Application of Artificial Neural Networks To Predict Intraday Trading Signals

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Abstract: This paper proposes an Artificial Neural Networks (ANN) model which feeds on inputs from popular technical indicators to predict trading signals, which is expected to be useful for active intra-day traders. The data used to build the model is the high frequency data of intra-day stocks from some industry sectors in the Indonesia Stock Exchange market. The technical indicators used as the inputs are the Price Channel Indicator, the Adaptive Moving Averages, the Relative Strength Index, the Stochastic Oscillator, the Moving Average Convergence-Divergence, the Moving Averages Crossovers and the Commodity Channel Index. The network architecture used in this paper is the multi layer feedforward perceptron with one hidden layer and trained using the backpropagation method. The performance of the model will be compared to a naïve buy-and-hold strategy and a maximum profit profile. The result of our experiments showed that the model performs better than the naïve strategy. Therefore, it can be concluded that the ANN is a useful method to generate trading signal predictors for intra-day traders from the high frequency data.

Key-Words: artificial neural networks, high frequency data, intra-day trading, stock trading, technical indicators, Indonesia Stock Exchange

1 Introduction

One of the most important creations of our society is the financial system, in which markets and institutions trade bonds, stocks and other forms of financial instrument. Madura [1] points out that, investors must earn a certain amount of return as an incentive to ensure the continuity of fund supply to the financial markets.

Financial market is the natural source for the use of high frequency data. Market data containing units of information such as price, volumes and trading position are transmitted across market participants with irregular space between them. Instruments which are very liquid, such as foreign exchange quotes, can generate hundreds of thousands of tick-by-tick data per day.

Yet Neely and Weller [2] points out that there is a time horizon mismatch between the practical technical analysis with academic studies. Studies often use a longer horizon such as daily or monthly data while intra-day trading are mostly based on tick-by-tick movement of trading prices.

Dempster, et al. [3] finds that studies on financial research are mostly limited to daily data. However, as the numbers of intra-day transactions grow in a staggering pace over the past few years, there is a big gap of un-researched area of high frequency intra-day data. Thomas [4] did a statistical analysis on the high frequency data to characterize the Indian equity markets.

Durbin [5] points out that from 2005 to 2009, the average daily volume of the New York Stock Exchange (NYSE) doubles, the average daily trades grows by ten folds, but the average trade size gets smaller by almost one third. Similar behaviors are also occuring in the Indonesia Stock Market (IDX) [6].

This phenomenon suggests that investor is moving towards quick small sized intra-day trading to pocket quick profits as the market moves during the day. Hence, the importance of studying intra-day data become obvious as the market is suggesting that this is a popular trading style.

As the industry grows, investors are developing trading techniques to maximize their returns, by forecasting the movement of the securities which they are holding or those which they are interested in. Kosala and Kumaradjaja [7] reviewed some successful uses of machine learning techniques for making decisions about trading in financial markets. Medsker, Turban, and Trippi [8] proposed the use of the Artificial Neural Networks (ANN), a machine learning method, to improve trading performance.

ANN is inspired by the studies of how the nervous system and the brain work. With the advance of computer's processing power, there have been studies to embed the enormous processing power with the flexibility of biological neurons, to solve logical problems such as forecasting and interpretation of financial market data to make an intelligent decision.

Zurada [9] explains that ANN try to simulate the human's brain biological neural network, which enables complex tasks to be performed instinctively. The process starts with a collection of inputs, with each input correspond to a single value or attribute. They are then feed into the next parallel nodes which will weigh the entering data as it is transferred layer to layer. The weight is actually a value of relative strength which translate into how important the input to the corresponding processing element.

The IDX has not been thoroughly researched with non-linear forecasting methods such as ANN. Moreover, there is also a lack of research using high frequency intra-day data. Hence, this research would focus on high frequency intra-day trading data with records of open, high, low & closing prices using data from the IDX database.

This paper proposes an Artificial Neural Networks (ANN) model which feeds on inputs from popular technical indicators to predict trading signals, which is expected to be useful for active intra-day traders. Technical indicators may be described as series of data which are calculated from price data of the security. They are then plotted into graphical form for easy visual scan. Hence, technical analysis (TA) traders can quickly note a price action, confirm a breakout, predict the price direction and take a trading position accordingly. Technical analysis practitioner does not rely on only one type of indicators. They will consider other indicators to confirm a trading signal before closing the deal. The data used to build the model is the high frequency data of intra-day stocks from some industry sectors in the Indonesia Stock Exchange market.

Some properties of ANN that makes them suitable for predicting trading signals from financial market data are as follows. Tsang and Martinez-Jaramillo [10] summarizes that the ANN learns, adapts to changes, and handles incomplete data without affecting the model's performance. Tan [11] points out that the ANN do not need any prior knowledge on the functional form of relations between the variables.

2 Problem Formulation

This research uses data taken from the Indonesian Stock Exchange market database. Information on each trading record which is considered useful is trading number, trading date, trading time, price, trade quantity, and transaction volumes.

We focus on the trading data from January 1, 2010 to April 30, 2010 inclusively. The first three month data would be treated as training data set, whereas the following one month data would be used as testing data set to measure the performance of the ANN model.

First, the data is sorted according to the trade number. Then, a macro is run to copy only one leg of the deal and paste it in a separate sheet. This is to ensure that no duplication caused by buying and selling records which are recorded as two instances in the raw data file.

The cleaned data is then split per 15-minutes periods to get the OHLC (Open, High, Low, Close) price for each period, of which then the technical indicators are generated. The technical indicators generated as the inputs are the Price Channel Indicator, the Adaptive Moving Averages, the Relative Strength Index, the Stochastic Oscillator, the Moving Average Convergence-Divergence, the Moving Averages Crossovers and the Commodity Channel Index. More information about these technical indicators can be found in [6].

This method is consistent with Dempster, et al. research on computational learning techniques using high frequency data from foreign exchange markets [3]. However, since the original data extracted from the IDX market database failed to record a reliable timestamp data, the data of each trading data are split evenly into 20 periods of 15-minutes interval, to reflect the total IDX trading hour of 5 hours per day. Also, since there is no information on bid-ask price for the respective trades, the open price of each period will be used as trading price.

During the course of data preparation, there have been thoughts on whether additional financial data which are affecting the IDX, such as the Consumer Price Index (CPI), the Bank Indonesia reference rate (BI rate), or daily USD against IDR foreign exchange rate, should be included in the model. However, there will be a significant time difference between the occurrence of those data with the time frame of high frequency data. If they should occur, then they would affect the whole intra-day data. Thus we suspect that they have minimal effects to the prediction results. Due to this reason, those financial data will not be incorporated into our model.

3 Problem Solution

As the model is built with the intention as an agent to intra-day trading predictor, there is a need to balance between the numbers of computation effort with the speed of the execution. Choosing the right amount of hidden layers in the model can be tricky. According to Cybenko [12], for a continuous function with limited set of discontinuities, a single hidden layer should be sufficient to an ANN model. Because the characteristic of the data which is being used in this study fits the definition, then only one hidden layer will be used in this model. Figure 1 shows the ANN which is going to be used in the simulation.

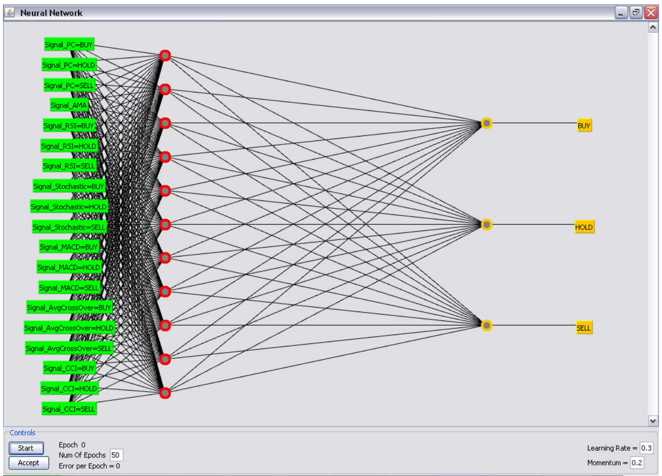

Figure 1. Hidden Layers and Nodes in the Simulation Model

The following steps are performed in building the ANN model. Firstly, the training data alone are going to be feed into the model, and then testing will be done on the training data itself. By doing so whilst increasing the number of epoch, the model will learn and resulting in the reduced error rate. This is done to obtain a proper number of neurons in the hidden layer while making sure that the ANN still can learn from the data.

Secondly, the training data is split into two parts, with one big part of about 66% of the data is treated as actual training data, and the rest are treated as the testing data. Then again, the model is run while varying the number of epoch, to the point that the error rate will increase at a certain point. This point will be marked as the over-fitting point, which is a character of ANN modeling. There is no correct formula to calculate the exact point where the over-fitting occurs, so it will have to be tested in a trial and error basis.

Finally, after finding the number of epoch which results in over-fitting, the model is run using a ten-fold cross validation to arrive in a robust model which has sufficient training and ready to run the simulation.

The simulation will be using Weka, a GNU Public License software for Machine Learning which is developed by the Department of Computer Science, University of Waikato, New Zealand. The function to be used is the ANN's MultiLayerPerceptron, which is using the back propagation method.

4 Experiment Results

There are two types of benchmark which are going to be used to check the performance of the ANN model. The first one is the naïve buy-and-hold strategy, this portfolio will only take on position once by buying the stock at the beginning of the period and selling it at the end. Hence, the return of this strategy would therefore be the difference between the prices at the beginning of the testing period to the end. The second one is the maximum profit profile. This would be the ideal portfolio in which all of the trades are 'won', thus resulting in the maximum possible return for each trades. The maximum profit is calculated by comparing the difference between the highest and lowest prices of the next 5 trades with the open price of each session.

The naïve Buy-and-Hold strategy gives a pretty good result as shown in Table 1. We can conclude that even with a very passive portfolio management, by naively buying and holding the instrument during the testing period, will result in relatively good return with only 2 stocks, BMRI (Bank Mandiri) & TLKM (Telekomunikasi Indonesia), losing their value. The other 7 stocks give a positive return on investment (ROI) with 4 stocks actually beat the Jakarta composite index (JKSE).

Next the ideal maximum profit profile is shown in Table 2. Investment indicates the lowest price of each stock in the first five trade periods. The result of the maximum profit profile is very good, all with more than 50% ROI over the course of the testing month.

Then the model is tested to find the over-fitting point. After the parameter has been setup to use 1 hidden layer with learning rate of 0.3 and momentum of 0.2, the training data is then feed into the model to find the over-fitting point. In the first run, the model is trained on itself while on the second run, the training data is split into two at 66% separation. After that the model is run by varying the epoch and we noted the change in mean squared error (MSE) and plotted into a graph, as can be seen in Figure 2.

Table 1. Result of the Naïve Buy-and-Hold Strategy

Stock Ticker	Start of Period	End of Period	Difference	ROI
ADRO	1,970.00	2,200.00	230.00	11.68%
ASII	42,400.00	47,150.00	4,750.00	11.20%
BMRI	5,300.00	5,800.00	500.00	9.43%
ELTY	240.00	235.00	(5.00)	-2.08%
INDF	3,750.00	3,900.00	150.00	4.00%
INTP	14,300.00	15,800.00	1,500.00	10.49%
TLKM	8,050.00	7,850.00	(200.00)	-2.48%
UNSP	490.00	500.00	10.00	2.04%
UNTR	18,500.00	19,500.00	1,000.00	5.41%
JKSE	**2,777.70**	**2,971.25**	**193.55**	**6.97%**

Table 2. Maximum Profit ROI Profile

Stock Ticker	Investment	Net Profit	ROI
ADRO	1,730.00	1,710.00	98.84%
ASII	42,400.00	37,305.00	87.97%
BMRI	5,300.00	5,000.00	94.34%
ELTY	240.00	225.00	93.75%
INDF	3,750.00	2,500.00	66.67%
INTP	14,300.00	12,300.00	86.01%
TLKM	8,050.00	4,285.00	53.23%
UNSP	490.00	380.00	77.55%
UNTR	18,500.00	14,350.00	77.57%

By checking at the graph in Figure 2 and the result values, we can conclude that the optimum epoch for the model is at approximately 50 epochs. This relatively low number maybe due to the fact that the huge volume of training data helps the model to learn earlier.

The model can now be applied to run the simulation. The necessary training data and testing data are then loaded into the simulator. The parameter of the simulation is set to be identical with the parameter used in the over-fitting test, with epoch set at 50.

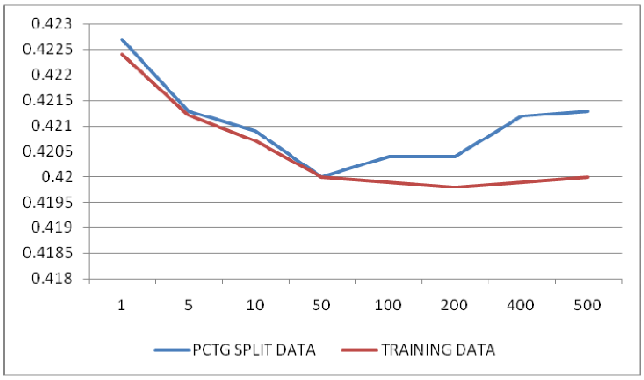

Figure 2. Over-Fitting Test Result

Table 3 shows the simulation results. We can see that the simulation gives varying results among the testing data, with prediction for ASII (Astra International) gives the lowest correctness in predicting the output, and ELTY (Bakrieland Development) gives the highest. However, our concern is more into the resulting trading signal when applied to the actual trading simulation.

Table 3. Simulation Results

Dataset	% Correct	MEA	RMSE
Final-TrainingData	62.17%	0.3564	0.4224
ADRO_TestData	70.00%	0.2819	0.3918
ASII_TestData	43.20%	0.4005	0.4704
BMRI_TestData	59.05%	0.3605	0.4358
ELTY_TestData	80.48%	0.2189	0.3378
INDF_TestData	54.52%	0.3524	0.4337
INTP_TestData	50.71%	0.3959	0.4594
TLKM_TestData	64.52%	0.3154	0.4142
UNSP_TestData	73.57%	0.2658	0.3798
UNTR_TestData	49.90%	0.3999	0.4640

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Table 4 shows the results of applying the trading signals into the open price per trading period. The results straight out of the model needs adjustment, as in some cases the model failed to sell off the stock before the end of the period. As a result, there are some negative ROIs due to the long position. Hence, in order to get a normalized results for the model, these long positions may be forcefully closed because it has come to the end of the testing period choosen deliberately for this research. Therefore, sell signals are forced on the last cycle of the testing period, giving the final portfolio a clean position on the stocks and cash from the profits of the trades minus the initial investment.

We can now have a better understanding on the performance of the model. In overall, the model gives varying result of achievement when compared to the ideal scenario of maximum profit profile.

Summarizing the outputs, Figure 3 shows the ROI comparison between the models. The simulation results show that the application of ANN on the model to determine trading signals based on multiple popular technical indicators is a promising framework.

Table 4. Simulation Trading Performance After Adjusment

Dataset	Trading Performance		
	Max Profit	Result	% Result
ADRO_TestData	1,710.00	475.00	27.78%
ASII_TestData	37,305.00	6,800.00	18.23%
BMRI_TestData	5,006.00	475.00	9.49%
ELTY_TestData	225.00	45.00	20.00%
INDF_TestData	2,500.00	250.00	10.00%
INTP_TestData	12,302.00	100.00	0.81%
TLKM_TestData	4,287.00	250.00	5.83%
UNSP_TestData	380.00	135.00	35.53%
UNTR_TestData	14,329.00	1,750.00	12.21%

5 Conclusion

The importance of studying intraday data become obvious as some recent studies in the financial market are suggesting that this is a popular trading style. However, there is still a wide gap of research subjects and methodologies, especially in the Indonesian financial market. Studies such as the use of the high frequency intraday data, using artificial neural networks or other machine learning techniques can surely bring benefits and new perspectives.

In this paper, we proposes an Artificial Neural Networks (ANN) model which feeds on inputs from popular technical indicators to predict trading signals. From the experiment results, it can be concluded that the artificial neural networks are indeed promising methods to develop forecasting tools to generate trading signals for intraday trading. The ANN model developed in this study performs better than the naïve Buy-and-Hold strategy, and in some occasions also performs better than the Jakarta composite index.

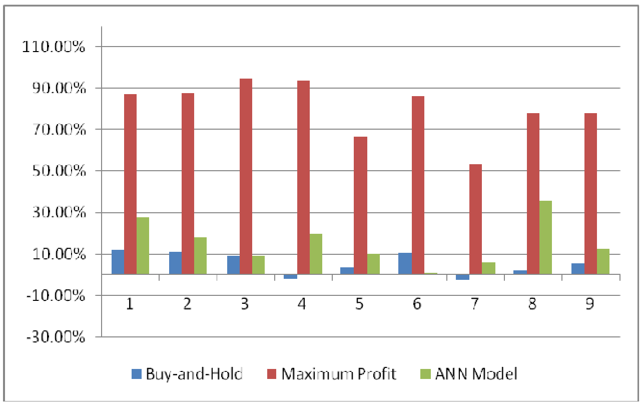

Figure 3. ROI Comparison Between the Models

Further studies may be done in the form of application of the methodology to a more specific stock, with the effort of simulating a bid and offer spread and incorporating the transaction costs.

Variations in the result of the ANN model in this study which caused by the carried long position of the trades can also hint for a study in which the position of the portfolio is also feed into the system. One can add a parameter to indicate whether it is carrying a long or short trades, how long can the agent hold a position, and must square the position before the testing period ends. Also, risk indicators such as the standard deviation of the position, how much of profit or loss can the agent hold before it must square off the position, can also be used to enrich the inputs.

Finally, there is also a proposal to add more rich data and information as suggested in [7]. This can be done, for example, by means of feeding relevant news, twitter feeds, RSS feeds, adding graphics or other multimedia content into the ANN system. An effort by Kurniady and Kosala [13] to include news into a machine learning scheme has shown a promising proof that the additional content helps the model to gain better performance, although the results has not been consistent.

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