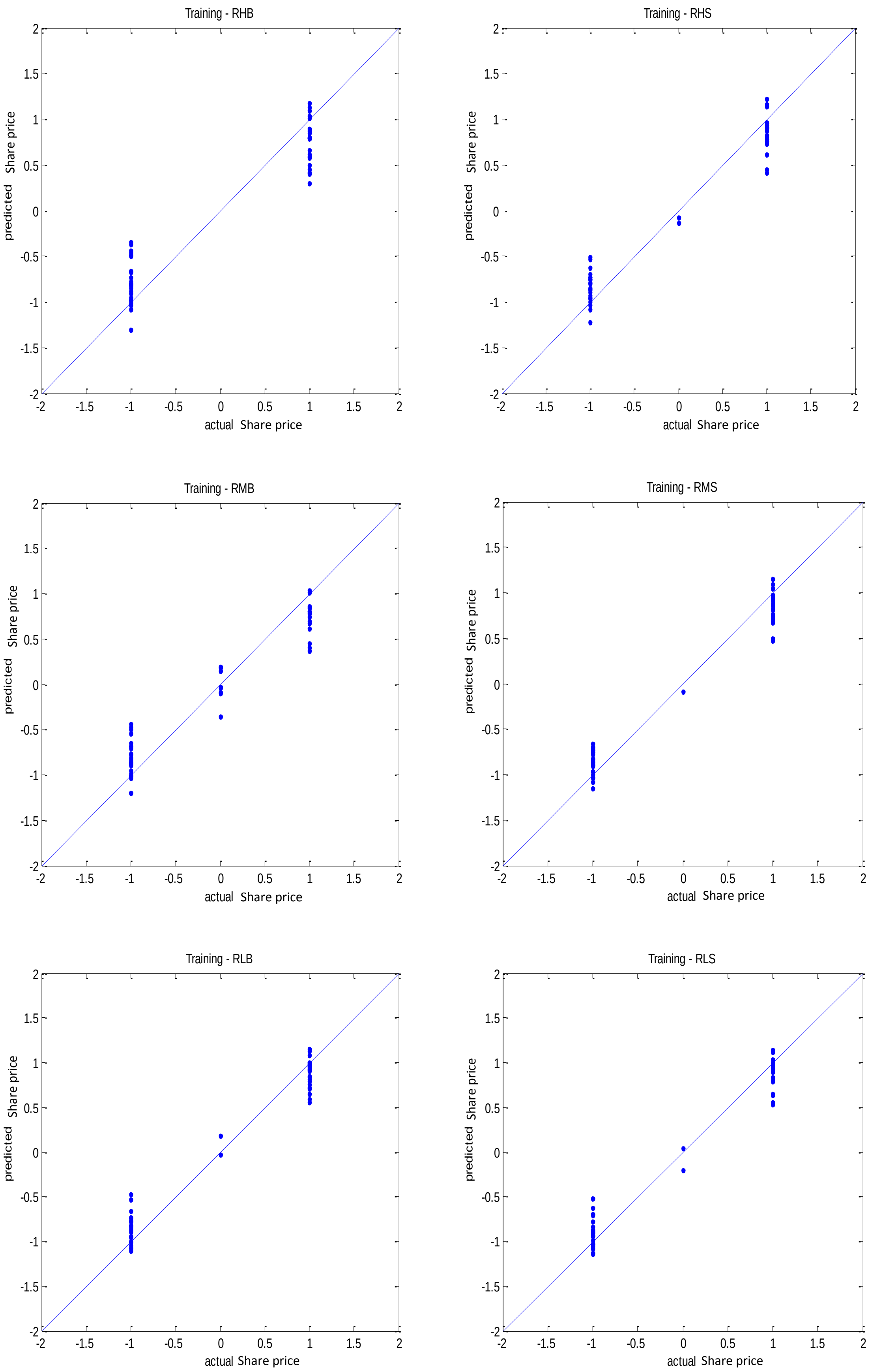


Figure 6.10: RMS Training results (multi-stage type 1 share price) using weighted average technique

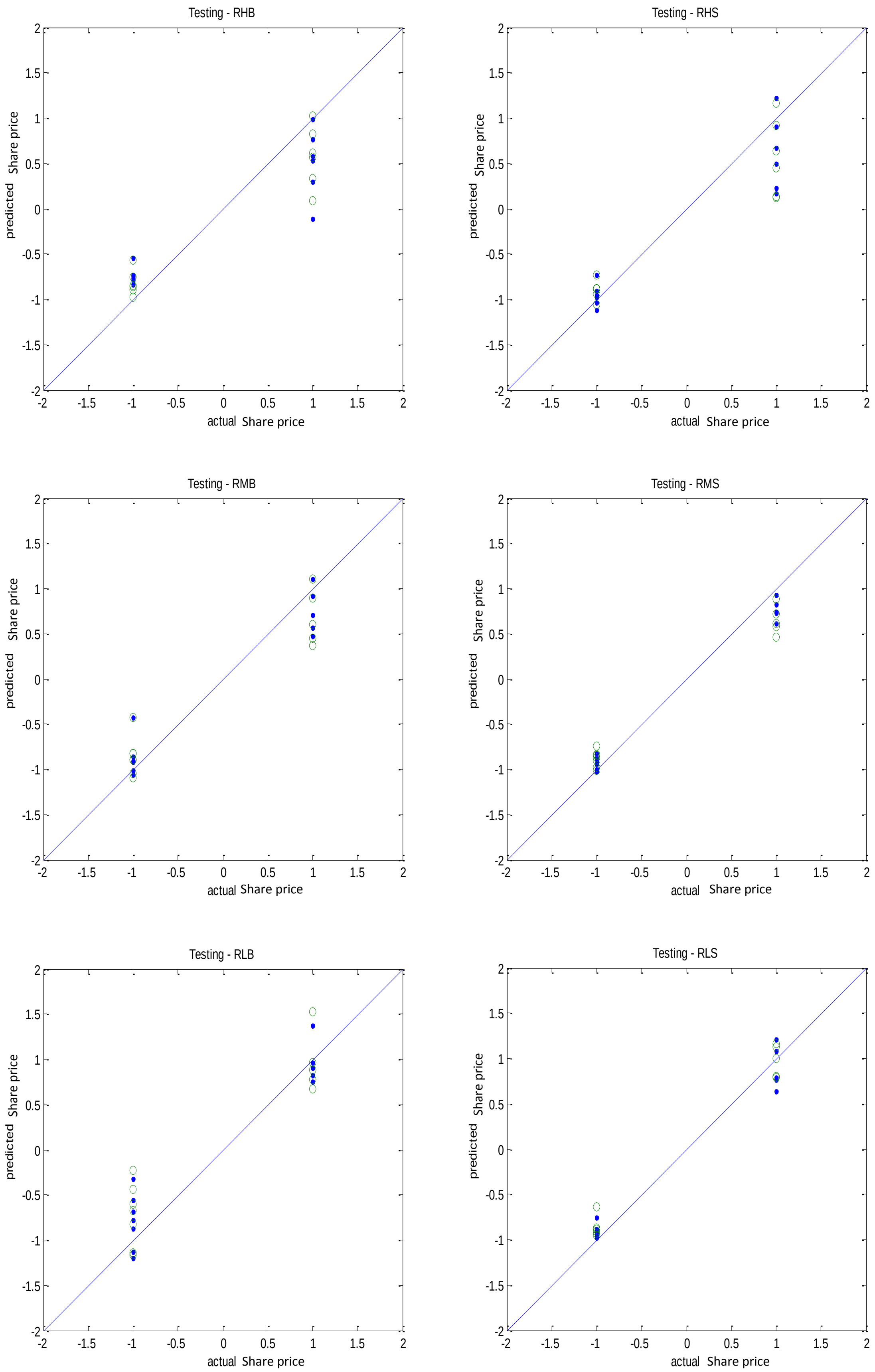


Figure 6.11: RMS Testing results (multi-stage type 1 share price) using weighted average technique

6.3.3.3 Results of GA Optimized Weighted Average Model

Lastly, the multi-stage type-1 model which is a combination of FF and VBM has been reported using the GA optimized weighted average. The settings of the GA: Population size 20, No. of generations 100, mutation rate 0.05 and crossover rate 0.8. From the shareholder perspective, Table 6.7 states that RMS training values are 0.2340, 0.1262, 0.1367, 0.0313, 0.0686, and 0.0935 and for testing are 0.2111, 0.1767, 0.1222, 0.0899, 0.0996, 0.0701, for all the stock portfolios respectively. Moreover, Figures 6.12 and 6.13 indicate that investment and dividend decisions for shareholders are predicted with the maximum accuracy, as all the portfolios. In the case of share prices, RMS training values, as reported by Table 6.7, are 0.2455, 0.2161, 0.2620, 0.1130, 0.1410, 0.1334 and testing values are 0.2932, 0.3565, 0.2691, 0.1624, 0.1034, and 0.0870, respectively for all the portfolios. Both the training & testing and shareholder and share price RMS values generated by GA are least, on average, as compared to all the methods of ANN, average and weighted average. Furthermore, Figures 6.14 and 6.15 point out that there is growth, fall and speculative fall expectations in the share prices of all the portfolios. These expectations are correct and near to perfect in almost all the portfolios.

Table 6.7: shareholder & share price RMS Training and Testing Results for GA

Multi-Stage Type 1:	**RMS**	**RHB**	**RHS**	**RMB**	**RMS**	**RLB**	**RLS**
Shareholder	Train	0.234	0.1262	0.1367	0.0313	0.0686	0.0935
	Test	0.2111	0.1767	0.1222	0.0899	0.0996	0.0701
Share price	Train	0.2455	0.2161	0.262	0.113	0.141	0.1334
	Test	0.2932	0.3565	0.2691	0.1624	0.1034	0.087

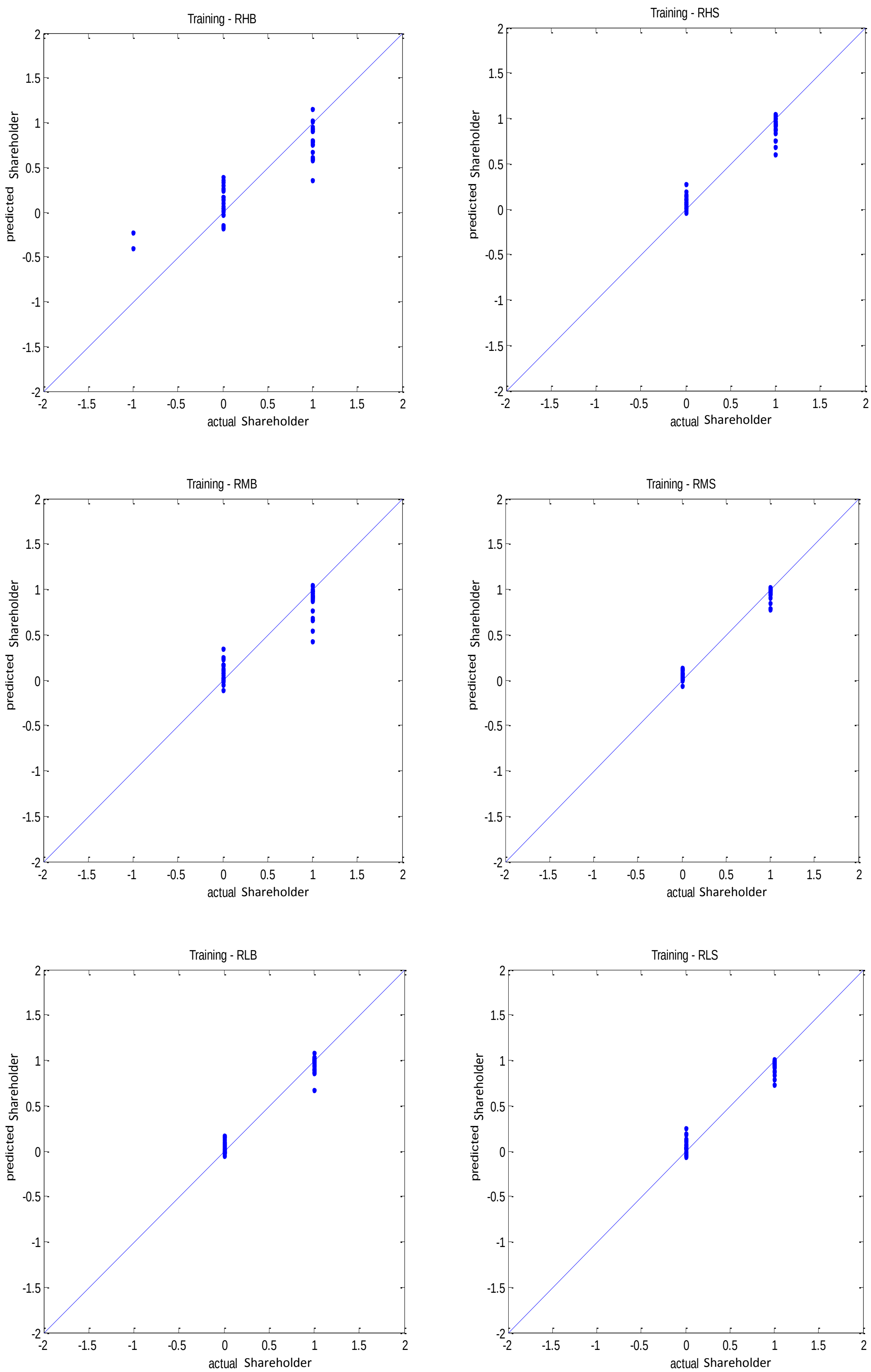


Figure 6.12: RMS Training results (multi-stage type 1 shareholder) using GA technique

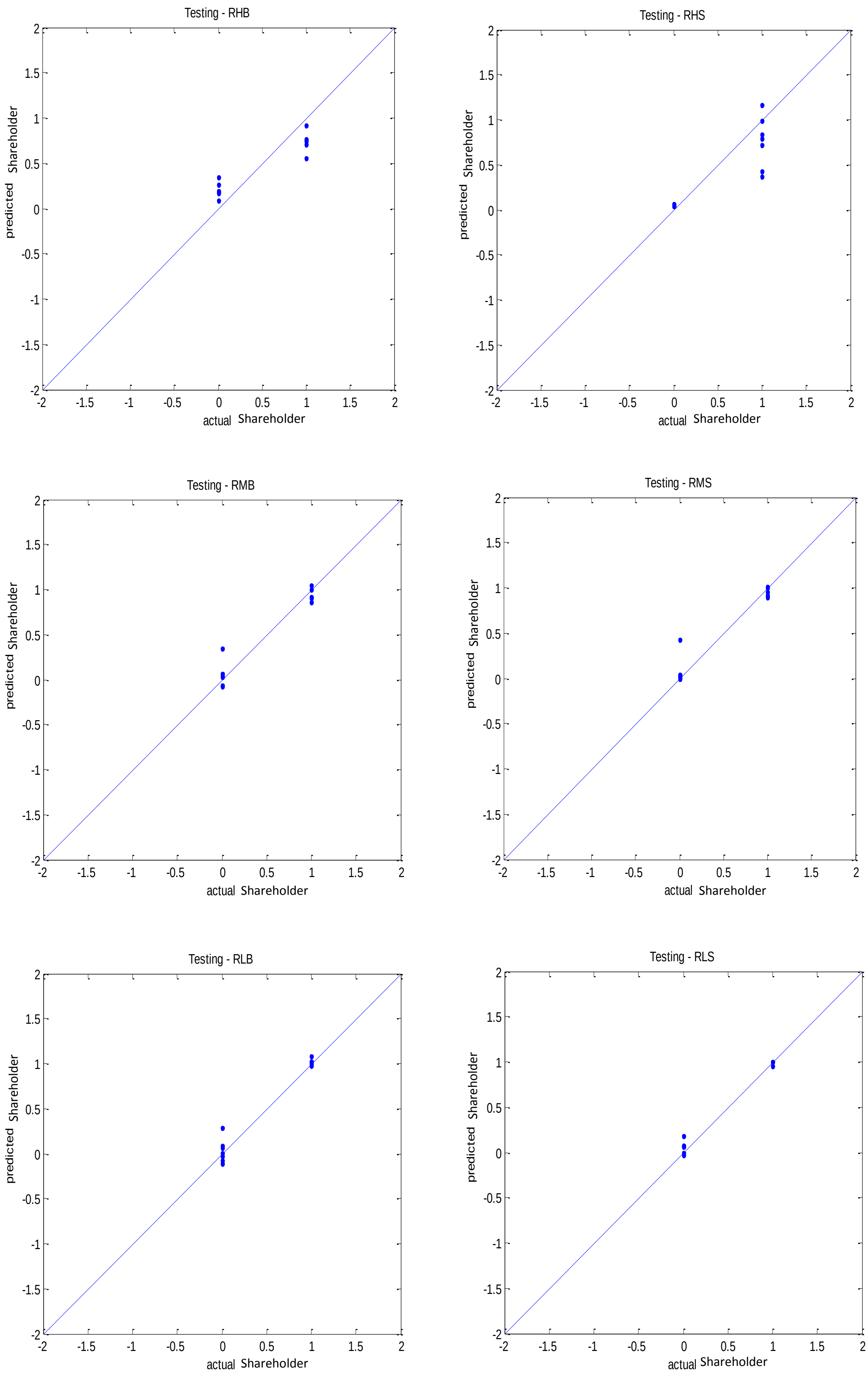


Figure 6.13: RMS Testing results (multi-stage type 1 shareholder) using GA technique

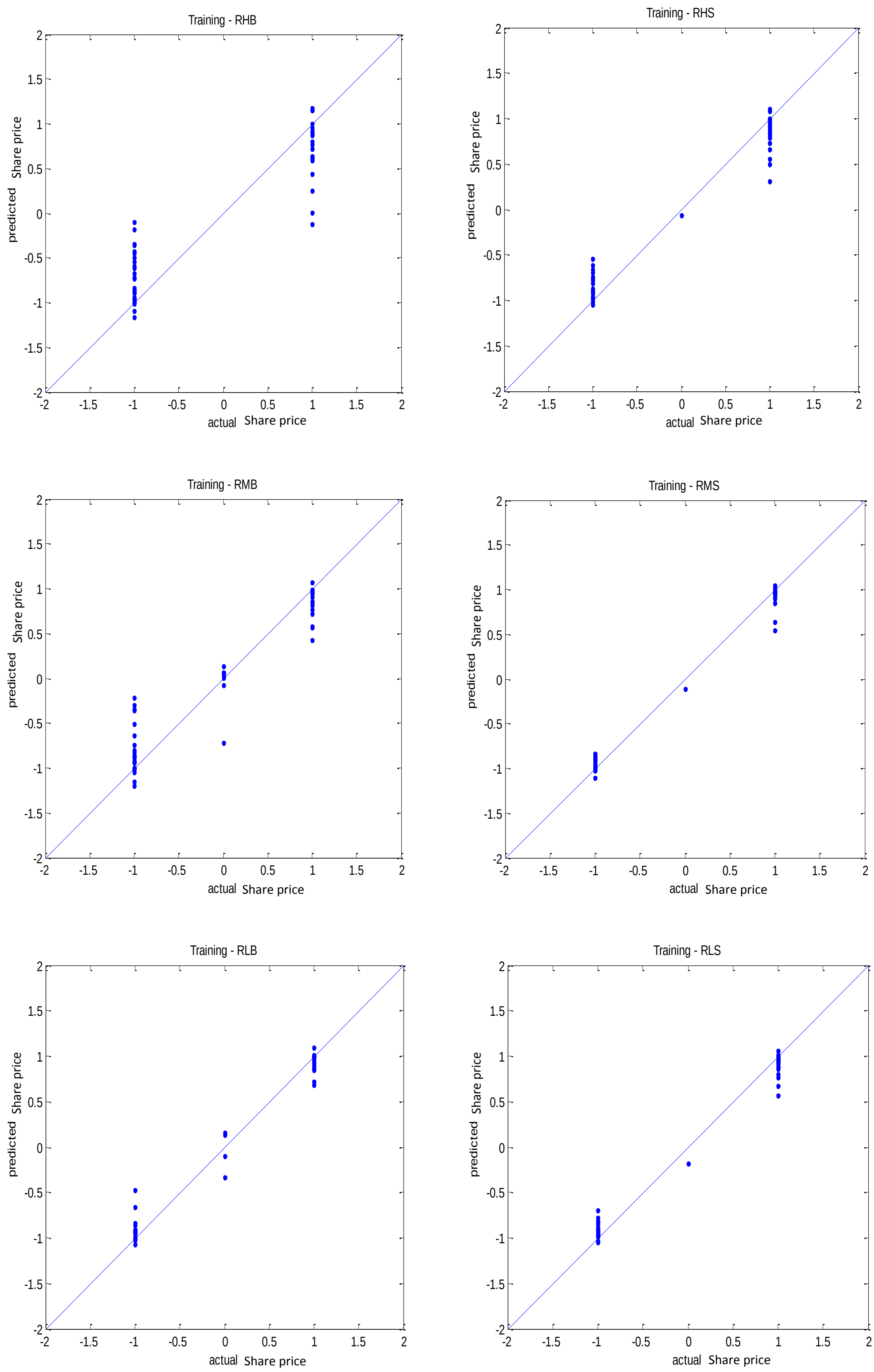


Figure 6.14: RMS Training results (multi-stage type 1 share price) using GA technique

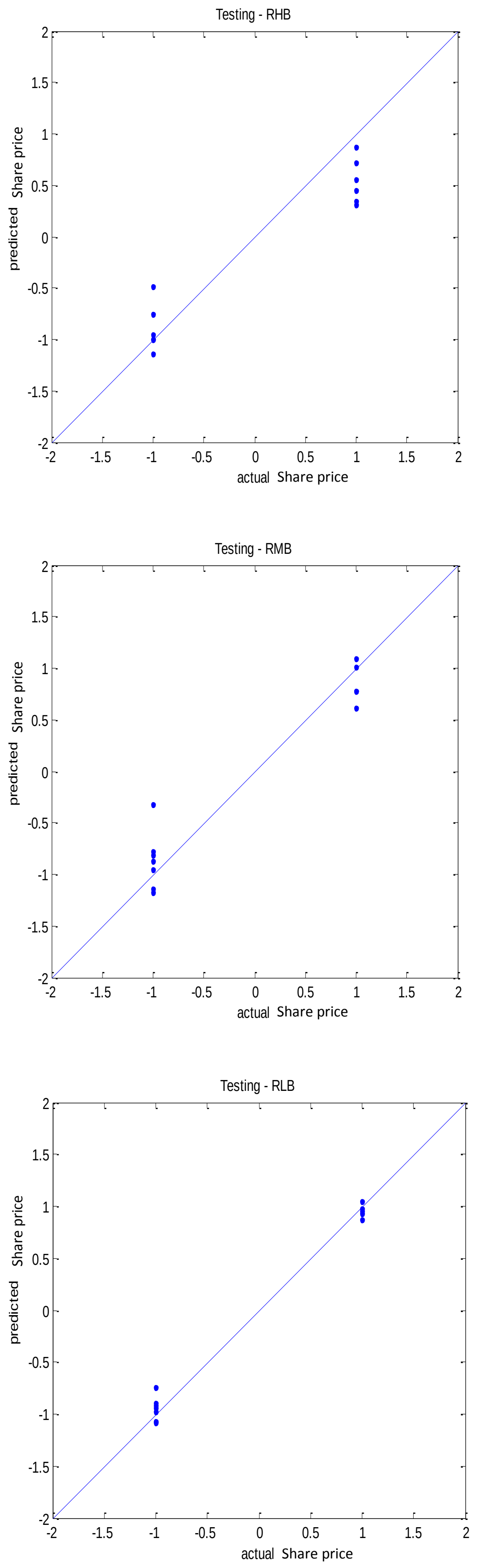


Figure 6.15: RMS Testing results (multi-stage type 1 share price) using GA technique

6.4 Forecasting Multi-Stage Type 2 Model

This section reports the RMS values of training and testing for all portfolios (RHB, RHS, RMB, RMS, RLB, and RLS) for the multi-stage type 2 model, which is the combination of CAPM and VBM for shareholders and share price, respectively as shown in Figure 6.16. Different ANN techniques and ANFIS, average, weighted average and GA are utilized to predict and make decisions with respect to shareholder and share price.

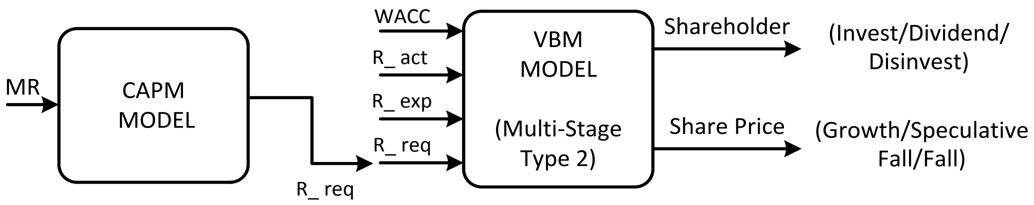


Figure 6.16: Multi-Stage Type 2 model

6.4.1 Results of Artificial Neural Networks Model

The ANN parameters and topology are illustrated in Table 6.8. According to Table 6.9, which is for shareholders, the best prediction is by both FF and FIT techniques of ANN for RHB and RMB where the training RMS values are 0.4313 and 0.1459 and testing values are 0.5026 and 0.3268. The returns of these two portfolios can be best predicted by using these two ANN techniques. However, DTDDNN is best for RHS, RLB and RLS with training values of 0.2321, 0.1446 and 0.1563 (testing values are 0.8099, 0.1475, and 0.1386). Finally, CF is the best ANN model for the RMS portfolio with training value of 0.1206 and testing value of 0.1915. According the figures given in Appendix E for ANN prediction using multi-stage type 2 model (CAPM and VBM), it can be inferred that predictions are relatively strong for invest , dividend and disinvest decisions.

Similarly, for share price decisions, Table 6.10 shows that FFTD is best the ANN technique for return predictions where RMS values are 0.4123 and 0.2982 for training and 1.1265 and 0.4978 for testing in the portfolios RH and RMB respectively. DTDNN is the best ANN technique for return predictions where RMS values are 0.2750, 0.2244, 0.1762 and 0.2519 for training and 0.6785, 0.1533, 0.1724 and 0.2317 for testing in the portfolios RHS, RMS, RLB and RLS respectively. The figures are given in Appendix F indicate that prediction is relatively correct and there are growth, fall and speculative fall expectations in the share prices.

Table 6.8: ANN Parameters and Topologies

TYPE	Topology	Train /valid	Training epochs	Training function
FF	4-5-1	80/20	500	Levenberg-Marquardt
ELM	4-5-1	80/20	500	Gradient descent
CF	4-5-1	80/20	500	Levenberg-Marquardt
RB	4-5-1	80/20	500	Radial Bases Functions
FFTD	4-5-1	80/20	500	Levenberg-Marquardt
DTDNN	4-5-1	80/20	500	Levenberg-Marquardt
FIT	4-5-1	80/20	500	Levenberg-Marquardt

Table 6.9: shareholder RMS Training and Testing Results for ANNs

Multi-Stage Type 2: Shareholder	RMS	RHB	RHS	RMB	RMS	RLB	RLS
CF	Train	0.4303	0.2538	0.1899	0.1206	0.1896	0.2039
	Test	0.5121	0.8521	0.4845	0.1915	0.2627	0.3006
ELM	Train	0.5026	0.3257	0.3714	0.2666	0.256	0.2794
	Test	0.5061	0.8753	0.4012	0.3324	0.2831	0.2836
FFTD	Train	0.4177	0.2211	0.1522	0.0728	0.107	0.1267
	Test	0.5463	0.8475	0.4169	0.1966	0.1577	0.1393
FF	Train	0.4313	0.2157	0.1959	0.0515	0.1046	0.1652
	Test	0.5026	0.8199	0.3268	0.1984	0.1648	0.1611
DTDNN	Train	0.4212	0.2321	0.1727	0.0742	0.1446	0.1563
	Test	0.5088	0.8099	0.3891	0.2023	0.1475	0.1386
FIT	Train	0.4313	0.2157	0.1959	0.0515	0.1046	0.1652
	Test	0.5026	0.8199	0.3268	0.1984	0.1648	0.1611
RB	Train	0.4881	0.3128	0.364	0.2818	0.2807	0.2767
	Test	0.5259	0.8926	0.4007	0.3444	0.2714	0.2762

Table 6.10: share price RMS Training and Testing Results for ANNs

Multi-Stage Type 2: Share price	RMS	RHB	RHS	RMB	RMS	RLB	RLS
CF	Train	0.4554	0.4313	0.3122	0.24	0.3159	0.2752
	Test	1.1666	0.7955	0.7133	0.3906	0.5973	0.4501
ELM	Train	0.6243	0.644	0.5502	0.5215	0.4946	0.5099
	Test	1.1877	0.7613	0.6937	0.605	0.5111	0.5589
FFTD	Train	0.4123	0.391	0.2982	0.1521	0.1861	0.2178
	Test	1.1265	0.766	0.4978	0.2456	0.2111	0.2494
FF	Train	0.4343	0.3283	0.2905	0.1376	0.1903	0.2099
	Test	1.2367	0.6845	0.5804	0.234	0.2192	0.365
DTDNN	Train	0.4047	0.275	0.2786	0.2244	0.1762	0.2519
	Test	1.2083	0.6785	0.5081	0.1533	0.1724	0.2317
FIT	Train	0.4343	0.3283	0.2905	0.1376	0.1903	0.2099
	Test	1.2367	0.6845	0.5804	0.234	0.2192	0.365
RB	Train	0.6013	0.626	0.5867	0.5436	0.5416	0.4811
	Test	1.1495	0.8458	0.843	0.6305	0.4466	0.5877

6.4.2 Results of Adaptive Neural Fuzzy Inference Systems model

The settings of the ANFIS: Type of membership: Gaussian and number of fuzzy rules are 16, 24, 32, 24, 32, 24, 32, 128, 54 and 144. Along with the ANN techniques, Table 6.11 reports the RMS values of the adaptive neural fuzzy inference system (ANFIS) for both training and testing for shareholder and share price, respectively. According to Table 6.11 the RMS for training are 0.1144, 0.1107, 0.0605, 0.0388, 0.0266, 0.0455, and for testing are 2.8005, 2.4625, 1.2168, 0.2940, 0.3261, and 0.5842. According to Table 6.11, the RMS training values for share price perspective are 0.1703, 0.1732, 0.1140, 0.1145, 0.0916, 0.1158 and testing values are 1.1878, 1.8070, 0.1116, 0.8085, 1.1878, and 0.5486. Overall it can be concluded that value-based decision making remains for invest, dividend and disinvest and expectations are for growth, fall and speculative fall in share prices. The figures are given in Appendices E and F.

Table 6.11: shareholder & share price RMS Training and Testing Results for ANFIS

Multi-stage Type 2	RMS	RHB	RHS	RMB	RMS	RLB	RLS
Shareholder	Train	0.1144	0.1107	0.0605	0.0388	0.0266	0.0455
	Test	2.8005	2.4625	1.2168	0.294	0.3261	0.5842
Share price	Train	0.1703	0.1732	0.114	0.1145	0.0916	0.1158
	Test	1.1878	1.807	0.1116	0.8085	1.1878	0.5486

6.4.3 Ensembled model

6.4.3.1 Results of Average Ensemble model

The present study not only used different ANN techniques for the multi-stage type 2 model, but also used the simple average method of all ANN and ANFIS models. The average method has stronger prediction accuracy, compared to individual ANN and ANFIS models. With respect to the shareholder perspective, in Table 6.12 the RMS values for training are 0.3869, 0.2252, 0.1797, 0.1102, 0.1353, and 0.1542 and for testing are 0.450, 0.795, 0.3199, 0.1718, 0.1421, and 0.1341. According to Figures 6.17 and 6.18, the decisions for shareholders are invest, dividend and disinvest .With respect to share price movements, in Table 6.12 training RMS values are 0.4083, 0.2661, 0.2954, 0.2233, 0.1290, 0.2491 and the testing RMS values are 1.0726, 0.6561, 0.4859, 0.1476, 0.1295 and 0.2204. The expectations are growth, fall and speculative fall in share prices. However, these results for the average method are better than those of the individual ANN and ANFIS technique, with better prediction of decisions about stock portfolios as shown in Figures 19 and 20.

The equation for the average is:

$$Average = \frac{\sum_{i=1}^{n} para(i)}{n} \qquad (6.4)$$

Table 6.12: shareholder & share price RMS Training and Testing Results for Average Ensemble Model

Multi-stage Type 2	RMS	RHB	RHS	RMB	RMS	RLB	RLS
	Train	0.3869	0.2252	0.1797	0.1102	0.1353	0.1542
Shareholder	Test	0.4500	0.7950	0.3199	0.1718	0.1421	0.1341
	Train	0.4083	0.2661	0.2954	0.2233	0.1290	0.2491
Share price	Test	1.0726	0.6561	0.4859	0.1476	0.1295	0.2204

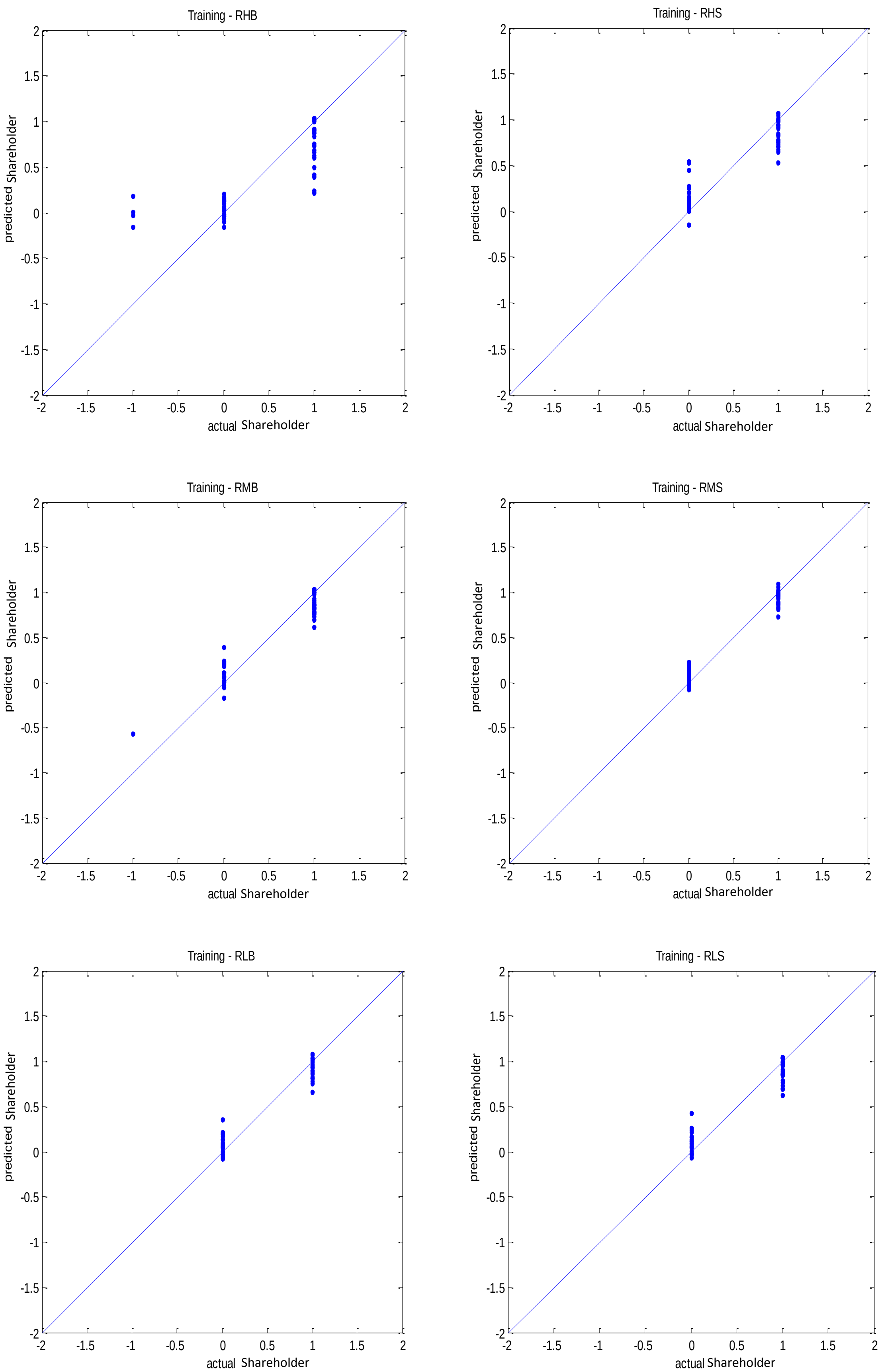


Figure 6.17: RMS Training results (Multi-Stage Type 2 shareholder) using average technique

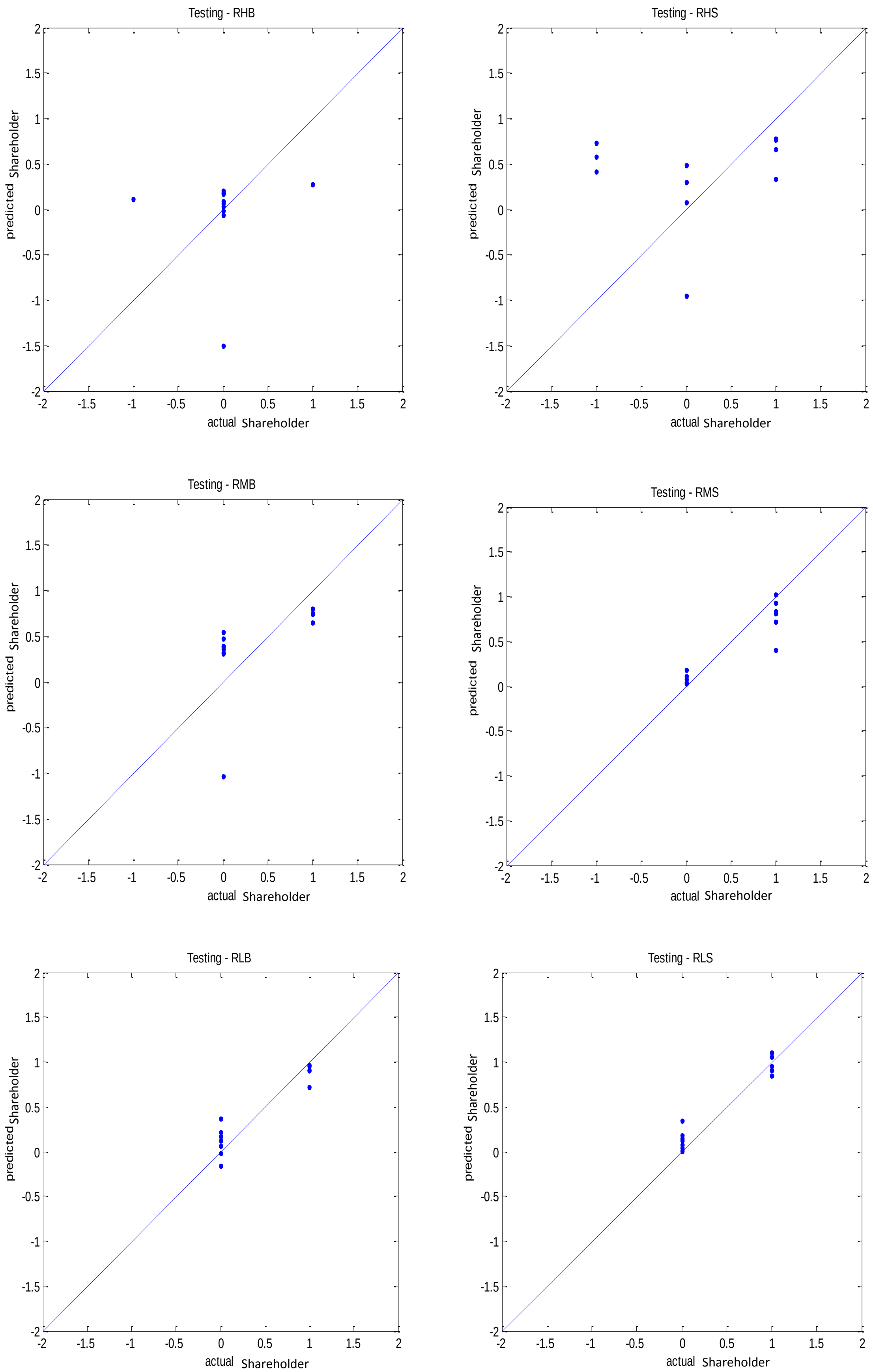


Figure 6.18: RMS Testing results (Multi-Stage Type 2 shareholder) using average technique

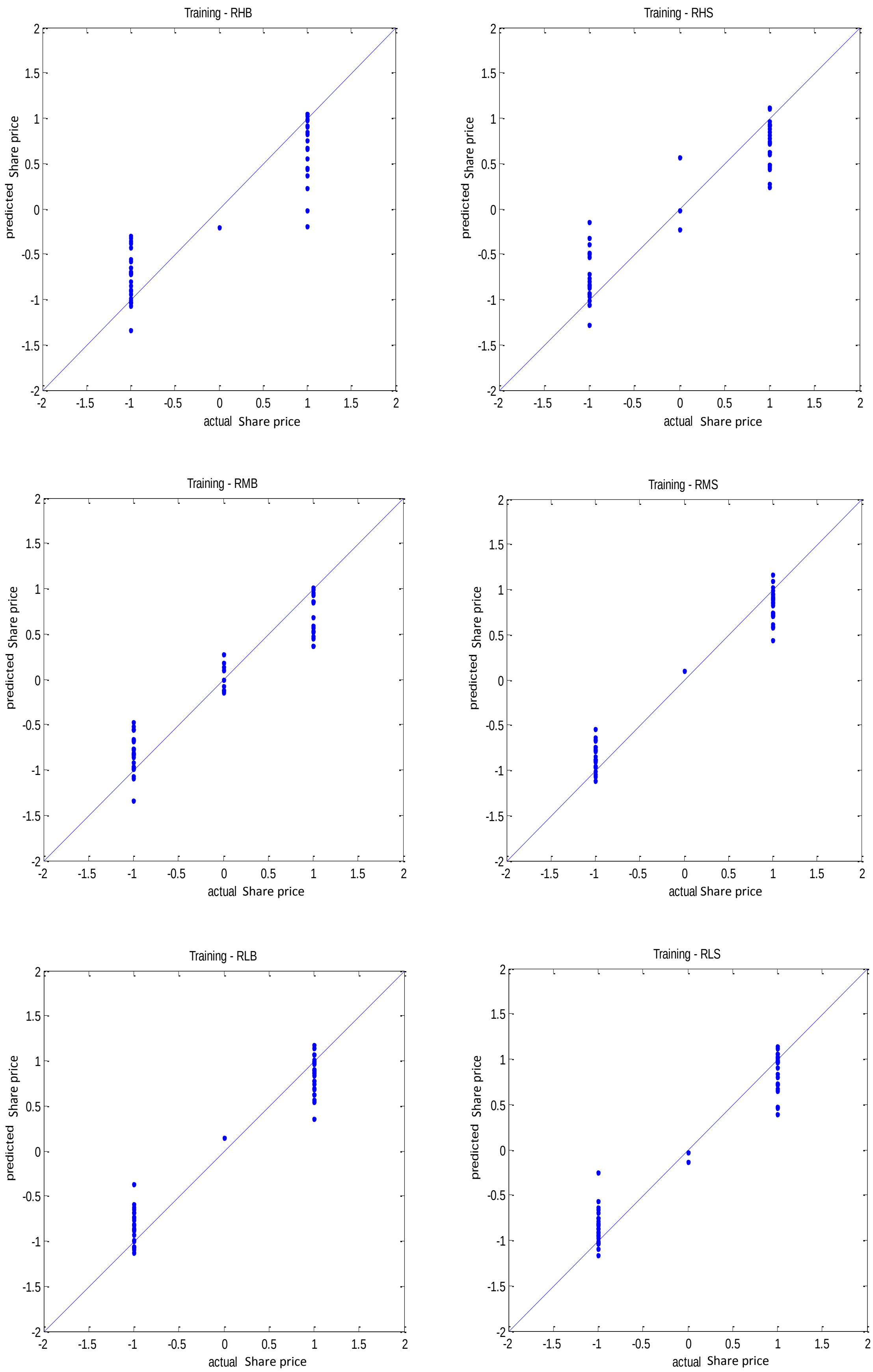


Figure 6.19: RMS Training results (Multi-Stage Type 2 share price) using average technique

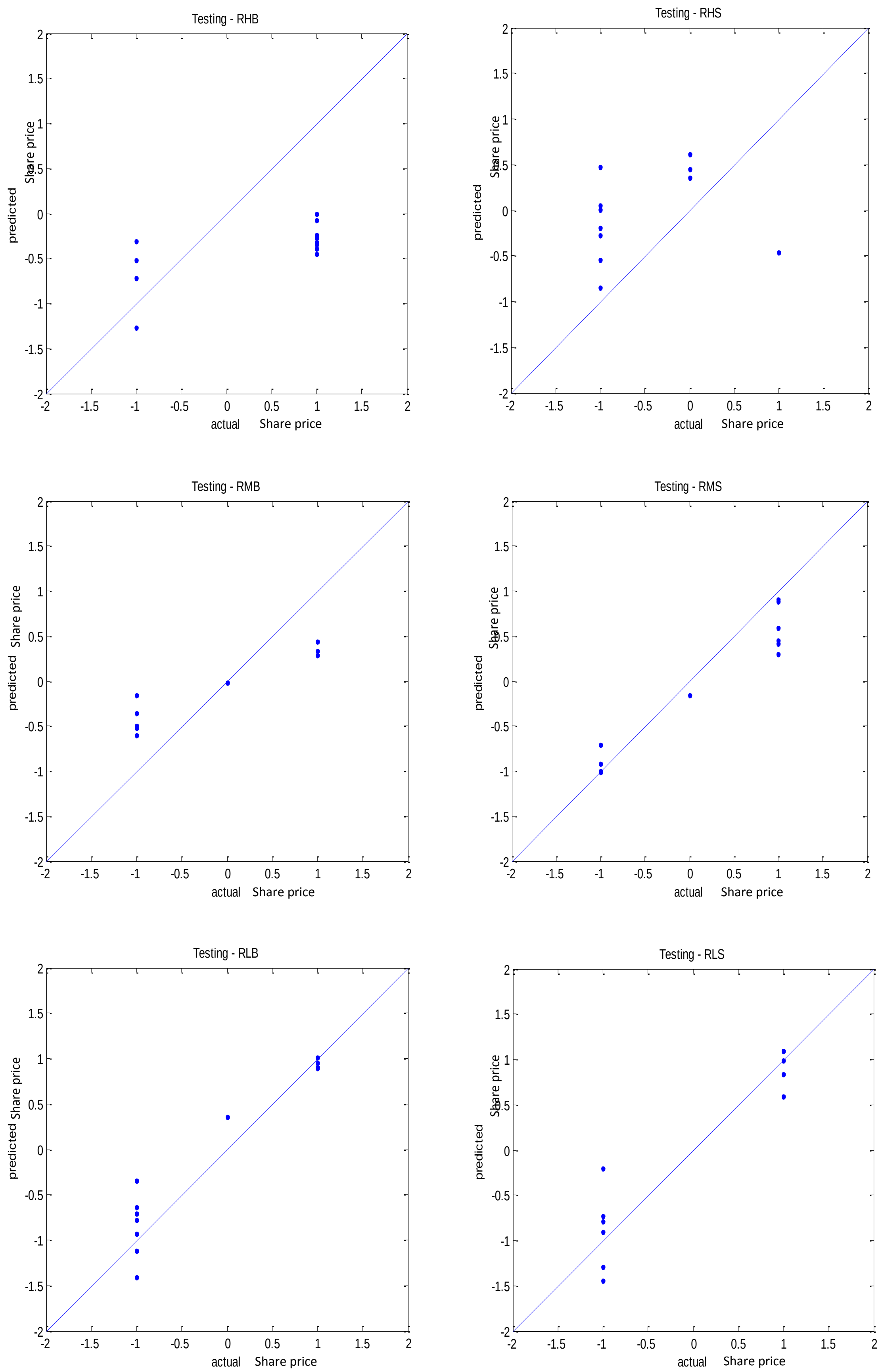


Figure 6.20: RMS Testing results (Multi-Stage Type 2 share price) using average technique

6.4.3.2 Results of Weighted Average Model

This accuracy level of prediction and decision making improves more by using the weighted average of ANN and ANFIS, instead of the simple average. In Table 6.13 the training RMS values for shareholders are 0.3855, 0.2217, 0.1797, 0.1099, 0.1353, 0.1509 and testing RMS values for shareholders are 0.4400, 0.7850, 0.3199, 0.1705, 0.1421, and 0.1335. The prediction accuracy has been increased. Figures 6.21 and 6.22 state that the predictions are strong where decisions are invest, dividend and disinvest. In the case of share prices, in Table 6.13 the training RMS values are 0.3937, 0.2630, 0.2954, 0.2230, 0.1250, 0.2425 and the testing RMS values are 1.0549, 0.6380, 0.4859, 0.1465, 0.1290, and 0.2177. There are expectations about the growth, fall and speculative fall in share prices as shown in Figures 23 and 24. The equations of weighted average are:

$$Weight\ average = \frac{\sum_{i=1}^{n} para(i)\ x\ W(i)}{\sum_{i=1}^{n} W(i)} \qquad (6.5)$$

Table 6.13: shareholder & share price RMS Training and Testing Results for Weighted Average

Multi-stage Type 2	RMS	RHB	RHS	RMB	RMS	RLB	RLS
Shareholder	Train	0.3855	0.2217	0.1797	0.1099	0.1353	0.1509
	Test	0.4400	0.7850	0.3199	0.1705	0.1421	0.1335
Share price	Train	0.3937	0.2630	0.2954	0.2230	0.1250	0.2425
	Test	1.0549	0.6380	0.4859	0.1465	0.1290	0.2177

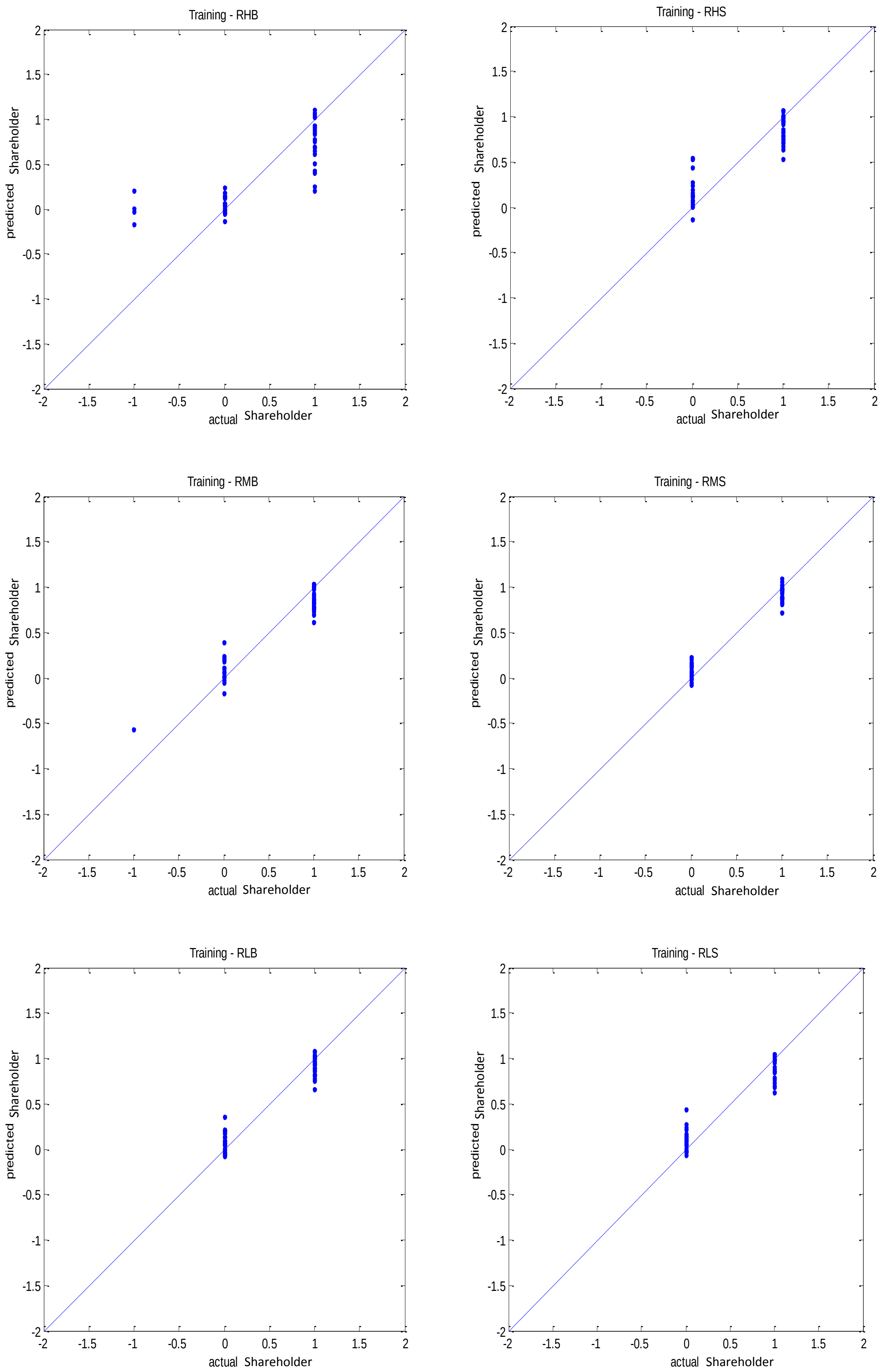


Figure 6.21: RMS Training results (Multi-Stage Type 2 shareholder) using weighted average technique

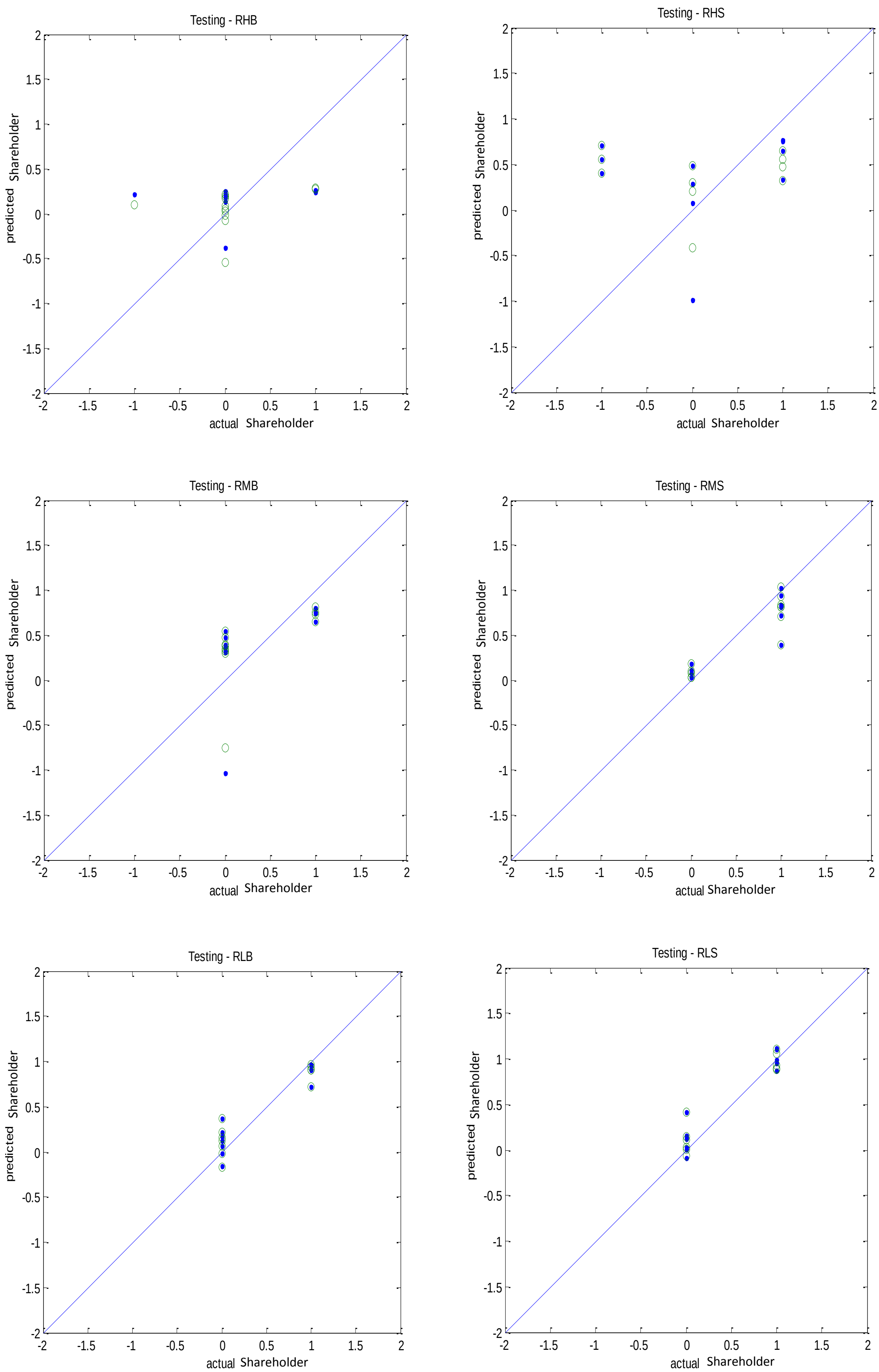


Figure 6.22: RMS Testing results (Multi-Stage Type 2 shareholder) using weighted average technique

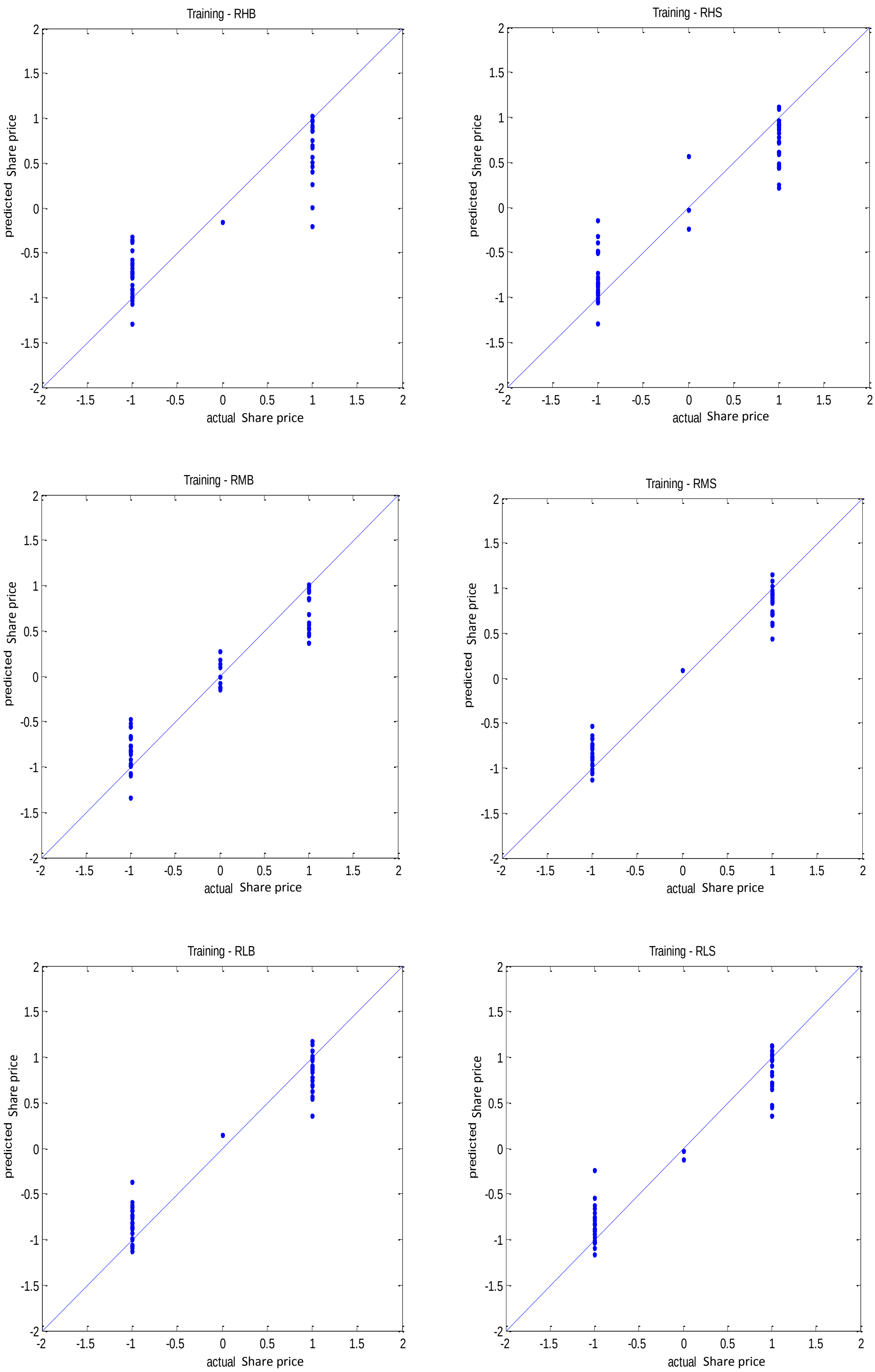


Figure 6.23: RMS Training results (Multi-Stage Type 2 share price) using weighted average technique

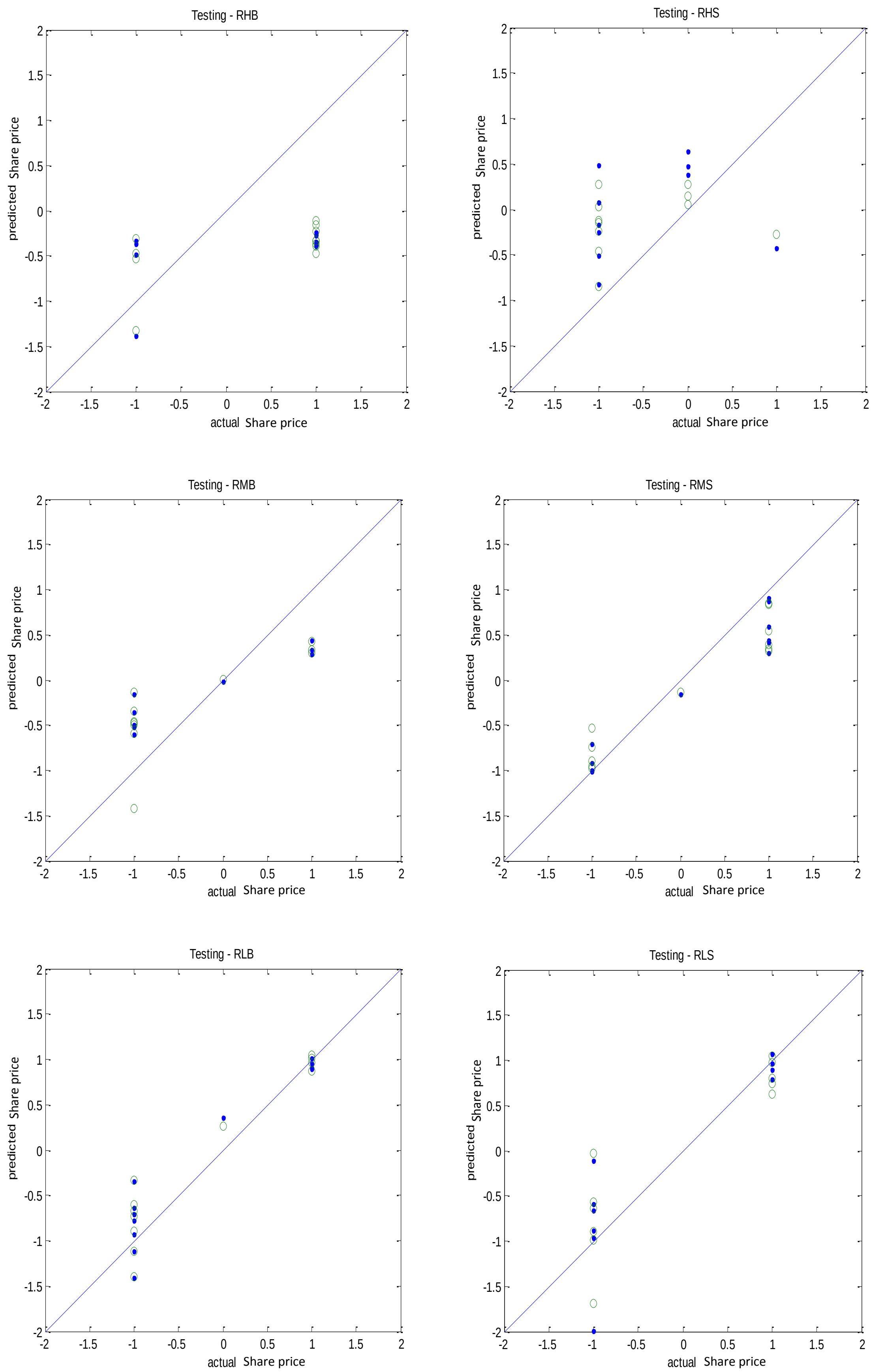


Figure 6.24: RMS Testing results (Multi-Stage Type 2 share price) using weighted average technique

6.4.3.3 Results of GA Optimized Weighted Average Model

Finally, a genetic algorithm was used to optimize the average, and used to predict the stock returns on the underlying six portfolios. The settings of the GA: Population size 20, No. of generations 100, mutation function 0.05 and crossover function 0.08. In Table 6.14 for the shareholders perspective, GA predicted the stock returns with the maximum accuracy where the RMS values for RHB, RHS, RMB, RMS, RLB, RLS for training are 0.3708, 0.1996, 0.1464, 0.0499, 0.0773, 0.1061, and for testing are 0.415, 0.715, 0.3127, 0.1614, 0.1315, and 0.1211, respectively. According to Figures 6.25 and 6.26, stock returns are predicted with the highest accuracy in the case of all portfolios and decisions for shareholders are investing dividend and disinvesting.

In the case of share prices, in Table 6.14 RMS values for training are 0.2536, 0.2508, 0.2807, 0.1387, 0.1169, and 0.1639 and for testing are 0.9162, 0.5836, 0.4746, 0.1105, 0.1228, and 0.2028 for RHB, RHS, RMB, RMS, RLB, and RLS portfolios, respectively. According to Figures 6.27 and 6.28, there are much stronger expectations about growth, fall and speculative fall in stock prices. These RMS values are least among all the models used and discussed above for predicting stock returns in the multi-stage type 2 model which is a combination of CAPM and VBM. The decisions about shareholders and expectations in share prices are much stronger, compared to all the other techniques used.

Table 6.14: shareholder & share price RMS Training and Testing Results for GA

Multi-Stage Type 2	RMS	RHB	RHS	RMB	RMS	RLB	RLS
Shareholder	Train	0.3708	0.1996	0.1464	0.0499	0.0773	0.1061
	Test	0.4150	0.7150	0.3127	0.1614	0.1315	0.1211
Share price	Train	0.2536	0.2508	0.2807	0.1387	0.1169	0.1639
	Test	0.9162	0.5836	0.4746	0.1105	0.1228	0.2028

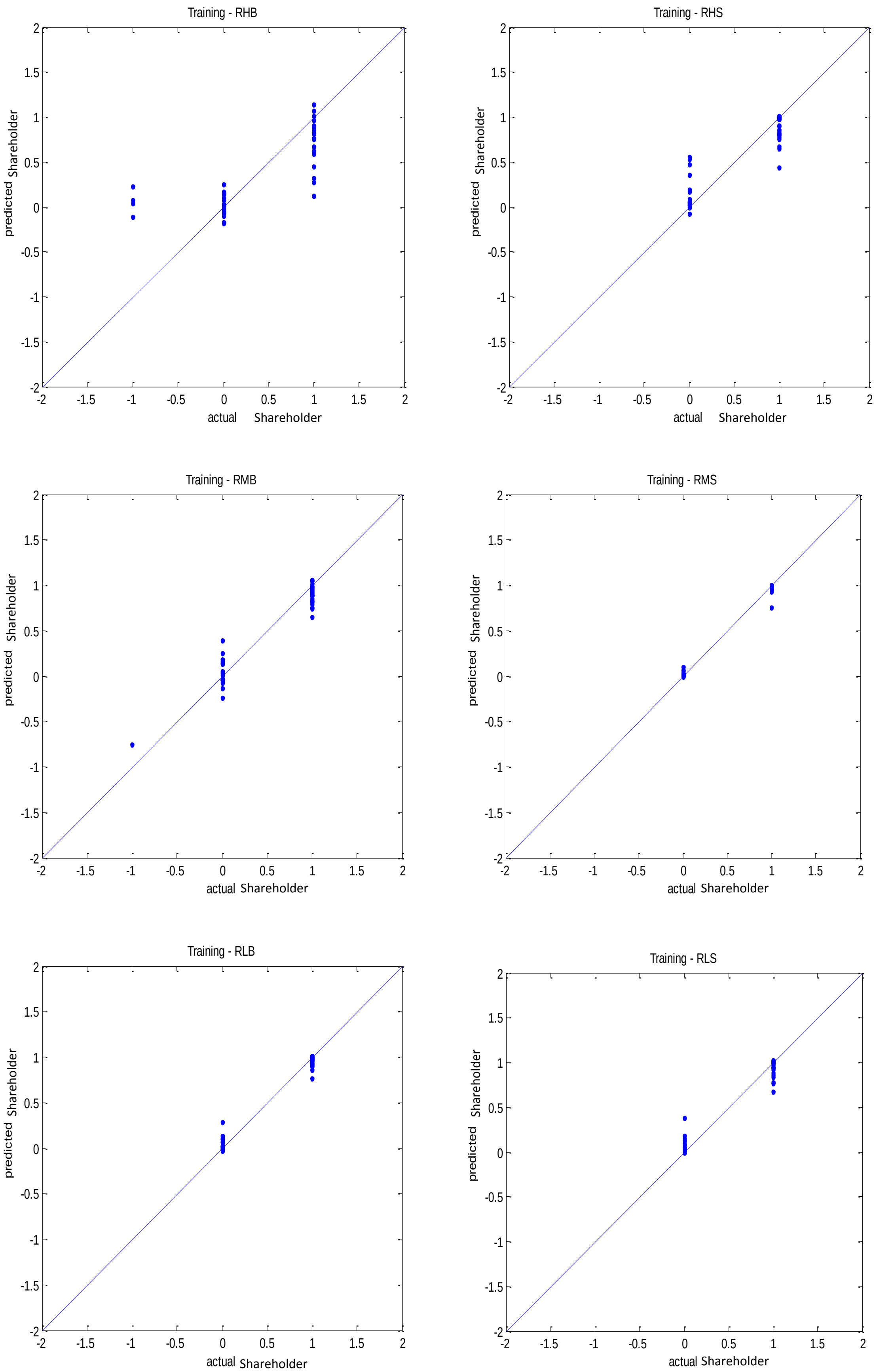


Figure 6.25: RMS Training results (Multi-Stage Type 2 shareholder) using GA technique

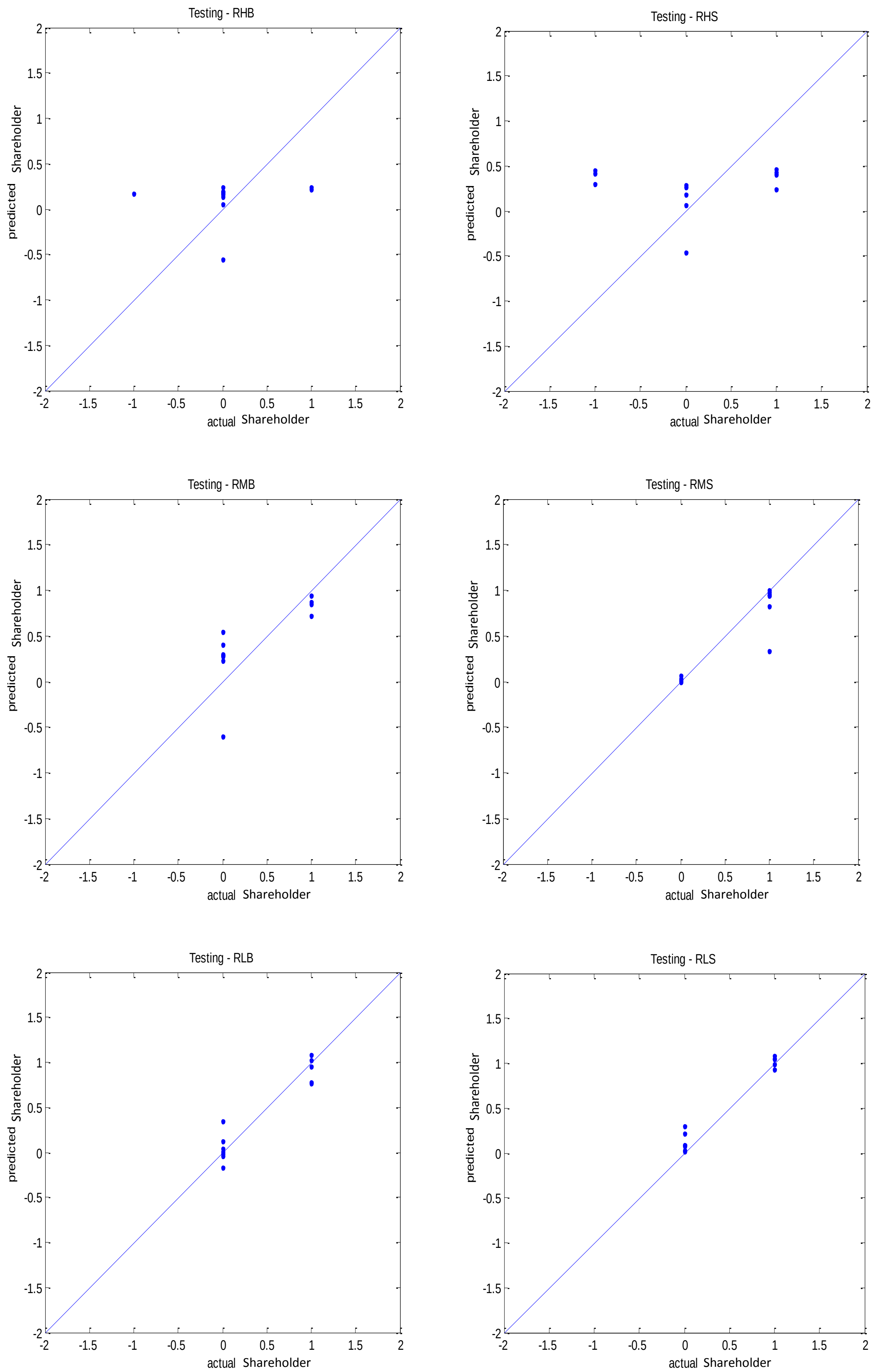


Figure 6.26: RMS Testing results (Multi-Stage Type 2 shareholder) using GA technique

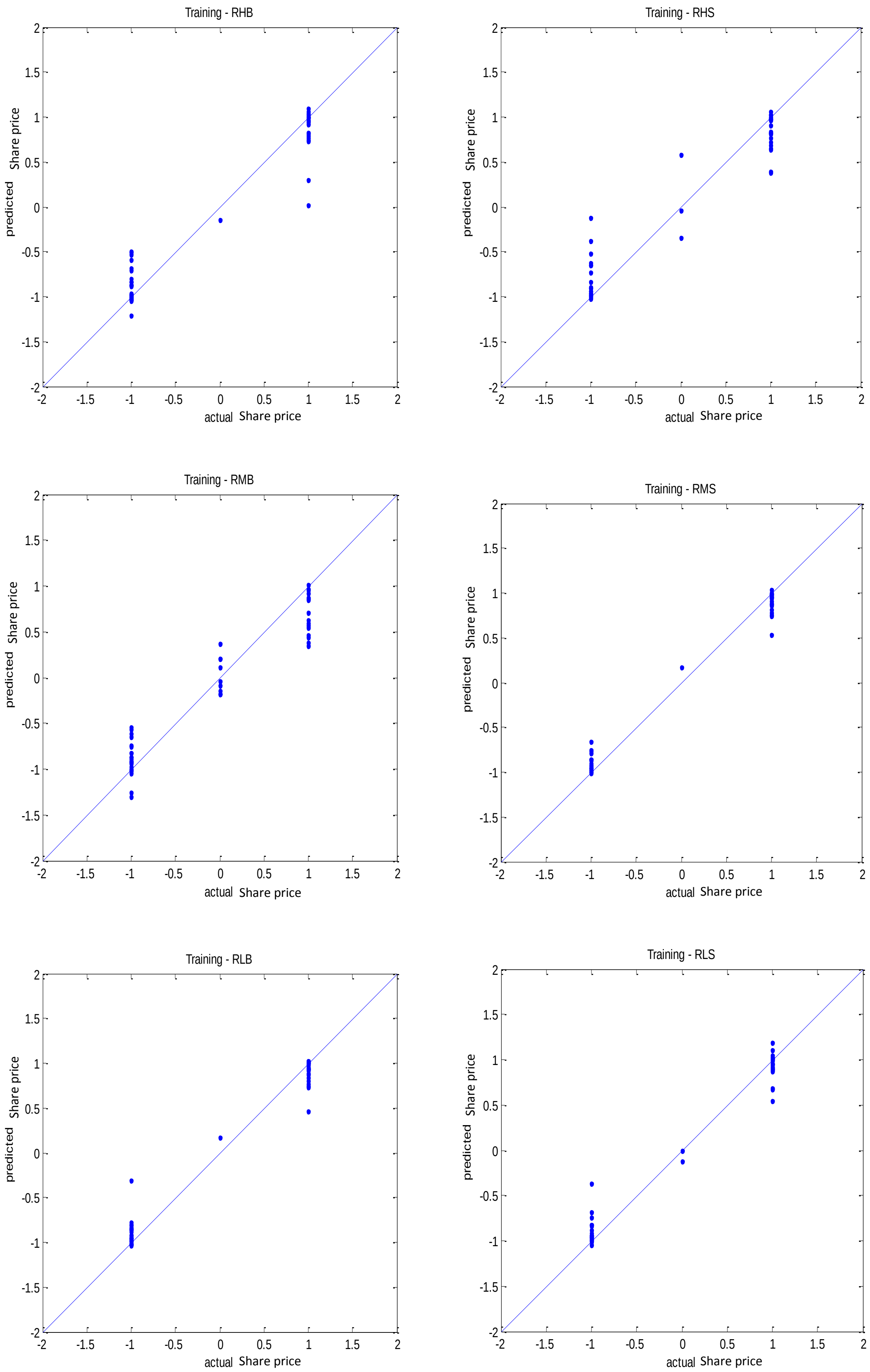


Figure 6.27: RMS Training results (Multi-Stage Type 2 share price) using GA technique

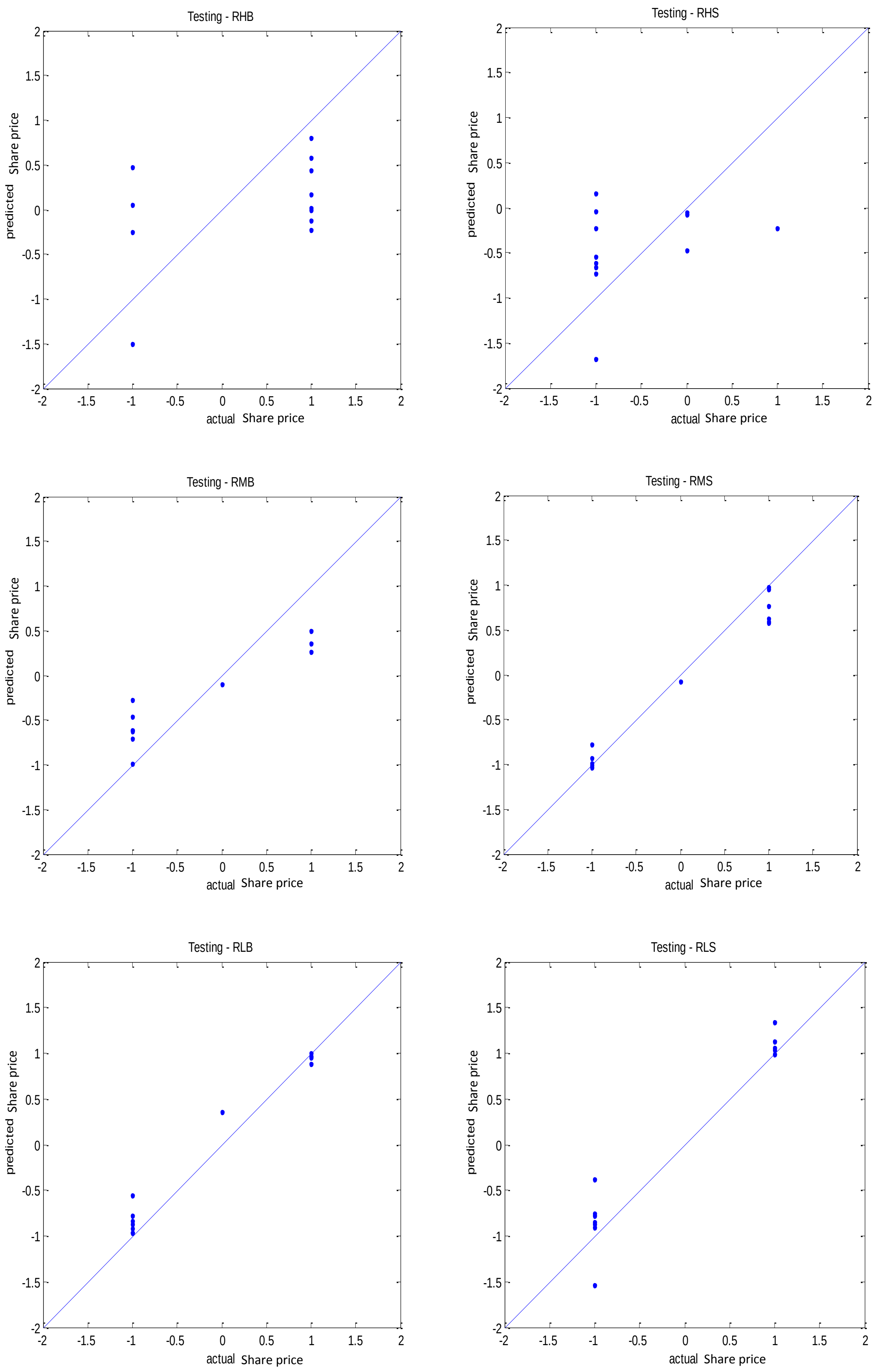


Figure 6.28: RMS Testing results (Multi-Stage Type 2 share price) using GA technique

6.5 Comparison between Multi-Stage Type-1 and Multi-Stage Type-2 models

When comparing the two multi-stage models used in this chapter for making value-based decisions for shareholders and share prices, the conclusion is that the shareholder perspective and decision making based upon multi-stage type-1 (FF + VBM) models provided the best results when using the GA optimized weighted average. The invest, dividend and decisions are recommended for shareholders in almost all the portfolios, however, the level of accuracy of these recommended decisions increased with the use of the multi-stage type-1 model, based upon the GA optimized weighted average. Similarly, with respect to expectations in stock price movements, the results suggested that growth, fall and speculative fall expectations are found in the share prices of the Saudi Arabian Stock Market. The perfection of expectations increases for all the stock portfolios when the average and weighted average methods are used, instead of individual ANN techniques. This prediction accuracy and perfection is considered to be best if used with the GA optimized weighted average method. In comparison, it can by summarized that the multi-stage type-1 model, which is based upon the FF model and value-based management, is better and provided the best results compared to the multi-stage type-2 model, based upon CAPM and VBM, for both shareholders and share prices movements, as shown in Tables 6.15 and 6.16. So in our study sample of the Saudi Arabian stock market, the multi-stage type-1 model is preferable.

Table 6.15: Results multi-stage type 1 and multi-stage type 2 Models for GA shareholder

shareholder		RHB	RHS	RMB	RMS	RLB	RLS
Multi-stage type 1	Train	0.2340	0.1262	0.1367	0.0313	0.0686	0.0935
	Test	0.2111	0.1767	0.1222	0.0899	0.0996	0.0701
Multi-stage type 2	Train	0.3708	0.1996	0.1464	0.0499	0.0773	0.1061
	Test	0.4150	0.7150	0.3127	0.1614	0.1315	0.1211

Table 6.16: Results multi-stage type 1 and multi-stage type 2 Models for GA Share price

Share price		RHB	RHS	RMB	RMS	RLB	RLS
Multi-stage type 1	Train	0.2455	0.2161	0.262	0.113	0.141	0.1334
	Test	0.2932	0.3565	0.2691	0.1624	0.1034	0.087
Multi-stage type 2	Train	0.2536	0.2508	0.2807	0.1387	0.1169	0.1639
	Test	0.9162	0.50836	0.4746	0.1105	0.1228	0.2028

6.6 Graphical User Interface

In addition to proposing a stock market prediction model for the Saudi financial market, the study also created a Graphical User Interface (GUI) in Matlab software. This is an input-output based interface which returns the suggested decision for shareholder and share price based upon the best model (multi-stage type 1 based upon FF + VBM), recommended by the earlier analysis. There are seven inputs, namely company type, market return, size effect, book to market ratio, WACC, (Rexp), and (Ract). Outputs are the decisions for shareholder and share prices movement. The company type is its classification of portfolio such as any one of RHB, RHS, RMB, RMS, RLB, RLS etc. Market return, size, and book to market ratio are the inputs of the FF model, which gives outputs of required return then using that with WACC, (Rexp), and (Ract), as input for VBM Model. The output will be either for shareholder decision making in terms of invest, dividend or disinvest as well as for share price expectations such as growth, fall or speculative fall. The algorithm behind this user interface applies the value-based management model along with FF on the basis of required returns, WACC, (Rexp), and (Ract). (As discussed in the methodology) and delivers the decision/expectation to the user in a much easier manner. The users or investors do not have to carry out many calculations and they can easily make investment decisions and predict price movements based upon the output of this interface. This may prove to be very helpful in investment decision making for Saudi investors. We can also get the best result when making the evaluation of this application and the methodology working behind this graphic user interface validated by users and investors by providing feedback regarding this decision-making model and system. The GUI front page is shown in Figure 6.29.

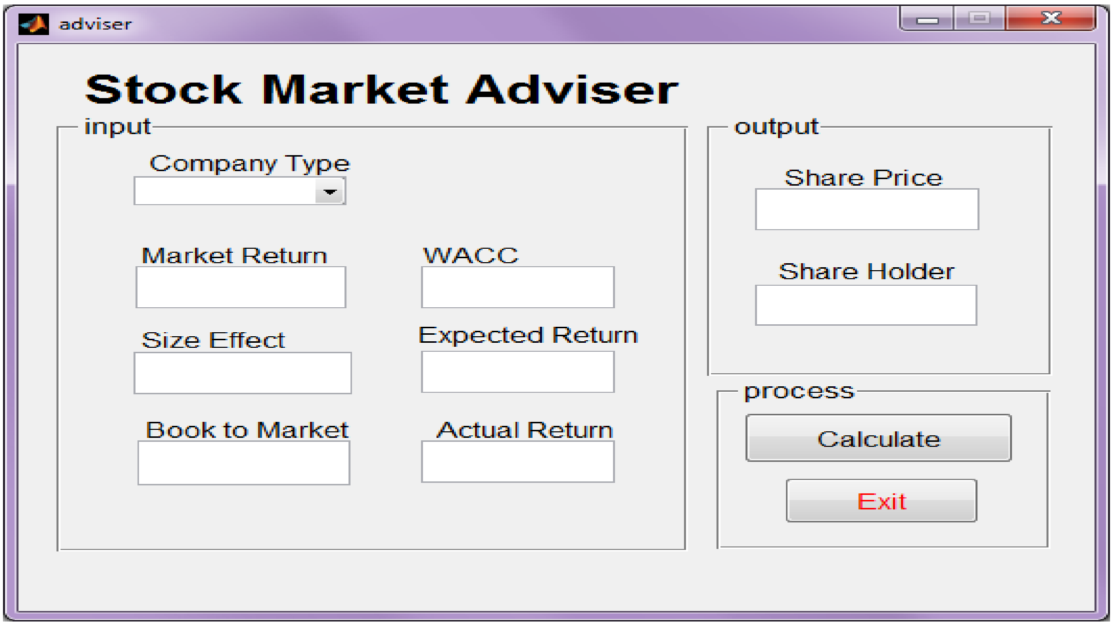


Figure 6.29: The GUI front page.

6.7 Summary

Forecasting of stock market returns is an important phenomenon in financial economics literature. This is also one of the most researched empirical issues in finance and researchers tried their best to discover the best techniques to predict stock returns, so than market anomalies can be minimized. Two frameworks have been designed in this study and it is called the multi-stage type 1 VBM and FF model, and the multi-stage type 2 VBM and CAPM Model. The multi-stage type 1 model first executes the processes under the framework of the VBM model. The one of the input to the VBM model is given as an output of the FF model for further processing. The design of this model is very flexible, estimating the weighted average cost of capital, the expected investment return, the actual return of investments and the required return on invested capital. The multi-stage type 2 model first executes the processes under the framework of the VBM model. The one of the input to the VBM model is given as an output of the CAPM model for further processing. The design of this model is very flexible, estimating the weighted average cost of capital, the expected investment return, the actual return of investments and required return on invested capital. In this regard, the present chapter uses different ANN-based forecasting techniques in order to predict stock returns, based upon CAPM and Fama and French concepts for different portfolios and to make appropriate decisions for shareholders about expectations of share prices in the Saudi Arabian Stock Exchange. This present chapter applies two different multi-stage type models, one of which is a combination of FF and VBM, whereas the other one is based upon CAPM and VBM. The decisions given to shareholders are to invest, disinvest or dividend, whereas stock price expectations are assumed to be fall, growth and speculative fall. The results concluded that ANN techniques, optimized by the GA weighted average and based upon the multi-stage type 1 model of FF + VBM, could be used in the best manner by investors in the Saudi Arabian financial market to make value-based investment decisions. GA is the best technique to predict stock returns in Saudi Arabia and the multi-stage type 1 model of FF + VBM applies to decision making by investors, because it improves the level of predicting accuracy for stock market returns, investment decisions and the movement of future stock prices in the emerging market of Saudi Arabia. Matlab software also generated a graphic user interface (GUI) for Saudi investors to participate in the investing activities more easily, by following the rules finalized in the results discussion of this research study. This may prove to be very helpful in investment decision-making for Saudi investors who do not have enough time or expertise to make such complex investing calculations. In the future can be further verified and validated by obtaining feedback from the investors participating in the Saudi Arabia Stock Exchange to improve this application.

CHAPTER 7

Conclusions and Future Work

7.1 Conclusions

Stock markets play a crucial role in the economic development of any country and they are considered as the barometer of a country's progress. The stock markets are developed if the level of investing activities is enhanced and investors are making more and more transactions. Investment activities depend on the stock price prediction capability of investors which is a very tricky and complicated task in financial markets as these prices behave in a random fashion and vary over time. Owing to the potential of returns and the inherent risk factors in stock market returns, researchers have proposed various stock market prediction models and decision support systems to provide investors with an optimal forecast of stock prices and returns. Forecasting of stock market returns is an important phenomenon in financial economics literature. It is also one of the most researched empirical issues in finance and researchers have tried their best to find out the best techniques to predict stock returns so that market anomalies can be minimized. Two of these commonly used stock return prediction models are the capital asset pricing model (CAPM) and the three-factor model proposed by Fama and French in their empirical research papers. Usually, these models assume that the relationship of stock returns and their independent variables is linear and researchers have applied linear econometric models to forecast stock prices and returns. However, the greater level of complexity inherent in the relationship of stock market prices and their risk factors made intelligent prediction paradigms highly significant, as well as forecasting stock prices using the conventional prediction models of CAPM and Fama and French.

The present study is a preliminary attempt in this regard to apply artificial neural network techniques (along with adaptive neural fuzzy inference systems and genetic algorithm) to stock market prediction models (capital asset pricing models and Fama French three-factor model) to stock prices and returns on the Saudi Arabian Stock Exchange using monthly data starting from January 2007 to December 2011. Predicted stock returns have been obtained for both stock market prediction models, CAPM and the Fama French model, and the output has been used in a value-based decision-making model. The value-based management model focuses on four dimensions: required rate of returns, expected returns on investment, actual return of investment, and weighted cost of capital. The study makes a contribution to stock prediction by design a value-based decision-making model to investing activities which is done by developing a graphic user interface simple application. This application tries to be helpful for investors who do not have much knowledge about background stock prediction.

In order to boost the predictive power of stock prediction models, various ANN models have been applied as well. For both CAPM and Fama and French, forecasting has been done by using a linear regression model along with eight ANN models – Cascade-Forward Network (CF), Elman Neural Networks (ELM), Feed Forward Input Time-Delay Back Propagation Network (FFTD), Feedforward Neural Networks (FF), Distributed Time Delay Neural Network (DTDNN), Fitting Networks (FIT), Radial Basis Function Network (RB) and Adaptive Neural Fuzzy Inference Systems (ANFIS). Along with this, the simple average and weighted average of all these ANN models, as well as the Genetic Algorithm (GA), are also used as stock return prediction models for the Saudi Arabian Stock Exchange for the period of January 2007 to December 2011 using MATLAB software. There have been six portfolios constructed namely RHB, RHS, RMB, RMS, RLB, and RLS for which training and testing returns have been obtained during the sample period by applying linear as well as non-linear techniques of ANN.

The findings of stock market predictions based upon CAPM and Fama and French indicate that linear models provide the weakest prediction of stock returns both in the case of CAPM and Fama and French. Moreover, this prediction power of stock prices and returns tends to increase when non-linear models of artificial neural network were applied for estimating returns on portfolios of selected securities on the Saudi Arabian Stock Exchange. ANN also provides better results compared to adaptive neural fuzzy inference systems (ANFIS). The improved prediction power after the application of non-linear artificial neural network model techniques improves even more when the average and weighted average method is used instead of using an individual model of artificial neural networks. However, when the genetic algorithm (GA) was used in stock market prediction, it provided the best results and can be considered as the best prediction model in the case of the Saudi Arabian Stock Market, providing the best estimates of stock returns with lowest prediction error as measured by root mean square error. After the genetic algorithm, the weighted average method of ANN and average method provide the best results, respectively. So GA is the best technique to use in the case of the Saudi Arabian Stock Market returns prediction, followed by the weighted average of ANN models, because it improves the level of predicating accuracy for stock market returns, investment decisions and the movement of future stock prices in the emerging market of Saudi Arabia.

If the results of predicted stock returns calculated on the basis of CAPM and Fama and French are compared, it becomes evident that Fama and French is a better model for estimating stock market prices and returns with greater accuracy and less estimation error in the Saudi Arabian Stock Exchange. In addition, the returns predicted using Fama and French model are plotted closer to the prediction line in figures as compared to CAPM, where actual return points are located relatively far from the main prediction line. So, it can be summarised that Fama and French model is better and preferable to CAPM when using the Genetic Algorithm method in the case of our sample of Saudi Arabian stock portfolios. Like many other emerging and developing capital markets, the Saudi Arabian Stock Exchange provides for the applicability of the Fama and French three-factor model in comparison to the capital asset pricing mode. This preference for Fama and French model might be due to the size effect anomaly present in the Saudi market which causes CAPM to be less effective.

In the second stage, the study used a value-based management model on the basis of predicted return values obtained through Fama and French model, as well as the CAPM by estimating the model in linear and nonlinear artificial neural network techniques. These results are called multi-stage type-1 and multi-stage type-2 for the purpose of investment decision-making, also called value-based management in the Saudi Arabian Stock Exchange. This is based upon shareholders' perspective as well as share price perspective. Using the Value- Based Management (VBM) model of decision-making and prediction of stock portfolio returns with the help of Artificial Neural Networks (ANN), expectations of shareholders and portfolio investors to take investment decisions and the behaviour of stock prices are discussed. The perspective of the shareholder narrates the decision-making done by shareholders which consists of investing, dividends and disinvesting decisions, whereas the perspective of share prices narrates movements and behaviour of stock prices in terms of fall, speculative fall and growth.

The findings summarized that multi type 1 model, which is the combination of Fama and French three-factors predicted returns plus the value-based management model, provided the best results when obtained using the genetic algorithm optimized weighted average with a focus on shareholder perspective. The results of the multi-stage type-1 model recommend shareholders' decisions such as dividends and investing more in stocks in almost all the stock portfolios obtained, however, the accuracy of results is at its peak when these predicted stock returns are obtained using the genetic algorithm optimized weighted average. On the other hand, the multi-stage type-1 model with a perspective of share prices suggests that there are expectations about growth and fall in share prices on the Saudi Arabian Stock Exchange during the sample period. Just like previously, the prediction accuracy is at its best when predicted returns are obtained through the genetic algorithm-optimised weighted average instead of various individual artificial neural network techniques. In summary, it can be concluded that multi-stage type-1 model, a combination of Fama and French three factors and value based management, is better than multi-stage type-2 which is the combination of the capital asset pricing model and value-based management, in terms of greater accuracy and less error for both shareholders' perspective as well as share prices' perspective. Hence, in the case of our research, the multi-stage type-1 model is preferable in the case of the Saudi Arabian stock market.

Finally, along with comparing and selecting a stock market prediction model for the Saudi Arabian Stock Exchange on the basis of value-based management, Matlab software also generated a graphic user interface for Saudi investors to participate in the investing activities more easily, by following the rules finalized in the results discussion of this research study. This interface is an input/output based application returning the recommended decision for investors from the shareholder perspective as well as from the share price perspective, using the best model of this study i.e. multi-stage type-1 of Fama and French and value-based management. Using several inputs such as type of stock, market returns, size, value, WACC etc., this application recommends different investing decisions to Saudi investors. The advantage of this interface is that the investors do not need to perform many complex and difficult calculations and he/she can easily make investment decisions and observe price movements based upon the output of this graphic user interface. This may prove to be very helpful in investment decision-making for Saudi investors who do not have enough time or expertise to make such complex investing calculations.

The findings of the present study also provide some practical implications for the investors and regulators. It is found that the Fama and French model is better applicable to the Saudi Stock Exchange, which is an indication that there exists a size anomaly in the Saudi capital market. The investors must be careful while investing in the Saudi stock market regarding the size and value effects, as these are important predictors of stock returns variations in Saudi Arabia. Moreover, value-based management can be proven to be a significant decision- making tool in the capital markets of emerging markets, particularly when estimated non-linearly by the use of the genetic algorithm optimized weighted average of artificial neural network techniques. Investors should use the Fama and French model estimated in its non-linear form to make best investment decisions both from the shareholders' perspective as well as from the share prices' perspective. This model is best when investors want to make investment or disinvestment decisions equally or when they wish to see the behaviour of the stock prices on the Saudi Arabian Stock Exchange. Moreover, the regulators must also be careful regarding the stock market of Saudi Arabia because investment activity can be improved in the market by providing information and training about the latest artificial intelligence stock market prediction tools and techniques which not only increase the market turnover and liquidity but also the market capitalization of the Saudi stock market.

7.2 Future Work

The findings of the present study also provide some important future guidelines for researchers in the field of economics and finance, particularly those conducting research in capital markets with a focus on stock price and returns forecasts for better investment decisions. This study recommends that other models related to artificial intelligence systems for stock price prediction and forecasts successfully implemented in the developed capital markets should be applied to the Saudi Arabia market by adding new variables at the micro level such as market, size and book to market and macro level like term structure and default risk Fama and French (1993) that relate to the nature of the religion and culture. These models should not only differ in their estimation methodology but also in the process of estimation of stock returns. For instance, the arbitrage pricing theory of Ross or the inter-temporal capital asset pricing model of Merton can also be used to compare the results of the capital asset pricing model and Fama and French three-factor models used in the present study. Not only these, but the extensions of Fama and French model such as the five-factor model, zero beta model and others can be used in a similar way to predict stock market behaviour in Saudi Arabia.

Moreover, the scope of this study is limited to only sixty monthly observations with a limited number of companies listed on the Saudi Arabian Stock Exchange. Future research studies can overcome this limitation by adding more companies to the sample, as well as conducting the research over a longer time period. This may obtain better results regarding stock market returns estimation and the value-based management model. In addition, the market efficiency of the Saudi Arabian Market must be tested in depth by applying the Efficient Market Hypothesis tests at the three forms to improve the confidence of Saudi investors regarding risk-adjusted return reward investing background in front of speculating methodology. Furthermore, a comparative analysis of stock prediction models among Gulf countries, as well as the Middle East and North Africa (MENA) region, should be carried out to better compare and contrast the results regionally among developing markets. This will provide a better picture of value-based management in different economies.

Last but not least, the graphic user interface developed in this study can be further verified and validated by obtaining feedback from the investors participating in the Saudi Arabia Stock Exchange. The feedback of the investors and users is not only helpful in improving the decision-making in the value-based management model, but other extensions of this graphic user interface can be proposed by modifying it into a more user-friendly version. The evaluation of this application and the methodology working behind this graphic user interface can also be validated by users and investors by providing feedback regarding this decision-making model and system.

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Appendix

Appendix A : Prediction Result using FF Model

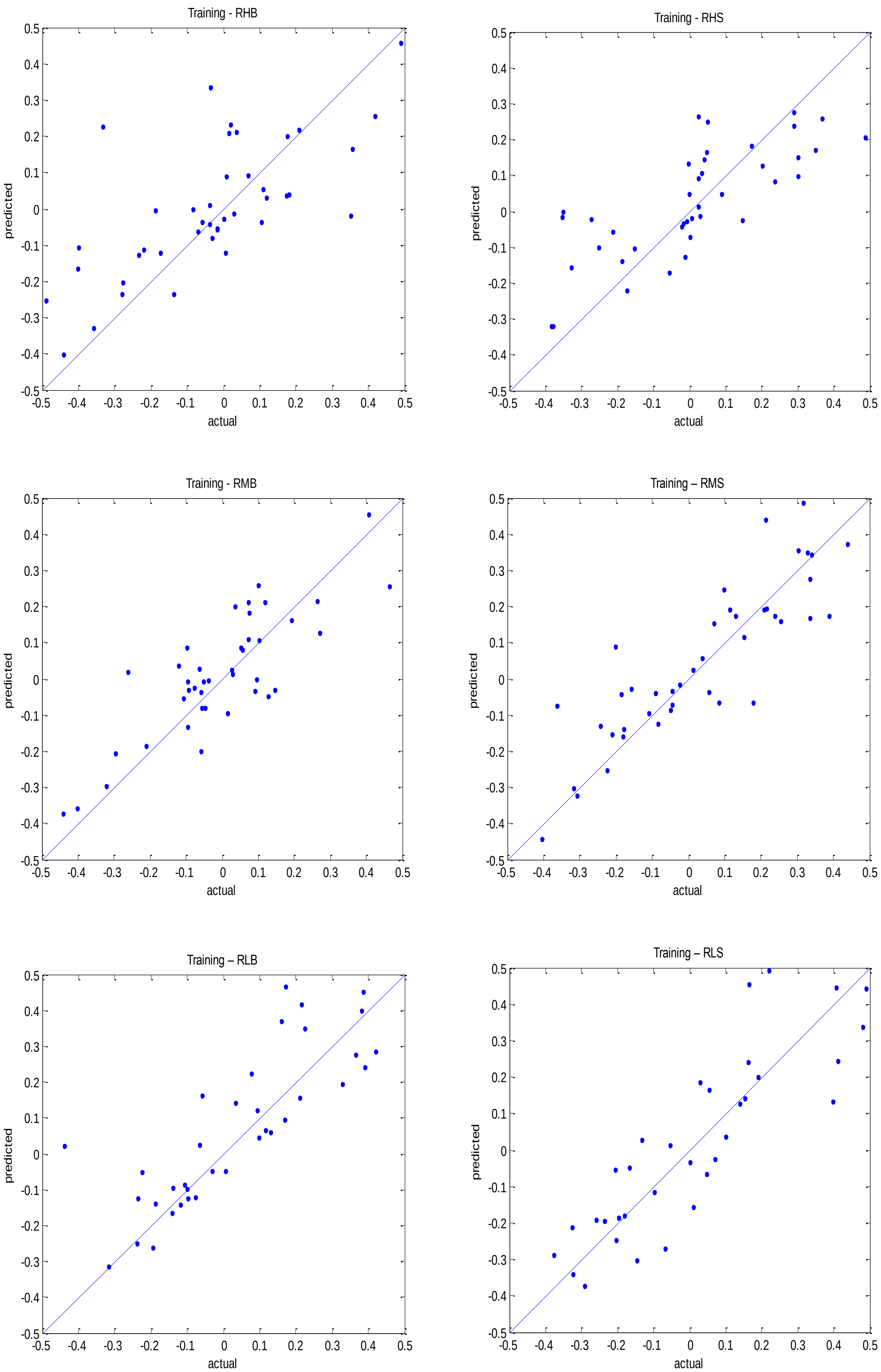

Figure A1: training results (FF) using ANN technique (NEWCF).

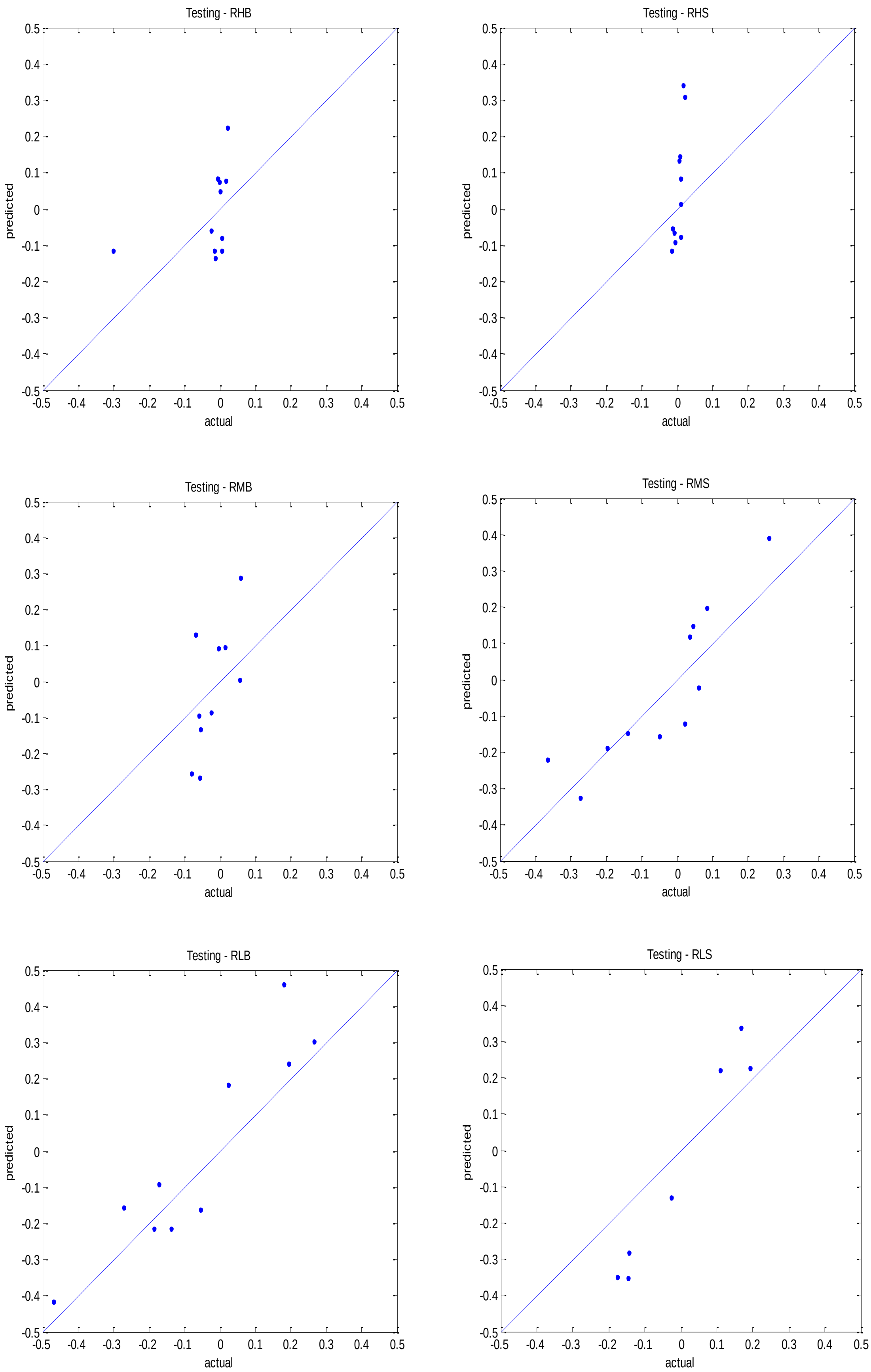

Figure A2: testing results (FF) using ANN technique (NEWCF).

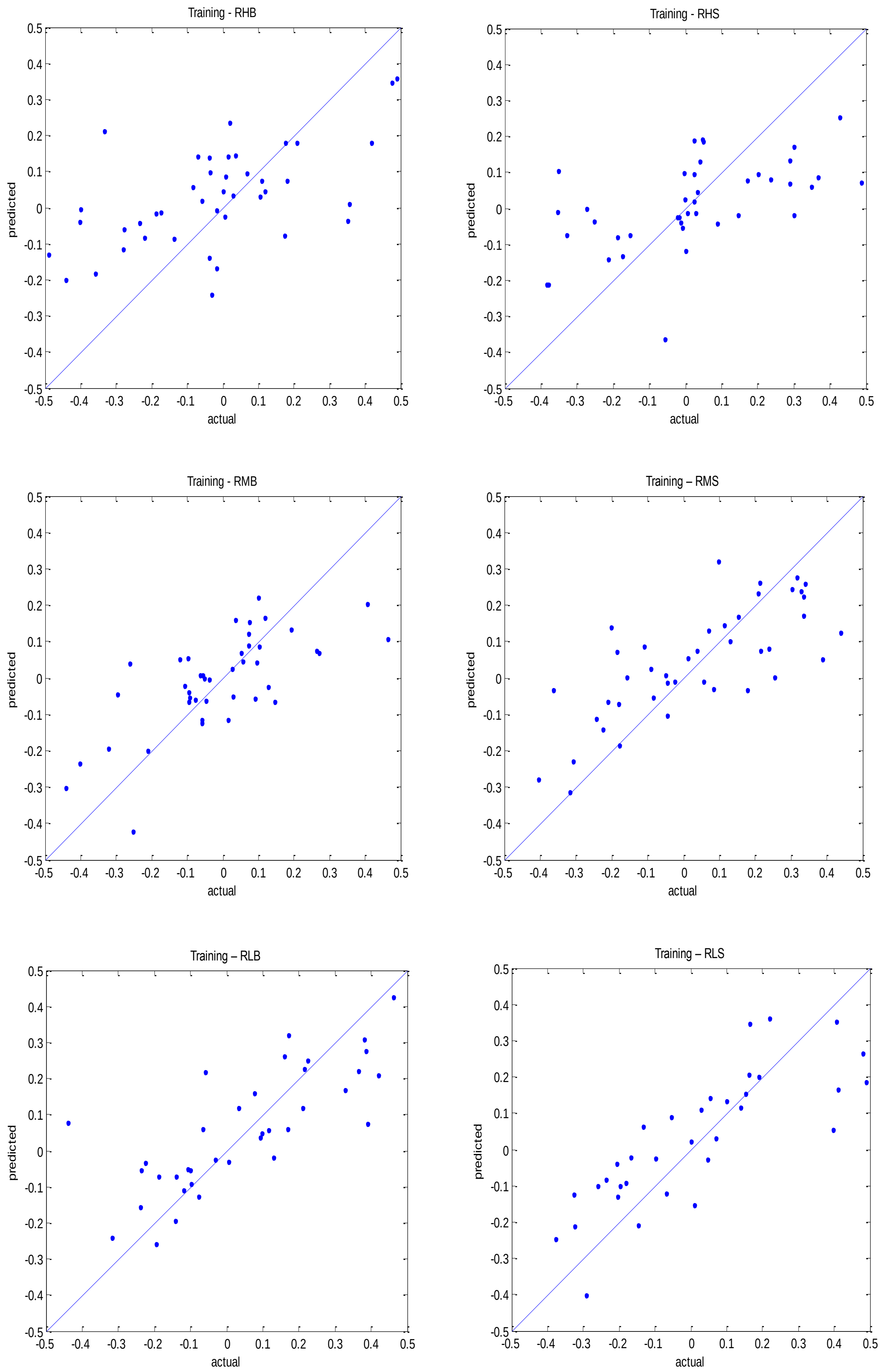

Figure A3: training results (FF) using ANN technique (NEWELM).

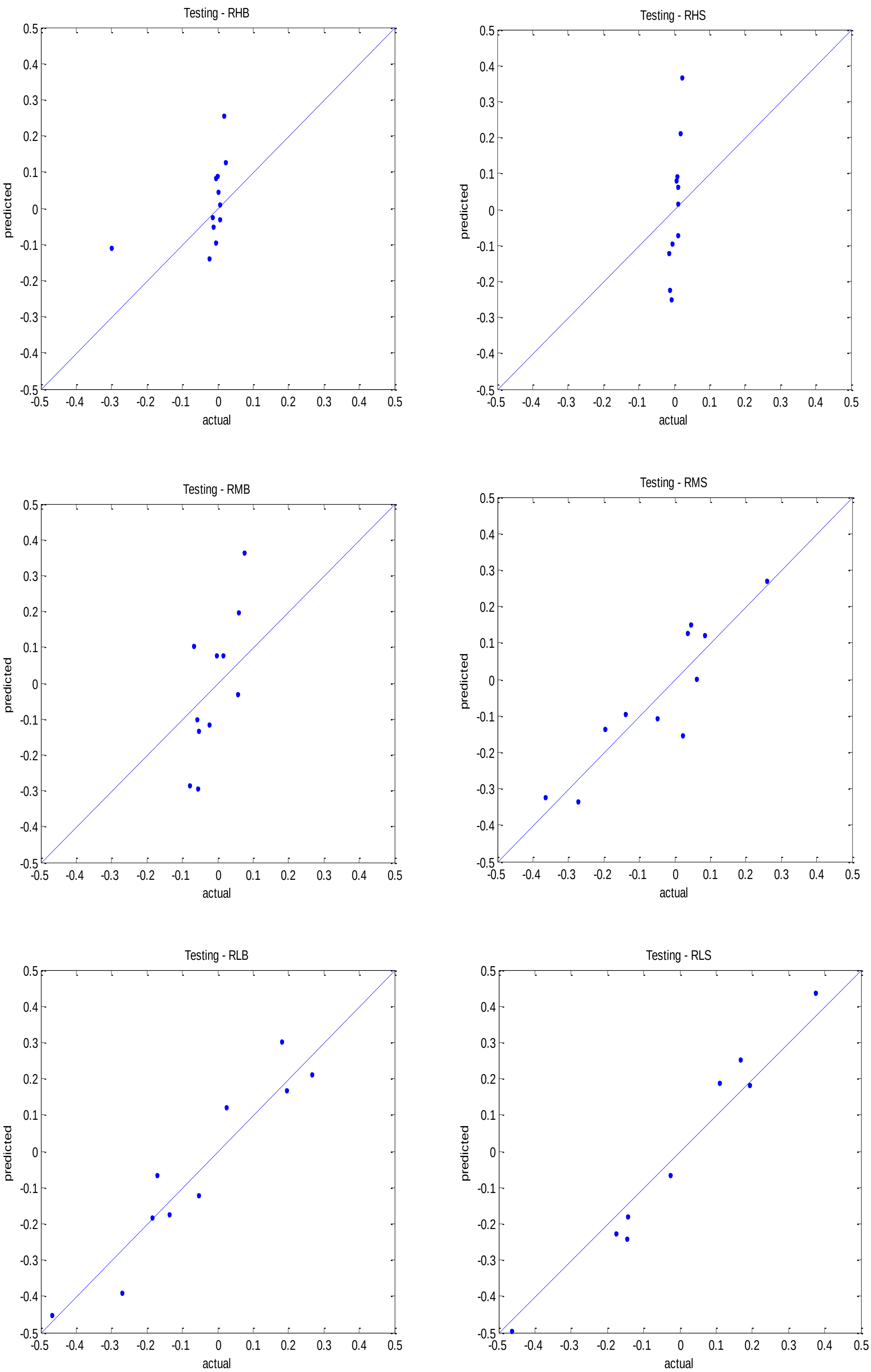

Figure A4: testing results (FF) using ANN technique (NEWELM).

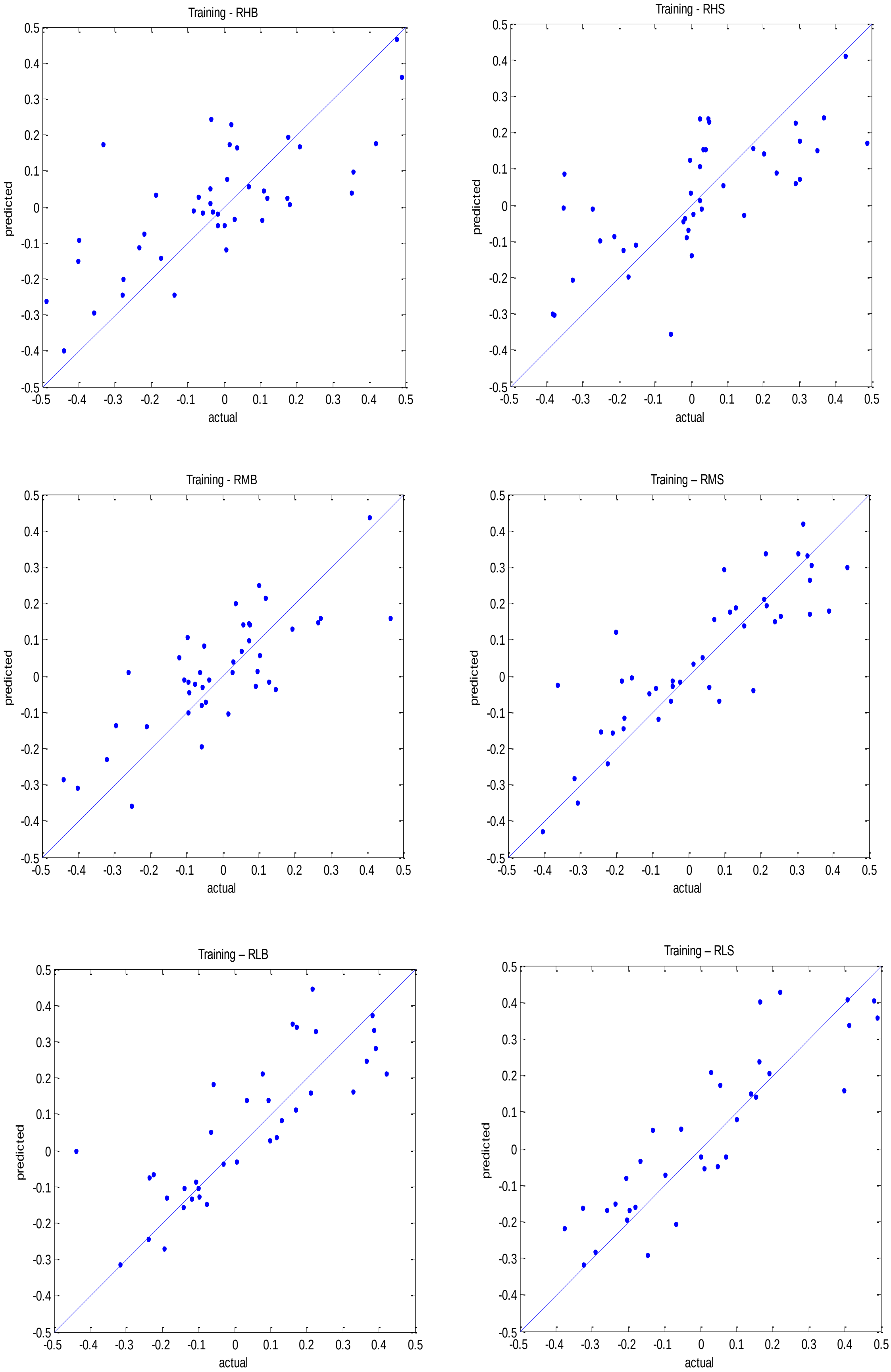

Figure A5: training results (FF) using ANN technique (NEWFFTD).

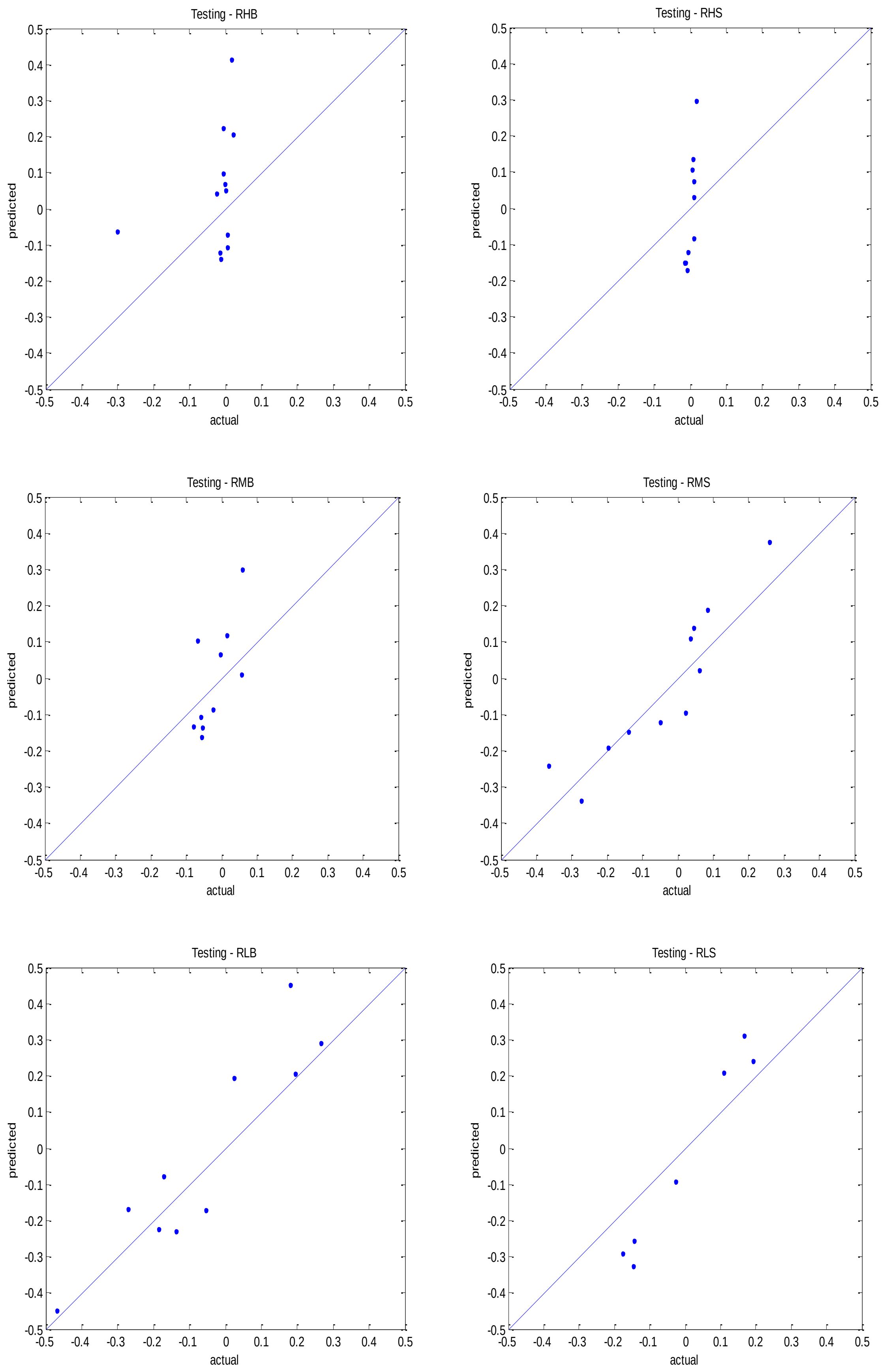

Figure A6: testing results (FF) using ANN technique (NEWFFTD).

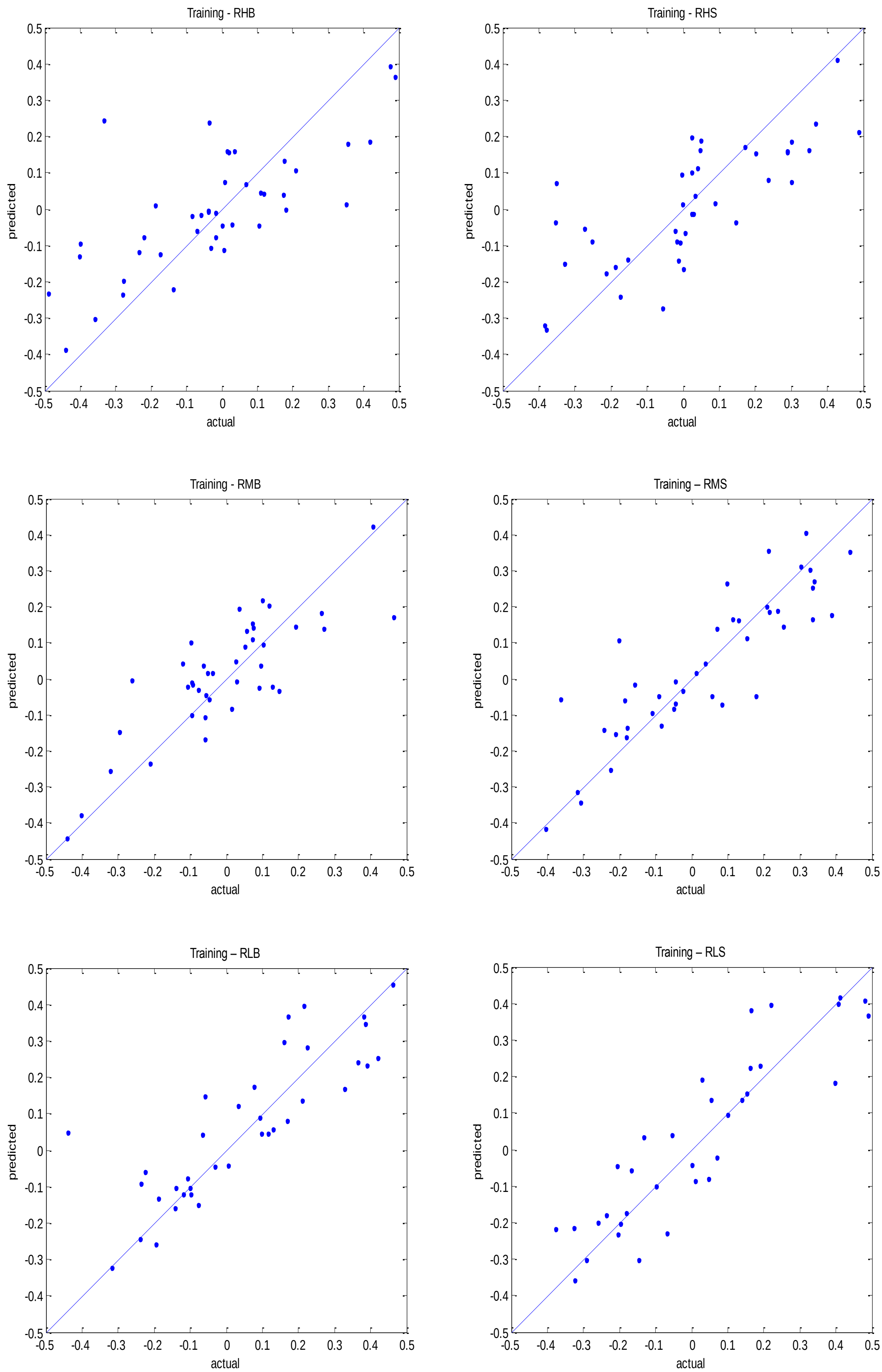

Figure A7: training results (FF) using ANN technique (NEWFF).

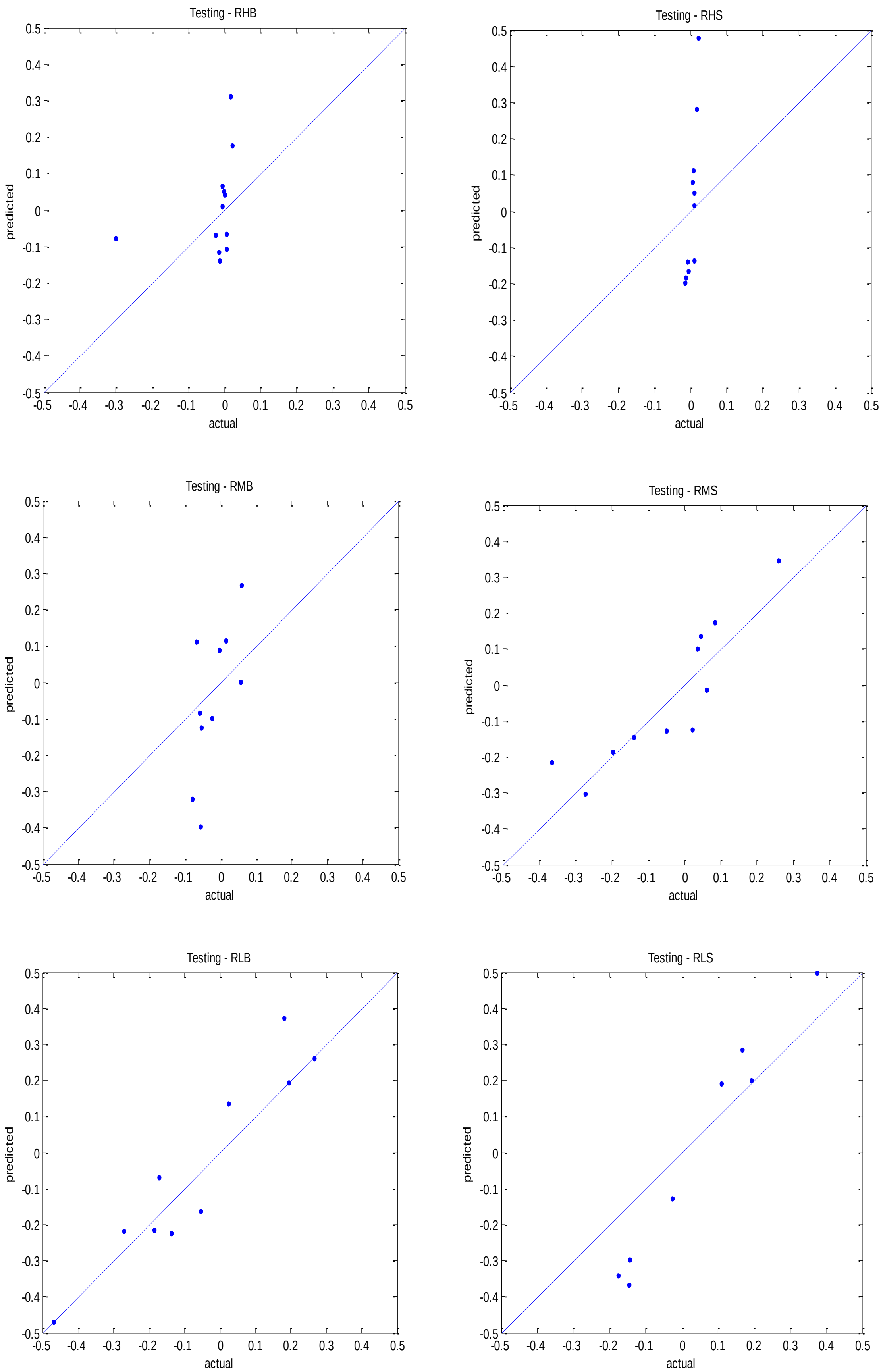

Figure A8: testing results (FF) using ANN technique (NEWFF).

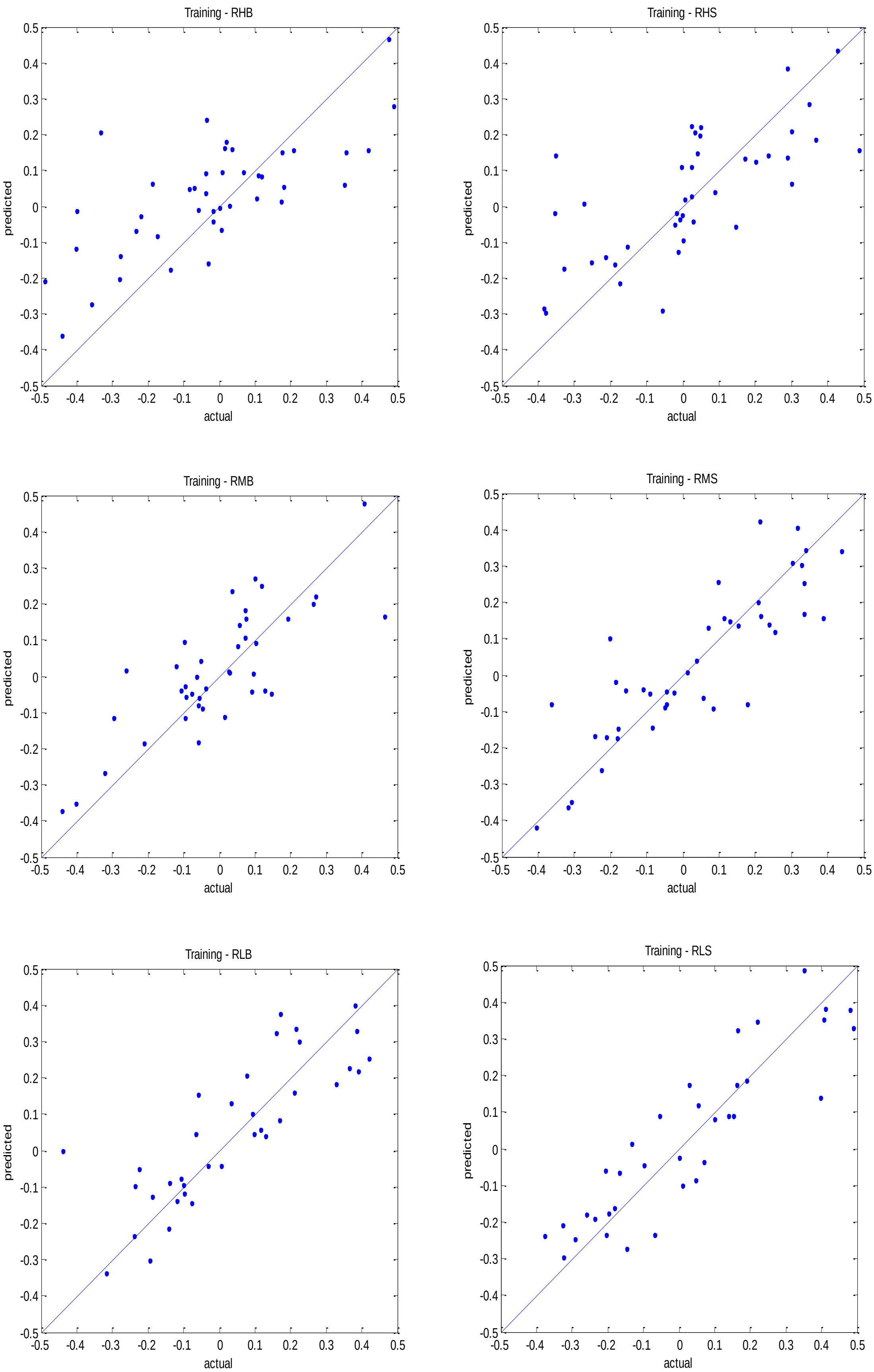

Figure A9: training results (FF) using ANN technique (NEWDTDNN).

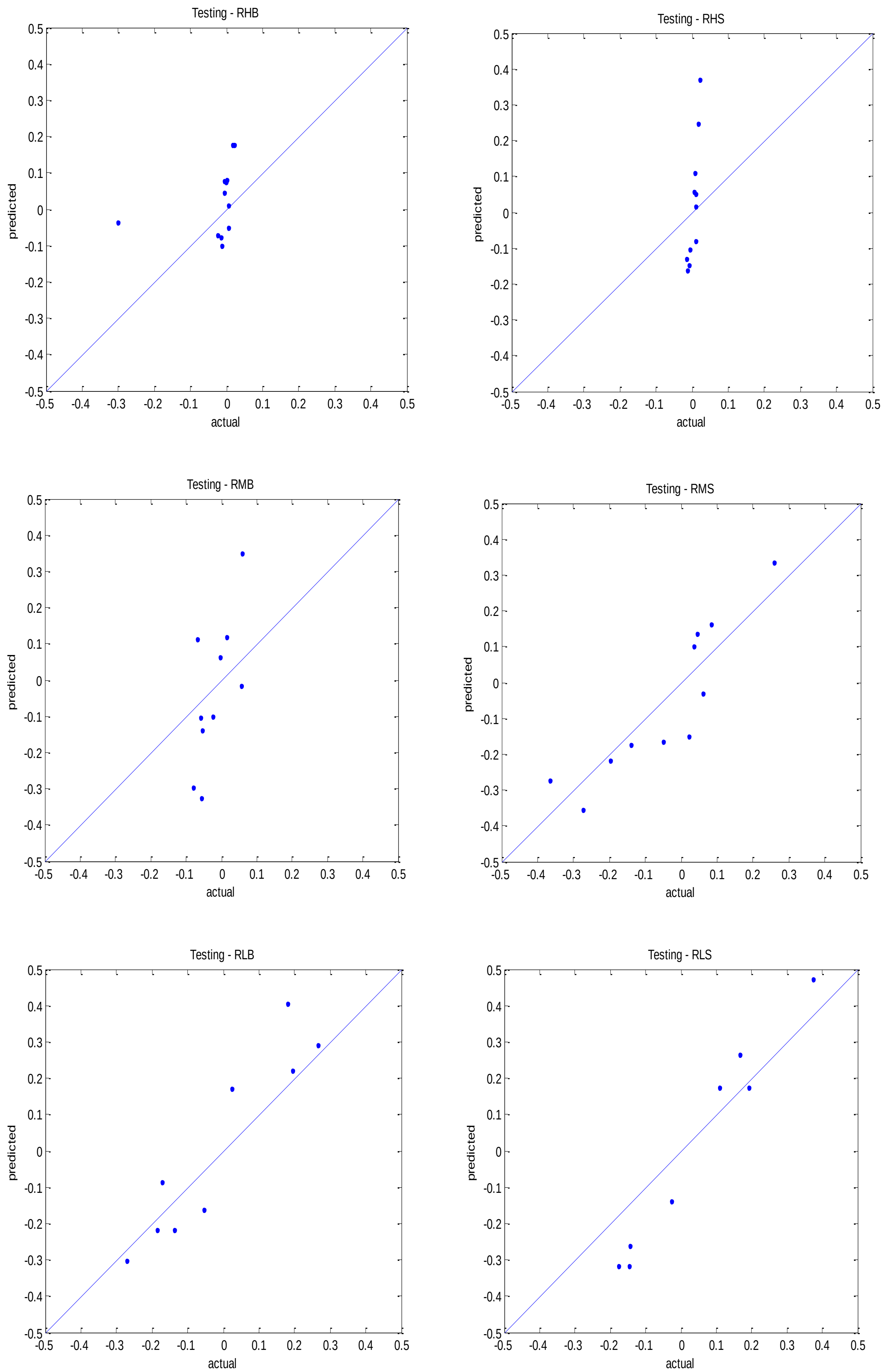

Figure A10: testing results (FF) using ANN technique (NEWDTDNN).

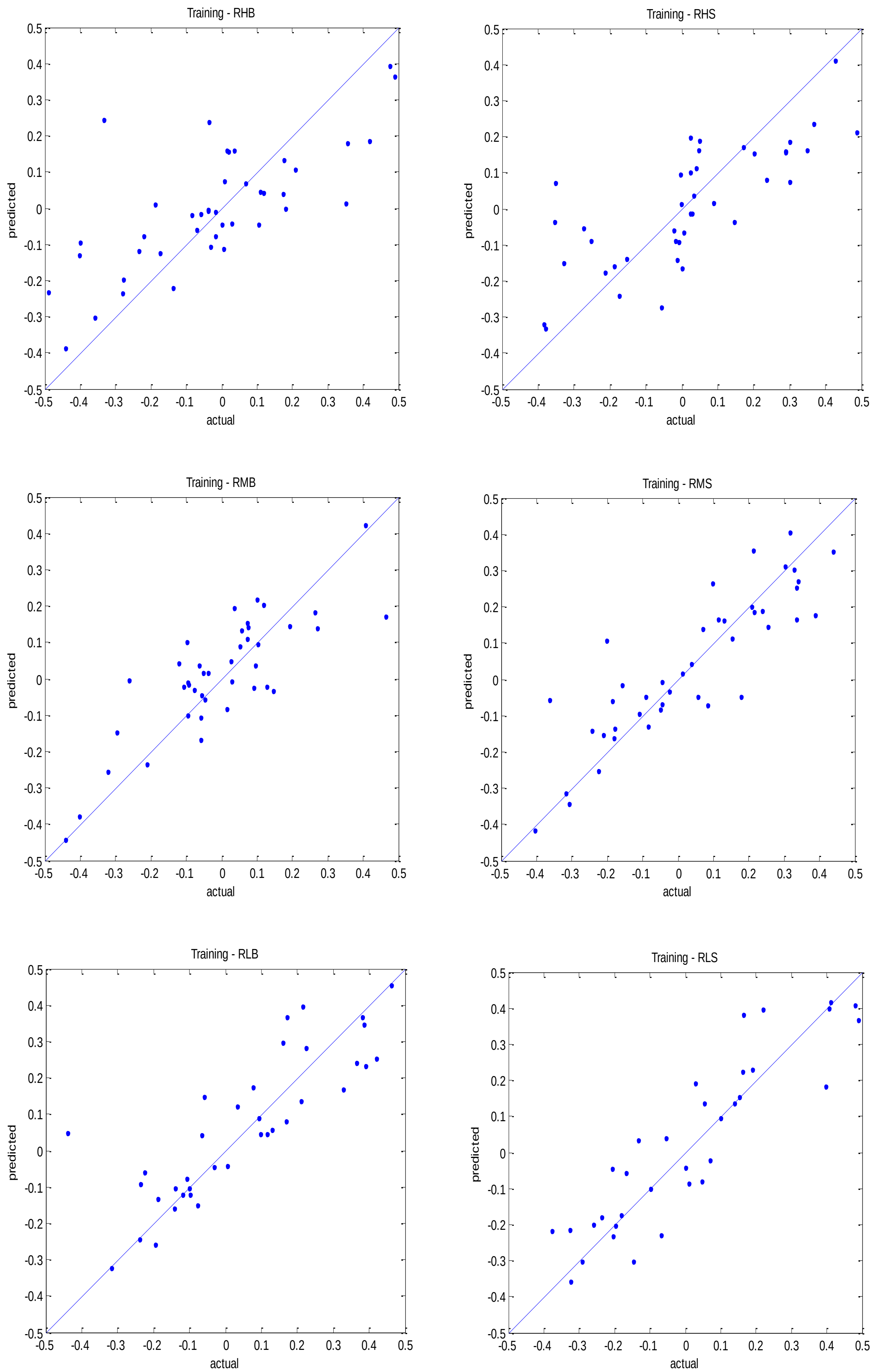

Figure A11: training results (FF) using ANN technique (NEWFIT).

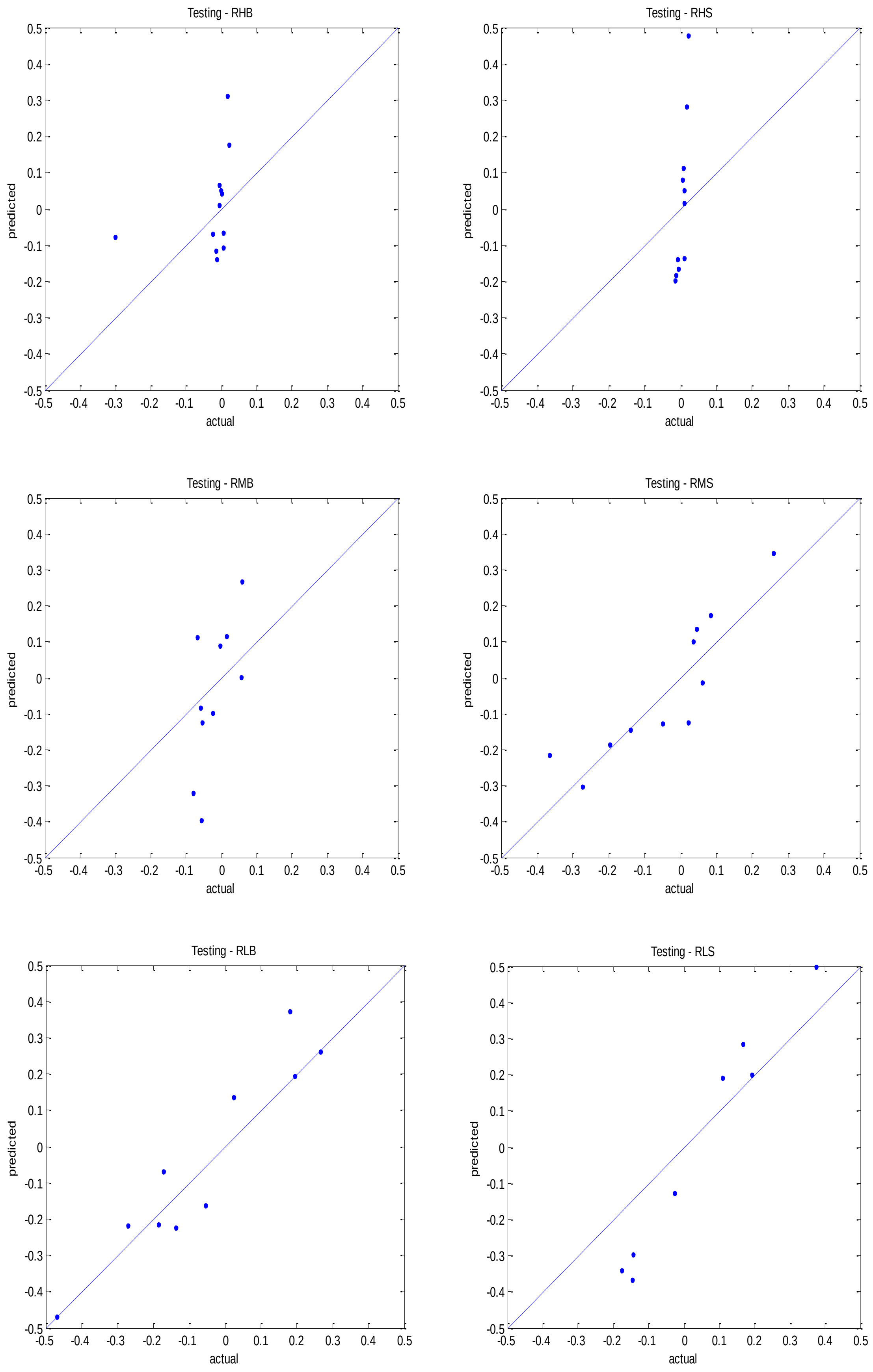

Figure A12: testing results (FF) using ANN technique (NEWFIT).

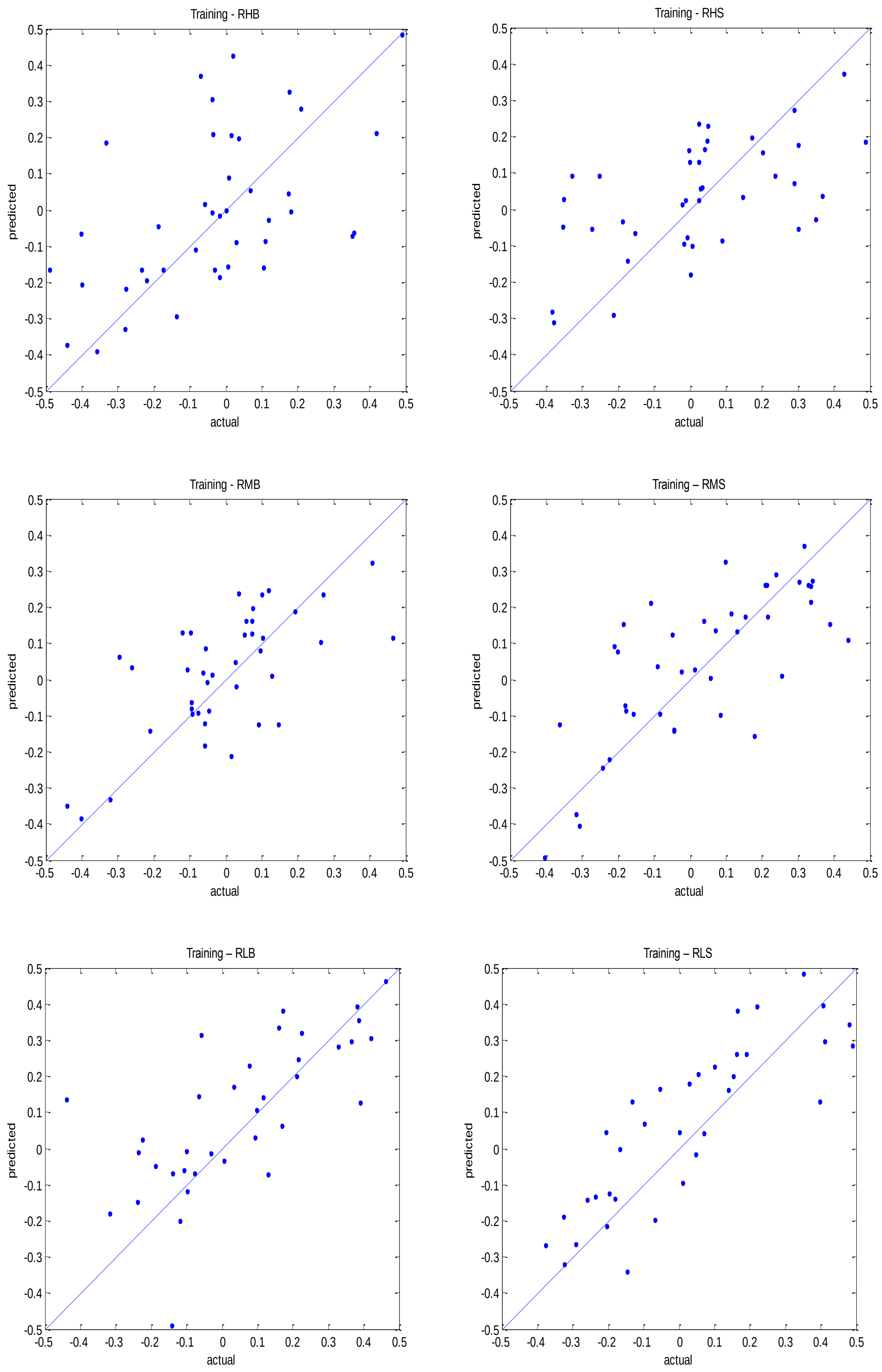

Figure A13: training results (FF) using ANN technique (NEWRB).

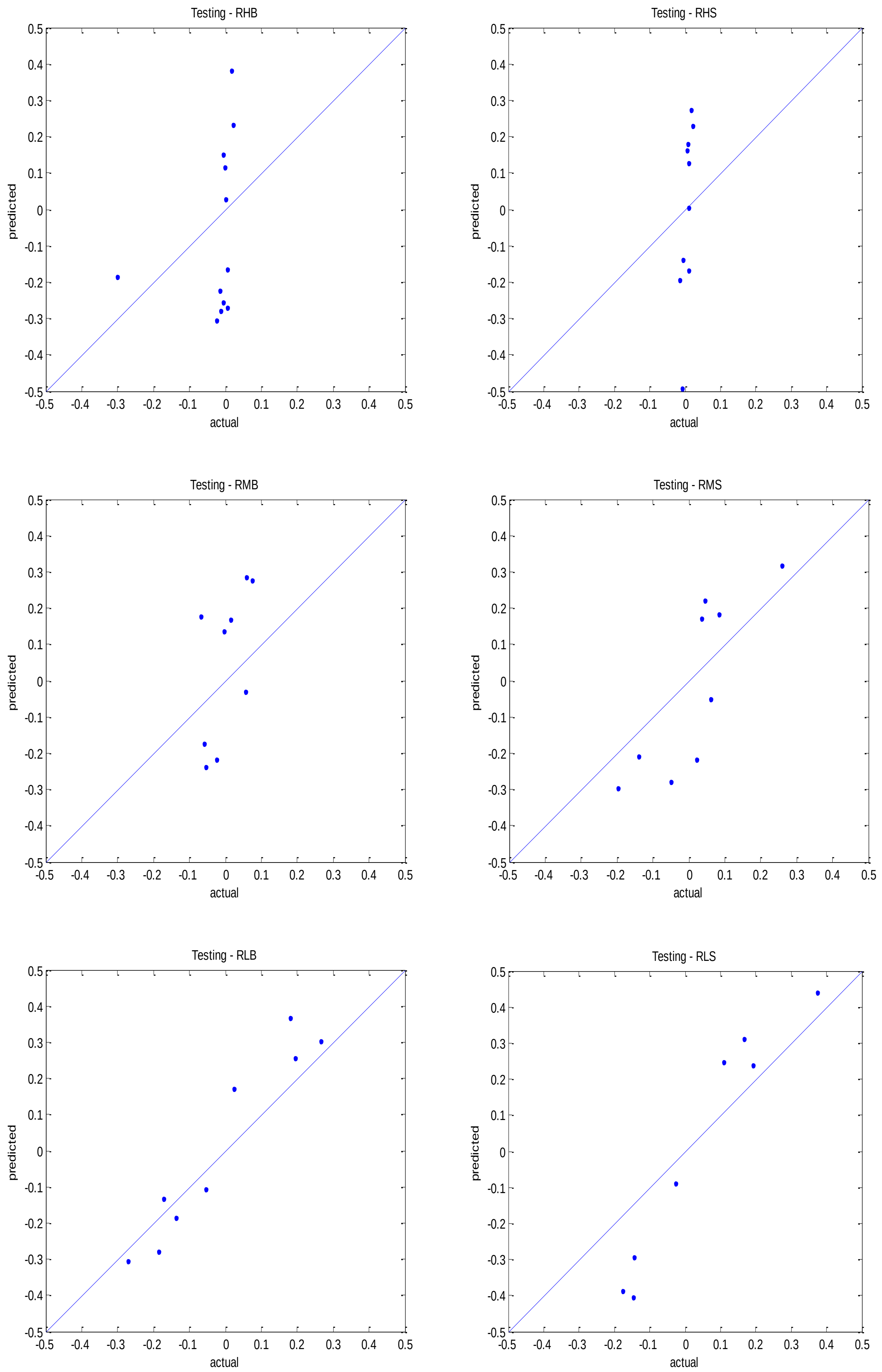

Figure A14: testing results (FF) using ANN technique (NEWRB).

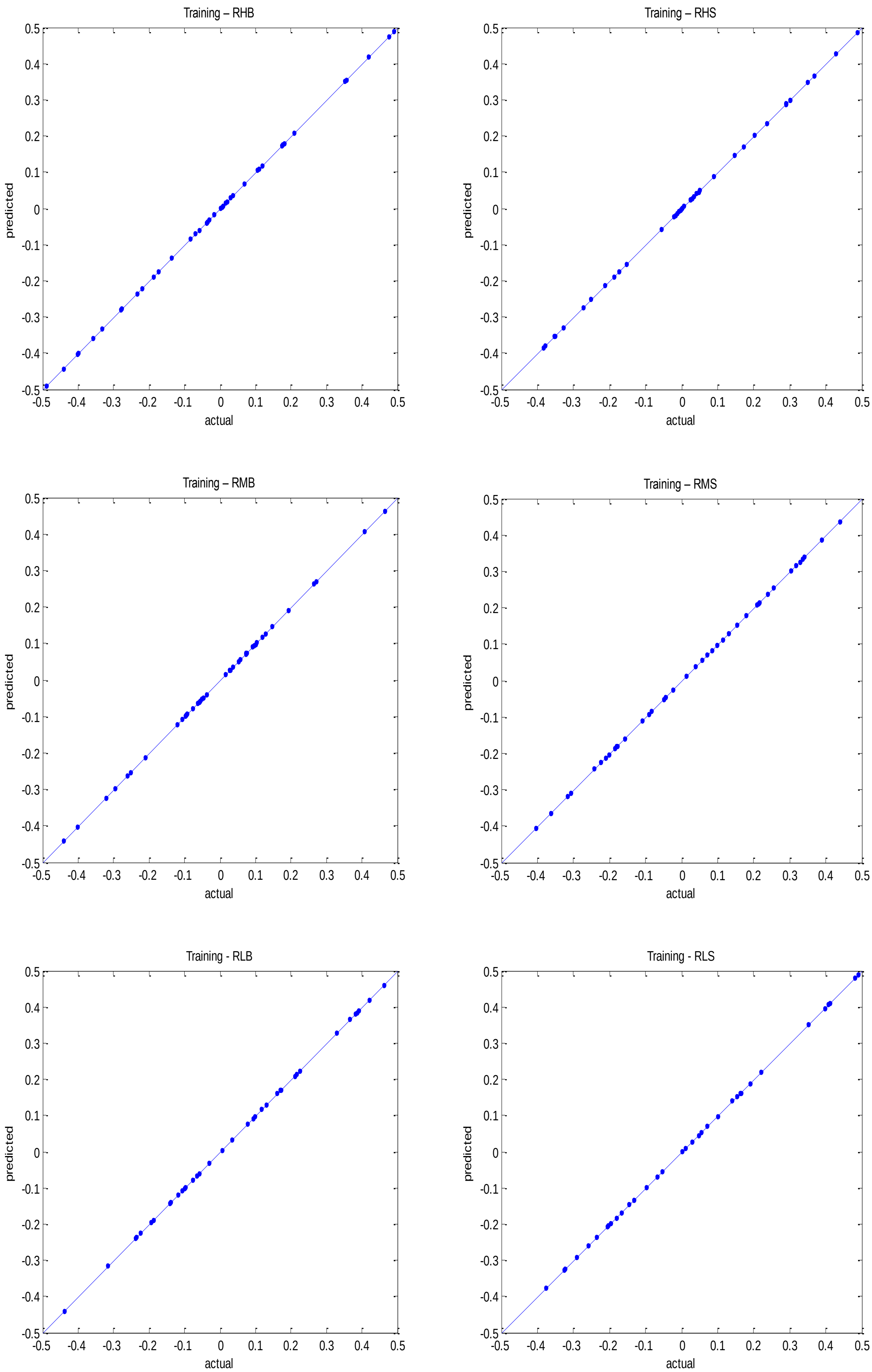

Figure A15: training results (FF) using ANFIS technique.

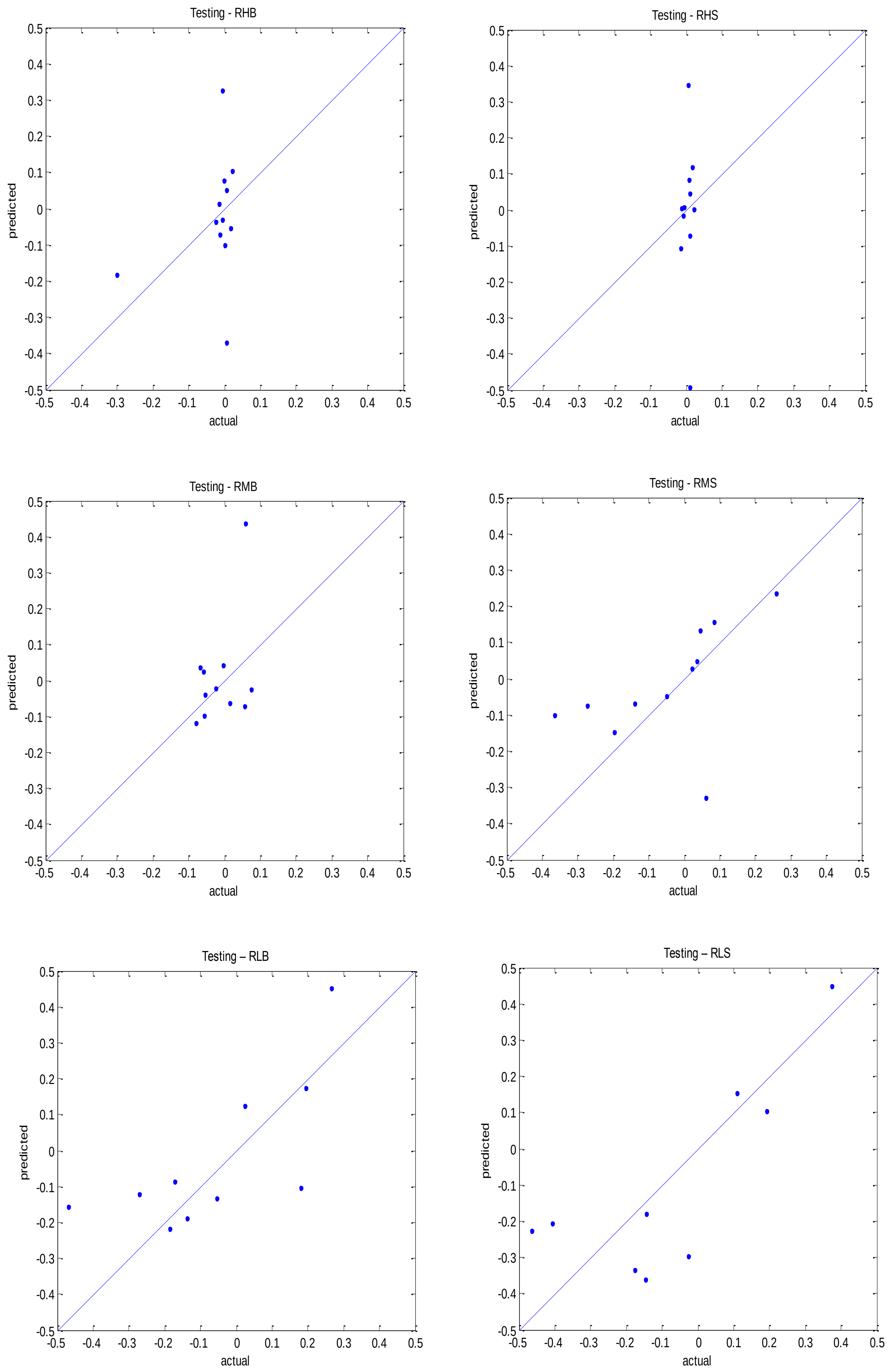

Figure A16: testing results (FF) using ANFIS technique.

Appendix B: Prediction Result using CAPM Model

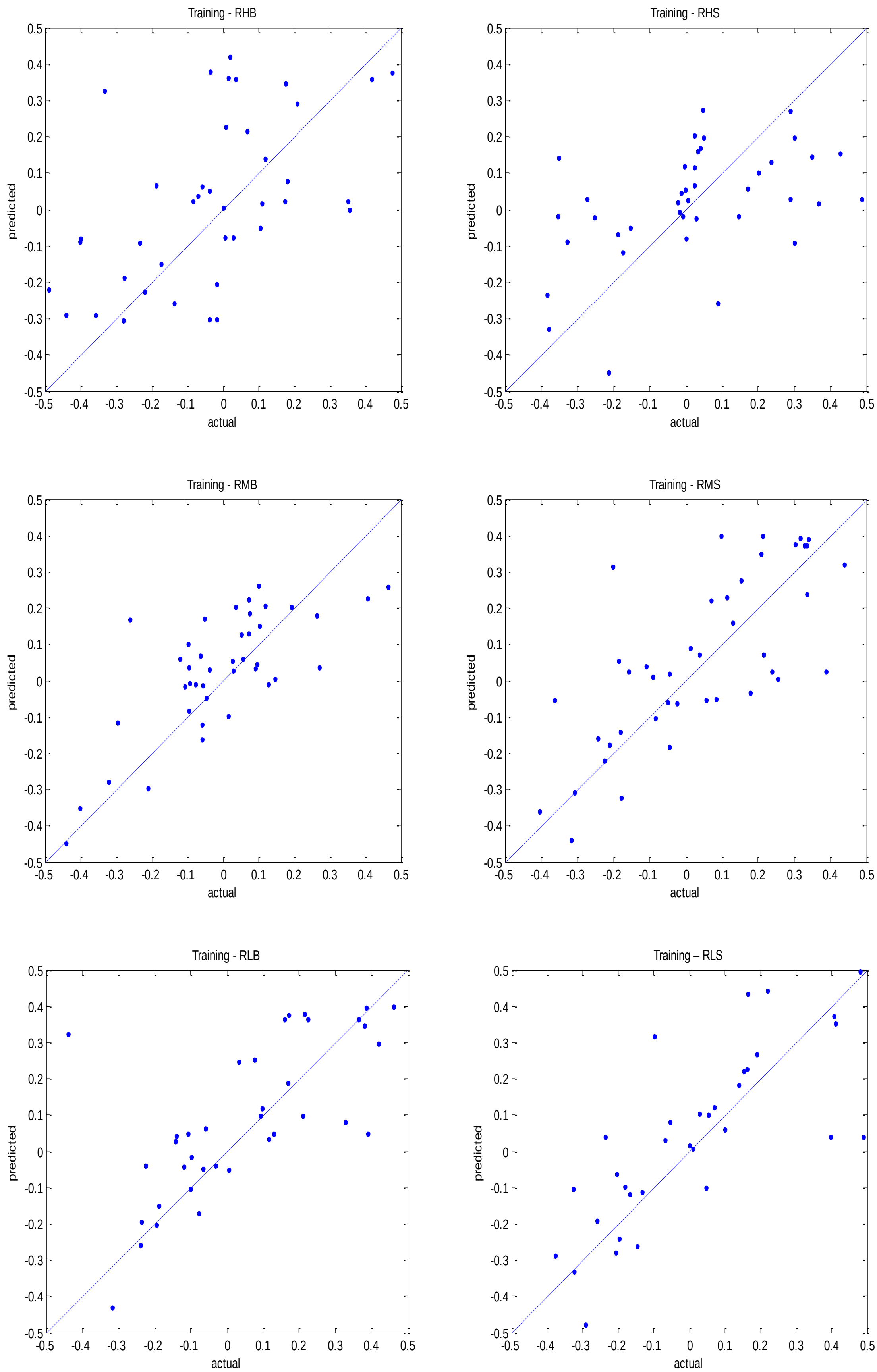

Figure B1: training results (CAPM) using ANN technique (NEWCF).

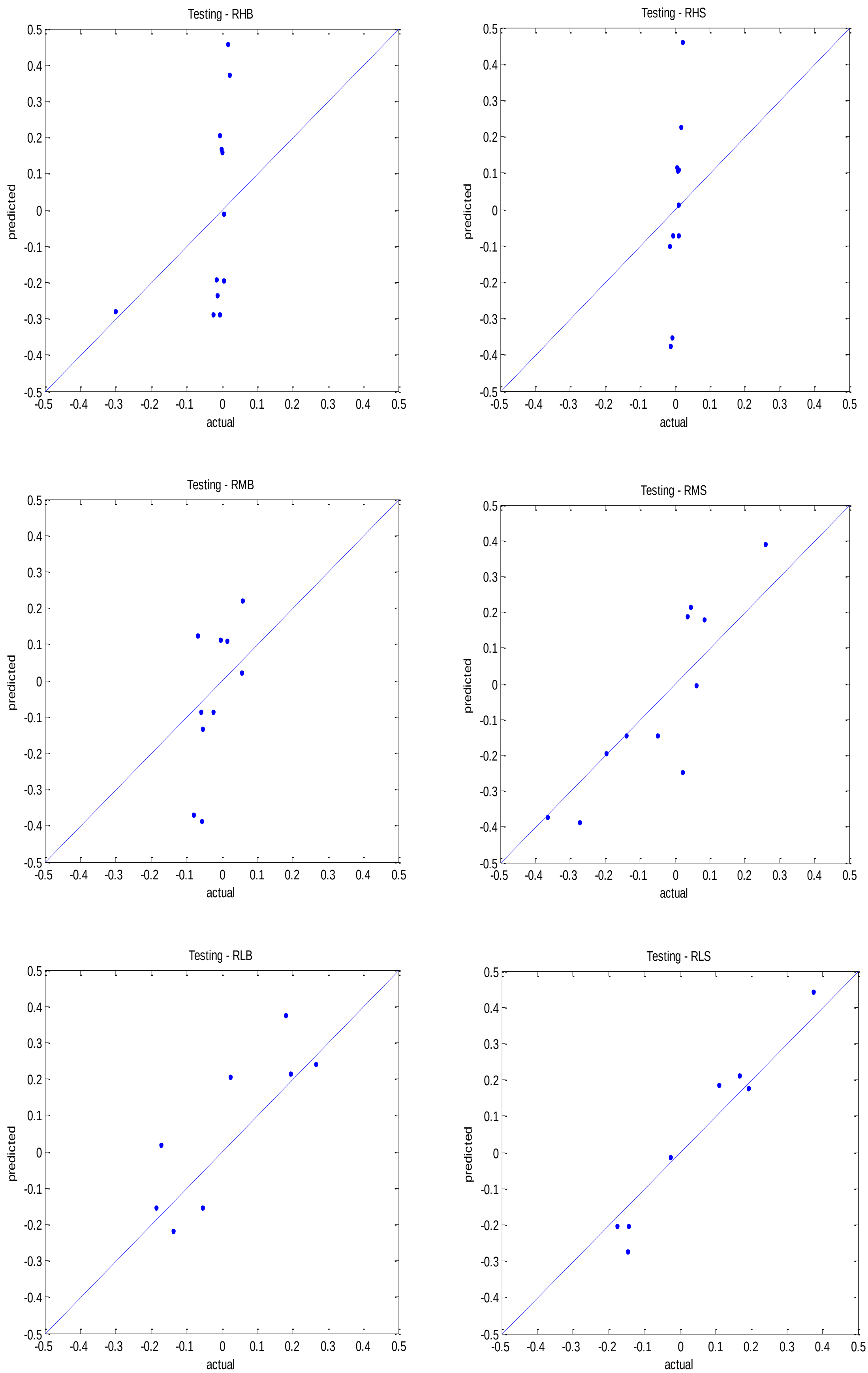

Figure B2: testing results (CAPM) using ANN technique (NEWCF).

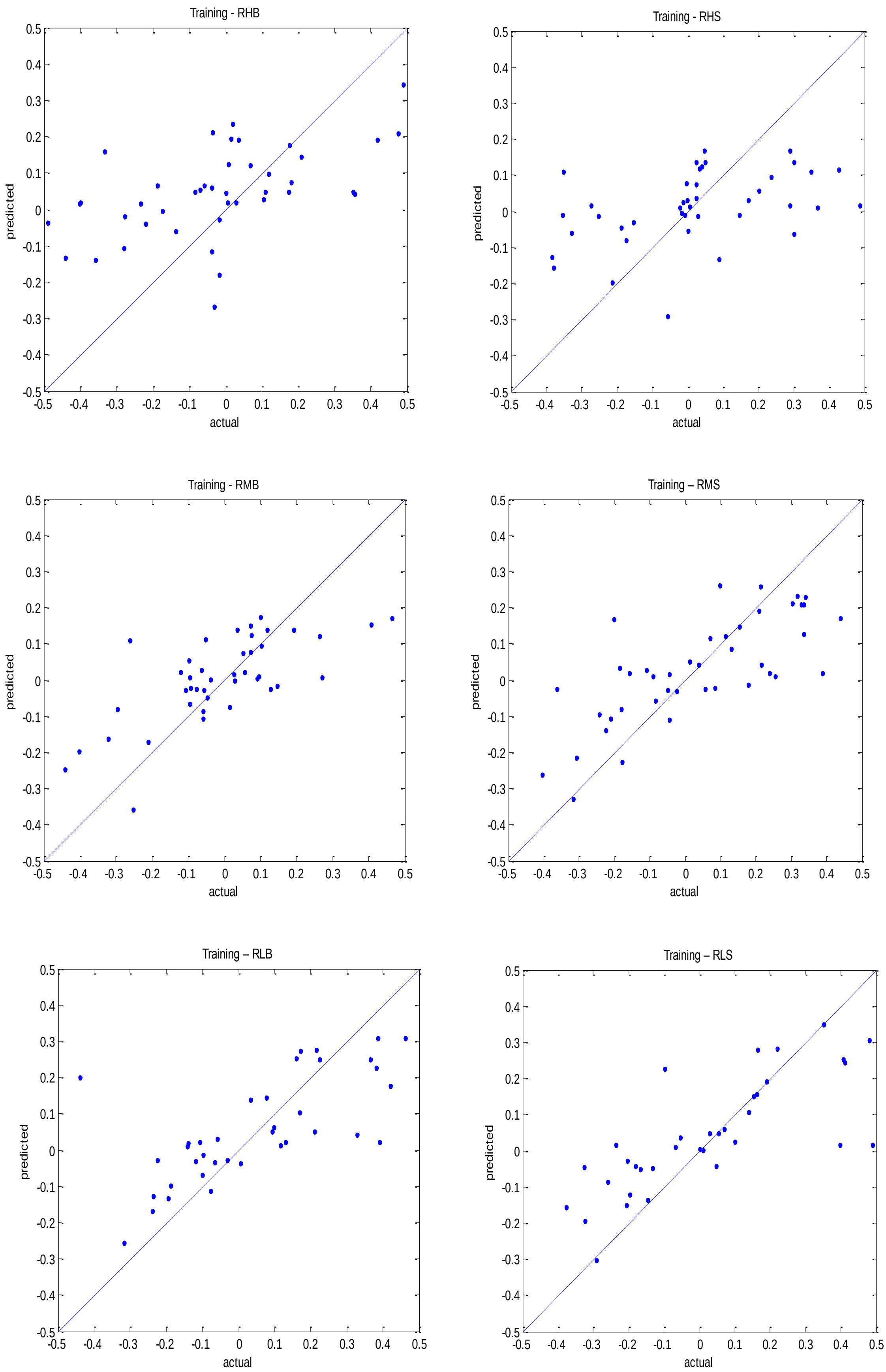

Figure B3: training results (CAPM) using ANN technique (NEWELM).

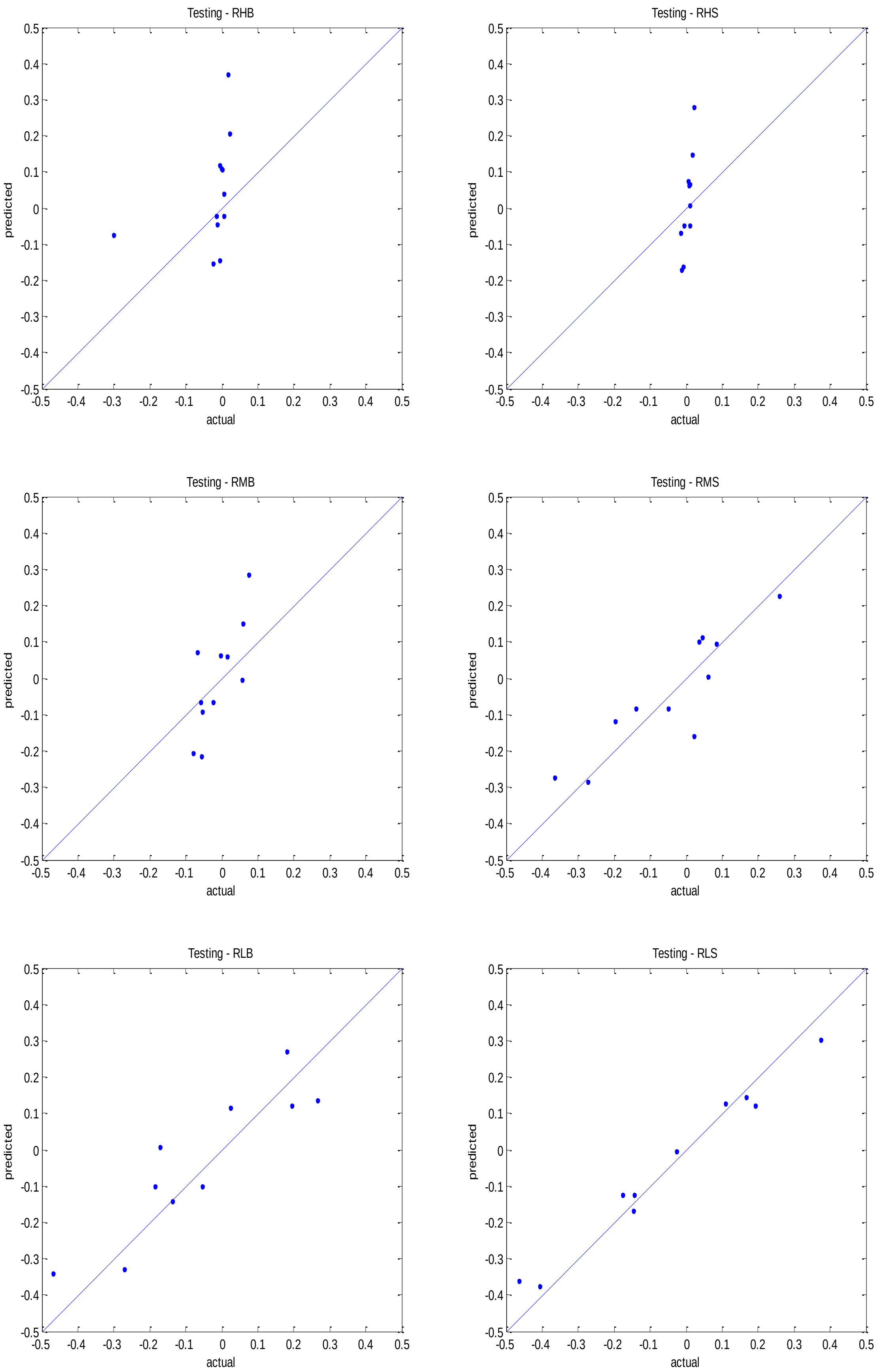

Figure B4: testing results (CAPM) using ANN technique (NEWELM).

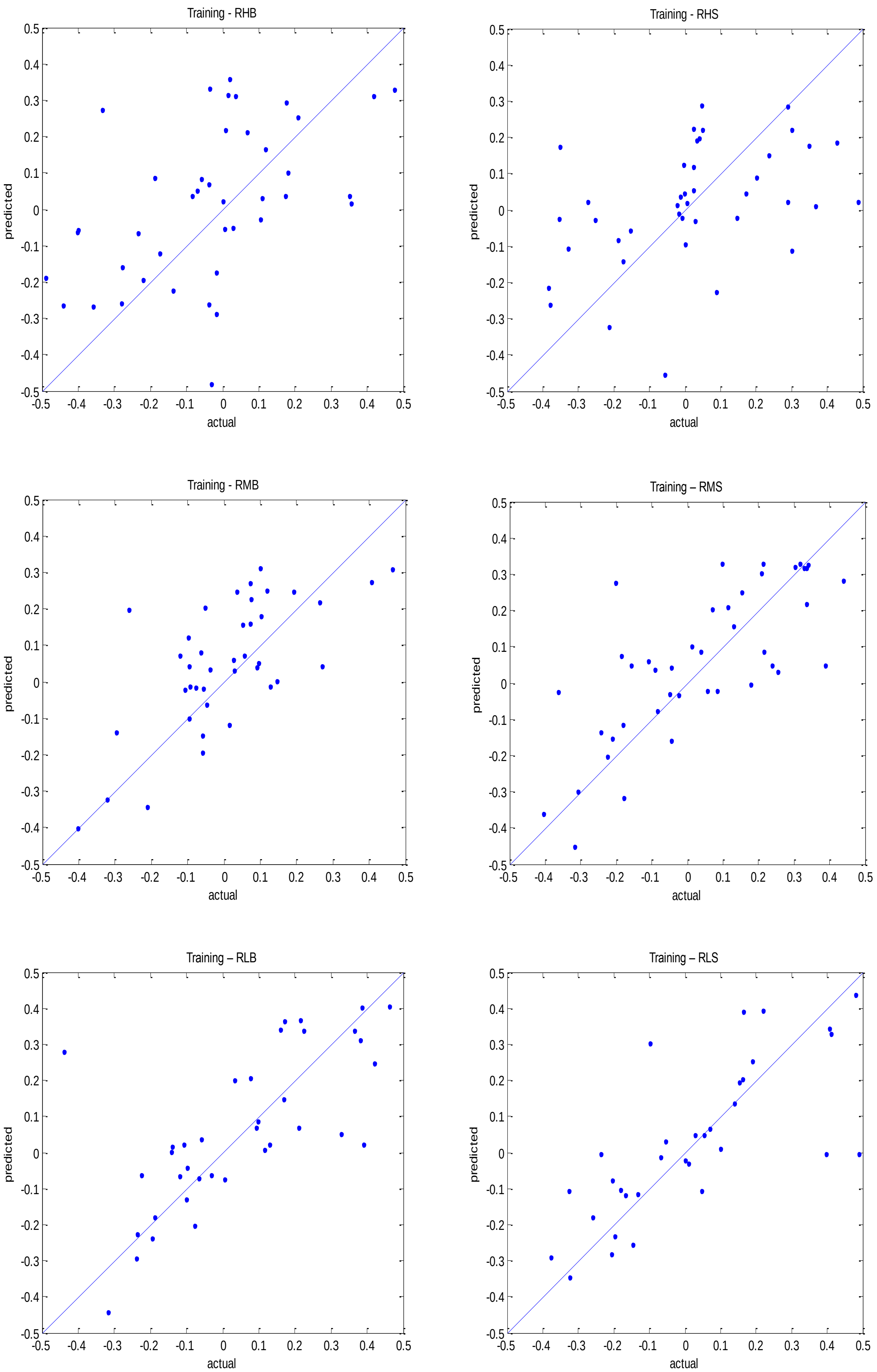

Figure B5: training results (CAPM) using ANN technique (NEWFFTD).

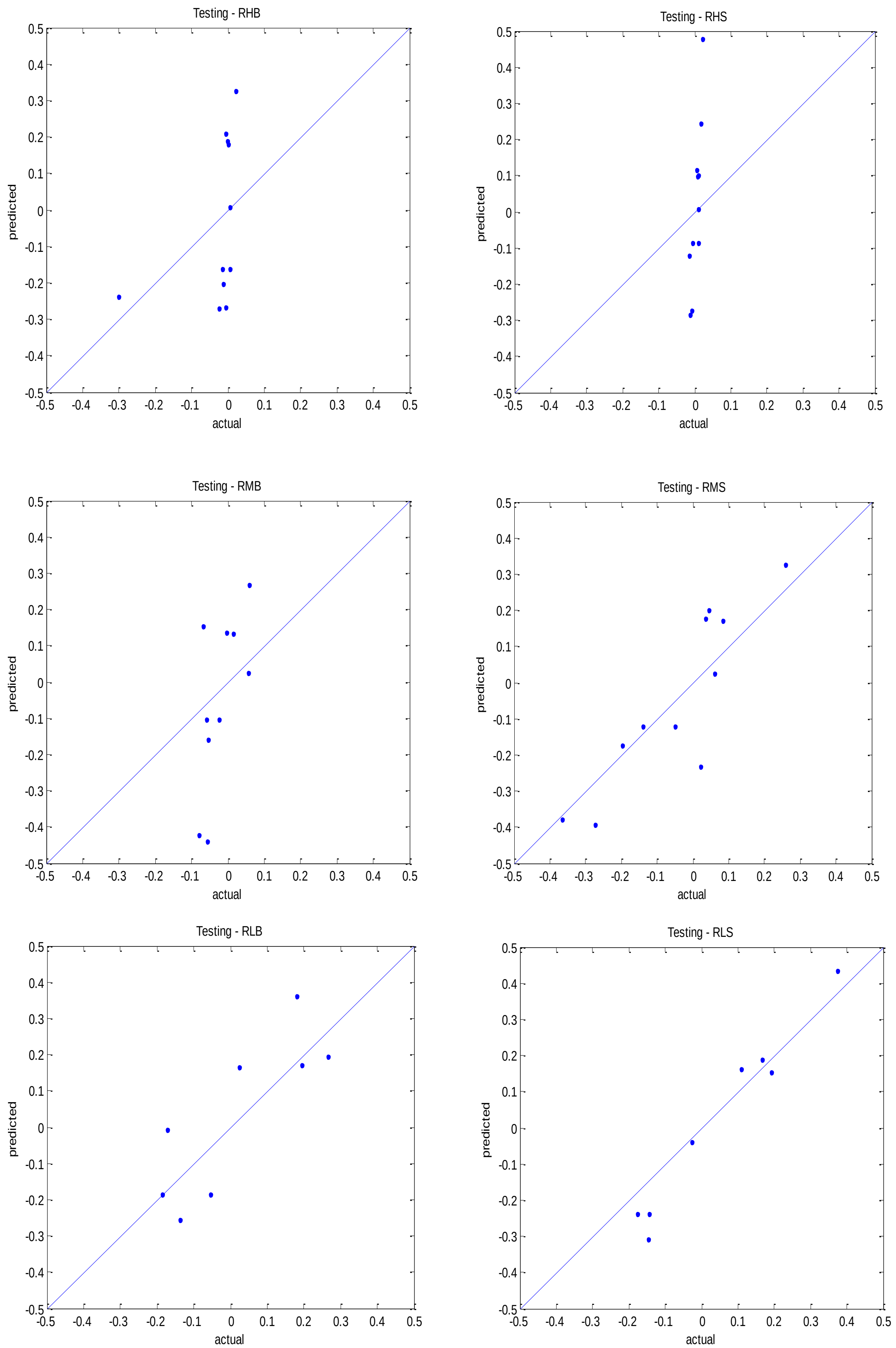

Figure B6: testing results (CAPM) using ANN technique (NEWFFTD).

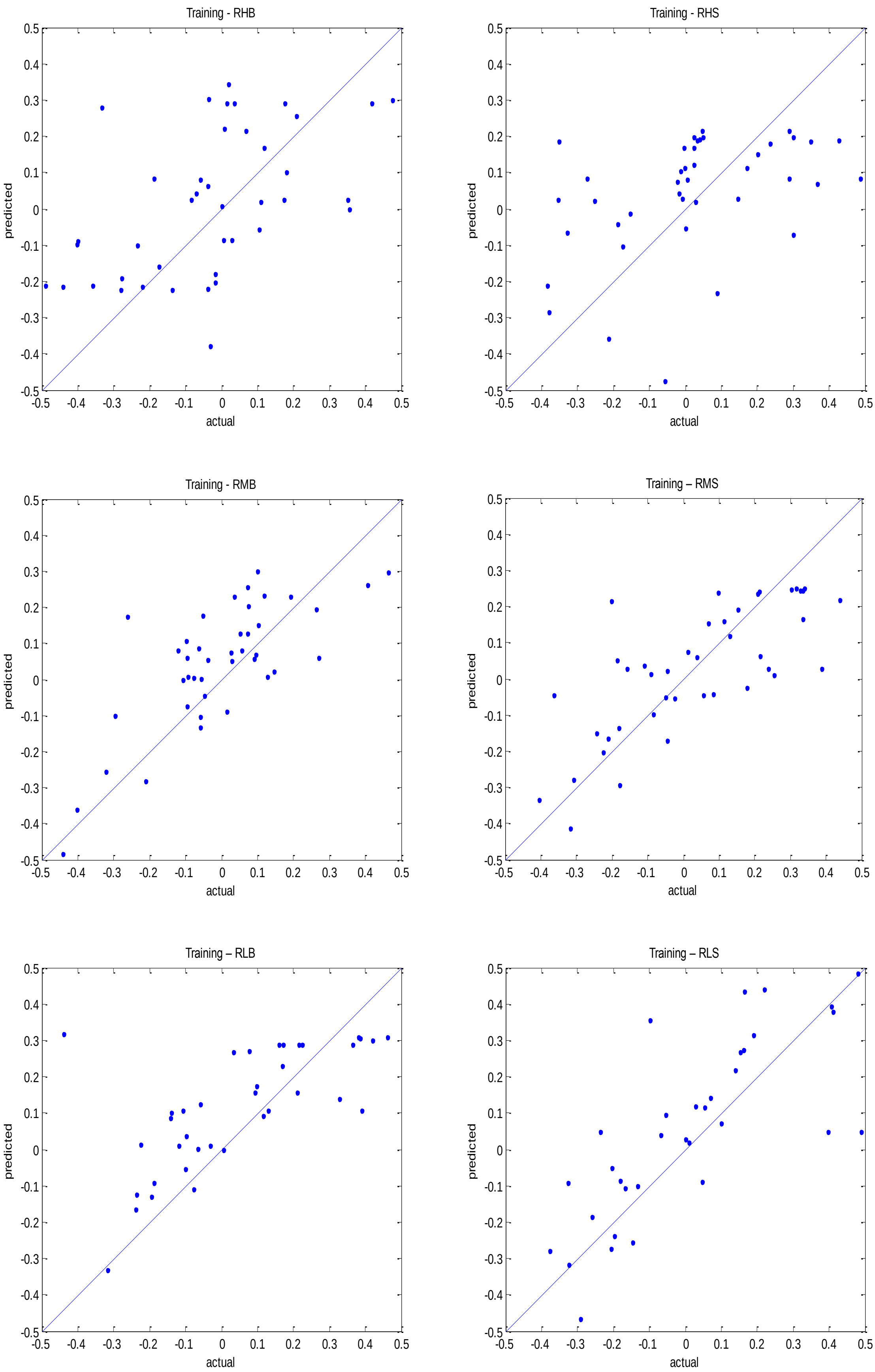

Figure B7: training results (CAPM) using ANN technique (NEWFF).

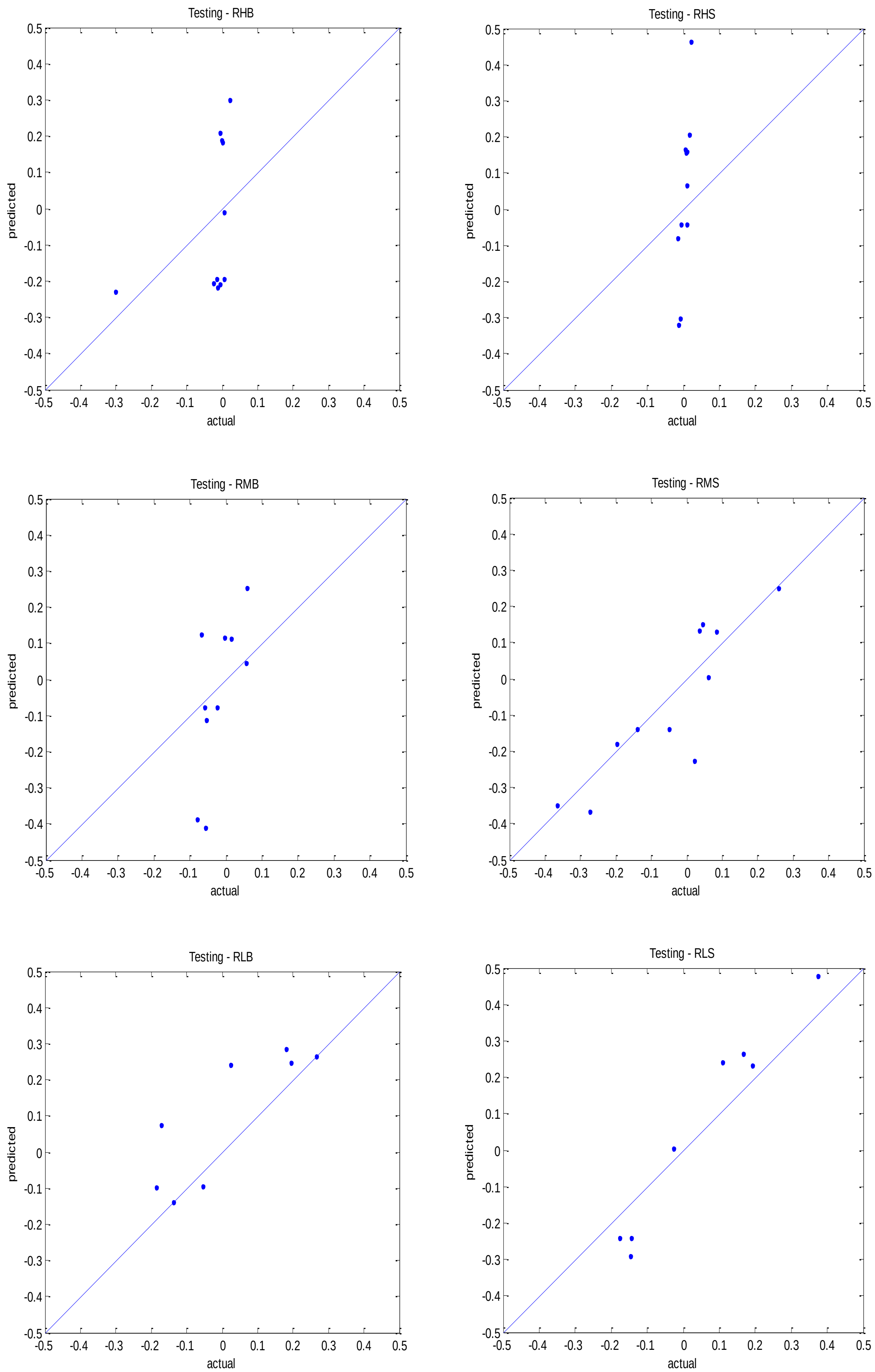

Figure B8: testing results (CAPM) using ANN technique (NEWFF).

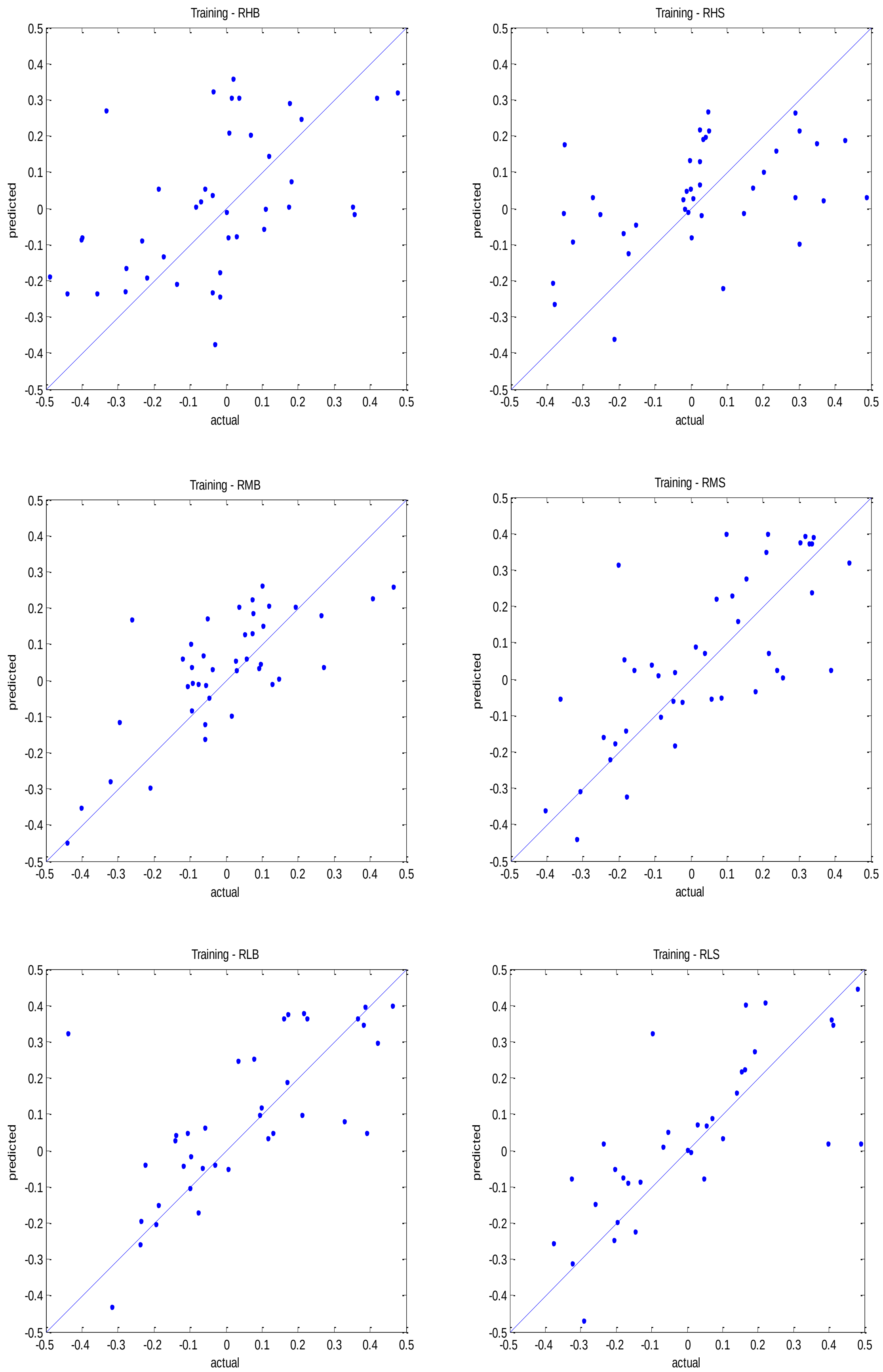

Figure B9: training results (CAPM) using ANN technique (NEWDTDNN).

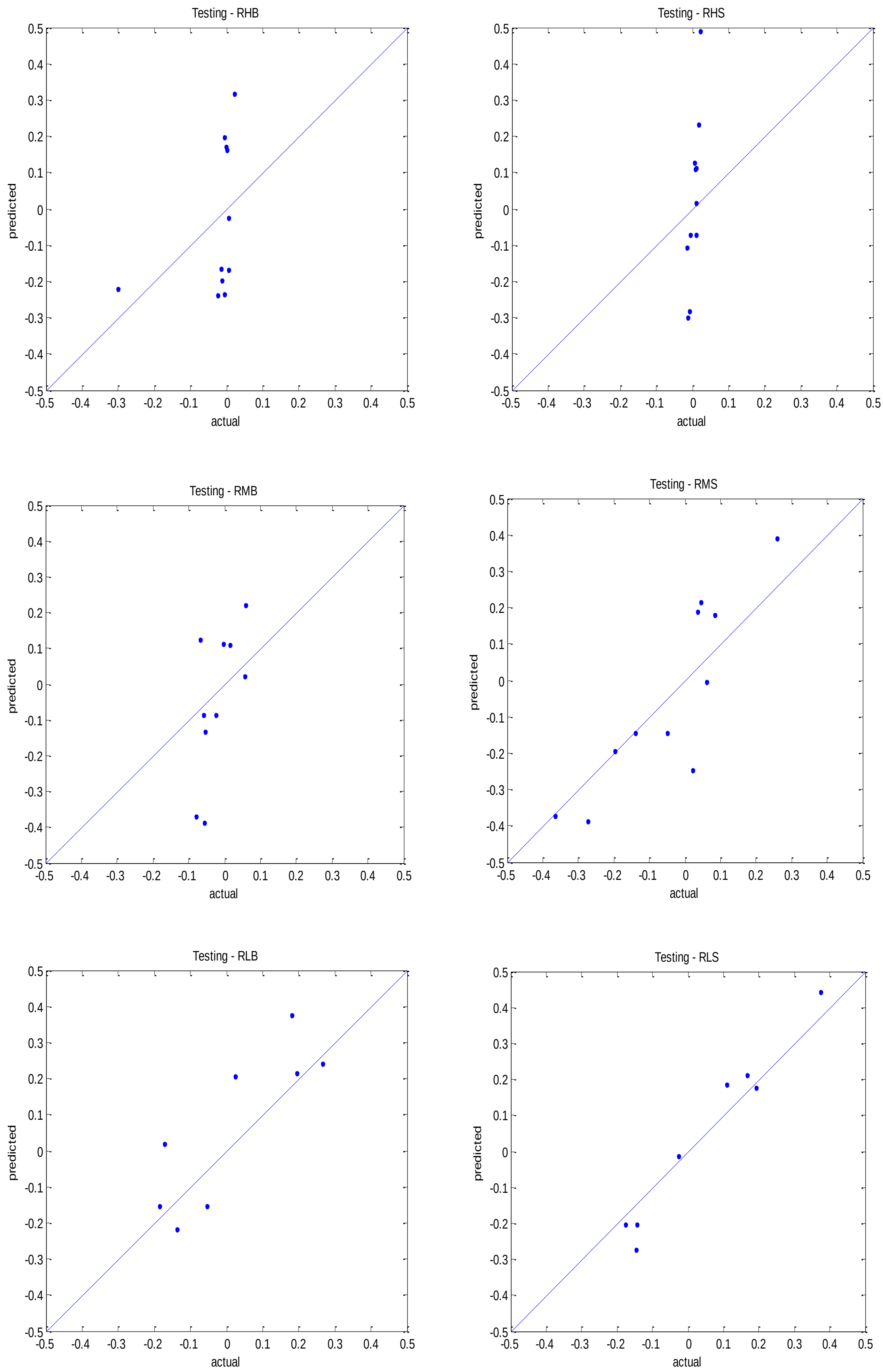

Figure B10: testing results (CAPM) using ANN technique (NEWDTDNN).

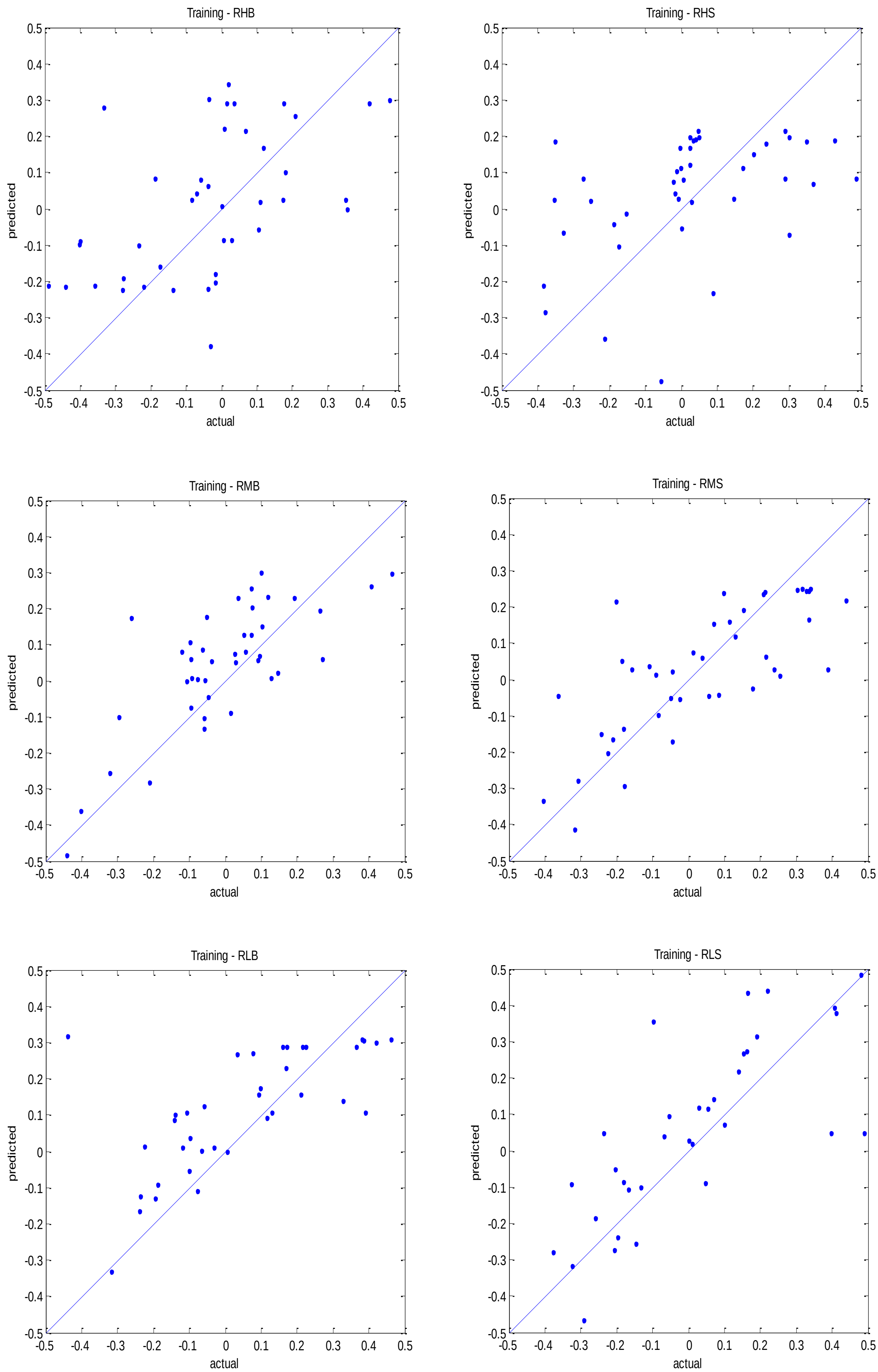

Figure B11: training results (CAPM) using ANN technique (NEWFIT).

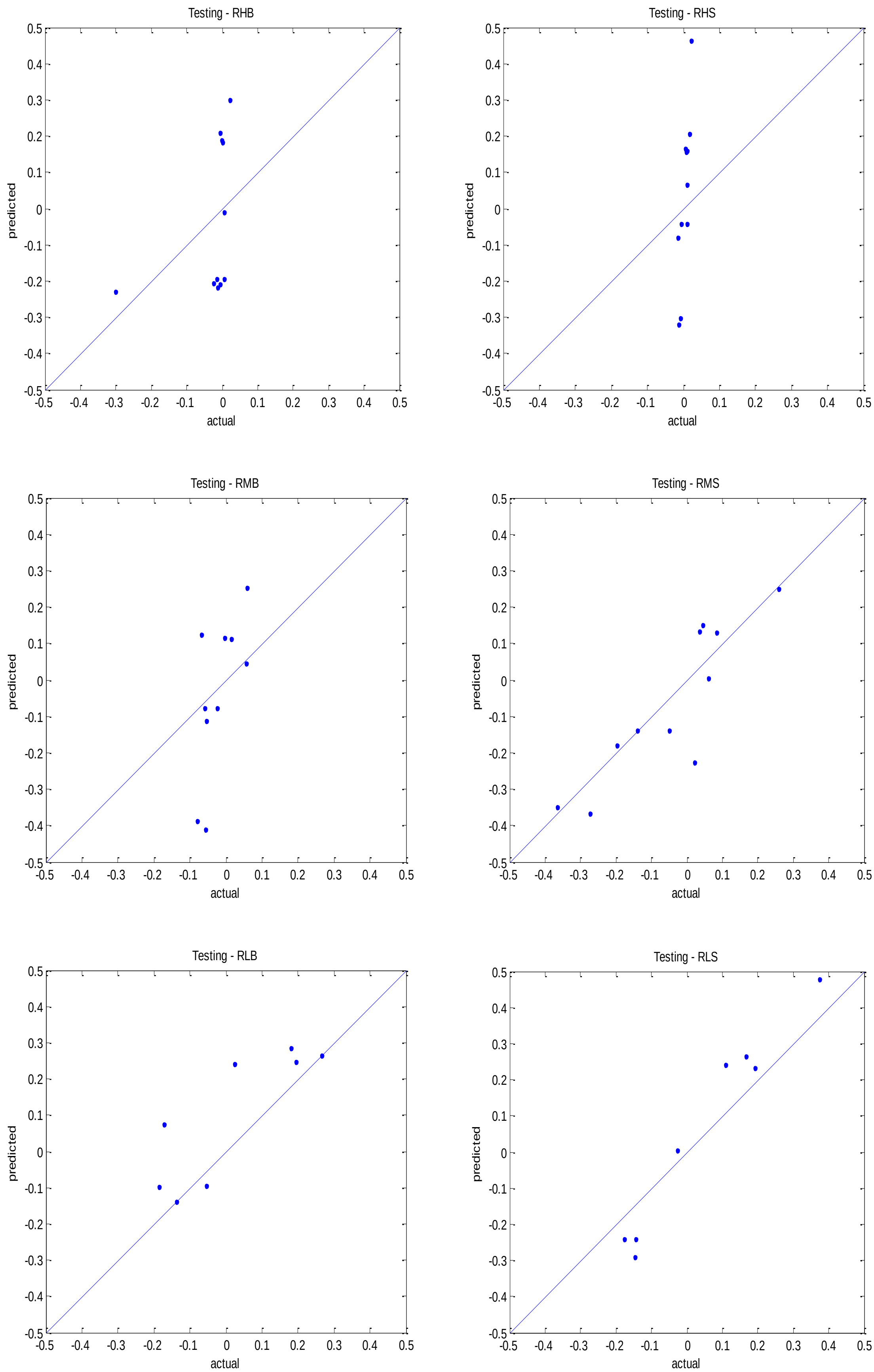

Figure B12: testing results (CAPM) using ANN technique (NEWFIT).

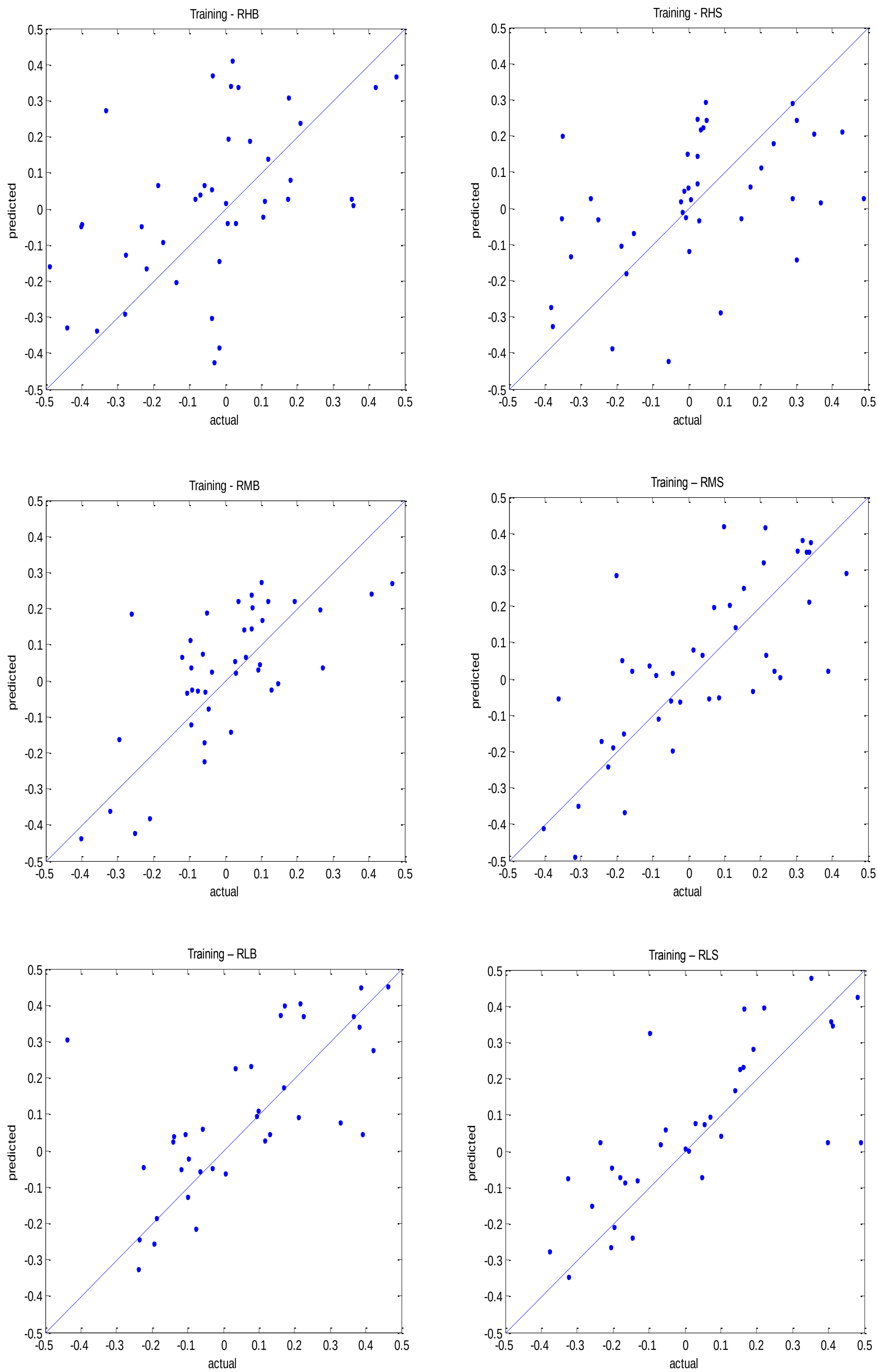

Figure B13: training results (CAPM) using ANN technique (NEWRB).

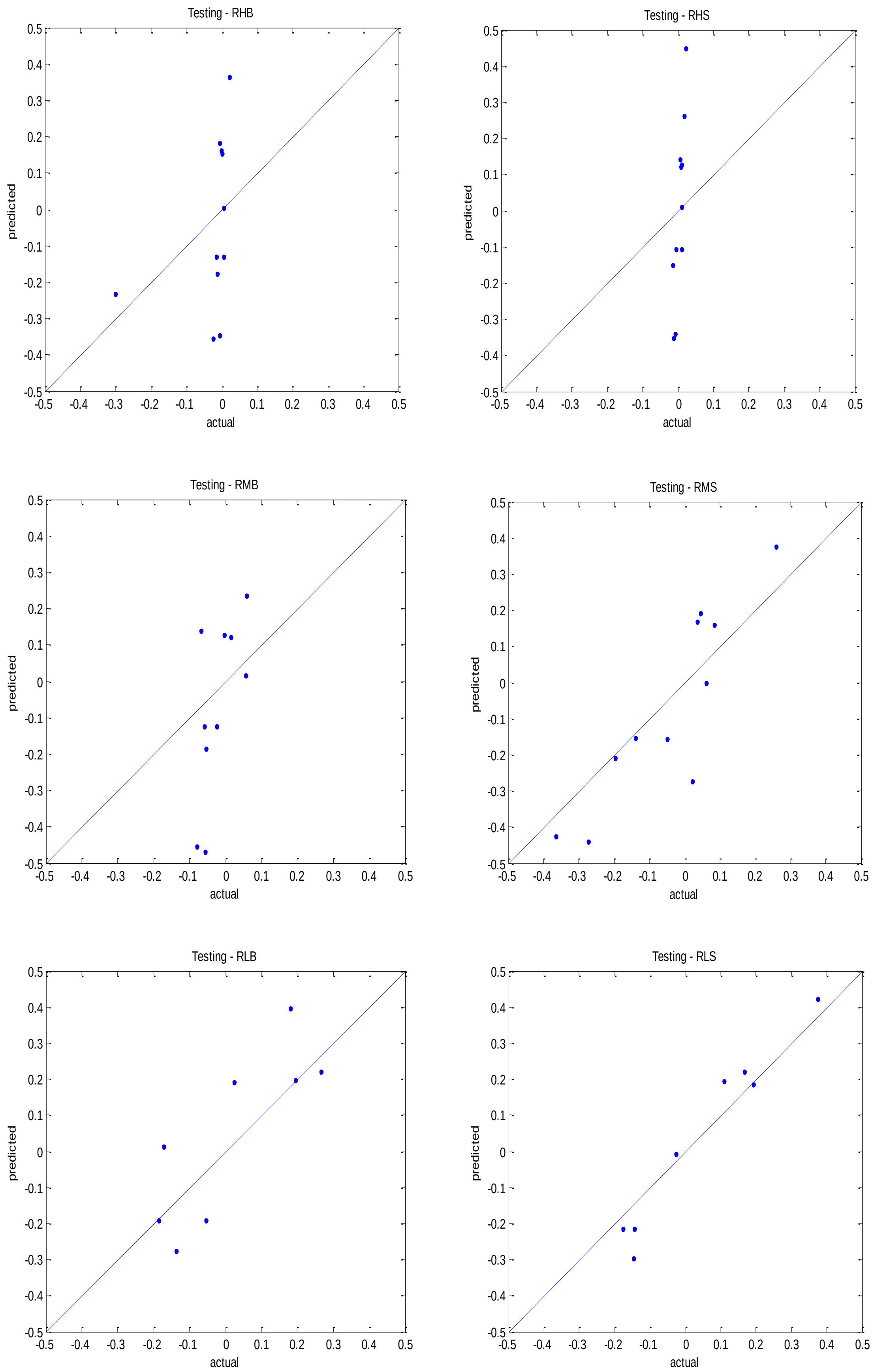

Figure B14: testing results (CAPM) using ANN technique (NEWRB).

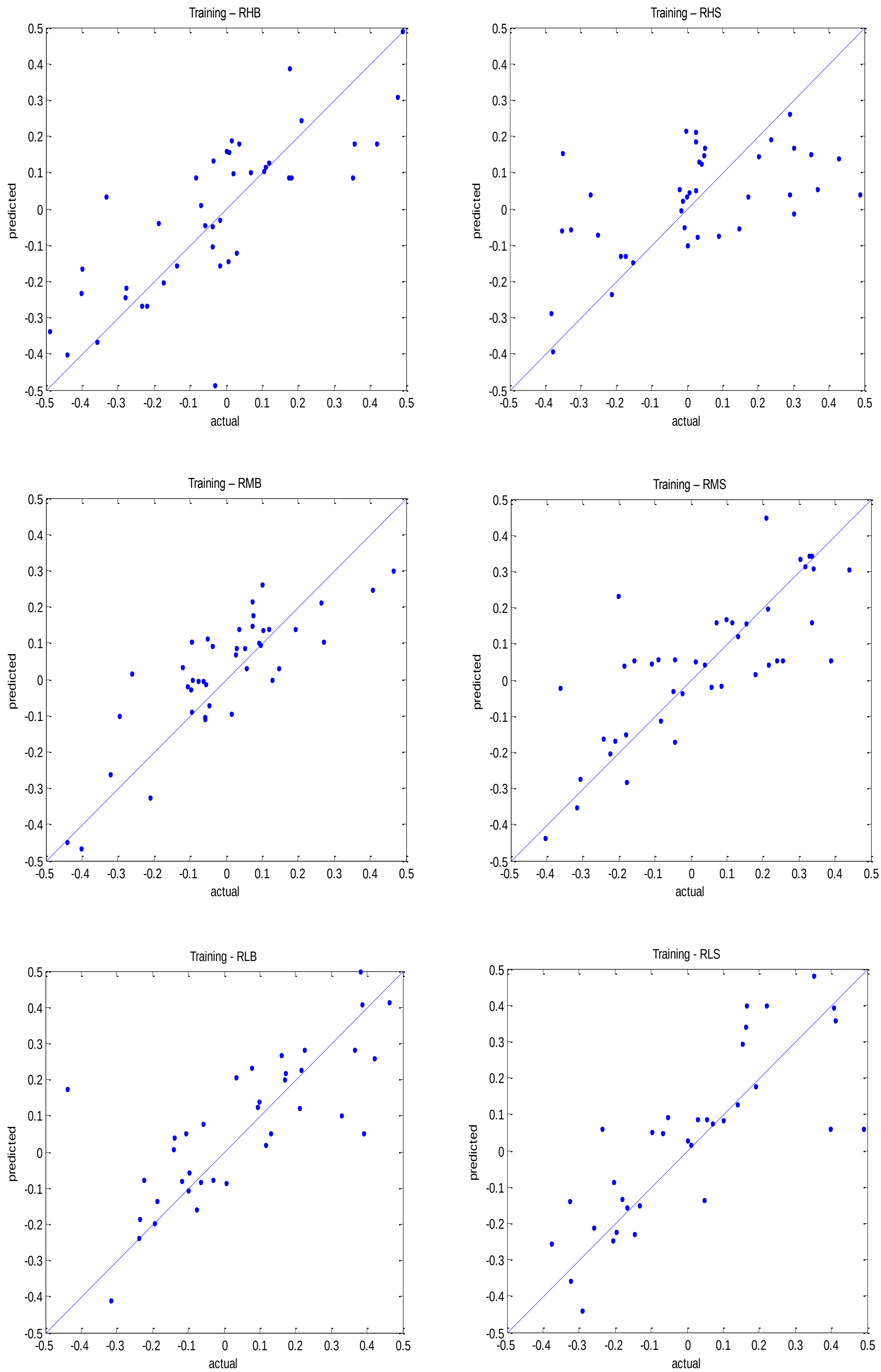

Figure B15: training results (CAPM) using ANFIS technique.

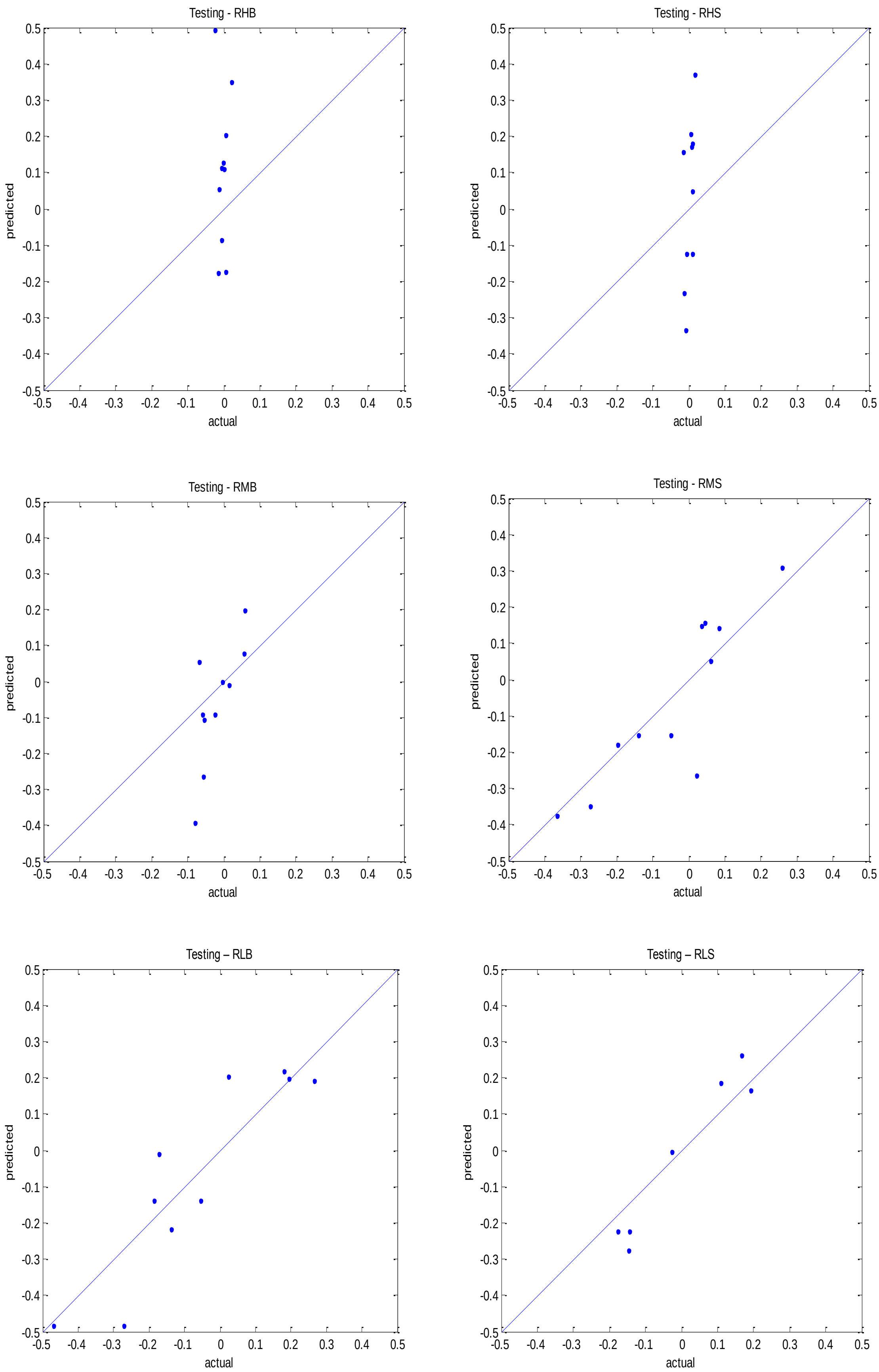

Figure B16: testing results (CAPM) using ANFIS technique.

Appendix C: Prediction Result using Multi-Stage Type-1 Model (Shareholder)

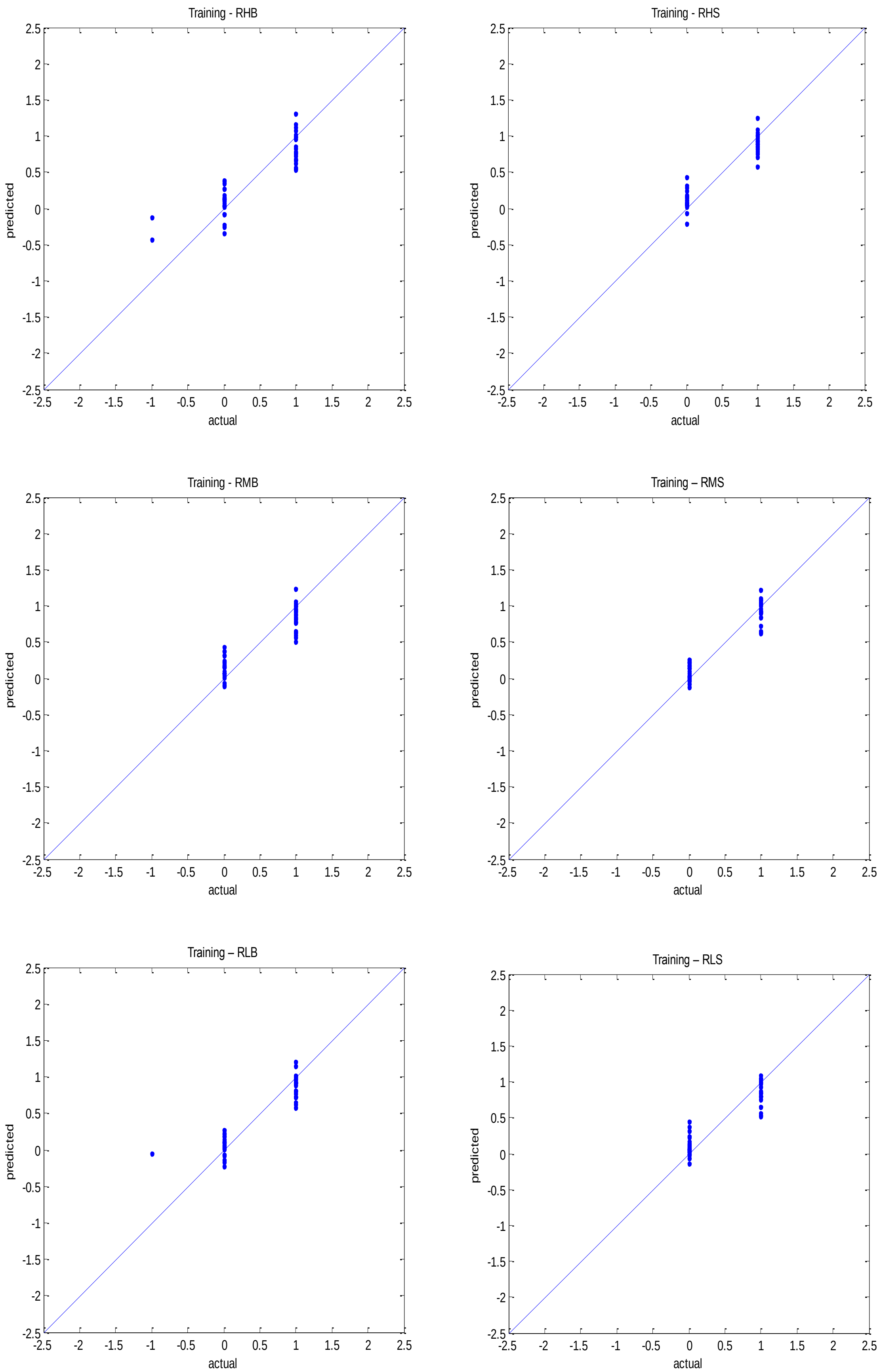

Figure C1: Training results (Type1 shareholder) using ANN technique (NEWCF).

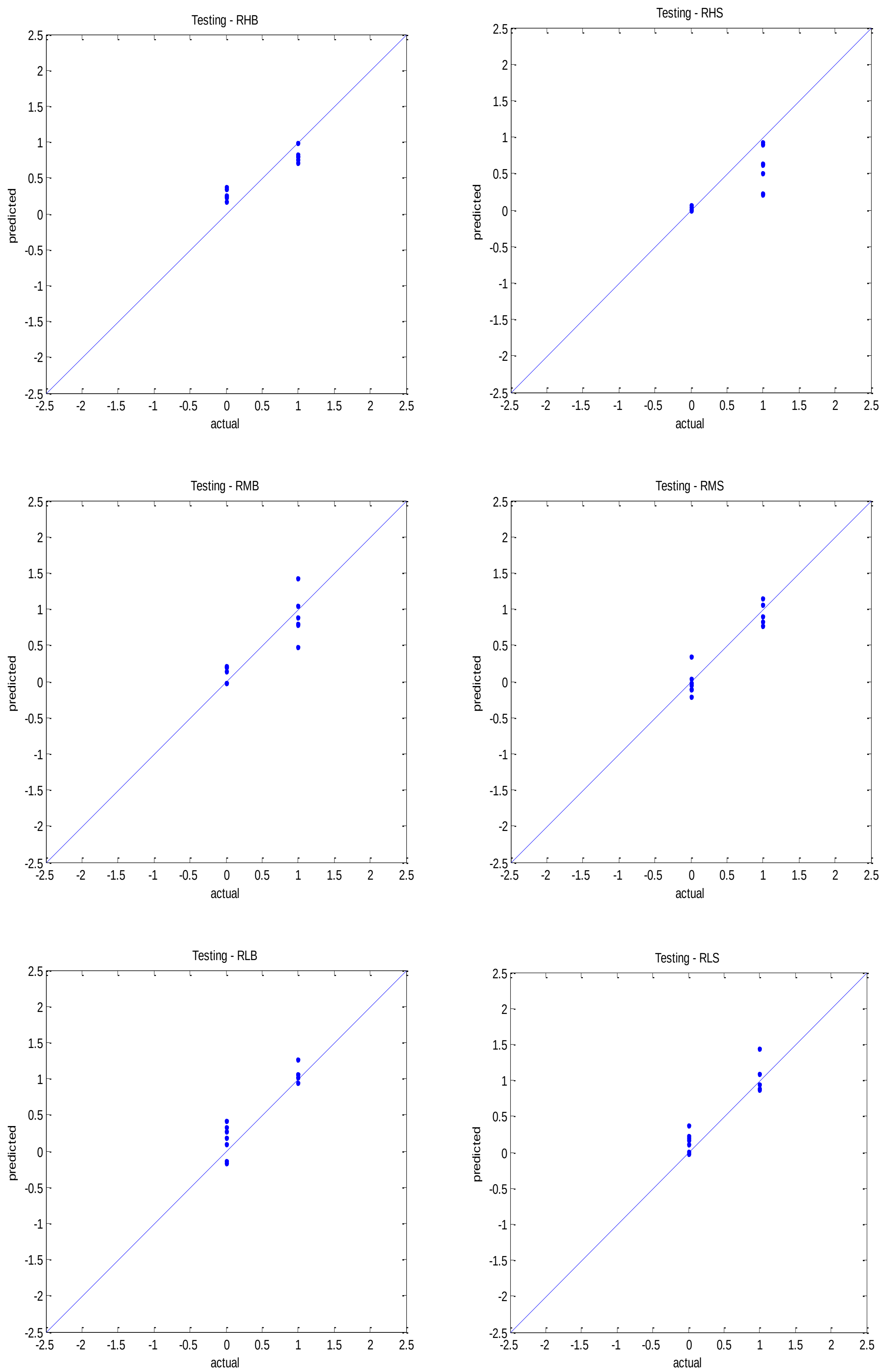

Figure C2: Testing results (Type1 shareholder) using ANN technique (NEWCF).

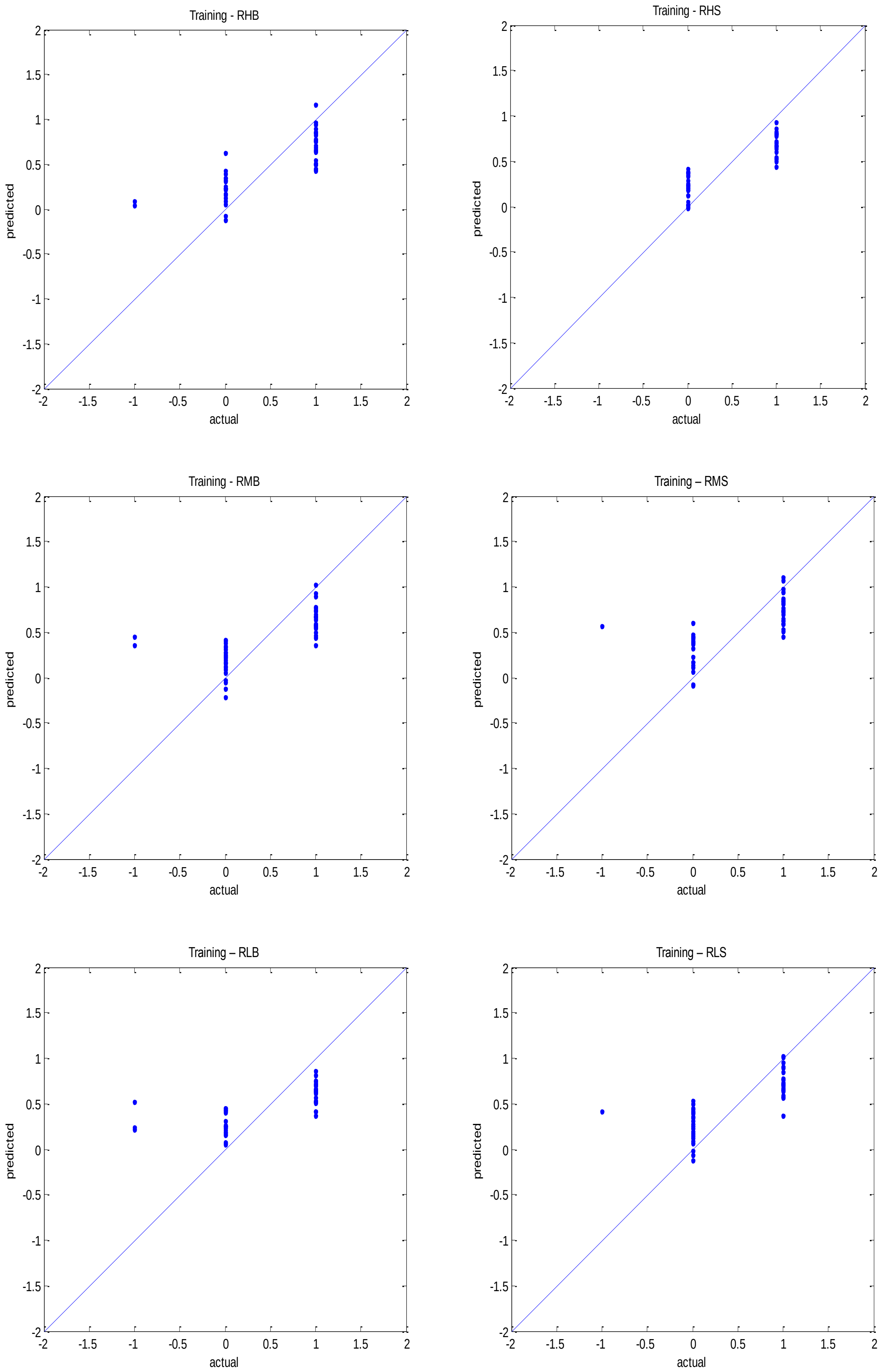

Figure C3: Training results (Type1 shareholder) using ANN technique (NEWELM).

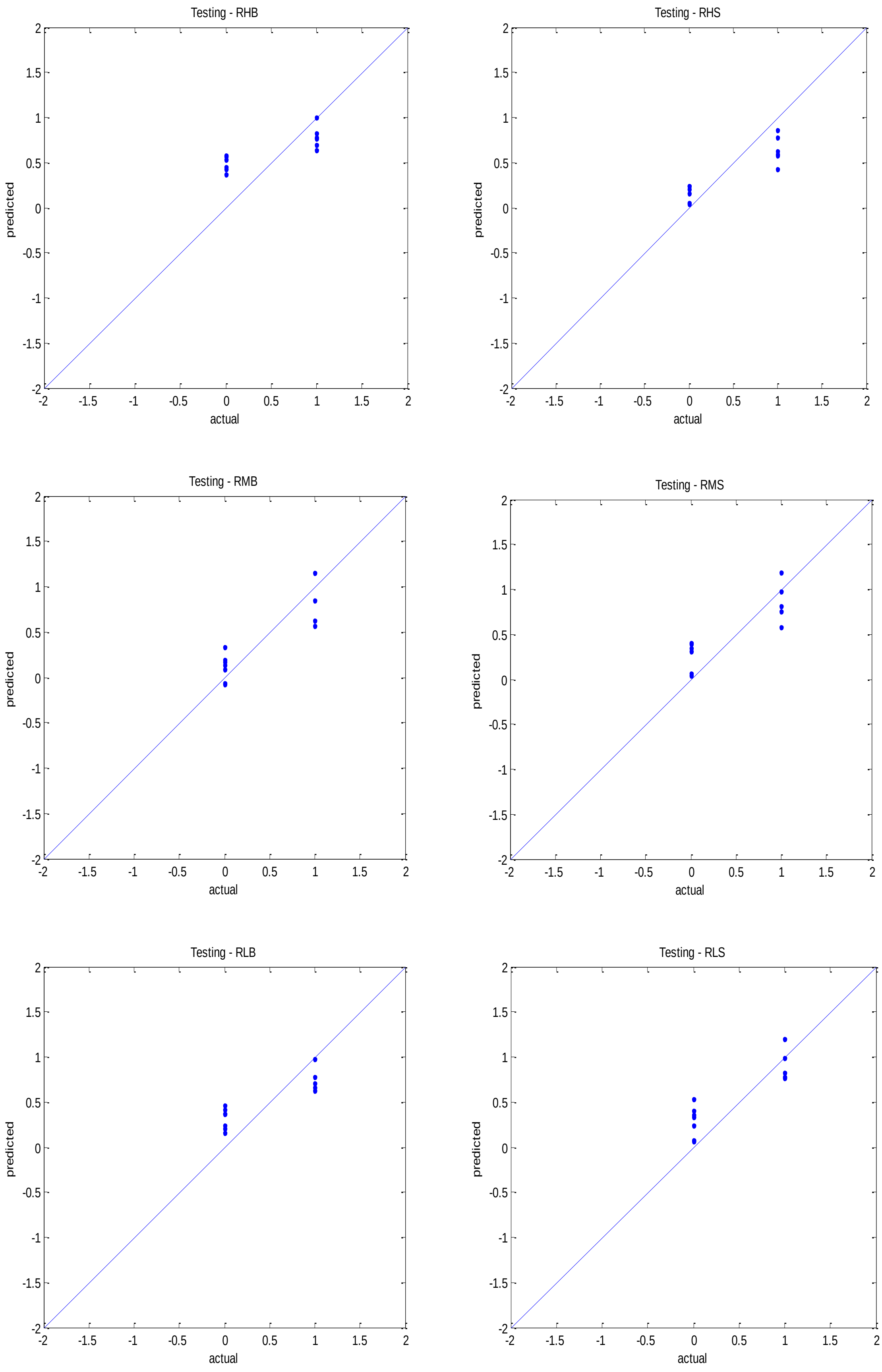

Figure C4: Testing results (Type1 shareholder) using ANN technique (NEWELM).

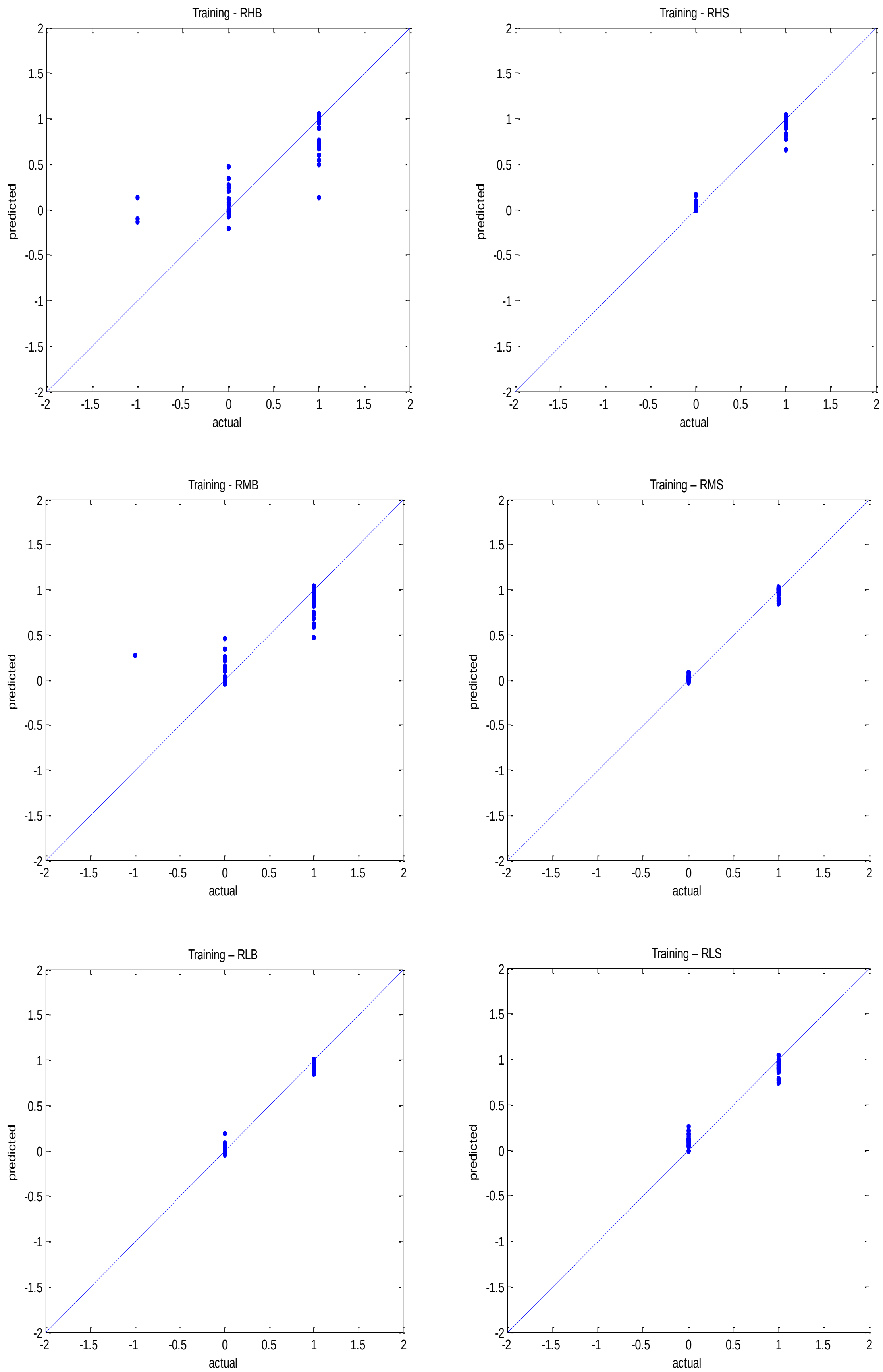

Figure C5: Training results (Type1 shareholder) using ANN technique (NEWFFTD).

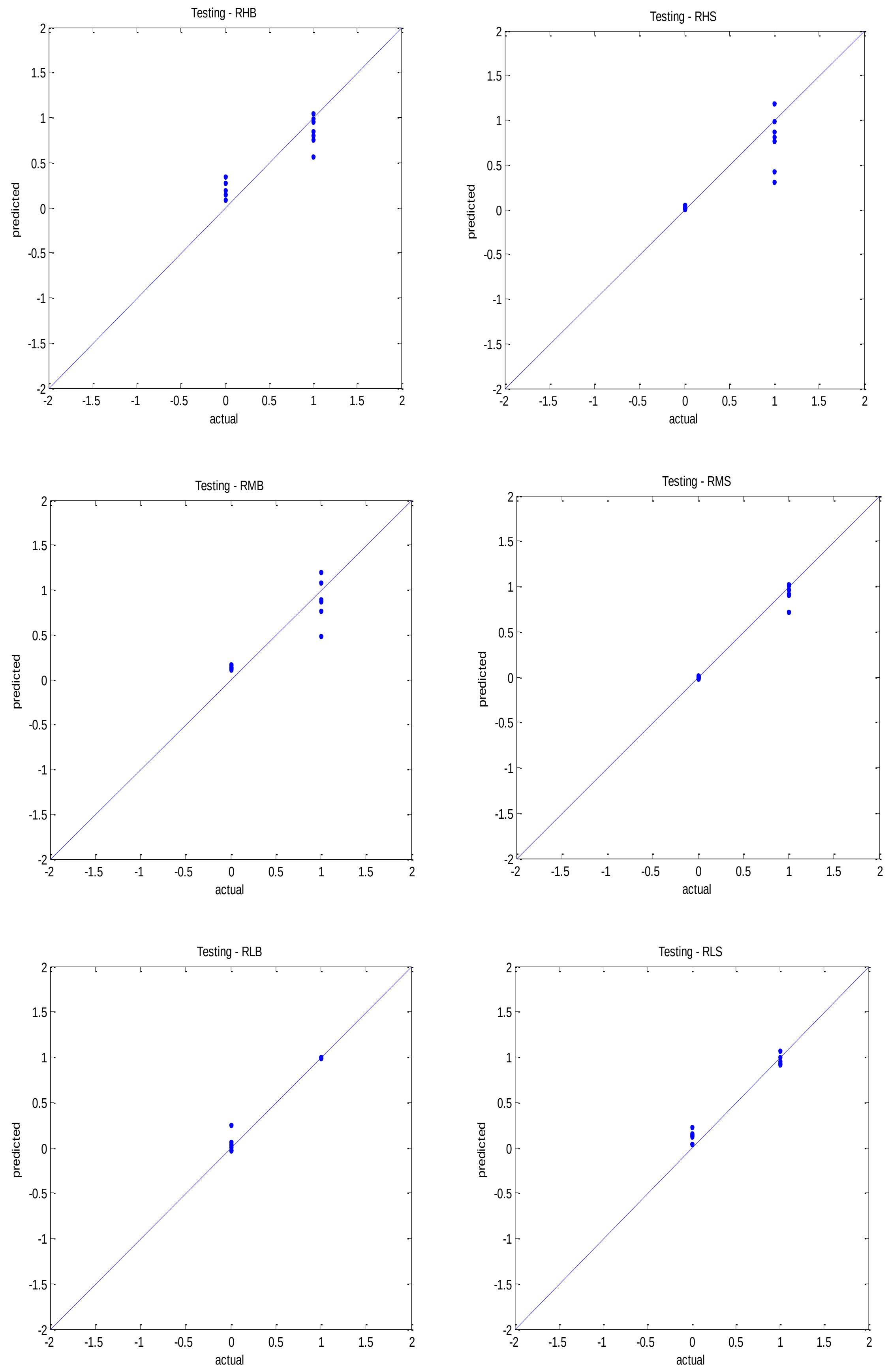

Figure C6: Testing results (Type1 shareholder) using ANN technique (NEWFFTD).

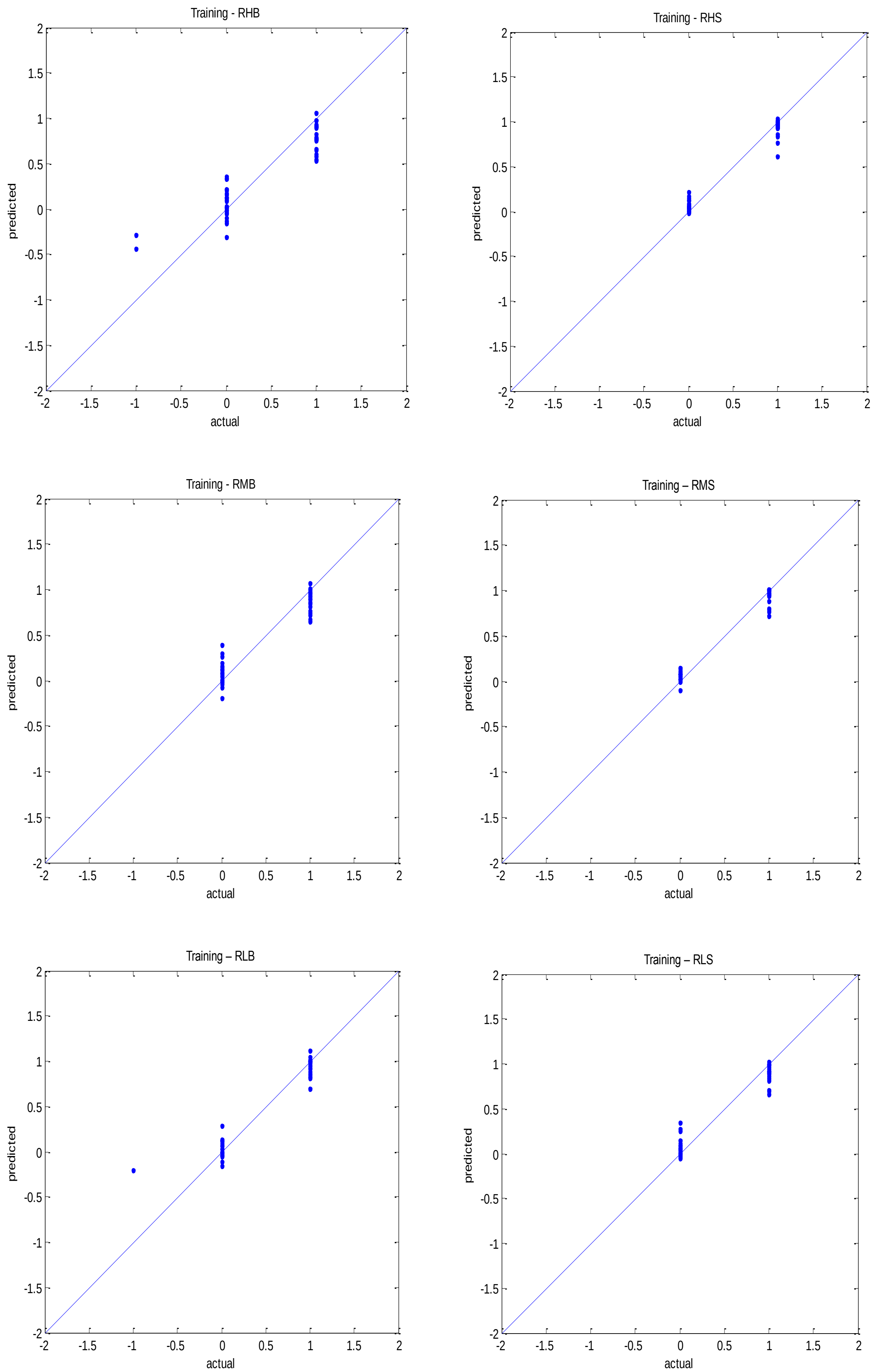

Figure C7: Training results (Type1 shareholder) using ANN technique (NEWFF).

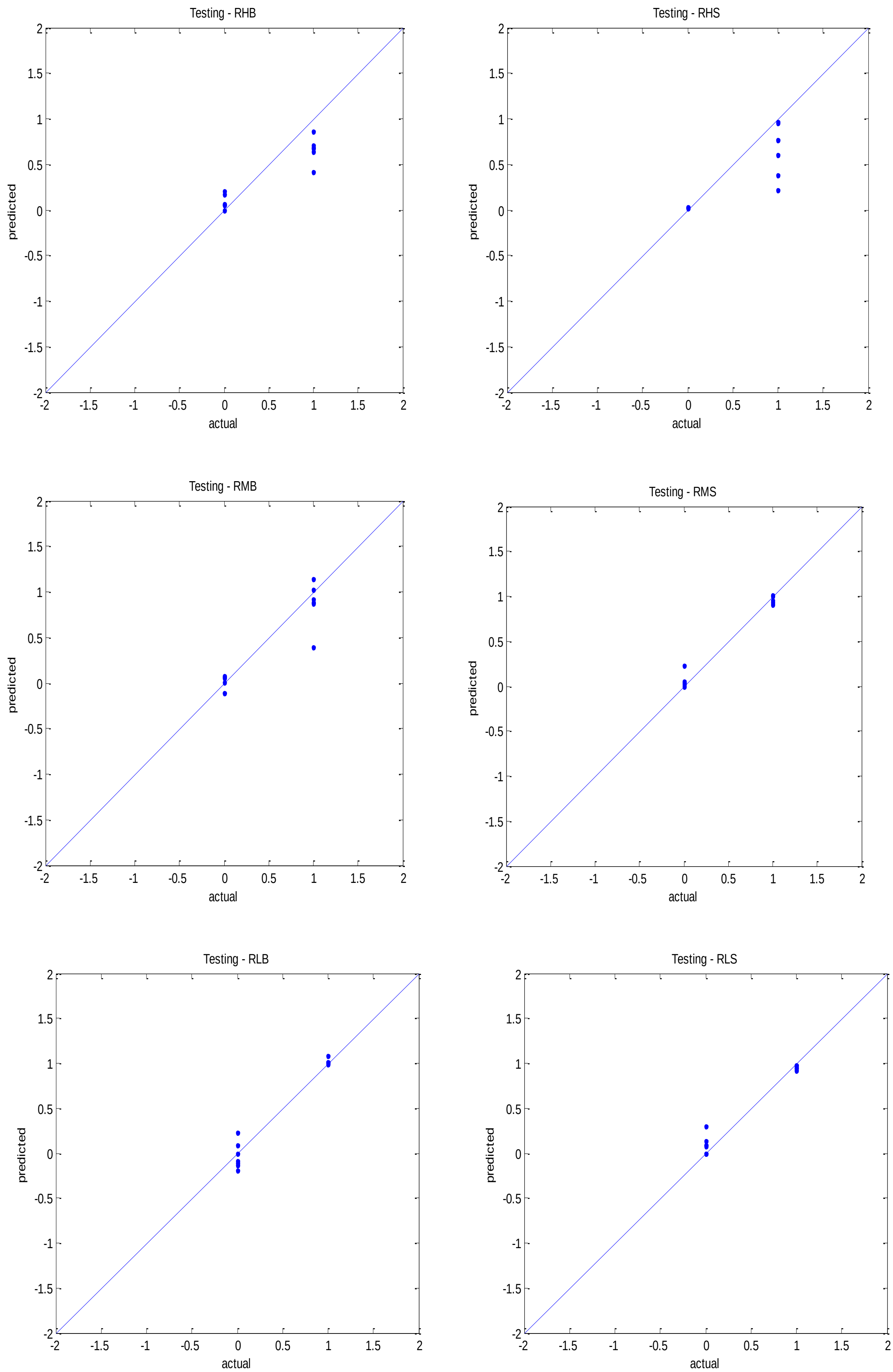

Figure C8: Testing results (Type1 shareholder) using ANN technique (NEWFF).

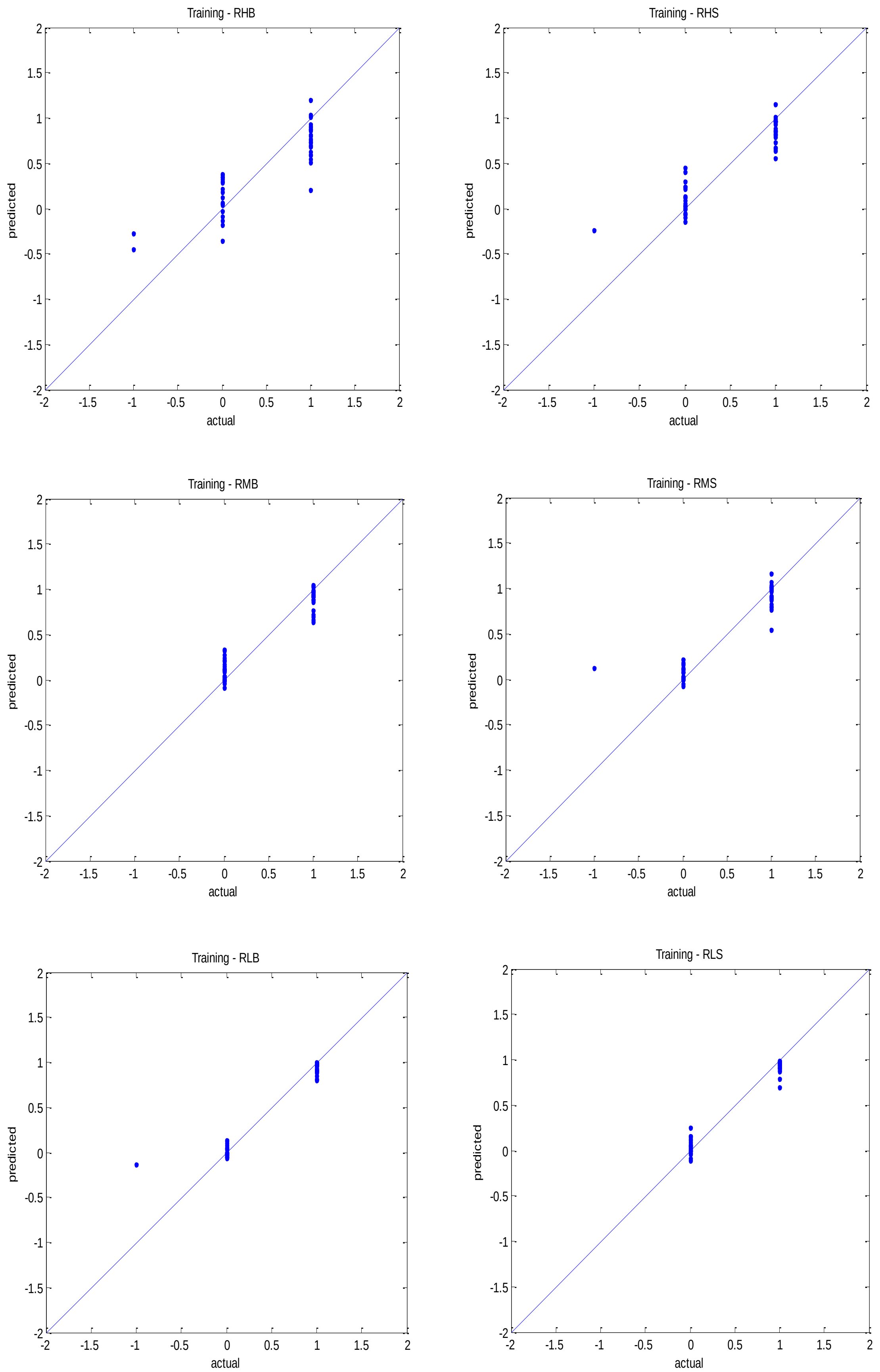

Figure C9: Training results (Type1 shareholder) using ANN technique (NEWDTDNN).

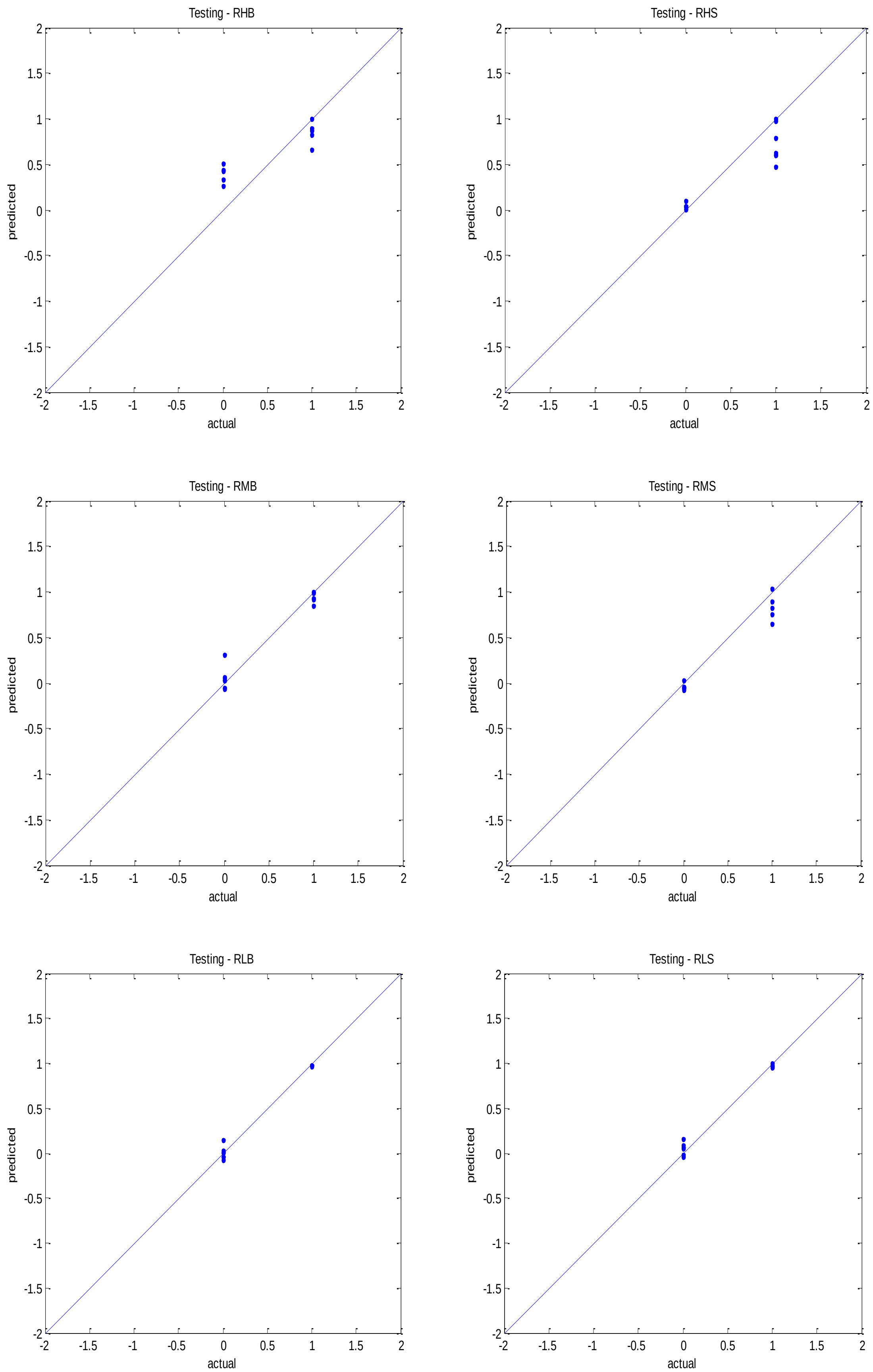

Figure C10: Testing results (Type1 shareholder) using ANN technique (NEWDTDNN).

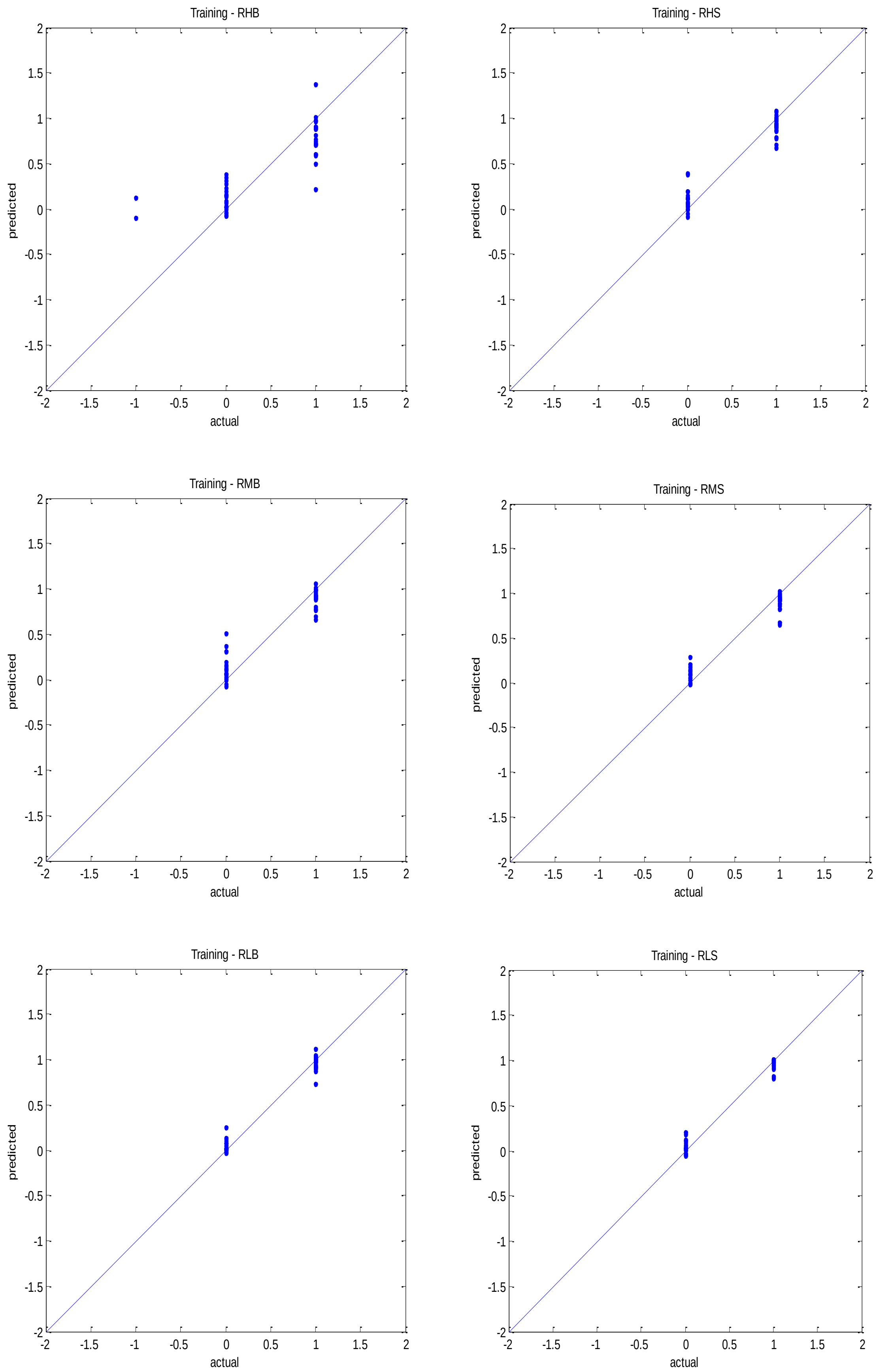

Figure C11: Training results (Type1 shareholder) using ANN technique (NEWFIT).

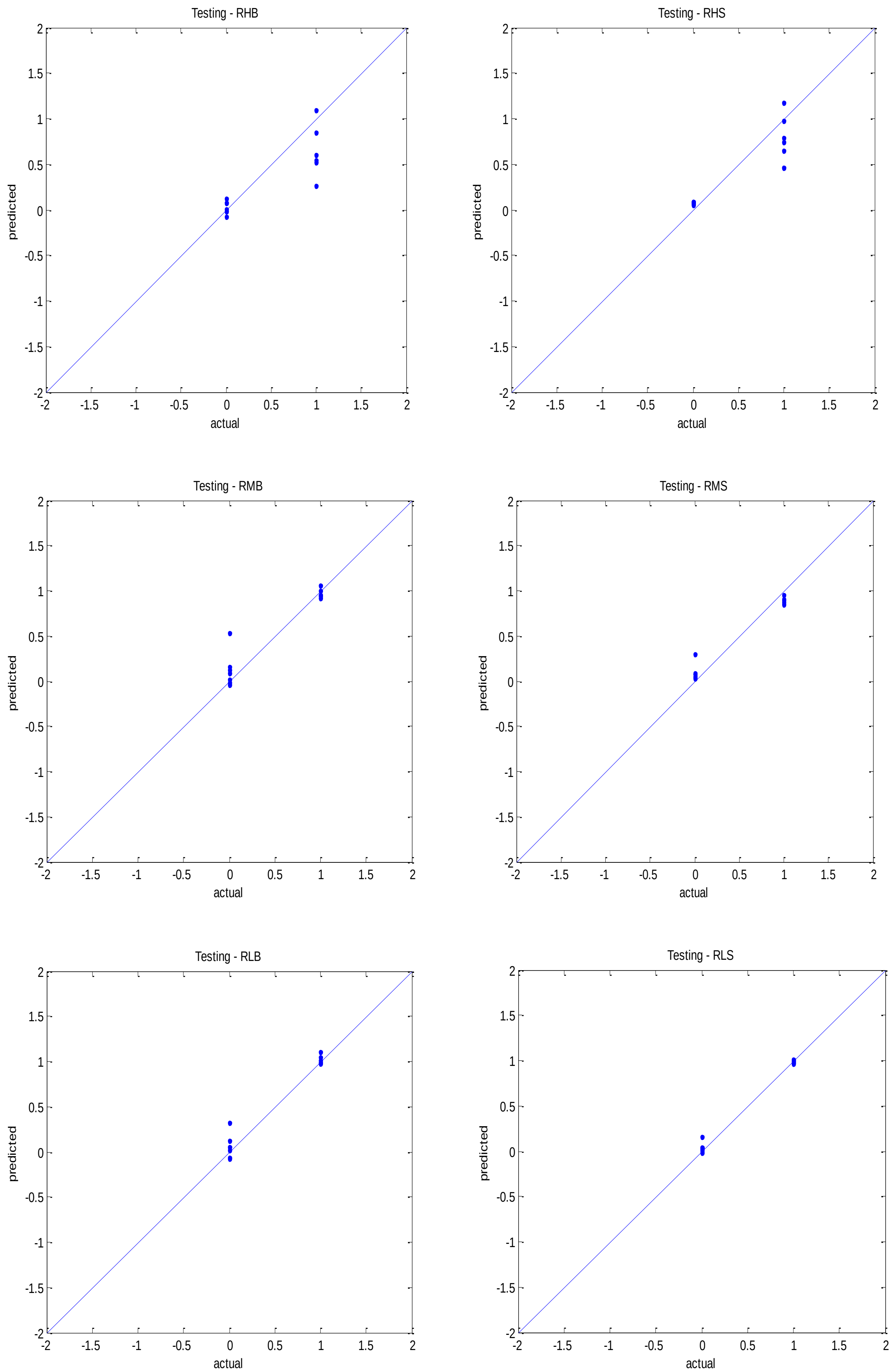

Figure C12: Testing results (Type1 shareholder) using ANN technique (NEWFIT).

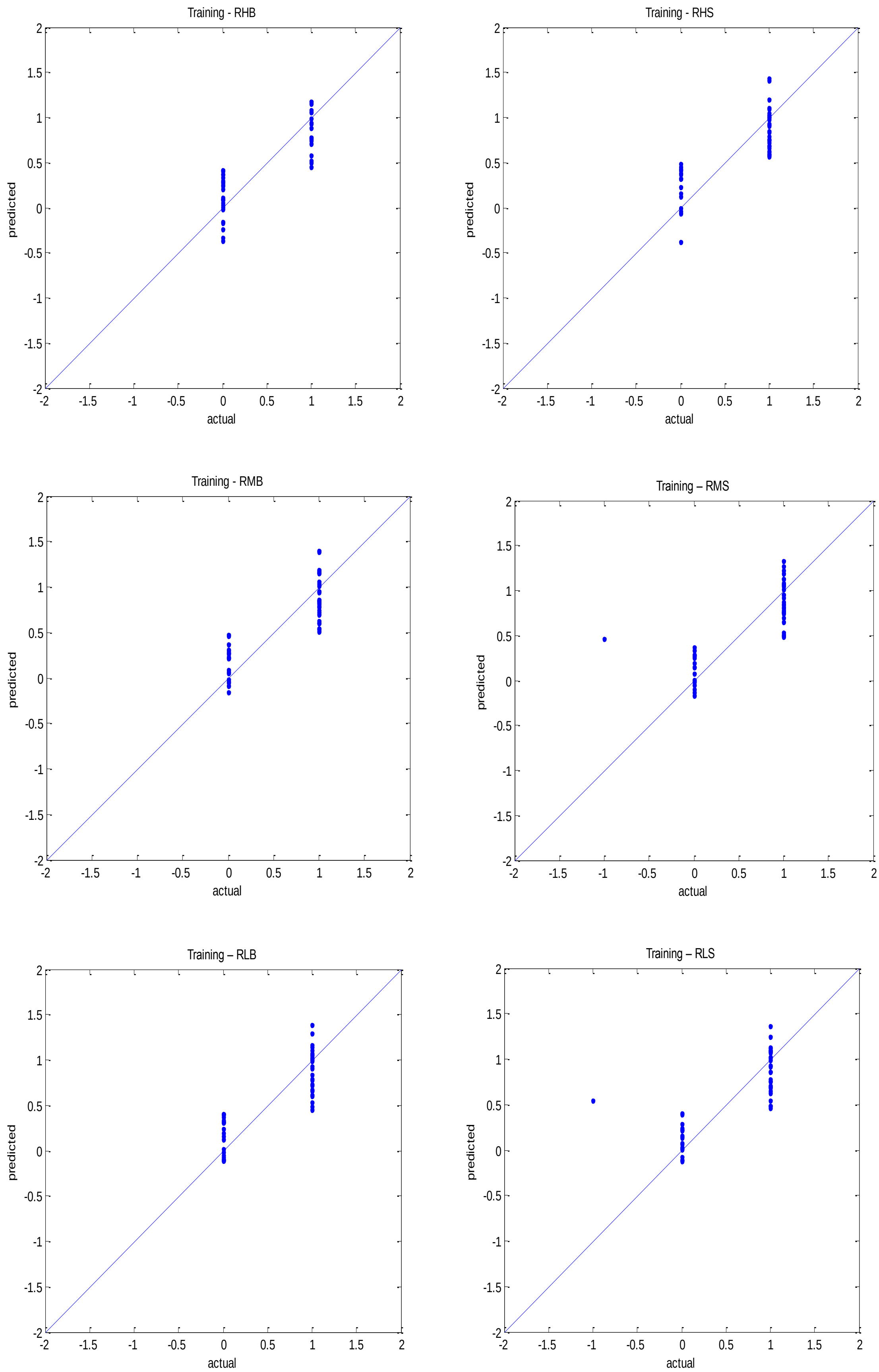

Figure C13: Training results (Type1 shareholder) using ANN technique (NEWRB).

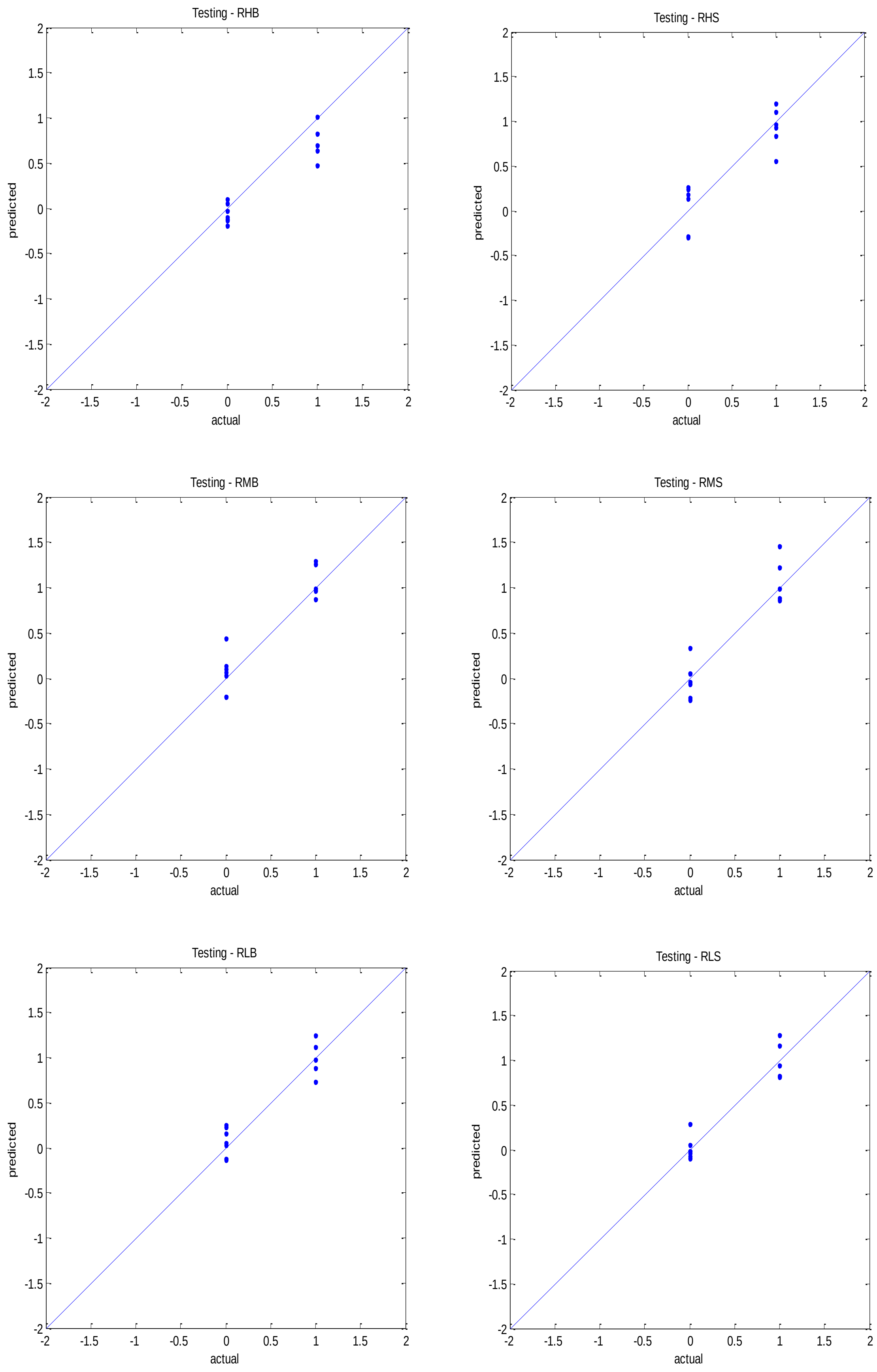

Figure C14: testing results (Type1 shareholder) using ANN technique (NEWRB).

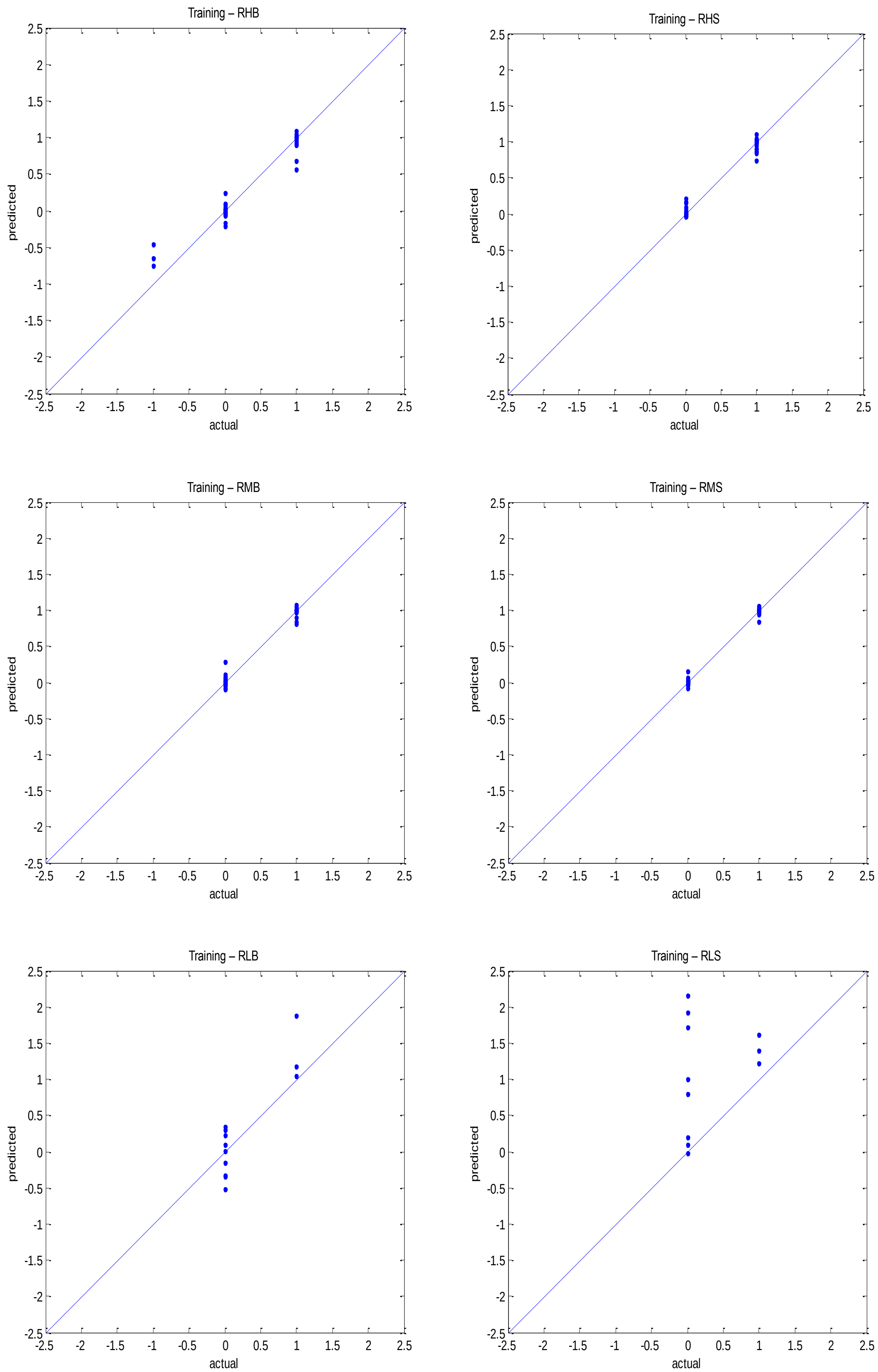

Figure C15: Training results (Type1 shareholder) using ANFIS technique.

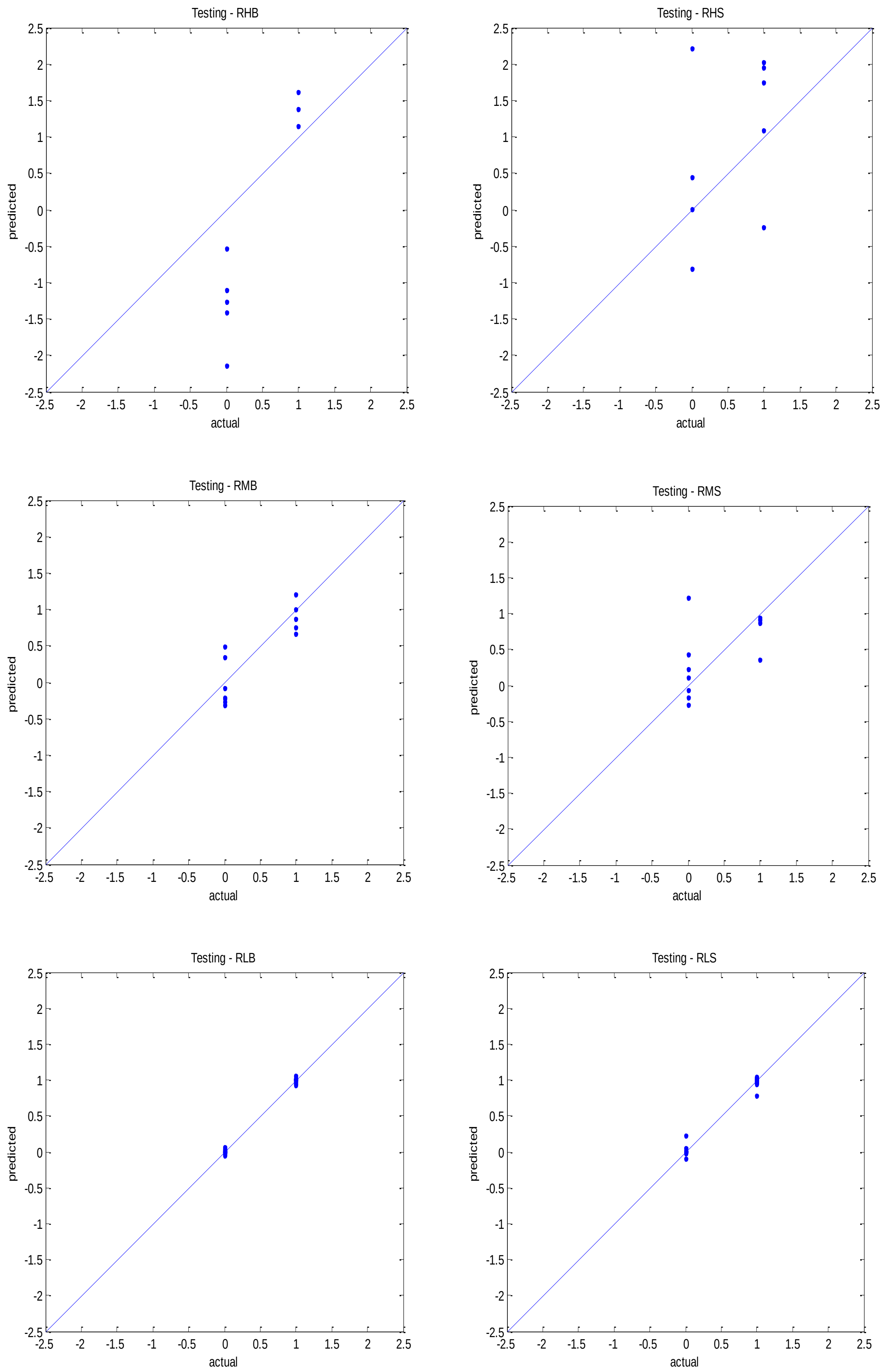

Figure C16: Testing results (Type1 shareholder) using ANFIS technique.

Appendix D: Prediction Result using Multi-Stage Type-1 Model (share price)

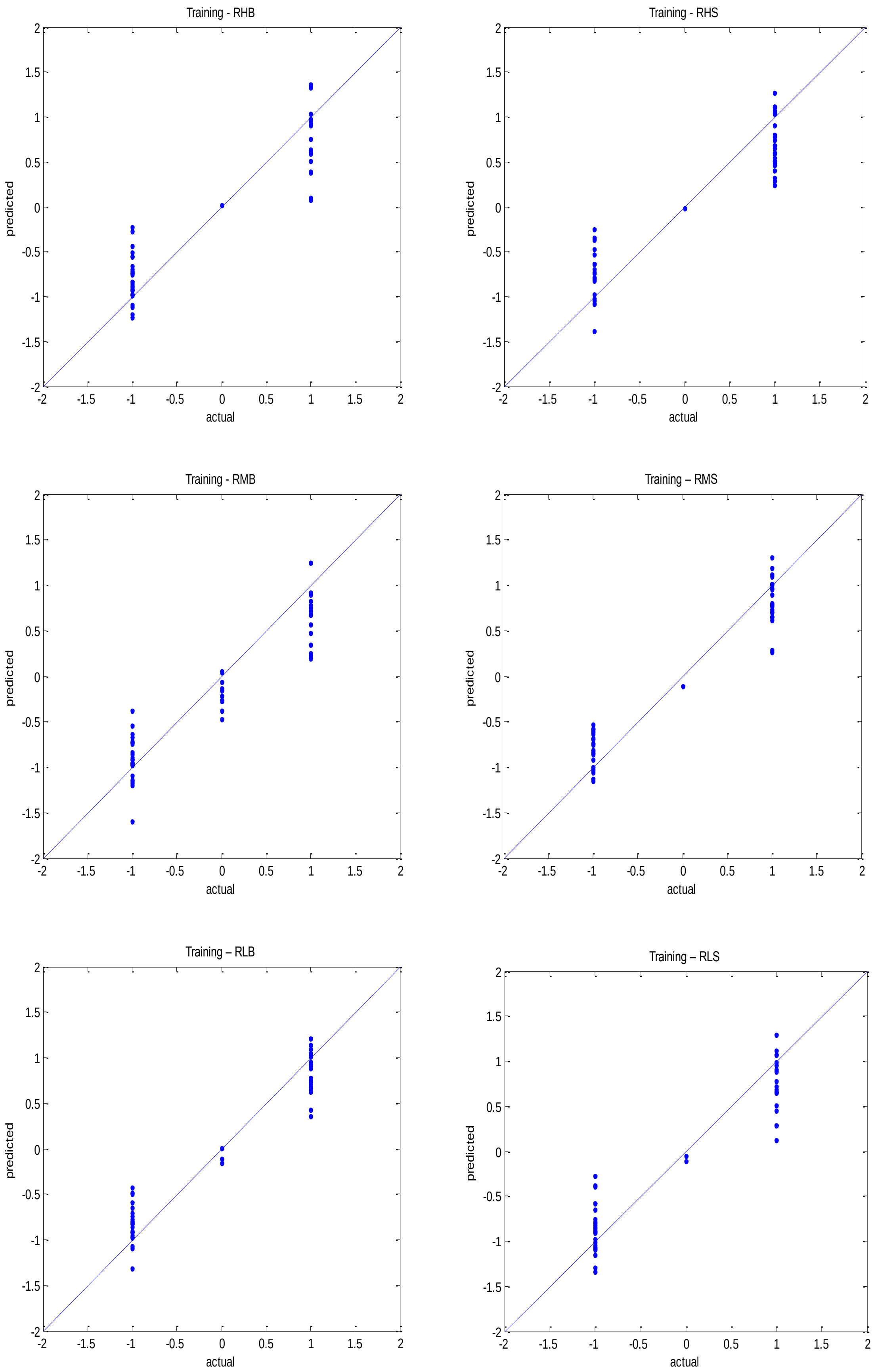

Figure D1: Training results (Type1 share price) using ANN technique (NEWCF).

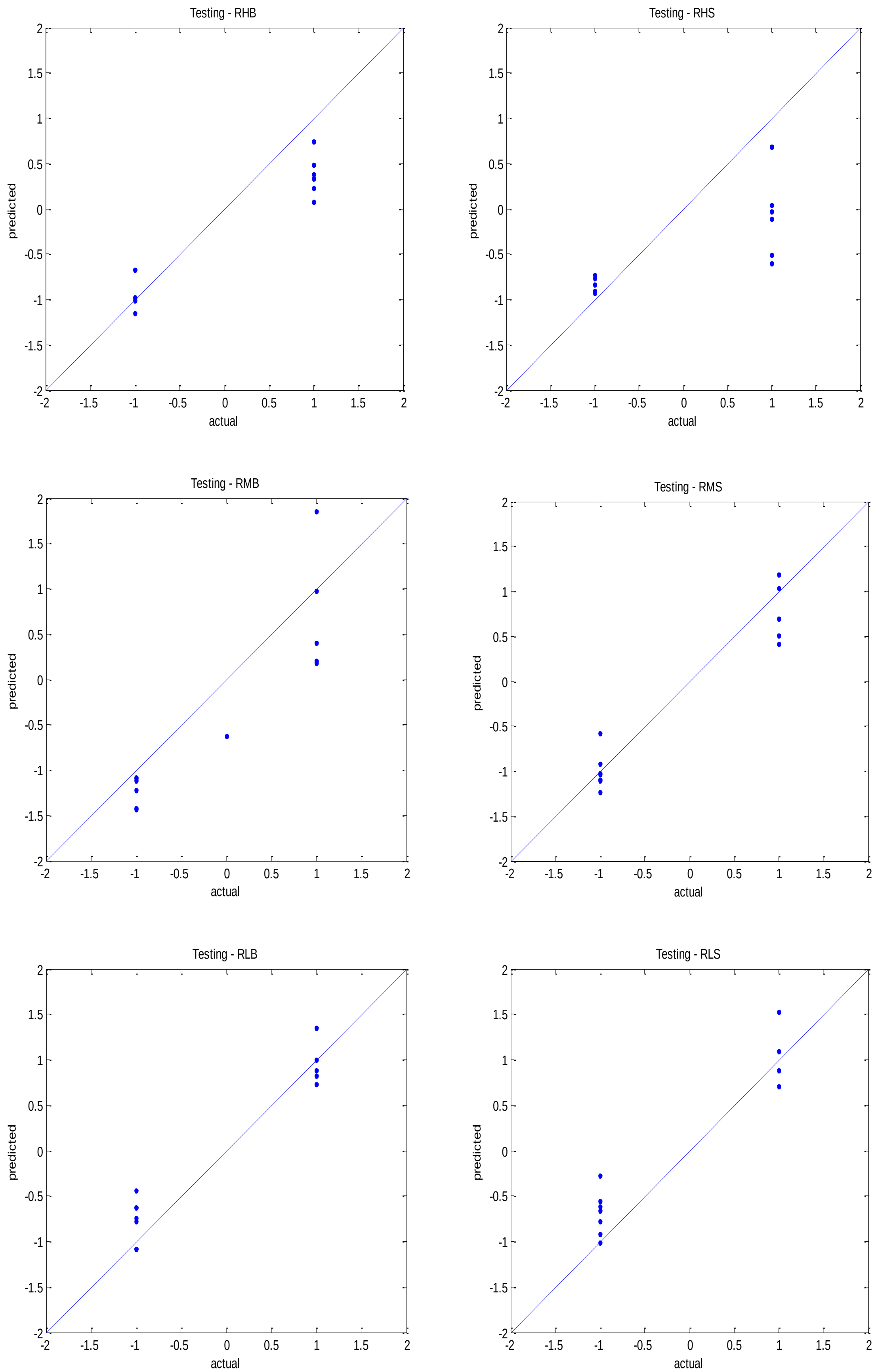

Figure D2: Testing results (Type1 share price) using ANN technique (NEWCF).

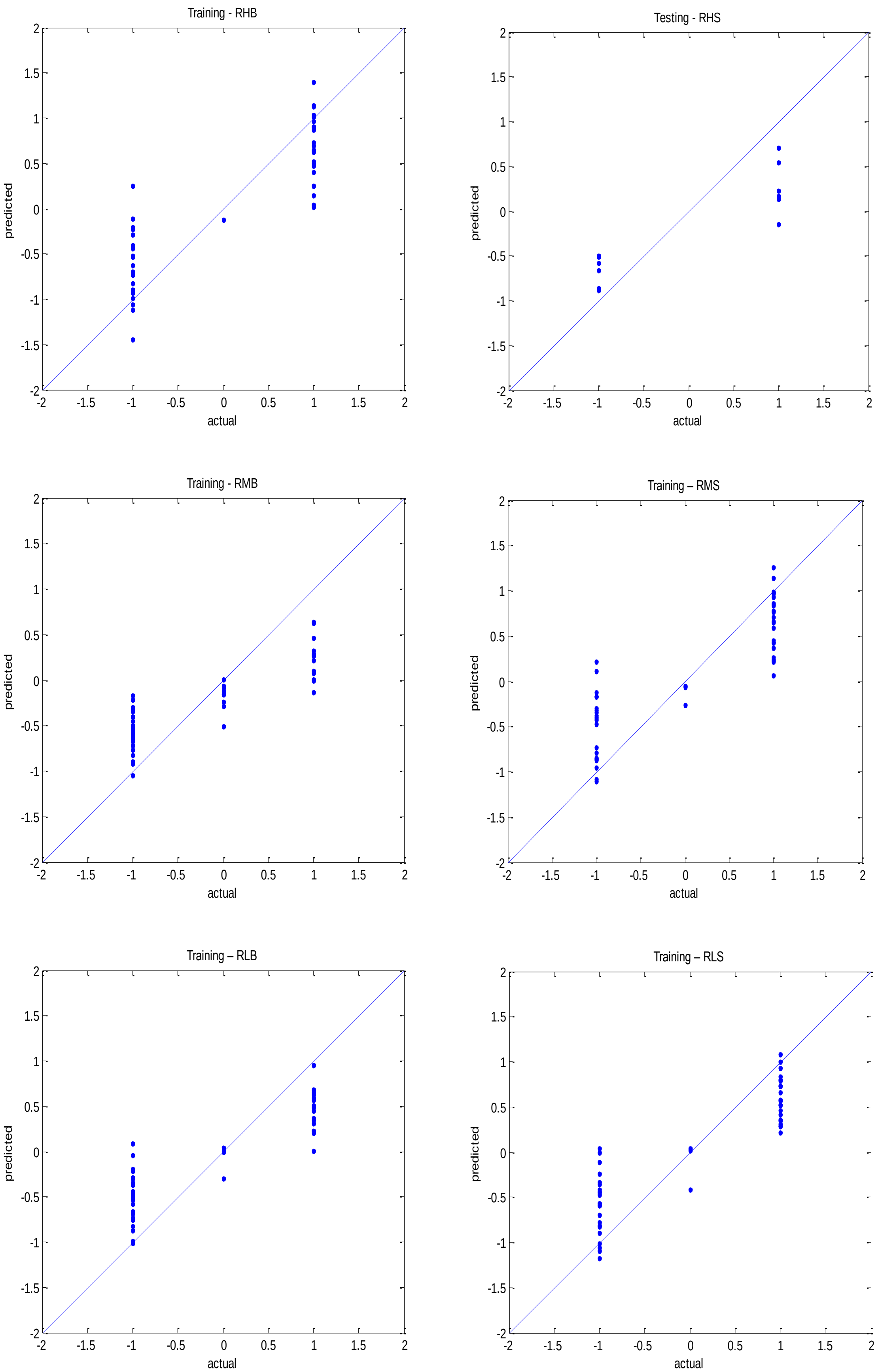

Figure D3: Training results (Type1 share price) using ANN technique (NEWELM).

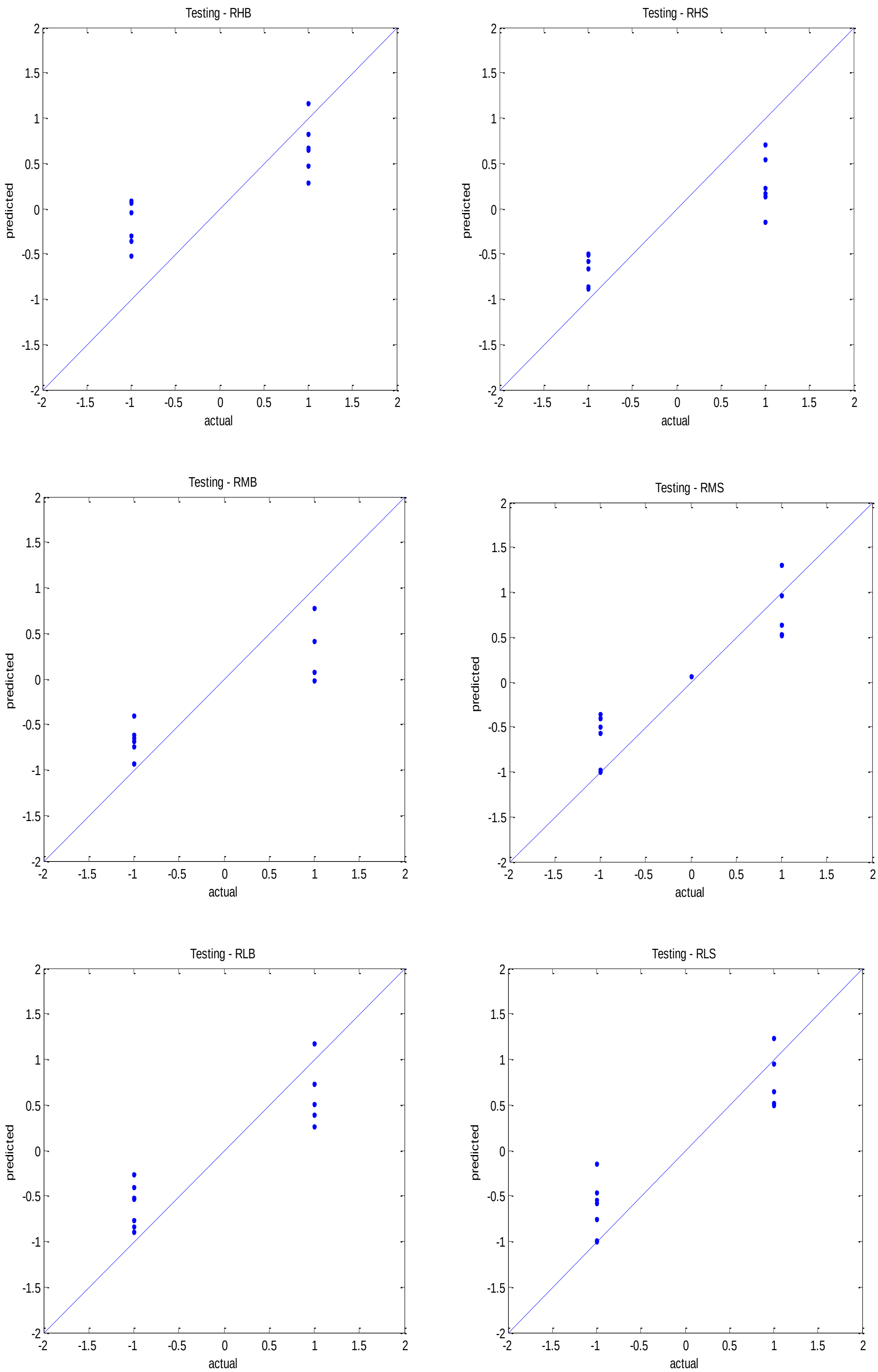

Figure D4: Testing results (Type1 share price) using ANN technique (NEWELM).

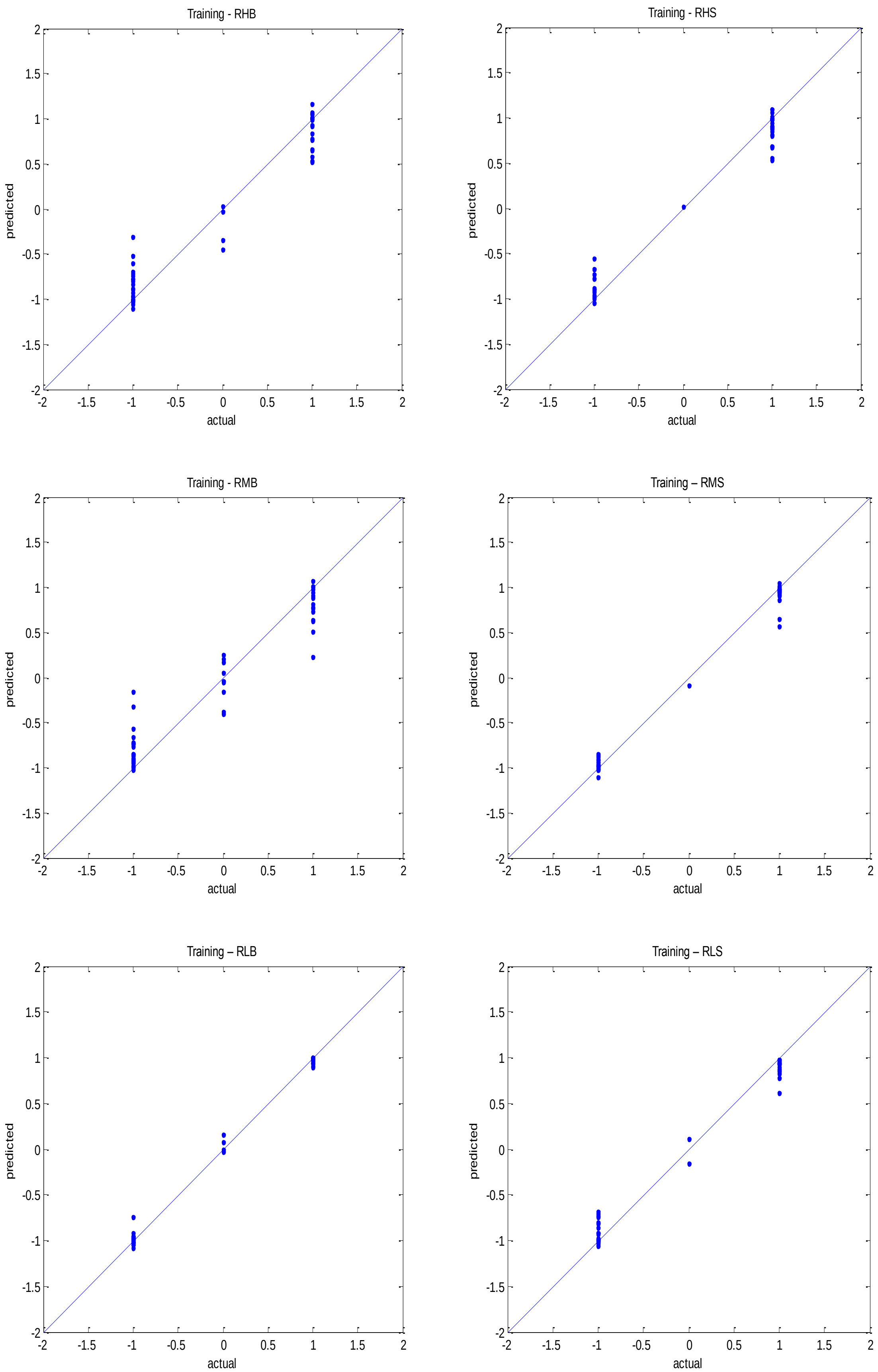

Figure D5: Training results (Type1 share price) using ANN technique (NEWFFTD).

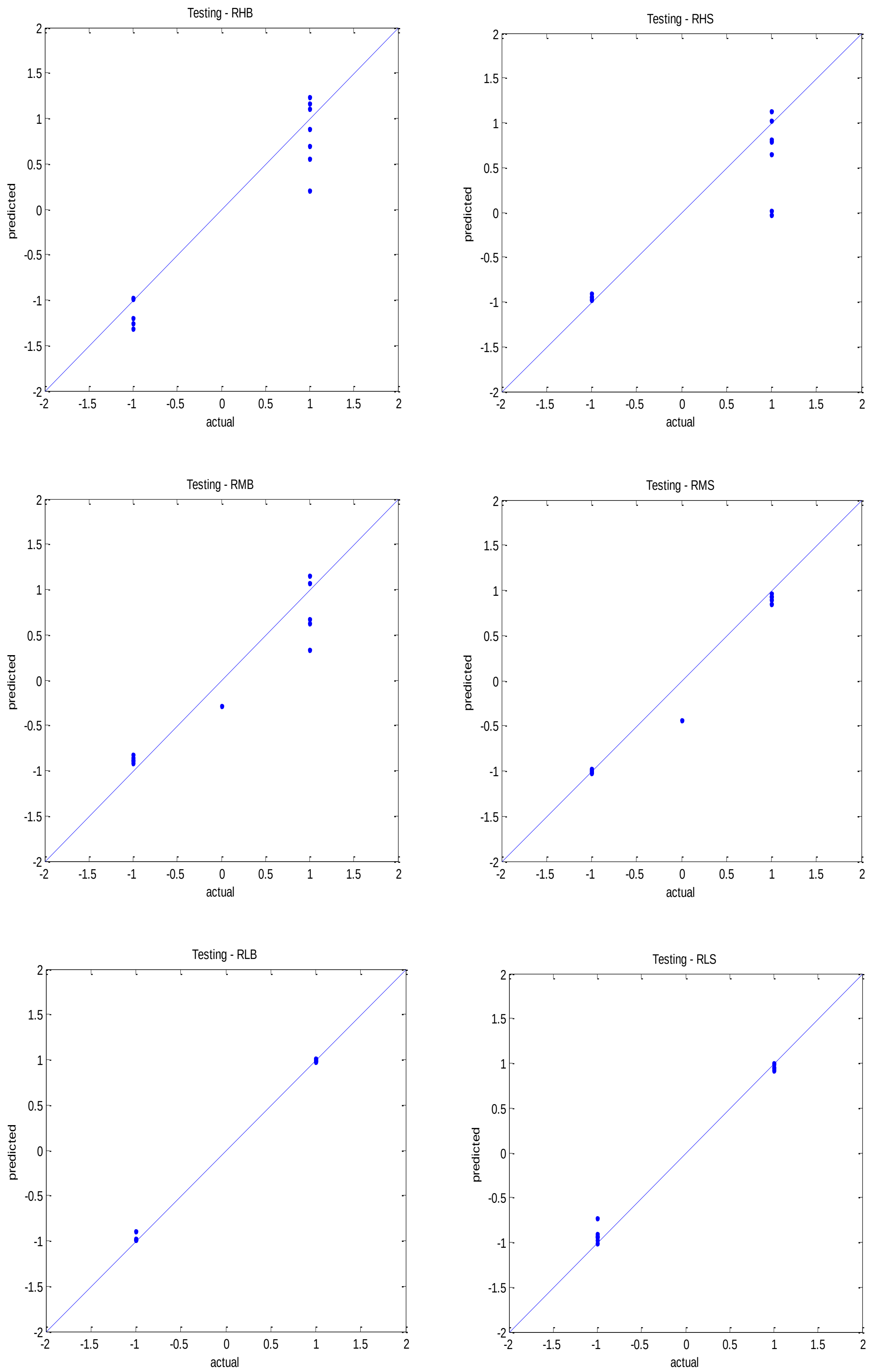

Figure D6: Testing results (Type1 share price) using ANN technique (NEWFFTD).

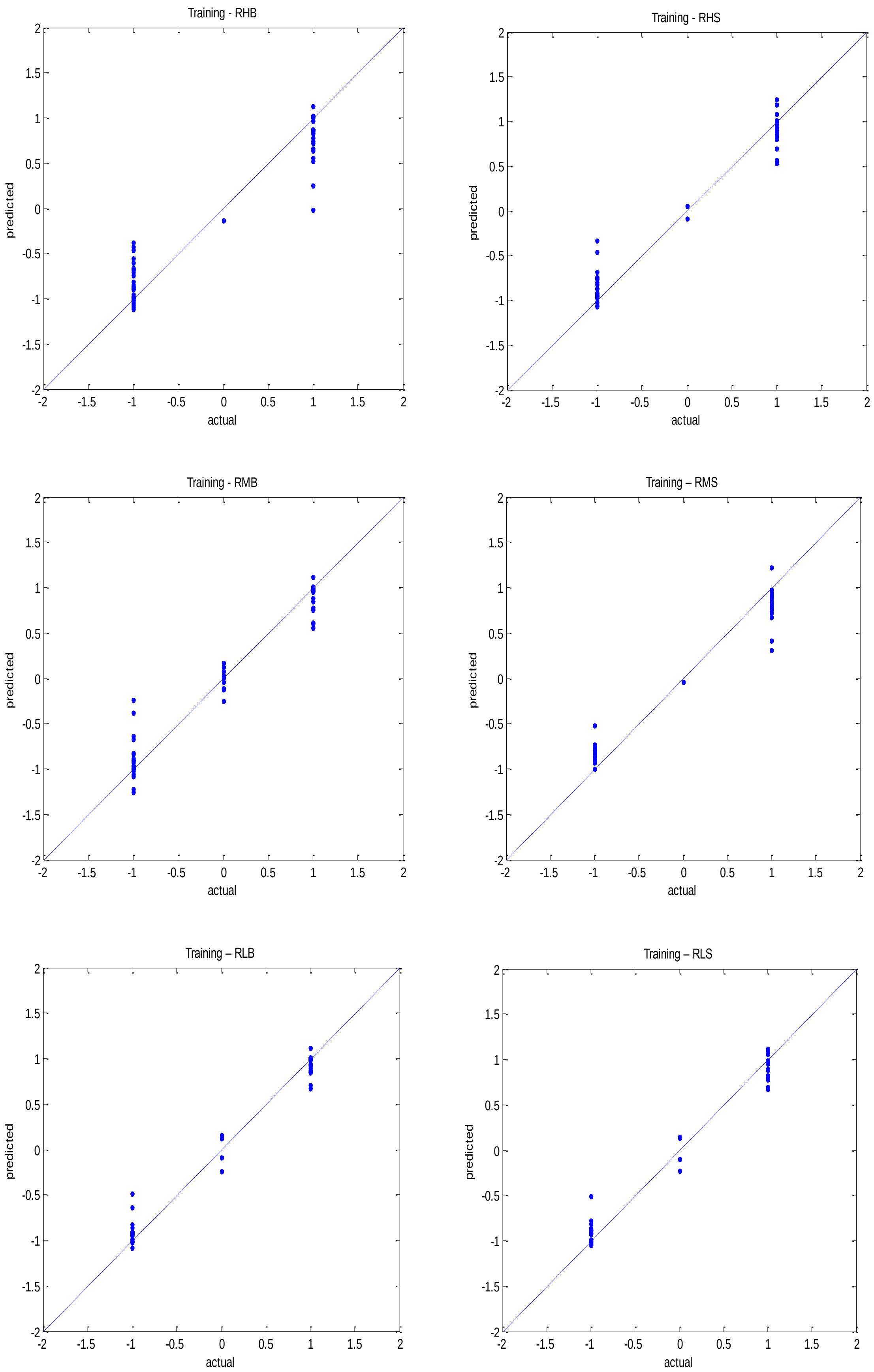

Figure D7: Training results (Type1 share price) using ANN technique (NEWFF).

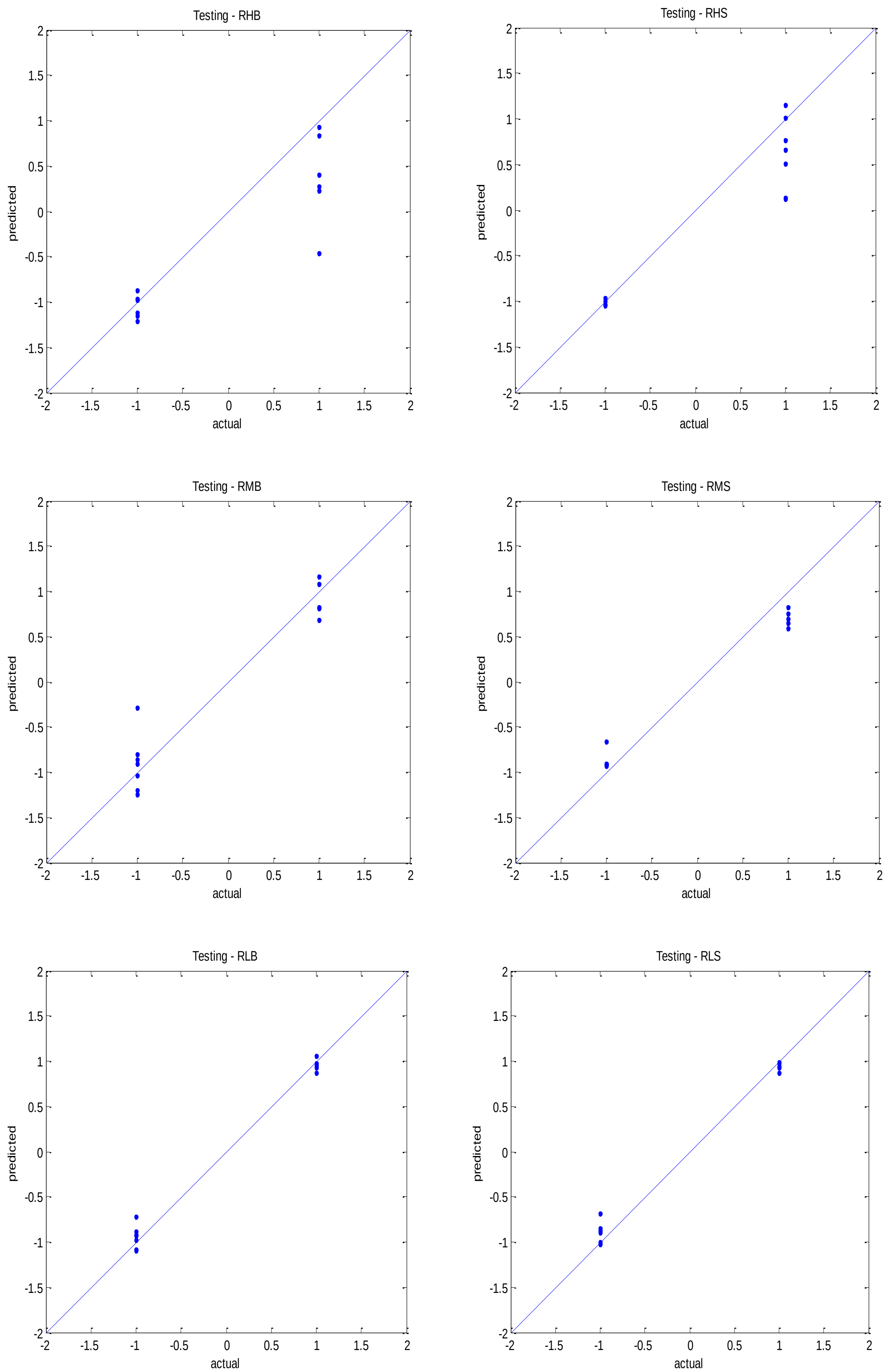

Figure D8: Testing results (Type1 share price) using ANN technique (NEWFF).

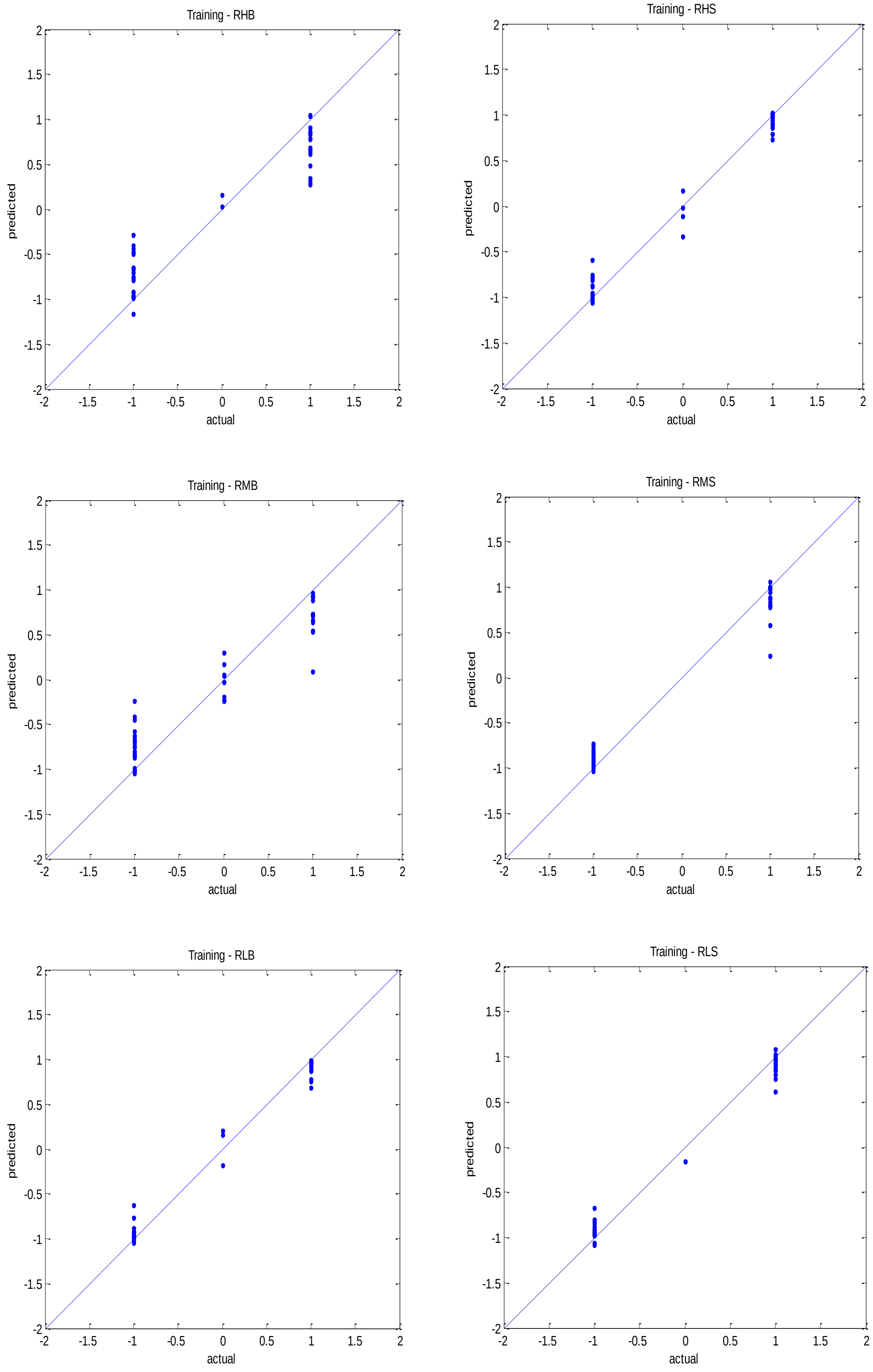

Figure D9: Training results (Type1 share price) using ANN technique (NEWDTDNN).

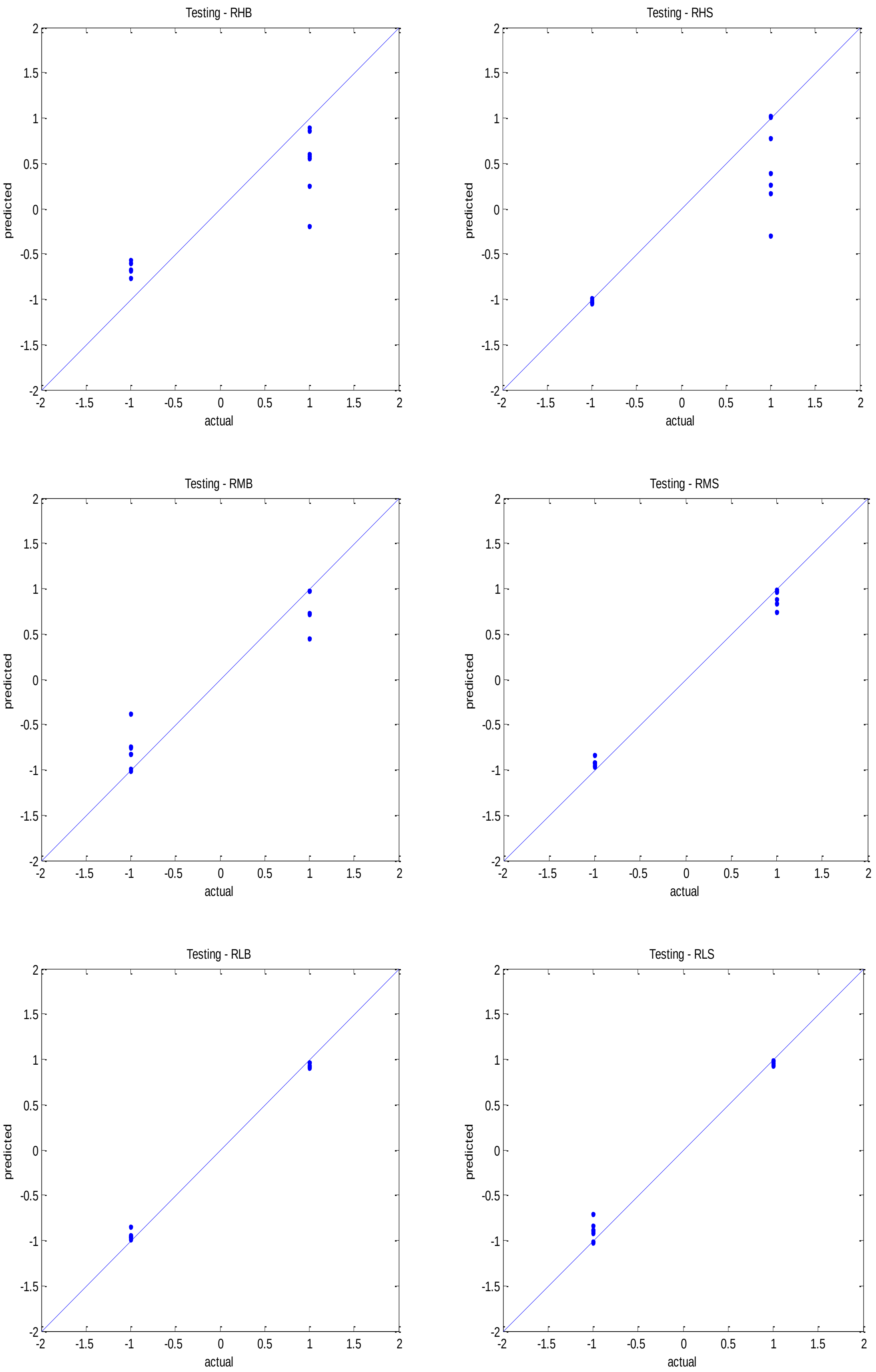

Figure D10: Testing results (Type1 share price) using ANN technique (NEWDTDNN).

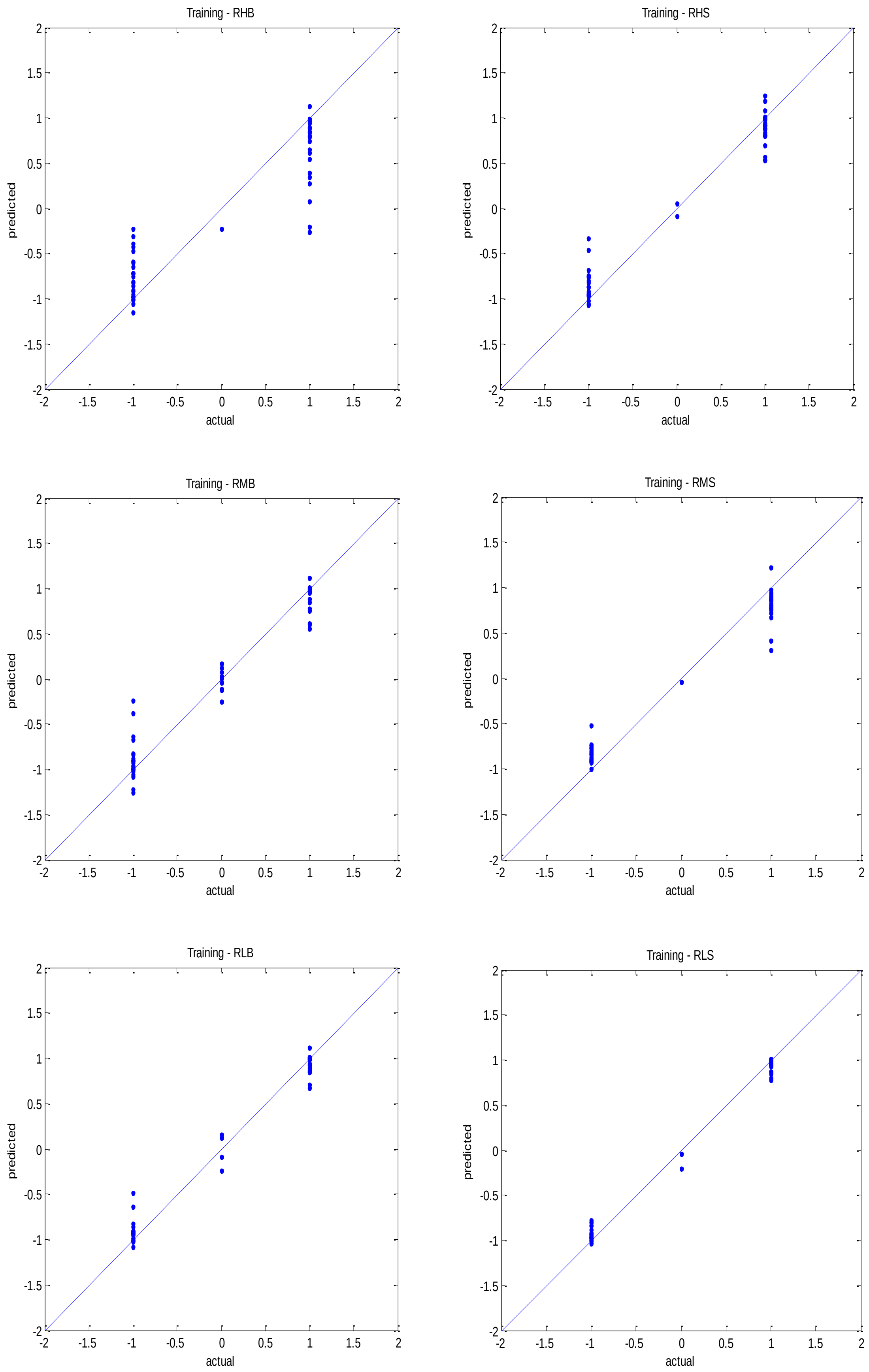

Figure D11: Training results (Type1 share price) using ANN technique (NEWFIT).

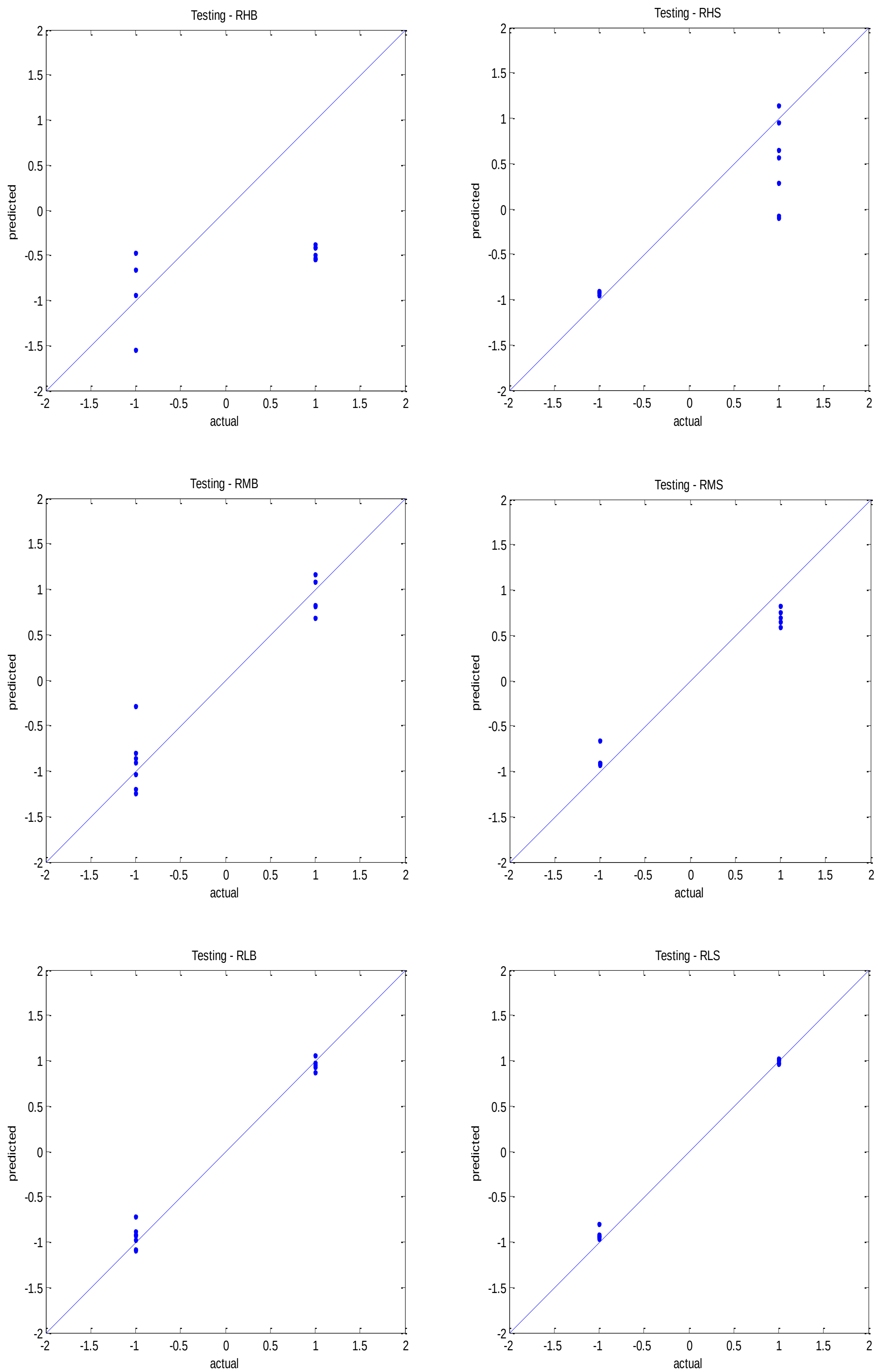

Figure D12: Testing results (Type1 share price) using ANN technique (NEWFIT).

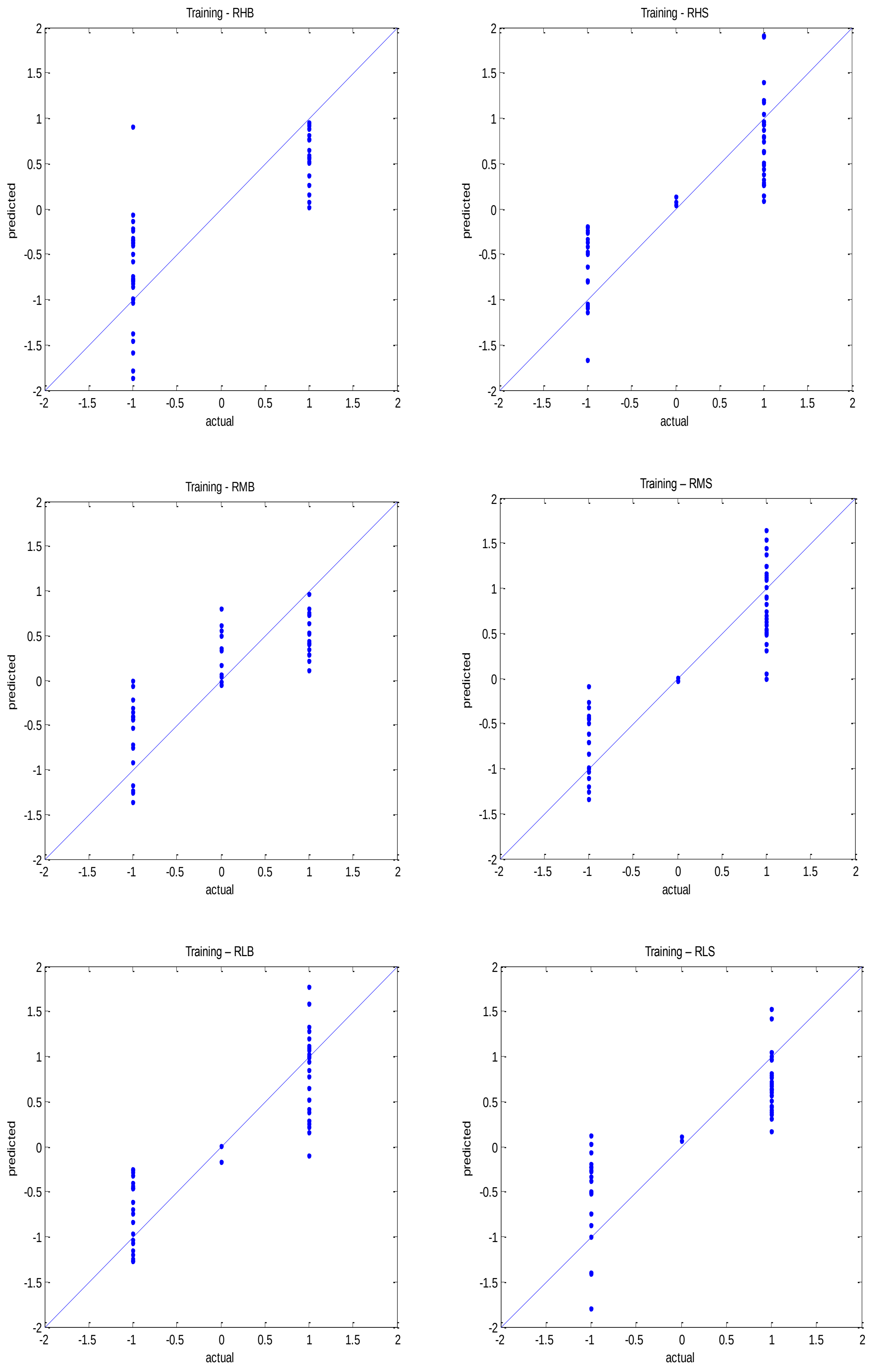

Figure D13: Training results (Type1 share price) using ANN technique (NEWRB).

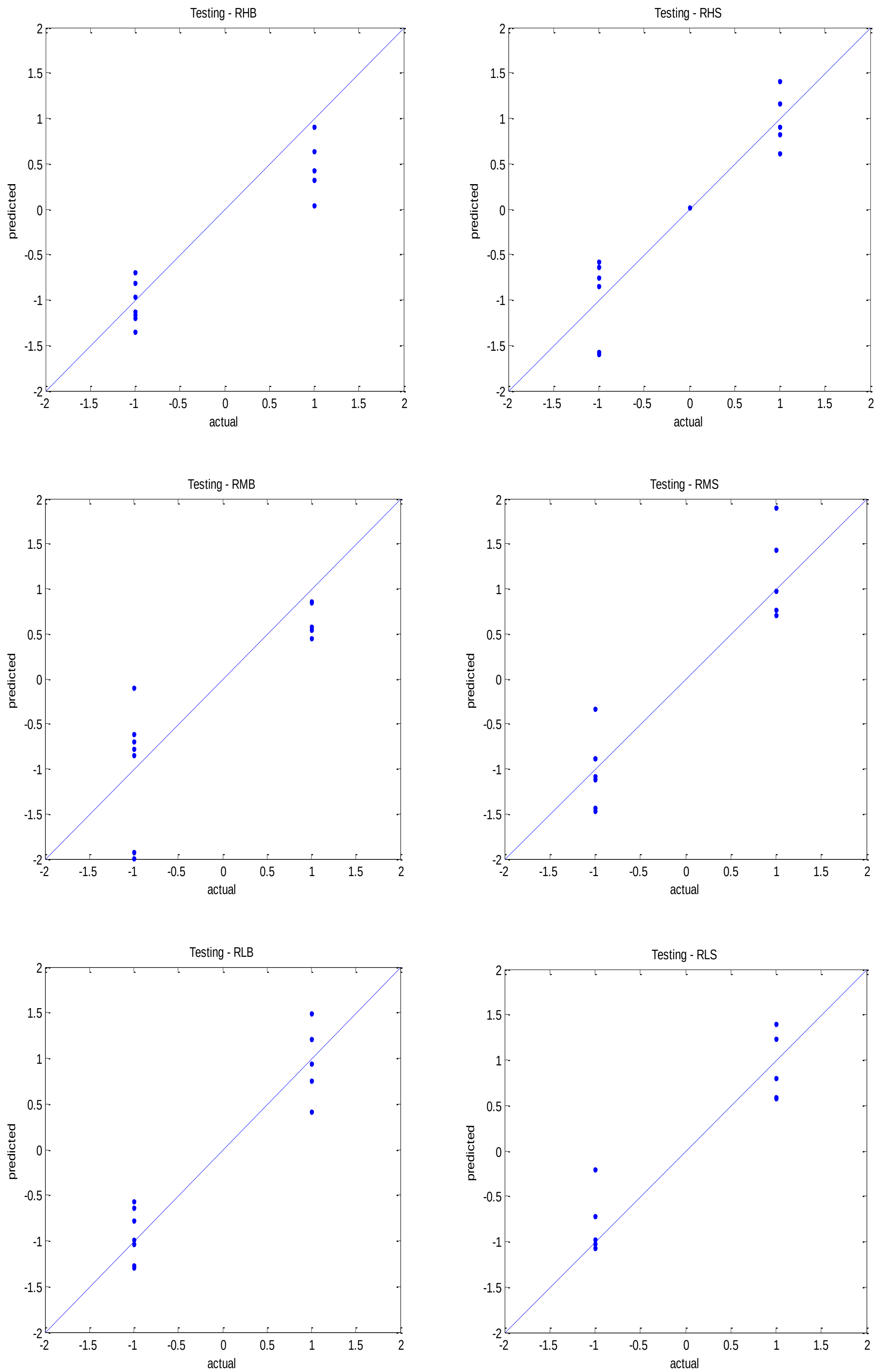

Figure D14: Testing results (Type1 share price) using ANN technique (NEWRB).

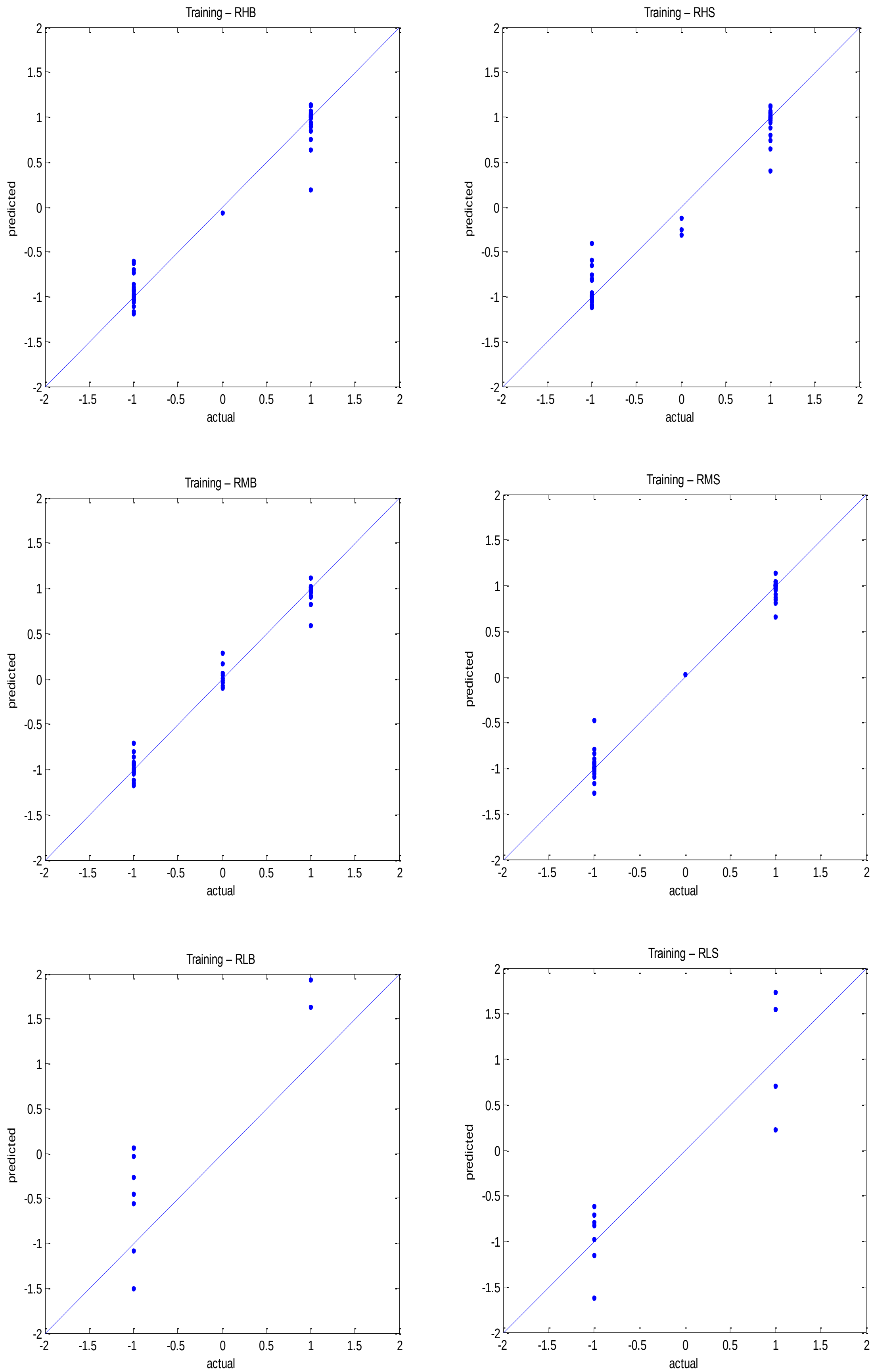

Figure D15: Training results (Type1 share price) using ANFIS technique.

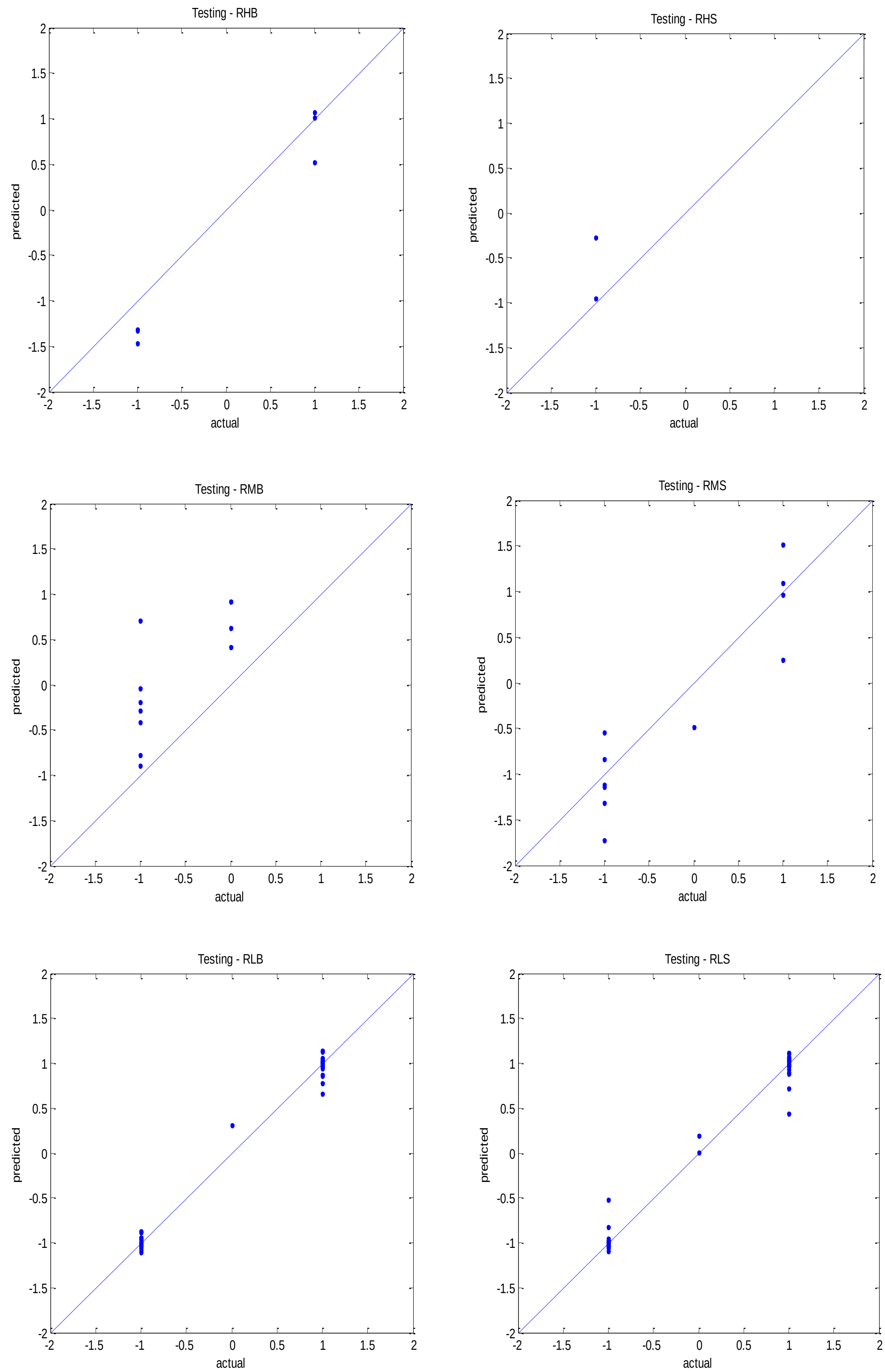

Figure D16: Testing results (Type1 share price) using ANFIS technique.

Appendix E: Prediction Result using Multi-Stage Type-2 Model (Shareholder)

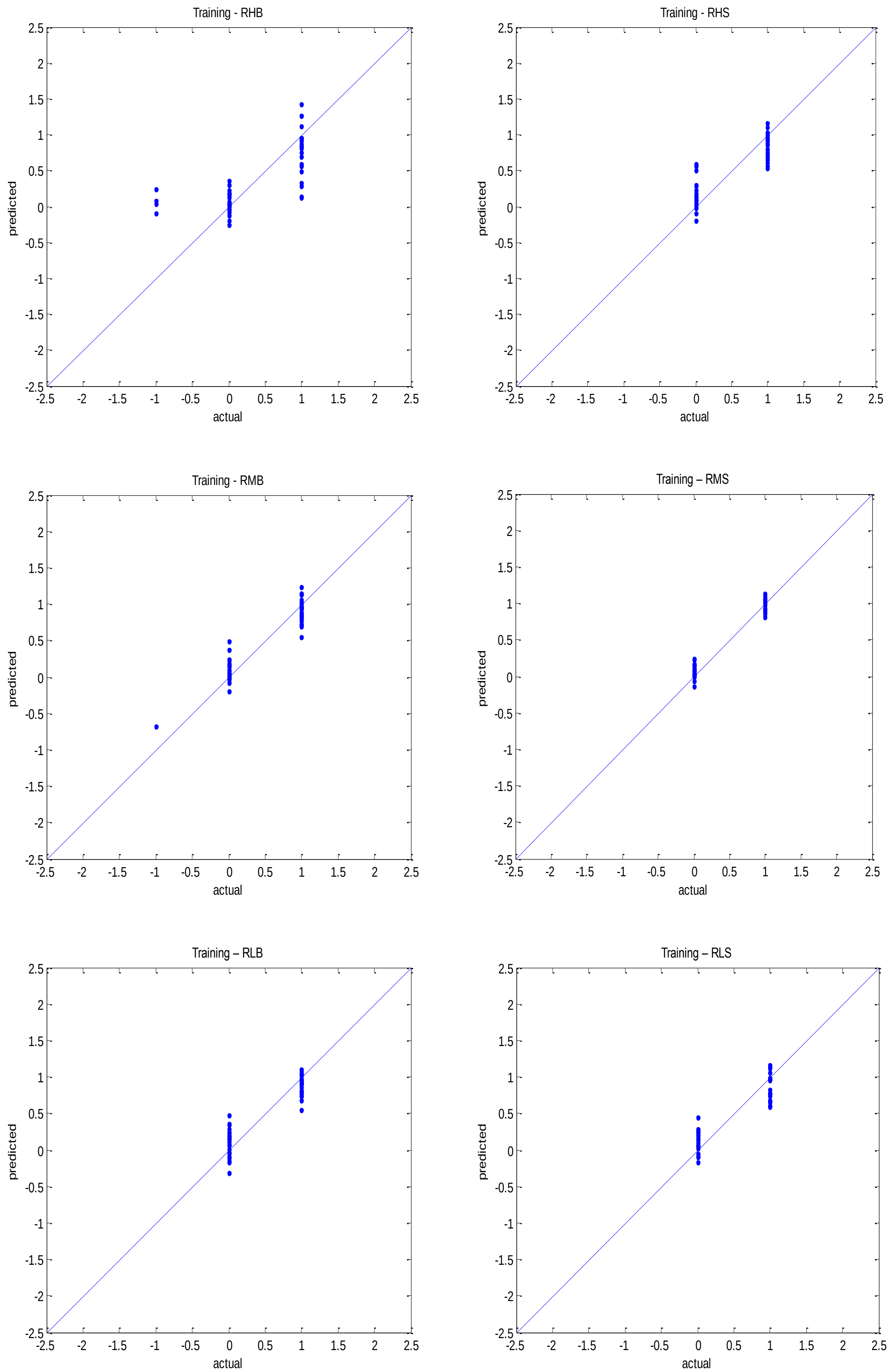

Figure E1: Training results (Type 2 shareholder) using ANN technique (NEWCF).

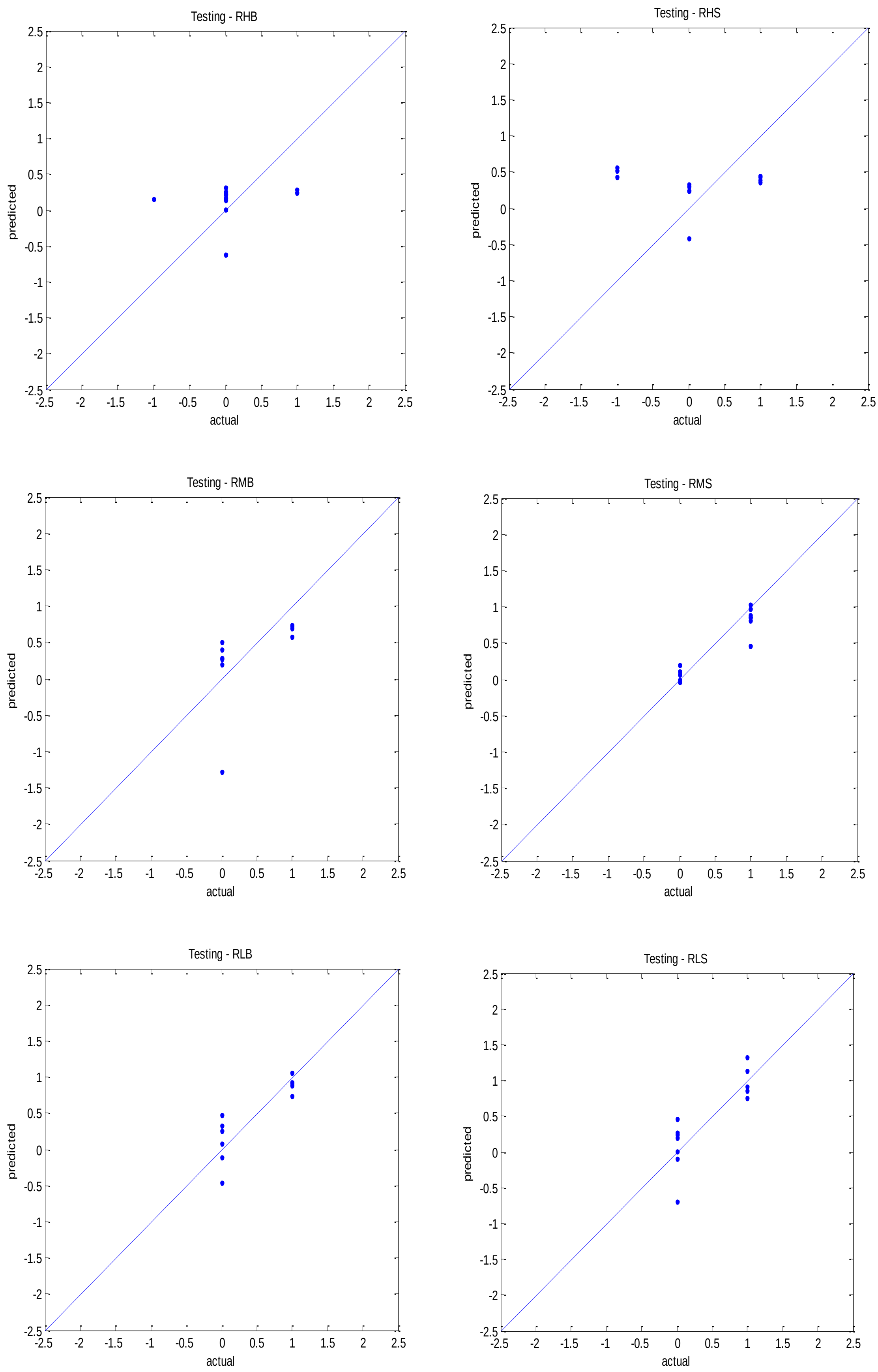

Figure E2: Testing results (Type2 shareholder) using ANN technique (NEWCF).

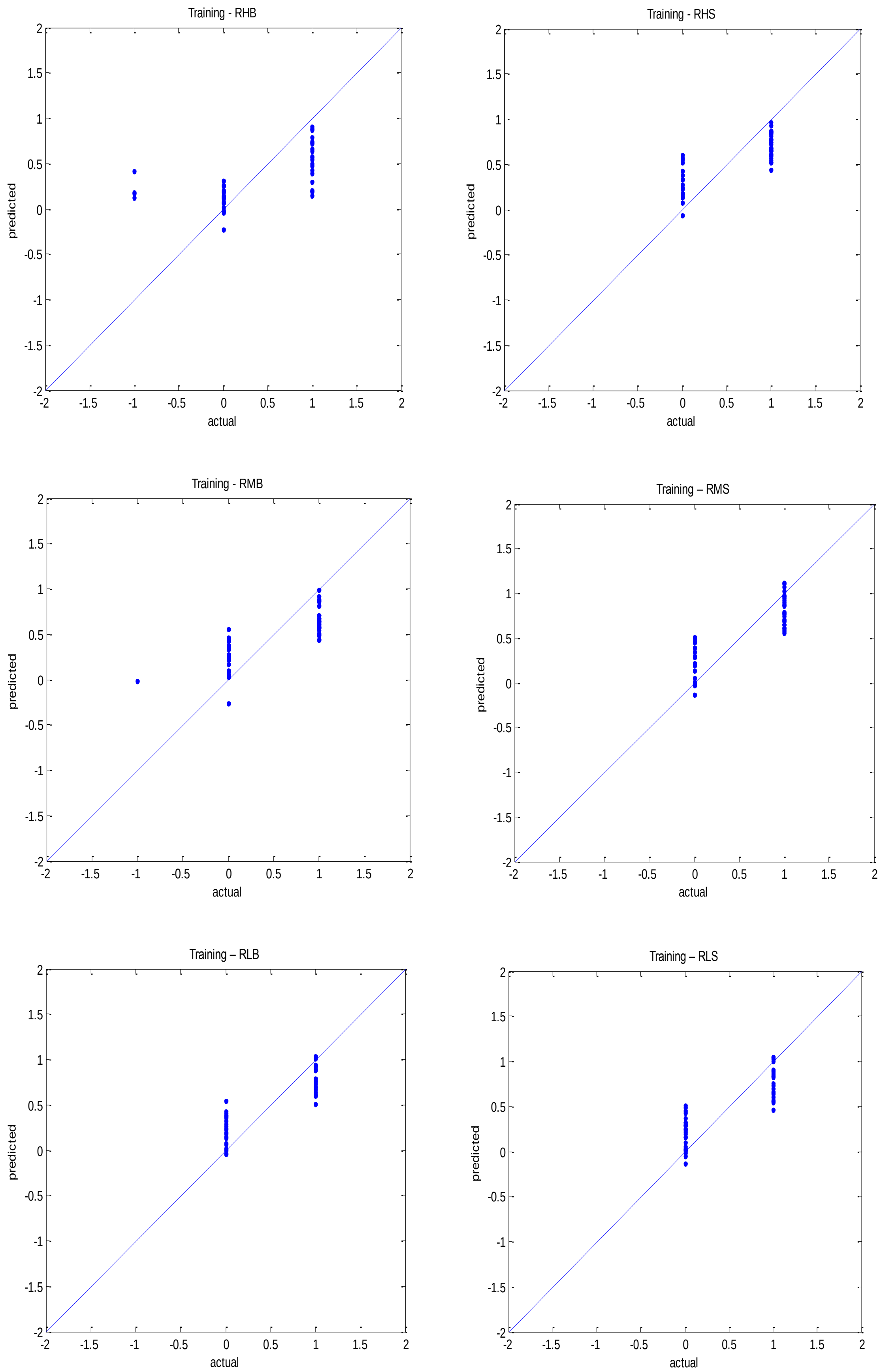

Figure E3: Training results (Type2 shareholder) using ANN technique (NEWELM).

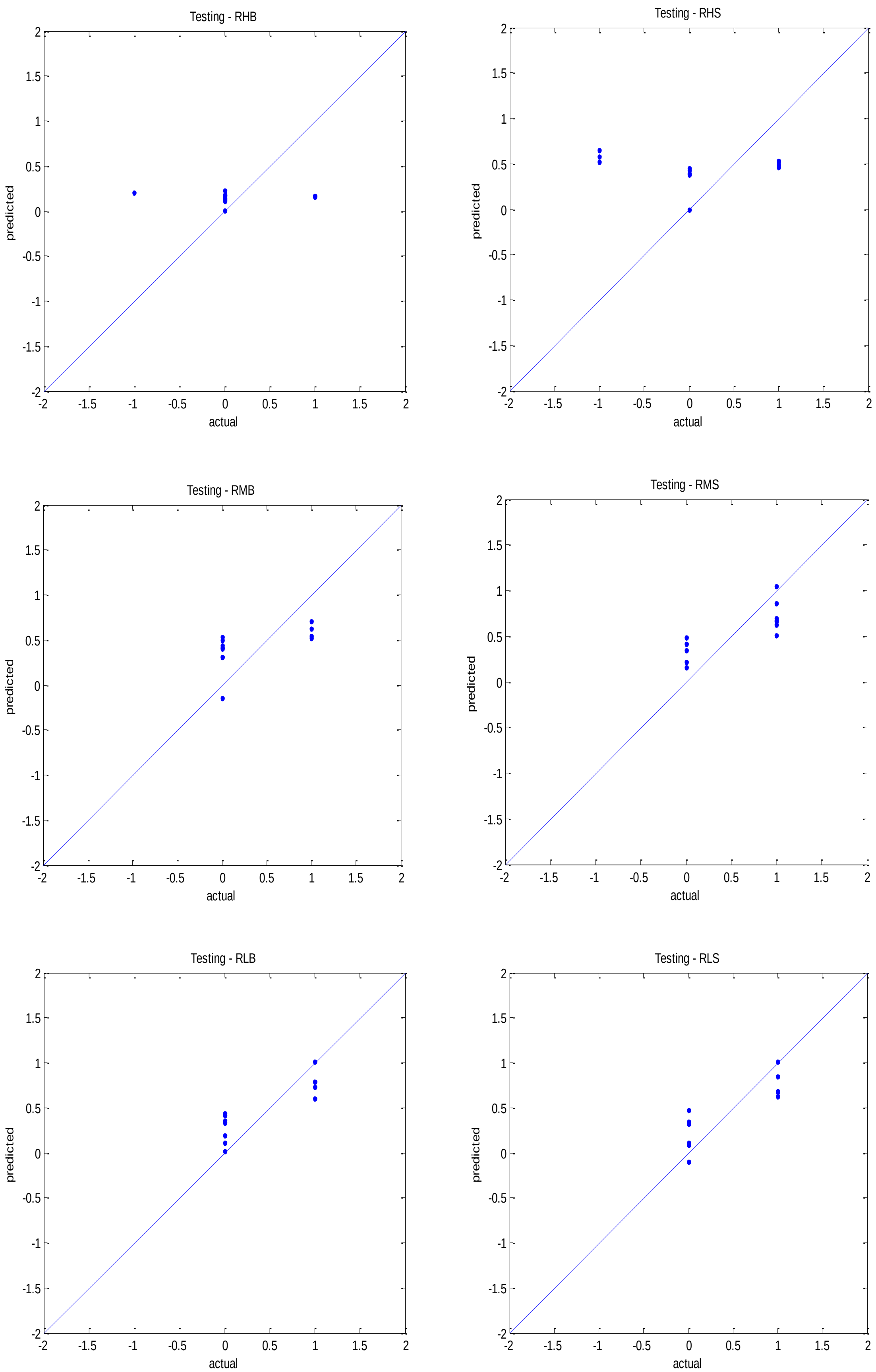

Figure E4: Testing results (Type2 shareholder) using ANN technique (NEWELM).

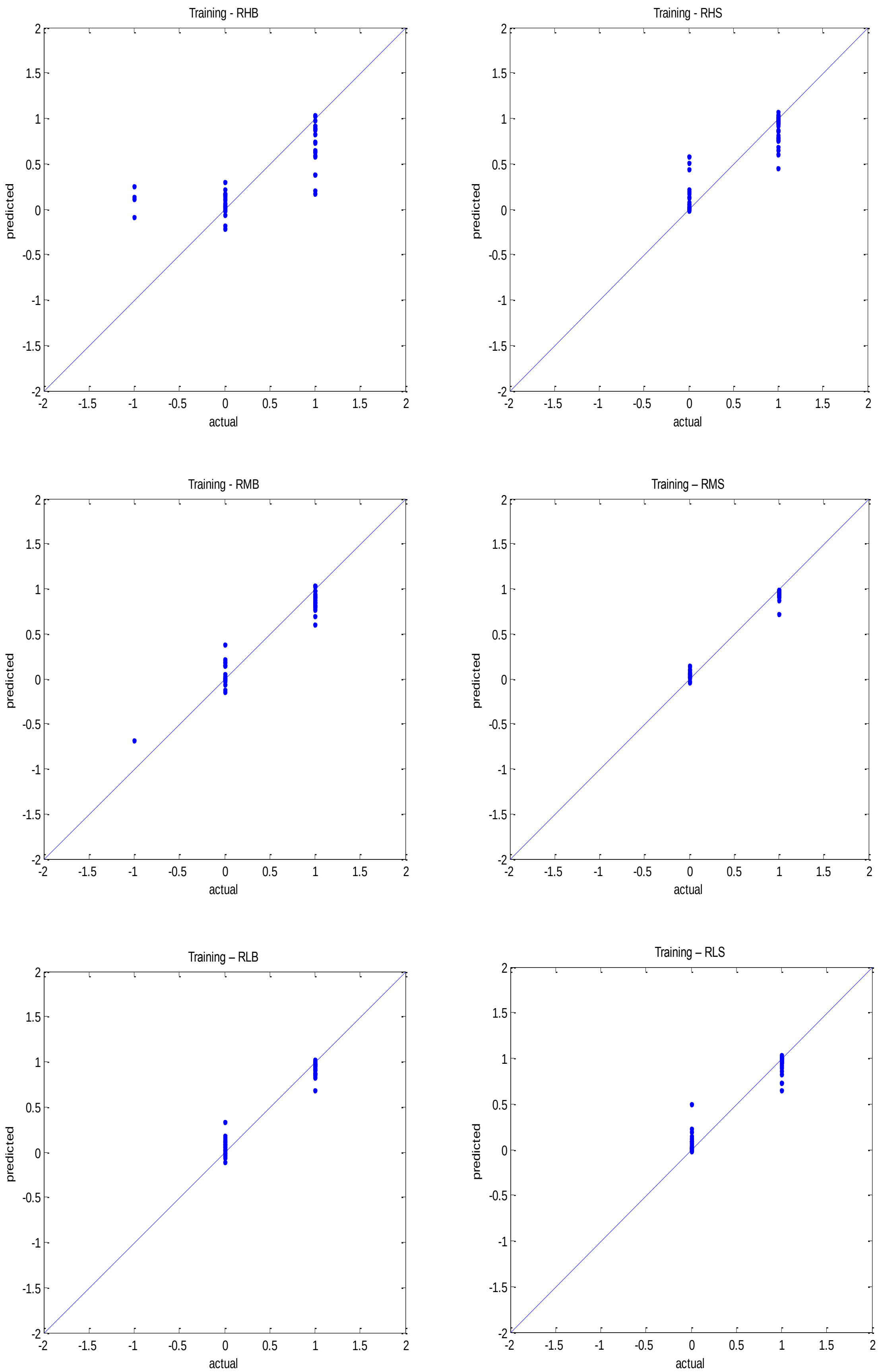

Figure E5: Training results (Type2 shareholder) using ANN technique (NEWFFTD).

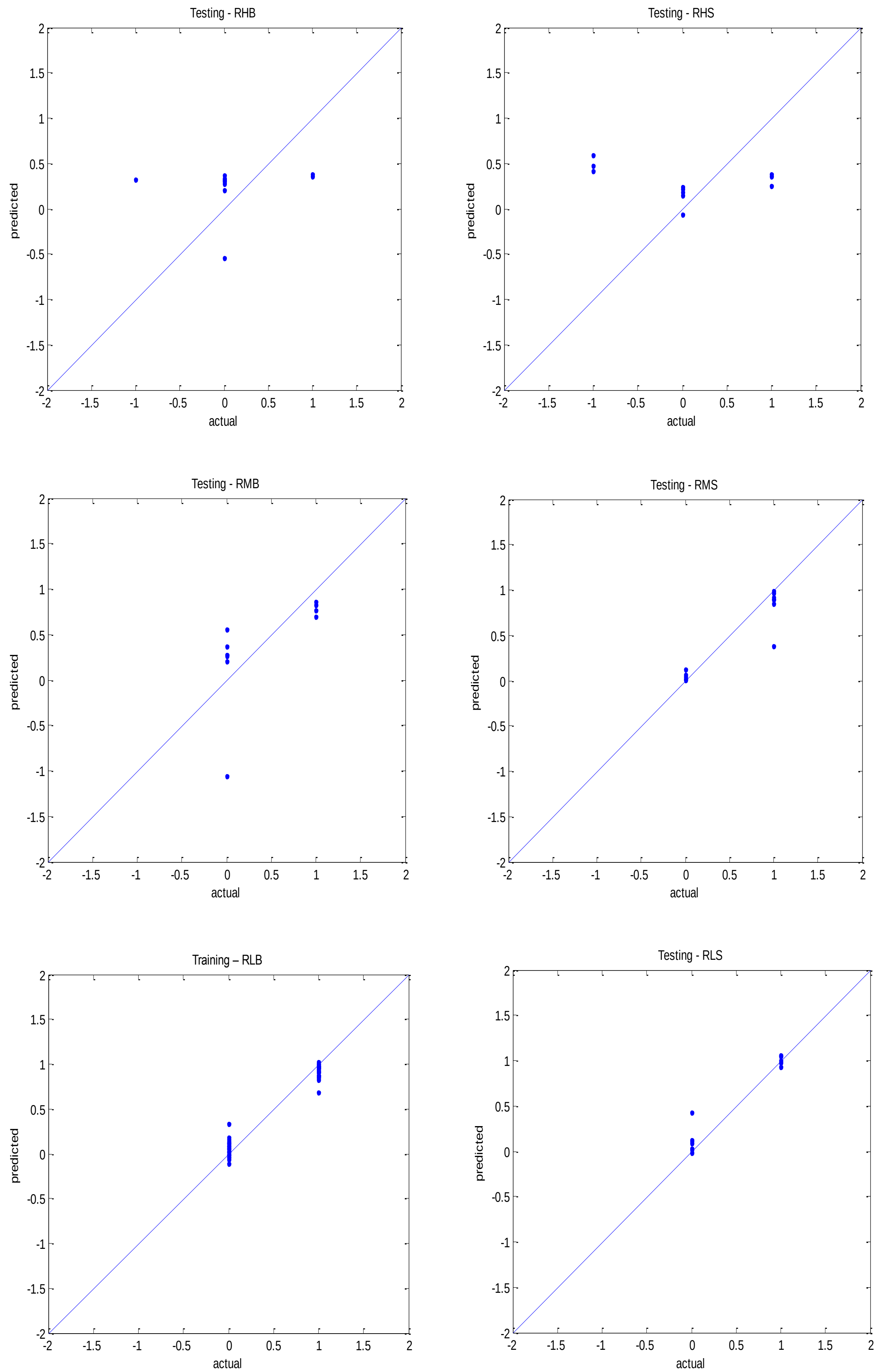

Figure E6: Testing results (Type2 shareholder) using ANN technique (NEWFFTD).

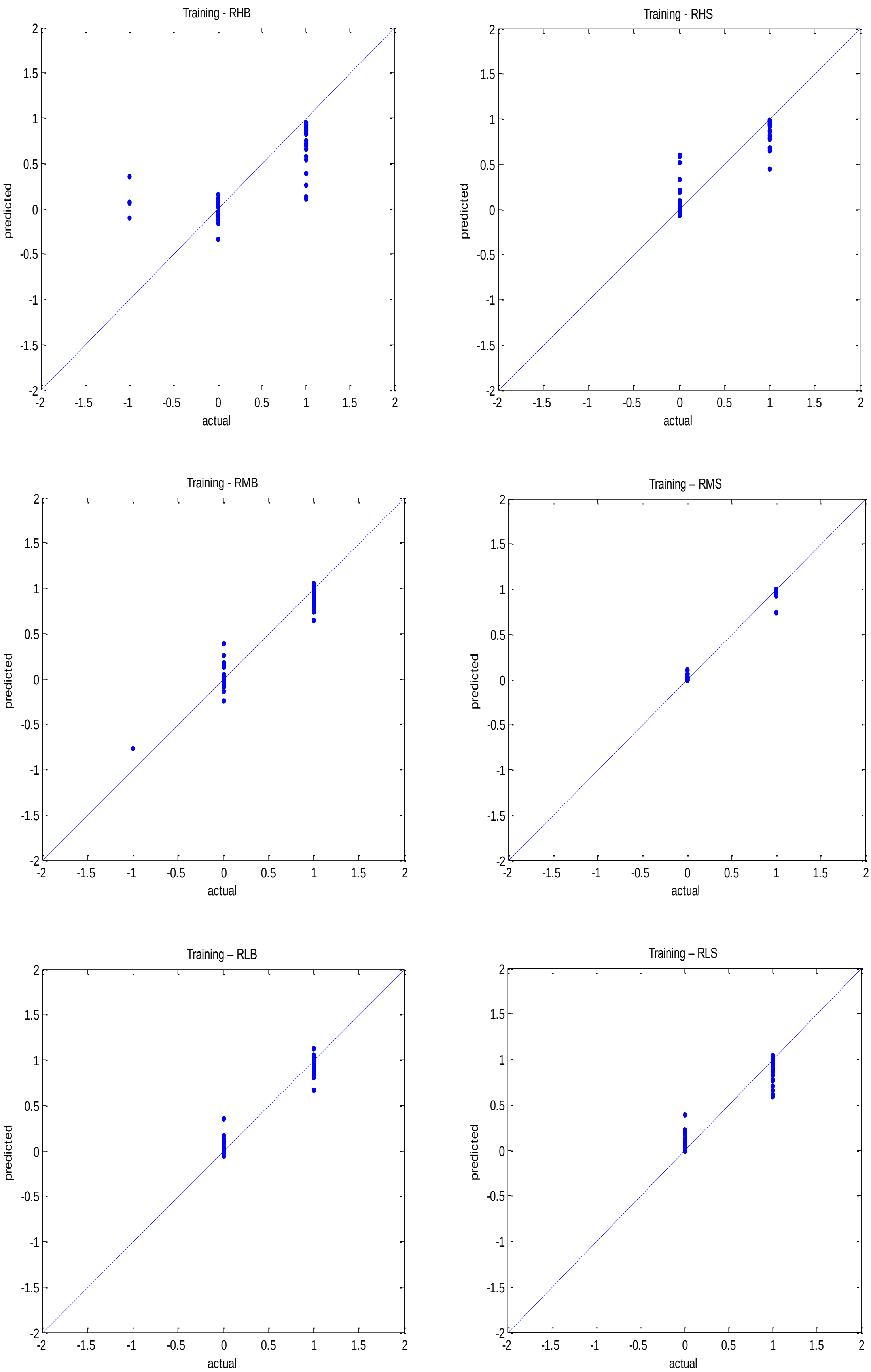

Figure E7: Training results (Type2 shareholder) using ANN technique (NEWFF).

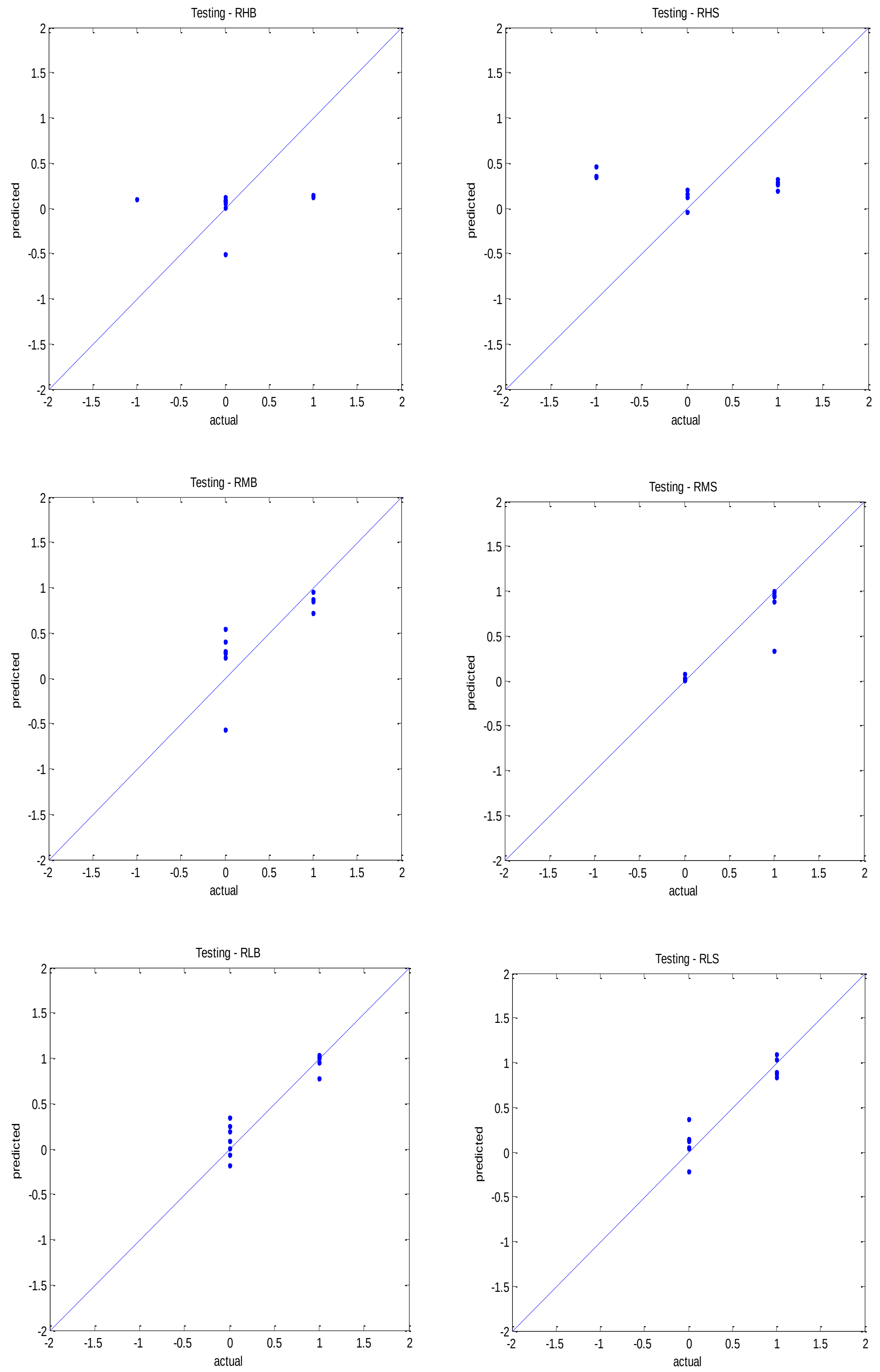

Figure E8: Training results (Type2 shareholder) using ANN technique (NEWFF).

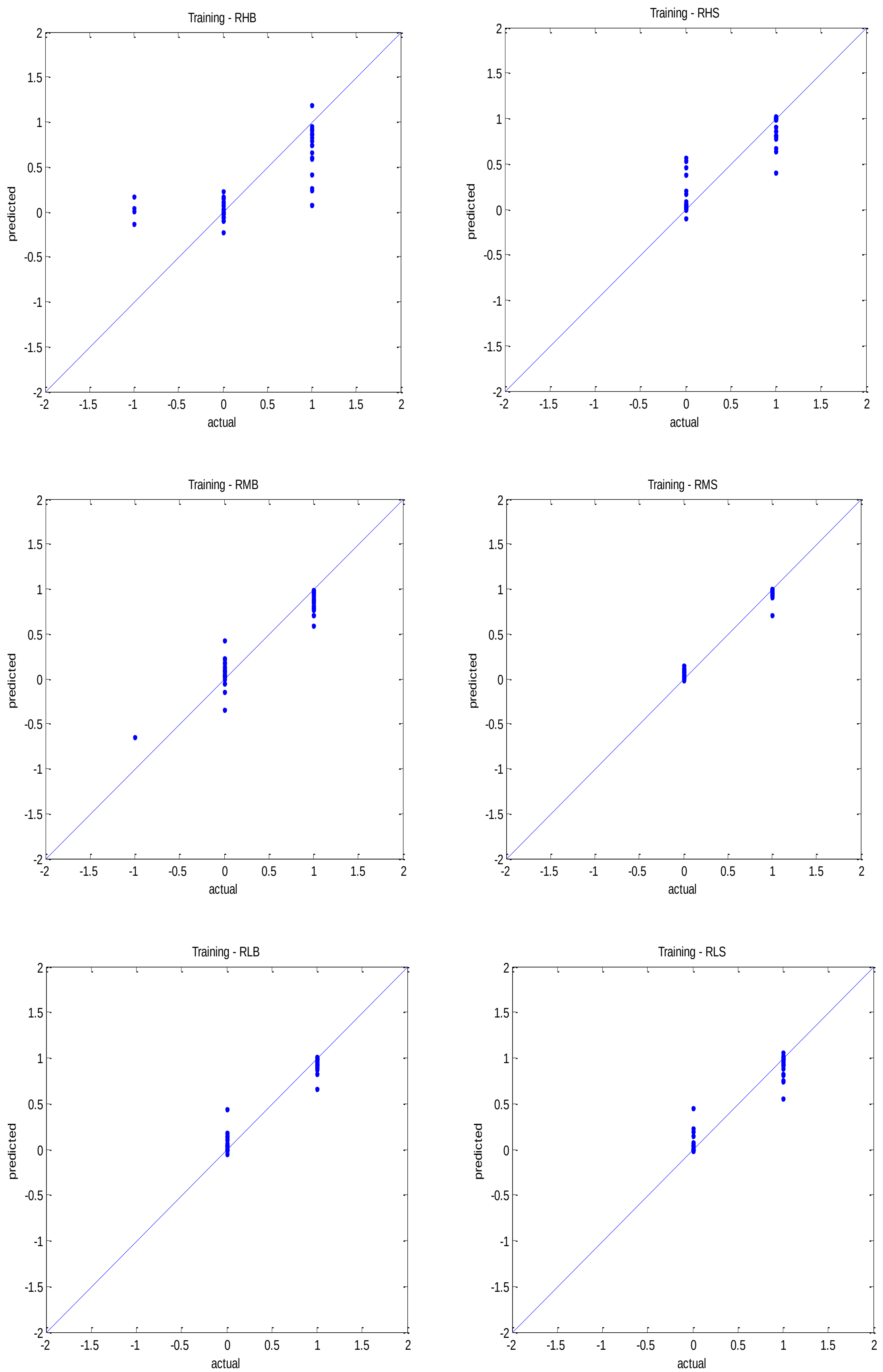

Figure E9: Training results (Type2 shareholder) using ANN technique (NEWDTDNN).

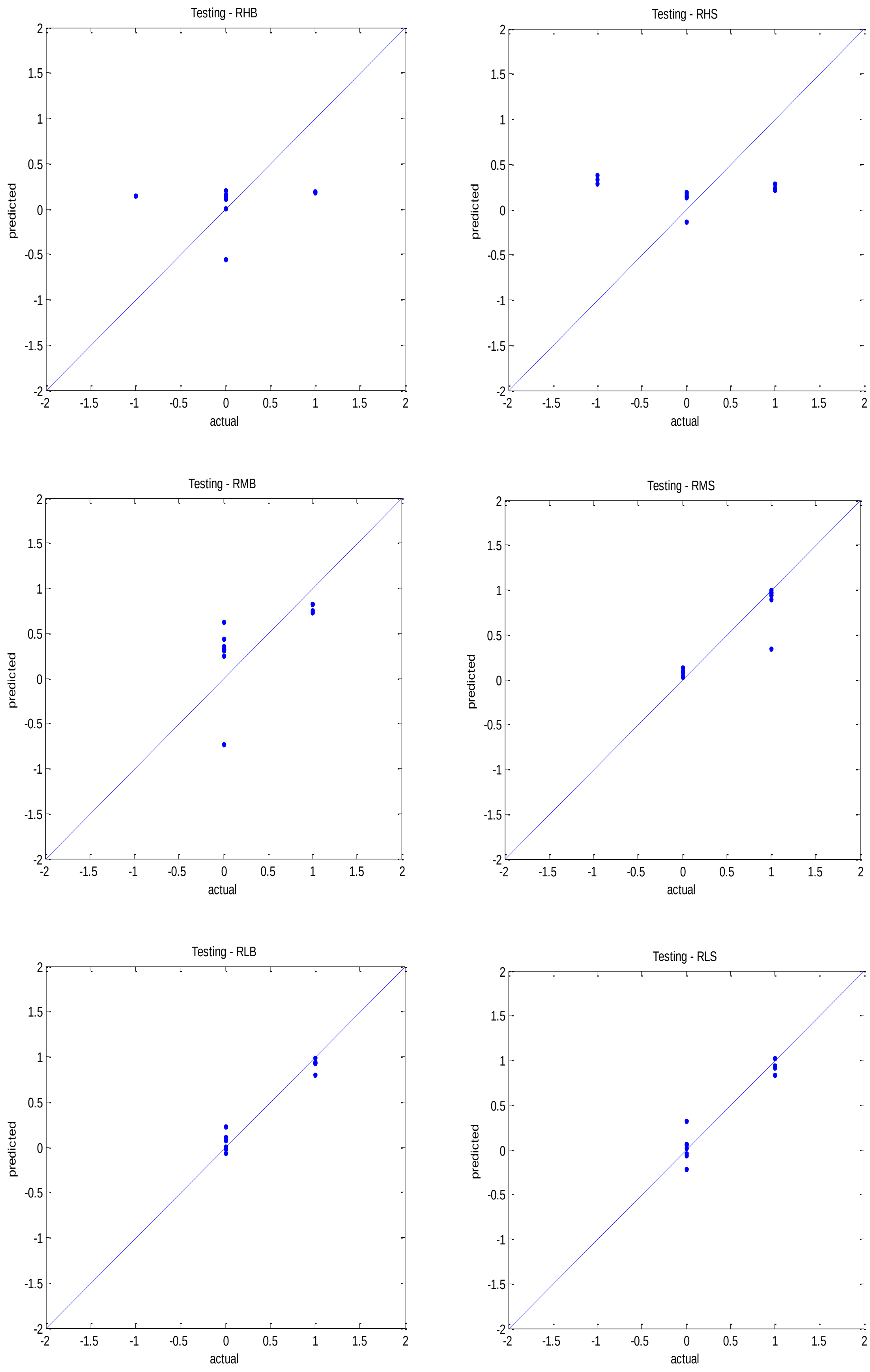

Figure E10: Testing results (Type2 shareholder) using ANN technique (NEWDTDNN).

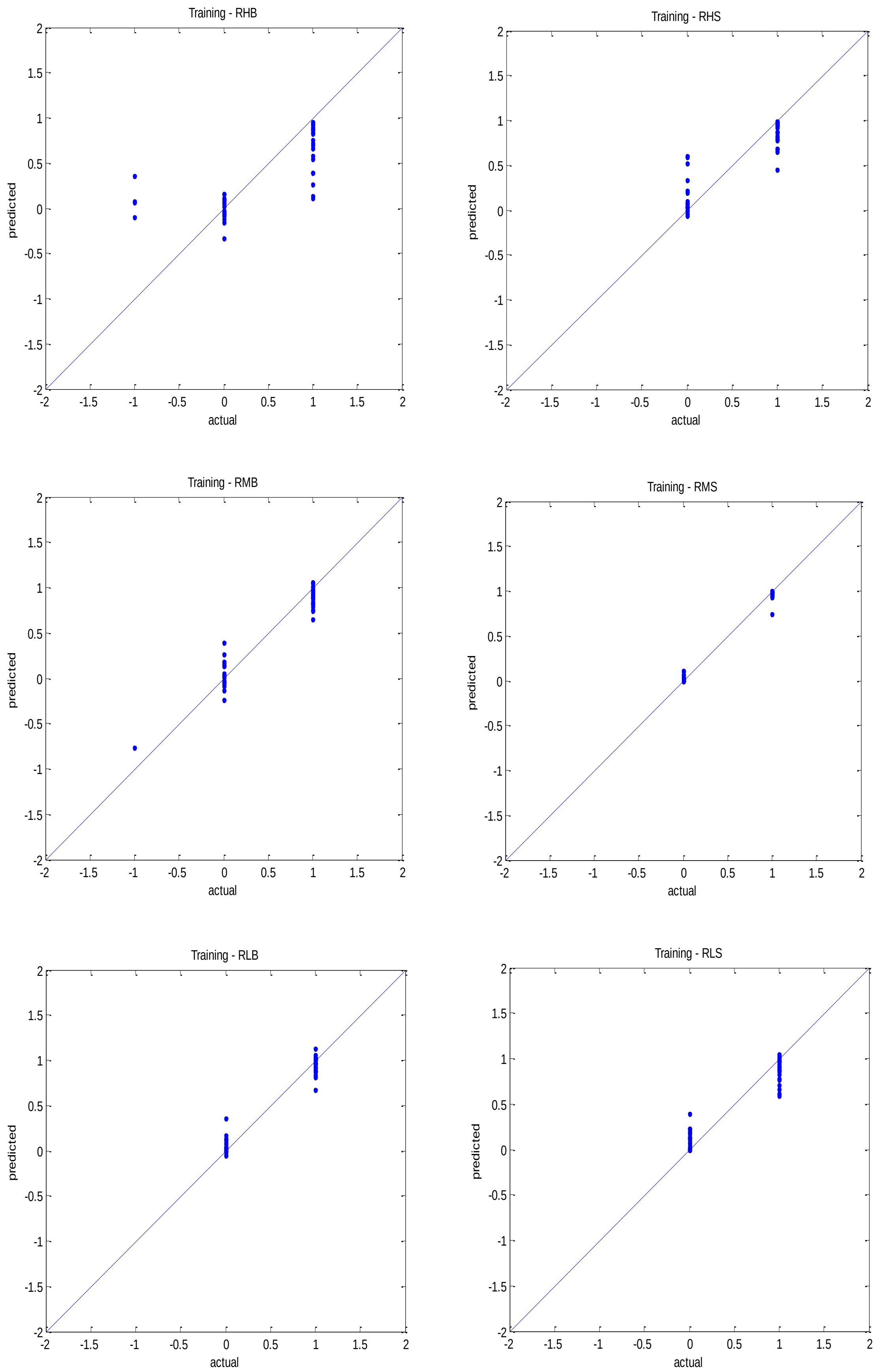

Figure E11: Training results (Type2 shareholder) using ANN technique (NEWFIT).

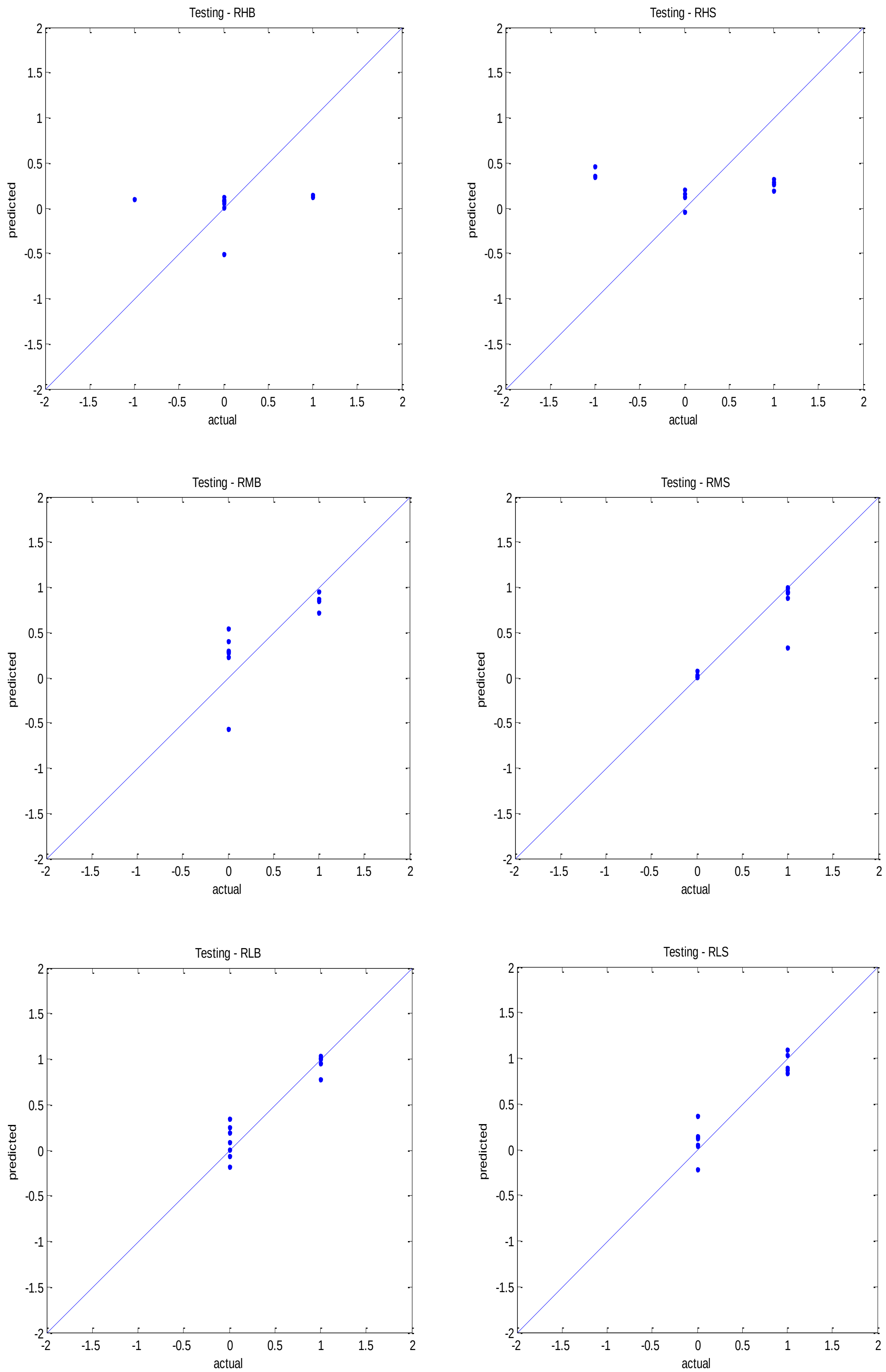

Figure E12: Testing results (Type2 shareholder) using ANN technique (NEWFIT).

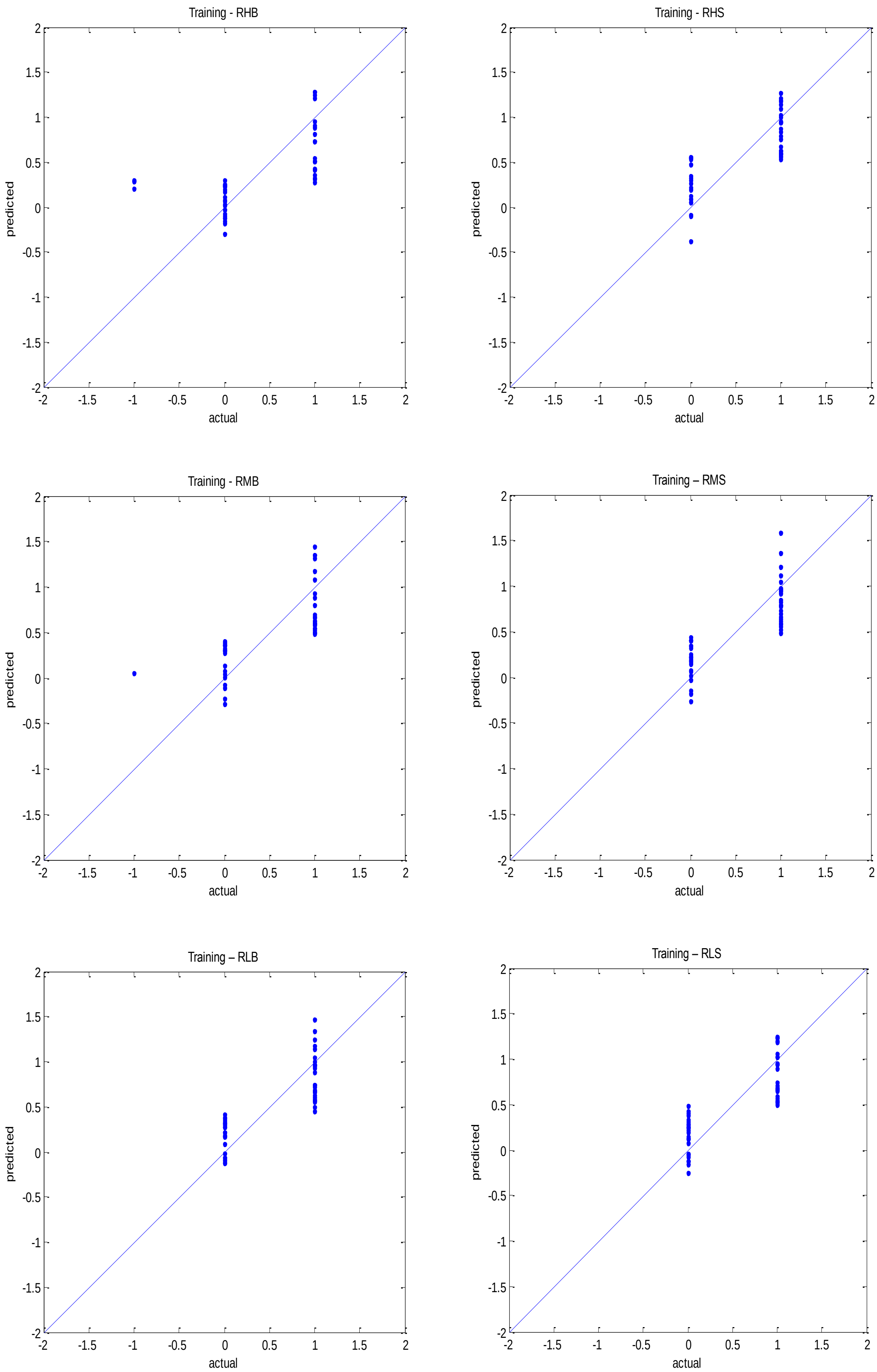

Figure E13: Training results (Type2 shareholder) using ANN technique (NEWRB).

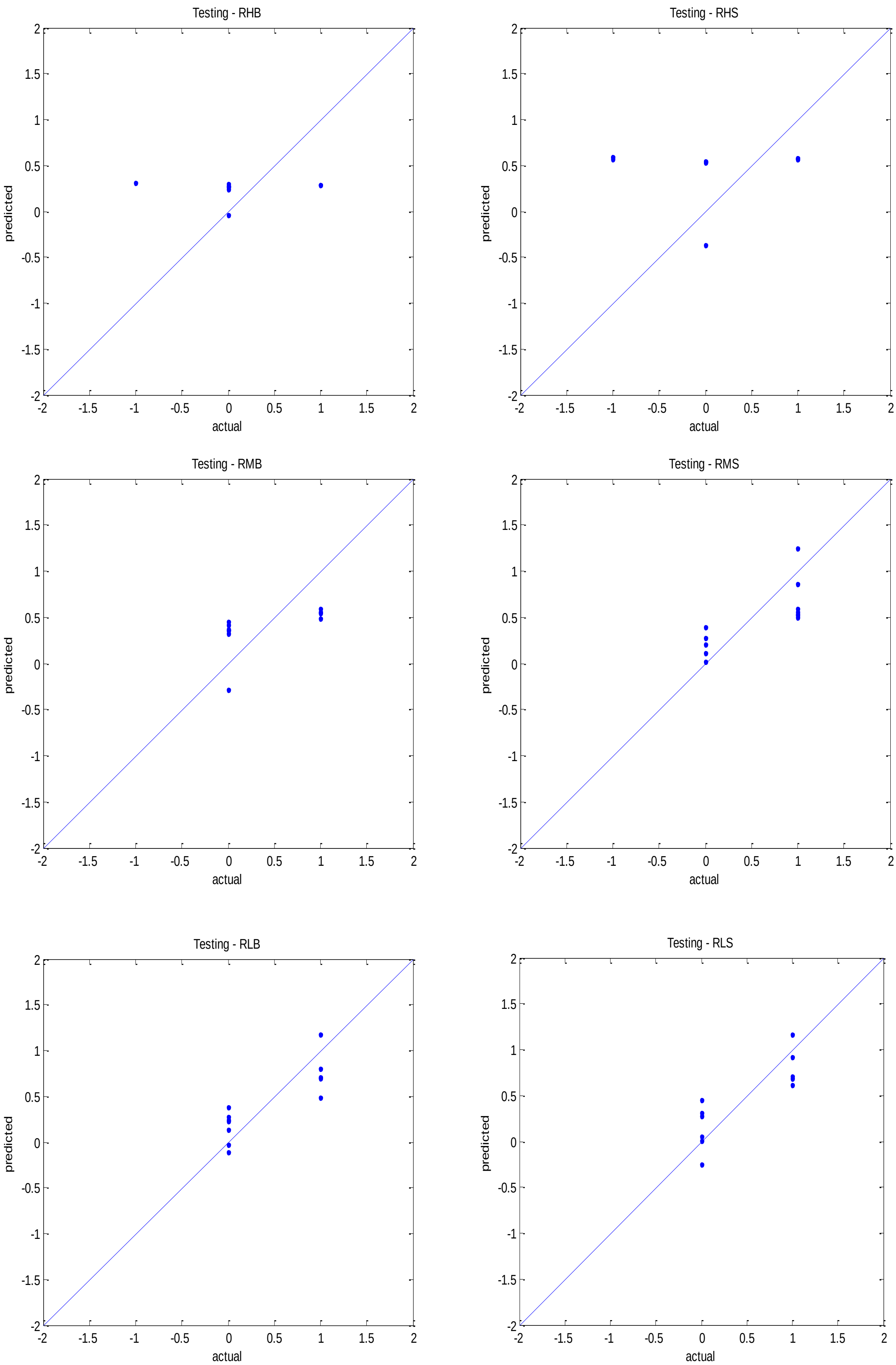

Figure E14: Testing results (Type2 shareholder) using ANN technique (NEWRB).

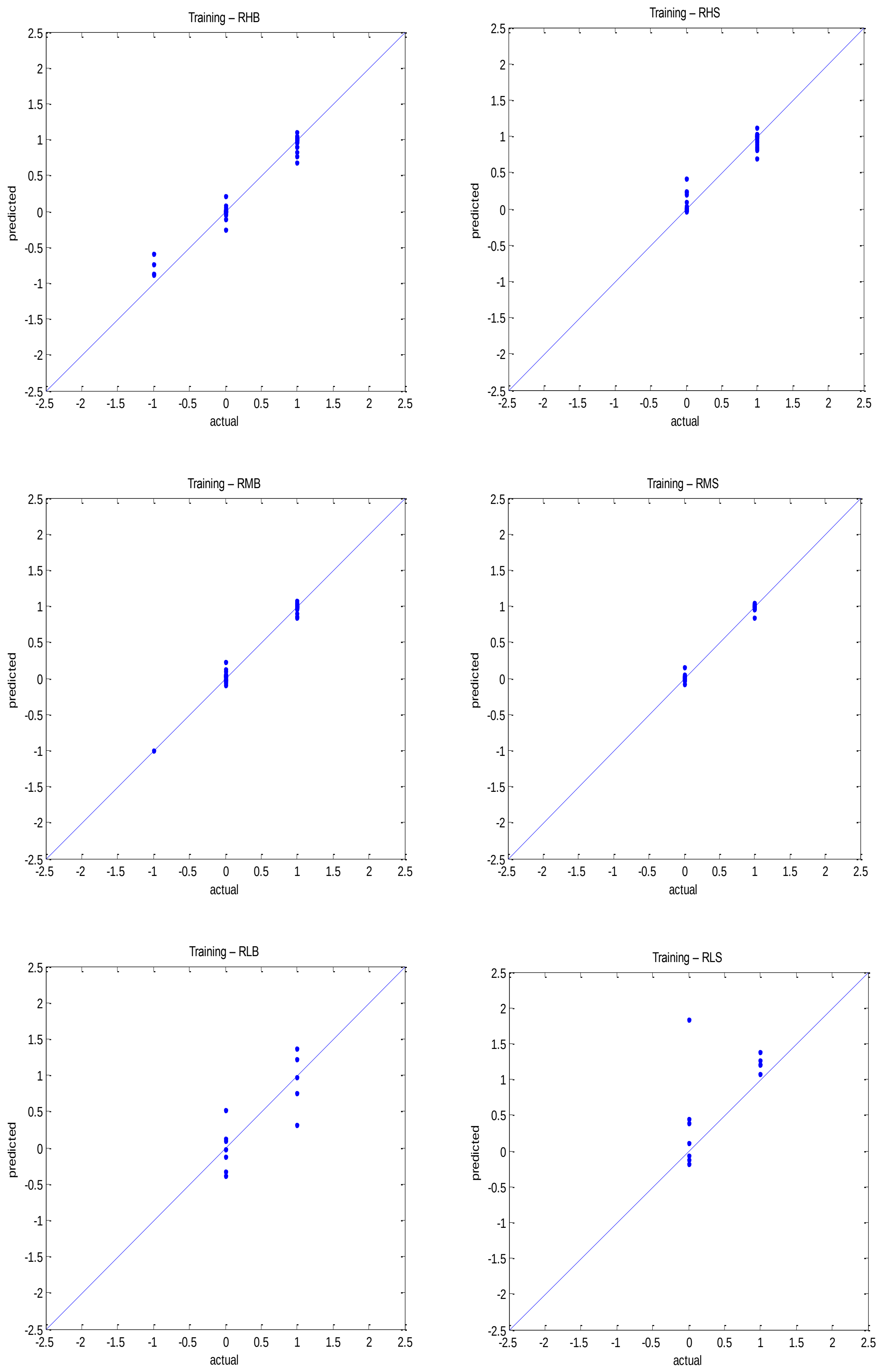

Figure E15: Training results (Type2 shareholder) using ANFIS technique.

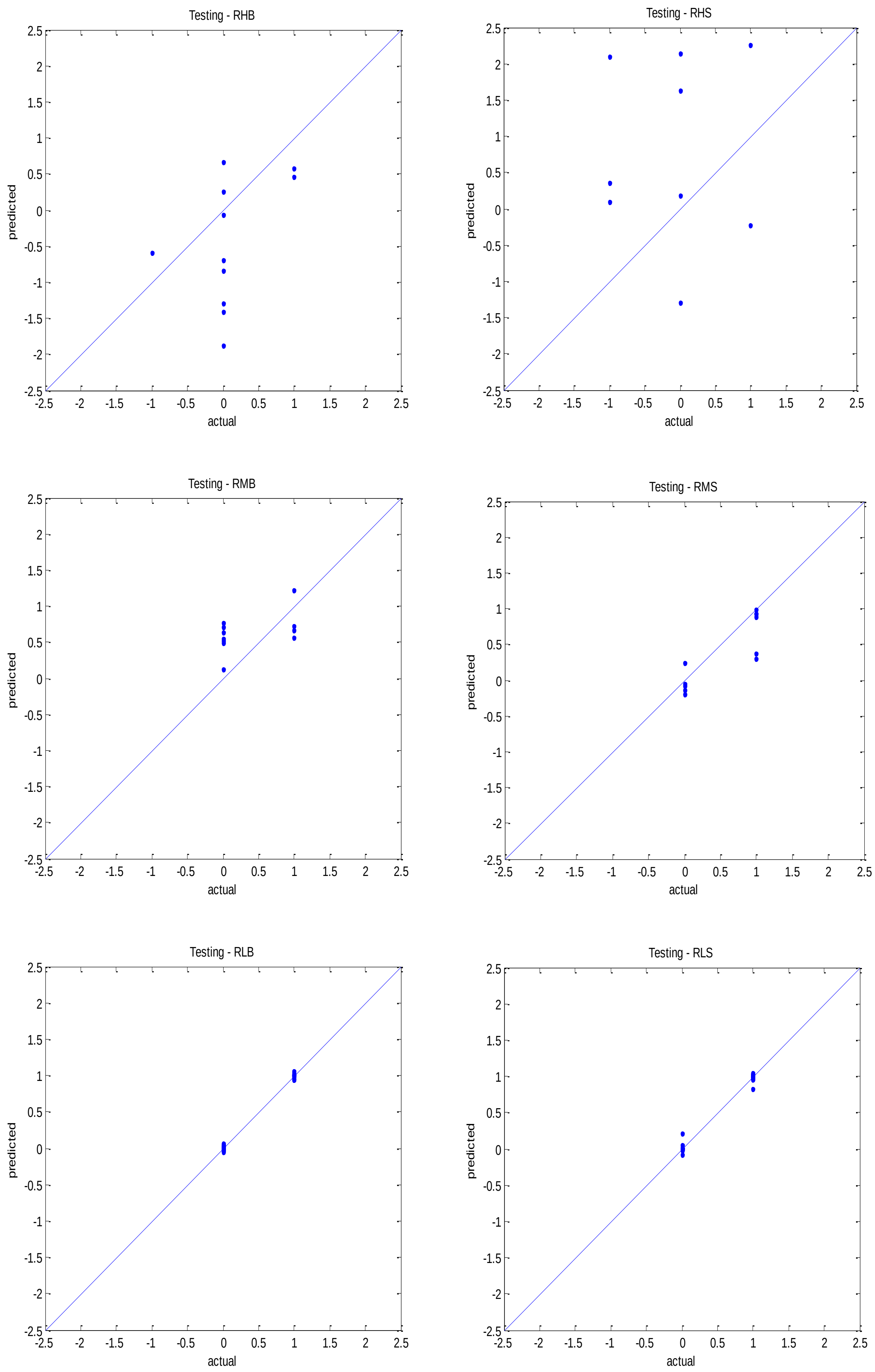

Figure E16: Testing results (Type2 shareholder) using ANFIS technique.

Appendix F: Prediction Result using Multi-Stage Type 2 Model (share price)

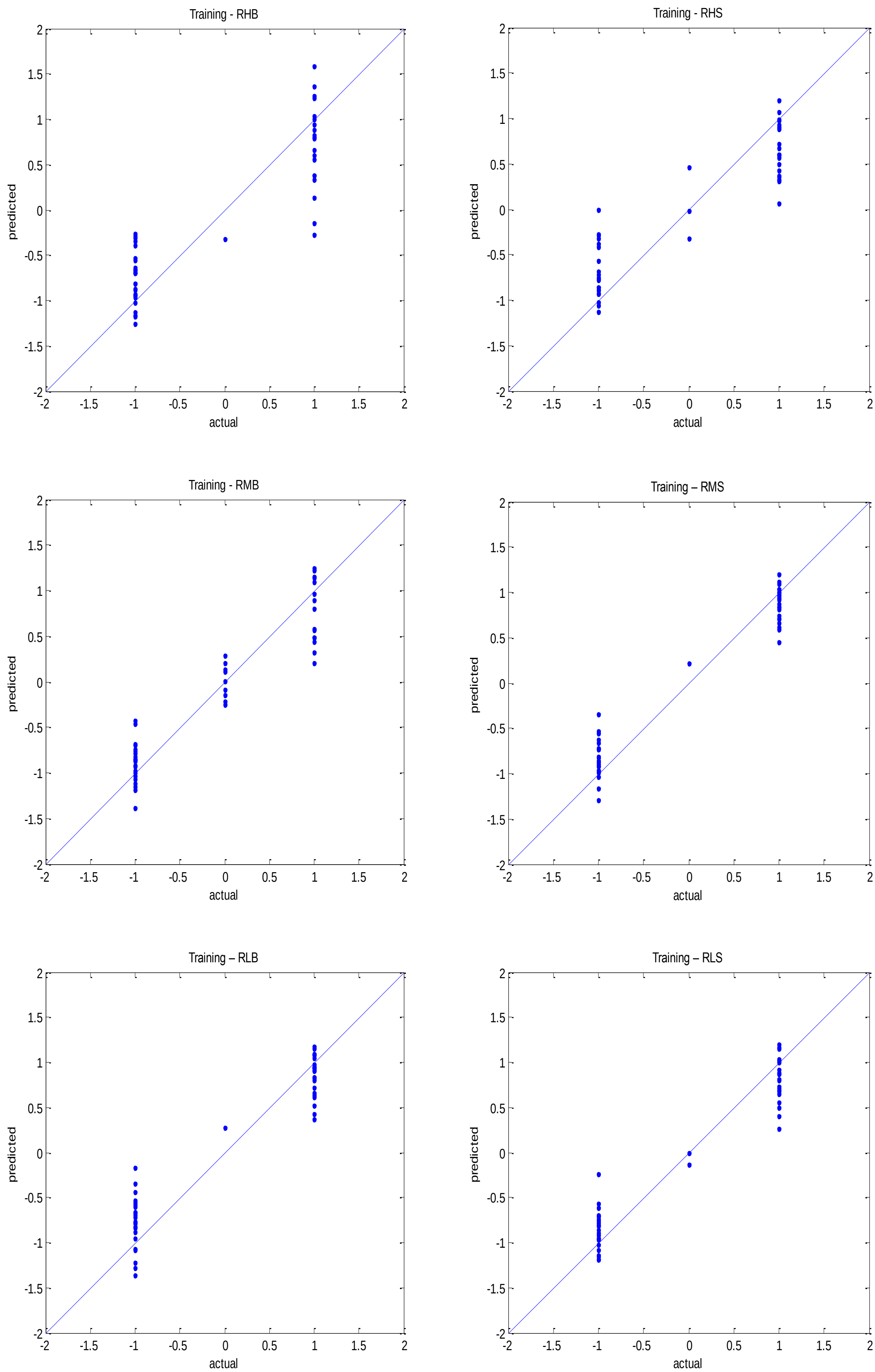

Figure F1: Training results (Type2 share price) using ANN technique (NEWCF).

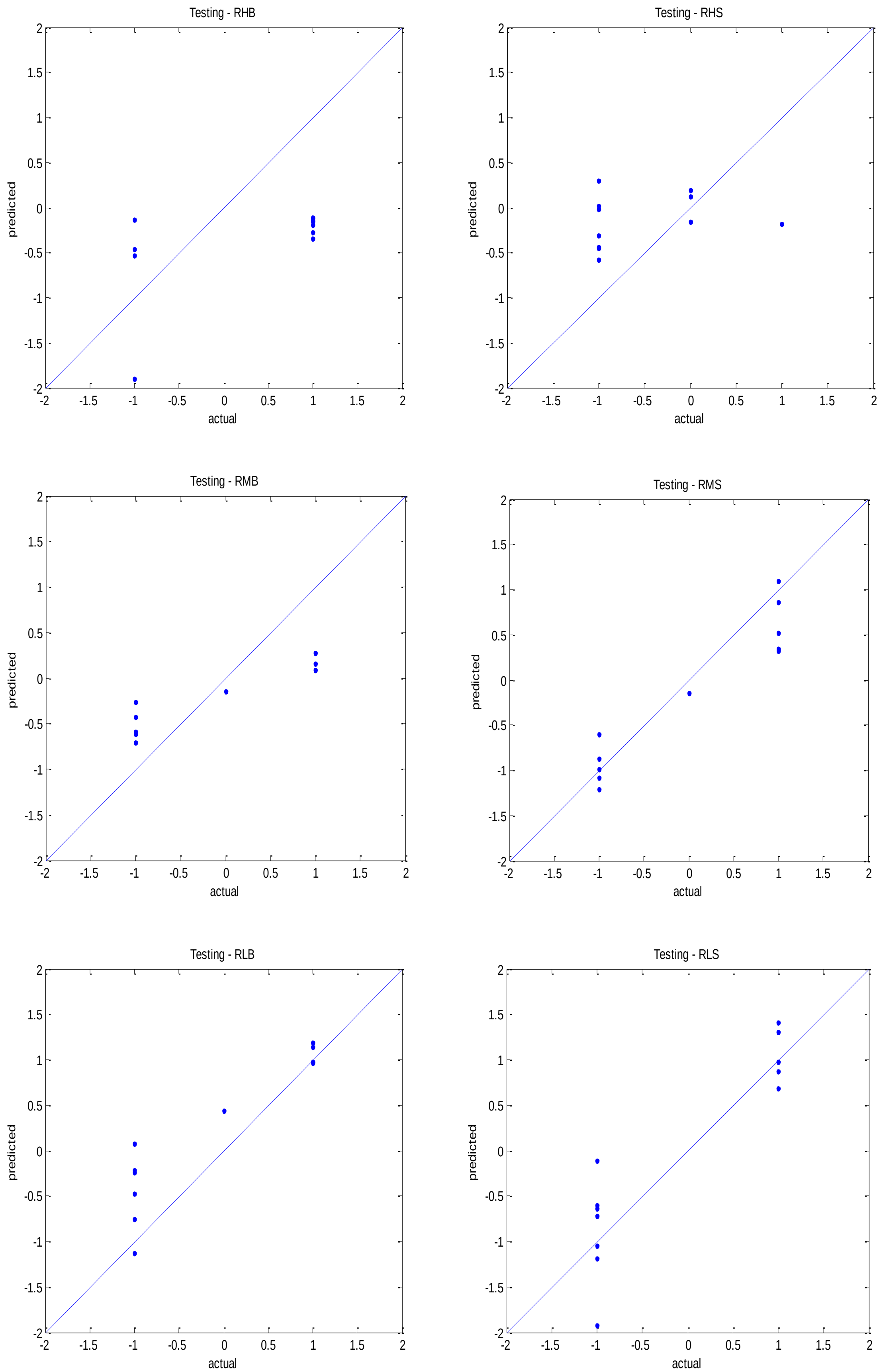

Figure F2: Testing results (Type2 share price) using ANN technique (NEWCF).

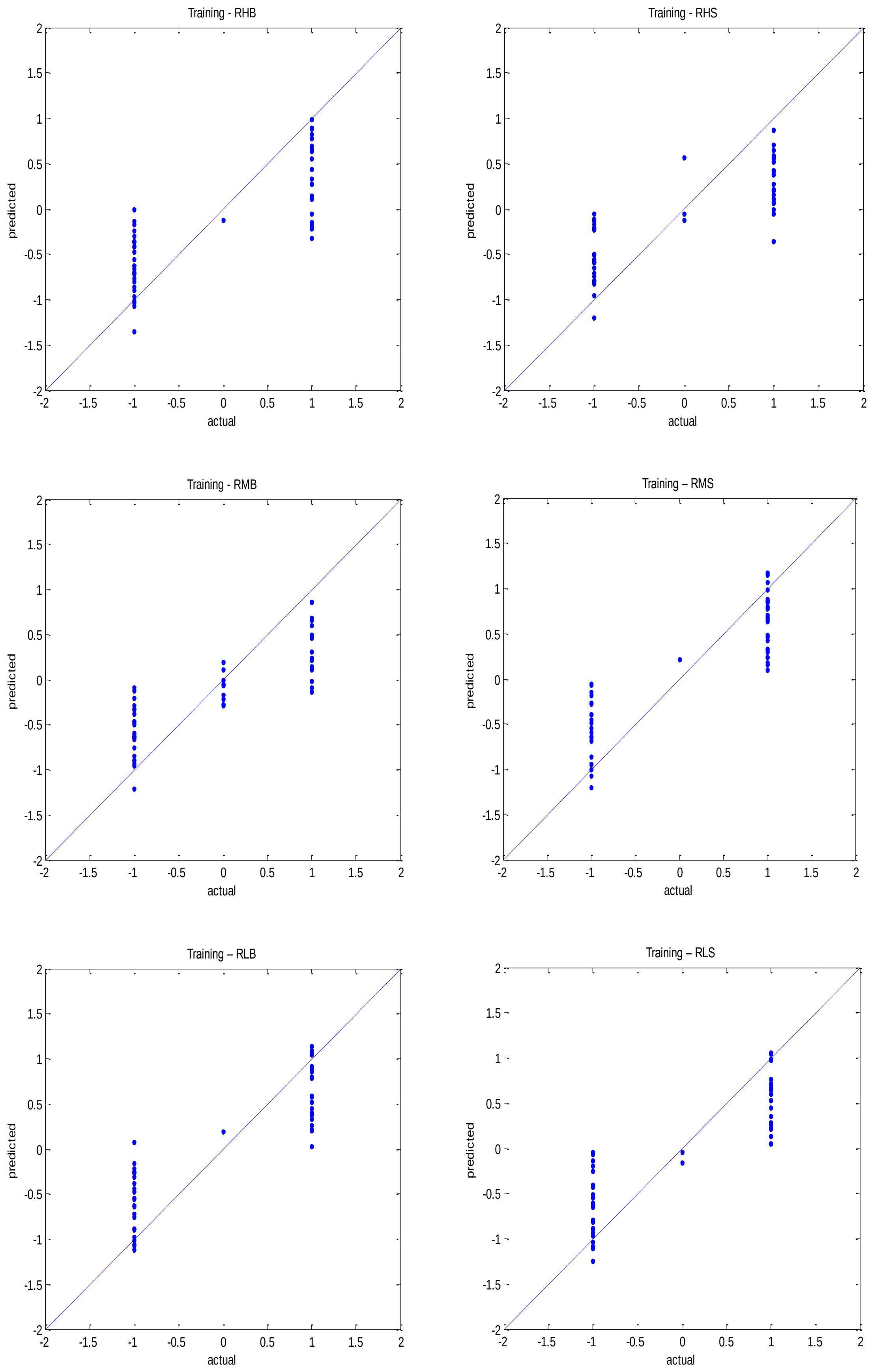

Figure F3: Training results (Type2 share price) using ANN technique (NEWELM).

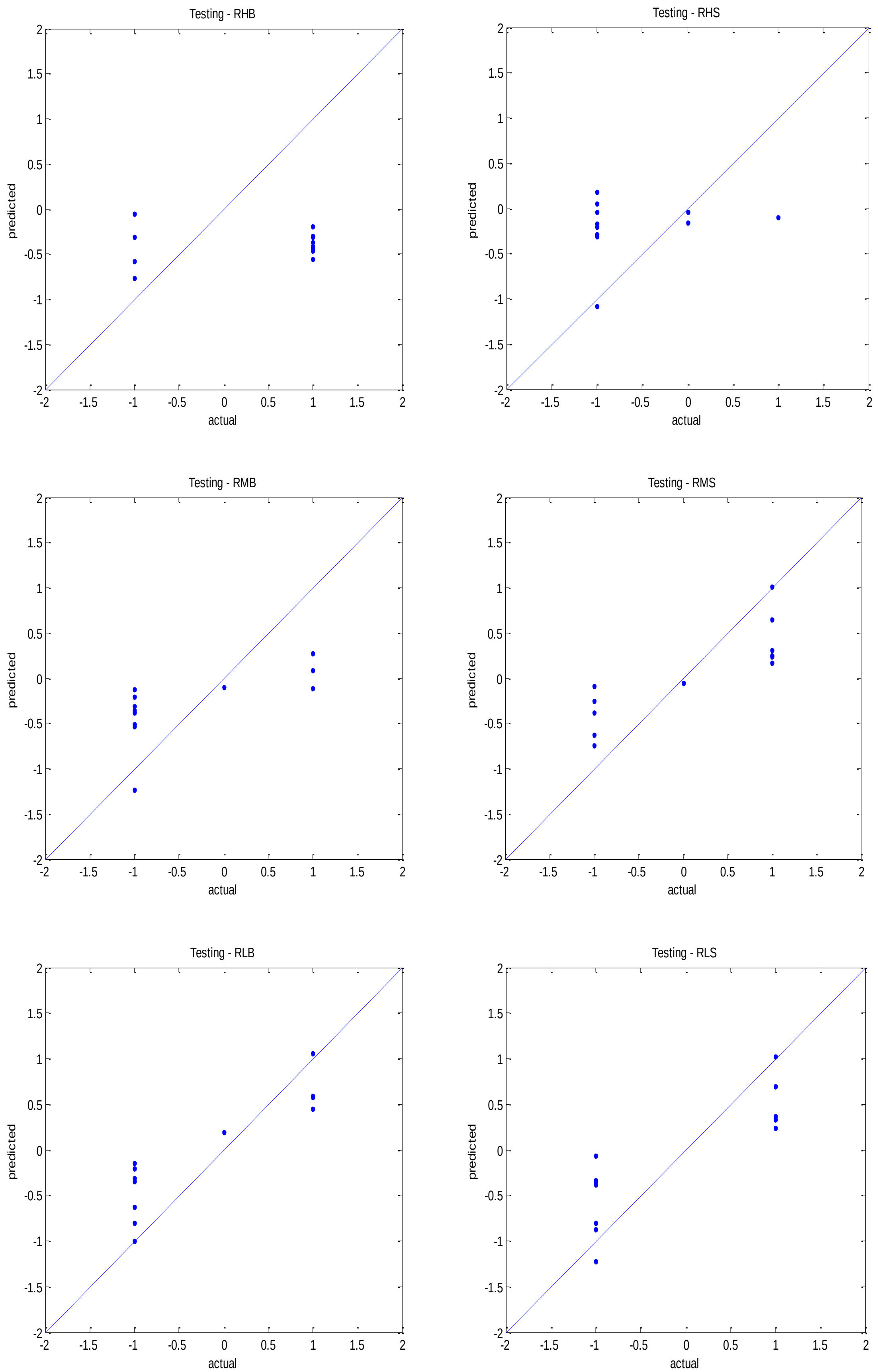

Figure F4: Testing results (Type2 share price) using ANN technique (NEWELM).

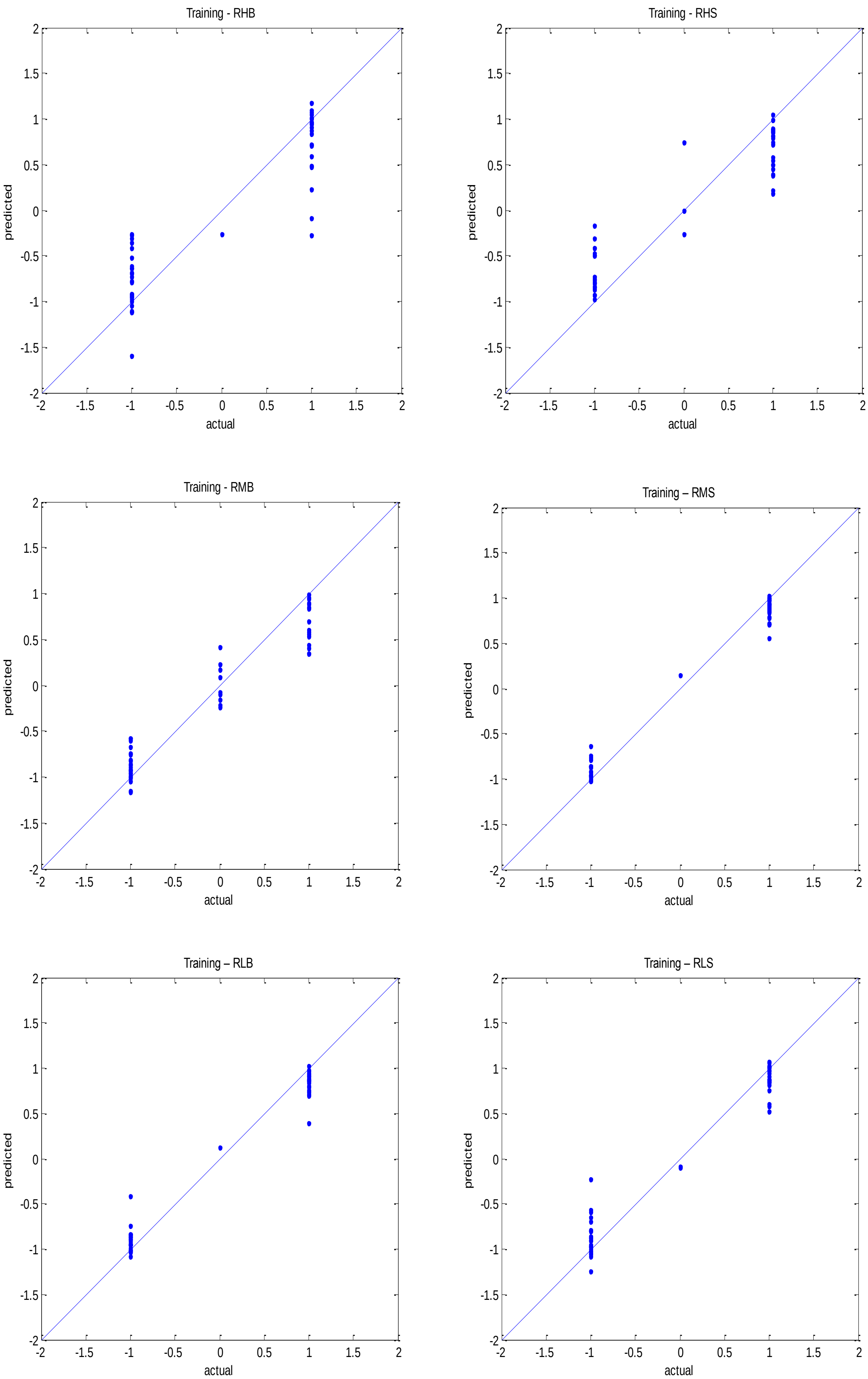

Figure F5: Training results (Type2 share price) using ANN technique (NEWFFTD).

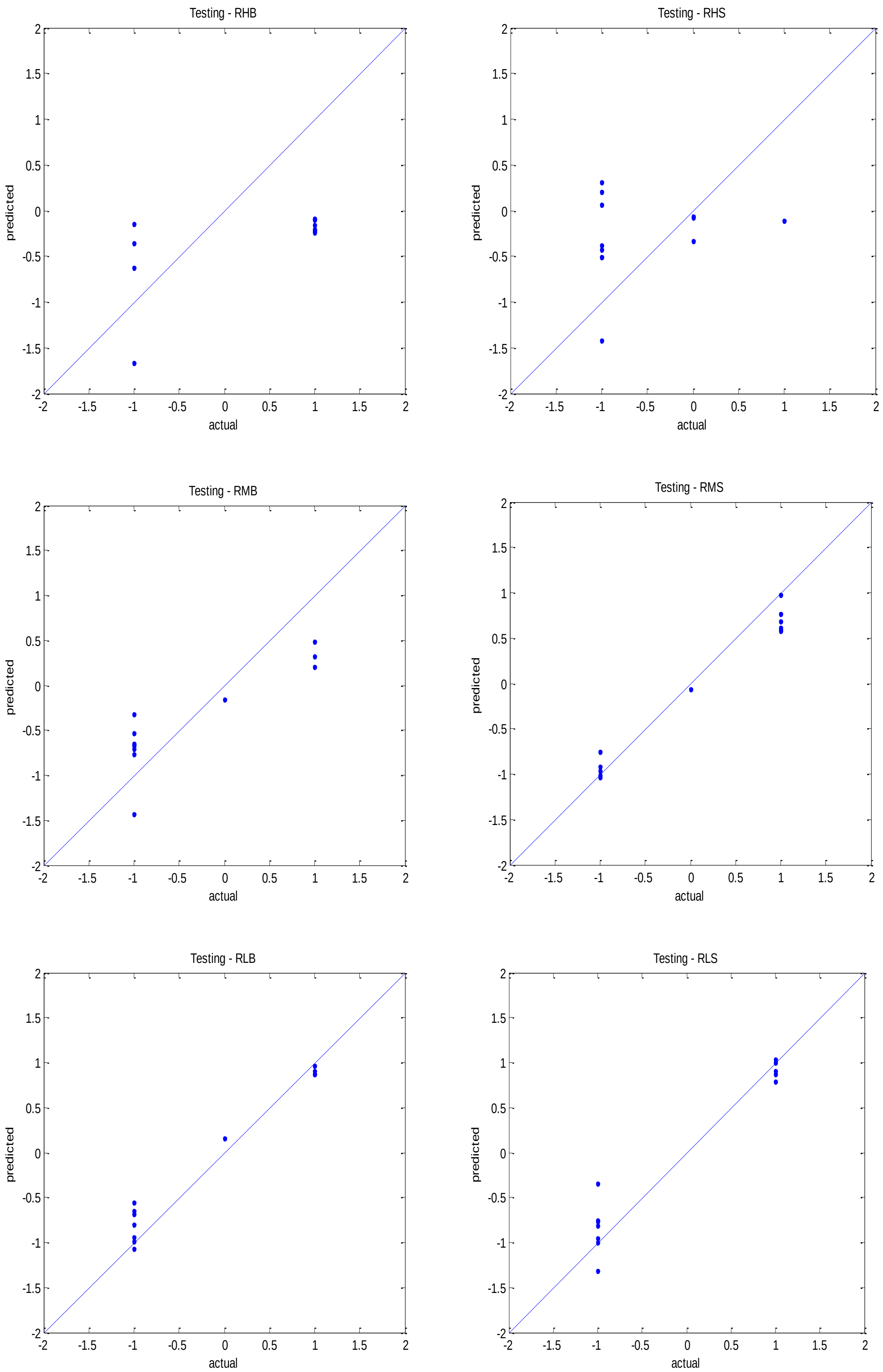

Figure F6: Testing results (Type2 share price) using ANN technique (NEWFFTD).

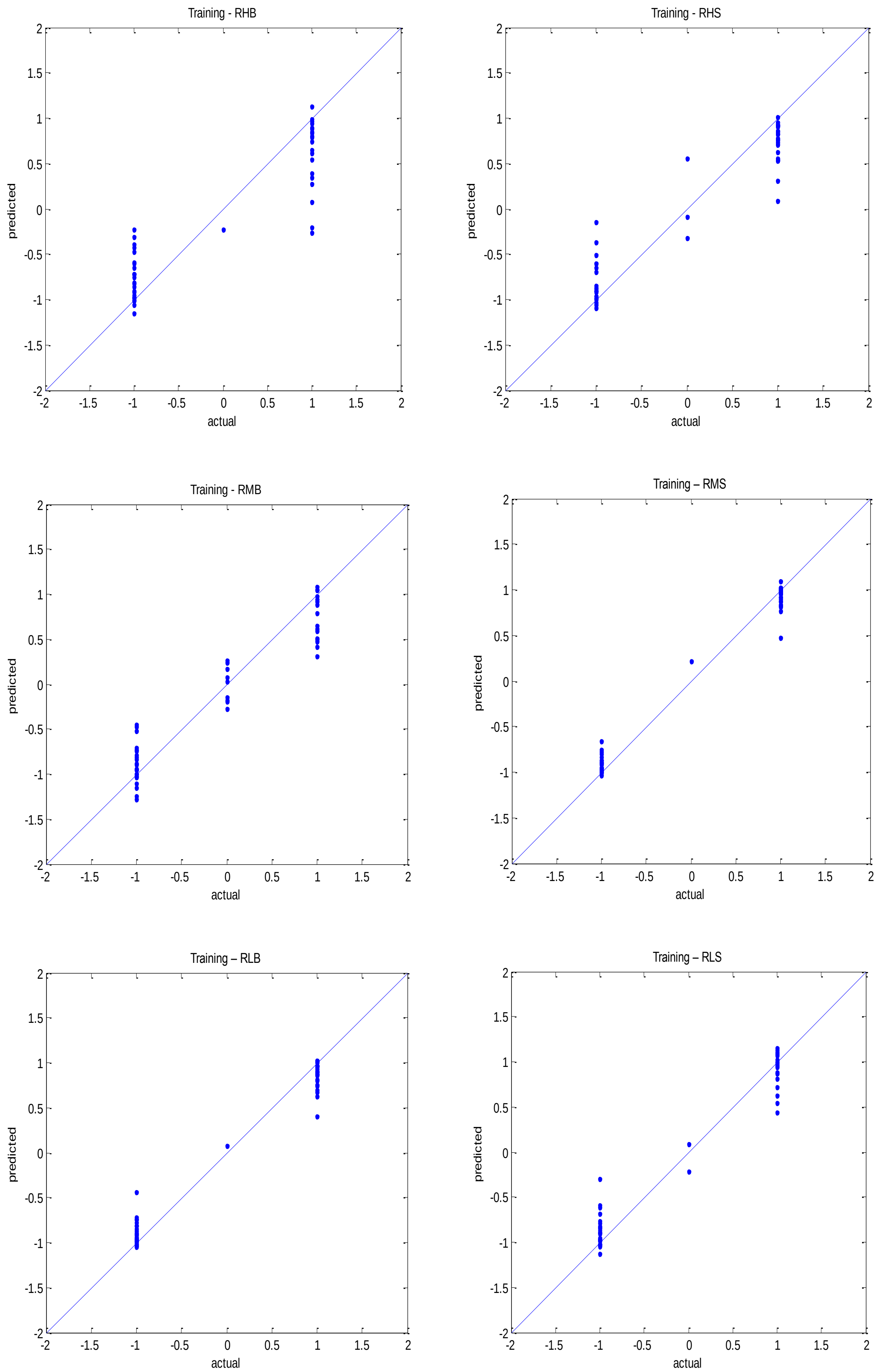

Figure F7: Training results (Type2 share price) using ANN technique (NEWFF).

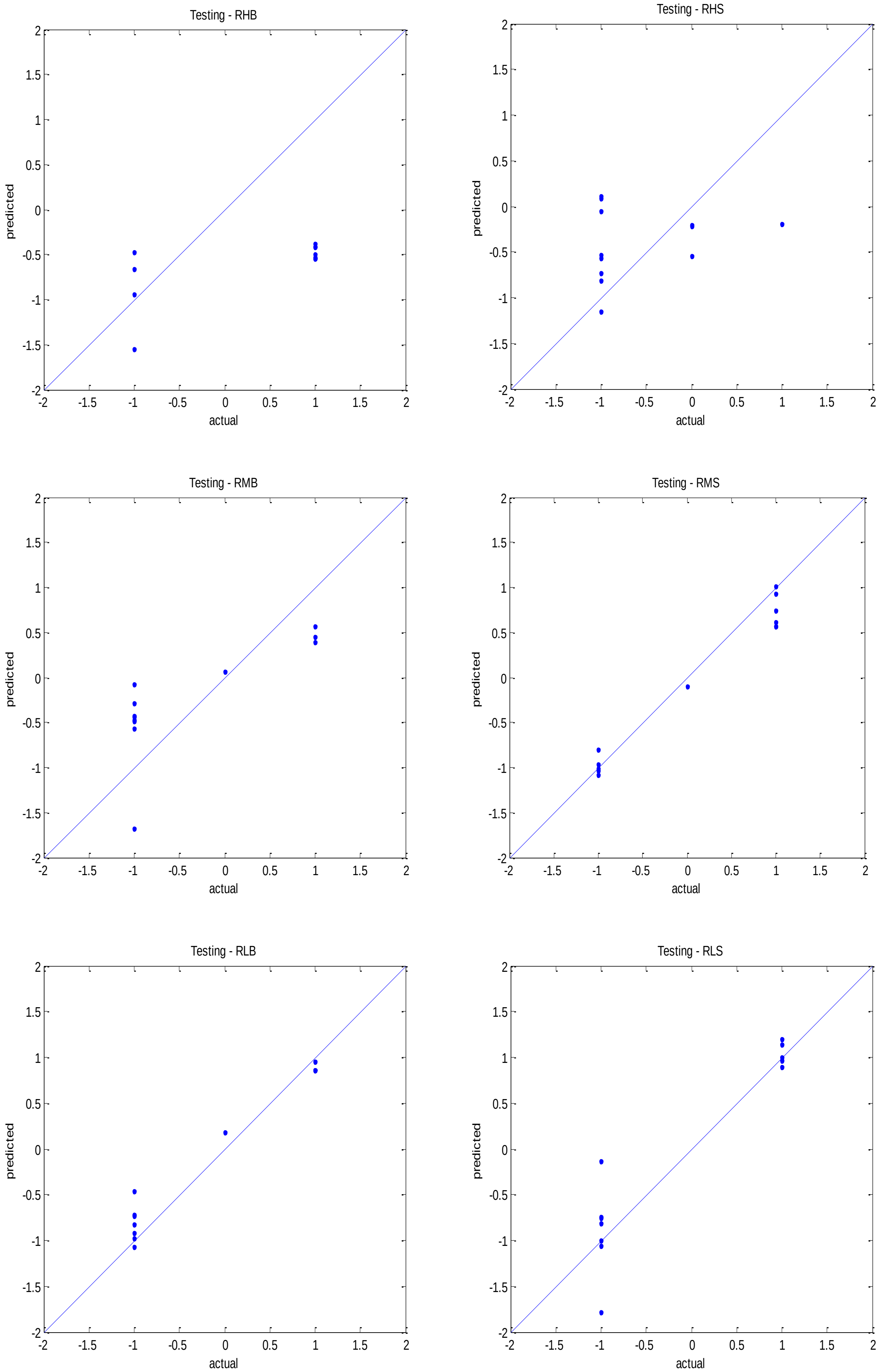

Figure F8: Testing results (Type2 share price) using ANN technique (NEWFF).

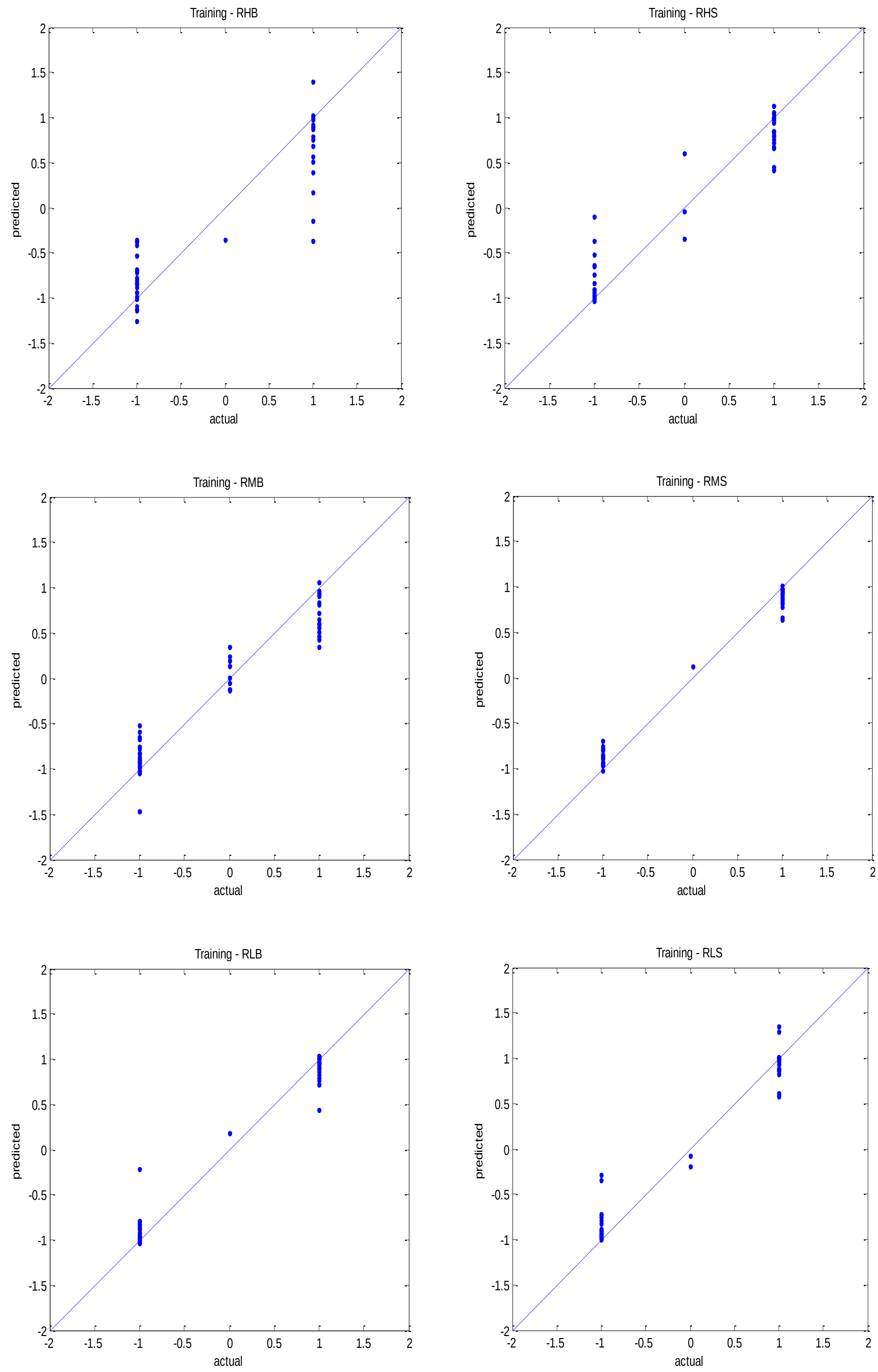

Figure F9: Training results (Type2 share price) using ANN technique (NEWDTDNN).

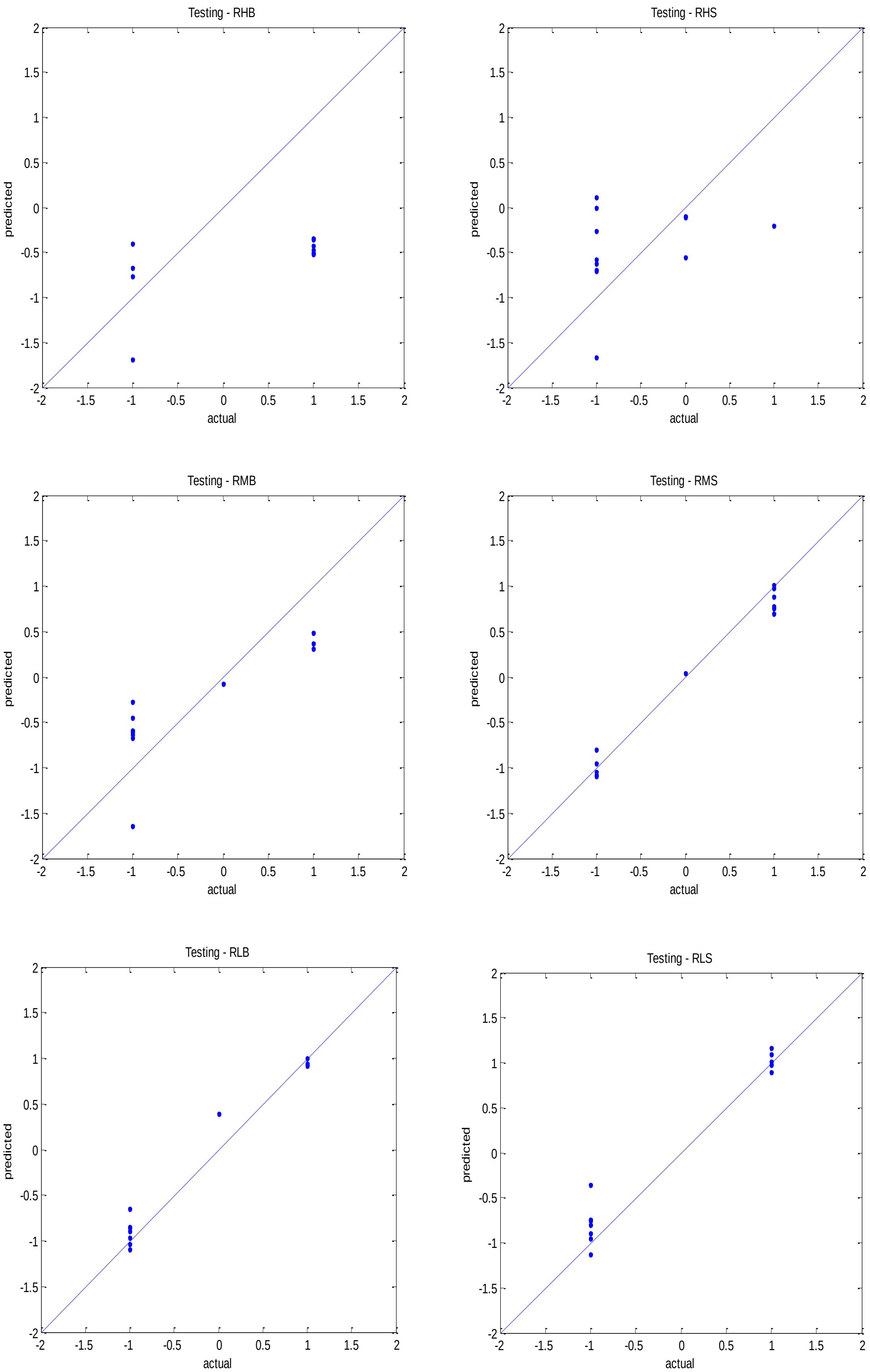

Figure F10: Testing results (Type2 share price) using ANN technique (NEWDTDNN).

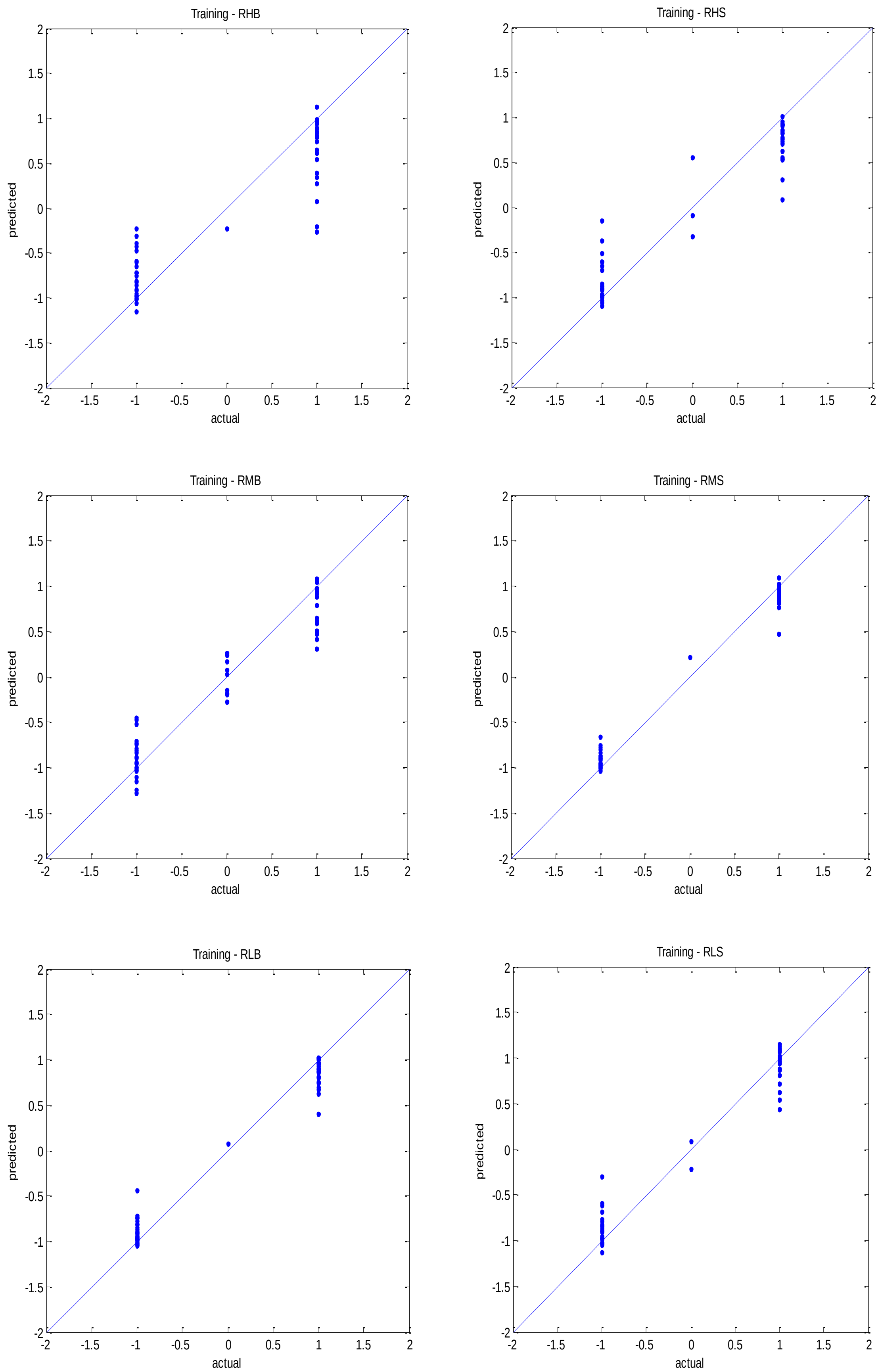

Figure F11: Training results (Type2 share price) using ANN technique (NEWFIT).

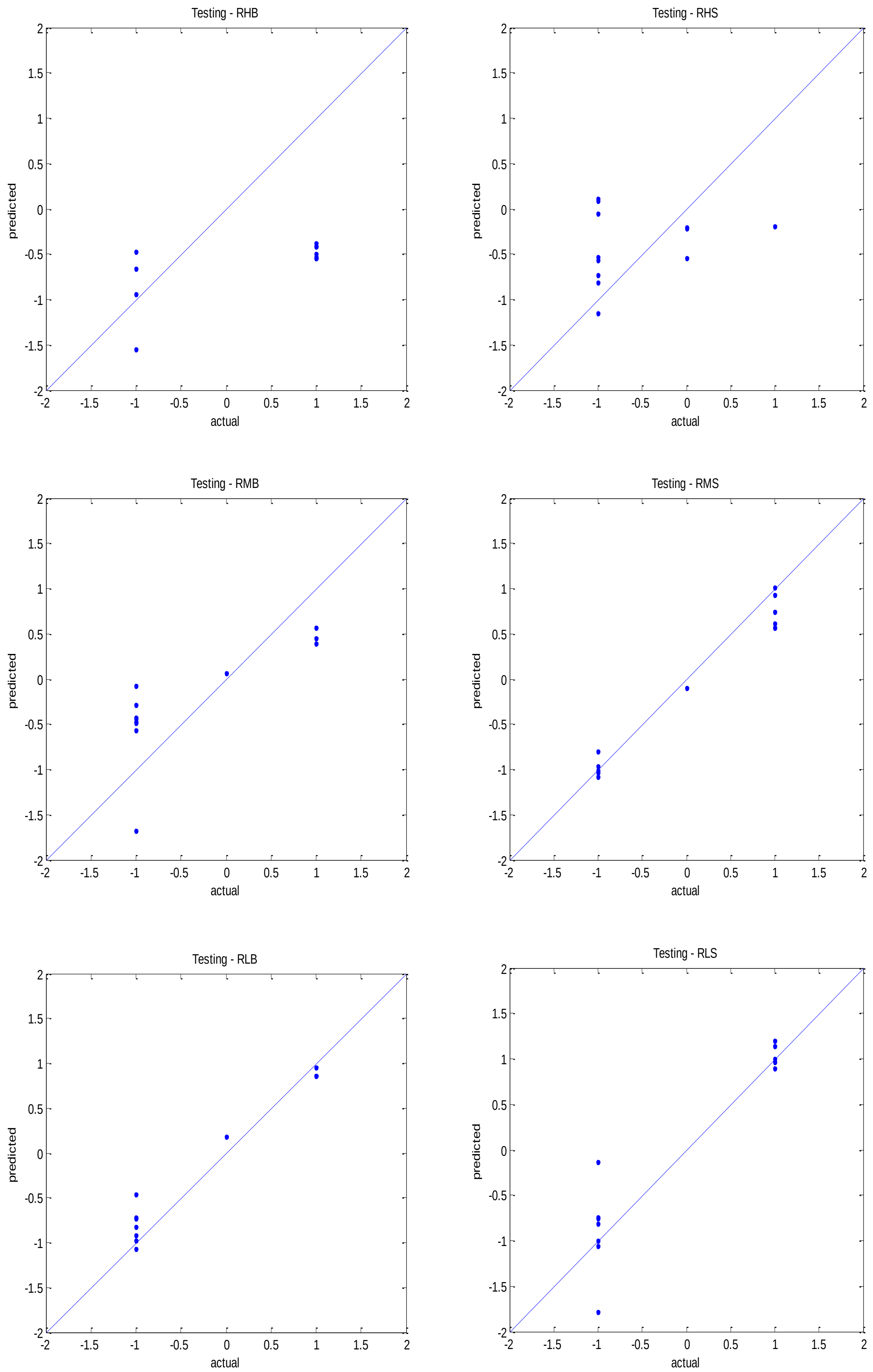

Figure F12: Testing results (Type2 share price) using ANN technique (NEWFIT).

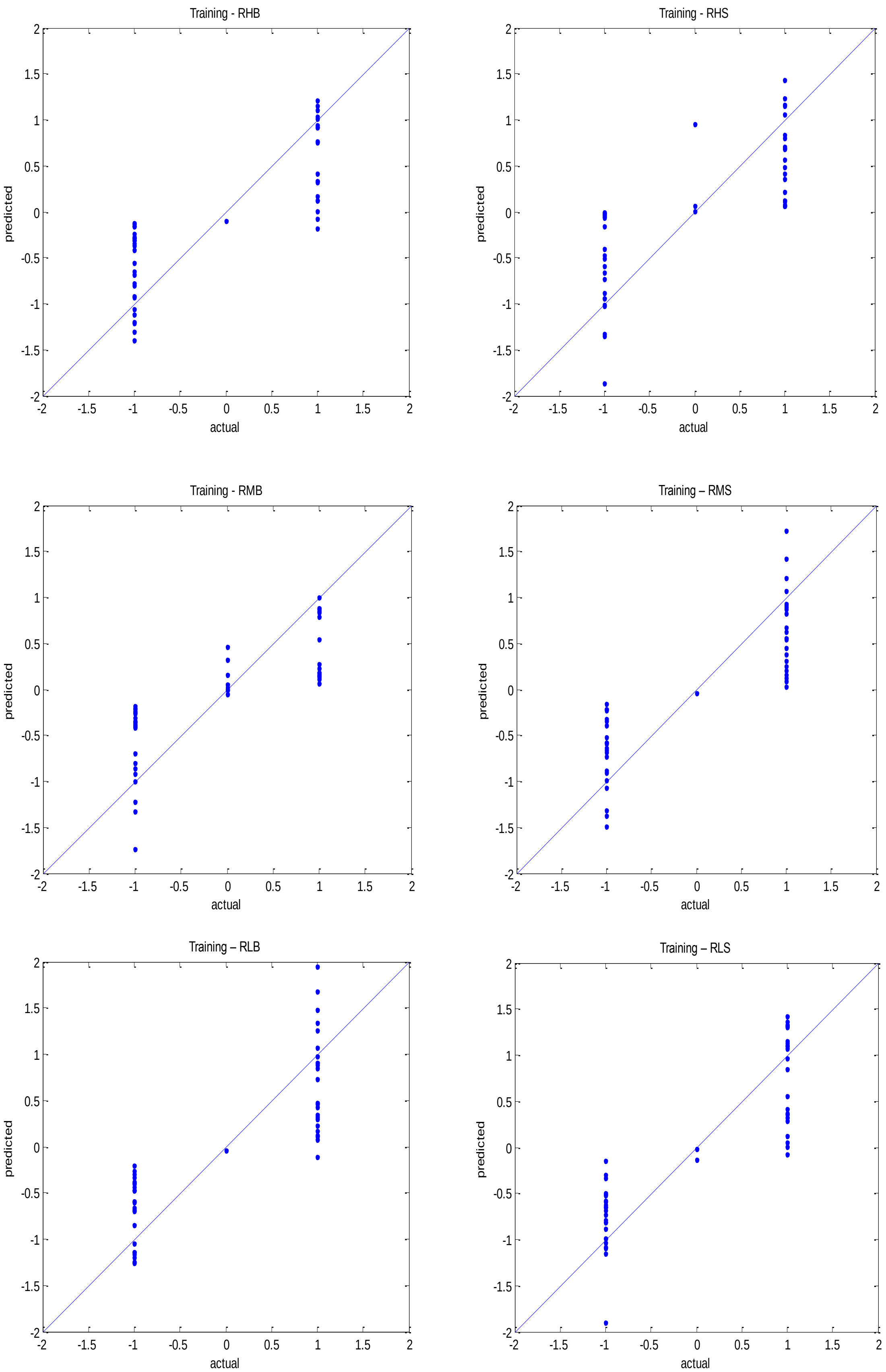

Figure F13: Training results (Type2 share price) using ANN technique (NEWRB).

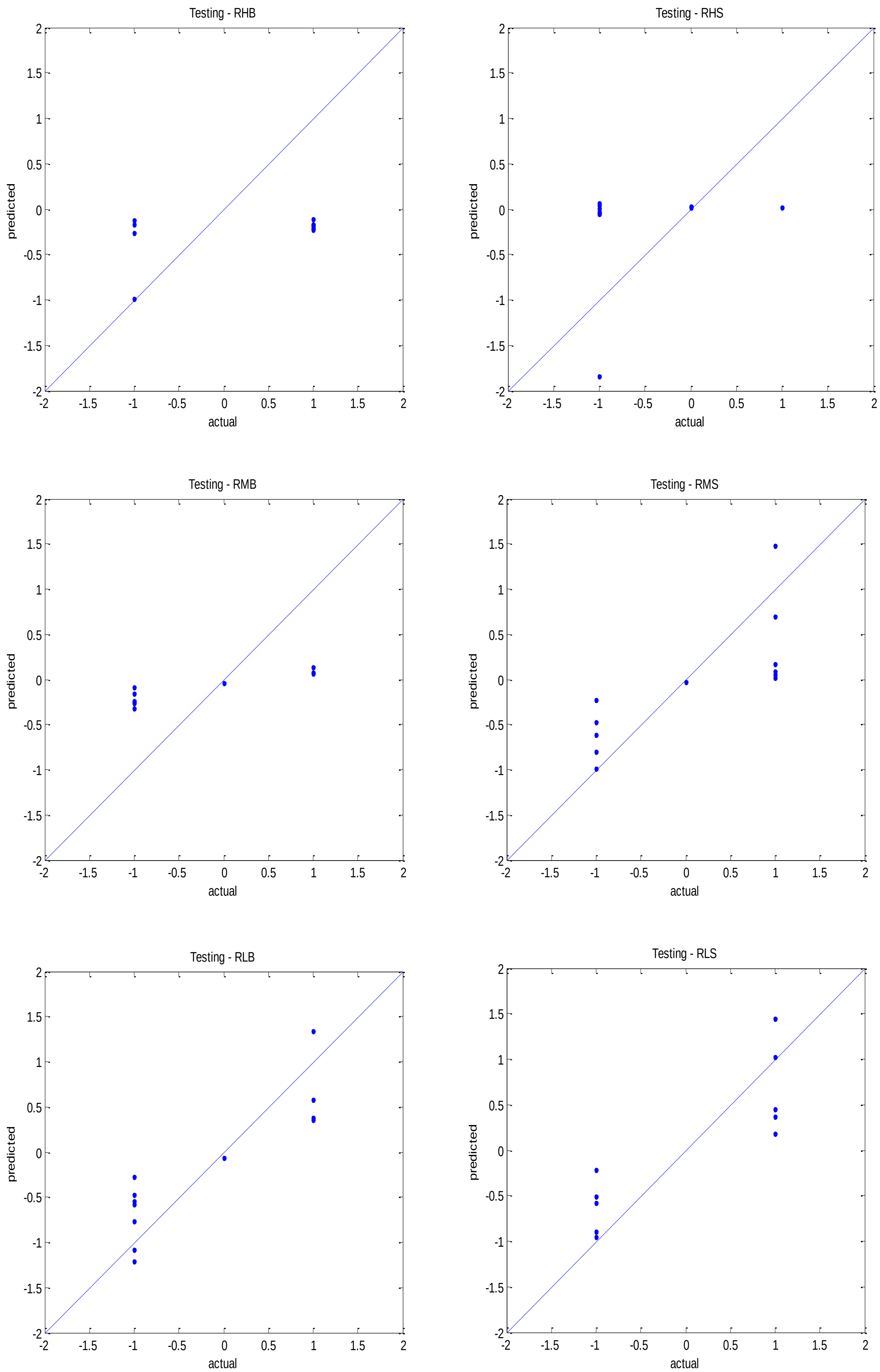

Figure F14: Testing results (Type2 share price) using ANN technique (NEWRB).

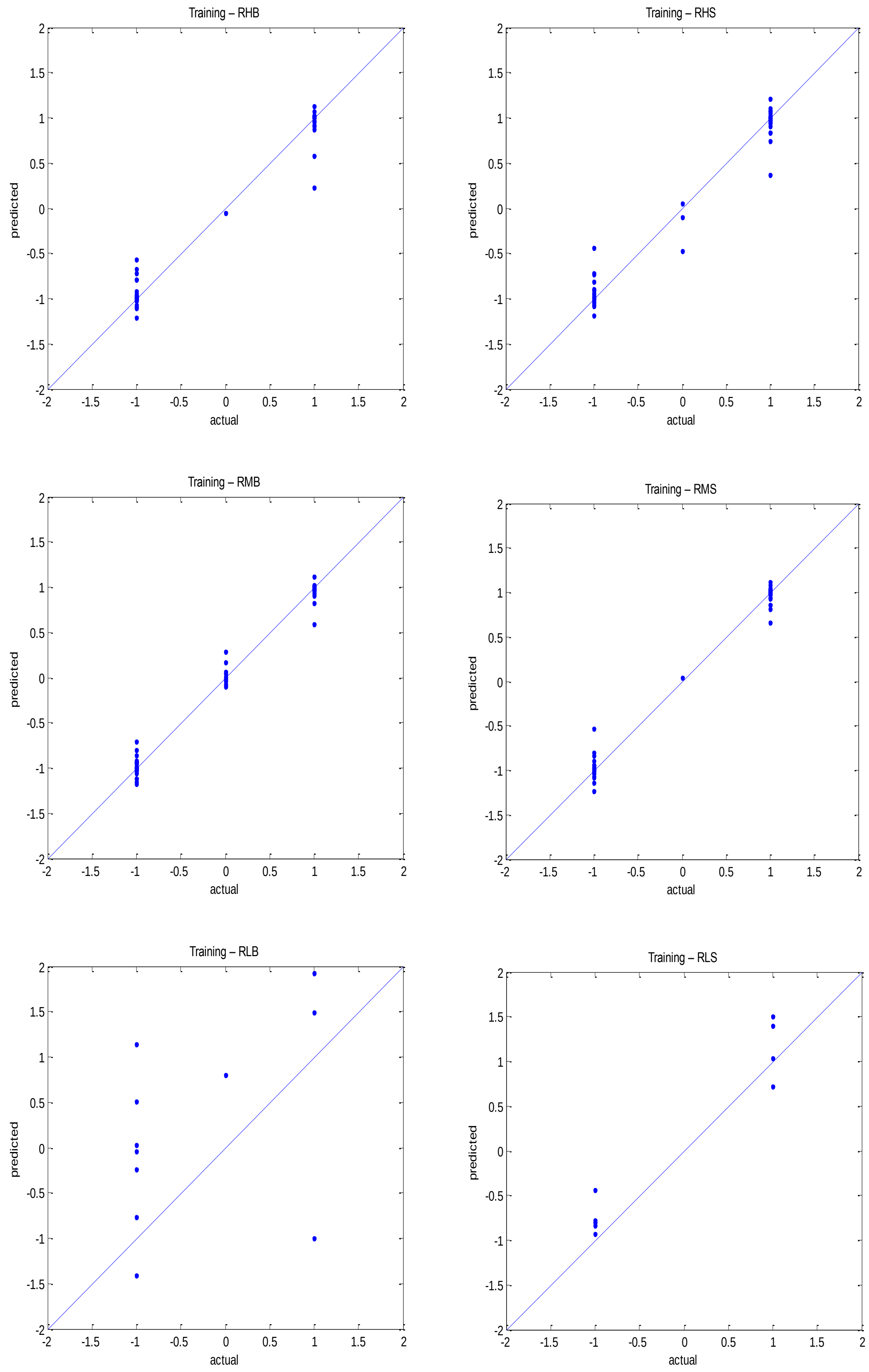

Figure F15: Training results (Type2 share price) using ANFIS technique.

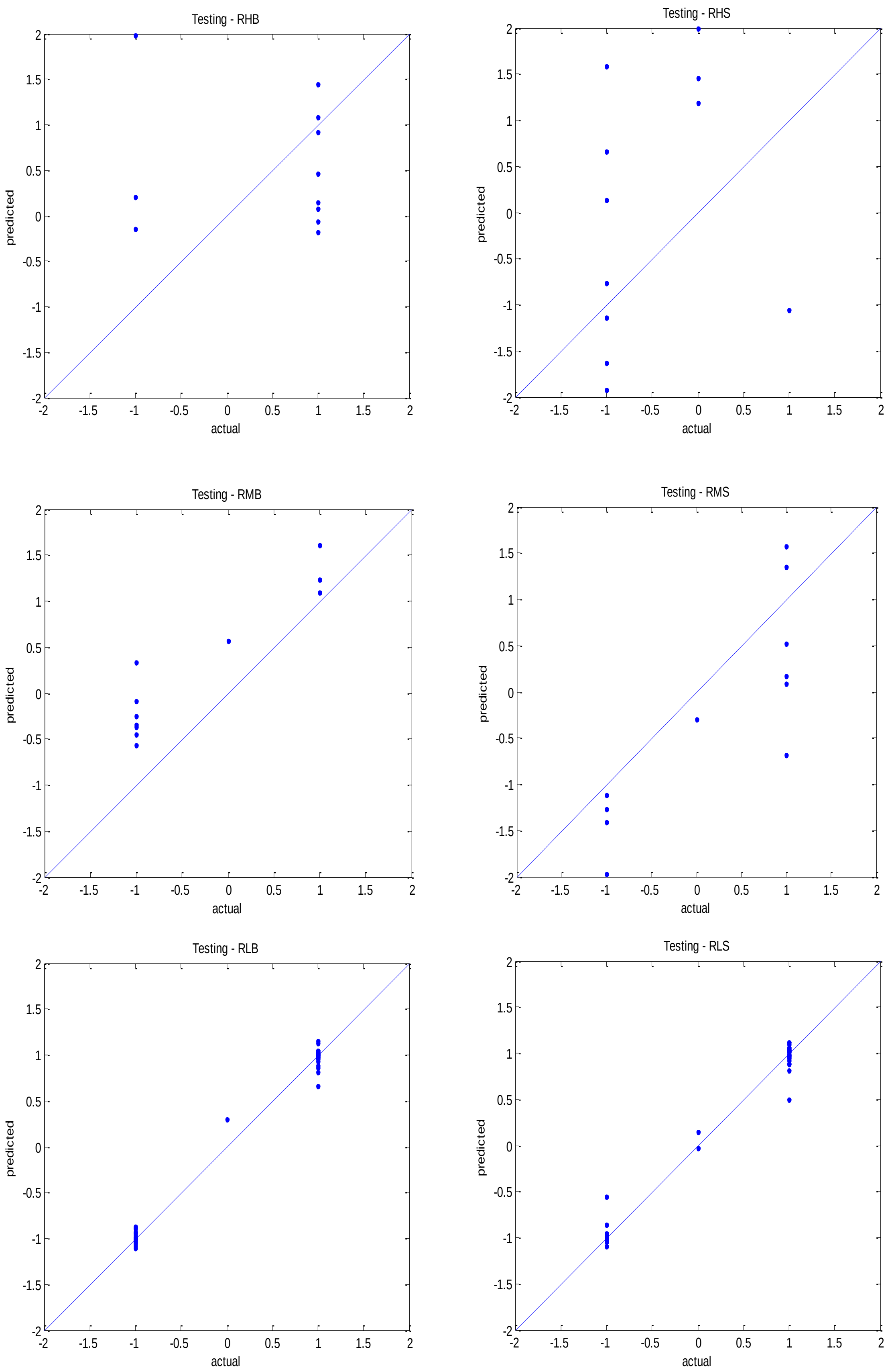

Figure F16: Testing results (Type2 share price) using ANFIS technique.