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# Forecasting Monthly RMG Exports Demand in Bangladesh: with or without Change-Point Approach

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**Abstract**

Time series models assume stationarity, but in reality, the mean and variance of time series often change over time. While various methods can stabilize the variance, none are able to stabilize the mean. For effective modeling and prediction, it is therefore essential to identify change points in the mean in order to segment the data and preserve stationarity in each segment. This study forecasted Bangladesh's demand for ready-made garment (RMG) exports using the Binary Segmentation method and the Cumulative Summation (CUSUM) test, utilizing change point strategies in the mean. This study determines that, between July 2011 and July 2021, the mean monthly average export in million USD of specialized textiles from Bangladesh has two significant change points: data points 24 (in June 2013) and 85 (in July 2018).To forecast, an ARMA (0,0) model with a non-zero mean is fitted for the data with the change points, while an ARIMA (2,0,0) (1,0,0) [12] model with a non-zero mean is estimated for the entire dataset without the change points. The findings indicate that the accuracy of forecasting using the change points model (MSE = 88.587, RSME = 9.412, MAE = 1.308, and MAPE = 3.011) is higher as compared to forecasting without change points (MSE = 89.141, RSME = 9.441, MAE = 1.321, and MAPE = 3.083). Therefore, this study suggests that incorporating change point techniques in time series analysis can improve the forecasting process by considering the potential existence of a change point in the data.

**Keywords:** ARMA; Binary Segmentation algorithm; Change point; CUSUM test; SARIMA.

## Introduction

Ready Made Garment (RMG) sector has emerged as the primary industry in Bangladesh in terms of generating foreign currency and employment opportunities.

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In the 1980s, traditional goods such as raw jute, jute goods, and tea accounted for around 90% of the country's export earnings, holding a dominant position. Conversely, products like RMG, Knitwear, leather, and leather goods only contributed about 10% of the total exports [1]. However, over time, these items gained significance in the export portfolio, with garments eventually becoming the leading exports from Bangladesh. Presently, the RMG industry is a multibillion-dollar export and manufacturing sector that significantly contributes to various economic sectors in Bangladesh, including banking, insurance, shipping, and more [2].Over the past three decades, Bangladesh has become the world's second-largest exporter of Ready Made Garment (RMG) products, trailing only behind China [3]. The readymade garment industry holds a remarkable position in Bangladesh's exports, accounting for approximately 81.16% of the total export earnings in the fiscal year 2020-2021, a stark contrast to its negligible contribution of only 0.001% in 1976 [4]. By 2005, its share had risen significantly to 76% [5, 6]. In the budgetary year 2021-2022, the value of Bangladesh's garment exports reached 42,613.15 million USD, comprising approximately 81.82% of the country's total export value of $52,082.66 million.

A significant amount of research has been conducted regarding the prediction of textile and garment exports from various countries. Authors from China have utilized the Grey Method for export forecasting [7]. In 1990, the authors examined the values of garment exports from China and utilized a few years' worth of data to forecast future exports using the Grey Method [8]. In 2010, another group of authors predicted Chinese textile and garment exports by employing the Holt Model [9]. Additionally, the authors utilized the Grey Method (1,1) to anticipate garment exports from China in 2011 [10]. In 2015, a different set of authors forecasted the exports of clothing from the United States using ARIMA and regression models [11]. Several studies have also been conducted on the Ready-Made Garment (RMG) sector in Bangladesh. However, most of these studies have a descriptive nature [2, 12-16]. The authors of these studies primarily focused on the problems, performance, and challenges within the RMG sector, as well as the working conditions, the effectiveness of labor laws, and the sector's contribution to the country's economy and development.Some researchers have employed trend models or simple regression models to forecast future values of exports or earnings in the Ready-Made Garment (RMG) industry. In a study by Rashid et al. (2020), a fuzzy logic-based approach was proposed to predict the export of knitted RMG from Bangladesh in 2020 [17]. Another study conducted by Hossain and Uddin (2021) utilized various trend models to determine the most suitable model for forecasting RMG exports [6]. They found that the semi-log parabolic trend model provided the best fit for capturing the trend pattern of RMG exports in Bangladesh. Similarly, Rahman and Jiban (2015) explored different trend models to analyze the foreign exchange earnings of the garment sector, concluding that the semi-log trend model was the most appropriate fit for the earnings trend [18]. Hasan et al. (2016) employed a linear regression model to examine the relationship between GDP and RMG exports and also utilized a linear trend model to identify the overall trend in RMG exports [2]. However, none of the researchers have focused on incorporating change point analysis into their forecasting models, despite the fact that change points are commonly observed in real-world time series data, and the assumption of data stationarity is often violated. When dealing with nonstationary data, various techniques can be employed to stabilize the variance, but stabilizing the mean is more challenging. Therefore, it becomes crucial to detect change points in the mean of time series data in order to segment the data and maintain stationarity within each segment. The study aims to identify change point(s) in the mean of a real-time series dataset titled "the monthly export of specialized textiles in Bangladesh from July 2011 to July 2021", fit an appropriate time series model for each segment, forecast observations with and without change point(s), evaluate the forecasting performance with and without change point(s), and ultimately determine the most effective approach for forecasting purposes.

## 2. Methodology

### *2.1 Change Point Analysis for Mean*

Non-parametric methods are considered to be more suitable in practical scenarios. Within this section, we explored the procedure for estimating the point of change and its accompanying hypothesis testing.

#### *2.1.1 Single Mean Model for CUSUM Test*

The classical model for a change point with a single change in the mean is given by equation (2.1),

$$X_i = \begin{cases} \mu + e_i, & 1 \le i \le m \\ \mu + \delta + e_i, & m < i \le n \end{cases} \tag{2.1}$$

where μ, δ and m are unknown parameters, $n$ is the total number of observations, and $m$ is the point of change. In the nonparametric setting, we assume that the errors $(e_i)$ are i.i.d., but unobservable, with$E(e_i) = 0,\ 0 < E\left(e_i^2\right) = \sigma^2 < \infty,\ E(e_i)^v < \infty\ for\ some\ v > 2.$

#### *2.1.2 Test of Hypothesis for Single Mean Change Point*

To detect or test for a change point, the test hypothesis (2.2) is as follows:

$$H_0: \mu_1 = \cdots = \mu_n, against \tag{2.2}$$

$$H_1: \mu_1 = \cdots = \mu_m = \mu;\ \mu_{m+1} = \mu_1 = \mu + \delta$$

Here, $m$ is an unknown index for the point of change, with values ranging from $1\ to\ n-1$, and the initial values of $\mu$ and $\delta$ (either $\delta > 0\ or\ \delta \neq 0$) are also unknown.

### *2.1.3 Test Statistics for Single Mean Change Point*

**CUMSUM Test Statistic**

Our primary interest in this study is to use the weighted CUSUM test[19, 20]for detecting the change point in the mean model of AMOC (2.1) using hypothesis (2.2), andthe test statistic is defined by (2.3) for the two-sided alternative with ($\delta \neq 0$), whereas for the one-sided alternative ($\delta > 0$), the test statistic is given by equation (2.4),

$$T_n^{(1)} = \max_{1 \le k < n} \left\{ \frac{1}{\sigma} \left| \sqrt{\frac{n}{k(n-k)}} \sum_{i=1}^{k} (X_i - \bar{X}_n) \right| \right\} \tag{2.3}$$

$$T_n^{(1)} = \max_{1 \le k < n} \left\{ \frac{1}{\sigma} \sqrt{\frac{n}{k(n-k)} \sum_{i=1}^{k} (X_i - \bar{X}_n)} \right\} \tag{2.4}$$

**Asymptotic Critical Values:**

Approximatecritical values for the CUMSUM test statistic for large $n$ using the asymptotic probabilities under $H_0$ in (2.2) [21,22] is computed using equation (2.5):

$$c_\alpha = \frac{1}{A(\log n)} \left( -\log\left( -\frac{\log(1-\alpha)}{2} \right) + D(\log n) \right) \tag{2.5}$$

### *2.1.4 Estimation of Single Mean Change Point*

Using a convention, proposed by[23], the estimator for the change point is,

$$\hat{m} = \arg max \left\{ \sqrt{\frac{n}{k(n-k)}} \left| \sum_{i=1}^{k} (X_i - \bar{X}_n) \right|; k \epsilon (1, \dots, n-1) \right\}.$$

### *2.1.5 Multiple Mean Change Point Estimation*

The procedure for the Binary Segmentation algorithm[24] to identify multiple change points using the weighted CUSUM test (as described in equation 2.3) is as follows:

**Algorithm 1:** The generic Binary Segmentation Algorithm

1: Set the data for testing $X_1, \dots, X_n$.

2: Calculate the test statistic ${T_n}^{(1)}$ and critical value $c_\alpha$ at α level of significance; if ${T_n}^{(1)} > c_\alpha$ then select ${\widetilde{m}_1}^{(1)} \coloneqq \arg\max\left|{T_n}^{(1)}\right|$.

3: Split the data into two segments, i.e., $X_1, \dots, X_{\widetilde{m}_1}$ and $X_{\widetilde{m}_1+1}, \dots, X_n$ and repeat step 1 and 2 for each segment until no significant change points are detected.

4: Obtain ${\widetilde{m}_1}^{(1)}, \dots, {\widetilde{m}_q}^{(1)}$.

### *2.2 Time Series Model*

#### *2.2.1Autoregressive Moving Average Process (ARMA) Model*

The ARMA model denoted as ARMA (p, q),is defined as $X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$, where $\varphi$ and $\theta$ are the parameters of the autoregressive and moving average models, respectively. The constant $c$ represents a fixed value, while $\varepsilon$ refers to the white noise error terms.

#### *2.2.2 Autoregressive Integrated Moving Average (ARIMA) Model*

The ARIMA model written as ARIMA (p, d, q), involves the autoregressive component of order p, differencing of order d, and the moving average component of order q [25]. The Box-Jenkins methodology is commonly used to determine suitable values for p, d, and q. The ARIMA (p, d, q) process can be expressed as a differential equation where $\{X_t\}$ satisfies$\phi^*(B)X_t \equiv \phi(B)(1-B)^d X_t = \theta(B)Z_t$, with $\{Z_t\} \sim WN(0,\sigma^2)$ and$\phi(z)$and $\theta(z)$are polynomials with degrees p and q, respectively.

#### *2.2.3 Seasonal Autoregressive Integrated Moving Average (SARIMA) Model*

If $d$and $D$are nonnegative integers, then $\{X_t\}$ is a seasonal $ARIMA(p,d,q) \times (P,D,Q)^s$ process with period $s$ if the differenced series $Y_t = (1-B)^d(1-B^s)^D X_t$is a causal ARMA process defined [25]as, $\phi(B)\phi(B^s)Y_t = \theta(B)\,\Theta(B^s)Z_t$, where $\{Z_t\} \sim WN(0,\sigma^2)$. The polynomial $\phi(B)$,$\Phi(z)$, $\theta(z)$, and$\Theta(z)$are defined as $\left(1-\phi_1 z - \cdots - \phi_p z^p\right)$,$\left(1-\Phi_1 z - \cdots - \Phi_p z^p\right)$, $\left(1+\theta_1 z + \cdots + \theta_p z^p\right)$, and $(1+\Theta_1 z + \cdots + \Theta_Q z^Q)$, respectively. The process $\{Y_t\}$ is causal if and only if $\varphi(z) \neq 0$ and $\Phi(z) \neq 0$ for $|z| \leq 1$.

### *2.3 Model Selection Criteria*

Model selection criteria are guidelines employed to choose the most suitable statistical model from a group of potential models, using observed data. The criteria usually aim to minimize the anticipated difference, calculated by the Kullback-Leibler divergence, between the selected model and the actual model. In this research, we utilize Akaike's information criterion (AIC), Corrected Akaike's Information Criterion (AICc) [26], and Bayesian information criterion (BIC) [25].

### *2.4 Forecasting Performance Measures*

Once the dataset has been split into the training set and the test set, the selected models' performance is assessed and compared to the test dataset using different metrics[27]. The performance metrics, defined below, utilize the following variables:$y_t$ represents the true value, $f_t$ represents the predicted value, $e_t$ equals the difference between the true ($y_t$) and predicted ($f_t$) values (i.e., the forecast error), and $n$ refers to the number of observations in the test set.

The mean absolute error (MAE) is defined as
$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|e_t| \tag{2.6}$$

The Mean Absolute Percentage Error (MAPE) is
$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| \times 100 \tag{2.7}$$

The Mean Squared Error (MSE) is
$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \tag{2.8}$$

Mathematically, Root Mean Squared Error (RMSE) is
$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2} \tag{2.9}$$

## 3. Results and Analysis

### *3.1 Study Data*

The monthly export value of specialized textiles in Bangladesh was chosen as the dataset for this study. The data was obtained from the Export Promotion Bureau, Bangladesh's website. The Export Promotion Bureau is overseen by the Bangladesh Ministry of Commerce, and it publishes monthly cumulative data from July of each fiscal year to June of the following year for various categories, including textiles and readymade garments (RMG). This study focuses specifically on the monthly export of specialized textiles in Bangladesh from July 2011 to July 2021.

The graph depicted in Figure 1 displays the time series of the monthly export value (in millions of US dollars) of specialized textiles in Bangladesh from July 2011 to July 2021. The mean monthly export of specialized textiles in Bangladesh does not exhibit any discernible trend and has a minor additive seasonal component.

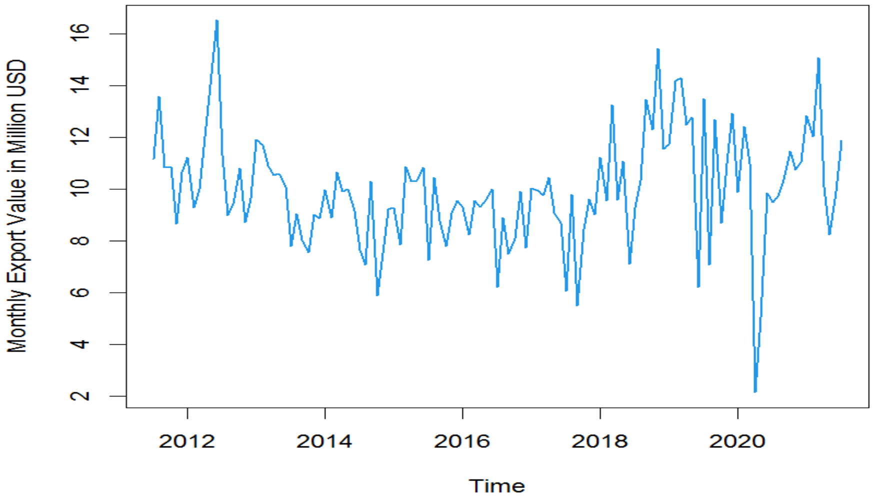


**Figure 1.** Monthly export value in million USD of Specialized Textiles in Bangladesh from July 2011 to July 2021.

The auto-correlation function (ACF) plot in Figure 2 displays that our analysis of the time series data indicates that it has seasonality, non-stationarity, and no trend pattern or outliers. Meanwhile, Figure 3, which is the seasonal subseries plot, shows that the highest monthly export value was recorded in June 2011, with an amount of almost 16.5 million USD, while the lowest export value was in April 2020, which was around 0.2 million USD. The horizontal lines indicate the means for each month, and the highest monthly mean occurred in March, with around 11.5 million USD, while the lowest monthly means were in July and October, with approximately 9.2 million USD.

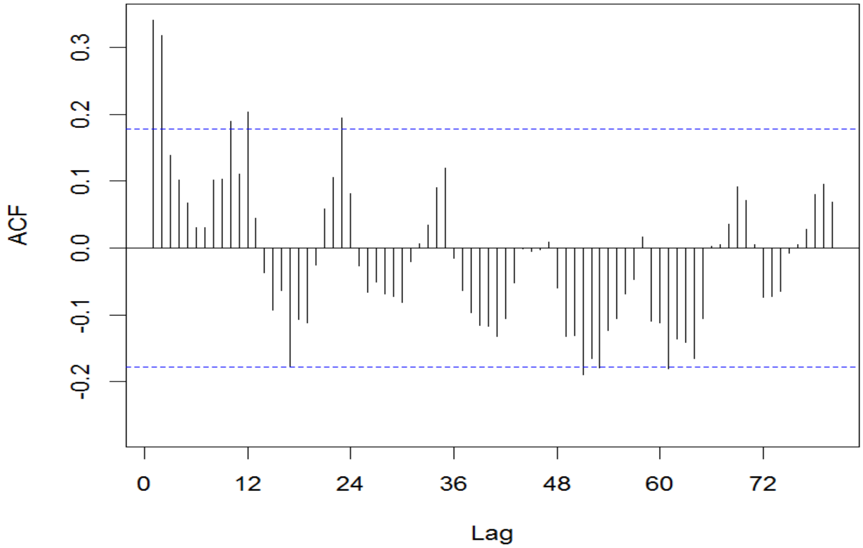


**Figure 2.** ACF of Monthly export value in million USD of Specialized Textiles in Bangladesh from July 2011 to July 2021.

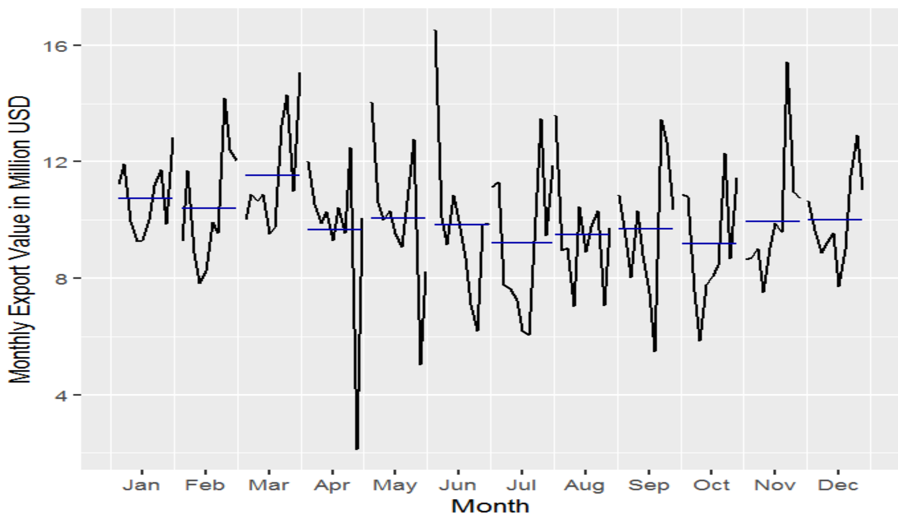


**Figure 3.** Seasonal subseries plot of monthly export value in million USD of Specialized Textiles in Bangladesh from July 2011 to July 2021.

### *3.2 Detection and Estimation of Change Point(s) for Mean*

By utilizing the CUSUM test statistic (2.3) and hypothesis (2.2), an asymptotic critical value (2.5) was estimated to determine the mean change point of the study data. If the CUSUM process for the study data crossed the asymptotic critical value line, it indicated a change point in the mean. Then, the index of the maximum value of the CUSUM process represented the first change point, which is shown in Figure 4.

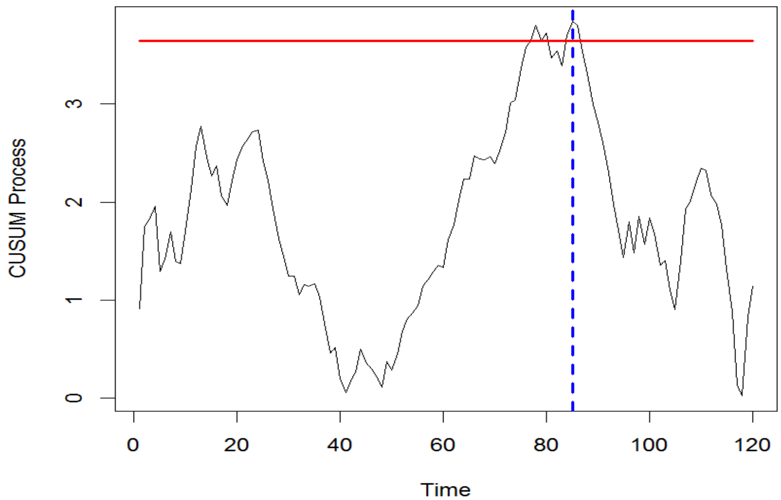


**Figure 4.** Detection of Change Point in mean for the monthly average export of Specialized Textiles in Bangladesh from July 2011 to July 2021 using CUSUM process (2.3), the red horizontal line is the asymptotic critical value and the blue dotted vertical line is the estimated change point.

The blue dotted vertical line in Figure 4 represents the change point in the mean at data point 85 (July 2018). Further change points in the monthly average export of Specialized Textiles in Bangladesh can be detected and estimated using the binary segmentation algorithm. The study revealed that there were two different average exports of Specialized Textiles in Bangladesh for the two different data segments, 'July 2011 to June 2018' and 'August 2018 to July 2021'. The CUSUM test statistic (2.3) and hypothesis (2.2) were used to conduct the change point test for both segments with the asymptotic critical value (2.5). However, there was no significant change in the monthly average export of Specialized Textiles in Bangladesh from August 2018 to July 2021. On the other hand, for the data segment 'July 2011 to June 2018', one significant change point was identified, and the result is presented in Figure 5.

Figure 5 displays a blue dotted vertical line located at data point 24, which corresponds to June 2013. This line represents the second change point in the mean for the average export of Specialized Textiles in Bangladesh between July 2011 and June 2018. We utilized the binary segmentation algorithm to identify and approximate any additional change points for the two data segments, namely 'July 2011 to May 2013' and 'July 2013 to June 2018.' However, we did not observe any change point in these two different average exports of Specialized Textiles in Bangladesh.

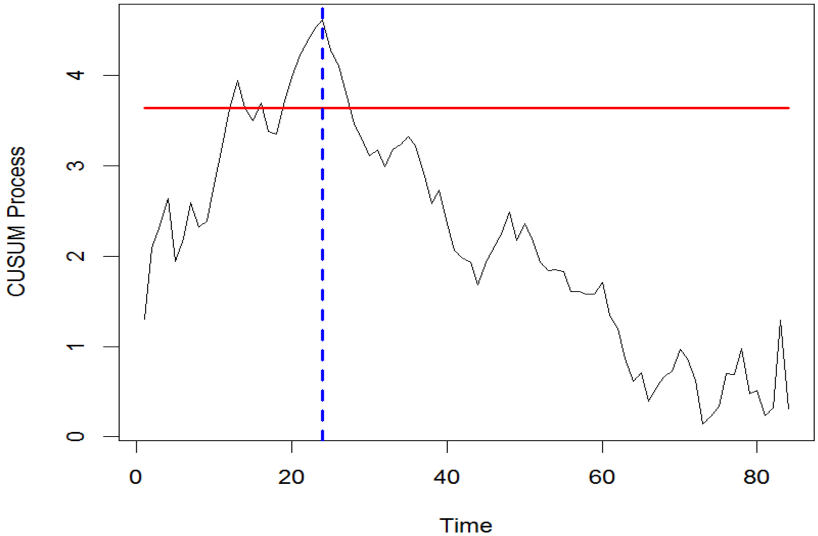


**Figure 5.** Detection of Change Point in mean for the monthly average export of Specialized Textiles in Bangladesh during July 2011 – June 2018 using CUSUM process (2.3), the red horizontal line is the asymptotic critical value and the blue dotted vertical line is the estimated change point.

### *3.2.1 Estimation Change Point(s) and Mean(s) of Study Data*

Figure 6 shows that the monthly average export value of Specialized Textiles in Bangladesh in million USD, from July 2011 to July 2021, has two change points, which occurred at data points 85 (July 2018) and 24 (June 2013).As a result, we identified three distinct patterns of monthly average export values for three different data segments: 'July 2011 to June 2013', 'July 2013 to July 2018', and 'August 2018 to July 2021', each with a different estimated mean. The three different red horizontal lines in Figure 6 correspond to the three different estimated means, which are 10.9704 million USD, 9.0149 million USD, and 10.9297 million USD.

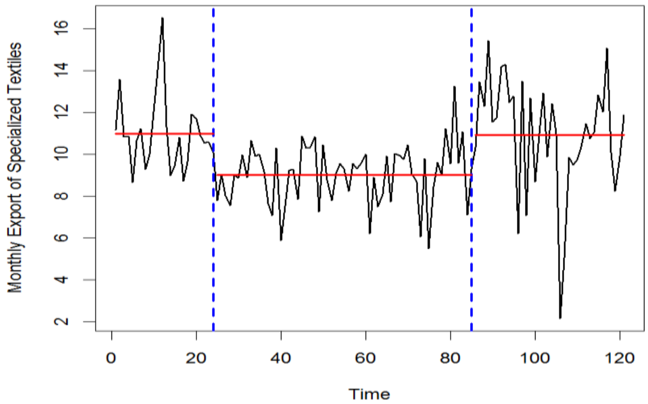


**Figure 6.** Estimated change points (blue dotted vertical lines) and the estimated means for the monthly average export of Specialized Textiles in Bangladesh (red horizontal lines).

### *3.3 Forecasting without Change Point*

The objective of this section is to select a suitable time series model for the entire dataset, without taking the change point into account. To achieve this, we will assess the stationarity of the data as a whole, and generate an ACF plot and partial auto-correlation function (PACF) plot for the stationary data. These plots will guide us in selecting a suitable Auto-Regressive Integrated Moving Average (ARIMA) type model.

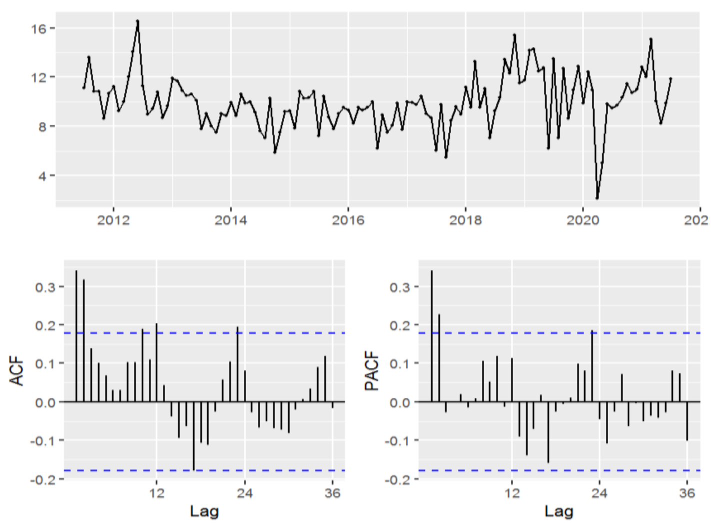


**Figure 7.** ACF and PACF of the monthly average export of Specialized Textiles in Bangladesh.

| **KPSS Test for Level Stationarity** |
| --- |
| KPSS Level = 0.2478, Truncation lag parameter = 4, p-value = 0.1 |

The results of the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test indicate that the series is stationary, as demonstrated by a p-value equal to 0.10. This means that differencing is unnecessary. Using the auto.arima function in the R software forecast package, the entire dataset of the monthly average export of Specialized Textiles in Bangladesh was fitted with a Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model, specifically an ARIMA(2,0,0)(1,0,0)[12] model with a non-zero mean (as shown in equation 3.1).

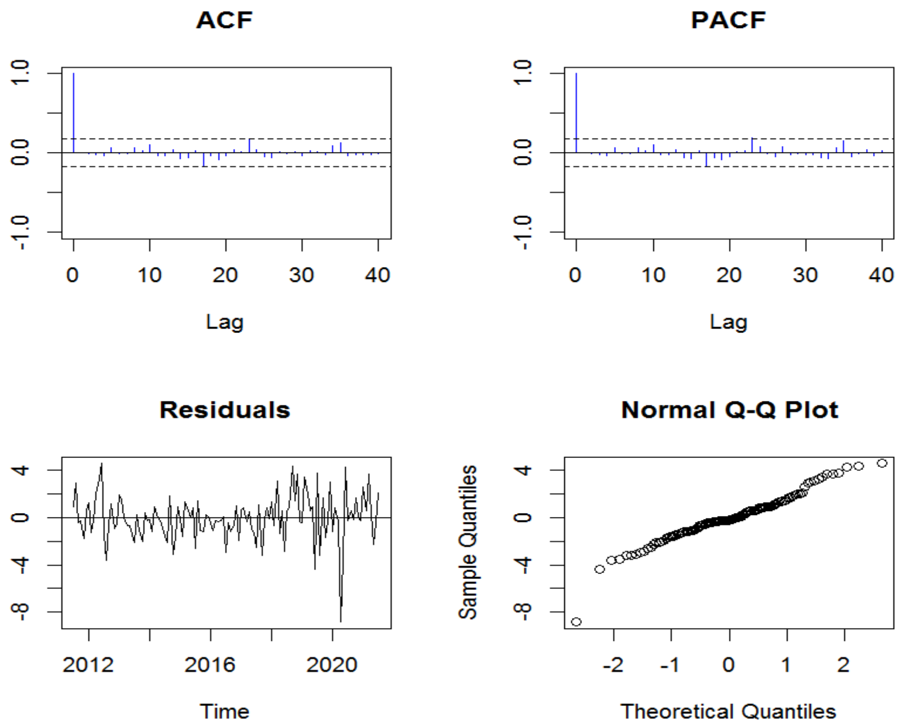


**Figure 8.** Plot of residuals diagnostic checking for ARIMA(2,0,0)(1,0,0)[12] with non-zero mean model.

Meanwhile, Figure 7 reveals from the ACF plot that the non-seasonal Moving Average (MA) order is q=2, while the seasonal MA order is Q=1. From the PACF plot, we find that the non-seasonal Auto-Regressive (AR) order is p=2, and the seasonal AR order is P=0. As a result, a SARIMA model with a seasonal period of

12, i.e., ARIMA(2,0,2)(0,0,1)[12], is necessary for the entire dataset. This is further illustrated in the fitted model (3.2).The estimated ARIMA(2,0,0)(1,0,0)[12] model with non-zero mean represents the monthly average export of Specialized Textiles in Bangladesh from July 2011 to July 2021, given by equation 3.1. It can be written as

$$(1 - 0.2534B - 0.247B^2)(1 - 0.2449B^{12})(y_t - 10.1006) = Z_t, \quad (3.1)$$

$$\text{where } \{Z_t\} \sim WN(0, \hat{\sigma}^2 = 3.867).$$

Similarly, the estimated ARIMA(2,0,2)(0,0,1)[12] with non-zero mean model the same data set, given by equation 3.2, which can be expressed as

$$(1 - 0.2818B - 0.1896B^2)(y_t - 10.0730) = (1 - 0.0186B + 0.0518B^2)(1 + 0.2199B^{12})Z_t, \quad (3.2)$$

$$\text{where } \{Z_t\} \sim WN(0, \hat{\sigma}^2 = 3.96).$$

**Table 1.** Model selection criteria of the fitted SARIMA models.

| Model | AIC | AICc | BIC |
|---|---|---|---|
| ARIMA(2,0,0)(1,0,0)[12] with non-zero mean | **513.94** | **514.46** | **527.92** |
| ARIMA(2,0,2)(0,0,1)[12] with non-zero mean | 518.58 | 519.58 | 538.16 |

Table 1 displays that the SARIMA model, specifically ARIMA (2,0,0)(1,0,0)[12] with non-zero mean, has produced small values for various model selection criteria such as Akaike information criterion (AIC), Bayesian information criterion (BIC) and Akaike information criterion corrected (AICc). This suggests that the ARIMA (2,0,0)(1,0,0)[12] with non-zero mean model has outperformed the ARIMA (2,0,2)(0,0,1)[12] with non-zero mean model. Therefore, Figure 8 and Table 2 present diagnostic tests for the estimated residuals of the better-performing ARIMA (2,0,0)(1,0,0)[12] with the non-zero mean model.

**Table 2.** Different Tests for estimated residuals of ARIMA(2,0,0)(1,0,0)[12] with non-zero mean model using $H_0$ : Residuals are IID noise.

| Test | Distribution | Statistic | p-value |
|---|---|---|---|
| Ljung-Box Q | Q ~ chisq(20) | 9.44 | 0.9772 |
| McLeod-Li Q | Q ~ chisq(20) | 20.79 | 0.4098 |
| Turning points T | (T-79.3)/4.6 ~ N(0,1) | 82 | 0.5624 |
| Diff signs S | (S-60)/3.2 ~ N(0,1) | 58 | 0.5305 |
| Rank P | (P-3630)/223.2 ~ N(0,1) | 3893 | 0.2386 |

By examining the ACF and PACF plot of the residuals (in Figure 8), we observe that only one lag is outside the significance bound, while all other lags are inside the bound. This indicates that the residuals are random. The Q-Q plot also confirms this finding. We then conducted a white noise test to determine whether the residuals are i.i.d noise (or not), and the results are presented in Table 2. Based on the test result, we conclude that the residuals are indeed i.i.d noise. Therefore, we consider the ARIMA(2,0,0)(1,0,0)[12] model as the most suitable model for forecasting purposes. Table 3 lists the forecasted values for the monthly average export value of Specialized Textiles in Bangladesh without change point(s), derived from this model.

**Table 3.** Forecasted (without change point) monthly average export value of Specialized Textiles in Bangladesh using ARIMA(2,0,0)(1,0,0)[12] with non-zero mean model (3.1).

| Date | Point Forecast | 80 % Confidence Interval (Lower – Upper Limits) | | 95 % Confidence Interval (Lower– Upper Limits) | |
|---|---|---|---|---|---|
| Aug 2021 | 10.458 | 7.938 | 12.978 | 6.604 | 14.312 |
| Sep 2021 | 10.746 | 8.146 | 13.345 | 6.770 | 14.721 |
| Oct 2021 | 10.691 | 7.976 | 13.406 | 6.538 | 14.844 |
| Nov 2021 | 10.470 | 7.732 | 13.209 | 6.282 | 14.659 |
| Dec 2021 | 10.446 | 7.692 | 13.199 | 6.235 | 14.657 |
| Jan 2022 | 10.853 | 8.095 | 13.611 | 6.635 | 15.071 |
| Feb 2022 | 10.623 | 7.863 | 13.383 | 6.401 | 14.844 |
| Mar 2022 | 11.350 | 8.589 | 14.111 | 7.128 | 15.573 |
| Apr 2022 | 10.114 | 7.352 | 12.875 | 5.890 | 14.337 |
| May 2022 | 9.653 | 6.892 | 12.415 | 5.430 | 13.877 |
| Jun 2022 | 10.060 | 7.298 | 12.822 | 5.836 | 14.284 |
| Jul 2022 | 10.537 | 7.775 | 13.299 | 6.313 | 14.761 |

### *3.4 Forecasting with change point*

In section 3.2, we identified two significant changes in the mean monthly average export of Specialized Textiles in Bangladesh, measured in million USD, between July 2011 and July 2021. These changes occurred at data points 85 (July 2018) and

24 (June 2013). Consequently, we sought to estimate different time series models for the three distinct data segments of the monthly average export: 'July 2011 to June 2013', 'July 2013 to July 2018', and 'August 2018 to July 2021'. The estimated models for these data segments are ARIMA(0,0,1) with non-zero mean, ARMA(0,0) with non-zero mean, and ARMA(0,0) with non-zero mean, respectively, which are presented as models (3.3), (3.4), and (3.5). The equations for these models are as follows:

$$y_t = \begin{cases} 10.9322 + (1 + 0.4763\,B)Z_t, \text{ where } Z_t \sim \text{WN}(0, \hat{\sigma}^2 = 2.643), & 1 \le t \le 24 \quad (3.3) \\ 9.0149 + Z_t, \quad \text{where } Z_t \sim \text{WN}(0, \hat{\sigma}^2 = 2.038), & 24 < t \le 85 \quad (3.4) \\ 10.9297 + Z_t, \quad \text{where } Z_t \sim \text{WN}(0, \hat{\sigma}^2 = 7.612), & 85 < t \le n. \quad (3.5) \end{cases}$$

**Table 4.** Estimated time series models for different segments of data to forecast the monthly average export in million USD of Specialized Textiles in Bangladesh with AIC, BIC, and AICc information criteria.

| **Data Segment** | **Model** | **AIC** | **AICc** | **BIC** |
|---|---|---|---|---|
| JUL 2011 - JUN 2013 | ARIMA(0,0,1) with non-zero mean, model **(3.3)** | 95.6 | 96.8 | 99.14 |
| JUL 2013 - JUL 2018 | ARMA(0,0) with non-zero mean, model**(3.4)** | 219.54 | 219.74 | 223.76 |
| AUG 2018 - JUL 2018 | ARMA(0,0) with non-zero mean, model **(3.5)** | 178.22 | 178.58 | 181.39 |

Table 4 represents the value of three criteria, namely Akaike information criterion (AIC), Bayesian information criterion (BIC), and Akaike information criterion corrected (AICc), for the three models (3.3), (3.4), and (3.5). By examining the value of accuracy metrics, we have determined that a much simpler ARMA(0,0) model (3.5) is more suitable for forecasting, taking into account the impact of the change point(s). Therefore, to predict the average export value in million USD of Specialized Textiles in Bangladesh, we use the (3.5) model, also known as forecasting with change point(s). Table 5 presents the predicted monthly average export values of Specialized Textiles in Bangladesh using the (3.5) model along with the change point(s).

**Table 5.** Forecasted (with change point) monthly average export value of Specialized Textiles in Bangladesh using ARMA(0,0) with non-zero mean model (3.5).

| Date | Point Forecast | 80 % Confidence Interval (Lower – Upper Limits) | | 95 % Confidence Interval (Lower– Upper Limits) | |
|---|---|---|---|---|---|
| Aug 2021 | 10.930 | 7.394 | 14.465 | 5.522 | 16.337 |
| Sep 2021 | 10.930 | 7.394 | 14.465 | 5.522 | 16.337 |
| Oct 2021 | 10.930 | 7.394 | 14.465 | 5.522 | 16.337 |
| Nov 2021 | 10.930 | 7.394 | 14.465 | 5.522 | 16.337 |
| Dec 2021 | 10.930 | 7.394 | 14.465 | 5.522 | 16.337 |
| Jan 2022 | 10.930 | 7.394 | 14.465 | 5.522 | 16.337 |
| Feb 2022 | 10.930 | 7.394 | 14.465 | 5.522 | 16.337 |
| Mar 2022 | 10.930 | 7.394 | 14.465 | 5.522 | 16.337 |
| Apr 2022 | 10.930 | 7.394 | 14.465 | 5.522 | 16.337 |
| May 2022 | 10.930 | 7.394 | 14.465 | 5.522 | 16.337 |
| Jun 2022 | 10.930 | 7.394 | 14.465 | 5.522 | 16.337 |
| Jul 2022 | 10.930 | 7.394 | 14.465 | 5.522 | 16.337 |

### *3.5 Forecasting evaluation*

Our study's main objective is to evaluate the effectiveness of selected time series models in predicting future values, both with and without change points. In Table 3 and Table 5, we have provided the forecasted values for the chosen models, 3.1 (without change point) and 3.5 (with change point), respectively. To assess the forecasting performance of the estimated ARIMA(2,0,0)(1,0,0)[12] with non-zero mean model (3.1) and the estimated ARMA(0,0) with non-zero mean model (3.5), we utilized equations 2.6, 2.7, 2.8, and 2.9 to compute the values of MAE, MAPE, MSE, and RSME. We have presented these assessment results in Table 6.

**Table 6.** Forecasting accuracy measures of different estimated models.

| Model | MSE | RMSE | MAE | MAPE |
|---|---|---|---|---|
| ARIMA(2,0,0)(1,0,0)[12] with non-zero mean, model **(3.1)** | 89.14135 | 9.441469 | 1.321595 | 3.083283 |
| ARMA(0,0) with non-zero mean, model **(3.5)** | **88.58795** | **9.412117** | **1.308182** | **3.011582** |

Based on the results presented in Table 6, it can be observed that the ARMA(0,0) model with non-zero mean (model 3.5) has the lowest values for forecasting accuracy measures such as MAE, MAPE, MSE, and RMSE compared to other estimated model. Thus, it can be concluded that incorporating a change point into the model results in a higher level of accuracy in forecasting compared to a model without a change point.

## 4. Conclusion

This study identifies two significant changes in the mean of monthly average exports of specialized textiles in Bangladesh from July 2011 to July 2021. The CUSUM test (2.3) and binary segmentation algorithm are used to detect these changes, which occurred in June 2013 (24) and July 2018 (85). As a result, ours aim to estimate time series models for three different data segments: July 2011 to June 2013, July 2013 to July 2018, and August 2018 to July 2021. The estimated models for these segments are ARIMA(0,0,1) with non-zero mean, ARMA(0,0) with non-zero mean, and ARMA(0,0) with non-zero mean, respectively, as shown in models (3.3), (3.4), and (3.5). However, for forecasting with a change point, the monthly export value of specialized textiles in Bangladesh from August 2018 to July 2021 is considered, and the best-fitted model is found to be ARMA(0,0) with non-zero mean model (3.5). The entire dataset is used to estimate the time series model without considering any change point in the forecasting process. Two SARIMA models are estimated, namely ARIMA (2,0,0)(1,0,0)[12] with non-zero mean model (3.1) and ARIMA (2,0,2)(0,0,1)[12] with non-zero mean model (3.2). And the ARIMA (2,0,0)(1,0,0)[12] with non-zero mean model has smaller values for model selection criteria, such as AIC, BIC, and AICc, indicating its better fit. Therefore, forecasting without a change point is carried out using the ARIMA (2,0,0)(1,0,0)[12] with non-zero mean model. To compare the accuracy of forecasting performance between the two models, different forecasting accuracy measures are calculated. The ARMA (0,0) with non-zero mean model (3.5) was found to have the smallest values of forecasting accuracy measures, such as MSE, RMSE, MAE, and MAPE, when compared to ARIMA (2,0,0)(1,0,0)[12] with non-zero mean model (3.1). Therefore, the study suggests that forecasting with a change point yields higher accuracy.

The principal aim of our research is to assess the precision of forecasts with and without change points. To accomplish this, we utilize change point techniques in time series analysis to detect any change points and enhance the forecasting process by considering the possibility of their presence. Our findings reveal that incorporating change points in forecasting leads to greater accuracy compared to forecasting without taking change points into account.

## Declarations

**Ethical statement:** We adhere to the principles of transparency, equity, and truthfulness in our reporting. Every piece of information in this manuscript has been thoroughly examined and verified to the best of our knowledge.

**Availability of data and materials:** The datasets that support the findings of this study are available on request.

**Funding Information:** There is no funding for this study.

**Authors' Contributions:** PS participated in the data processing, analysis, and paper drafting as well as the result interpretation and interpretation. MAK participated in the data collection, analysis, interpretation, and manuscript editing. SM provided insightful feedback on the interpretation of the findings, the literature review, editing and critically reviewing the manuscript. TB edited and provided a critical critique of the work. RR supervised the study's design and formulated the research idea. Every author has given their approval to the final version.

**Conflicts of interest:** The authors declare that they have no competing interests.

## References

[1] Shourave MSJ. Ready-made Garments, FDI and Total Exports of Bangladesh: A Time Series Analysis. South Asian J Soc Stud Econ 2022;13:57–66. https://doi.org/10.9734/sajsse/2022/v13i130349.

[2] Hasan KMF, Mia MS, Rahman MM, Ullah ANMA, Ullah MS. Role of Textile and Clothing Industries in the Growth and Development of Trade & Business Strategies of Bangladesh in the Global Economy. Int J Text Sci 2016;5:39–48. https://doi.org/10.5923/j.textile.20160503.01.

[3] Farhana K, Syduzzaman M, Munir MS. PRESENT STATUS OF WORKERS IN READY- MADE GARMENTS INDUSTRIES IN BANGLADESH. Eur Sci J 2015;11:564–74.

[4] Khandker A. Trends in the Growth Rate of RMG Exports of Bangladesh. AIUB J Bus Econ 2011;10:89–108.

[5] Adnan A, Rakib A, Rahman M. Export Trend of Bangladesh: the Dominance of Ready-Made Garments Industry. Res J Econ Bus Ict 2015;10:31.

[6] Hossain MS, Uddin MT. Export Trend of Ready Made Garments (RMG) Sector of Bangladesh. J Sci Res 2021;13:101–10. https://doi.org/10.3329/jsr.v13i1.47810.

[7] Ju-Long D. Control problems of grey systems. Syst Control Lett 1982;1:288–94. https://doi.org/10.1016/S0167-6911(82)80025-X.

[8] Wu Y, Jing Y, Xu P. The application of grey model forecasting and programming in Chinese textile industry. Proc ISUMA 1990 - 1st Int Symp Uncertain Model Anal 1990:517–21. https://doi.org/10.1109/ISUMA.1990.151308.

[9] Li X, Guo Y, Song W. Forecast to textile and garment exports based on holt model. Proc - 2010 Int Conf Inf Sci Manag Eng ISME 2010 2010;1:274–7. https://doi.org/10.1109/ISME.2010.44.

[10] Li X, Kong F, Liu Y, Qin Y. Applying GM (1,1) model in China's apparel export forecasting. Proc - 2011 4th Int Symp Comput Intell Des Isc 2011 2011;2:245–7. https://doi.org/10.1109/ISCID.2011.163.

[11] Lu J. Forecasting of U.S. total textiles and apparel export to the world in next 10 years (2015-2025). J Text Apparel, Technol Manag 2015;9:1–8.

[12] Sharma V. Imperfect work conditions in Bangladesh RMG sector. Int J Law Manag 2015;57:28–37.

[13] Talapatra S, Uddin MK. Some obstacles that affect the TQM implementation in Bangladeshi RMG sector: An empirical study. Proc Int Conf Ind Eng Oper Manag 2018;2018-March:1290–302.

[14] Chowdhury MAM, Ali MM, Rahman R. WTO, Post-MFA Era and the Bangladesh RMG Sector: An Assessment of Performance and Challenges. South Asian J Manag 2006;13:76.

[15] Barua U, Ansary MA. Workplace safety in Bangladesh ready-made garment sector: 3 years after the Rana Plaza collapse. Int J Occup Saf Ergon 2017;23:578–83. https://doi.org/10.1080/10803548.2016.1251150.

[16] Mia S, Akter M. Ready-Made Garments Sector of Bangladesh: Its Growth, Contribution and Challenges. Econ World 2019;7:17–26. https://doi.org/10.17265/2328-7144/2019.01.004.

[17] Rashid MM, Khan MR, Ghosh SK. A fuzzy logic based approach towards sales forecasting: Case study of knit garments industry. Proc Int Conf Ind Eng Oper Manag 2020;0:345–52.

[18] Rahman A, Jiban MJH. Trend of Foreign Currency Earnings by the Garment Sectors in Bangladesh. Mathemethical Theory Model 2015;5.

[19] Kirch C, Steinebach J. Permutation principles for the change analysis of stochastic processes under strong invariance. J Comput Appl Math 2006;186:64–88. https://doi.org/10.1016/j.cam.2005.03.065.

[20] Rois R, Prima AT, Shanta MA. An Application of Bootstrapping for CUSUM Test in Mean Change-Point Model and Forecasting. World Sci News 2019;125:217–29.

[21] Darling DA, Erdös P. A limit theorem for the maximum sums of independent random. Duke Math J 1955;18:143–55.

[22] Csörgö M, Horváth L. Limit theorems in change-point analysis. New York: John Wiley & Sons Inc.; 1997.

[23] Antoch J, Hušková M. Permutation tests in change point analysis. Stat Probab Lett 2001;53:37–46. https://doi.org/10.1016/S0167-7152(01)00009-8.

[24] Vostrikova LY. Detecting “disorder” in multidimensional random processes. Uspekhi Mat Nauk 1981;259:270–4.

[25] Brockwell PJ, Davis RA. Introduction to Time Series and Forecasting. 2nd ed. New York: Springer; 2002.

[26] Hurvich CM, Tsai C-L. Regression and time series model selection in small samples. Biometrika 1989;76:297–307.

[27] Tudose AM, Picioroaga II, Sidea DO, Bulac C, Boicea VA. Short-term load forecasting using convolutional neural networks in covid-19 context: The Romanian case study. Energies 2021;14. https://doi.org/10.3390/en14134046.