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# Volatility forecast with artificial neural networks as univariate time series, with examples from stock market indexes

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**Abstract**

The tools that are offered to investors in financial markets are fluctuating. As this fluctuation causes losses as well as earnings, it is characterised as a risk for the investor. Especially, fluctuations that may occur in globally important markets and financial instruments have great significance, not just for investor but also for the global economy. Volatility, as a measure of fluctuations taking place in markets, is often used particularly by investors and all economic actors. Therefore, in recent years, future volatility predictions have gained importance. The aim of this research is forecasting future volatility values using the historical data of S&P 500, FTSE 100 and NIKKEI 225 stock market indexes. The progress of historical volatility values in years is presented and generated univariate time series is modelled with artificial neural networks. Future forecasts are done with the obtained model and results are interpreted.

Keywords: Artificial neural networks, volatility, time series analysis, stock market indexes.

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## 1. Introduction

Volatility forecasting has gained importance recently and has attracted academics, policy makers, practitioners (Yu, 2002) and every one affected by financial markets. Volatility is a measure of the fluctuations of any financial asset's price, and due to its importance, it plays a critical role in investment decisions, portfolio management, option pricing, risk management and in implementing trading strategies (Kumar & Maheswaran, 2014).

A wide range of literature exists on volatility forecasting. Most of the studies use heteroskedastic models such as autoregressive conditional heteroskedasticity (ARCH) Bera and Higgins (1997), Bollerslev, Chou and Kroner (1992), Bollerslev, Engle and Nelson (1994), Diebold and Lopez (1995), Engle (1982), generalised ARCH (GARCH) Andersen and Bollerslev (1998), Andersen, Bollerslev and Lange (1999), Bollerslev (1986), Boudt, Danielsson and Laurent (2013), exponential GARCH (EGARCH) (Nelson, 1991), Glosten–Jagannathan–Runkle GARCH (GJRGARCH) (1993), and fuzzy-GARCH (Popov & Bykhanov, 2005) models. Also, smooth transition exponential smoothing model (Taylor, 2004) and exponentially weighted moving average (Morgan, 1996) are some other examples.

Artificial neural networks (ANNs) do not make any assumptions about the time series, whether it is linear, non-linear, stationary or non-stationary (Singh & Mishra, 2015). Therefore, it seems to be possible to model any time series with artificial neural networks. In recent years, the number of studies modelling and forecasting volatility with ANN is increasing.

Hamid and Iqbal (2004) forecasted the volatility of the S&P 500 Index futures prices using 16 nearest futures contracts, three spot indexes and one-day lagged S&P 500 futures prices, a total of 20 input variables. Hu and Tsoukalas (1999) use ANN to improve the performance of four conditional volatility models (GARCH, EGARCH, IGARCH and MAV) applied to the European Monetary System exchange rates. Malliaris and Salchenberger (1996) forecasted S&P 100 implied volatility with 13 selected input variables. Donaldson and Kamstra (1997) construct a semi-non-parametric non-linear GARCH model based on ANN to forecast the conditional volatility of stock returns of four international markets. Roh (2007) constructs hybrid ANN-time series models. Kristjanpoller and Minutolo (2015) use an ANN–GARCH hybrid model to forecast gold price volatility. The neural network model uses Euro/dollar and dollar/Yen daily variations, Dow Jones Industrial and Financial Time Stock Exchange daily index returns and daily price variations of oil as inputs.

In this paper, the volatility of three major stock market indexes, S&P 500, FTSE 100 and NIKKEI 225 is modelled with ANNs. A total of 13 weeks' historical volatility values are calculated as weekly volatility value, and for each stock market index a univariate time series is constructed, consisting of weekly volatility values. Next, each time series is modelled with ANNs to forecast weekly volatility values of year 2015. The forecasting performance is evaluated and the results are discussed.

This study is organised as follows: Section 2 is about basic definitions and mathematical relations on volatility and neural networks. In Section 3, data and the neural network model used in the study are described. Section 4 is on application, results and discussions.

## 2. Definitions

### *2.1. Volatility*

Volatility is usually defined as standard deviation ($\sigma$) or variance ($\sigma^2$) of returns (Poon & Granger, 2003). Variance could be calculated using the formula

$$\hat{\sigma}^2 = \frac{1}{N-1}\sum_{t=1}^{N}(R_t - \bar{R})^2 \tag{1}$$

$R_t$ is the return of the asset during the time interval $t$ and could be calculated as (Huang, Peng, Li & Ke, 2011)

$$R_t = \ln\left(\frac{S_t}{S_{t-1}}\right) \tag{2}$$

$S_t$ is the market value of the asset at time $t$ and $S_{t-1}$ is the value at time $t-1$.

### *2.2. Neural Networks*

Neural networks are some kind of an information processing technology, modelling the relationships between inputs and outputs mathematically (Malliaris & Salchenberger, 1996). The purpose is to mimic the human brain's data processing and pattern of understanding (Hamid & Iqbal, 2004). A neural network is composed of nodes that are imitations of the human brain's neurons. Important members of the network architecture are nodes that are structured as layers, transfer function and weights. The neurons or nodes are connected with others and are arranged as layers. A node in one layer cannot connect with a node in the same layer; they can connect only the next layer's nodes. The neurons can be fully connected or partially connected (Hamid & Iqbal, 2004). In a fully connected architecture, neurons in one layer are connected to all the neurons in the next layer. Basically, there are three kinds of layers: input layer, hidden layers and output layer. The common usage is one input, one output and one or two hidden layers. The network may not have any hidden layer or may have more than one hidden layer. To increase the number of hidden layers increases the risk of overfitting as well as computation time (Vortelinos, 2015). For financial forecasting, typically one hidden layer may be sufficient to map input data to output data (Hamid & Iqbal, 2004).

The number of neurons in the input layer shows the number of the inputs taken to process. Similarly, the number of the neurons in the output layer is the number of the output needed to execute. Choosing the number of input and output neurons is an easier process than choosing the number of hidden neurons. Determining the optimal number of hidden nodes has always been a question in neural network studies. If the number of hidden neurons is too few, then 'underfitting' may occur and if necessarily more neurons are present, then also the problem of 'overfitting' may occur (Karsoliya, 2012). Panchal and Panchal (2014) list some methods to decide the number of hidden neurons as a trial-and-error method, rule of thumb method, simple method, two-phase method and sequential orthogonal approach. However, in most cases the number of the hidden neurons is determined by intuition (Wanas, Auda, Kamel & Karray, 1998).

Each of the connected neurons sends/receives data to/from other neurons. Each input data coming from other neurons multiplied by a weight and then passes through a transfer function which converts the sum into a value. Through this function a network seeks to make sense of the input data (Hamid & Iqbal, 2004). Some common transfer functions are (Panchal & Panchal, 2014) linear activation function, piecewise linear activation function, hyperbolic tangent function, sigmoidal function and threshold function.

The way how neurons are connected is called the topology or the architecture of the network. Various possible interconnections of the neurons result in various types of topologies. ANNs could be classified into two main groups according to their topologies (Krenker, Bester & Kos, 2011):

- *Feed-Forward Neural Networks*: In feed-forward neural networks information flows only from the input to output direction. No back-loop is present. There are no limitations in the number of layers, type of transfer function or the number of connection between neurons.
- *Recurrent ANNs*: As the name suggests, a recurrent neural network has a recurrent topology. It is similar to feed forward neural network, except for the back-loops rule. In recurrent neural networks, information flows not only in one direction (input to output) but also backwards. Some

important kinds of recurrent neural networks are fully recurrent ANN, Hopfield ANN, Elman–Jordan ANN and self-organising map.

The learning methods of neural networks could be classified into three types: supervised learning, unsupervised learning and reinforced learning (Panchal & Panchal, 2014). In supervised learning, a teacher is present and the expected outputs are already present. In unsupervised learning, the teacher and the expected output are absent. The network learns and adapts itself to the structure of the input pattern. Reinforced learning is a network in which the teacher is present but the output is not, but indicating that the output is right or wrong. If the output is wrong, a penalty is given and if it is right, a reward is given (Panchal & Panchal, 2014).

As Zhang, Pattuwo and Hu (1998) state, for an explanatory forecasting problem the inputs of the neural network are usually the independent variables, and the relationship estimated by the network is

$$y = f(x_1, x_2, \ldots, x_p) \tag{3}$$

where $x_1$, $x_2$,…,$x_p$ are independent and $y$ is the dependent variable. For an extrapolative or time series forecasting problem, inputs would be past observations of the time series and the output is the future value which is to be forecasted. Then the relation would be (Zhang, Pattuwo & Hu, 2001)

$$y_t = f(y_{t-1}, y_{t-2}, \ldots, y_{t-p}) \tag{4}$$

where $y_t$ is the value to forecast at time $t$ meaning the output and $p$ is the number of past data which are the inputs.

## 3. Data and Model

### *3.1. Data*

Stock market indexes are good indicators to measure the stock market performance. In this work, three major stock market indexes are under consideration. The first major index is Standard & Poor's 500 of United States or S&P 500. S&P 500 is an American stock market index based on the market capitalisations of 500 large companies which have common stock listed on the New York Stock Exchange or NASDAQ. The dataset consists of weekly close prices and starts from the first week of 1980, which starts from first workday, 2.1.1980, Wednesday. Another major index is Financial Times 100 Index of United Kingdom, FTSE 100, which listed 100 companies from the London Stock Exchange with the highest market capitalisation. The weekly close price data used in this study starts from the first week of 1984, which is 3.1.1984. The third major index used in the study is NIKKEI 225 of Japan. The index has 225 companies from the Tokyo Stock Exchange and it is a price-weighted stock market index. Data of NIKKEI 225 is weekly close prices and starts from the first week of 1984. All of the three index datasets end with the last week of 2015.

Weekly close prices are used to calculate the weekly returns. Then for every week, 13 weeks of historical volatility are calculated from weekly returns. Some descriptive statistics of 13 weeks' historical weekly volatility data are as follows.

Table 1. Historical weekly volatility data (13 weeks)

| **Index name** | **S&P 500** | **FTSE 100** | **NIKKEI 225** |
|---|---|---|---|
| Number of the data | 1865 | 1657 | 1645 |
| Mean | 2.0662 | 2.1348 | 2.6444 |
| Median | 1.8312 | 1.9076 | 2.5111 |
| Highest value | 8.4939 | 9.7921 | 10.3423 |
| Lowest value | 0.5567 | 0.5765 | 0.6548 |
| Standard deviation | 0.9909 | 1.0884 | 1.1626 |

### *3.2. Network Model*

A feed-forward ANN is used in this study. In all types of network architectures, especially for prediction purposes, the feed-forward neural network with backpropagation training algorithm is most commonly used (Hamid & Iqbal, 2004). In backpropagation training, after forward propagation of inputs, the error term propagates to all nodes backward. Then necessary changes of all input weights are done accordingly. There are three main modes of backpropagation: stochastic, online and batch. In online and stochastic backpropagation, the weight updates are done immediately after each iteration. In batch backpropagation before updating the weights, a number of iterations occur.

Another important paradigm is the learning rate. It affects the speed and quality of learning. A higher learning rate causes faster training of the neurons while a lower learning rate causes more accurate training. Backpropagation also has a momentum value. Momentum is used to prevent the system from converging to a local minimum. A high momentum value increases the speed of convergence, but a too high value causes overshooting the minimum and an unstable system. Lower values may not prevent the system from local minimum and may also slow down the training process. The learning rate and momentum value changes in the range from 0 to 1. In this study, the learning rate is taken as 0.3 and the momentum value as 0.9.

In this study, the number of the layers is set to three: one input layer, one output layer and one hidden layer. The output layer consists of one output neuron as one step forecasting is demanded. The input layer is important, because the number of the input neurons show the number of the inputs. Inputs are explanatory variables, and in univariate time series, they are the lagged past values of the series. Therefore, first, how many inputs are used is decided. In financial time series, the number of the inputs is selected usually according to time cycles. If data are daily, then the explanatory time cycle could be a month (20 days–20 inputs). If data are hourly, the past lagged one-day data could be used as input (24 inputs). In this study, weekly data are used and a quarter (13 weeks) of data is considered to be suitable as input data. Therefore, the number of the input neurons is 13.

One of the rule of thumb methods states that the number of hidden neurons would be between the input neuron size and the output neuron size (Karsoliya, 2012). In this study, the number of the hidden neurons is chosen as 6. Therefore, the architecture used in this study is 13 – 6 – 1 feed-forward neural network.

## 4. Application and Results

In this study, the Alyuda Neurointelligence® software version 2.2 is used for modelling and calculation of neural networks. For each index time series data, the last 52 weeks of the data are forecasted stepwise, which is the whole year of 2015. Meaning, all the datasets before the first week of 2015 are used to forecast historical volatility of the first week of 2015. Then for the second week forecasting, all the datasets before the second week, including the first week dataset, are used. In every forecasting step, data analyzing, data partition, data pre-processing and training procedures are performed, respectively. In the data partition step, 75% of the data is allocated as training data and 25% of it is used as validating data. One dataset, which is the last dataset of the time series, is used as test dataset, which is used for calculating the forecasting performance. Training and validating datasets are determined randomly by the software.

Data pre-processing is done by scaling the data into [−1,1] intervals by the software. The training procedure is done by batch backpropagation method with a learning rate of 0.3 and a momentum value of 0.9. Training is done with 20,000 iterations and by retaining and restoring the best network in these iterations. Table 2 shows the results of the forecasting processes.

Table 2. Forecasting results

| **Index name** | **S&P 500** | **FTSE 100** | **NIKKEI 225** |
|---|---|---|---|
| Mean squared error (MSE) | 0.0362 | 0.0406 | 0.0619 |
| Root MSE | 0.1904 | 0.2016 | 0.2488 |
| Mean absolute error | 0.1237 | 0.1439 | 0.1618 |
| Mean absolute percentage error (MAPE) | 7.23% | 6.82% | 7.34% |
| Coefficient of determination ($R^2$) | 0.8559 | 0.7592 | 0.8601 |
| Correlation coefficient ($R$) | 0.9251 | 0.8713 | 0.9274 |

Table 2 shows the results of the ANN model developed in this study to forecast the historical volatility for three major stock market indexes. The mean square error values of 0.0362 (S&P 500), 0.0406 (FTSE 100) and 0.0619 (NIKKEI 225) between the real and forecasted values are calculated. The mean absolute percentage error (MAPE) in the range of 6.82% –7.34% shows a good error value. Also, correlation coefficients of 0.9251 (S&P 500), 0.8713 (FTSE 100) and 0.9274 (NIKKEI 225) indicate a very good fit of model forecasts.

In Figures 1–3, the real weekly historical volatility and forecasted weekly historical values are presented for S&P 500, FTSE 100 and NIKKEI 225 indexes, respectively.

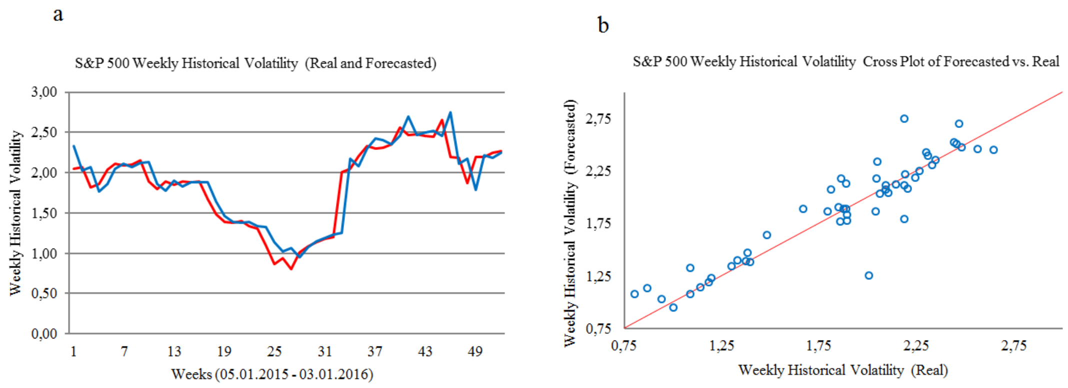


Figure 1. (a) Real (red) and forecasted (blue) weekly historical volatility values of S&P 500 index: 52 weeks of year 2015 (05.01.2015–03.03.2016). (b) Cross plot of forecasted (blue) versus real historical volatility of S&P 500 index

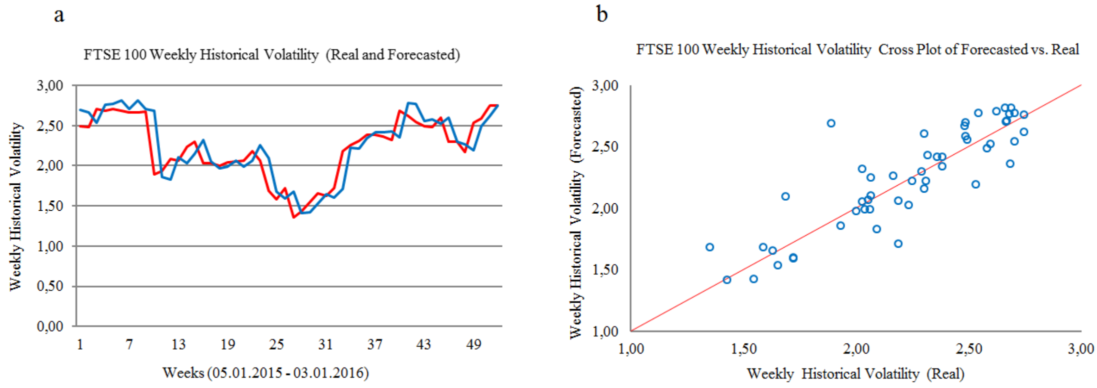


Figure 2. (a) Real (red) and forecasted (blue) weekly historical volatility values of FTSE 100 index: 52 weeks of year 2015 (05.01.2015–03.03.2016). (b) Cross plot of forecasted (blue) versus real historical volatility of FTSE 100 index

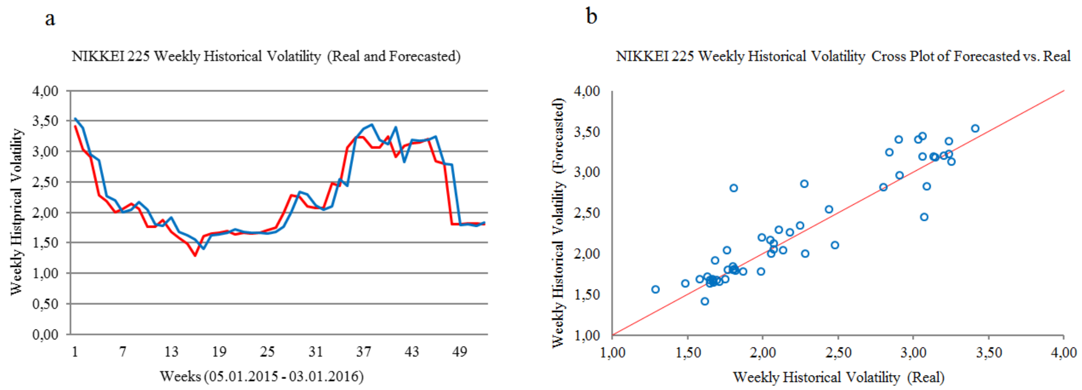


Figure 3. (a) Real (red) and forecasted (blue) weekly historical volatility values of NIKKEI 225 index: 52 weeks of year 2015 (05.01.2015–03.03.2016). (b) Cross plot of forecasted (blue) versus real historical volatility of NIKKEI 225 index

The software used in this study also gives input importance values in each of the training and forecasting process. Input importance shows the relative importance of the input and gives an idea of which inputs have the most or the least effect on the output. It is calculated as degradation in the network performance after the input is removed and is not used by the network. Since data worked on is univariate time series and all the inputs are lagged values of the output, the input importance shows which past weeks' historical volatilities have the most effect on the next week's historical volatility. Table 3 shows the minimum, maximum and average important values of the inputs in 52 forecasts.

Table 3. Input importance results

| Input number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| S&P 500 | | | | | | | | | | | | | |
| MIN | 0.11 | 0.01 | 0.00 | 0.01 | 0.02 | 0.09 | 0.17 | 0.01 | 0.02 | 0.02 | 0.02 | 0.09 | 5.38 |
| MAX | 92.53 | 40.86 | 18.39 | 3.45 | 1.81 | 8.82 | 7.92 | 2.85 | 1.94 | 2.47 | 3.32 | 20.71 | 88.51 |
| MEAN | 11.32 | 1.41 | 0.84 | 0.74 | 0.57 | 2.28 | 3.38 | 0.84 | 0.62 | 0.94 | 1.08 | 6.75 | 69.24 |
| FTSE 100 | | | | | | | | | | | | | |
| MIN | 0.31 | 0.07 | 0.00 | 0.04 | 0.01 | 0.02 | 0.05 | 0.03 | 0.01 | 0.05 | 0.16 | 0.12 | 7.08 |
| MAX | 91.64 | 15.06 | 5.23 | 3.52 | 2.60 | 2.15 | 11.06 | 3.12 | 1.49 | 3.11 | 5.51 | 5.64 | 93.80 |
| MEAN | 16.12 | 1.78 | 1.12 | 0.81 | 0.53 | 0.65 | 1.98 | 0.72 | 0.47 | 0.98 | 1.90 | 1.69 | 71.26 |
| NIKKEI 225 | | | | | | | | | | | | | |
| MIN | 0.03 | 0.06 | 0.01 | 0.01 | 0.01 | 0.01 | 0.10 | 0.01 | 0.00 | 0.01 | 0.02 | 0.12 | 5.48 |
| MAX | 91.66 | 92.25 | 3.27 | 5.43 | 2.20 | 2.60 | 6.40 | 1.70 | 1.86 | 1.73 | 5.91 | 6 | 94.30 |
| MEAN | 14.50 | 2.67 | 0.56 | 0.94 | 0.39 | 0.46 | 1.50 | 0.47 | 0.42 | 0.41 | 1.26 | 2.30 | 74.12 |

The average input importance of this week's value (Input 13), which seems to have the most effect on next week's value, ranges between 69.24% and 74.12%. Also, the 12th input which is last week's volatility value has an average of 1.69% (FTSE 100), 2.30% (NIKKEI 225) and 6.75 (S&P 500) importance on next week's value. Especially in financial time series, a relatively higher effect of closest data might be expected. But there is an interesting finding about Input 1, which is the 12th lagged week's data. Its average importance ranges between 11.32% and 16.12%. Another interesting finding is that the effect of Input 1 shows very unsteady behavior with respect to other inputs' effects.

Input 1 has low importance in most forecasting processes, which might reach the value under 1% in some cases, but in a few cases the importance of Input 1 has a very high value around 90%'s. This unsteady and interesting importance of 12th week lagged historical volatility value might need further research.

In this study, 13 weeks' historical volatility values of S&P 500, FTSE 100 and NIKKEI 225 stock market indexes are modeled with ANNs and these models are used to forecast the weekly historical volatility of year 2015 by one-step forecasting. For each stock market index 52 forecasting is done, meaning 52 models are constructed. In each modelling process, data analyzing, data pre-processing and training is done, respectively. The network architecture for all the models are set to 13-6-1 model with 13 inputs, 6 hidden nodes and 1 output node. All the activation functions are hyperbolic tangent. Also, for all the models training process is batch backpropagation with a learning rate of 0.3 and a momentum value of 0.9. The resulting forecasts show the forecasting performance with a low MAPE, ranging between 6.82% and 7.34% and a good model fit with correlation coefficient changes between 0.87 and 0.93.

Forecasting the future historical volatility may also give an idea about future returns and future close prices of the asset, and this could be also a further research subject. Also, some other assets like commodities, funds, bonds, foreign exchanges could be studied for volatility prediction by neural networks.

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