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Reducing demand uncertainty in the platelet supply chain through artificial neural networks and ARIMA models

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A R T I C L E I N F O

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A B S T R A C T

One of the significant issues in global healthcare systems is improving the supply chain performance and addressing the uncertainties in demand. Blood products, especially platelets, have the most challenging supply chains in the health system given their short shelf life and limited human resources. Therefore, proper management of blood products is critical, and in turn, could reduce loss and health costs, and help preserve these valuable resources. This study aims to predict blood platelet demands based on artificial neural networks (ANNs) and auto-regressive integrated moving average (ARIMA) models in order to reduce the uncertainty in the supply chain. To this end, daily demands for eight types of blood platelets from 2013 to 2018 were used in the current study. Data were collected from treatment centers and hospitals located in Zahedan, Iran. The results of this study indicated that ANNs and ARIMA models were more accurate in predicting the uncertainties in demand than the baseline model used in Zahedan Blood Transfusion Center. The highest and lowest prediction improvements based on ANNs and ARIMA models were associated with type O+ and A+ platelets, respectively. Given that the ANN models can significantly improve the prediction of uncertainties in demand, we highly recommend that the conventional statistical prediction methods in blood transfusion centers be replaced with these models.

1. Introduction

One of the central issues in global healthcare systems is the improvement of supply chain performance. The health system has one of the most complex and challenging supply chains since it is directly connected to the health of human beings [1]. Issues such as uncertainty in demand, planning for inventory management and ordering, expiration dates, and limited human resources are among key challenges in the health sector, particularly the supply chain of blood and its products [2–5]. Moreover, supply chain management and planning of blood products, especially blood platelets, are essential concerns for human life due to their high perishability [6]. Platelets are the most expensive blood products. As they have a shelf life of three days and high production costs, it is not economical to store them in large quantities in blood centers. Moreover, blood donation is often unpredictable, and demand for its products is random. The uncertainty in the supply chain of platelets has caused decision-makers and experts to face some challenges whenever there is a rise in the platelet demand (a shortage) or a fall in the number of referrals to blood collection centers (a surplus). Besides, issues such as restrictions might appear regarding platelet preservation as well as their excess production whenever there is a decline in demand or an increase in the number of referrals. For this reason, the production of platelets in blood centers must comply with the hospitals and medical centers' demands [6]. Chopra and Meindl [7] argued that accurate prediction and knowledge of the demand could facilitate planning in the supply chain. Having accurate information on demand, especially when the shelf life of the product is short, can help make a better decision on required products, address supply shortages, and reduce resource and health costs [4,8]. Therefore, this issue is of great importance in the supply chain.

Previous works have studied uncertainty in demands and investigated its effects on the performance of supply chains by applying different methods [9–15]. Also, in order to avoid wasting blood and its products, different research works have been carried out to change the

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planning and management policies of hospitals and blood banks [16–20], among which only a few studies have used BOX Jenkins or ARIMA to predict blood demand [4,21,22] as discussed below.

In 2016, the monthly demand forecast of blood supply at New York City Blood Center was studied [4], and the optimal method for prediction was determined using MA, ES, ARMA and VARMA models. Results showed that the accuracy of the ARMA models and their simplicity compared to VARMA has turned them into best models in predicting blood demand. Filho et al. [21] sought to predict demand for distribution of blood components in a supply chain with the aim to improve planning and to create a balanced inventory process. To predict these blood components, they used the univariate multiplicative seasonal model of BOX-Jenkins and ARIMA methods. Authors of the prior study believed that using this model instead of traditional methods of moving averages (MA) with weekly lags, could improve the efficiency and accuracy of the planning. Filho et al. [22] in another study proposed a decision-making tool to predict demand for blood components in the supply chain. In their study, instead of adopting a weekly moving average method, a more complex parametric model based on BOX-Jenkins was proposed, and the results proved that the employed model was much better than the moving average. These studies indicate the supremacy of the ARIMA method compared to the linear statistical techniques (MA, ES, VARMA) and the univariate multiplicative seasonal model of BOX-Jenkins and ARMIA methods. However, in order to better diagnose data dynamics and underlying patterns in the observations (demand uncertainties), other methods of artificial neural networks (ANNs) could be used alongside these techniques [23].

Artificial neural networks, one of the components of computational intelligence, have recently received extensive attention from scholars in various fields of science. These networks are robust and competent tools for decision-making since they are intelligent, adaptable to environmental changes, generalizable to nonlinear complex systems, and able to process data at high speed [24–26].

In previous studies, a demand forecast of blood supply has been done through linear statistical techniques and BOX-Jenkins models. On the other hand, currently, the averaging method is being used to predict demands in blood transfusion organizations. Also, the above methods consider blood demand (data behavior) as consistent with relatively regular alterations, whereas in reality, nonlinear behaviors are observed as well. Thus, blood issues, especially the blood platelet demand, are a combination of both linear and nonlinear behaviors in which the nonlinear part has been ignored in earlier studies. Moreover, linear methods cannot address the complexities associated with changes in demand. Hence, in order to fill this gap, the present study is an attempt to use ANNs and ARIMA models to reduce the demand uncertainty and predict demand in the platelet supply chain of Zahedan Blood Transfusion Center. This prediction can reduce waste and production costs and alleviate the supply shortage.

The rest of this paper is organized as follows: Section 2 presents an overview of ARIMA and neural network methods. Section 3 investigates findings on existing methods where the best models appropriate for various blood types are chosen. Finally, conclusion and managerial implications are presented in Section 4 and 5.

2. Materials and methods

2.1. Data collection

The data for this study were collected from the education department of Blood Transfusion Center in Sistan and Baluchistan province, Zahedan, Iran. This center is the foremost supplier of blood and its products for hospitals and medical centers in the province. To plan for producing and supplying the demanded platelets, the staff in this center uses an averaging method and the available data on demands from previous days to forecast requests for upcoming days. We have used the data on platelet demands of Zahedan hospitals and health centers only for two reasons: First, this city has a wide blood supply chain. And second, adequate electronic data on other cities of the province were not available. The data associated with daily demand for eight blood type platelets (O +, O-, A +, A-, B +, B-, AB +, AB-) from 2013 to 2018 were used in this study. The data for the eight-time series were analyzed using Eviews and MATLAB.

2.2. The ARMA method

A time series is a sequence of observations arranged by time and classified as discrete (at specific intervals) or continuous [27]. The most important step in analyzing these series is to find the appropriate model, among which, the most famous is a multi-stage strategy described as ARIMA. Box-Jenkins wa the first to propose this model in 1970. An ARIMA model is a linear combination of past errors and past values of a stationary series. The three parameters representing this model are; *p, q,* and *d*, which respectively stand for the autoregressive order parameter, the moving average component, and the required differencing order for stationary,. The first differencing order ($d = 1$) suggests differencing between two successive periods of demand for the entire data set, and if the demand is stationary ($d = 0$), the ARIMA model (p, d, q) is converted to the ARMA model (p, q) and does not require differencing anymore [27,28]. The general ARIMA model is given by equation (1):

$$y_t = c + \sum_{i=1}^{p} \varphi_i y_{t-i} - \sum_{i=1}^{q} \theta_i u_{t-i} + e_t \tag{1}$$

Table 1
Description of the ARMA model.

Method	Description	Reference
AIC SBC	These two criteria are used to measure the goodness of fit and determine the choice of optimal lags in the model. In fact, they establish a balance between the accuracy of the model and its complexity. The values of these criteria are calculated using Eviews software program. These values indicate that adding or removing variables to the model or any other changes would make AIC and SBC negative, meaning that the model would be sounder. SBC is used for large samples, while AIC is used for small ones.	Young [31] Burnham and Anderson [32]
Durbin-Watson (DW)	The Durbin Watson statistic is a criterion used to examine the correlation between residuals in regression analysis. The value of this criterion ranges from 0 to 4. A value close to 2 indicates the lack of correlation between the residuals, while values close to zero and 4 propose a positive and negative correlation, respectively.	Durbin and Watson [33]
Q-test (Ljung-Box test)	This test is used to examine the significance of concurrent self-correlations with several lags. The purpose is to investigate the randomness of residuals using self-correlation charts. In fact, instead of investigating randomness at each separate lag, it examines the total randomness based on a few lags. H_0 means the data are random, and H_1 means they are not.	Ljung and Box [34] Tsay [35]
Unit root	The purpose of this test is to examine whether the data is stationary and does not have a unit root. In case the data is non-stationary, more differencing is needed. The unit root test examines the first order and second order differences in different states such as level.	Bhargava [36] Hamilton [30]
Augmented Dickey Fuller (ADF) test Phillips and Perron test	Both tests are most commonly used to examine the unit root in the data. They determine whether the mean and the variance of the data are constant over time (static). H0 in both tests signifies the existence of a unit root, and H1 implies its absence. The Phillips and Perron test is more accurate than ADF.	Aoki [38] Montgomery et al. [37]

where y_t, c, φ_i $(i = 1, \ldots, p)$, θ_i $(i = 1, \ldots, q)$, y_{t-i}, u_{t-i}, and e_t represent the time series, a constant coefficient, the parameters of the autoregressive model, the moving average model parameters, the pth lags of the dependent variable, the qth lags of the previous error, and the prediction error of the model at time t, respectively [29].

In this research, we used the ARIMA method, which includes three stages of identifying, estimating, and testing the diagnostic model. In the identifying stage, after processing and reviewing information, data stationary (absence of a unit root) needs to be ensured: if data pattern is not stationary, the error of prediction model will increase [30].

Therefore, the hypothesis of data stationarity is tested using standardized Augmented Dicky-Fuller and Phillips–Perron tests in Eviews.

The explanations about the ARIMA test are given in detail in Table 1. The autocorrelation function (ACF) and partial autocorrelation function (PACF) are used to identify the type and order of the model and examine its reversibility. If both of the self-correlation functions converge to zero, the model is inverse, and our prediction values will be correct and trustworthy. The least-squares (LS) method was used to estimate the model parameters, and the significance of coefficients was verified at 95% confidence level. Next, to select the appropriate model, the following criteria were applied: Akaike information criterion (AIC), Schwarz-Bayesian criterion (SBC), and Durbin Watson statistics (DW stat). In the stage of testing the model, the fitness of the selected model is evaluated using the Ljung-Box test, and if the selected model is inappropriate, it will be modified and corrected. Finally, after identifying the best models of ARIMA, the platelet demand for the next period is predicted [30,39]. All settings of the ARIMA model are adjusted using Eviews.

2.3. Artificial neural networks

As a data-driven and non-hypothetical approach, neural networks have proven a modern and trustworthy approach to the approximation of complex functions. A neural network includes a network of simple processing elements called neurons. The function of the neuron is receiving inputs, processing them, and sending output signals. A series of neurons in a row form a layer, and multi-layers connected together, shape a network [24,40].

In order to design an artificial neural network, besides selecting a set of input variables, we need to identify the best-predicted network

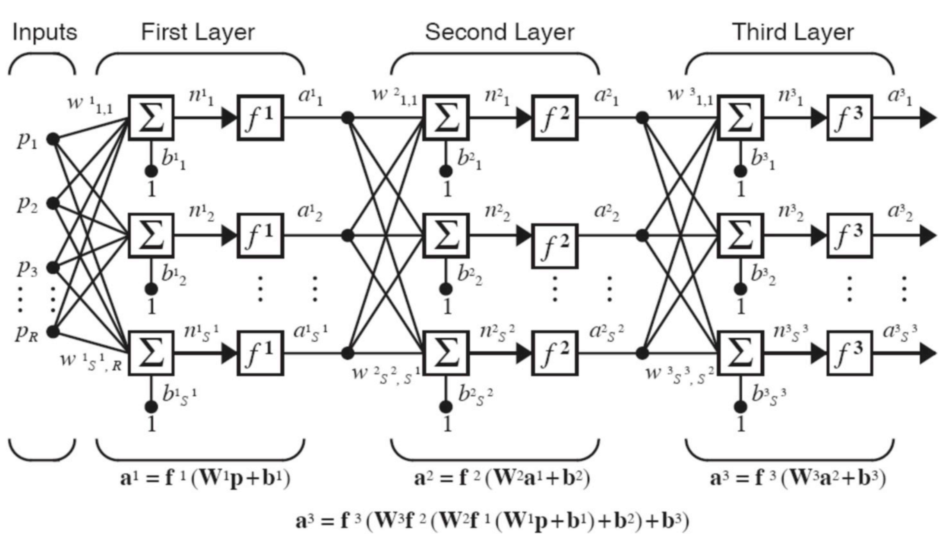

Fig. 1. An artificial neural network structure employing the back-propagation learning rule [24].

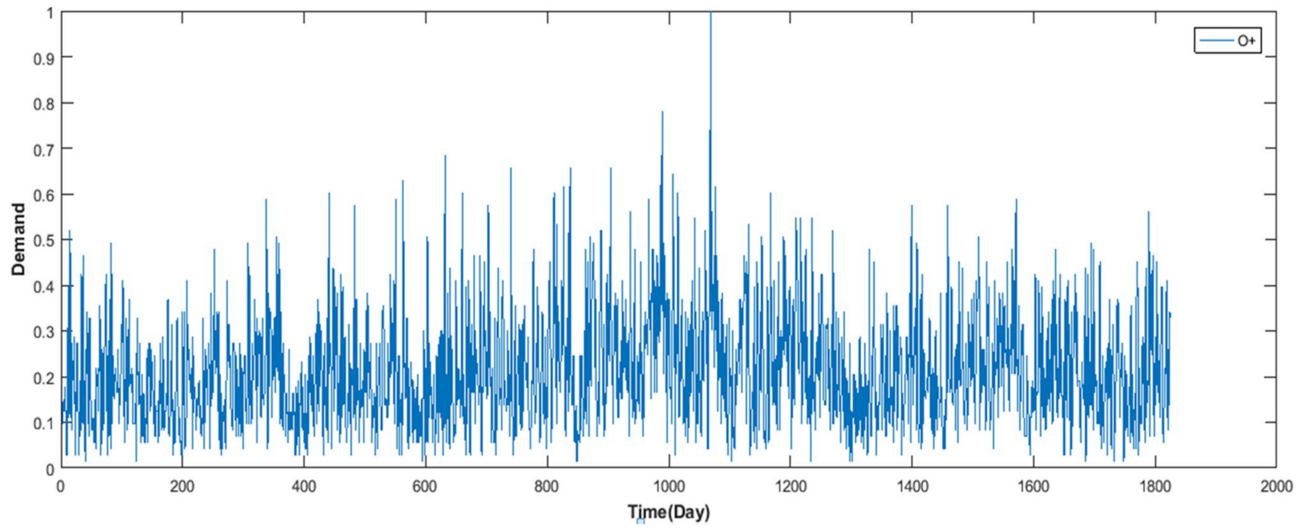

Fig. 2. Time series graph for O+ platelet.

Table 2
Dickey-Fuller and Phillips-Perron stationarity tests for blood platelet types.

Decision	Critical value at 1%	T -statistics		differencing (d)	Platelet type
		ADF	Phillips & Perron		
Stationary	−3.433	−11.347	−41.687	0	O^+
Stationary	−3.433	−11.787	−42.149	0	O^-
Stationary	−3.433	−7.630	−41.918	0	A^+
Stationary	−3.433	−12.190	−40.949	0	A^-
Stationary	−3.433	−10.455	−40.515	0	B^+
Stationary	−3.433	−15.125	−41.829	0	B^-
Stationary	−3.433	−10.254	−40.578	0	AB^+
Stationary	−3.433	−42.219	−42.220	0	AB^-

structure using trial and error. In the present study, a multi-layer perceptron (MLP) neural network is used as depicted in Fig. 1. In a multi-layer perceptron network, every neuron in each layer is connected to all the neurons in the previous layer. This network is trained by the error back-propagation learning rule. In fact, the back-propagation algorithm follows two paths in this type of networks. Functional signals are distributed from layer to layer in a network (functional computing signals), and other signals are error signals that propagate in the return path of the network (calculating error signals).

This neural network consists of three layers: The input layer, the hidden (first and second) layers, and the output (third) layer, where *R*, *S*, *f*, *a*, *b* and *W*, represent the number of inputs (*p*), the number of neurons (*n*) in each layer, the activation function (f), the output of each layer (a), the bias (b), and the vectors of weights (W), respectively (Fig. 1).

3. Results

Fig. 2 demonstrates a time series graph used in the ARIMA model to predict O+ type platelet demands. As the series for different blood type platelet demands are similar to one another, only the graph for this platelet is presented. The series includes platelet demand for 1826 days between 2013 and 2018.

For ARIMA modeling, the stationarity of the blood platelets series was first tested using Dickey-Fuller and Phillips Perron tests. The results are presented in Table 2.

H0. There is unit root for the series.

H1. There is no unit root for the series.

Decision: |T - statistics| > |Critical value|: Reject the null hypothesis [4].

As noted in Table 2, the absolute value of the *t*-test is higher than the absolute critical value at 99% confidence level in all cases, and in both the ADF and Phillips-Peron tests. Therefore, we can reject the null hypothesis, that is: there is not a unit root for series; hence, the data is stationary. Thus, there is no need to difference the series, and the differencing order *d* for all cases is zero *(d = 0)*. The ARIMA (*p, d, q*) models were henceforward converted to ARMA (*p, q*) models. Then, to

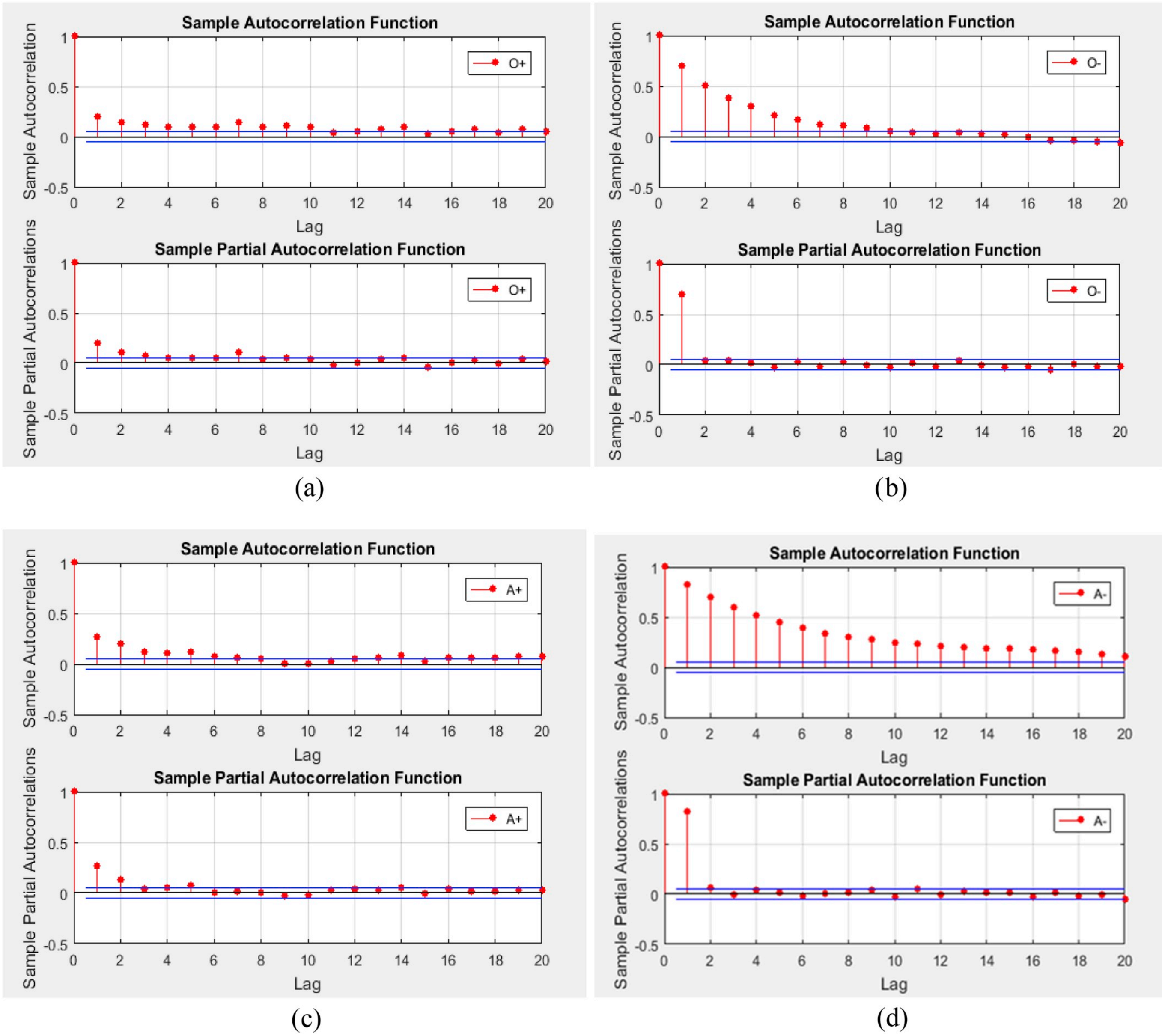

Fig. 3. ACF and PACF charts at a significance level of 5% for type A-, A+, O-, O+ platelets.

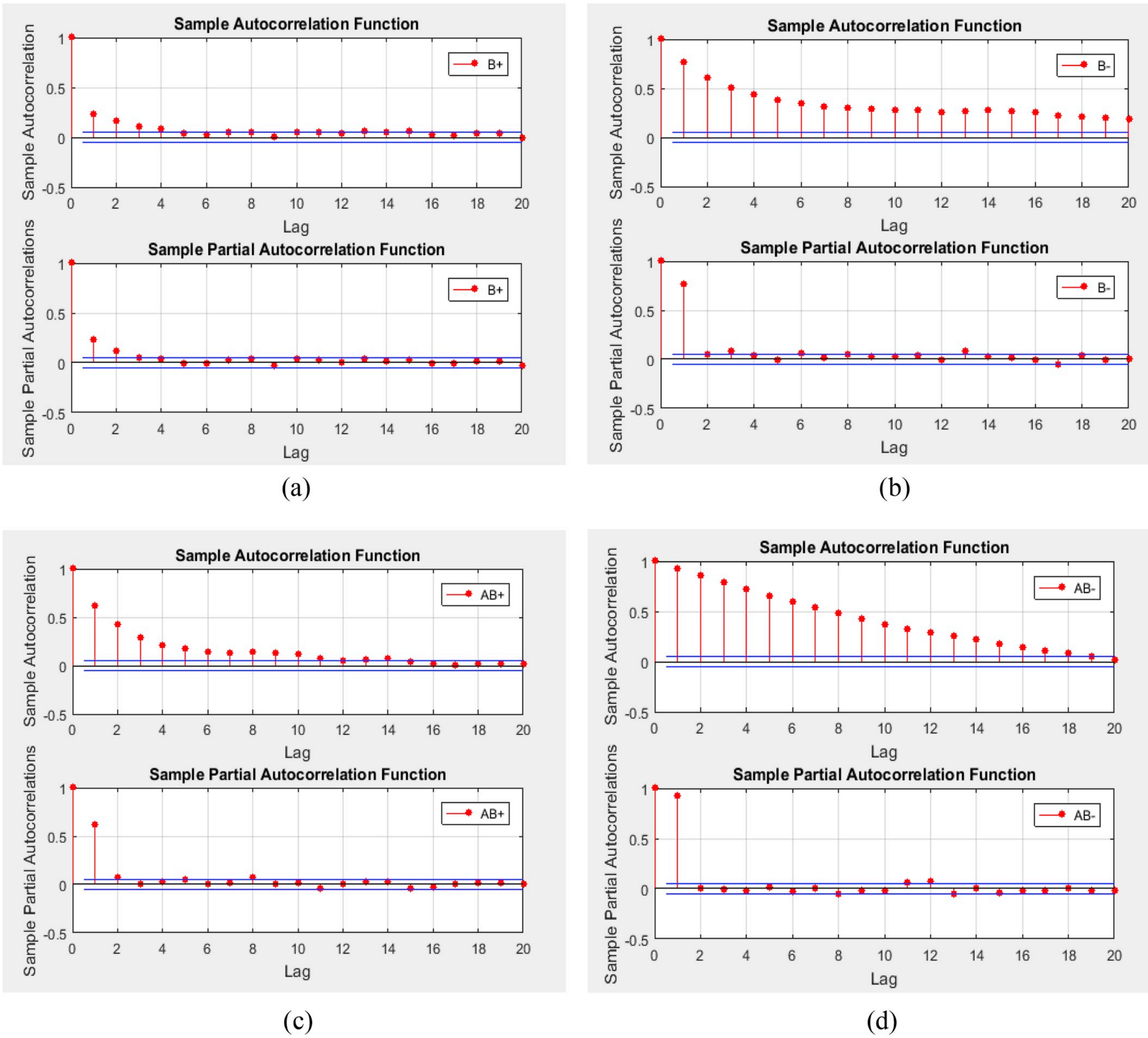

Fig. 4. ACF and PACF charts at a significance level of 5% for type AB-, AB+, B-, B+ platelets.

Table 3
AIC and SBC metrics, DW statistics for the selected ARMA models.

DW	SBC	AIC	Model	Platelet type
1.999	−1.2429	−1.2519	ARMA (1,1)	O^+
1.9382	−1.3581	−1.3853	ARMA (4,4)	O^-
2.001	−0.8693	−0.8965	ARMA (5,3)	A^+
2.012	−1.4721	−1.4812	ARMA (1,1)	A^-
2.010	−0.7062	−0.7213	ARMA (2,2)	B^+
2.036	−2.400	−2.4096	ARMA (1,1)	B^-
1.9657	−1.2883	−1.2974	ARMA (1,1)	AB^+
1.990	−2.7029	−2.7120	ARMA (1,1)	AB^-

examine the reversibility and identify the type and order of the model, the ACF and PACF charts were used for eight time-series as depicted in Figs. 3 and 4.

As observed in Figs. 3 and 4, all the ACF and PACF charts have an exponential or oscillating trend and converge to zero. This means that the series are reversible, and the predicted values are trustable. To check the validity of this issue, we examined various combinations of MA and AR lags. Considering that all the calculations for all types of platelets are similar, and due to the variety of platelets and space constraints, we only presented a description for O+ platelets. According to Fig. 3(a) of ACF and PACF charts, the lags considered for the O+ platelets have a decreasing trend from 10 to 7 lags respectively.

Table 4
The results of the Ljung-Box test for the platelets.

P-Value	DF	Chi-Square	Lag	Ljung-Box
				Platelet type with the selected Arma model
0.099	9	14.7	12	O^+
0.340	33	35.8	36	
0.103	3	6.2	12	O^-
0.082	27	37.8	36	
0.153	3	5.3	12	A^+
0.082	27	37.7	36	
0.271	9	11.1	12	A^-
0.652	33	29.3	36	
0.080	7	12.7	12	B^+
0.296	31	34.7	36	
0.284	9	10.9	12	B^-
0.279	33	37.3	36	
0.488	9	8.5	12	AB^+
0.415	33	34.1	36	
0.081	7	12.7	12	AB^-
0.712	31	26.2	36	

Thus, the pauses are $p = 1,2, \ldots,7$, $q = 1,2, \ldots, 10$ and, $d = 0$, which in total makes 70 models. In the process of estimating and testing the prescribed parameters from the 70 models available for O+ platelets, we only accepted the meaningful ones. A meaningful model must meet two requirements: its coefficients need to be in the interval [-1, 1], and also significant (P-value $\leq$ 0.05) [39]. This way, the rejected models were removed. Then, small values of the AIC, SBC, and the closeness of the DW value to 2 were considered as the criteria for choosing the best ARIMA model among the accepted models [see, e.g., 26–28]. Based on these criteria, the ARMA model (1.1) with AIC = -1.2519, SBC = -1.2429, and DW = 1.999 is the best choice for the O+ series (see Table 3). To verify this, the independence and randomness of residuals in the selected model were examined using the Ljung-Box test (see Table 4).

For each of the eight time-series analyzed using the Ljung-Box test, in both 12 and 36 lags, the P-value is higher than the considered confidence level (P-value > 0.05). Meaning that, the correlation between the components of the model suggests a random sampling process [34]. Therefore, it is concluded that the ARMA model (1.1) chosen for the O+ platelet is the best predicting model for this series (see Table 4). Similarly, for the other types of platelets, the same procedure was followed, and the final model for each type was recorded (see Table 5). In this study RMSE is used as a critical indicator since; a) relative values are closer to real world, b) the target variable in our prediction model is numeric, c) small standard deviation of error in RMSE will not cause dramatic changes, and d) the object of study is to evaluate total accuracy of the data.

In order to select the most appropriate neural network model to predict the platelet demands, different structures of the perceptron network were designed. MATLAB (R2016b) was used for computations. Since the platelet demand varies over the course of the week (annual or daily) and such changes follow a specific historical trend, in order to discover the latent patterns in these series, we considered 13 input variables of previous demand data including delays associated with: the current day, 1 day ago, 2 days ago, 3 days ago, 4 days ago, 5 days ago, 6 days ago, 1 week ago, 15 days ago, 30 days ago, 90 days ago, 120 days ago, and 365 days ago. There exists no single rule for determining the number of hidden layer neurons. Hence in this research, the constant approach technique of Castro and Boyd (1996) has been used. Initially, the network was trained with several different hidden neurons. Next, by evaluating a RMSE criterion on the experiment data set, the network was selected with a number of optimal neurons (the lowest RMSE) at the range of 2–15. The output layer predicts daily platelet demand. Considering the fact that there is also no rule for determining the size of the test and experiment data set, various ratios of data were examined. Eventually, with a ratio of 70 to 30, the network showed a better performance. This way, 70%, 15%, and 15% of the data were used for network training, validation, and network testing, respectively. Related settings for the transfer function of each platelet type in the hidden and output layers are the sigmoid and Purelin functions, respectively. Results are shown in Table 6.

After selecting the optimal models of ARIMA and artificial neural network, we predicted the demand for blood platelets on a daily basis as our studied blood center needed daily statistics. It should be noted that the averaging method is currently being used to predict platelet demand in this blood center. The procedure is that they use previous data (past demands) for averaging in order to use it in future predictions.

We considered the current trend (averaging method) as the baseline and tabulated the improvement of the prediction achieved by both ARIMA and ANN methods according to the RMSE criterion (see Table 7). The positive sign indicates that the prediction model performs worse than the baseline, and the prediction errors are high. Similarly, the negative sign indicates that the prediction model performs better than the baseline, and as a result, prediction errors are low [4]. Table 7 shows that the artificial neural network model has a better prediction capability than the baseline and could improve it significantly. Also, based on the RMSE criterion, the prediction accuracy in the neural network is higher than that of the ARIMA method. For example, for O+ type platelets, ANN, and ARIMA could improve predicted outcomes by 66% and 55%, respectively. An improvement of 66% means that the prediction errors of the baseline model (if the ANN method is used for prediction) have reduced from ± 0.286 to ± 0.098. In all platelet groups, except for type B- in which both the ANN and ARIMA methods have almost the same accuracy, ANN is more accurate than ARIMA and

Table 5
The best ARMA models to predict the demand for blood platelets.

Parameters	RMSE	best model	Platelet type
$y_t = 0.2051 + 0.9232y_{t-1} + 0.8207U_{t-1} + 0.129$	0.129	ARMA (1,1)	O^+
$y_t = 0.0720 - 0.4626y_{t-1} - 0.07456y_{t-2} + 0.4297y_{t-3} + 0.9112y_{t-4} - 0.4964U_{t-1} - 0.1479U_{t-2} + 0.3686U_{t-3} + 0.8482U_{t-4} + 0.120$	0.120	ARMA (4,4)	O^-
$y_t = 0.1783 - 0.3134y_{t-1} + 0.4363y_{t-2} + 0.9761y_{t-3} - 0.0955y_{t-4} - 0.0832y_{t-5} - 0.4321U_{t-1} + 0.2640U_{t-2} + 0.9218U_{t-3} + 0.154$	0.154	ARMA (5,3)	A^+
$y_t = 0.0445 + 0.8465y_{t-1} + 0.7826U_{t-1} + 0.115$	0.115	ARMA (1,1)	A^-
$y_t = 0.1949 - 0.1076y_{t-1} + 0.8679y_{t-2} - 0.2402U_{t-1} + 0.7552U_{t-2} + 0.168$	0.168	ARMA (2,2)	B^+
$y_t = 0.0227 + 0.8947y_{t-1} + 0.8213U_{t-1} + 0.072$	0.072	ARMA (1,1)	B^-
$y_t = 0.0782 + 0.9055y_{t-1} + 0.8280U_{t-1} + 0.126$	0.126	ARMA (1,1)	AB^+
$y_t = 0.0199 - 0.9721y_{t-1} - 0.9843U_{t-1} + 0.062$	0.062	ARMA (1,1)	AB^-

Table 6
The best neural network model for all types of blood platelets according to the RMSE criteria.

(number of input variables: number of neurons: number of output variables)								Platelet Type
AB^-	AB^+	B^-	B^+	A^-	A^+	O^-	O^+	
(13:5:1)	(13:8:1)	(13:9:1)	(13:7:1)	(13:5:1)	(13:8:1)	(13:5:1)	(13:7:1)	Network Architect
0.054	0.106	0.061	0.126	0.091	0.132	0.092	0.098	RMSE

Table 7
Improvement of prediction by the artificial neural network and ARIMA models compared to the baseline forecast.

Platelet type	Baseline Mean (RMSE)	RMSE direction	
		ARIMA	ANN
O^+	0.287	55%-	−66%
O^-	0.198	- 40%	- 53%
A^+	0.213	- 27%	- 38%
A^-	0.163	- 29%	- 44%
B^+	0.242	- 31%	- 47%
B^-	0.145	- 50%	- 58%
AB^+	0.179	- 30%	- 41%
AB^-	0.136	- 54%	- 60%

the baseline. One of the drawbacks of using the baseline is its lack of sensitivity to changes in demands, and its inability to discriminate between the changes in demands, occurred in the far past and in the recent past, successively resulting in substantial errors during the prediction procedure.

4. Discussion

Although the ARMA method is linear similar to the averaging method, it has a better performance. As the results indicate, the artificial neural network method is more sensitive to changes in demands and the actual trend in data. It proves that this method could improve the prediction significantly (as shown in Fig. 2 of the Appendix). In fact, one main reason that ANNs result in more accurate prediction compared to linear statistical methods is that ANNs can reproduce the dynamic interaction of multiple factors simultaneously, allowing the study of complexity. They are also able to draw conclusions on an individual basis and not as common trends [41].

5. Conclusion and future directions

This study strives to minimize the production of waste and costs by predicting platelet demands more precisely and consequently reducing uncertainty in demands. Artificial neural networks and ARIMA models were used for this purpose. The results showed that the models have high accuracy in predicting the demands for this blood product. According to the neural network and ARIMA, the highest accuracy was associated with the type O+ platelet. These models could improve the predicted outcomes by 66% and 55% respectively, compared with the baseline (averaging). The lowest prediction improvement in ANN and ARIMA was related to type A+ platelets (38% and 27%).

Both artificial neural network and ARIMA models had an almost similar improvement (58% and 55%) in all platelet groups, except for type B, in which the artificial neural network model is superior to ARIMA and the baseline. Therefore, as demand forecasts are more accurate, the amount of uncertainty in demand decreases. This means that these methods, especially the artificial neural network, could be good alternatives to the current methods used in the blood transfusion center.

The final models and parameters in this research have been designed specifically for the studied blood center, so the results cannot be used for other blood centers. However, by generalizing these models to other centers, it would be possible to calculate the specific results for each center. Future studies can use other neural network methods, such as dynamic neural networks, adaptive neuro-fuzzy inference systems (ANFIS), and integer-valued autoregressive (INAR) models for the same purpose. Combining neural networks with metaheuristic algorithms is another potential research to pursue.

On one hand, the platelet supply chain often faces challenges due to its short shelf life and uncertainty in its production. For instance, in times of crisis (natural disasters), medical emergencies, specific diseases, etc., certain conditions occur. For this purpose, including them in this supply chain can enhance its performance (could cover more uncertain situations/adapt to the real world).

On the other hand, due to the uncertainty in platelet demand, it is possible to better take into account the real-world states (uncertainty.), and use the fuzzy neural network (ANFIS) by entering into grey numbers field. Since the neural network can combine with different algorithms and therefore estimate any nonlinear function with arbitrary approximation, we could either use the combination of this network with meta-heuristics, or study its (NARX) dynamical modes.

Conflicts of interest

The authors declared no conflicts of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compbiomed.2019.103415.

Appendix

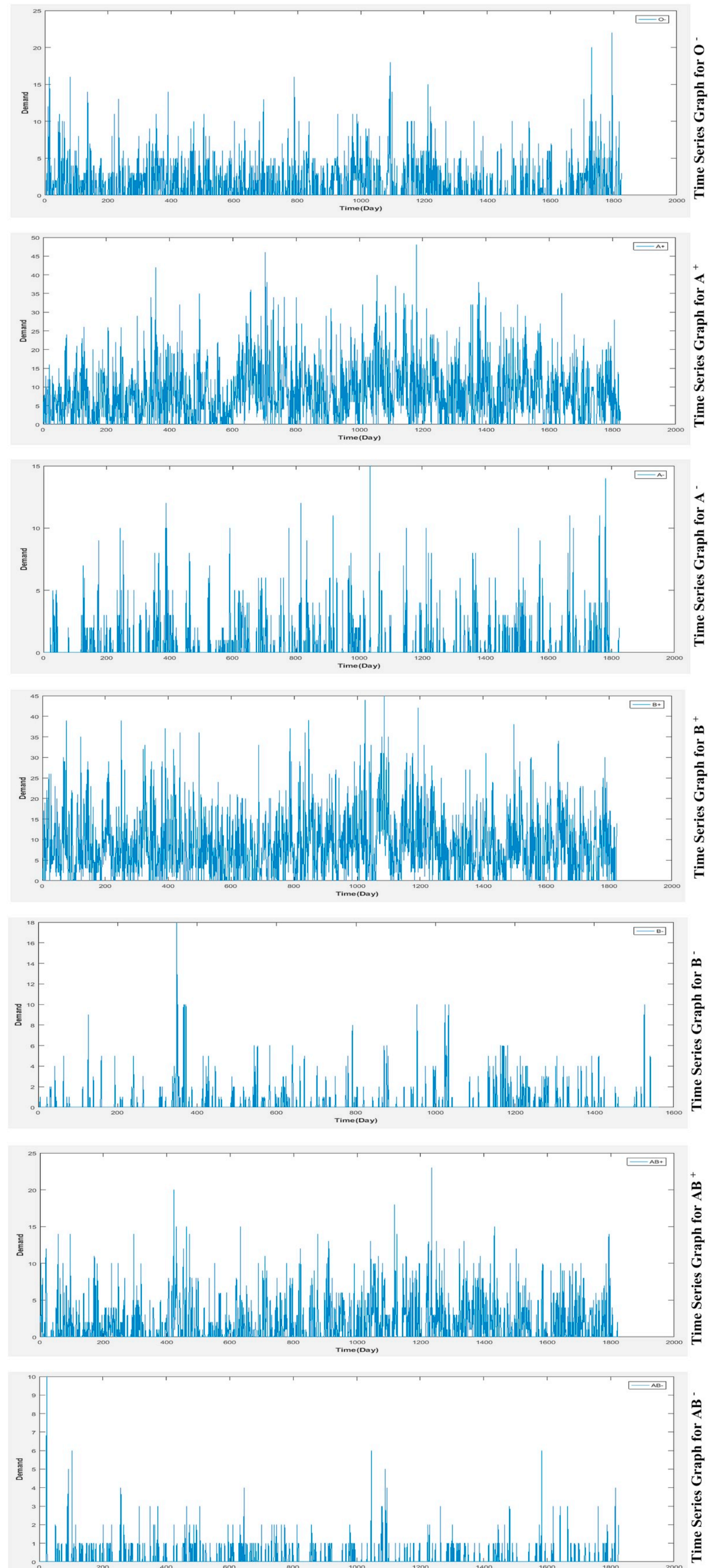

Fig. 1. Time series graph for other platelet types (O-, A+, A-, B +, B-, AB+, AB-).

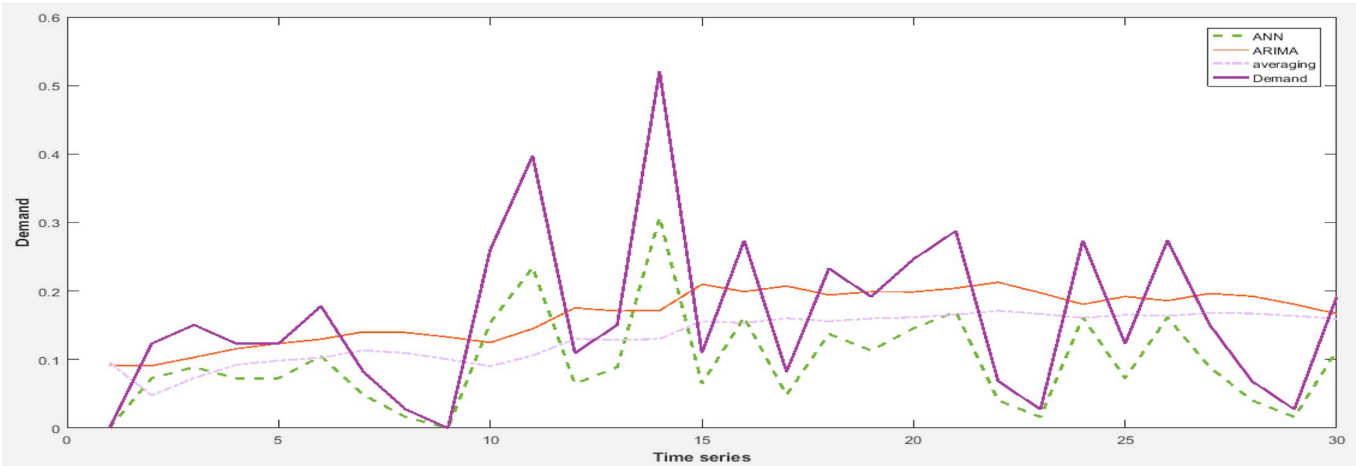

Fig. 2. Comparison of prediction models with real O+ platelet demand data for 30 days.

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