Forecasting Stock Returns, Exchange Rate and Oil Price: An Empirical Investigation of SAARC Countries

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- Stock exchange returns
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A thesis submitted in partial fulfillment of the requirements for the Degree of Master of Philosophy/Science in Management with specialization in Finance at
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FORWARDING SHEET

The thesis entitled "Forecasting Stock Returns, Exchange Rate and Oil Price: An Empirical Investigation of SAARC Countries" submitted by Mr. Awais Ur Rehman in partial fulfillment of M.S degree in Management Sciences with specialization in Finance, has been completed under my guidance and supervision. I am satisfied with the quality of student's research work and allow him to submit this thesis for further process as per IIU rules & regulations.

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Date: 26. 2. 2015.

بسم الله الرحمن الرحيم

In the name of Allah, the most merciful and beneficent

Dedication

"To my great parents, my sisters and my wife who are praise worthy for their sustenance of me on right lines because I am today, only due to their efforts for my sake"

ABSTRACT

Security prices are too complicated to be successfully predicted and have not been consistent in theory so far. Security prices movement is driven by numerous factors, both at national and international levels, and because of the multiplicative effect of these factors, the markets movement has been majorly random and very less predictable. A number of research studies have been undertaken in the past to model the Security prices movement. Research analysts are continuously charting data and conducting fundamental analyses to identify securities so as to design multi-bagger portfolio's which can outperform the benchmark index. Any model, which can predict the security prices movement would be helpful to investors to reduce their risk exposure, increase hedging effectiveness and maximize returns.

This study used to forecast the stock index, crude oil prices and exchange rate with respect to USD, using past data from January 2000 to December 2013 on monthly basis with the time span of 14 years. First part of study predicted future security prices using data of SAARC countries i.e. Pakistan, Srilanka and India. And in second part compare the forecasting accuracy of the two models ie. Artificial Neural Network (ANN) and Geometric Random Walk Model (GRWM). Predicting power of the these models are compared by the different techniques i.e. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Median of Absolute Deviation (MAD) and Success Ratio (SR).

The result is concluded that best methodology varying with situation with its accuracy or significance of results as, mean return and standard deviation create volatility changes in the prices. For example, in forecasting exchange rate, stock price and crude oil prices if the investor risk lover then GRWM is best suitable model; better than ANN model and if investor want to forecast directions in this case better ANN model is better than GRWM.

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DECLARATION

I hereby declare that this thesis, neither as a whole nor as a part thereof, has been copied out from any source. It is further declared that I have prepared this thesis entirely on the basis of my personal effort made under the sincere guidenance of my supervisor.

No portion of the work, presented in this thesis, has been submitted in support of any application for any degree or qualification of this or any other university or institute of learning.

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Abbreviations

ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
BPNN	Back-Propagation Neural Network
BSE	Bombay Stock Exchange
CSE	Colombo Stock Exchange
DPS	Dividend per Share
EPS	Earning Per Share
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GRWM	Geometric Random Walk Model
KSE	Karachi Stock Exchange
MAD	Median of Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
REER	Real Effective Exchange Rate
RMSE	Root Mean Square Error
SAARC	South Asian Association for Regional Cooperation
WNN	Windows Neural Network

1. Introduction:

Volatility may have become a topic of huge significance to almost anyone who is concerned in the financial markets, even as an observer. To many among the general public, the term is simply identical with risk: high volatility is thought of as an indication of market commotion. To them, volatility is meant as securities, exchange rate and prices of oil are not being cost pretty and the investment industry is not performing as well as it should. But for those who deal with mixture investments, knowing movements, predicting it perfectly, and handling the visibility of their domain investment portfolios to its results are essential.

Modern choice costs concept, starting with Dark and Scholes (1973), according to movements a main part in identifying the reasonable worth for a choice, or any mixture device with choice characteristics. Whereas the profits movements of the actual resource is only one out of five factors in the basic Black-Scholes (BS) choice costs system, its significance is amplified by the reality that it is only one that is not straight visible. Stock cost, attack cost, a chance to choice expiry, and the interest amount are all well-known or able to be quickly acquired from industry, however movements should be estimated. Even though the noticed movements above latest times can quickly be calculated out of traditional data, an option's theoretical value nowadays relies on the movements that would be knowledgeable later on, over the choices entire staying life-time.

From the starting, movements forecast has presented significant problems for those enthusiastic about implementing types assessment designs, but the problems has become greater recently as the maturities of available equipment have prolonged considerably. In Nineteen seventies, most dealing choices were in value choices with maturities of only a small number of months. Whereas it was identified that a come back movements of security can be predicted to vary eventually, on condition that this only happens progressively, it should be probable to achieve a logically fine temporary predict via simple supposition of that movements above long run would stay regarding the same as it was observed in the earlier period. Those suppositions become less reasonable as longer the adulthood of the choice that is costed.

Now there is effective dealing in types of all varieties with maturities that might be 10years or more than it. How one should go regarding identifying the suitable movement's limit to assess a decade cap agreement on the Deutschemark / money return rate? On the other hand one chooses to do such kind of forecast, it is limited to be topic to significant mistake. To what extinct doubt is present regarding the finest feasible forecast for a moment period like that? Several problems are there that will concentrate on in this monograph.

This research will talk about and assess the significant techniques for predicting movements, always with an eye toward forecast rather than modeling and describing movement's actions. Moreover, this research would be mainly involved with precision of forecast, not with theoretical or econometric beauty, as beauty habitually comes at the cost of sturdiness in out-of-sample predicting. The rest of this release would think about the essential query about what the movements actually is? And why individuals want to forecast it? Out of many significant complications in solving the justifications on either type dealing improves the market's movements one is that the phrase is recognized in various ways by dissimilar individuals.

Limiting our interest to expert types investors and investments companies who use statistical choice costs designs, and to the instructors who develop them, one might anticipate pretty close contract about how to determine movements, at least as far as how it is used in the designs.

This study adds to the accessible body of literature in such a way that the method that adopted in this study i.e. the comparison of Artificial Neural Network (ANN) and Geometric Random Walk Model (GRWM) are unique in the context of SAARC countries these methods are very less used and are not ever compared all together before. So this study contributes to literature that it has provide a caparison in this regards. Moreover the variables used in this study are less discussed in research related to SAARC countries. These variables are separately studied in research but this study provide a comprehensive analysis by studying the variable stock returns, exchange rate and oil prices collectively. It has been observed the stock returns extensively studied before in literature but forecasting exchange rate and oil prices on the bases of these two methods of forecasting that used in this study are very least or even not studied extensively in literature. So this study will open new horizons for research related to these constructs in detail.

1.1 Problem Statement:

This study aimed to predict the future prices of the securities by comparing the predicting models that are widely used by the analyst namely Artificial Neural network and Geometric Random Walk Model. Thus to the question regarding which model is best predicting model in the context of SAARC countries. In SAARC countries almost all the countries are developing economies and the fluctuations in the oil prices, exchange rates and stock returns are phenomenal, and these are the most important components of the economy. So there is desperate need to forecast/predict/estimate about these indicators for SAARC.

1.2 Objectives:

The aim of this study is:

- To forecast prices of crude oil markets, stock exchanges return and exchange rate.
- Comparing the forecasting accuracy of the Artificial Neural Network (ANN) and Geometric Random Walk Model (GRWM).

1.3 Research Question:

This thesis looks for to answer the subsequent research question:

How could SAARC countries predict long-term stock prices, exchange rate and fuel prices in better way to improve the makeover of the economy of these countries to face current intimidation improve logistics planning and improve financial planning?

Giving answer to this question the following exploratory questions will be deal with:

1. What forecast model has been most exact at predicting historically stock returns, exchange rate and fuel prices?
2. Which model is performed better in context of developing countries like SAARC countries?

1.4 Significance:

As for as the significance of this study is concern, this study is conducted on developing economies that are the significant members of the SAARC. As far as the methodology of this study is concern, the study has used unique methods to conduct research on developing economies. The variables studied are also not studied in combine before this study. In this study forecast are being made about stock retune, exchange rate and oil prices on the basis of financial data of countries that include Pakistan, India and Sri Lanka. So this study will be beneficial for the policy makers while establishing financial policies for the developing economies like the SAARC countries. Another important contribution is the unique method of comparison between ANN and GRWM. So this will help to provide empirical evidence that which method of forecasting will best suit the developing economies. So this study will be a beneficial addition to the existing body of literature in the above discusses ways.

In this highly dynamic environment, it has been observed that 95% of the research that has been compared contrasted and tested theories methods and construct is conducted in the developed countries (Farashahi, Hafso, and Molz, 2005) and only 5% of this sort of research is conducted in the developing countries. Considering this demand of conducting research in developed countries and providing and empirical evidence to the existing body of literature the focus of this study is on the countries that are the significant South Asian Association for Regional Cooperation (SAARC)'s members. The countries which are studied for this purpose of research include Pakistan, India, and Sri Lanka. The main focus of this research will be on the financial data of our forecasted variables of these countries which are listed above. In this research after collecting data from the stock market, forex market and form commodity market of the above countries forecast will be made about the following; stock returns, exchange rate and oil prices which are the main variables of this study. For the purpose of forecasting these variables two methods of forecasting are used which are Artificial Neural Network (ANN) and Geometric Random Walk Model (GRWM) to forecast these variable and compare its result with other two models. In this study a comparison will be made between these two methods and as a result empirical evidence can be found that would illustrate that which method of forecasting will suit those SAARC countries.

1.4.1 Contextual Contribution:

This paper will serves as the bases for policy makers to adjust the oil prices, quantities of trades of fuel and how to protect from unseen volatility of these prices. as for as stock market is concern, this study analysis would be base on two major forecasting techniques i.e. ANN and GRWM so having conclusion regarding predictions of stock prices this research will be able to make recommendations necessary for stock market investors, hedgers and other stakeholders. When we came towards exchange rate, it is a main participant of the forex market and its volatility has several economic implications for whole economy and for sub-sectors of the economy, hence it might be very useful to forecast the future movements in the local currencies of SAARC countries.

1.4.2 Theoretical Contribution:

This paper is different from previous studies in a significant manner. First this paper is using specifically data of SAARC countries jointly and individually. Secondly our attempt is to declare the best forecasting method for stock market, exchange rate and oil prices for SAARC. It opens a new debate regarding interconnections of these most important economic factors.

2. Literature Review:

2.1 Stock Return and Artificial Neural Network:

People used to invest in common stock as it is of its high returns over time. Many highly interrelated economic, political, psychological and even social factors effect on Stock market and these factors act together in a very complex way. Consequently, it is very complicated to predict the whereabouts of stock markets (Abdoh, 2000). Inspired artificial neural networks in the brain and nerve cells (neurons) exist. Although human knowledge about the human brain is very limited, but too many details are in connection with the anatomy and physiology of the brain has neurons. The output of each neuron is axons that are disciplines that have seen too long. Artificial neural network protected a much smaller sized range that scientific sensory systems and the capability of scientific sensory systems are much less. What actually is the capability to perform computational system in a particular activity is such as pushing a function approximation. Symptoms or electrical impulses are produced by atomic nerves and axons that are moved through the divisions. The systems are analyzed in three main areas: one, Network atmosphere and training data, two, Network Company and three, Network efficiency.

Stock industry forecast is very difficult. The efficient industry speculation declares that the present rate fully shows all available details. What this means is that past and present details is integrated into inventory cost, thus cost changes are merely due to new details and unrelated to current details. Since news happen arbitrarily and cannot be estimated, inventory cost should follow a unique move design. If this speculation is true, then any efforts to estimate industry will be useless. The unique move design has been examined substantially in various marketplaces. The results are combined and some timeframes contrary.

However, most of the recent studies (Gallagher and Taylor (2002), Gately (1996), Gooijer and Hyndman (2006), Hurst (1951), Rotundo and Valente (1999), Refenes (1995) on inventory markets decline the unique move actions of inventory values. Although numerous reviews produce proof that inventory values are not simply unique, they all agree that the actions of inventory values is approximately close to a unique move procedure.

Moreover, if the actual procedure to a market time sequence is a fraxel unique move, which can be deduced by calculating the Hurst exponent, then the only methods available for forecast are the sensory algorithms (Rotundo and Valente (1999), Qian and Rasheed (2004)).

An artificial neural network is a statistical design or a computational design based on scientific sensory techniques or, in other terms, is an emulation of a scientific sensory system. It includes a connected number of artificial neural networks and procedures information using a connectionist strategy to calculations. The ANN is a highly effective device for nonlinear time sequence designs and, in the last years, was used with achievements in fixing nonlinear forecast and predicting problems. In particular, ANNs are used to forecast marketplaces, since they are able to understand nonlinear mappings between information and results, the systems' design is no required (no priori supposition is needed) and can be used to non fixed information. Neural system predicting designs have been commonly used in economical time sequence research during the last decade (Enke and Thawornmong (2005), Gately (1996), McNelis (2005), Moreno and Olmeda (2007), Priddy and Keller (2005), Walczak (2001), Zirilli (1997).

Birgul Egeli, Meltem Ozturan, Bertan Badur analyzed Research conducted on Turkish inventory return has suggested that the information to the system may be taken as: past day's catalog value, past day's TL/USD return amount, past day's overnight interest amount and 5 phony factors each comprising the business days of the week. After the information has been identified, the information has been collected for the period of July 1, 2001 through Feb 28, 2003 from the Central Bank of Republic of Poultry. Coaching set is identified to include about 90% of the information set and the rest 10% will be used for examining purposes. System structure is identified to be Multi Layer Preceptor and General Feed Forward systems. Coaching and examining is conducted using these two network Architectures. However, it shows that artificial neural network have better activities than moving earnings.

Artificial neural network has been used in inventory return forecast during the last decade. One of the first projects was by Kimoto et. al. (1990) who had used ANN for the forecast of Seattle inventory return catalog.

Mizuno et. al. (1998) used ANN again to Seattle inventory return to predict dealing alerts with an overall forecast amount of 63%. Sexton et. al. (1998) determined in 1998 that use of strength and start of learning at unique points may fix the problems that may occur in training process. Phuaet. al. (2000) used sensory network with genetic criteria to the inventory return industry of Singapore and expected the industry direction with a precision of 81%.

Abbas Vahediin 2012 predicted the stock price of Tehran Stock Exchange Using Artificial Neural Network for annual data from 2000 to 2008. In this regard this approach is established with investment income, stock sales income, earnings per share and net assets as independent (Input) variables. Results showed that estimation and predictions of stock price with Artificial Neural Network is possible and have suitable and stronger outcomes. Most excellent structural design is a network which has unseen layers and twelve two neuron in unseen layers alongwith hyperbolic tangent transfer function both in unseen and output layers with Quasi -Newton training algorithm.

Mahdi Salehi, ValiKhodadadi and Hakim Abdolkhani (2011) try to design a model to forecast stock price of steel industry, using artificial neural networks. The designed model used a three-layer network a sigmoid transfer function, 7% Alpha, 2% Etta and Windows Neural Network (WNN) software. The input variables of the network include net assets, P/E ratio, dividend per share (DPS), earning per share (EPS), amount of stock transactions, and stock price network output of companies being studied. The results from designed model show that if an artificial neural network is taught correctly, it can recognize the relationship between variables and it can help to forecast the stock price of steel industry with minimum error (35% in this research). Investors can forecast the stock price of steel manufacturing companies using these inputs variables and WNN software.

2.2 Exchange Rate and Artificial Neural Network:

In the earlier period, balance of payments was used to determine foreign exchange rates. The balance of payments was the only way of listing receipts and payments in country's international transactions. Payments involve a demand for foreign currencies and a supply of the domestic currency. Receipts involve a supply of foreign currencies and a demand for the domestic currency. The export and import of goods were used to determine the balance. As a result, the forecasting of the exchange rates was not a difficult problem in the earlier period.

Unluckily, the local and international supply-demand factors and interest rates had become more related to each currency afterwards. The fixed foreign exchange rates were abandoned and a floating exchange rate system was executed by the industrialized nations in 1973 on the top of this. In recent times, further liberalization of trades is discussed in General Agreement on Trade and Tariffs.

The economic theory has not supplied econometric models so far to produce efficient forecasts of exchange rates, even though many studies have been dedicated to the equilibrium of exchange rate's estimation from the 20s to the recent years (Vincenzo Pacelli, 2012). Many flourishing claims of using neural network based market forecasting systems have been published. Unluckily, much of this work has to bear insufficient documentation concerning methodology (Binks and Allinson (1991), Collard (1991), Lee and Park, (1992)) or claims of positive results not backed up by comparisons with other relevant forecasting techniques (Binks and Allinson (1991), Lee and Park, (1992), Collard (1991) Weigend et al (1992)). So it is difficult to make both duplicate preceding work and achieve an exact evaluation that how good connectionist methods really act upon in comparison to other techniques of forecasting.

Joarder Kamruzzaman and Ruhul A. Sarker (2004) have examined artificial neural networks based on prediction of modeling of foreign currency rates using three learning algorithms, named as, Standard Back propagation (SBP), Scaled Conjugate Gradient (SCG) and Back propagation with Bayesian Regularization (BPR). The models were being train from past data using five technical indicators to predict six currency raedtes against Australian dollar. The predicting performance of the models was assessed using a number of extensively used statistical metrics and contrasted. Outcomes show that considerably close forecasting can be made using simple technical indicators without wide information of market data. Amongst the three models, SCG based model outperforms other models when measured on two commonly used metrics and achieved comparable outcomes with BPR based model on other three metrics. The result of network architecture on the act of the forecasting model is also offered.

Anastakis and Mort (2009), Majhi, Panda and Sahoo (2009), Bereau, Lopez and Villavicencio (2010), Bildirici, Alp and Ersen (2010), have studied the predictability of the dynamics of exchange rates of non-linear models such as artificial neural networks, genetic algorithms, expert systems or fuzzy models, leading however to conflicting results.

Mehdi Khashei and Mehdi Bijari (2011) an improved design of the artificial neural network is suggested using autoregressive incorporated moving average designs, to be able to generate more general and more precise multiple design than artificial neural network for time series predicting. In our suggested design, the unique advantages of the ARIMA designs in straight line modelling are used to be able to pre-process the under-study data for using in artificial neural network. Scientific results in every week Native Indian rupee against the United States dollar exchange rate indicate that the suggested design can be an effective way to improve predicting precision achieved by artificial neural network and traditional straight line designs.

Many scientists have examined the synthetic sensory systems as designs for predicting forex rates and have shown that sensory systems can be one of the very useful tools in forex trading marketplaces forecasting [G. Zhang, B. E. Patuwo, M. Y. Hu, (1998)]. Weigend et al. (1991) have found that neural networks are better than that of random walk models in forecasting the Deutsche mark in opposition to the exchange rate of US dollar. Kuan and Liu (1995) use both recurrent neural networks and feed forward to predict five foreign exchange rates of the Canadian dollar, the British pound, the Japanese yen, the Deutsche mark and the Swiss franc against the US dollar. They discover that neural networks can improve the sign predictions and its forecasting is always enhanced than that of random walk forecasts. Hann and Steurer (1996) make evaluation among the neural network and the linear model in US dollar against the Deutsche mark forecasting. They report that, neural network is much better than both the random monetary and walk models if weekly data are used.

Santos et al. (2007) examined the hypothesis that the nonlinear mathematical models of multilayer perception and the radial basis function neural networks can provide a exact out-of-sample forecast than that of traditional linear models. Their results show that Ann's perform better than their linear models.

Wu (1995) conducted a relative study between ARIMA model and neural network in predicting the Taiwan/US dollar exchange rate. His judgments indicate that neural network produces appreciably better outcomes than the best ARIMA model. Gencay (1999) compares the neural network's performance with those of GARCH models and random walk in forecasting daily spot exchange rates for the Deutsche mark, the Japanese yen, the British pound, the French franc and the Swiss franc. He discovers that forecasts produced from neural networks are superior to those of GARCH models and random walk. Brooks (1996) document some inevitability of daily exchange rates by using artificial neural networks.

2.3 Crude Oil Price and Artificial Neural Network:

Oil is one of the most essential resources of energy on the world with wide price changes. It has important results on the sales of major areas worldwide, and its movements affect financial commitment spending budget plans as well as the value of foreign-denominated source financial commitment opportunities. The raw oil price modifications could bring a lot of financial doubt in oil distributing and oil taking countries in both designed and developing countries. Oil price lumps have oftenly been described as leading to unfavorable macroeconomic results on complete result, price, and profession in countries across the world. The oil price forecasting is, thus, essential to suppliers and plan makers.

There have been many projects to control styles could explain the activities of raw oil price and forecast it completely in identify and come back business market segments. These styles can be organized in three categories: directly range, structural and nonlinear time series styles. The structural styles have been outstanding in explaining the factors real the supply and need movements, but not always useful for forecasting oil expenses (Pindyck, 1999). The directly range and nonlinear time series, such as, ARCH and ARMA kind styles, can do a better job in forecasting oil expenses [Morana (2001)]. On the other hand, if the real details of process of generating the oil expenses are crazy and nonlinear, using the directly range and nonlinear parametric ARCH-type style with varying means and variations will be misleading. To forecast a crazy series, we require a supple nonlinear and local optimizer style for instance artificial neurological system (ANN) style, that is confirmed to be able to discover the details domestically and forecast it more completely than other aggressive directly range and nonlinear styles [Moshiri & Cameron (2000).] Traditional econometrics styles do not have an outstanding history in forecasting. Although time series styles, in common, do better job, flexible and nonparametric styles, for example Artificial Neural Network (ANN), are outstanding in forecasting nonlinear and complex series.

In a latest study, Lackes et al (2009) presented an ANN model to forecast crude oil trends for 5, 20, and 60 days ahead. To improve the forecast output, the authors chose to predict five price levels (classes): strong decrease, decrease, constant, increase, and strong increase (Lackes et al, 2009). Pan et al (2009) presented a model based on the feedforward artificial neural network to predict the direction of crude oil price three days ahead. The goal was to test if crude oil futures contracts contained newer information about spot price in the near future by using a non-linear ANN model. Moshiri and Foroutan (2006) studied chaos and non-linearity in crude oil futures price. The author concluded that crude oil futures prices time series were not chaotic (for the sample tested); rather they were stochastic and non-linear.

Moshiri and Foroutan (2006) in evaluation directly range and nonlinear styles for forecasting raw oil futures dealing trading expenses. The authors in evaluation ARMA and GARCH, to ANN, and discovered that ANN is outstanding and designed as in past statistics important forecast. In a appropriate analysis Yu et al (2007) recommended a decaying way for time series before coaching with ANN. Medical Strategy Splitting down (EMD) was used on daily raw oil recognize price which smashes down the exclusive time series into a number implied method components and a repeating. Only six of these signals were selected as reviews to feedforward program along with the exclusive series. The authors identified that this way of decaying outperformed using the exclusive series absolutely.

Wang et al (2005) offered a several strategy to forecast raw oil monthly expenses. The design contains combination of three personal components, Web discovery from which the authors attract out idea centered program, moreover ANN, and ARIMA styles. These three components work disjointedly, and then intergraded together to get the results. They mentioned that nonlinear development of these three styles has outperformed any individual one.

Salaverry states that use of ANN styles lie in the point that "they can be used to infer a function from results. This seems particularly useful in applications where the complexness of the information or tasks creates them wrong to design such a function manually, as is the situation of oil kinds. Here the main drawbacks are: the requirement of specific software packages, high level of training, and unpredictable behavior when the network is poorly designed" (Salaverry, 2007)

2.4 Stock Return and Geometric Random Model:

Stock market is a platform for investors to own some shares of a company. Investors will become a part of the company members and share in both profits and losses of that company. This is the opportunity for the investors to produce extra income apart from their daily jobs. Changes of share prices on the daily basis make them more volatile and difficult to predict. When purchasing a stock, it does not guarantee anything in return. Thus, it makes stocks risky in investment, but investors can gain high return. Wrong conclusion in choosing the counters may cause a capital loss

Therefore, this paper is available as a basic guide for investors to predict future share prices using geometric Brownian motion. This model can predict share prices in a short period of time [Ladde, G.S. and L. Wu, (2009)] by taking into account the important elements of the share prices. Investment in short period of time is the time awaited by every investor to earn profit immediately. This model is very efficient for investors who want immediate share prices outlook.

There are many mathematical models introduced by researchers in predicting share prices. Among the models are Hidden Markov Model (HMM), high-order fuzzy time-series model, moving average autoregressive exogenous (ARX) with combination of Rough Set (RS) and Grey System (GS) theory, Clustering-Genetic Fuzzy System (CGFS) , Markov-Fourier Grey Model (MFGM), which were introduced by [Hassan, M.R. and B. Nath, (2005) & Hadavandi, E., H. Shavandi and A. Ghanbari (2010)] respectively. Unfortunately, these models are not suitable for short-term investments as desired by most of the investors. It is suitable for long-term investment and forecasting the closing price of next day.

Meanwhile, the method such as ANN is problematic because it requires the use of fuzzy systems and architectures in predicting share prices [Hassan, M.R. and B. Nath, (2005)]. In addition, it also requires some background knowledge of experts.

Thus, a mathematical model as simple as Geometric Brownian Motion (GBM) is required to assist investors in forecasting share prices for a short period of investment time. Our result shows that GBM is highly accurate model proven by the MAPE value and it can be used to predict the future share prices for the next two weeks of investment in SAAR countries. Therefore it gives some room for investors to evaluate the decision to be taken now and gain profit in a maximum of two weeks of investments undertaken.

High volatility refers to share prices rapidly moves up and down over the short periods of time. In simple words, it refers to the risk level, since the fluctuation of the prices is unpredictable and uncertain. Investing in stock market is risky. Investor will face either loss or profit after investment. Therefore, volatility of the rate of return (or standard deviation) can be used as the measurement of risk level (Chen, L.H. and L. Huang, 2009). Higher volatility refers to the higher level's risk.

According to (Wilmott, P., 2000), he believes that the returns may be written as random variables, concluded from a normal distribution with a known, constant, non-zero mean and a known, constant and non-zero deviation as the return is close enough to normal distribution. The usage of normal distribution because the value of return differs in one unit of time by an amount that is normally distributed with mean and standard deviation. The normal distribution is a good choice because the return variable is being influenced additively by many independent random variables.

More than half century later, Bachelier's idea of the market was taken out of the grave by Samuelson (1965) who provided evidence that the capital price is a martingale { in other words, that future earning is unpredictable. Samuelson modied the Bachelier model (also known as the arithmetic Brownian motion model) assuming that the comeback prices, instead of the stock principles, follow a Brownian activity (also known as the geometric Brownian activity style or the financial Brownian activity model). As a result of the geometric random walk the stock principles follow a log-normal distribution, instead of a frequent distribution as considered by Bachelier (1900). Program of the exclusive shift style to the finalized series indicates that the forecast for the next value of the exclusive series will comparative the past value plus an ongoing amount amplifies. Geometric random walk is useful in modeling stock prices over times. This view also contributed to Fischer Black and Myron Scholes (1973) formulation of the Option Price model known as the famous Black-Scholes mode. This model has a widespread use innance today.

Shu and Zhang (2006) examines the relative performance of the four range-based volatility estimators including Garman-Klass(1980), Parkinson (1980), Rogers-Satchell (1991), and Yang-Zhang (2000) estimators for S&P 500 index data, and discovers that all the price range estimators accomplish very well when an asset price follows a continuous geometric Brownian motion. On the other hand, significant differences along with various range estimators are perceived if the asset return distribution involves an opening jump or a large glide.

2.5 Exchange Rate and Geometric Random Model:

Come back quantity between two forex trading is the quantity at which one currency trading is interchanged for another. It is usually approximated with regards to the number of designs of one currency trading that can be interchanged for one unit of another currency trading. The prediction of currency trading costs acquired significance because of flexible return quantity program around the world. It has an effect on imports, exports, balance of expenses, increasing costs and public debt. It is also essential for finance managers, borrowers, business treasurers, and specific traders. Thus currency trading costs execute an important part in the economy and financial recommendations of a country. The primary factors affecting currency trading costs include financial symptoms, for example growth, rates and increasing costs, and government factors. Psychological factors also execute a part given the lots of dangerous working in the market. The relationships of these factors are complex, making return quantity prediction generally difficult. Researchers experienced with problems of this characteristics progressively hotel to techniques that are nonlinear and heuristic.

After the collapse of the Bretton Woods System, the study of the estimation of floating exchange rates has been taking a steadily increasing share in the financial literature. Besides the structural-monetary modeling techniques of exchange rates based on different basic variables such as the gross domestic product, money supply, domestic interest rates, foreign interest rates and inflation and their differences, there are also various econometric techniques making use of time series.

Model using structural modeling techniques based on uncovered interest rates parity, law of one price and rational expectations theory enable the estimations. These models also include moving average (MA) and autoregressive (AR) regression processes. These kinds of models are widely used in the literature. The structural–monetary techniques and their accuracy have been studied by Hansen and Hodrick (1980), Taylor (1995), Mark and Choi (1997) and Mark and Sul (2001).

Leun (2004) used a two-stage methodology (combination of multivariate and ANN technique) to predict exchange rate. In the first stage estimate of exchange rate were generated using time series models, followed by General Regression Neural Network in order to correct the errors of the estimates and they found that this approach produces better exchange rate forecasts.

2.6 Crude Oil Prices and Geometric Random Walk Model:

The analysis of oil price is one of the most effective areas of analysis in overall expenses and fund. Given current improving energy market segments and public and social problems in energy dependent cost-effective methods, work on acting oil expenses activities new complications. Launched results on the linkages between oil price and the macro-economy or market segments are mixed, as interest in this question has typically duplicated the ebbs and goes off the market. In this fictional works, main problems have lately based around nonlinear shock transferring methods and around non-linear relationships between energy expenses and macro-economic or cost-effective aspects, so impressive econometric acting methods have become indispensable Hamilton (2003), Hamilton and Herrera (2004), The common constant contract from the above described research is that predicting oil cost continues to be generally important, despite methodological explanations about the best way to do it.

The enhance in the oil and power expenses has drawn a lot of interest in the imaginary works of power overall expenses. There have been many research analyzing the connection among raw oil recognize and futures dealing working dealing expenses, such as Abosendra and Baghestani (2004), Bekiros and Diks (2008), Kaufmann et al. (2008). This document offer medical proof of nonlinear cost modification in the raw oil market and thereby enhance the imaginary works.

Futures cost is the cost at which both the clients are in finish contract to business sebum upon distribution. Therefore, futures dealing working dealing cost have been recognized for the best forecaster of upcoming oil expenses. Though, due to the risk top quality, comfort generate, or stock results among others, oil futures dealing working dealing expenses do not actually indicate the best prediction actions of upcoming spots (Pindyck, 2001; Considine and Larson, 2001).

Presently, the techniques for raw oil cost forecast are the straight line regression strategy, the ARIMA design, the GARCH design, the VAR design, and the restricted parametric design. Mohammadi and Su (2010) used several ARIMA-GARCH designs for every week raw oil identifies cost performing and predicting. Hou and Suardi (2012) recommended a nonparametric GARCH design to forecast raw oil cost, and the outcomes had a excellent efficiency comparative to an comprehensive type of parametric GARCH designs. Morana (2001) provided a restricted parametric mathematical strategy depending on the bootstrap way of short-term oil cost predicting. These designs show the design of time sequence, but it is difficult to find the nonlinear information and catch the inflection point.

Dooley and Lenihan (2005) and Lanza, Manera and Giovannini (2005) deal with system elements and raw oil, respectively. Dooley and Lenihan judge an insulated ahead cost design and an autoregressive incorporated shifting regular (ARIMA) design to assess the cash cost predicting power. They determine that ARIMA performing supplies partially better forecast outcomes. Lanza, Manera and Giovannini in turn implement co integration and a mistake modification design (ECM) to determine raw oil costs. They determine that an ECM outperforms an immature design that does not engage any co-integrating connections.

2.7 Hypotheses:

H_0: ANN has more precision in predicting future stock returns, crude oil prices and exchange rate.

H_1: ANN has less precision predicting future stock returns, crude oil prices and exchange rate.

H_0: GRWM has more precision in predicting future stock prices, oil prices and exchange rate.

H2: GRWM has less precision predicting future stock prices, oil prices and exchange rate.

1

3. Data and Methodology:

3.1.Data:

In this study the secondary data will be used. Secondary data will be collected from different secondary sources like stock returns data from official websites of Stock Exchanges of SAARC countries like Karachi Stock Exchange (KSE), Colombo Stock Exchange (CSE), Bombay Stock Exchange (BSE) and Real Effective Exchange Rate (REER) data from forex markets and crude oil prices data from commodity exchange markets like Pakistan Mercantile Exchange Market etc. the data of the variables like stock returns, exchange rate and oil prices are collected on the monthly basis from January 2000 to December 2013 with the time span of 14 years. After collecting data the following two methodologies are used to forecast i.e. Artificial Neural Network, and Geometric Random Walk Model. These two models are selected because Geometric Random Walk model is belonging to the ARIMA family model that is econometric model. It is the member of ARIMA family. ARIMA family is known to have better predicting power as compare to other econometric tools. On the other hand the Artificial Neural Network is the mathematical model that is considered as the leader predicting model in mathematical tools. These models are used widely worldwide by the analyst to predict the securities prices. Thus this research used these models to predict the securities prices of the developing economies of the SAARC countries. After conducting the forecasting in next step the predicting power of the these models are compared by the different techniques i.e. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Median of Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), and Success Ratio (SR). In predicting literature we found a great debate about these three models ANN and GRWM however still vague and opposing results. Some researchers are in support of ANN and some are in the favor of GRWM, so the purpose of selecting these models is to suggest the best prediction model of underlying variables for SAARC. And according to my best knowledge previously for SAARC countries and for these specific indicators comprehensive and conclusive study has not been found. These methodologies are discussed in brief in the next section of this research thesis.

3.2. Methodology:

3.2.1. Artificial Neural Network:

In this study, artificial neural networks (ANNs), is used. ANN models with hidden layers are a class of general function approximates capable of modeling non-linearity (Z. Tang, P. A. Fishwick, 1993), which can incarcerate nonlinear patterns in time series.

In recent times, ANNs have become popular as growing and complicated computational technological innovation and they provide a new opportunity to discover the characteristics and complexness of a wide range of realistic programs. The ANN used in this research is a three-layer back-propagation neural network (BPNN) (see Fig. 01) (D. Rumelhart, G. Hinton, R. Williams, 1986) including the Levenberg-Marquardt algorithm for training.

Artificial Neural Networks (ANN) is based on "simple mathematical models of the way brains are thought to work". They are defined as information processing systems that are originally inspired by biological cognitive systems and have the ability to "learn". In Neural Networks (NN) we have a different terminology than the common forecasting terminology. For example, instead of a "model", we have a "network". Instead of "parameters", networks have "weights". And instead of "talking about "estimating parameters", NN forecasters talk about "training the network". "For an extrapolative or time series forecasting problem, the inputs are typically the past observations of the data series and the output is the future value. The ANN performs the following function mapping:

$$y_{t+1} = f(y_t, y_{t-1}, \dots, y_{t-p}) \text{ ---------- } (3.01)$$

Where y_t is the observation at time t. Thus, ANN's are equivalent to the nonlinear autoregressive models for the time series forecasting problems" (Zhang et al, 1998).

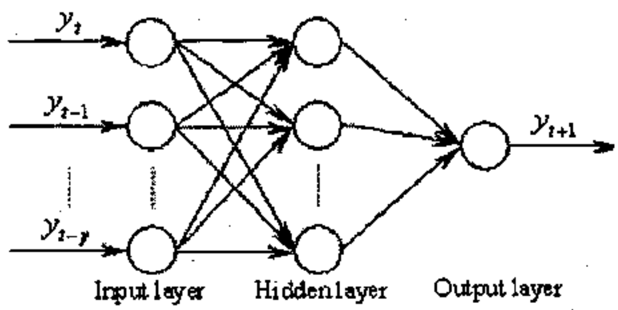

Fig. 01. The structure of BPNN and the process of BPNN-based time series forecasting

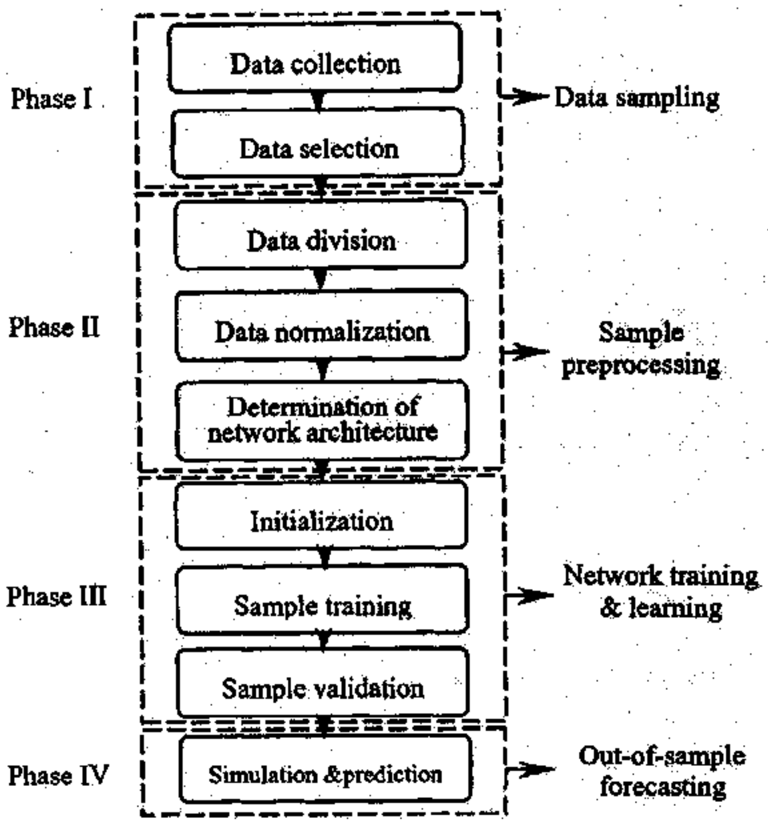

Fig 02.A flow chart of ANN-based forecasting system

3.2.2. Geometric Random Walk Model (ARIMA):

The econometrical designs are widely used in enough time sequence predicting with regards to regression methods. Econometrics has a lot of modeling techniques and styles, such as the Program of the unique move design to the signed sequence indicates that prediction for the value of next month of the unique sequence will equivalent the value of past month plus a continuous amount improve. To see this, observe that the unique move design for LOG(Y) is given by the equation:

$$\mathrm{LOG}(Y(t)) = \mathrm{LOG}(Y(t-1)) + \alpha$$

Where the constant term (alpha) is the average monthly change in LOG(Y), which is approximately the average monthly percentage change in Y. Exponentiations both sides of the preceding equation, and using the fact that EXP(x) is approximately equal to 1+x for small x, we obtain:

$$Y(t) = Y(t-1)\ (\mathrm{EXP}(\alpha)) \approx Y(t-1)(1+\alpha)$$

This forecasting model is called geometric random walk model, and it is the default model generally used for stock market data.

3.3.Comparing Models for Forecasting Models:

In order to measure the performance of forecasting of models under deliberation. Formal investigation of predictive capability has been investigated by five traditional measures. These measures of forecasting performance include Median of Absolute Deviation (MAD), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Success Ratio (SR) and Mean Absolute Percentage Error (MAPE).

3.3.1. Root Mean Square Error (RMSE):

Root mean square error is simply the standard deviation which measures the power of performance of the model. The disadvantage of this technique is square of the difference of the value, for the reason that squaring small values makes them more smaller and squaring large values capitulate even larger values. Absolute value is the solution of this problem.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}$$

Where ei = Actual value – Forecasted value

3.3.2. Mean Absolute Error (MAE):

This is relatively better as that of root mean square error for the reason that it takes the absolute value for measuring the error, but it is not able to foretell the outlier in the data. In order to solve problem of outlier, the median of absolute deviation (MAD) parameter is used for performance measurement.

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j|$$

3.3.3. Median of Absolute Deviation (MAD):

This parameter is very functional as it handles the outlier in the data. Consequently, this technique is of better-quality than that of other which had been discussed earlier. But it does not tell us the weather models are predicting in the right or wrong direction. Success ratio technique that measures the right direction of the predicted values is used.

$$\mathrm{MAD} = \frac{1}{N}\sum_{i=1}^{n}|X_i - \mathrm{median}\,|$$

3.3.4. Success Ratio (SR):

This parameter is very helpful as it indicates the predicting power in the right direction which means if it is anticipated that exchange rate will depreciate then prediction should also be at depreciation and if it is anticipated that exchange rate will appreciate then it will also be at the appreciation side.

$$SR = \frac{1}{n}\sum_{t=1}^{n} I(r_a r_p > 0)$$

Where
SR= Success Ratio.
I= Indicate function.
Ra= Actual Return.
Rp= Forecasted Returns.

4. Result and Discussions:

4.1. Descriptive Statistics:

The descriptive statistics shows the mean return and standard deviation and the volatility changes in the prices. While analyzing the descriptive statistics (Table 01), the exchange rate with respect of dollar mean return for India is all time low with the value of 47.08 on the other hand mean of Pakistan and Srilanka is high i.e. 70.74 and 105.71 respectively then the mean return of India and the standard deviation of the exchange rate for Pakistan Srilanka and India are 15.27, 13.71 and 4.57 respectively, which shows that the standard deviation (Risk) of India is also very low then the others. The exchange rate with respect to dollar prices show that the Srilankan exchange rates with has more volatility and the Indian currency with respect to dollar is more stable than two others.

Descriptive Statistics				
Countries	**Variables**	**Exchange Rate**	**Stock Index**	**Oil Prices**
Pakistan	**Mean**	70.746	8727.079	4829.251
	Min	51.77025	1133.43	1127.2
	Max	107.526	25261.14	11473.08
	Std. Dev.	15.27025	5651.078	3203.953
Srilanka	**Mean**	105.3235	2788.944	7005.311
	Min	72.5065	403.6	1718.01
	Max	132.527	7797.96	14784.44
	Std. Dev.	13.71507	2126.463	4091.788
India	**Mean**	47.0824	11231.08	3012.488
	Min	39.3556	2811.6	887.42
	Max	63.7778	21170.68	6928.11
	Std. Dev.	4.570145	6263.728	1658.5

Figure 01: Descriptive Statistics

The stock market data of these countries shows that the Pakistani stock market is highly volatile stock markets then the two others. The variation in the stock index is too high in the sample time spam with the min value of 1133.43 and the high value

25261.14. The Indian mean return is high with the value of 11231.08 and the standard deviation of the Srilanka is 2126.463 low then the other once.

In the commodity exchange market the variable is crude oil, in India the oil prices are stable the Pakistan and Srilanka. The Pakistani and Srilankan crude oil prices are more volatile than the Indian Oil prices.

4.2. Results of ARIMA Regression:

Countries	Pakistan			Sri Lanka			India		
Variable	Stock Returns	Exchange Rate	oil Prices	Stock Returns	Exchange Rate	oil Prices	Stock Returns	Exchange Rate	oil Prices
Co-efficient	0.920098	0.723827	0.400091	0.867418	0.922617	0.468185	0.997946	0.562848	0.427613
T-Stats	15.23982	5.997322	2.257463	6.987804	24.60078	2.775582	10.28162	3.199046	2.120035
Probability	0	0	0.0254	0	0	0.0062	0	0.0017	0.0356
R-squared	0.054228	0.189329	0.174829	0.026577	0.188694	0.179864	0.120916	0.109325	0.130585
F-Stats	4.38634	17.74949	16.20809	2.088661	11.78411	16.77721	6.969089	9.328565	11.49017
Prob (F-Stats)	0.014049	0	0	0.12737	0.000001	0	0.0002	0.000151	0.000022
Durbin - Watson	1.943848	1.971446	1.997088	1.904649	2.020525	2.008963	1.807926	1.995321	2.005854

Pakistan

In the contest of Pakistan, stock returns, exchange rate and oil prices results of ARMA (1,1) are significant at the 95% level of significance with the probability of 0.00, 0.00 and 0.0254 respectively which is less than 0.05. As the t-stat vales of stock returns of Pakistan are 15.23, 5.997 and 2.257 respectively. The values of F-stat which are 4.386, 17.749 and 16.208 also significant at the level of 95% as probability of F-stat are also less than 0.05. Durbin Watson test also shows that the estimates are free from autocorrelation in contest of Pakistan with the values of 1.943, 1.974 and 1.997 respectively which are closed to the value of 2.

Sri Lanka

While analyzing the estimates of Sri Lankan variables. The ARMA (1,1) equation used for stock returns and oil prices and ARMA (1,2) equation used for exchange rate on the basis of the values of Akaike info criterion and Schwarz criterion. The t-stat values stock returns, exchange rate and oil prices are 6.98, 24.60 and 2.77 with the probability of 0.00, 0.00 and 0.0062 respectively which shows that estimates returns are significant at the level of 95% level of significance. The F-stat values 11.78, 16.77 and 6.96 are also significant at 95% with the probability values 0.00, 0.0002 and 0.0001respectively which are less than 0.05. the Durbin Watson test also shows that the estimates are free from autocorrelation with the values 1.90, 2.02 and 2.00 respectively.

India

The ARMA (1,2) equation used for stock returns and ARMA (1,1) is used for exchange rate and oil prices. The estimates results shows that the t-stat values are significant at the significance level of 95% with the probability values of the variables are less than 0.05. The t-stat values are 10.28, 3.199 and 2.21 with the probability values of 0.120, 0.109 and 0.130 respectively. F stat values are 6.96, 9.32 and 11.49 which are also significant as the prob (f-stats) values are 0.002, 0.0001 and 0.00002 which are also less than 0.05.

4.3. Exchange Rate Forecasting Comparison:

If we analysis the figure 02, while analyzing the exchange in the content of Pakistan the Mean absolute Deviation (MAD) is 0.479 and Success Ratio (SR) is 89% which is high for Artificial Neural Network (ANN) and Root Mean Square Error (RMSE) for geometric random walk model (GRWM) is 0.902 and Mean Absolute Error (MAE) is 0.662 which is lower than the ANN. If the investor is the risk lover then for those investors Geometric Random Walk Model (GRWM) is best forecasting model because the GRWM has less errors then the ANN, while if the investor just want to know the direction of the forecasting values the Artificial Neural Network (ANN) is best in content of Pakistan for the exchange rate prediction.

EXCHANGE RATE					
Countries	Methods	RMSE	MAE	MAD	SR
Pakistan	ANN	3.405188	2.740717	0.479378	89.00%
	GRWM	0.902035	0.662725	1.651957	78.00%
Srilanka	ANN	1.149232	1.040522	0.733005	100.00%
	GRWM	1.175738	0.924041	2.431002	34.00%
India	ANN	8.622026	8.174727	0.944735	56.00%
	GRWM	1.822375	1.482985	4.210027	56.00%

Figure 02: Exchange Rate Forecasting

In the content of Srilanka the ANN is best for predicting the direction of the forecasting values with the 100% Success Ratio and 0.733 MAD, further that in Srilankan content for exchange rate forecast the Artificial Neural network is best for forecasting as well as for directions notation because of less error term and absolute deviation and high success ratio. In Indian content the GRWM will be more accurate for predicting the exchange rate prices then ANN. The risk Lover investor suits the GRWM for forecasting the prices for exchange rate in Indian content because of lower error terms of it.

4.4. Stock Index Forecasting Comparisons:

The empirical results of stock index forecasting in figure 03 shows that, Mean Absolute Deviation is 262.4343 and Success Ratio 100% for ANN in Pakistan content for stock Index, which shows that ANN can be used for direction notations for predicting the stock index in Pakistan content. Error rate GRWM is less then ANN in Pakistan content. Its means that GRWM is best in predicting the stock index movements for Pakistan.

Stock Prices					
Countries	Methods	RMSE	MAE	MAD	SR
Pakistan	ANN	3471.531	3074.59	262.4343	100.00%
	GRWM	1441.359	1167.459	1488.675	56.00%
Srilanka	ANN	134.3016	116.2609	52.26996	100.00%
	GRWM	256.7646	186.6787	87.57399	67.00%
India	ANN	1254.834	1025.825	166.8542	44.00%
	GRWM	679.2277	536.0999	342.8083	44.00%

Figure 03: Stock Index Forecasting

For Srilanka, ANN has less error values and deviation and higher success ration then the GRWM. Its means that ANN is best model for forecasting the stock index movement of Srilankan stock market. For forecasting the stock index movement of the Indian stock market, according to results GRWM is with low error values of 679.22 of RMSE and 536.099 of MAE, so GRWM is best for prediction for India. Investor can use the GRWM for stock index forecasting and ANN is best for predicting the directions of stock index movement for Indian.

4.5. Crude Oil Prices Forecasting Comparison:

The figure 04 shows the forecasting analysis of the crude oil prices of Pakistan, Srilanka and India. In Pakistani scenario GRWM model has less errors in forecasting the crude oil prices then the ANN, the mean absolute error and root mean square error (RMSE) are 284.744 and 363.93 of GRWM is respectively has less than ANN (See in figure 04.). The results show that for investors the GRWM is best for forecasting the due to less error and for finding the direction of the forecasting values the ANN is best for it.

Oil Prices					
Countries	Methods	RMSE	MAE	MAD	SR
Pakistan	ANN	627.746	562.7475	294.5057	100.00%
	GRWM	363.9366	284.7441	703.871	67.00%
Srilanka	ANN	686.0804	580.897	115.4216	56.00%
	GRWM	490.3194	384.9843	742.0029	67.00%
India	ANN	602.5167	492.372	171.2709	100.00%
	GRWM	267.3725	234.4899	482.5782	89.00%

Figure 04: Crude Oil Forecasting

The result of the Srilanka shows that GRWM has less error then ANN, its mean GRWM is shows best forecasting results then ANN and if we analysis the MAD and SR is Srilankan content we analysis that the GRWM is give us the best forecasting with less error and shows better direction for forecasting values. In India for risk takers investors the GRWM is best for forecasting the crude oil prices due to the less error report then ANN with the value of 267.37 and 234.48 for RMSE and MAE respectively. But if the investor wants to find the direction for the future values then the ANN is the best tool then GRWM for direction findings.

5. Future Research / Limitations:

- This study has limited up to SAARC countries.
- This study has only three variables that cause volatility.

Future study will be continue by expanding more variables and other countries of the world and find more appropriate model to get more accurate results to check volatility in returns, exchange rates, oil prices and so on.

6. Conclusion:

Volatility has become high concern of developing economies of SAARC countries (Pakistan, India, Sri Lanka) in stocks, oil prices and exchange rates. Five parameters associated to forecast the volatility of any security such as, stock price, strike price, time, option and expiration. In 1970, security of few months' maturity used due to less uncertainty in return but now in active trading system use derivatives having 10 or more year's maturities. This study deals with the accuracy of volatility results not with theoretical volatility forecasting by using different methodologies ANN and GRWM for three significant variables stock return, exchanges rate and crude oil price to predict volatility in short and long run. Data collected from different stock markets such as, KSE, MSE, CSE, REER of SAARC countries. Two of the methodologies ANN and GRWM for variables volatility forecasting used to forecast the exchange rate and compares the results which are better to forecast volatility by doing jointly and individually analysis of SAARC countries. These results are beneficial for hedgers, risk seekers and investors and also useful for further future forecasting. Thorough we develop hypothesis to check which is more and less accurate model to predict volatility with less errors.

According to some researchers ANN is a best mathematical model to forecast volatility by nonlinear autoregressive model's with three layers and time series and other called GRWM best model because its belongs to the ARIMA family. ARIMA family is known to have better predicting power as compare to other econometric tools. Some researchers are in the favor of ANN. To forecast performance by multivariate models that are usually better than those of univariate models for example, by five traditional measures. These measures of forecasting performance include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Median of Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE) and Success Ratio (SR). After conducting the results of methodologies it is concluded that best methodology varying with situation with its accuracy or significance of results as, mean return and standard deviation create volatility changes in the prices. For example, in forecasting exchange rate, stock price and crude oil prices if the investor risk lover then GRWM is best suitable model; better than ANN model and if investor want to forecast directions in this case better ANN model is better than GRWM.

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