Original Article

Analysis of Blood Collection of National Blood Transfusion Service, Sri Lanka: A Time Series Analysis

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ABSTRACT

Background and Objectives: Blood transfusion is a widely accepted treatment modality in modern medical practice and it has no substitute. Therefore, blood is a scarce resource, and proper management of bloodstock is essential. Transfusion service is responsible to maintain an adequate blood stock to ensure the supply of blood for hospitals while minimizing blood wastage due to postexpiry. To achieve efficient bloodstock management, the pattern of blood collection should be identified. This study was designed to establish a time series model for monthly blood collection of Sri Lanka. **Methods:** Data on monthly blood collection of Sri Lanka were collected from the year 2010 to 2020 and time series models were developed using "R" statistical software. **Results:** Time series data clearly exhibited an increasing trend with seasonality in blood collection. Therefore, seasonal time series models were fitted and the best seasonal autoregressive integrated moving average (ARIMA) model was selected as ARIMA (0, 1, 1) (0, 1, 2) (12) which showed the lowest Akaike information criteria value. **Conclusion:** It is suitable for forecasting the monthly blood collection.

KEYWORDS: *Blood collection, blood donation, forecasting, national blood transfusion service, Sri Lanka, time series analysis*

INTRODUCTION

Blood products cannot be manufactured artificially and transfusion services depend on blood collection. Maintaining adequate blood stock is a challenge that every blood service faces, as blood products have a limited shelf-life. There are many factors that contribute for the capacity of blood collection, most of which cannot be controlled.[1] It is important to identify those factors to improve blood collection to manage the inventory efficiently. Lack of blood products could result in adverse events. For instance, bloodstock shortage has caused even closing of inner-city trauma centers.[2] This highlights the importance of maintaining an adequate blood supply. On the other hand, it is a risk to collect and store a large amount of blood products as they can be discarded due to the limited shelf life.[3] Outdating due to the nonuse of collected blood is a common reason for blood wastage.[4] Furthermore, inventory management can reduce the average age of red cells that are transfused to patients. For this also, good blood inventory management is essential.[5] Redistribution of close expiry blood units is advantageous in minimizing the postexpiry.[6]

Accurate forecasting is an essential step in bloodstock management. A series of values collected sequentially over a period of time is called a time series. The considered time period may in seconds, minutes, hours, days, weeks, months, quarters, and years.[7] Time series data are commonly used in business, agriculture, meteorology, ecology, biology, and medicine and it is a powerful tool used for forecasting. The objectives of time series analysis are to understand or model the stochastic mechanism that gives rise to an observed series and to predict or forecast the future values of a series based on the available data so far. They are commonly used in public health data.[8] Time series analysis aid in describing the observed values and identify the causative factors for the observations. More importantly, time series analysis is used to forecast future values using past experience. Hence, a time series is beneficial in blood inventory management. Identifying an appropriate model for time series is crucial. For this, it is necessary to plot the data against time, make calculations, and draft a model which must be validated later. Furthermore, knowledge about the subject should also be applied. Finally, the fitted model can be assessed with model diagnostics.

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Although there are published articles on forecasting blood collection worldwide,[9-13] island-wide blood collection of Sri Lanka has not been studied. This study would address some of the above challenges faced by the National Blood Transfusion Service (NBTS) of Sri Lanka, by identifying the pattern of monthly blood collection and forecasting, which will allow them to be ready for the upcoming blood shortage. Furthermore, it can reduce the wastage of this scarce resource.

The main objective of the study was to analyze the blood collection in Sri Lanka with time series analysis and to develop a model, identify the parameters to accurately predict the monthly blood collection, and finally, validate the developed model.

Materials and Methods

This is a retrospective study. As the NBTS of Sri Lanka is the sole supplier of blood products to the hospital, the data on the monthly blood collection of NBTS were gathered from the statistics unit of the NBTS after obtaining administrative permission.

Monthly blood collection data were collected from the year 2010 to 2020. Total blood donations in every month covering the whole country were considered. However, the number of donors was not considered, as this study is focused on the number of donations. Hence, due to regular blood donors, the figures in this study cannot be applied to the number of blood donors.

Ethics

Research review committee of NBTS approved the research proposal. Permission was taken from the director of the NBTS to obtain the necessary data from the statistics unit.

Data were entered into the “Numbers” spreadsheet software. “R” statistical software was used for statistical analysis.[14] Preliminary analysis on the data was carried out using the time series package of the software. Time series plots were created. Finally, the seasonal autoregressive integrated moving average (SARIMA) model for the time series was developed using the software.

According to the Box and Jenkins (BJ) time series modeling, there are three basic steps in time series analysis, namely, identification, estimation, and diagnostic checking. Model identification is the initial step, in which the possible best-fitted SARIMA model is determined. Stationary conditions should be satisfied to develop a SARIMA model. If the time series random variable is (yt: $t \in T$), then a SARIMA process can be given in the form depicted in the following Equation 1.

$$\varnothing_p\left(B^s\right) \varnothing\left(B\right)\nabla_S^D\ \nabla^d Y_t = \propto\ +\ \theta_Q\left(B^S\right)\theta\left(B\right)\varepsilon_t \tag{1}$$

Where εt is the Gaussian white noise process, $\emptyset B$ and $\theta(B)$ for the ordinary autoregressive and moving average operators of orders p and q. $\Phi p\ B^s$ and $\theta Q(B^s)$ are termed for seasonal autoregressive and moving average operators of orders P and Q, respectively. The ordinary differencing component is defined as ∇^d where ∇^d = $(1–B)^d$ whereas the seasonal differencing component is defined as ∇_S^D where $\nabla_S^D = (1–B^S)^D$.

Mean absolute percentage error (MAPE) is calculated according to the following formula.

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100\% \tag{2}$$

Where, yt is the actual value, yt is the forecasted number of collections, and n is the number of selected periods. Lower MAPE value has a high forecasting accuracy. Moreover, the model with the lowest MAPE value is selected.

However, those calculations would be performed using the “Forecasting: Principles and Practice” package (2nd ed., 2018) of R statistical software.[14]

In diagnostic checking, residuals are checked to see whether they follow a white noise process. This is performed by inspecting the run chart and probability plot of the residuals. If the model fails these diagnostic checks, the process should be returned to the identification stage to find a better model. The best model is then can be used to forecast.

Results

According to the gathered data, in Sri Lanka, monthly blood collection has a mean of 32,365 with a standard deviation (SD) of 4942.097. Moreover, the median was 32,704. During the study period, the minimum collection was 17,550 whereas the maximum was 41,188. The first quadrille was 29,315, and the third quadrille was 35,984.

All parameters of the time series model were calculated using the “Forecasting: Principles and Practice” package (2nd ed., 2018) of R statistical software.[14]

Time series model was developed using data from 2010 to 2018 (training dataset), and data from 2019 to 2020 were reserved to validate the model. Initially, the pattern was examined visually using time series plot. Figure 1 shows the time series of monthly blood collection from 2010 to 2018.

Data have trends and are not stationary with respect to variance and mean. Therefore, the log value was taken to make the data set stable in variance. Then, the first difference was taken to remove the trend. Figure 2 shows the differenced log data of monthly blood collection from 2010 to 2018. In that, the trend has been removed, and the data set is relatively stationary.

Figure 3 shows the cyclical changes of blood collection against the month.

MAPE and mean square forecast error were used as the common forecast accuracy criteria, explained as the average of differences between the true and forecasted values. Akaike information criteria (AIC) were used to model diagnostics, in which the lowest AIC value was considered a good model. Figure 4 shows the output from the software.

The best autoregressive integrated moving average (ARIMA) model selected is, ARIMA (0, 1, 1) (0, 1, 2) (12) Residuals are checked using Ljung–Box test. Figure 5 shows the results. 2019 and 2020 monthly collections were forecasted and compared with the actual collection.

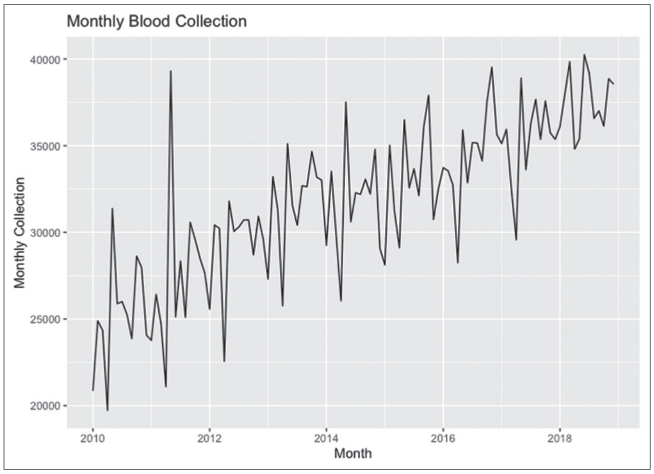

Figure 1: Illustrates the monthly blood collection from Sri Lanka from 2010 to 2018. At a glance, it is evident that, even with fluctuations, there is an increasing trend throughout the selected time period. The data set is not stationary with reference to trend and variance

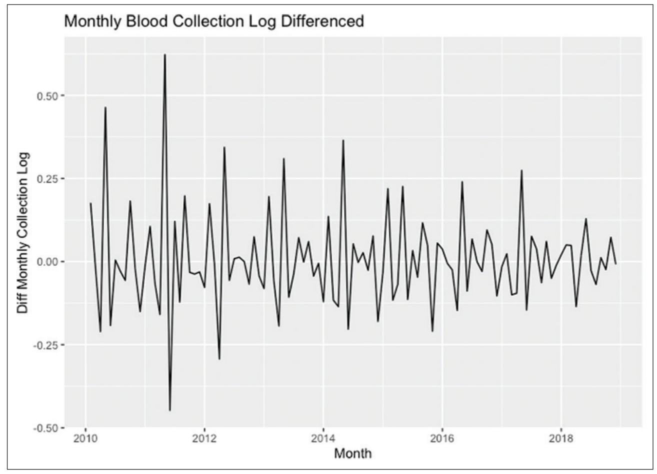

Figure 2: As the original data set is not stationary with respect to mean and variance, log differenced values are taken. Log values have made the variance stable while differencing has removed the trend making the mean stable

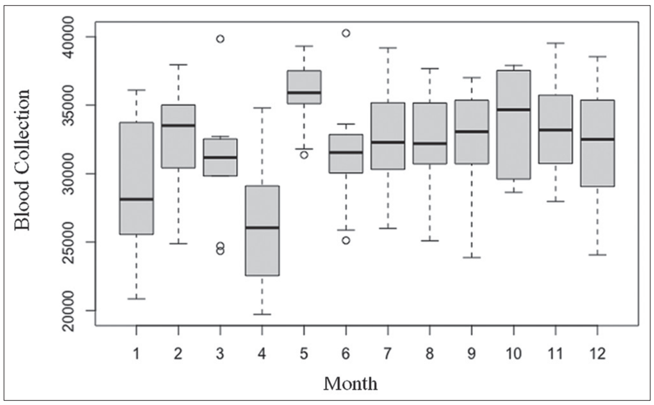

Figure 3: Demonstrates the blood collection against months. It is obvious that the highest collection is in the month of May, whereas the lowest is observed in April every year

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Coefficients:
          ma1     sma1    sma2
      -0.8867  -0.7386  0.2173
s.e.   0.0449   0.1276  0.1251

sigma^2 estimated as 0.004842:  log likelihood=115.77
AIC=-223.55   AICc=-223.1   BIC=-213.33

Training set error measures:
                       ME       RMSE        MAE         MPE      MAPE      MASE       ACF1
Training set -0.008066268 0.06422447 0.04765524 -0.07941228 0.4585847 0.6319225 -0.1020337
```

Figure 4: Parameters of the selected ARIMA model. ARIMA: Autoregressive integrated moving average

Table 1 shows the forecasted and actual monthly blood collection in the years 2019 and 2020.

Discussion

Blood transfusion is lifesaving in modern medicine and blood cannot be replaced by any other pharmaceutical product. However, blood collection is generally unpredictable, and demand for its products fluctuates. Maintaining adequate blood stock while minimizing the discards due to postexpiry is challenging, as blood products have a limited shelf life. For optimal bloodstock management, identifying the pattern of blood collection is crucial. Many factors affect the blood supply which is dynamic. Uncertainty of blood collection is a great barrier to manage blood stocks efficiently. Interestingly, studying of factors affecting blood collection and developing models is still wide open irrespective of the published studies.[15] Hence, this study was carried out to analyze the monthly blood collection of the National Blood Transfusion of Sri Lanka.

The analyzed data shows that there is a mean monthly collection of 32,365 (SD = 4942.097) and has a trend of increasing over the past decade. The growth could be due to population growth, expanding of health services. Not surprisingly, in many countries, this has been observed.[16,17] Interestingly, there are published data where some blood services experienced a reduction in blood demand and collection. In a study carried out in the United States, Ellingson *et al*. described the decline in blood collection.[18] They have mentioned the rationale use of blood products, advance technological approaches in surgeries, systematic blood ordering, the introduction of patient blood management programs, and recommendations provided by recent studies, as the possible reasons for the gradual decline of blood demand and collection. Greinacher *et al*. have highlighted that understanding the changes of the blood supply is crucial in future planning.[19] Hence, this is an important finding about blood collection in Sri Lanka.

At a glance, it is evident that the highest collection is observed in the month of May. In Sri Lanka, the majority of the population are Buddhists, hence the Vesak festival is celebrated glamorously in this month. As they pay special attention for donations due to their religious beliefs, they tend to arrange more blood donation campaigns during this period. It is the obvious reason to get the highest number of blood collections in May every year. Therefore, during this period, special attention should be given to limit blood collection as excess blood collection could result in wastage due to postexpiry. On the other hand, the lowest blood collection is observed in the month of April every year. As most of people,

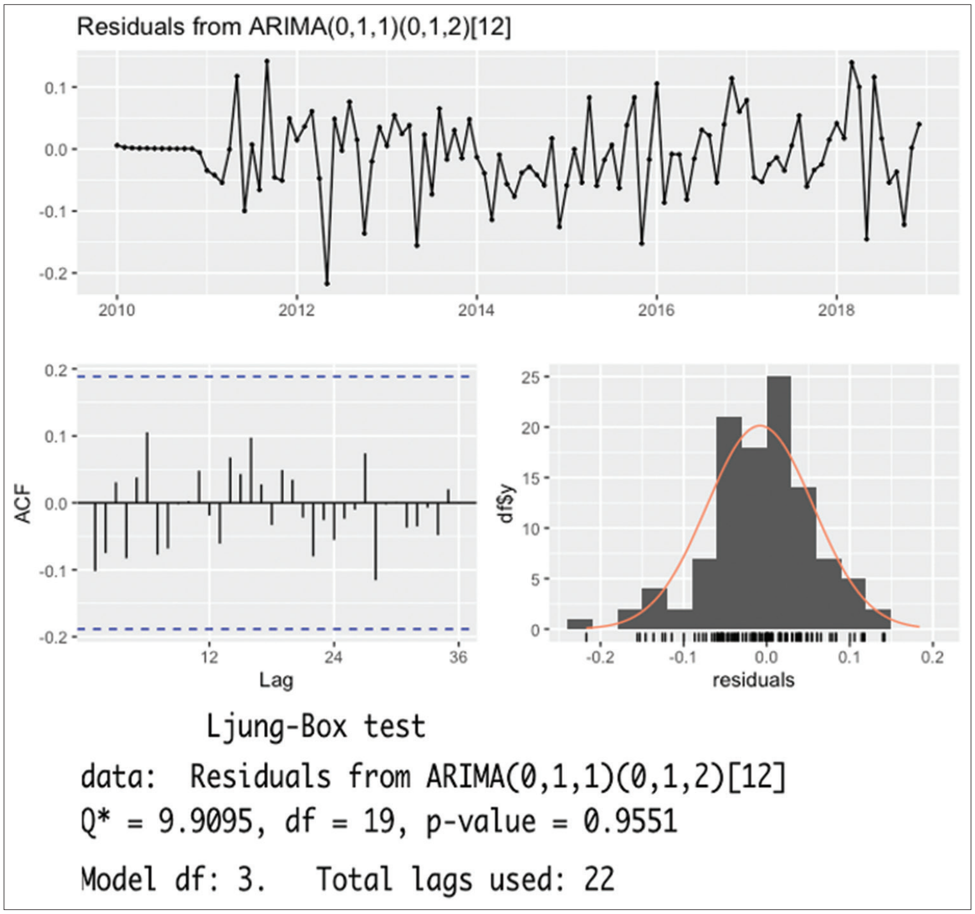

Figure 5: This illustrates the residual analysis after developing the model. This is the outcome from the statistical software in residual analysis using Ljung–Box test. Randomness of residuals is highlighted here as $P > 0.05$. Hence, the model is satisfactory

Sinhala and Hindu, celebrate the traditional New Year in this month and do not engage in blood donations compared to the other months. Interestingly, published data shows that in other countries also, blood collection drops when there are cultural activities. A published article on the blood collection of Saudi Arabia has concluded that monthly blood collection drops in the months of June and September, in which Ramadan and Hajj festivals are celebrated, respectively.[20] Therefore, we can conclude that cultural and religious activities could affect blood collection positively or negatively.

It is important to identify the time periods that have low blood collection to implement strategies to improve blood collection. According to the results, NBTS of Sri Lanka collects low blood units in April; therefore, taking necessary actions to face low blood stock levels is needed. Moreover, blood collection should be actively enhanced during this period. In contrast, when blood collection is high as in May in Sri Lanka, it is important to redistribute the blood stocks to minimize the wastage due to postexpiry.

As blood collection is a univariate series, it is suitable to apply the BJ ARIMA model. This procedure can identify the most appropriate model. Then, it would provide the statistical significance of the monthly blood collection. Furthermore, developing a SARIMA model will describe the seasonality of the blood collection.

An ARIMA model was developed using the data on monthly blood collection from 2010 to 2018. For the monthly blood collection of Sri Lanka, the best ARIMA model selected is ARIMA (0, 1, 1) (0, 1, 2) (12) which showed the lowest AIC value.

Filho *et al*. have concluded that the BJ procedure is superior to the moving-average method in the forecasting of blood component supply and easier to apply.[9,11] So that, establishing an ARIMA model is a crucial step in forecasting blood collection. Fanoodi *et al*. also mentioned in their study that the ARMA method has better reliability than the moving average method.[10] They have further suggested that developing an artificial neural network (ANN) with contributing factors would be more helpful in forecasting blood collection as it can assess multiple factors. However, a multivariate vector autoregressive moving average model will be needed for a category of blood products.[11] Hence, the developed ARIMA model in this study is suitable for forecasting the monthly blood collection of Sri Lanka.

Using the developed ARIMA model, the collection was predicted for 2019 and 2020, and compared with the actual collection. Although blood collection is highest in the month of May, it has been significantly reduced in the year 2019. The reason was the terrorist attack occurred on April 21, 2019. Several suicide bombers were able to attack hotels

Table 1: Predicted values and the actual values in 2019 – 2020

Years	Months	Forecasted collection	Actual collection
2019	January	37,399	37,922
	February	38,901	40,335
	March	37,154	37,043
	April	33,173	32,587
	May	40,206	35,864
	June	37,960	38,975
	July	39,682	37,868
	August	39,397	38,425
	September	38,623	33,901
	October	40,453	35,513
	November	40,164	34,894
	December	39,031	41,188
2020	January	39,116	38,122
	February	40,514	38,987
	March	39,755	29,335
	April	35,313	17,550
	May	40,674	33,403
	June	40,505	40,557
	July	41,557	30,730
	August	40,645	38,512
	September	39,942	37,989
	October	41,029	27,203
	November	41,722	32,536
	December	40,885	32,909

and churches during the Easter celebrations in Sri Lanka.[21] Due to this attack, the Government of Sri Lanka suspended all gatherings including religious activities. Hence, in the following month, May 2019, there was an unexpected decline in blood collection. However, the collection has been improved by the month of June.

In 2020, blood collection was mainly affected by the SARS-CoV-2 or COVID-19 pandemic. Hence, the expected collection was not observed throughout the year. This has been a challenge in the medical field including blood banks. COVID-19 had a significant negative effect on blood collection in Sri Lanka as an island-wide lockdown was imposed to control the spread of the disease. Furthermore, blood donors were not willing to come to the hospital to donate blood as much as they did before the pandemic. This effect was not evident only in Sri Lanka, bus also other countries faced this challenge.[22,23] Importantly, there must be vigilant stock management and monitoring to overcome challenges during a such pandemic. However, if the demand is also reduced during the pandemic, the effect is minimal for bloodstock management.[23]

In spite of the exceptional blood collections observed in those years, the selected model is effective in predicting blood collection. Therefore, this model is useful in decision-making for the NBTS of Sri Lanka. Furthermore, this model could be further revised with incorporating the data in preceding years. Necessary actions to maintain adequate blood stocks and to minimize blood wastage could be taken in advance.

These results are subject to the following limitations. First, the data were taken only considering the blood collection. However, blood groups were not considered in the study. It is important to note that the blood demand is based on the blood groups. Even an adequate total bloodstock is available, blood from a specific blood group could be unavailable. Furthermore, attending this into specific blood products, such as platelets, could be useful.

Then, the factors affecting the variation in blood collection are not described in this study and they should be identified. This could be used to develop an ANN for blood collection of Sri Lanka.

Conclusion

Blood inventory management is challenging for the health system because of their short shelf life and limited supply. On the other hand, having excess stock will result in wastage due to postexpiry. Considering those factors, it is important to manage the blood inventory rationally, and in turn, could reduce the cost for blood supply, and preserve this scarce resource, while providing adequately to needy patients.

Statistical analysis of blood collection in terms of time series provided from monthly data is useful in forecasting future collection. The analysis also can identify the type of the model, estimating its parameters, and finally, validating a SARIMA model for these time series. Those forecasting models could be utilized to improve blood collection and to find the balance between demand and supply. Forecasting of the blood components can allow the blood service to minimize the wastage and the associated cost with an excess of inventory that could lead in the discarding of the blood products. Hence, it is recommended that the statistical prediction with time series methods on blood collection should be implemented by the transfusion services.

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S. S. Conceptualized the study and was involved in data collection. All authors were involved in data analysis and interpretation. S. S. Drafted the manuscript and R. A. Revised it. All authors read and approved the final manuscript.

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Conflicts of interest

There are no conflicts of interest.

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