The Forecasting of Agriculture Exchange-Traded Funds (ETFs):
Using Grey Relational Analysis (GRA) and Artificial Neural Networks (ANNs)

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Abstract: This study aims to predict agricultural exchange traded funds (ETFs) and exchange traded notes (ETNs) through grey relational analysis (GRA) and two types of artificial neural network (ANN) models, namely, back-propagation perception network model (BPN) and time delay recurrent neural network (TDRNN). Seven variables, namely, Euro, commodity research bureau index (CRB), put/call ratio, New York Stock Exchange composite index (NYA), short-term trading index, volatility index, and weather index (WINX), are applied. The results of GRA indicate that CRB and NYA have a strong effect on agricultural ETFs. Agricultural ETNs are strongly influenced by CRB, NYA, WINX, and Euro. The BPN model strongly suggests that using 10% of the data is the most suitable for forecasting, whereas the TDRNN model suggests the use of 33% and 50%. GRA and the ANN model strongly capture nonlinear trends and improve the precision in forecasting agricultural ETFs and ETNs.

Keywords: Agriculture ETFs, ETNs, Grey Relational Analysis, Forecasting, Artificial Neural Networks

1. Introduction

Agricultural commodities have been studied extensively in recent years. Agriculture influences economic development and is a significant factor in environmental sustainability (Blandford et al., 2014). Agriculture has a strong correlation with land scarcity and climate change because agricultural products are utilized for food production, and agricultural wastes are used to benefit the environment. Crop growth in large areas and the extensive use of chemicals and machinery in farming have considerable effects on the environment (Coletta, 2014). Agricultural commodities remain a favorable investment for investors. Therefore, many agricultural commodity portfolios, such as agricultural exchange trade funds (ETFs) and exchange traded notes (ETNs), have grown rapidly.

ETFs and ETNs have become popular research topics. Since their introduction in 1993, ETFs have experienced significant growth, with more than 4,980 ETFs currently being offered to investors. This rapid growth is attributed to the advantages of ETFs, which outnumber those of mutual funds. ETFs offer investors with the liquidity because they are traded daily in the securities
industry. Second, ETFs are exempted from taxes and charge lower annual fees than mutual funds (Poterba and Shoven, 2002; Miffre, 2004). Investing in ETFs diversifies portfolios (Harper et al., 2006; Huang and Lin, 2011).

ETNs are utilized to design investment products that are distributed by a major bank or provider as senior debt notes. In contrast to ETFs, ETNs contain an actual security, a commodity, or a currency derivative, such as futures, forwards, and options. When investors have related purchase obligation connected with the ETN structure, they actually purchase a debt product similar to bonds. By contrast, when investors purchase an ETF, they actually purchase an asset similar to a stock or index. Given that ETNs are supported by a bank with a high credit rating, these notes are categorized as secure products. ETNs also have a lower credit risk than ETFs.

ETNs have exhibited rapid growth since their introduction in 2006 by Barclays Bank PLC. Similar to ETFs, ETNs have many categories, such as commodity, currency, emerging market, and strategy ETNs. An example of commodity ETNs is agricultural ETNs. Both agricultural ETFs and ETNs are desired by investors because of their rapid growth.

Several studies have investigated ETFs and ETNs. Charupat and Miu (2011) examined the performance of leveraged ETFs, and Alexander and Barbosa (2008) explained the hedging index for ETFs. By examining how ETFs diversifies the private information of informed traders, Steeley and Park (2010) found that there were lower adverse selection costs for ETFs than their control securities. Several studies have focused on the spillover, leverage, and asymmetric volatility effects of ETFs and ETNs (Chen and Huang, 2010; Chen, 2011; Chen and Diaz, 2012; Krause and Tse, 2013; Chen and Malinda, 2014).

Several researchers have also predicted ETFs. DeFusco et al. (2011) employed the exponential generalized autoregressive heteroscedasticity model (EGARCH) and vector error correction model. They found that the price deviations of the three most liquid ETFs, namely, Spiders (S&P500 tracking ETF), Diamonds (Dow Jones Industrial Average tracking ETF), and Cubes (NASDAQ 100 tracking ETF), are stationary and predictable and entail an additional implicit transaction cost. Bollapragada et al. (2013) employed simple linear regression, multiple regression, Holt’s exponential smoothing, and various versions of Box–Jenkins (ARIMA) models and found that the multiple regression technique is the ideal procedure for ETF forecasting.

Bekiros and Georgoutsos (2008) and Sookhanaphibarn et al. (2007) tested the predictive power of the artificial neural network (ANN) model in the financial area. They found that the ANN model provides accurate forecasts in financial areas. Ho et al. (2002) and Zhang (2003) found that the ANN model has better forecasting capability than ARIMA models. By using the ANN model, Singhal and Swarup (2011) found that electricity price follows a strong trend in deregulated markets. Hamzaçebi (2008) compared the results of the ANN model with those of traditional statistical models and found that the ANN model outperforms other models.

Donaldson and Kamstra (1997) built semi nonparametric nonlinear GARCH, EGARCH, and Glosten–Jagannathan–Runkle (GJR) GARCH models based on ANN. They also estimated the ability of these models to forecast stock return volatilities in London, New York, Tokyo, and Toronto to capture the underlying volatility effects and produce out-of-sample volatility forecasts that encompass those of other models.

By using the ANN model to investigate the stock index option price, Tseng et al. (2008) discovered that compared with other volatility approaches, grey–exponential generalized

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1 http://etf.about.com/od/etfbasics/a/ETN_ETF_Differs.htm
2 http://etf.about.com/od/etfbasics/a/List-Of-Etns.htm
3 http://etfdb.com/type/commodity/agriculture/#returns
autoregressive heteroscedasticity volatility offers better expectedness. Hadavandi et al. (2010) found that genetic fuzzy systems and ANNs are the best models for forecasting stock movements in information technology and airline sectors. Ticknor (2013) demonstrated the effectiveness of the Bayesian regularized ANN method in forecasting financial market behaviors.

However, despite the many studies on ETFs, only a few have examined agricultural ETFs and ETNs. This study aims to fill this research gap and help investors select the best investment by identifying the best model to forecast agricultural ETFs and ETNs. To the best of our knowledge, this study is the first to forecast agricultural ETFs and ETNs through grey relational analysis (GRA) and two types of the ANN model, namely, back-propagation perception network (BPN) and time-delay recurrent neural network (TDRNN). This study also compares agricultural ETFs and ETNs.

Macroeconomic and financial variables are extracted to examine their effects on agricultural ETFs and ETNs. Several variables, namely, put/call ratio, EUR/USD exchange rate, the volatility index (VIX), commodity research bureau index (CRB), short-term trading index (TRIN), New York Stock Exchange composite index (NYA), and weather index (WINX), are utilized.

This study aims to provide unique evidence on the forecasting of agricultural ETFs and ETNs. Agricultural ETNs are strongly influenced by CRB, NYA, WINX, and EUR/USD, whereas agricultural ETFs are strongly influenced by CRB and NYA. The BPN model suggests that 10% of the time series data must be utilized to forecast agricultural ETFs and ETNs, whereas the TDRNN model suggests that 33% and 50% of the time series data must be used in the forecasting. GRA and the ANN model can strongly capture nonlinear trends and improve the precision of forecasting the agricultural ETFs and ETNs. Investors, fund managers, and traders can effectively use CRB, NYA, WINX, and EUR/USD to forecast agricultural ETFs and ETNs.

This paper is organized as follows. Section II provides the data and methodology of the study. Section III presents the empirical results, and Section IV provides the conclusions.

2. Data and Methodology

2.1 Data

The daily closing prices of five agricultural ETFs and five agricultural ETNs were used in this study. The study period was from different inception days to March 30, 2014. Table 1 shows the categories, names, and abbreviations of the selected agricultural ETFs and ETNs. Table 2 shows the macroeconomic and financial inputs, such as put/call ratio, EUR/USD exchange rate, VIX, CRB, TRIN, NYA, and WINX. The effects of these inputs on agricultural ETFs and ETNs were examined.

To analyze the sentiment of the market for investors, the PCR can be measured as the number of traded put options divided by the number of traded call options. Simon and Wiggins (2001) find that sentiment measure such as the PCR exhibits the negative relationships with the Standard and

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4 ETFs are financial instruments with unique advantages over mutual funds (http://www.investopedia.com).
5 ETNs are unsecured, unsubordinated debt securities first issued by Barclays Bank PLC (http://www.investopedia.com).
7 www.finance.yahoo.com
Poor (S&P) Futures Index. This paper also uses the financial variable such as exchange rate to examine the impact of the Euro on the equity market. Previous studies found that the VIX as an evaluated fear was a variable opposite the S&P Futures Index (Simon and Wiggins, 2001). The CRB index can be applied to track the directional movement of prices in commodity trading. Göleç, et al., (2012) and Ho et al. (2010) found that there is a bidirectional connection between the CRB index and the Shanghai Index as well as the Gold Futures Index. To measure overall market sentiment, TRIN is a technical analysis indicator that combines advancing and declining stock issues and trading volumes. Also referred to as the Arms Index, TRIN is used to predict future price movements for overbought and oversold in the market on an intraday basis. Simon and Wiggins (2001) revealed that there is a negative relationship between TRIN and the S&P Futures Index. The NYSE Composite Index is a stock market index to measure the performance of all common stocks listed on the NYSE and to evaluate the changes in the aggregate market value. The weather index is added because agricultural products are influenced by weather conditions.

Table 1. Agriculture ETFs and ETNs

<table>
<thead>
<tr>
<th>Category</th>
<th>ETFs and ETNs</th>
<th>Inception days</th>
<th>Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>ETFs</td>
<td>Teucrium Corn</td>
<td>6/9/2010</td>
<td>CORN</td>
</tr>
<tr>
<td>ETFs</td>
<td>ETFs Commodity Securities Limit</td>
<td>12/31/2007</td>
<td>COTN.L</td>
</tr>
<tr>
<td>ETFs</td>
<td>iShares Global Agriculture Common</td>
<td>12/20/2007</td>
<td>COW.TO</td>
</tr>
<tr>
<td>ETFs</td>
<td>PowerShares DB Agriculture</td>
<td>1/8/2007</td>
<td>DBA</td>
</tr>
<tr>
<td>ETFs</td>
<td>Teucrium Wheat</td>
<td>9/21/2011</td>
<td>WEAT</td>
</tr>
<tr>
<td>ETNs</td>
<td>PowerShares DB Agriculture Dble Long ETN</td>
<td>4/15/2008</td>
<td>DAG</td>
</tr>
<tr>
<td>ETNs</td>
<td>ELEMENTS MLCX Grains Index TR ETN</td>
<td>2/15/2008</td>
<td>GRU</td>
</tr>
<tr>
<td>ETNs</td>
<td>iPath DJ-UBS Agriculture TR Sub-Idx ETN</td>
<td>10/25/2007</td>
<td>JJA</td>
</tr>
<tr>
<td>ETNs</td>
<td>ELEMENTS Rogers Intl Commodity Agri ETN</td>
<td>10/19/2007</td>
<td>RJA</td>
</tr>
<tr>
<td>ETNs</td>
<td>UBS E-TRACS CMCI Agriculture TR ETN</td>
<td>4/4/2008</td>
<td>UAG</td>
</tr>
</tbody>
</table>

Table 2. Macroeconomic and Financial Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Resource</th>
</tr>
</thead>
<tbody>
<tr>
<td>Put and Call ratio (PC)</td>
<td><a href="http://www.schwab.com">www.schwab.com</a></td>
</tr>
<tr>
<td>EUR/USD</td>
<td><a href="http://www.investing.com/currencies">www.investing.com/currencies</a></td>
</tr>
<tr>
<td>Volatility Index (VIX)</td>
<td>finance.yahoo.com</td>
</tr>
<tr>
<td>Commodity Research Bureau Index (CRB)</td>
<td>topforeignstocks.com</td>
</tr>
<tr>
<td>Short-Term Trading Index (TRIN index)</td>
<td><a href="http://www.traderslog.com/market-internals">www.traderslog.com/market-internals</a></td>
</tr>
<tr>
<td>New York Stock Exchange Composite Index (NYA)</td>
<td>finance.yahoo.com</td>
</tr>
<tr>
<td>Weather Index (WINX)</td>
<td><a href="http://www.cmegroup.com/market-data/reports">www.cmegroup.com/market-data/reports</a></td>
</tr>
</tbody>
</table>
2.2 Methodology

Agricultural ETFs and ETNs were forecasted through GRA and with ANN models.

2.2.1. Grey Relation Analysis (GRA)

Proposed by Deng (1989), GRA theory measures the relationship between two discrete time series in a grey system. GRA has been widely applied in the analysis of financial variables. It can calculate missing messages in various anxious factors that examine random factor series. GRA only requires a small amount of data to control the correlation among determinants.

Many previous studies have utilized GRA in financial applications. Kung and Wen (2007) employed GRA to identify several important financial ratios that affect the financial operation of capital enterprises in Taiwan. Lin and Wu (2011) used the GRA model to analyze the financial data of various establishments and found that the model can provide banks with early warning signals of an impending financial crisis. Hamzaçebi and Pekkaya (2011) used GRA and found that the financial ratios utilized for stock selection are normally found in the manufacturing sector. Jiang and He (2012) also found that the GRA model can accurately compute and predict three real financial time series in China.

The GRA model can help investors evaluate and understand the performance and attributes of capital enterprises and subsequently minimize their investment risks. The data processing of GRA was originally based on Deng (1989). Chang et al. (2013) and Hamzaçebi and Pekkaya (2011) described the data processing method of GRA as follows.

1. Describe the original series by using the formula

\[ x_i = (x_i(1), x_i(2), x_i(3), ..., x_i(k)) \in X \text{ and } k = 0, 1, 2, 3, ..., n \in N, i = 0, 1, 2, 3, ..., m \in X. \]

2. Define the reference series.

The reference series may indicate the presence of maximum or minimum values. When the measure requires maximization (minimization), the reference series value of the linked measure reflects the maximum (minimum) value of the alternative series.

3. Normalize the data.

Before computing the grey relation grade (GRG), a data pre-processing of grey relational generation should be performed. Afterward, the series can be treated depending on the following situations:

i. A large predictable objective (i.e., profit) is favorable under “the larger, the better” expectation. The following equation can be applied.

\[ x_i^*(k) = \frac{x_i^{(k)} - \min x_i^{(0)}(k)}{\max x_i^{(0)}(k) - \min x_i^{(0)}(k)} \] (1)

ii. A small predictable objective (i.e., cost or loss) is favorable under “the smaller, the better” expectation. The following equation can be applied:

\[ x_i^*(k) = \frac{\max x_i^{(0)}(k) - x_i^{(0)}(k)}{\max x_i^{(0)}(k) - \min x_i^{(0)}(k)} \] (2)

iii. The best nominal expectation is favorable if specific value gains are expected between the maximum and minimum objectives (i.e., age). The following equation can be applied.

\[ x_i^*(k) = 1 - \frac{\left| x_i^{(0)}(k) - OB \right|}{\max \left\{ \max \left[ x_i^{(0)}(k) - OB, OB - \min x_i^{(0)}(k) \right] \right\}} \] (3)
where \( x_i^{(0)}(k) \) stands for the value of grey relation, \( \min_i. x_i^{(0)}(k) \): \( x_i^{(0)} \) is the minimum value, \( \max_i. x_i^{(0)}(k) \): \( x_i^{(0)} \) is the maximum value, and \( OB: x_i^{(0)}(k) \) denotes the object value.

4. Calculate the grey relation coefficient.

Localization GRA reflects the association between the reference sequences \( x_i^{(0)}(k) \) (selected by localization GRG) and relative sequences \( x_i^*(k) \). The grey relational coefficient \( \varepsilon(x_0(k), x_i(k)) \) is illustrated as follows:

\[
\Delta_{0i}(k) = |x_0(k) - x_i(k)|,
\]

\[
\Delta_{\min} = \min_{i} \min_{k} \Delta_{0i}(k) = \min_{i} \min_{k} |x_0(k) - x_i(k)|, \quad \text{and}
\]

\[
\Delta_{\min} = \max_{i} \max_{k} \Delta_{0i}(k) = \max_{i} \max_{k} |x_0(k) - x_i(k)|.
\]

5. Calculate GRG.

GRG measures the association between the sequences analyzed and categorized into localization and globalization GRG. When all criteria are equal, GRG can be calculated with Equation (5); otherwise, it can be calculated with Equation (6).

(i) \( \gamma(x_0, x_i) = \sum_{k=1}^{n} \beta_k \varepsilon(x_0(k), x_i(k)) \),

(ii) \( \gamma(x_i, x_j) = \sum_{k=1}^{n} \beta_k \varepsilon(x_i(k), x_j(k)) \),

where \( \beta_k \) represents the weight value and \( \sum_{k=1}^{n} \beta_k = 1 \). According to the importance of each determinant in the sample, \( \beta_k \) can be ranked for different weights. GRG is applied by equal weights and is derived from the average value of the grey relational coefficient. Therefore, \( \beta_k = \frac{1}{n} \), \( k = 1, 2, \ldots, n \).

GRG is then ranked in descending order. The grey relational order defines the main factors of the series that are associated with the reference series. The variable with the highest value has the strongest effect, and the variable with the lowest value has the weakest effect.

2.2.2 ANNs

ANNs can perform parallel computations for data processing. The abundant connected artificial neurals can be utilized to duplicate the biological neural network for data processing. Artificial neurals are non-organic imitations of biological neurals that produce outputs by receiving the external situation or other artificial neurals. The application of ANNs in the financial area develops yearly. Wong et al. (1997) and Wong and Selvi (1998) reviewed journal articles that discussed the business applications of neural networks. Many of these articles were able to demonstrate the applications of ANNs for a diverse range of business activities. Kaastra and Boyd (1996) revealed that neural networks can forecast models through the use of economic time series data. Enke and Thawornwong (2005) forecasted stock market returns and found that trading strategies guided by an organizational model generate higher risk-adjusted profits than those guided by the buy-and-hold strategy. The current study employs two neural networks, namely, BPN and TDRN.
2.2.2.1 BPN

BPN has been applied in many studies. Chang and Wang (2006) utilized the BPN model to forecast sales in the printed circuit board industry. Li et al. (2012) demonstrated the use of BPN in optical fiber detection. Wang et al. (2011) found that BPN is an effective algorithm for predicting the Shanghai Composite Index. Guresen et al. (2011) applied multi-layer perception, dynamic ANN, and hybrid neural networks that employ GARCH to extract new input variables for forecasting the NASDAQ Stock Exchange index.

BPN employs multilayer perception as its architecture and error back propagation as its learning algorithm (Huang and Wang, 2008). BPN involves the direct transmission of the input from the input layer to the hidden layer and the computation of the weighted accumulation to generate an output with transfer functions; this output is then transmitted to the output layer. The sigmoid transfer function is normally expressed as follows:

\[ f(x) = \frac{1}{1 + e^{-x}}. \]  

(7)

In \( f(x) \), function \( (x) \) is called the input layer. The network augments a hidden layer that shows the relationships among input processing elements. Reduction of the error function requires the use of the smooth transition function and the gradient steepest descent method. The formula of the modified network weights is derived when the output of the processing element in the layer becomes the nonlinear function of the output of the processing element in layer \( n-1 \).

\[ A^n_j = f\left(\text{net}^n_j\right) = f\left(\sum_i w_{ij} A^{n-1}_i - \theta_j\right), \]  

(8)

where \( f \) is the transfer function and \( w_{ij} \) indicates the weight of \( \text{net}^n_j \), which is equivalent to the activity function of processing element \( i \) in layer \( n-1 \) and that of processing element \( j \) in layer \( n \). \( \theta_j \) explains the bias of processing element \( j \) in layer \( n \) or the threshold value.

BPN reduces the differences between the actual network output and the target output. The learning quality of this supervised learning is provided by error function \( E \) as follows:

\[ E = \frac{1}{2} \sum_j (T_j - A_j)^2, \]  

(9)

where \( T_j \) is the target output of processing element \( j \) and \( A_j \) indicates the network output of processing element \( j \).

BPN adjusts the weights in the network during ongoing training. These functions are computed as follows:

\[ \Delta W_{ij} = -\eta \frac{\partial E}{\partial W_{ij}} , \]  

(10)

where \( \eta \) stands for the learning rate, which identifies the amplitude for the gradient steepest descent method to adjust the error function. \( W_{ij} \) represents the output and hidden layers. It is calculated as follows:

\[ \frac{\partial E}{\partial W_{ij}} = -\delta_j \cdot A^{n-1}_i , \]  

(11)

where \( A^{n-1}_i \) is the output of the processing element in the lower layer, which is linked by \( W_{ij} \), and
\( \delta_j^n \) is the gap of the processing element in the upper layer, which is linked by \( W_{ij} \). By substituting the above equation into \( \Delta W_{ij} = -\eta \cdot \frac{\partial E}{\partial W_{ij}} \), we obtain
\[
\Delta W_{ij} = \eta \cdot \delta_j^n \cdot A_{i}^{n-1}.
\]
This equation shows that the adjusted inputs serve as training samples of the weights and as the key equation for the back propagation algorithm.

### 2.2.2.2 TDRNN

The TDRNN model is an extensive neural model that has the advantages of adaptive time delays and recurrences. This model manipulates the temporal information of input sequences by utilizing adaptive time delays and recurrent connections. The internal state units serve as additional inputs at time \( t \) and as duplicates from the processes of hidden units at time \( t-1 \). TDRNN has adjusted both adaptable synaptic weights and adjustable time lags generated from the interconnections between the input and hidden units. The delay box, which is a unique feature of this ANN model, comprises the interconnections from the input layer to the first hidden layer and from the internal state layer to the first hidden layer.

The net inputs from the activation values of the previous neuron are summed up by using the equivalent time delays on each connection line at time \( t \) of unit \( j \) on layer \( h \), which receives a weighted sum (Kim, 1998; Lin et al., 1992). These inputs are summed up as follows:
\[
net_{j,h}(t_n) = \sum_{i \in N_{h-1}} \sum_{k=1}^{K_{j,i,h-1}} \alpha_{j,i,h-1} (t_n - \tau_{j,i,h-1}),
\]
where \( \alpha_{i,h-1}(t_n - \tau_{j,i,h-1}) \) represents the activation level of unit \( i \) on layer \( h-1 \) at time \( t_n - \tau_{j,i,h-1} \), \( N_{h-1} \) is the set of nodes of layer \( h-1 \), and \( K_{j,i,h-1} \) is the total number of connections from node \( i \) of layer \( h-1 \) to node \( j \) of layer \( h \).

By selecting a sigmoid function, the output of node \( j \) is administered by a non-diminishing function \( f \) of the net input (Kim, 1998).
\[
\alpha_{j,h}(t_n) = \begin{cases} f_{j,h}(net_{j,h}(t_n)) & \text{if } h \geq 2, \\ \alpha_{j,0}(t_n) & \text{if } h = 1, \end{cases}
\]
\[
f_{j,h}(net) = \frac{\beta_{j,h}}{1 + e^{-\alpha_{j,h,net} - \gamma_{j,h}}},
\]
where \( \alpha_{j,0}(t_n) \) is the \( j \)th channel of the input signal at time \( t_n \); \( \alpha_{j,h}, \beta_{j,h} \) and \( \gamma_{j,h} \) stand for real numbers; and \( -\gamma_{j,h} \) and \( \beta_{j,h} - \gamma_{j,h} \) represent the upper and lower limits of the sigmoid function, respectively. The steepness of \( f_{j,h}(net) \), computed as \( f_{j,h}'(0) \), is \( (\alpha_{j,h}, \beta_{j,h})/4 \) (Kim, 1998; Lin et al., 1992).

The internal state vector at time \( t_n \), \( S_{h-1}(t_n) \) is described as
\[
S_{h-1}(t_n) = A_{h+1}(t_{n-1}),
\]
where \( A_{h+1}(t_{n-1}) \) is the activation vector of the second hidden unit at time \( t_{n-1} \).
The instantaneous error measure is defined as the mean-squared error (Kim, 1998; Lin et al., 1992) and is computed as follows:

\[ E(t_n) = \frac{1}{2} \sum_{j \in N_{h+2}} (d_j(t_n) - a_{j,h+2}(t_n))^2, \]  

(17)

where \( N_{h+2} \) is the set of nodes of the output layer and \( d_j(t_n) \) is the preferred target number of output node \( j \) at time \( t_n \).

The weights \( (w) \) and time delays \( (\tau) \) are restructured by an amount that is equivalent to the opposite direction of the error gradient (Kim, 1998; Lin et al., 1992). Specifically, the weights are computed as follows:

\[ \Delta w_{jik,h} = -\eta_1 \frac{\partial E(t_n)}{\partial w_{jik,h}}, \]  

(18)

\[ \Delta \tau_{jik,h} = -\eta_2 \frac{\partial E(t_n)}{\partial \tau_{jik,h}}, \]  

(19)

where \( \eta_1 \) and \( \eta_2 \) are the learning rates.

The learning rules are summarized as follows:

\[ \Delta w_{jik,h-1} = \eta_1 \delta_{j,h}(t_n) a_{i,h-1}(t_n - \tau_{jik,h-1}), \]  

(20)

\[ \Delta \tau_{jik,h-1} = \eta_2 \rho_{j,h}(t_n) w_{jik,h-1} a_{i,h-1}(t_n - \tau_{jik,h-1}), \]  

(21)

where

\[ \delta_{j,h}(t_n) = \begin{cases} (d_j(t_n) - a_{j,h}(t_n)) f'(\text{net}_{j,h}(t_n)), & \text{if } j \text{ is an output unit,} \\ \sum_{p \in N_{i+1}} \sum_{q=1}^{K_{p,i}} \delta_{p,h+1}(t_n) w_{pq,h}(t_n) f'(\text{net}_{j,h}(t_n)), & \text{if } j \text{ is an output unit,} \end{cases} \]  

(22)

and

\[ \rho_{j,h}(t_n) = \begin{cases} (d_j(t_n) - a_{j,h}(t_n)) f'(\text{net}_{j,h}(t_n)), & \text{if } j \text{ is an output unit,} \\ \sum_{p \in N_{i+1}} \sum_{q=1}^{K_{p,i}} \rho_{p,h+1}(t_n) w_{pq,h}(t_n) f'(\text{net}_{j,h}(t_n)), & \text{if } j \text{ is an output unit.} \end{cases} \]  

(23)

Two statistical tests, namely, mean square error (MSE) and normalized mean square error (NMSE), were performed to appraise the performance of ANN models (Qi, 1999; Chen et al., 2003; Yümlü et al., 2005) and measure the strength and direction of the linear relationship between two variables. The Pearson product–moment correlation coefficient was used to estimate the correlation between the model and observations (Pearson, 1895).

3. Empirical Results

Table 3 presents the GRG results for agricultural ETFs. CRB and NYA exerted the most influence on agricultural ETFs. Short-term TRIN exerted the least influence on all agricultural ETFs. NYA had a strong influence on iShares Global Agriculture Common (COW.TO) traded at Toronto Canada ETF. Other findings revealed that WINX in the U.S. ranked second in terms of influence on ETFs in Commodity Securities Limit (COTN.L) trading in the London market.
With regard to agricultural ETNs, CRB exerted the most influence on Power Shares DB Agriculture Short ETN (ADZ), ELEMENTS MLCX Grains Index TR ETN (GRU), and ELEMENTS Rogers Intl Commodity Agri ETN (RJA). NYA strongly influenced iPath DJ-UBS Agriculture TR Sub-Idx ETN (JJA). UBS E-TRACS CMCI Agriculture TR ETN (UAG) was strongly influenced by the EUR/USD variable. WINX exerted a strong influence on ADZ.

### Table 3. The GRG Result of Agricultural ETFs and ETNs

<table>
<thead>
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Tables 4 and 5 illustrate the ability of BPN and TDRNN to forecast agricultural ETFs and ETNs. Kim (1998) and Li et al. (2012) argued that both BPN and TDRNN can effectively predict time series data. The lowest MSE value obtained by Li et al. (2012) and the lowest NMSE value obtained by Kim (1998) were used in the current study to identify the fittest hidden layer for the BPN and TDRNN models. Pearson’s correlation coefficient (r) was employed to measure the strength and the linear relationship between two variables. Following previous studies, 10%, 20%, 33%, and 50% of the data were utilized to test the available forecasting information of the time series data (Andreou et al., 2002; Chen and Fang, 2011; Diaz, 2012).

Table 4 shows that most agricultural ETFs obtained the fittest hidden layer of the BPN model in all variables by using 10% of the time series data. The MSE and NMSE results of CORN, COW.TO, and WEAT are consistent with r value. DBA obtained the lowest MSE and NMSE in a high-ranking variable by using 50% of the data. Therefore, a better DBA prediction result can be obtained by using more time series data. Similar to agricultural ETFs, agricultural ETNs can use 10% of the time series data to obtain a better forecast result.

Table 5 shows the results of the TDRNN model. Kim (1998) and Ge et al. (2009) found that TDRNN can forecast stock market trends and identify and control dynamic systems better than other models. This table presents information on the agricultural ETFs in all variable groups. TDRNN obtained better forecasting results for CORN, COW.TO, and WEAT when 10% of the
data were used. Better forecasting results were obtained for DBA when 50% of the data were used. Similarly, better forecasting results were obtained for COTN.L when 33% of the data were used. Sporadic results were obtained for agricultural ETNs. Meanwhile, better forecasting results were obtained for ADZ and AGA when 10% of the data were used. Better forecasting result was obtained for GRU when 33% or 50% of the data were used. Better forecasting results were obtained for RJA when 33% of the data were used. Likewise, better forecasting results were obtained for UAG when 20% of the data were used. The $r$ value revealed a strong correlation when 50% of the data were used.

4. Conclusion

The empirical results revealed that CRB and stock indexes strongly influence agricultural ETFs and ETNs. The agricultural ETNs, such as ADZ, is strongly influenced by WINX. The sources of these ETNs are corn, wheat, soybean, and sugar. CRB and NYA can benefit investors, traders, and fund managers when they invest in agricultural ETFs, and CRB, NYA, EUR/US, and WINX can benefit them when they invest in agricultural ETNs. The brief analysis with the GRA model strongly suggested that investors should pay more attention to CRB, NYA and WINX.

GRA and ANN models can accurately forecast agricultural ETFs and ETNs and can support investors, fund managers, and traders in making better predictions. Both BPN and TDRNN are appropriate for forecasting agricultural ETFs and ETNs. The BPN model revealed that most agricultural ETFs and ETNs can be accurately predicted by using 10% of the time series data. However, the TDRNN model suggests the use of 10% of the time series data for dispersed variables and 33% or 50% of the time series data to obtain the fittest hidden layer. The $r$ value showed that most of the variables are strongly correlated when 10% and 50% of the time series data are used for the BPN and TDRNN models, respectively.
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Table 5. The Time Delay Recurrent Neural Network Agriculture ETFs and ETNs for All Variable

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References


