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MODELLING OF MOVING CENTERLINE EXPONENTIALLY WEIGHTED MOVING AVERAGE (MCEWMA) WITH BOOTSTRAP APPROACH: CASE STUDY ON SUKUK MUSYARAKAH OF RANTAU ABANG CAPITAL BERHAD, MALAYSIA

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Abstract: *Sukuk Musyarakah is known as a debt instrument of Islamic securities which currently issued in Bursa Malaysia. The uniqueness of this sukuk is a pre-agreed price between Musyarakah partners will be equivalently to the face value of sukuk, if only the sukuk yield no profit. In terms of returns, this sukuk complies with nature of Syariah-compliant securities, where the fixed return and the element of interest are prohibited. Similar to conventional securities, the non-fixed returns usually autocorrelated and categorised as a dependent data. This kind of special data has been getting more attention whether in financial fields or statistical fields. Unfortunately, the research related to monitoring autocorrelated data of sukuk seems lack of attention compared to conventional securities. Thus, in this study an application of Moving Centerline Exponentially Weighted Moving Average (MCEWMA) chart is used to monitor autocorrelated returns of sukuk Musyarakah. In Statistical Control Chart, the chart has given extensive research on monitoring volatility of security investment. However, an internal issue of MCEWMA chart detected where it is influenced by inaccurate estimation whether on base model or the limits itself, due to large error and high probability of signalling out-of-control process for false alarm. In order to solve this problem, a bootstrap approach is hybridised into the based MCEWMA model. The objectives of this approach are to reduce error value of base model using sampling with replacement method and introduce a new modelling of Bootstrap MCEWMA chart. The application of hybrid model is on sukuk Musyarakah which was issued by Rantau Abang Capital Berhad. The performance of hybrid model and original model are tested by efficiency of point estimator, interval estimator and false alarm. From the result, Bootstrap MCEWMA model is more efficient compare to MCEWMA model due to smaller error value, shorter length of interval and smaller false alarm. Thus, it is*

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statistically proven that the bootstrap method fixed the inaccuracy whether in estimating and monitoring of MCEWMA chart.

Keyword: *Bootstrap, MCEWMA chart, sukuk Musyarakah, point estimator*

1. INTRODUCTION

Volatility plays an important role in providing useful evidence on either risks or returns of securities over a period of time of its issuance. In financial, the high volatility is refered to be the dramatical changes of securities price in a short-term period. This changes give an initial impression of securities where it is said to be more risky and probably give a high returns. Typically in reality, the higher-yielding securities report and remain strong in financial markets are conventional securities, see for example Gonza'lez-Rivera, Lee and Mishra (2004); Lee and Saltoglu (2010); McMillan and Kambouroudis (2000). However, an interesting situation is arisen, where an alternative securities of Shariah-compliant concept is introduced in financial field. This kind of securities actually are based on finance certificate or known as Islamic bon where it issuance synonymous with Asia countries such as Malaysia. Islamic bon, or specifically named as sukuk is an investment instrument where its modus operandi based on prohibition of any kind of transaction involving usury, interest and fixed returns. Since it was introduced in Malaysia, early 2000, the most famous instruments of sukuk issued are Ijarah, Baitahamal Ajil (BBA) and Musyarakah which represent the transaction of leasing, morging and equity investment respectively. Despite of 15 years of issuance in Malaysia market, the study is still limited to introduction of sukuk concepts and the comparison of sukuk instrument and conventional bon (Cakir & Raei, 2007; Godlewski, Turk-Ariss, & Weill, 2013). A need of serious study on exploring the volatility of sukuk instrument had to be done, for example, a serious observation on fluactuation of sukuk price, where in the reality, such study is still remains to be the undiscussion topic.

Moreover, in statistical process control (SPC), the monitoring process of volatility is to observe the changes of volatility point in control chart. Basically, the changes occurred when the chart detects the existence of any point of volatility that is out of limit control and it eventually creats a shift observation process from in-control to out-of-control. The volatility points are said to be non-random and the observed information of current data is dependent and correlated to previous data (Montgomery, 2005; Nembhard & Nembhard, 2000; O'shaughnesssy & Haugh, 2002). This nature of data, actually does not meet the basic assumption of standard control chart. As for previous study, the standard chat did not applicable to monitor the correlate data, where it seems to detect several dubious point of out-of-control limit and eventually caused the unreliable chart due to its false representation of shift process. Therefore, an alternative chart have been proposed by Montgomery and Mastrangelo (1991) namely Moving Centerline Exponential Weighted Moving Average, MCEWMA chart. This chart is devoted to monitor the autocorrelated data and it most applied in financial and engineering field (Montgomery, 2005; Nembhard & Nembhard, 2000).

Despite of its advantages of monitoring the autocorrelated data, an uncertainty influence of efficiency estimation exists in MCEWMA chart, i.e. similar issue in any standard chart in SPC. The cause of this issue comes from MCEWMA base model estimation, where it is influenced by its inherent residual in the model. Basically, the large residual would probably result the dubious, or false, estimation of base model and eventually reduce the effectiveness of base model. Furthermore, the impact of inaccuracy of estimating will cause the inefficiency and invalidity of chart monitoring process

Objective of the Study

Most of previous studies covered the discussion of various solution of inaccuracy estimation issue and the effectiveness of base model, i.e. or model, and control chart, see for example Castagliola and Taung (2005); Khoo, Teh, Ang, and Ng (2011); Ramjee, Crato, and Ray (2002). One of the popular solutions is using bootstrap method as mentioned by Chatterjee, Chand, and Tang (2009); Edopka and Ogbeide (2013); Teyarachakul, Chand, and Tang (2006), where these studies hybridised the bootstrap approach in to the limit control of Cumulative Sum chart (CUSUM) and EWMA chart. Meanwhile, in financial field, a number of papers have been proposed the hybridization of standard model with bootstrap method, see for example Chiou, Hung and Hseu (2008); Lee, Chiu, and Cheng (2010); Pascual, Romo, and Ruiz (2006). These studies have shown showed that the bootstrap method helped to provide accuarete estimation where it was eventually improved the effectiveness of original model and chart.

As introduced by Efron in early 1979, the bootstrap is the alternative non-parametric method for jackniffe where it is basically a common approach to statistical inferens based on the construction of sampling distribution of statistic which resembles the real sample distribution used. The term of sampling here means the sampling with replacement method from real sample. The most advantage of bootstrap method is that it does not hold any assumption of distribution, such as normal distribution and skewed distribution in a certain population. This kind of advantage eventually provided a solution of uncertainty of accuracy estimation, especially in sample data with a large scale of population (Efron, 2003; Efron & Tibshirani, 1993). The advatange of using boortstrap method and the interesting results found from previous studies have motivated this study to hybrid the bootstrap method into model of MCEWMA chart. Therefore, the main objective of this hybridisation is to reduce the error value that inherent in MCEWMA model using bootstrap method and eventually introduces a new modelling of Bootstrap MCEWMA, namely, BMCEWMA chart.

2. LITERATURE REVIEW

The MCEWMA control chart is often reviewed in the application of dependent sample data or autocorrelation data. For example, Nembhard and Nembhard (2000) used this chart as Moving-centerline Demerit (MCD) for monitoring process data where the product nonconformities contained varying degree of severity. This chart seems to give an exclusive efficiency in detecting any point of autocorrelation data which have exceeded the control limit. Basically, the limit of this chart is based on the expected of one-step-ahead error. Therefore, the control limit gives an advantage to the chart for monitoring the independent and identically distribution, i.i.d. In the time series forecasting, Ramjee, Crato, and Ray (2002) stated that any chart which used the expected one-step-ahead error for its limit control, specifically used to test the shift level for long term observation of dependet data.

It is generally known that investment observation data use in the volatility estimation, usually can be categorised as dependent data. This nature of data basically met the characteristic of sample data for bootstrap method. Tong, Chang, Jin, and Saminathan (2012) mentioned that the nature of sample data used in bootstrap method should be i.i.d. Compared to the time series data, it is usually shows that a different patterns, as it often non-random, dependent and correlated, i.e. observation data often showed an existing relationship between current observation with previous observation. Despite of the nature issue, however, it is not a major problem because the bootstrap method of standard error is the suitable solution to analyse the distribution of dependet data. This method was introduced by Efron dan Tibshirani (1993) as for alternative solution for handling the non-i.i.d sample data. The bootstrap procedure uses the sampling with replacement method, where the drawing process is randomly done to get complete sets of bootstrap sample.

In SPC, the bootstrap method is found to be hybridised in the limit control, as for example the limit of Shewhart, CUSUM and EWMA chart. The bootstrap approach is used because of its main advantage, where the assumption of observation data distribution is disregarded. For example from previous study, i.e. Teyarachakul, Chand, and Tang (2006), the bootstrap method was hybridised to the limit of Shewhart chart and the applied data came from unknown distribution. The aim of the hybridised is to reduce the error value in limit estimation when the unknown distribution equated either to normal or non-normal distribution.

Furthermore, the performance of bootstrap model and the whole chart are estimated in this study, where the effectiveness and efficiencies of the developed model and its chart can be proved statistically. The estimation of performance is encourage by several previous studies such as Apley and Lee (2003); Khoo, Teh, Ang and Ng (2011); O'shaughessy and Haugh (2002) where the effective model is based on mean square error (MSE) estimation and root mean square deviation (RMSD) estimation. While for efficiency of the chart, those studies used the average run length estimation (ARL_0) and false alarm rate for in-control-process.

For completing this study, a set of real data is applied into the developed model and its chart. The real data is daily returns of Islamic securities, where this kind of securities is understand to has none fixed returns and no alements of usury. In terms of research field, the sukuk data is not well explored by reaserchers. Basically, the scopes of the previous studies only focus on introduction concepts, returns comparison of sukuk and conventional bonds. As for example, Cakir and Raei (2007) have compared the maximum lost generated by sukuk and conventional bonds using value-at-risk (VaR) estimation. The result of this study is expected, where sukuk has lower value of VaR compare to conventional.

3. RESEARCH MODEL

MCEWMA Control Chart

In this study, the mean process will be considered in monitoring the individual observation of X_1, X_2,…,X_n with the initial assumption, i.e. it is dependent distributed and correlated. Thus, MCEWMA-base model and its residual are given by

$$W_i = \lambda x_i + (1-\lambda)W_{i-1},\ \text{with} \tag{1}$$

$$e_i = x_i - W_{i-1},\ i = 1,2,\ldots,n \tag{2}$$

where $W_0 = \mu_0$ and x_i refers to the i-th observation data. Meanwhile $\lambda \in (0,1)$ and instead of minimizing sum of squares of one-step-ahead prediction error (SSE) for base Model (1), an alternative approach used in this study to choose the value of λ. The method is proposed by Cox (1961) and known as optimizing the value of λ. By using base Model (1) as the centreline, the one-step-ahead prediction limits are

$$CL_{xi+1} = W_i \pm L_e \sigma_e \tag{3}$$

where L_e is denote as control limit parameter and selection of L_e is dependent on the value of λ used. For in-control process, 3 sigma formally use for high value of

λ such as 0.90 to get $ARL_0 \approx 500$ (Montgromery, 2005). While σ_e in Equation (3) is denote as standard deviation of one-step-ahead error.

BMCEWMA Control Chart

The main focus of hybridization is on bootstrapping the Model (1) using sampling with replacement method of residual Model (2). Due to this bootstrapping, a new model, i.e. bootstrap MCEWMA (BMCEWMA) with one-step-ahead control limit can be introduced and written as follows:

$$\hat{W}_i^B = \hat{\lambda} x_i^B + \left(1-\hat{\lambda}\right) \hat{W}_{i-1}^B, \tag{4}$$

$$CL_{x_{i+1}^B} = \hat{W}_i^B \pm 3\sigma_{e^B} \tag{5}$$

where σ_{e^B} is differences of bootstrap data and BMCEWMA model. Moreover, residual estimation for hybrid model can be given by

$$\hat{e}_i^B = x_i^B - \hat{W}_{i-1}^B \tag{6}$$

where x_i^B is bootstrap data.

ESTIMATOR OF MODEL PERFORMANCE

Interval Estimator

The performance of base model for hybrid chart, BMCEWMA estimates using interval estimator where two standard intervals (i.e. normal and student's-*t*) and bootstrap estimator, i.e. bias corrected and accelerated (BCa) has been considered to be use. These different kinds of estimator are holding a same theory, where it is understand that the shortest length of interval estimation shows the better performance of model tested. In this study, the main focus of tested model is BMCEWMA model.

Lower, $\hat{\theta}_B$ and upper, $\hat{\theta}_A$ for standard interval estimator is be given by

$$\left\lfloor \hat{\theta}_B, \hat{\theta}_A \right\rfloor = \left\lfloor \hat{\theta} - z^{\alpha} \bullet \hat{S}E, \hat{\theta} + z^{\alpha} \bullet \hat{S}E \right\rfloor, \tag{7}$$

$$\left\lfloor \hat{\theta}_B, \hat{\theta}_A \right\rfloor = \left\lfloor \hat{\theta} - t_{n-1}^{\alpha} \bullet \hat{S}E, \hat{\theta} + t_{n-1}^{\alpha} \bullet \hat{S}E \right\rfloor \tag{8}$$

where Equation (7) and Equation (8) are normal and student's-t respectively. For normal interval, z^{α} represent confidence interval of 100(1-2α)% for standard normal distribution. As student's-t interval, t_{n-1}^{α} is percentage of α with degree of freedom n-1 and the value of α is consider to be equal to 0.05. While $\hat{\theta}$ and $\hat{S}E$ for both equations are the estimation of mean sample bootstrap and the standard error respectively.

One of bootstrap interval estimator is familiarly known as BCa. The lower and upper for (1-2α) 100% BCa interval is basically written as follow:

$$\left\lfloor \hat{\theta}_B, \hat{\theta}_A \right\rfloor = \left\lfloor \hat{\theta}^{\alpha_1}, \hat{\theta}^{\alpha_2} \right\rfloor \tag{9}$$

where the data is completely from bootstrap sample. The value of α_1 and α_2 can be estimated using these equation below:

$$\alpha_1 = \Phi\left(\hat{z}_0 + \frac{\hat{z}_0 + z^{\alpha}}{1 - \hat{a}\left(\hat{z}_0 + z^{\alpha}\right)} \right), \quad \alpha_2 = \Phi\left(\hat{z}_0 + \frac{\hat{z}_0 + z^{(1-\alpha)}}{1 - \hat{a}\left(\hat{z}_0 + z^{(1-\alpha)}\right)} \right) \tag{10}$$

where $\Phi(\cdot)$ is the standard cumulative distribution function, a represent the accelerate value and z^{α} refer to the normal confidence interval with α = 0.05. When the both value of â and z_0 is equall to zero, thus

$$\alpha_1 = \Phi(z^{\alpha}) = \alpha, \quad \alpha_2 = \Phi(z^{1-\alpha}) = 1 - \alpha \tag{11}$$

Point Estimator

For point estimator, the performance of base model of BMCEWMA chart can be described in terms of effectiveness of model estimation on MSE and RMSE estimation. By following the basic theory of the best performance of model, the introduced model in this study should give the smallest error value on both point estimator. Thus, the point estimator which considered to be used in this study is given by:

$$MSE = \frac{\sum_{i=1}^{N} \left[e_i^B - E(e^B) \right]^2}{N} \quad RMSE = \sqrt{\frac{\sum_{i=1}^{N} \left[e_i^B - E(e^B) \right]^2}{N}} \tag{12}$$

where e_i^B refer to the residual sample data of hybrid model (10), while $E(e^B)$ is the average of e_i^B. Thus, for both Equation (13), it can simply describes to be the differences of true error, e_i^B with expected error, $E(e^B)$.

False Alarm

Despite of standard estimation of model performance, the control chart has tested on its effectiveness on providing smallest Type 1 error for in-control process. A familiar name for this Type 1 error is known as false alarm rate and it occurs when the chart detects a shift of out-of-control point even though it is still in control process, i.e. a mistaken shift detected (Khoo,Teh, Ang, & Ng, 2011). Therefore, the smallest false alarm rate means the probability of signalling out-of-control process is small.

Theoretically, false alarm rate for mean $\mu_0 = 0$ is small or approaching the target value of false alarm (Khoo,Teh, Ang, & Ng, 2011). In this study, the target value is considered equal to 0.002, i.e. the value of ARL_0 is considered to be 500 as used by Montgomery (2005).Therefore, the estimation of false alarm rate can be given by:

$$FA = \frac{1}{ARL_d} \tag{13}$$

where ARL_d refers to the average value of average run length for out-of-control signal detected by control chart, hich can be estimated using Shewhart method.

The summary of this section can be simply combined in a flow of algirthm below:

Step 1: Let $X_t = x_1,\ldots x_i$ was a sampel of sukuk Musyarakah data with time $i = 1,\ldots m$. This data will be used to choose the parameter value of λ. Using the data and parameter value, the volatility of sukuk Musyarakah can be estimated by Model (1), $\hat{W}_i = \hat{\lambda} x_i + (1–\hat{\lambda})\ \hat{W}_{i–1}$. The sukuk data also used to estimate the residual Model (2), $\hat{e}_i = x_i – \hat{W}_{i–1}$ which is assumed to be independent and identically distributed.

Step 2: The estimated residual in Step 1 will be used in sampling with replacement method to get residual bootstrap, $e_i^{B(t)}$ where B refers to the number of bootstrap replication. Therefore, the residual bootstrap can be written as follows:

$$\hat{e}_i^{B(t)} = \begin{bmatrix} \hat{e}_1^{B(1)}, & \cdots & ,\hat{e}_1^{B(c)} \\ \vdots & & \vdots \\ \hat{e}_m^{B(1)}, & \cdots & ,\hat{e}_m^{B(c)} \end{bmatrix} \tag{14}$$

where $t = 1,\ldots,c$

Step 3: To obtain a new set of data of $x_i^{B(t)}$ can be calculating from residual equation in Step 1.

$$x_i^{B(t)} = \begin{bmatrix} x_1^{B(1)}, & \cdots & ,x_1^{B(c)} \\ \vdots & & \vdots \\ x_m^{B(1)}, & \cdots & ,x_m^{B(c)} \end{bmatrix} \tag{15}$$

Step 4: The bootstrap data can be obtained by calculate the average of every row of $x_i^{B(t)}$ matrix, using a simple equation below:

$$x_i^B = \frac{\sum_{i=1}^{c} x_i^{B(t)}}{c} \tag{16}$$

where c represent the number of bootstrap replication, as for example, $c = 500$.

Step 5: Bootstrap data, x_i^B will be used in estimating BMCEWMA model, i.e. Model (4) and its control limit, i.e. Equation (5).

Step 6: To verify the performance of hybrid Model (4), the bootstrap data x_i^B was used to estimate the normal interval, student's-*t* interval and BCa.

Step 7: By using the residual Model (6), the MSE and RMSE will be estimated.

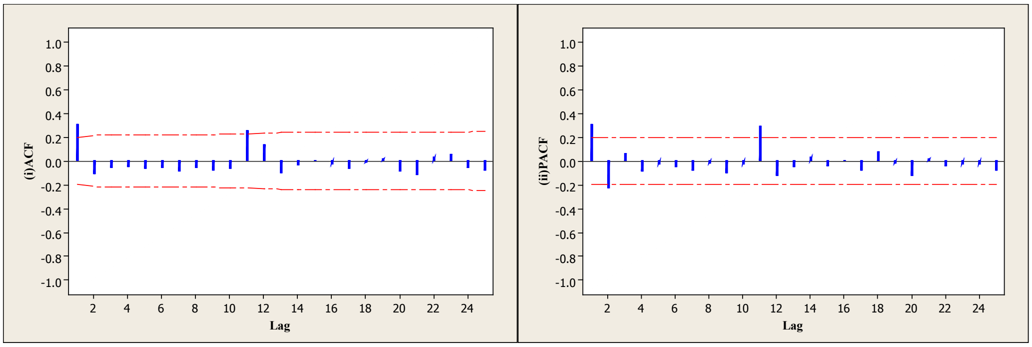
Step 8: The effectiveness of hybrid chart, BMCEWMA the false alarm rate is estimated using the Equation (13) and ARL estimation of Shewhart method.

Step 9: As for comparison of performance, the Step 6 until Step 8 is repeated for original model and control chart, i.e. MCEWMA using real data, sukuk Musyarakah

4. DATA ANALYSIS

In this study, a set of data with respect to sukuk Musharaka sukuk in Malaysia is applied to the hybrid model. The information data of sukuk is taken from Rantau Abang Capital Berhad of bonds stocked code: VI060188 having the daily closing price of March 15, 2003 until March 3, 2011. The first step to monitor the daily returns of sukuk Musyrakah is to examine its correlation using ACF and PACF plot. According to Bisgaard and Kulahci (2005), even for a small detected correlation on AFC and PACF plot is said to be autocorrelated data. Therefore, the result of sukuk Musyarakah plots can be seen in Figure 1.

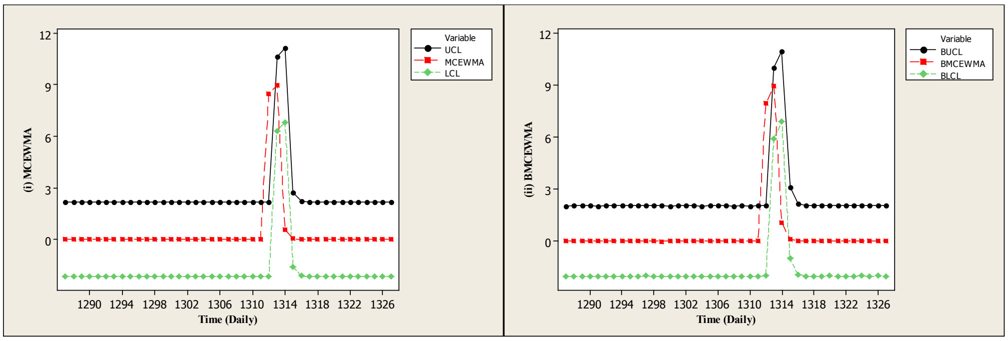
Figure 1: Sample of Sukuk Musyarakah Daily Returns (i) ACF and (ii) PACF



Based on Figure 1(i) ACF plot, sukuk Musyarakah sample detected to be exceeds the upper confident limit of the standard deviation at lag 1 and lag 11 where the correlation value are 0.3110070 and 0.253430 respectively. Similarly, in Figure 1(ii) PACF plot gave correlation value 0.311007, -0.227070 and 0.295223 at lag 1, lag 2, and lag 11 respectively. Although the correlation that exists is small, but it was enough to affect the performance of control charts (Montgomery, 2005). Therefore, it can be seen that the daily returns of sukuk Musharaka sukuk is dependent and have small autocorrelation. This nature of data is suitable to be applied in BMCEWMA control chart for analysing and monitoring process for volatility of sukuk Musyarakah.

The next step is to use the algorithm in previous section for estimation of BMCEWMA model and original model, MCEWMA. The parameter value obtained in this study is 0.930, but the selection of the λ (optimum) is not critical and according to Cox (1961), the better decision of parameter value was to have a greater value than its λ_{opt}. Therefore, this study choosed the value of λ equal to 0.94, i.e. it will be used to estimate the hybrid model and original model. While for bootstrap method, the number of replication, B which will be used is 2250 where it was the repeation number of convergence condition using bias estimation versus the number of bootstrap replication. After considering the λ value and B, both of the charts are plotted due to monitoring the existence of differences of original chart MCEWMA and hybrid model, BMCEWMA which can be refered in Figure 14(i) and Figure 14(ii) for sukuk Musyarakah volatility.

Figure 2: Volatility Point on Chart (i) MCEWMA and (ii) BMCEWMA



Based on Figure 2, a slight difference detects between MCEWMA and BMCEWMA chart. The difference is in terms of its estimation where the hybrid chart give a smaller value estimation compared to the original chart. It was obiously detected on out-of-control point in Figure 2(i) and Figure 2(ii), i.e. the 1315th point, where BMCEWMA chart estimation was 8.9416686 while MCEWMA estimation is 8.9983371. This unexpected result for BMCEWMA can be also found in both control limits, for example 1315th point, the estimation result of UCL and LCL are 10.0082369 and 5.9232678 respectively. While for original chart is basically seems to give greater value, i.e. UCL=10.6537620 and LCL= 6.3147259. The smaller value of base model and its control limit estimation are an initial description of the estimation result is close to origin value. The approximation to the origin value making the hybrid chart more accurate in estimation and gives an idea of better performance compared to original chart, MCEWMA.

The interval estimation of base model of original and bootsrap model is shown in Table 1. Based on this table, the length of standard interval is shorter using bootstrap model, BMCEWMA. As for example, student's-*t* interval estimation, the length of BMCEWMA model is 0.0512791 compare to the original model, MCEWMA i.e. 0.0528885. This obious difference results from both models proved that the hybrid model with residual bootstrap fixed the interval estimation and shows that model of BMCEWMA control chart give a better performance. This comparision result of interval estimations can be viewed in Figure 3.

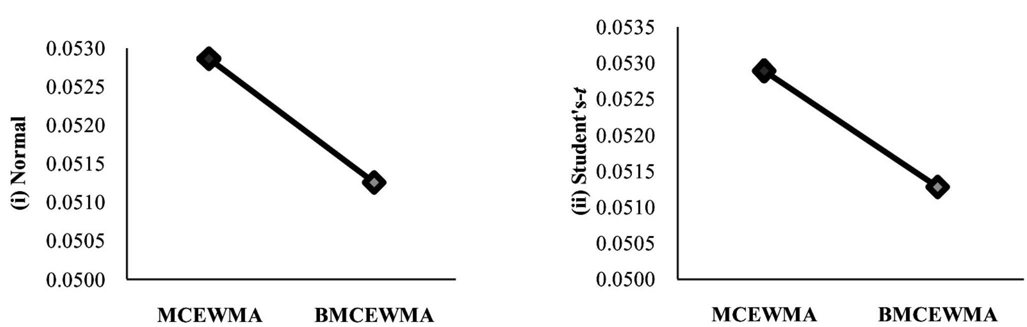
Table 1
Interval Estimation of MCEWMA Model and BMCEWMA Model

Model	*Estimation value*		
	Interval Boundry		*Length*
	Lower	*Upper*	
MCEWMA-N	0.0034845	0.0563488	0.0528643
MCEWMA-t	0.0034724	0.0563609	0.0528885
BMCEWMA-N	0.0038514	0.0551070	0.0512556
BMCEWMA-t	0.0038396	0.0551187	0.0512791
BMCEWMA-BCa	0.0250509	0.0339075	0.0088566

Lower, Upper and Length value is a measure for percentile of Gaussian distribution with 95% confident interval. BMCEWMA-N and BMCEWMA-*t* are normal confidence interval and confidence interval-*t* for bootstrap model respectively. BMCEWMA-BCa refers to the BCa confidence interval estimation.

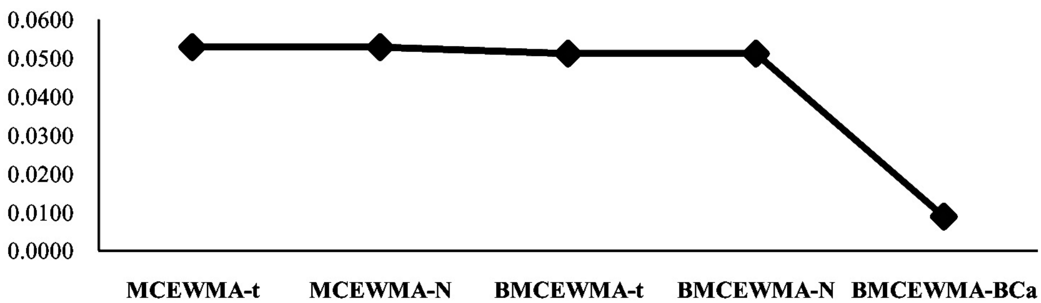
Even though the hybrid model give the shorter length for student's-*t* interval estimation, but the normal interval give a better result in terms of standard interval estimation. The length of BMCEWMA-N model is 0.0512556 compare to BMCEWMA-*t* model, i.e. 0.0512791. The same pattern of result can be found in MCEWMA model, where the normal estimation is 0.0528643 compare to student's-*t* estimation was 0.0528885.

Figure 3: Standard Interval Estimation of (i) Normal and (ii) Student's-*t*



An interesting result among the interval estimators was BCa method. Based on Table 1, the BCa give the shortest length estimation compare to standard interval that used the bootstrap model. For example, the length of interval estimation for BMCEWMA-N and BMCEWMA-*t* model is 0.0512556 and 0.0512791 respectively, compared to BMCEWMA-BCa model is 0.0088566. This obvious difference shows that bootstrap interval method give a better performance compare to standard interval estimation. The comparison can be clearly viewed in Figure 4, where the shortest length was BCa method, followed by BMCEWMA-N and BMCEWMA-*t*.

Figure 4: Interval estimator



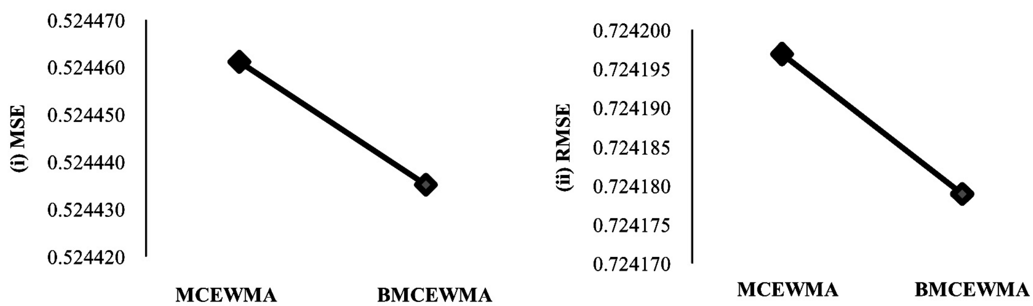
Based on Figure 4, it is shown that original model, MCEWMA give the longer length either on normal and student's-*t* interval estimation. The longest length is found to be MCEWMA-*t* model.

Table 2
Point Estimator of MCEWMA Model and BMCEWMA Model

Model	*Efficiency*	
	MSE	*RMSE*
MCEWMA	0.5244612	0.7241969
BMCEWMA	0.5244352	0.7241790

Based on the resulted in Table 2, the hybrid model give the smallest error estimation value compared to original model, MCEWMA. As for example, the MSE value is decreasing from 0.5244612 (MCEWMA model) to 0.5244352 (BMCEWMA model). Similar patterns of result found for RMSE, where the difference of error estimation value between original model and bootstrap model is about 1.79E-05. The results in Table 2, for both models, are plotted in Figure 5 for a better description.

Figure 5: Error Estimation Using (i) MSE and (i) RMSE



By referring the plot in Figure 5(i) and Figure 5(ii), it is shown that the bootstrap model meet the theoretical of effectiveness where BMCEWMA model clearly more effective than to the original model, MCEWMA. The effectiveness of bootstrap model is indirectly shows that the respective model give a better performance, as stated by Chaou, Chien, Changchien and Wu (2010) where a better performance model can be detected by its smallest error estimation value.

Furthermore, the monitoring process of volatility of sukuk Musyarakah continued using original chart, MCEWMA and hybrid chart, BMCEWMA for in-control process. The effectiveness of both charts can be statistically estimate using false alarm rate and its average run length value, ARL. The detail results can be refered to Table 3.

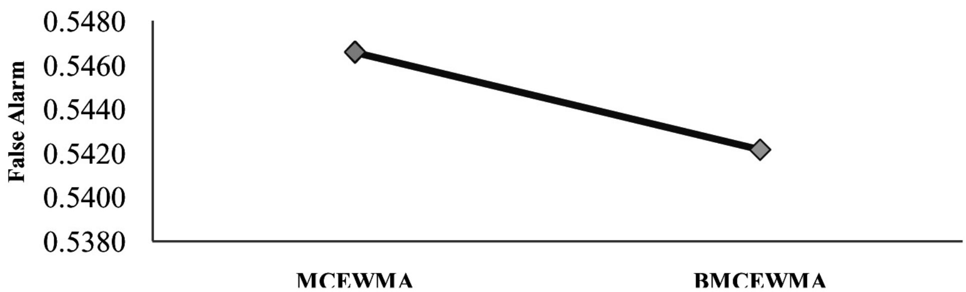
Table 3
Type 1 Error of MCEWMA Chart and BMCEWMA Chart

Control Chart	*Efficiency*	
	ARL	*False Alarm*
MCEWMA	1.8295230	0.5465906
BMCEWMA (Hybrid chart)	1.8444870	0.5421560

ARL and false alarm rate is a measurement of performance of in-control process. Original chart and hybrid chart can be refered as MCEWMA and BMCEWMA respectively.

Based on the results of ARL in Table 3, it demonstrated that BMCEWMA control chart gave the longest length of ARL for sukuk Musyarakah data, i.e. 1.8444870. Contrary to the results of MCEWMA chart where it give shorter length of ARL, which is valued 1.8295230. The different result shows that hybrid chart giving more length of ARL than the original chart. Basically, the result of ARL is proportional to the false alarm rate where theorically longer length of estimation of ARL was said to give smaller rate of false alarm. By referring the false alarm in Table 3, it is shown that hybrid chart give a smaller rate, i.e. 0.5421560 while the original chart give a greater rate which was valued 0.5465906. The difference result of false alaram rate using MCEWMA and BMCEWMA chart can be refered graphically to Figure 6.

Figure 6: False Alarm Estimation Using MCEWMA and BMCEWMA Chart



Based on Figure 6, it is showed that the estimation of false alarm rate dramatically decreased using BMCEWMA chart. By referring this result, it simply can be understand that hybrid model is more effective in monitoring the variablility of sukuk Musyarakah because, indirectly, it give a better performance of the chart, i.e. BMCEWMA itself.

5. DISCUSSION

Monitoring the volatility of sukuk Musyarakah is the major concern in this study. More specifically, the monitoring process is based on efficiency of estimation which to find the most accurate estimation model and also to observe the fluctuation of volatility points. In terms of interval estimation, the bootstrap model shows its effectiveness when using the normal interval and less effective using the student's-*t* interval method. The bootstrap model is most effective when using BCa interval method for interval estimation, where it is found to give shortest length due to its correction on biasness. Meanwhile, the original model has founded to be less effective due to the longer length compare to the bootstrap model. Moreover, the point estimator shows a slow decreasing value of error estimation from original model to bootstrap model. Dispite of low impact of error estimation, the bootstrap model basically can be reliable due to the successfully reducing the error value either in MSE or RMSE. A positive result is shown by bootstrap chart where it give the longest length and the smallest rate of false alarm compare to the original chart. Based on this result, it is indicated that the bootstrap chart have meet the theoretical efficiency of chart monitoring where the bootstrap chart is more efficient to detect the shifts process which is happened in in-control process. Furthermore, the smaller false alarm rate shows that the probability of bootstrap chart detecting the signal of out-of-control process is smaller than the original chart.

6. CONCLUSION

The main purpose of this study is to hybrid the base model of MCEWMA. The hybrid process covered an exclusive method, which known as sampling the error with replacement method where the draw of error was taken randomly. Therefore, with a complete algorithm process of hybridization, it was eventually developed a new base model, namely, bootstrap model of BMCEWMA chart. This new chart was used in the application of sukuk Musyarakah data for monitoring process, where the in-control process was used. Based on the results, the bootstrap model gave a better performance in the numerical estimation where the smallest of error value and shortest length of interval estimation were obtained. Therefore, regarding this result, it is shown that the bootstrap model, i.e. BMCEWMA model fixed the estimation value of original model, i.e. MCEWMA model and also demonstrated the accuracy to the estimation of BMCEWMA model. Continuity with this accuracy, it proved that the model of BMCEWMA chart gave the better performance compared to MCEWMA. In terms of interval estimation, the BCa method and standard normal interval estimator gave a better performance to BMCEWMA model. Furthermore, the performance of chart was estimated using false alarm rate where the bootstrap chart gave a smaller rate and more approached to target value. As a result, the bootstrap chart was proved to be more efficiency and statistically gave a better performance in monitoring sukuk Musyarakah, where BMCEWMA chart was fixed the performance of original chart, MCEWMA

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