COMPARISON OF GARCH MODEL AND ARTIFICIAL NEURAL NETWORK FOR MUTUAL FUND'S GROWTH PREDICTION

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***Abstract*— The trend of investment has moved towards open ended funds, which removes the burden of investment from investors and promise certain percentage of profit. An open-end fund is a specialized type of mutual fund through which an investor can invest at any time. This kind of funds buy and sell shares as per their Net Asset Value per unit (NAV per unit). The freedom of time for investment is a big plus for such funds. There is more vigilance/security required for open-end funds. Research tries to build prediction models based on publically available data of Asset Management Companies (AMCs) and predict the growth of funds based on the time series analysis. The data includes past ten years data of top 9 AMCs, which is pre-processed to build a model for prediction of price/value for both individual investors and AMCs. Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) and Artificial Neural Network (ANN) are applied separately on the data to predict the NAV for next five months. GARCH model gave predictions with a very less Mean Square Error (MSE), outperforming ANN with a significant difference.**

Keywords*—open ended funds, ANN, ARCH, GARCH, mutual funds, forecasting,

I. INTRODUCTION

A mutual fund is an investment vehicle made up of a pool of capital collected from many investors for the purpose of investing in a portfolio which is comprised of securities and similar assets. Majority of mutual funds are open-ended, means they do not have restrictions on the number of shares (NAV per unit) the fund can issue or the period of initial investment to be made by the investor. Mutual funds are highly correlated with the economic, political and social factors, which leaves them to have a complex and stochastic behavior. These factors include any political unrest, festivity or foreign investment in the country, which can affect the securities i.e. stocks, bonds etc. This fluctuates the growth of portfolio and the fund, hence, putting the burden on the fund manager to formulate and evaluate complex equation to reform the portfolio in order to gain the maximum profit out of the investment. Thus a deep analysis is required in order to forecast the upcoming prices and changes in different attributes related to the performance of the fund. The growth of the fund follows a defined pattern under time series analysis, which can be used to predict the growth using an automated process, removing the burden from fund manager. Multiple time series models are usually considered while working over such predictions.

Auto-Regressive Conditional Heteroscedacity (ARCH) and Generalized ARCH (GARCH) models are considered to be best for predicting fluctuating assets. Unlike the tradition time series models, ARCH/GARCH model perform analysis over the residual or error term calculating the volatility and providing forecast over a specified time. In this study, GARCH model is used to forecast the NAV per unit of top AMCs of Pakistan. Since Pakistan's financial market is highly volatile, therefore it is a challenge for many researchers to work over this problem.

The organization of this research paper is as follows. Section II describes the related work done in the context. The core concepts of Time Series Forecasting, ARCH/GARCH model and ANN are defined in Section III. Moreover, Section IV explains the process of data collection, extraction, cleaning and transformation to form the time series ready to be forecasted. The results of GARCH and ANN are included in Section V while a comparison is made is Section VI.

II. LITERATURE REVIEW

Research has been done in financial prediction systems, but least work has been done for Open-ended Funds, as funds are bought and sold very rigorously. However various financial systems have been developed for Stock Markets of the world. A hybrid financial trading system has been proposed by [1] that incorporates the application of chaos theory, nonlinear statistical models, and AI methods. In this study, researchers proposed a method comprised of three phases, Time series was chosen for modeling including the chaos theory in the first phase. Time series forecasting was done using Artificial Neural Networks (ANN) and nonlinear statistical modeling in the second phase. In the final phase Genetic Algorithm was used to forecast the financial trading systems involving the trading rules and money management systems. Another hybrid intelligent system was proposed by [2] for NASDAQ (World's second-largest Stock Market), which analyzed the 24 months stock data for NASDAQ -100 main index. The neural network was used for stock forecasting of next day and a neuro-fuzzy system for analyzing the trend of the predicted stock values. Another hybrid financial system was proposed [3] to model Karachi Stock Exchange index data, KSE100. These models were used for short-term forecasting of Karachi Stock Exchange index data, KSE100. It included the combination of ANN model with Auto-Regressive Moving Average (ARIMA) models and ARCH/GARCH models. Comparing ANN against ARIMA and ARCH/GARCH on the basis of forecast mean square of error (FMSE) gave the results in the favor of ANN. Moreover, it was found that the Hybrid model of ANN-ARCH/GARCH is superior to ANN and ANN-ARIMA in forecasting. A user interactive financial system was developed

[5] for investors in which users were linked with a system containing the data of funds which also predicted the performance of financial vehicles and provided training for trading options. Furthermore, it was proposed that artificial neural networks perform better in classification and forecasting of mutual funds as compared to traditional backpropagation neural networks [4]. Fast Adaptive Neural Network Classifier (FANNC) was used to forecast performance of mutual funds and compared to that of Back Propagation Network (BPN), hence it was found that FANNC not only takes less time but also has superior records as compared to BPN.

III. TIME SERIES FORECASTING

Time Series Forecasting has provided solution to diverse problems and is a way to predict the future values with respect to the past behavior of an entity may it be price of a land, sales of a company or growth of a stock. The aim of time series forecasting is to provide a better understanding of an entity based on the past trend that is how high or low can the entity be. Generally a time series is representation of an entity with respect to time, a time series is comprised of four basic elements that are the, trend, cycle effect, seasonal effect and an Irregular components. The four component of a time series can be defined as follows:

Trend is the relative increase or decrease of an entity over a period of time.

Cycle Effect or Cyclical is the medium-term changes which repeat over time. The time of a cycle is effect is more likely to extend over a long period of time

Seasonal effect can be determined to be the effect due a specific season or a specific period of time which effect the trend of the entity in a positive or a negative way. Seasonal effects usually extend over a short period of time. An example of seasonal effect could be the sales of warm clothes during winter.

Irregular components are the variations in the time series due to the random events such as political issues or disasters.

A time series may have all the components or may have some of them but the trend is always determined for a time series. Hence a time series could be formulated as to be:

$$\textit{Additive: } Y(t) = T(t) + S(t) + C(t) + I(t) \qquad \text{---(1)}$$

Or

$$\textit{Multiplicative: } Y(t) = T(t) \text{ x } S(t) \text{ x } C(t) \text{ x } I(t) \qquad \text{---(2)}$$

A time series could be Additive (1) or Multiplicative (2). An additive time series considers all the components of time series to be independent and having no influence of one over an other, while a multiplicative time series is likely to have some influence of a component on to another.

Time Series Analysis and Forecasting is a vast field and many researchers have worked over the phenomenon hence multiple models have been formed such as the traditional ARIMA models, Logistic Regression and ARCH/GARCH while certain population of researchers has implemented Artificial Neural Network (ANN) in order to forecast the time series, recently ANN have gained attraction of the researchers for forecasting of financial data. Hence In this paper two approaches are considered to forecast the mutual fund performance and grow the traditional GARCH model and Artificial Neural Networks.

A. ARCH/GARCH Model

ARCH/GARCH models are considered as a pioneer when performing tests and prediction over financial data, they out perform any other time series model and provide the best possible outcome in the field of applied econometrics. Robert Engle proposed ARCH/GARCH models as a tool for analysis and forecasting the performance of an asset based on its volatility. The invariants ARCH and GARCH work on the volatility and provide information about the size of error of the model. Based on the least square model which states that the expected value of all error terms when squared, is the same at any given point, known as the homoscedasticity, while the ARCH/GARCH model leaps a step ahead and considers the fact that in which the variance of the data term is not equal, also known as heteroscedasticity.

In order to generate an idea about the volatility of an asset, the ARCH/GARCH model make use of standard deviation and variance of the variables selected to carry out the process of forecasting performance of an asset. Furthermore considering ϵt as identical and independent process (also known as the white noise), Let the dependent variable be labeled r_t, which could be the return on an asset or portfolio. The mean value μ and the variance σ^2 will be defined relative to a past information set. Then, the return r_t in the present will be equal to the mean value of r_t plus the standard deviation of r_t times the error term for the present period. This can be determined by the following equation.

$$r_t = \mu + \epsilon_\tau \qquad (3)$$

$$\epsilon_\tau = \sigma_\tau \varepsilon_\tau \quad (4)$$

$$\sigma^2_\tau = \omega + \alpha\epsilon^2_\tau + \beta\sigma^2_{\tau-1} \quad (5)$$

Where,

r_t is the residual or mean error at time t.

ϵ_t is the Identical and Independent Distribution (i.i.d) term at time t.

σ_t is the standard deviation at time t.

σ^2_t is the variance or the volatility observed at time t.

B. Artificial Neural Network

A neural network is a process formed by the neuron cells in a human brain linked together to analyse, reason and solve a problem occurring in the daily human life and to provide a link between the human body and the brain. The neuron cells are electronic in nature and process information based on percepts from other neurons or human body parts, similarly an ANN tries to mimic the process of natural neural networks and forms a network of neurons in it self processing information in between the layers. In order to discuss the process an ANN follows let us understand how a neuron is represented in an ANN, A neuron consists of multiple weighted input channels, an activation or transfer function, a bias and a single ouput channel. The weights and the bias are random values that are estimated during the process of learning. Further more a neural network consists of layers of neurons grouped together to calculate a result. There are three layers the input layer, hidden layer and the output layer. The input layer comprises of neurons taking input from the outer world multiplying them with a weight and forwarding the value to the hidden layer based on the activation function. The hidden layer comprises of neurons which internally process the data and forward the information to the output layer which consists of a neurons which are responsible to provide an output.

Figure 4.1 shows the structure of Artificial Neural Network (ANN)

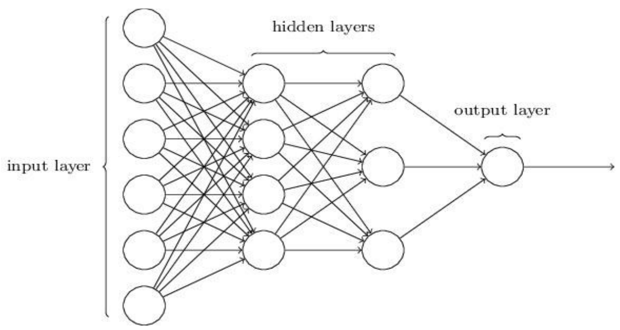

Figure 4.1 structure of Artificial Neural Network (ANN)

The input for a neuron in an ANN is called a feature, the independent variable as input and the dependent variable as the target. Let us consider a vector d = (x1,x2,x3….xn) that is the input layer, a vector h = (h1,h2,h3…hn) the hidden layer and and vector y = (y1,y2,y3…yn) that is an output layer.

The process flow of a neural network is The output of the j^{th} hidden unit is obtained by first forming a weighted linear combination of the 'd' input values and adding a bias. The activation of hidden unit 'j' can be obtained by transforming the linear sum using a logistic activation function

IV. METHODOLOGY

A. Fund Selection

This research is based on open ended mutual funds, which are operated by Asset Management Companies (AMC). They publish the performance of each of their funds through Fund Manager's Report (FMR) which is published monthly in PDF format. Hence, the only source for required data are the fund manager's reports.

To narrow down the window and provide real time prediction for this research with high accuracy we selected the top 9 (nine) Asset Management Companies of Pakistan based on their fund size and AMC rating. Table 4.1 shows the selected Funds categorized with their AMCs.

Table 4.1 List of selected funds from top 9 AMCs of Pakistan

AMC	Funds
Al Meezan	Al Meezan Mutual Fund
	Al Meezan Cash Fund
	Al Meezan Islamic Fund
NIT	NI(U)T
	NIT Islamic Equity
	NIT GTF
NBP Fullerton	NAFA Islamic Stock
	NAFA Moneymarket
	NAFA Stock Fund
UBL	Al Ameen Islamic Cash fund
	Al Ameen Islamic Dediicated Equity
	UBL Stock Advantage
HBL	HBL Cash Fund
	HBL Moneymarket Fund
	HBL Islamic Equity Fund
arif habib	MCB Cash Management Optimizer
	MCB Pakistan Stock Market Fund
	Al Hamra Islamic Stock Fund
ABL	ABL Cash Fund
	ABL Stock Fund
	ABL Islamic Stock
Al Falah GHP	Stock Fund
	Moneymarket Fund
	Alpha fund
Atlas	Atlas Islamic Stock Fund
	Atlas Money Market Fund
	Atlas Stock Market fund

The Funds were chosen from the categories of Islamic and Convention and their sub-categories of Money-market and

Equity.

Table 4.2 describes the clustering of Funds with respect to their categories.

Category	Sub Category	Funds
Islamic	Equity	Al Meezan Mutual Fund
		Al Meezan Islamic Fund
		NIT Islamic Equity
		NAFA Islamic Stock
		HBL Islamic Equity Fund
		Al Ameen Islamic Dediicated Equity
		Al Hamra Islamic Stock Fund
		ABL Islamic Stock
		Atlas Islamic Stock Fund
		Atlas Stock Market fund
	Money Market	Al Meezan Cash Fund
		Al Ameen Islamic Cash fund
Conventional	Equity	NI(U)T
		NAFA Stock Fund
		UBL Stock Advantage
		MCB Pakistan Stock Market Fund
		ABL Stock Fund
		Stock Fund
		Alpha fund
	Money Market	NIT GTF
		NAFA Moneymarket
		HBL Cash Fund
		HBL Moneymarket Fund
		MCB Cash Management Optimizer
		ABL Cash Fund
		Moneymarket Fund
		Atlas Money Market Fund

B. Data Collection

The data source defined above were collected form the websites of individual AMCs by modes of downloading using plugin and manual downloading where necessary. Hence reports of past 10 years of each AMC were collected and used for data extraction.

C. Extraction

The selected data sources were collected and ready for the process of extraction. A parser was implemented to parse and extract the required data and to structure in a csv file for further processing. Since the data source was in pdf, certain problems were faced in extraction of the required data. Hence the process of extraction is composed of certain steps which were applied in a series in order to extract the required data from the data source.

For the process of extraction, the data source was initially reviewed to analyze the general structure and commonalities between the data sources, such that a generic parser could be implemented and precise data extraction could be carried out in order to gain most out of a data source. Initially, analyzing the data source provided the following facts for extraction process.

- Certain data sources contained multiple funds while some were only comprised of single funds.
- The data source has a semi-structured format or unstructured based on AMC.
- The AMC information is categorized in a table format for each individual AMC standardized by MUFAP.
- The table format could vary based on the AMC.

As certain knowledge of document structure was assessed by the initial review of the data source. A C# based parser was implemented in order to extract the data from the data source and structure the data into a table format in a csv file. iTEXTSHARP library was used to read a PDF file and convert into string format. Certain problems were encountered, as the data source was semi-structured which are as follows:

- A PDF file format does not define any support for LTR or RTL standard.
- Each element in a PDF file format is written using a draw () function.
- The structure of text that could be seen in a PDF format would no longer remain if converted into string format and text alignment would also be disturbed.
- PDF defines no structure or standard for a table rather they are just borders.

There were three approaches explored for implementation of parser which are as follow.

- Substring the required value from the specified area in the converted string.
- Tokenization of converted string base on a delimiter and extraction of required value.
- Implementing an iEXTRACTIONSTRATEGY for the library used.

Out of the three strategies Tokenization of converted string was found to be best for extraction.

D. Cleaning

Since the Algorithms used for the prediction of investment funds and AMC growth are time series algorithms, therefore they require precisely accurate data and any missing or incorrect values can badly affect the prediction by disturbing the accuracy of the algorithm. To overcome such problems, certain cleaning and modification processes were applied on the extracted data to get data which is semantically correct.

Soon after the first extraction of data using the parser following issues were found which required the process of cleaning to be applied.

- MISSING VALUES

  AMC Rating and Risk variables had missing values.

- INCORRECT ORDERING OF DATA

  Net Assets (Fund Size) values in the structured data were not in place due to existence of separator in the value.

- HETEROGENEOUS VALUES

  Values for Net Assets (Fund Size) were found to be heterogeneous as some values were in PKR Million unit and some in PKR Billion unit.

E. Data Transformation

After Critical analysis of extracted data, multiple steps were taken to cleanse the data form errors.

- MANUAL ASSESSMENT OF MISSING VALUES AND CORRECTION

The extracted data was manually assessed for missing values and checked with the value in original data source. Missing values were then filled in manually as there was a low ratio of missing values in the extracted data.

- REMOVAL OF SEPARATOR

Parser was modified in order to remove the separator from the extracted values before writing them on to the structured csv file.9.

- CONVERSION OF UNITS

Parser was modified in order to make the variable homogeneous and convert all PKR Billion units to PKR Million units during extraction.

F. ARCH/GRACH Forecasting

Out of the extracted variables Net Asset Value per unit or NAV per unit and performance (Returns) of the fund were selected in order to perform forecasting. Multivariate GARCH model was then applied on the selected variable. Rolling forecast of 4 months and a predicted forecast of 1 month was made in order to analyze the performance of the fund. A mean model with AR = 1 and MA = 1 and a Variance model GARCH (1, 1) was specified for the multivariate forecasting. NAV per unit was predicted with respect to returns of the fund.

V. RESULTS

The 10 years of monthly NAV per unit and performance was divided into a training and a testing subset. The data consisted of 105 data points starting from 30th October 2007 till 30th September 2017. Total of 100 data points were used for training the GARCH model while 05 data point were predicted using 4 rolling prediction and 1 ahead prediction the equation for GRACH was established using (3).

The results gathered from the model were evaluated using the root mean squared error (RMSE) are listed in Table 5.1.

It can be observed from Table 5.1 that NAFA Stock Fund has least Root Mean Square Error (RMSE of 0.1326 whereas Al-Falah Stock Fund has highest RMSE of 8.2257.

Table 5.1 Root mean squared error (RMSE) of prediction through GARCH

Fund Name	RMSE
Nafa Stock Fund	0.132696
Al Falah Stock Fund	8.2257
Al Meezan Mutual Fund	0.686
Alfalah Alpha Fund	0.6136
Atlas Islamic Fund	4.07
Atlas Stock Market	3.108
Mcb Pakistan Stock Market	0.971
Meezan Islamic Fund	0.734
Ubl Stock Advantage	0.2798

For the most accurately predicted data, i.e of NAFA Stock Fund, the values for alpha (NAV), beta (NAV) and Omega (NAV) were calculated to be 0.057369, 0.859894 , 0.038759 respectively while the AR and MA values were found to be 0.991772, 0.083284 respectively for NAV per unit, Moreover The values for alpha (Returns) , beta (Returns) and Omega (Returns) were calculated to be 0.104416, 0.848259, 2.412137 respectively while the AR and MA values were found to be 0.00, 0.905 respectively for Monthly Returns.

The Dynamic Conditional Correlation (dcc) alpha and beta were found to be 0.000, 0.92964 respectively.

Table 5.2 List of parameters of trained model of NAFA Stock Fund's data

Parameter	Estimate
NAV.AR	0.991772
NAV.MA	0.083284
NAV.alpha	0.057369
NAV.beta	0.859894
NAV.omega	0.038759
Returns.AR	-0.954038
Returns.MA	0.923027
Returns.alpha	0.104416
Returns.beta	0.848259
Returns.omega	2.412137
dcc.alpha	0.000
dcc.beta	0.905761

Since Al-Falah Stock fund has the highest MSE of 13.53, the values for alpha (NAV), beta (NAV) and Omega (NAV) were calculated to be 0.000, 0.9878, 1.124 respectively while the AR and MA values were found to be 0.7965,0.1868 respectively for NAV per unit. Moreover The values for alpha (Returns) , beta (Returns) and gamma (Returns) were calculated to be 0.000, 0.99899, 0.0029 respectively while the AR and MA values were found to be 0. 0.835515, -1.000, respectively for Monthly Returns.

The Dynamic Conditional Correlation (dcc) alpha and beta were found to be 0.000, 0.9657 respectively. All of the above paramters of Al Falah Stock Fund is listed in Table 5.3.

Table 5.3 List of parameters of trained model of AL FALAH Stock Fund's data

Parameter	Estimate
NAV.AR	0.796503
NAV.MA	0.186820
NAV.alpha	0.000
NAV.beta	0.987859
NAV.omega	1.124620
Returns.AR	0.835515
Returns.MA	-1.000000
Returns.alpha	0.000
Returns.beta	0.998999
Returns.omega	0.002988
dcc.alpha	0.000
dcc.beta	0.965797

The results for ANN show that the sigma square value is estimated to be 1.34 and the RMSE for the last 5 month forecast are listed in table 5.4. The cumulative RMSE for the prediction of all 9 funds is found to be 219.36

Table 5.4 Root mean squared error (RMSE) of prediction through ANN

Fund Name	RMSE
NAFA Stock Fund	2.35690
Al Falah Stock Fund	16.5446
Al Meezan Mutual Fund	2.02788
Al Falah Alpha Fund	6.61892
Atlas Islamic Fund	69.4375
Atlas Stock Market	86.8305
Mcb Pakistan Stock Market	15.7346
Meezan Islamic Fund	9.99349
Ubl Stock Advantage	9.81096

VI. DISSCUSION

The RMSE values shows that the GARCH model performed accurately on most of the funds and hence predicting with high accuracy.

The results suggest that the forecast is highly persistent as beta + alpha -1 = 0.0283 for NAV and determines that the variance is highly reverting towards or decaying towards it long run average that is the quick reversion towards its mean. Furthermore for returns, the persistence is about 0.01211 that is the returns are rapidly decaying towards their mean similar to the NAV of the fund.

The value of omega for NAV determines that a high variance is observed hence having a greater effect of previous variance over the forecasted value. Furthermore alpha value for NAV and Returns indicate that the mean error between the previous and forecasted values highly low and certainly approximately equal to 0, while the beta value represent a high effect of the last periods variance on the forecasted value.

Results describe that the seasonal effect and cyclical effect for NAFA Stock Fund are found to be very low due to which the weightage (alpha) of long run returns is approximately equal to 0.057369. Whereas the weight (B) of long run variance is 0.859 which helps to predict the NAV value closely. As a result, the RMSE of NAFA stock fund is approximately equal to zero. Whereas for Al Falah Stock Fund, the seasonal effect is high due to which the weightage (alpha) of long run returns is equal to 0 and the weightage (Beta) of long run variance is 0.987. Having a high effect of long run variance over the prediction has resulted in higher error for predicted NAV. Hence RMSE of Al Falah stock fund is high and approximately equal to 8.2237.

The root mean square error for the prediction of same data through Artificial Neural Network(ANN) is 219.36 which is very high. Although ANN outperformed GARCH in the prediction of KSE 100 index stock market[3], but here the focus is on mutual funds which are comprised of not only stocks but other securities as well.

VII. CONCLUSION

Prediction of growth of investment vehicles is an important task for investors, through which they can maximize their profit. This researched focused on Open Ended Mutual Funds and compared the techniques to predict the growth of funds. GARCH and ANN were applied separately on 10 years' record of top nine Mutual Funds of Pakistan. Predictions were made for five months ahead Net Asset Value of funds and Root Mean Square Error was calculated. The RMSE for GARCH was found to be 2.1 whereas ANN gave RMSE of 219.36. Further research can be carried out to find the reason of failure of ANN for Open Ended Mutual Funds.

REFERENCES

[1] Clarence NW Tan. “A hybrid financial trading system incorporating chaos theory, statistical and artificial intelligence/soft computing methods”. In: Queensland Finance Conference. 1999.

[2] Ajith Abraham, Baikunth Nath, and Prabhat Kumar Mahanti. “Hybrid intelligent systems for stock market analysis”. In: International Confer- ence on Computational Science. Springer. 2001, pp. 337–345.

[3] Samreen Fatima and Ghulam Hussain. “Statistical models of KSE100 in- dex using hybrid financial systems”. In: Neurocomputing 71.13 (2008), pp. 2742–2746.

[4] Kehluh Wang and Szuwei Huang. “Using fast adaptive neural network classifier for mutual fund performance evaluation”. In: Expert Systems with Applications 37.8 (2010), pp. 6007–6011.

[5] Peter Hancock, Jeffrey Saltz, Andrew Abrahams, et al. User-interactive financial vehicle performance prediction, trading and training system and methods. US Patent 7,392,212. June 2008.

[6] Robert Engle. “GARCH 101: The use of ARCH/GARCH models in ap- plied econometrics”. In: The Journal of Economic Perspectives 15.4 (2001), pp. 157–168.

[7] Samreen Fatima. “COMPARISON OF ASYMMETRIC GARCH MOD- ELS WITH ARTIFICIAL NEURAL NETWORK FOR STOCK MAR- KETS PREDICTION, A CASE STUDY”. In: Journal of Engineering and Applied Sciences (JEAS), Peshawar 36.1 (2017).

[8] Patrick Burns. “Multivariate GARCH with only univariate estimation”.In: Available electronically at http://www. burns-stat.com/pages/Working/multgarchuni. pdf (2005).

[9] DC Indro, CX Jiang, BE Patuwo, et al. “Predicting mutual fund perfor- mance using artificial neural networks”. In: Omega 27.3 (1999), pp. 373– 380.

[10] W-C Chiang, Timothy L Urban, and Gable W Baldridge. “A neural net- work approach to mutual fund net asset value forecasting”. In: Omega 24.2 (1996), pp. 205–215.

[11] Mohamed M Mostafa. “Forecasting stock exchange movements using neu- ral networks: Empirical evidence from Kuwait”. In: Expert Systems with Applications 37.9 (2010), pp. 6302–6309.

[12] Erdinc Altay and M Hakan Satman. “Stock market forecasting: artificial neural network and linear regression comparison in an emerging market”. In: Journal of Financial Management & Analysis 18.2 (2005), p. 18.