Optimized Artificial Neural Network Model for the Prediction of Domestic Companies Index Direction under the Botswana Stock Market

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Abstract: ***The business sector has always encountered some challenges in predicting exact daily prices for stock market index and therefore more research methodologies have been proposed this far to address this problem. In every nation, there are several factors such as the state of politics, economic situations and trade expectations that have great impact on the stock market index. In this paper, we compare two types of input variables useful in the prediction of stock market path for daily markets index. Our main contribution presented through this study is the ability to predict the path flow for the next day's price in Botswana stock market index through the use of optimized Artificial Neural Network (ANN) model. To enhance efficiency in the prediction accuracy on future stock market trends, we employ Genetic Algorithms (GA) to optimize the ANN model. We further reveal and substantiate the predictability of stock price flow by employing the hybrid GA-ANN model and compare its performance to pre-existing methods. Practical results indicate that proper selection of input variables enhances efficiency in the optimized ANN model performance.***

Keywords: Stock Market, ANN Model, Domestic Companies Index, Genetic Algorithms, Optimization and Efficiency.

1. Introduction

Prediction of stock price return is a highly complicated and challenging task due to many factors such as political events, economic conditions, trader's expectations and other environmental factors that may influence stock prices. Most studies throughout literature are focusing more on accurate forecasting of stock price value. Predicting the direction of stock markets index is a practical issue that heavily influences a financial trader's decision to buy or sell an instrument. Accurate forecast on the trends of stock index can help investors to acquire opportunities for gaining profit in the stock exchange and therefore precise forecasting of this trends can extremely benefit investors (Gholamiangonabadi et al., 2014). (Leung et al., 2000) hold the view that trading could be made profitable by an accurate prediction of direction in the movement of stock index. Their work suggested that financial forecasters and traders should focus on accurately predicting the direction of movement so as to minimize the estimates' deviations from the actual observed values. (Mostafa, 2010) also argues that accurate prediction in the direction of stock price indices is very important for investors. However, the behavior of stock markets depends on many qualitative factors such as political, economic and natural factors among many others. The stock markets are dynamic and exhibit wide variation, and their predictions thus become a highly challenging task because of the non-linear nature and complex dimensionality (Guresen et al., 2011), (Lee and Chiu, 2002). Forecasting of the financial index is characterized by data intensity, noise, non-stationarity, unstructured nature of data, high degree of uncertainty, and hidden relationships (Khan, 2014), (Tay and Cao, 2001), (Hall, 1994).

Previous studies have applied various models in forecasting direction of the stock market index movement. (Huang and Nakamori, 2005) forecasted stock market movements using support vector machines (SVM), and concluded that the model was good at predicting the direction.(Kara et al., 2011) applied Artificial Neural Network (ANN) and SVM in predicting direction of the Istanbul stock exchange. Their study proves that the two different models are both useful prediction tools, and ANN is significantly better than the SVM model. (Şenol and Ozturan, 2008) applied seven different prediction models for predicting the direction of stock market index in Turkey, concluding that ANN could be one of the most robust techniques for forecasting. The ANN model has been popularly claimed to be a useful technique for stock index prediction because of its ability to capture subtle functional relationships among the empirical data even though the underlying relationships are unknown or hard to describe (Vellido et al., 1999), (Zhang et al., 1998). Application of ANN has become the most popular machine learning method, and it has been proven that such an approach can outperform most conventional methods (Fernando et al., 2000), (Lu, 2010), (Versace et al., 2004), (Specht, 1991), (Wang et al., 2015).

In this study, we attempt to apply an ANN model to forecast the direction of Botswana stock market Domestic Companies index. Our approach is motivated by methods and algorithms developed by (Qiu and Song, 2016), where ANN models were used to predict direction of Japanese stock market index. The most popular neural network training algorithm for financial forecasting is the back propagation (BP) algorithm, which is also a widely applied classical learning algorithm for neural networks (Jo, 2013), (Sexton and Gupta, 2000), (Werbos, 1994). The BP network has been widely used in the area of financial time series forecasting because of its broad applicability to many business problems and its pre-eminent learning ability (Kim, 2003). However, many studies have reported that the ANN model, trained by the BP algorithm, has some limitations in forecasting, and it can easily converge to the regional (local) minimum because of the tremendous noise and complex dimensionality of the stock market data. In view of these limitations, genetic algorithms (GA) has been proposed to overcome the local convergence issue for non-linear optimization problems. We attempt to determine the optimal set of weights and biases to enhance accuracy of the ANN model by using GA. The main objective of this study is to improve the prediction accuracy in the direction of stock price index movement by using the ANN model. The empirical results suggest that the proposed method improves the accuracy further for predicting stock market direction, in comparison with previous studies.

1.1 Organization of the paper

This paper is organized into 5 different sections as follows. Section 1 covers the Introduction and a quick review on similar studies. Section 2 describes the ANN model trained by the BP algorithm and its improvement using GA. The Experimental design and data description including two basic types of input variables that are used in forecasting and all prediction procedures are explained under Section 3. The experimental results in comparison to those of existing studies are projected under Section 4. Finally, Section 5 presents the discussions and conclusion.

2. Prediction Model

2.1 Artificial neural network (ANN) model

It has been shown that neural networks with sufficient complexity could approximate any unknown function to any degree of desired accuracy with only one hidden layer(Funahashi, 1989), (Hornik et al., 1989) . The ANN model in this study consists of an input layer, a hidden layer, and an output layer, each of which is connected to the other in the same sequence as projected by ANN architecture under Fig 1. The input layer corresponds to the input variables. We analyze two basic types of input variables for comparing the forecasting accuracy. The hidden layer is used for capturing the nonlinear relationships among variables. In this study, the output layer consists of only one neuron that represents the predicted direction of the daily stock market index.

2.2 Back propagation neural network

The BP algorithm is a widely applied classical learning algorithm for neural networks (Sexton and Gupta, 2000), (Werbos, 1994). As shown in Fig 1, the BP process determines the weights for connections among the nodes (i.e., $W11$ denotes the weight between Node 1 of the input layer and Node 1 of the hidden layer) and their biases (i.e., $\theta 1$ denotes the bias of Node 1 in the hidden layer) on the basis of training data. The network weights and biases are assigned initial values first, and the error between predicted and actual output values is back-propagated via the network for updating the weights and biases repeatedly (Wang, 2009). When the error is less than a specified value or when the termination criterion is satisfied, training is considered to be completed and therefore the weights and bias values of the network are stored. Detailed descriptions of using the BP algorithm for training the ANN model are discussed by (Chauvin and Rumelhart, 1995). Although researchers have commonly trained the ANN model by using the gradient technique of the BP algorithm, limitations of gradient search techniques are more apparent when ANNs are applied to complex non-linear optimization problems (Salchenberger et al., 1992). The BP algorithm has two significant shortfalls, i.e., slowness in convergence and an inability to escape local optima (Lee et al., 1991). In view of these limitations, global search techniques, such as GA, are proposed to overcome the local convergence problem for non-linear optimization problems. In this study, we propose to apply the GA tech- nique to optimize the weights and biases of the ANN model, and then predict the direction of daily closing price movement for the stock market index.

2.3 Improvement using Genetic Algorithms (GA)

Many studies have used GA-based hybrid models to overcome shortfalls under BP approach (Montana and Davis, 1989), (Kim and Han, 2000), (Nair et al., 2011). The results of these studies support the notion that GA can enhance the accuracy of ANN models and can decrease the time required for experimentation processes. In this study, the GA algorithm is utilized to optimize the initial weights and bias of the ANN model. Subsequently, the ANN model is trained by the BP algorithm using the determined weights and bias values. Fig 2 shows the procedures and processes for the proposed hybrid GA and BP algorithm. The algorithm consists of the following steps:

Step 1: Considering the wide range of the data, we normalize it to make sure that the value of all the variables scale down to vary between zero and one. The normalization is carried out as follows:

$$RN = \frac{R - R_{min}}{R_{max} - R_{min}} \tag{1}$$

where R is a sample data, RN is the normalized value of R, $Rmin$ is the minimum value of R and $Rmax$ is the maximum value of R.

Step 2: Encode all the weights and biases in the string and generate the initial population. Each solution generated from the GA is called a chromosome (or an individual) and the collection of chromosomes is called population. Here each chromosome describes the ANN with certain set of weights and bias values.

Step 3: Train the ANN Model using the BP Algorithm and then evaluate each chromosome for the current population using fitness function based on the MSE (mean square error) value.

$$MSE= \frac{1}{N} \sum_{t=1}^{N} (yt - y\hat{}t)^2 \tag{2}$$

where yt denotes the actual value, and $y\hat{}t$ is the predicted value. The value of predicted function is inversely proportional to the error.

Step 4: Rank all the individuals using the fitness proportion method and select individuals with a higher fitness value to pass on the next generation directly.

Step 5: Apply genetic algorithms (e.g. crossover, mutation) to the current population and create new chromosomes. Evaluate the fitness value of the new chromosomes and insert these new chromosomes into the population to replace worse individuals of the current population. As a result of all this, we get the new population.

Step 6: Repeat Steps 3-5 until the stop criterion is satisfied.

3. Experimental Design

3.1 Data

The Botswana Domestic Companies Index consists of only those companies traded in Botswana. The method used to calculate the price of the index is the weighted arithmetic average of the current prices of shares to their starting price. The weighting for each share is its market capitalization. The Domestic Companies Index (DCI) - Gaborone is a major stock market index which tracks the performance of the biggest companies trading under the Botswana Stock Exchange. The research data used in this study are technical indicators that are calculated from the daily price of the DCI - Gaborone. The total number of samples is 1,200 trading days, from January 2011 to December 2015. The entire data path is divided into two parts, 75% of the data (from January 2011 to September 2014) is used for in-sample training and the remaining 25% (September 2014 to December 2015) are considered as out-of-sample data. The in-sample data is used to determine the specifications of the model and parameters whereas the out-of-sample data is reserved for the evaluation of the model. The financial data used in this study is obtained from both Yahoo Finance repository data website and the Botswana Stock Exchange Annual Report of 2015 (Tsheole et al., 2015). The original data is normalized before being subjected to the ANN algorithm routine. The goal of linear scaling is to independently normalize each feature component to a specified range. It also ensures that the larger value input attributes do not overwhelm smaller value inputs, which in turn helps decrease prediction errors.

The prediction performance $Hit - ratio$ is evaluated using the following equation:

$$Hit - ratio = \frac{1}{n} \sum_{i=1}^{n} P_i (i = 1, 2, ..., n) \qquad (3)$$

where Pi is the prediction result for the i^{th} trading day as defined through Equation

3. The variable yt denote the actual value of the closing stock index for the i^{th} trading day and $\hat{y}t$ is the predicted value for the i^{th} trading day. The variable n denotes the number of test samples.

$$P_i = \begin{cases} 1, \ if \ (y_{t+1} - y_t)(\hat{y}_{t+1} - \hat{y}_t) > 0 \\ 0, \ otherwise \end{cases} \qquad (4)$$

3.2 Input variables

From many previous studies, it has been shown that various technical indicators may be used as input variables in the construction of prediction models to forecast the direction of movement of the stock price index (Saad et al., 1998). Most financial managers and investors have a common understanding on the efficiency of technical indicators and their utilization in forecasting future trends. On the basis of these reviews, we notice that most researchers prefer to choose the input variables as shown in Table 1, whereas only few prefer Type 2 input variables (shown in Table 2). Tables 1 and 2 list the selected features and their formulas, and we select these technical indicators as the feature subsets based on reviews from prior studies. In light of these we employ 12 and 9 technical indicators for Type 1 and Type 2 feature subset respectively. These indicators for the two types of input variables are usually used to predict the future trends and are derived from the real stock composite index.

3.3 Prediction process

After collecting the real stock composite index data and calculating the two types of input variables we further plug data into the optimized ANN model to forecast the future direction of the stock market. We conduct the prediction process as follows: Firstly, we calculate all the indicators for the two types of input variables and then normalize the data to reduce the experimental errors. Before entering data into the ANN model, we optimize all the weights and biases of the ANN model using the GA algorithm. We apply two types of indicators for predicting the direction of next day's movement by the GA-ANN hybrid model. Finally after all the experiments, we compare the performance of the two types of input variable sets with prior reports.

4. Experimental Results

4.1 Performance comparison for two types of input variables

In-sample data was used to train the GA-ANN hybrid model. In this section, we test the performance of two sets of input variables by using out-of-sample data, which includes 300 data points. The hybrid model requires a number of parameters that can influence the performance of the model, and these parameters are presented under Table 3. First, we conducted experiments based on the initial parameter setting, as projected under Table 3. We tested the performance of the two types of indicators by changing the different parameter combinations of the GA-ANN hybrid model. Table 4 shows the best performance of each type of input variables. The *Hit ratio* denotes the percentage of trials when the predicted direction was correct. From Table 4, we observe that the best *Hit ratio* for forecasting the direction correctly by applying Type 1 input variables is 55.47% and 79.5% for Type 2 input variables. We conclude that Type 2 input variables are more effective in predicting the direction of the daily closing price for the Botswana Domestic Companies Index than Type 1 input variables. We infer that ANN Model used with Type 2 input variables can be a useful tool for investors in predicting the direction of next day's closing price.

4.2 Comparison with similar studies

Predicting the direction of the stock market index is an important topic for most investors. There are many studies published in the recent past that focus on the prediction of these movements. Table 5 lists out some of these prior studies that aim to predict the direction of the stock market indices using various methods. The results of this study are also compared with these past research studies as shown under Table 5. From these results, we find that the prediction accuracy is significantly different in various studies, and our model is superior to all the other models. Thus, we consider the set of input indicators and the GA algorithm adopted in this study to be more appropriate for prediction. From the review of previous studies, many researchers have compared ANN with Support Vector Machines (SVM). For example, (Kim, 2003) applied SVM to predict the stock price index, and compared it with the back propagation neural networks. Their results show that SVM out performs BP neural networks in financial time-series forecasting. We observe that most studies focus on the parameter selection of BP neural networks when comparing it with other models. If selection of input variables is combined with the optimal adjustment of the weights and biases of the ANN model, then the optimized ANN model may provide good alternative to stock market prediction.

5. Conclusion

This study applied two types of technical indicators to predict the direction of next day's DCI movement. Weights and biases of the ANN model were adjusted using the GA algorithm. The performance of the GA-ANN hybrid model was tested by applying these two types of input variables and the predictions were compared with actual data. The experiments revealed that Type 2 input variables can provide better performance with the *Hit ratio* of 79.5%. We also compared the performance of the GA-ANN hybrid model with similar studies and the results showed that this method was more effective and resulted in higher prediction accuracy. However, the prediction performance of this study may be improved further through various means. Firstly, one may combine the two types of input indicators, or test a subset of these variables. In addition, few more variables can be included that may affect the prediction performance. Secondly, optimal methods other than the GA may also be utilized to adjust the parameters of ANN model and other models based on probabilistic neural networks for predicting the movement of the stock index may be used.

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Figures and Tables

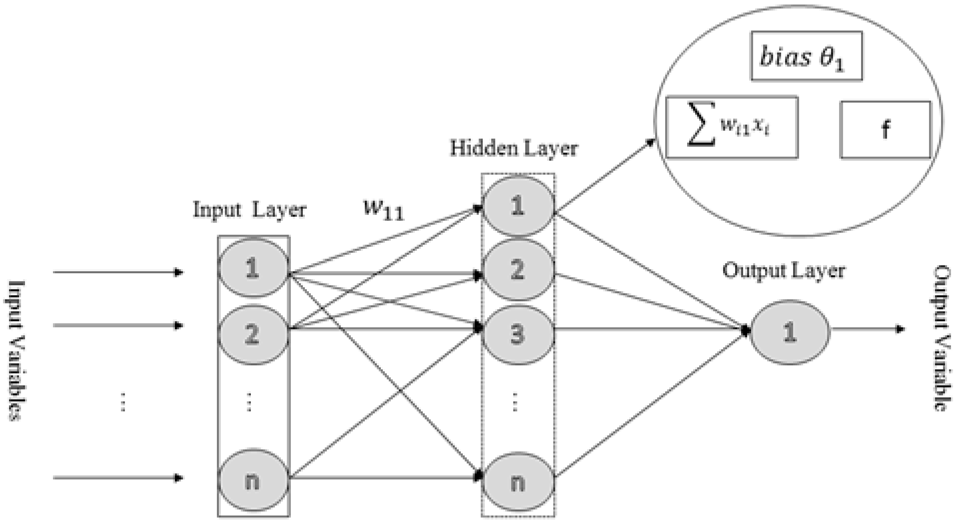

Figure 1: The architecture of back propagation neural network

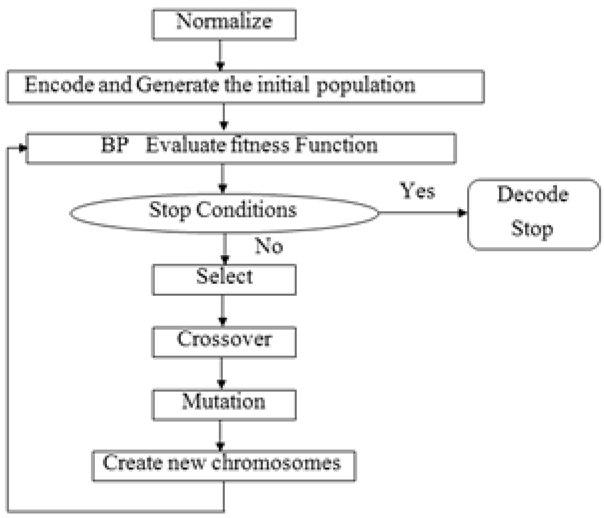

Figure 2: Process Flow of the Hybrid GA and BP Algorithm

Table 1: Type 1 technical indicators and their formulas

Name of feature (Type 1 Input variables)	Formulas
Stochastic %K	$(C_t - L_n)/(H_n - L_n)$x100
Stochastic %D	$\sum_{i=0}^{n-1} \%K_{t-i}/n$
Stochastic slow %D	$\sum_{i=0}^{n-1} \%D_{t-i}/n$
Momentum	$C_t - C_{t-4}$
ROC (rate of change)	$C_t/C_{(t-n)}$x100
LW%R (Larry William's %R)	$(H_n - C_t)/(H_n - L_n)$x100
A/O Oscillator (accumulation/distribution oscillator)	$(H_t - C_{t-1})/(H_t - L_t)$
Disparity in 5 days	C_t/MA_5x100
Disparity in 10 days	C_t/MA_{10}x100
OSCP (price oscillator)	$MA_5 - MA_{10}/MA_5$
CCI (Commodity Channel Index)	$(M_t - SM_t)/(0.015xD_t)$
RSI (relative Strength Index)	100-100/(1+$\frac{\sum_{i=0}^{n-1} Up_{t-1}}{n} / \frac{\sum_{i=0}^{n-1} Dw_{t-1}}{n}$)

C_t is the closing price and L_t is the lowest price of the DCI at time t. L_n is the lowest price of DCI in the last n days, H_t is the highest price at time t. H_n is the highest high price in the last n days. MA_n is the moving average of the price value in the last n days: $MA_n = (\sum_{i=1}^{n} C_{t-i+1})/n$, $M_t = \frac{H_t+L_t+C_t}{3}$. $SM_t = (\sum_{i=1}^{n} M_{t-i+1})/n$, $D_t = (\sum_{i=1}^{n} \mid M_{t-i+1} - SM_t \mid)/n$. Up_t is the upward price change of DCI at time t and Dw_t is the downward price change of DCI at time t.

Table 1: Type 1 technical indicators and their formulas

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Disparity in 10 days	C_t/MA_{10}x100
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Table 2: Type 2 technical indicators and their formulas

Name of feature (Type 2 Input variables)	Formulas
OBV	$OBV_t = OBV_{t-1} + \theta^* V_t$
MA_5	$MA_5 = (\sum_{i=1}^{5} C_{t-i+1})/5$
$BIAS_6$	$BIAS_6 = (\frac{C_t - MA_6}{MA_6})$x100%
PSY_{12}	$PSY_{12} = (A/12)$x100%
ASY_5	$ASY_5 = (\sum_{i=1}^{5} SY_{t-i+1})/5$
ASY_4	$ASY_4 = (\sum_{i=1}^{4} SY_{t-i+1})/4$
ASY_3	$ASY_3 = (\sum_{i=1}^{3} SY_{t-i+1})/3$
ASY_2	$ASY_2 = (\sum_{i=1}^{2} SY_{t-i+1})/2$
ASY_1	$ASY_1 = SY_{t-1}$

V_t is the volume of trade for DCI at time t, $\theta = \begin{cases} +1, & if\ C_t \geq C_{t-1} \\ -1, & if\ C_t < C_{t-1} \end{cases}$.

PSY_n is the ratio in the rising number of periods over the n day period. Variable A is the number of rising days in the last n days. SY_t represents the return of DCI at time t, $SY_t = (lnC_t - lnCt - 1)x100$. *$ASY_n$ is the average return in the last n days.*

Table 3: hybrid model parameters

Variable	Value	Defination
n	10	number of neurons in the hidden layer of the ANN model
ep	2000	number of iterations for the hybrid model
mc	0.3	momentum constant of the ANN model
l	0.2	value of learning rate of the ANN model
pcro	0.6	cross-over rate of the GA-ANN model
pmut	0.3	mutation rate of the GA-ANN model
popu	100	Initial population number of the GA-ANN model

Table 4: Hit ratio comparison between two types of input variables

	Input variables	
	Type 1	Type 2
Hit ratio(%)	55.47	79.5

Table 5: Comparison to other existing studies

Studies	Methods	Stock market	Hit ratio (%)
(Kim and Han, 2000)	GA feature discretization	Korea	61.7
(Leung et al., 2000)	Classification model	US, UK, Japan	68
(Huang and Nakamori, 2005)	SVM	Japan	75
(Kara et al., 2011)	BPNN	Istanbul	75.74
Own study	GA-ANN hybrid model	Botswana	79.5