Control Chart for Monitoring Stock Price and Trading Volume in Malaysia Stock Market

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Abstract. Traditional statistical control charts are rarely used as a tool to monitor the stock trading and portfolio analysis due to its capability of proving a buying, selling, or holding signal to the investor. Besides that, the normality assumption for a control chart is always violated due to the share prices and trading volumes are highly correlated. To overcome this problem, auto regressive integrated moving average (ARIMA) model can be integrated into the control chart scheme. In this paper, a moving limit ARIMA control scheme is developed to monitor both stock price and trading volume at the same time. A real-life stock exchange data has been used to demonstrate the effectiveness of the proposed control scheme as compared with the performances of the volume-weighted moving average (VWMA) and relative strength index (RSI) charts. The proposed control scheme shows better performance compared to VWMA and RSI charts.

Keywords: ARIMA model · Control chart · Stock price · Trading volume · Volume-weighted moving average

1 Introduction

Stock market represents a country's economy, financial status, and growth. A broad picture on the movement of the market or on a particular stock are always the main concern for most of the stock market trader. The detection of any upward or downward price trend is crucial for market traders in making trading decisions. To determine trading strategy, most of the market traders use technical charts, for example moving average convergence divergence, relative strength index, candle stick, smoothing moving average etc. In fact, market traders and quality controllers are relied on charts and both using chart to identify signals. Quality controllers use statistical control charts to detect a signal or possible assignable cause whenever the quality of a product is out of control. On the other hand, market traders use technical charts to detect a trend in making trading decision (buy, hold or sell the stock) in the market.

Statistical control charts are rarely explored as a charting technique in stock trading and portfolio analysis (Gandy 2012; Rebisz 2015). The lack of important information is the main concern where control charts not to be used in monitoring financial data (McNeese et al. 2002). Robert (1959) was first to suggest the use of control chart in

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studying market price levels and changes. Hubbard (1967) used logarithmic monthly values to construct control charts to determine the price trend thus compare with the gross national product and personal income trends. He identified ways to recognize signal for buying or holding stocks. Hubbard (1967) claimed that significant departures from the center line signals stock price overvaluation or undervaluation while small price fluctuates between the center line have no recognizable pattern and do not give any buy or sell signals to the market traders. Gandy (2012) used a wide range of different CUSUM control charts to detect changes in the performance of a credit portfolio. Dumiĉić and Žmuk (2015) used control chart for individual units, MR, EWMA and CUSUM control charts in monitoring performance of short-term stock trading in Croatia based.

Due to the non-normality and auto correlation constrain on stock trading data, control charts are seldom used on stock trading data in technical analysis. In this research, time series analysis will be incorporated into control chart. This new control charts can serve as an alternative technical analysis charting tools compare to other existing traditional technical charting tools such as trend line, candle stick, RSI, MACD, smoothing moving average etc.

2 Literature Review

Alexander (1961, 1964) was first introducing the filter trading rules. The filter trading rules is a sequence of buy-sell signals used to investigate stock price trends. Daily closing price is used to determine the buy-sell signals for an observed stock Buy signal is given if the closing price increases more than certain percentage from a subsequent low, while sell signal is given if the closing price decreases more than certain percentage from a subsequent high. Fama and Blume (1965), Dryden (1969), Sweeney (1988), Corrado and Lee (1992) and Sullivan et al. (1999) further developed and enhanced the rules. However, the filter trading rules only take stock price into consideration. Trading volume can be applied to further enhance the rules as trading volumes provide a measure of number of shares traded in a specific period. It is often overlooked but will be a powerful tool to maximize profit and minimize risk. The analysis of the relationship between trading volume and stock returns has received increasing attention from investors and researchers (Kaizoji, 2013). This is because many of them consider that stock returns might be predicted by trading volume. Kaizoji (2013) define return as the logarithmic daily price change whereas trading volume is defined as number of shares traded in a particular trading day.

Classical Shewhart control charts are measuring data without autocorrelation. Even a low degree of autocorrelation data will cause the Classical Shewhart control charts to be failed. Stochastic modelling of time series analysis is one of the ways to tackle the autocorrelation problem. Time series analysis is a theory of using mathematical statistic theory and random process in analyzing time series data. It is applying comprehensively in financial market. However, time series analyses are mainly used in forecasting and residuals testing in financial market. Rebisz (2015) and Dumiĉić and Žmuk (2015) claim that the control charts are not widely used in stock trading and portfolio analysis due to high rate of possible false alarms. They also claim that stock price is non-normally distributed and auto correlated. However, Žmuk (2016) introduce and develop additional statistical tools to support the decision-making process in stock trading. Žmuk (2016) overcome the autocorrelation problem by applying the ARIMA(p, d, q) model on the residual-based control chart. He shows that the residual-based EWMA and residual-based CUSUM control charts approach resulted higher portfolio profit in stock trading compared to pick and hold strategy. He also applies ARIMA model on the residual-based control chart for residuals testing. Zhang et al. (2009) use time series model to build the stock price forecast model for Shanghai Composite Index. Mondal et al. (2014) use ARIMA model to forecast the Indian stock for various sector and examine the accuracy based on different span of period data. They achieve more than 85% accuracy by using ARIMA model in forecasting the stock price for all the sectors. Ariyo et al. (2014) show that the ARIMA models are useful in predicting stock price on short term basis.

3 Methodology

In this research, we will apply ARIMA model on both the stock price and trading volume, respectively. Dumiĉić and Žmuk (2015) claim that the stock prices are non-normally distributed and auto correlated. Mohamad and Nassir (1995) find out that absolute price changes have a strong relationship with trading volume. They also claim that there is a lagged relationship interaction between price change and trading volume. Ying (1966) and Tauchen and Pitts (1983) findings also suggest that the absolute price changes are positively correlated to trading volume. In order to overcome the shortages, we used ARIMA model to build the control chart for stock price. This is because ARIMA model is widely used in modelling auto correlated data. Box et al. (2016) also states that ARIMA model can well fitted the non-normal and auto-correlated data. The autoregressive (AR) part of ARIMA able to forecast future behavior based on available past data. The moving average (MA) part take into accounts for a short-run of autocorrelation by forecast future behavior based on the mean of past observation. The integrated (I) part will turn the nonstationary data to stationary by compute difference between consecutive observations and the differencing process can be performed more than once. The purpose of these features is to make the model can fit auto-corelated and non-normal data as well as possible. ARIMA (p, d, q) model has the following general structure:

$$\boldsymbol{\Phi}_D(\boldsymbol{B}) \cdot \nabla^d x_t = \boldsymbol{\theta}_a(\boldsymbol{B})\varepsilon_t \tag{1}$$

where

$\boldsymbol{\Phi}_p(\boldsymbol{B}) = \left(1 - \varphi_1 B - \varphi_2 B^2 \ldots - \varphi_p B^p\right)$ is p-th order autoregressive polynomial,
$\boldsymbol{\theta}_a(\boldsymbol{B}) = \left(1 - \theta_1 B - \theta_2 B^2 \ldots - \theta_a B^q\right)$ is q-th order moving averages polynomial,
$\nabla^d = (1 - B)^d$ is the d-th difference operator, B is back shift operator as $B \cdot x_t = x_{t-1}, \ldots\ldots \varphi_1, \ldots \varphi_2, \ldots\ldots\ldots \varphi_p \cdot 1$ is the parameters of autoregressive model, $\theta_1, \theta_2, \ldots, \theta_Q$ is the parameters of moving averages model, ε_t is an error term, usually a white noise with normal distribution, $N(0, \sigma^2)$.

The 100(1 – k)% prediction interval for h period ahead is given by

$$\hat{x}_{t+h|T} \pm z_{kj}\widehat{\sigma_h} \tag{2}$$

where $0 < k < 1$

$\hat{x}_{t+h|T}$ is the forecast value for h period ahead,

$z_{k/2}$ is the two tailed k percentage point of a standard normal distribution, $\hat{\sigma}_h$ is the estimated forecast standard deviation.

We use the $100(1-k)$ % prediction interval of 1 period ahead as the upper and lower control limits (UCL, LCL) for our ARIMA control chart. Thus, the UCL and LCL are respectively have the form:

$$UCL = \hat{x}_{t+1|\tau} + z_{k/2}\hat{\sigma} \tag{3}$$

$$LCL = \hat{x}_{t+1|T} - z_{k/2}\hat{\sigma} \tag{4}$$

where

$\hat{x}_{\tau+1|\tau}$ is the 1 period ahead forecast value, $\hat{\sigma}$ is the standard deviation of the residuals, $z_{k/2}$ is the two tailed k percentage point of a standard normal distribution. The value of k could be set as the sensitivity of the ARIMA control chart. The sensitivity of ARIMA control chart decrease as k increases. Trading volumes for a particular stock normally are millions and depends on the total number of shares issued by the company. Thus, to standardize the trading volume, we will use stock participation rate instead of using trading volume. The participation rate is calculated as follow

$$participation\ rate = \frac{trading\ volume\ on\ a\ particular\ day}{total\ number\ of\ shares\ issued} \times 100\% \tag{5}$$

Relative Strength Index (RSI) was first introduced by Wilder (1978). RSI is a popular oscillator charting tool in technical analysis. Wilder (1978) obtained the buy and sell signal with RSI thresholds 30 and 70. He claimed that buy signal is obtained when RSI return to 30 from below and sell signal is obtained when RSI return to 70 from above. The equation for the RSI is as follow:

$$RSI_t = 100 - \left(\frac{100}{1 + RS}\right) \tag{6}$$

$$RS = \frac{Average\ of\ 14 day's\ closes\ UP}{Average\ of\ 14 day's\ closes\ DoWN} \tag{7}$$

Volume-weighted moving average (VWMA) is an average of a period of past closing prices with the weight depends on the volume of that period. Thus, the stock price with heavy trading activity will be given more weight than prices with light trading activity. Generally, we need to compute VWMA with different time period. VWMA with shorter duration is called short-term VWMA whereas VWMA with longer duration is called long-term VWMA. Buying and selling signal can be determined while the two VWMA line crossed. If short-term VWMA crosses the long-term VWMA from below means that the stock price is in uptrend and thus it is a buy signal. If short-term VWMA crosses the long-term VWMA from above means that the stock price is in downtrend and thus it is a sell signal. Volume-weighted moving average is chosen because it is a popular and easy chart in technical analysis. The equation for n-days VWMA is as follow:

$$n - \text{ days } VWMA = \frac{\sum_{t=1}^{n} v_t P_t}{\sum_{r=1}^{n2} v_t}. \quad (8)$$

where V_t is the traded volume at time t, P_t is the stock price at time t.

4 Result and Discussion

FBM KLCI constituent companies' stock price has been chosen for analysis. This is because FBM KLCI composed the 30 largest capital listed companies on Bursa Malaysia. The stock price for large-cap or blue- chip companies normally having smaller volatility and stable trading volume. Thus, any sudden change in stock price or volume might indicate an alert to investor. Besides, all the KLCI component companies have minimum of 15% free float and liquid enough to be traded as stated in the Ground Rules set by Bursa Malaysia. We apply the ARIMA control chart on a few of the FBM KLCI constituent companies, but we only discuss on one of the selected companies which is Genting Malaysia Berhad.

The UCL and LCL in constructing the control charts are using 99% prediction interval. The chart of the stock price, participation rate, UCL and LCL of Genting Malaysia Berhad has shown below. The control charts show that most of the time the stock prices and participation rates are between the UCL and LCL. The stock price moves above the UCL or move below the LCL will be consider as assignable causes. This assignable causes could be trading signals. When the stock price is above UCL indicate a buy signal and when the stock price is below the LCL indicate a sell signal. When participation rate is above the UCL indicate as unusual market behavior. Stock prices for year 2019 are use as training set to build the model while the stock prices for year 2020 are used as validation set in monitoring process. Below are the steps in building the control chart:

1. Firstly, use the stock prices (or trading volume) for year 2019 to build an ARIMA model using *auto.arima* function in R-program. *Auto.arima* function will return the ARIMA model with the least AIC values as the model.
2. Next, using the *forecast* function in R-program, compute the 99% prediction interval of the forecast value for 1 period ahead based on the selected ARIMA model.
3. The upper and lower bound of the prediction interval will be the UCL and LCL.
4. The stock price of next trading day is examine based on the UCL and LCL.
5. Trading signal is said to be detected when the stock price is above UCL or below the LCL.
6. Repeat Step 2 to Step 5 until the end of the validation set.

Figure 1 shows the ARIMA control chart for stock price of Genting Malaysia Berhad in year 2020. We can observe a few trading signals in Fig. 1 (buy signal on trading day 101, 110, 149 and 209; sell signal on trading day 42 and 51). Figure 2 shows the ARIMA control chart for participation rate of Genting Malaysia Berhad with signals on trading

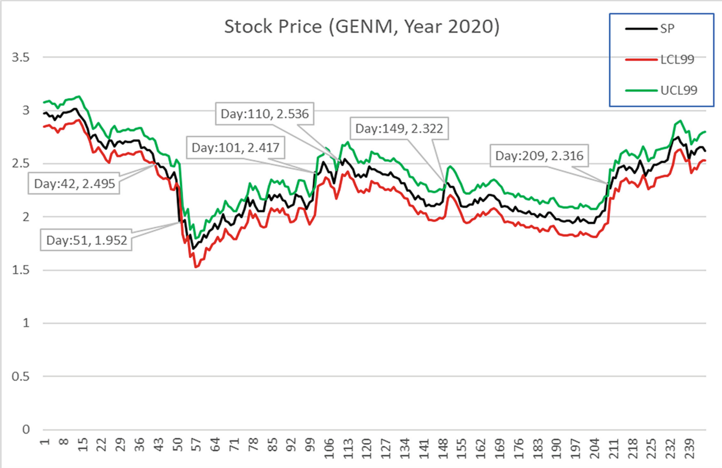

Fig. 1. ARIMA control chart for stock price of Genting Malaysia Berhad in year 2020.

day 155 and 209. These two signals are important as they show strong market force on the particular trading days. Figure 3 shows the RSI chart which indicate the overbought (above RSI = 70, green line) or oversold (below RSI = 30, red line). For VWMA chart, the 10-days volume-weighted moving average (blue line) and 60-days volume-weighted moving average (orange line) technical charts are show in Fig. 4 as a comparison. For weighted moving average chart, signal is identified when the blue line and the orange line crossover. It is a buy signal if the blue line crosses the orange line from below (i.e., trading day 86 and 210). Meanwhile it is a sell signal if the blue line crosses the orange line from above (i.e., trading day 19 and 138).

From Fig. 4, we notice that the buy and sell signals provided by the VWMA chart are alternating which means one sell signal followed by one buy signal. This will limit the market traders to do multiple of same trading actions (multiple buy or sell actions) within a specific time period. However, ARIMA control chart able to give multiple signals to guide the market traders in execute multiple trading action (consecutive sell signals on both day 42 and 51 and consecutive buy signals on day 101, 110, 149 and 209). This might be more useful for the market traders to have more various of the trading strategic in order to reallocation their portfolio. On the other hand, RSI chart always shows overbought (RSI fluctuate around 70) after trading day 130 which always indicate a sell signal. Besides that, there is no buy signal generate by RSI chart along year 2020. All this might result the traders miss out the opportunity to buy/hold the stock that shows an uptrend after trading day 200.

Figure 2 recorded a high participation rate (1%) and break the UCL in ARIMA Chart on trading day 155. The participation rate even double (2%) on trading day 209 and recorded a highest rate for the year 2020. The break of UCL for the participation rate on trading day 209 will strengthen the buy signal on trading day 209 obtained from Fig. 1. The signal on trading day 209 from both ARIMA control chart provide signal one day earlier than VWMA chart also shows that ARIMA control chart perform better than VWMA chart.

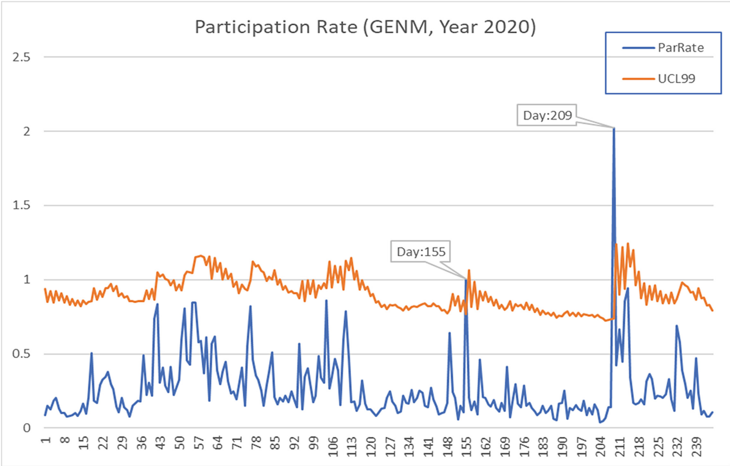

Fig. 2. ARIMA control chart for participation rate of Genting Malaysia Berhad in year 2020.

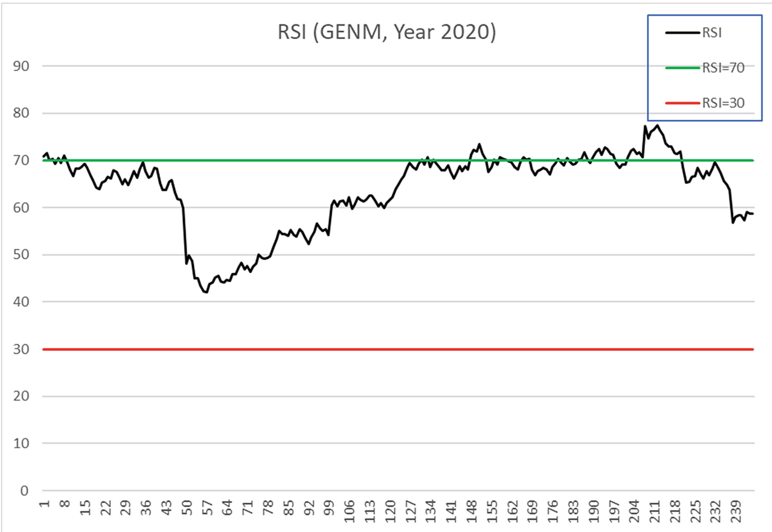

Fig. 3. RSI chart for Genting Malaysia Berhad in year 2020.

On 16 March 2020, Malaysia government announce a Movement Control Order (MCO) to be implement started on 18 March 2020 due to the outbreak of Covid-19 pandemic. This incident resulted that the market traders are in panic sell immediately after the announcement. From Fig. 1, ARIMA control chart able to provide a sell signal immediately after the announcement (trading day 51, 16 March 2020). This shows that ARIMA control chart is a very efficient technical chart.

One limitation of this ARIMA control chart is that it only can detect the signal after we have the closing price of the day where any of the news has been reflected on the

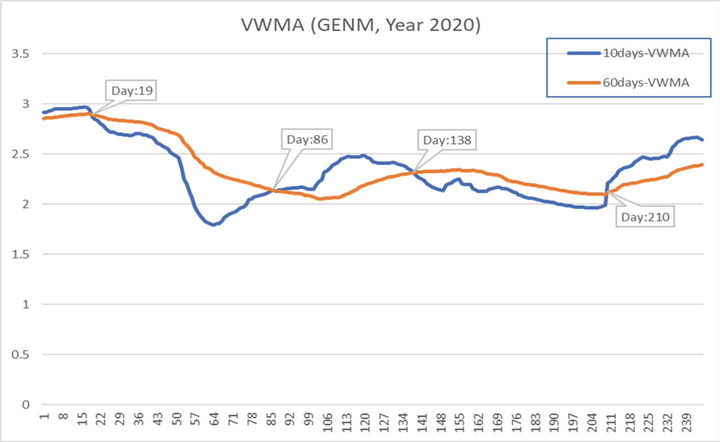

Fig. 4. 10-days and 60-days Volume-Weighted Moving Average for Genting Malaysia Berhad in year 2020.

share price. To overcome this problem, we can use data with shorter period for example, share price every hour or even every minute to better capture any news incorporate to the changes of share price. The downside of this implementation is that the model needs to handle huge data set. Limitation of the computer memory and time constrain will be the main concern on this implementation.

5 Conclusions

In conclusion, both stock price and trading volume (participation rate) ARIMA control chart have a comparable result in generating trading signals. ARIMA control chart can serve as an alternative charting tool in monitoring and generating signal in stock market. However, there is not any global economics event that happened during the examination period. Thus, the ability of the ARIMA control chart to capture the effect of global issues is needed for further investigation.

This ARIMA control chart can be improved by using interactive control chart i.e., combining stock price and trading volume incorporate into a single control chart. Besides, this research can be further enhanced by applying multivariate ARIMA model into the control chart and monitor stock price and trading volume together in one control chart. We can also further implement this ARIMA control chart other derivative market such as warrants, options, foreign exchanges, commodities, cryptocurrencies etc.

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