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Predicting Monthly Demand for Blood Using Artificial Neural Networks

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This study applied an Artificial Neural Networks (ANNs) model to predict blood demand in the central blood bank at Al-Haboubi Hospital in Nasiriyah City, south of Iraq. The network model was installed, validated and tested using incoming and outgoing blood data, submitted monthly for five consecutive years, from January 2013 to December 2017. The number of hidden neurons was estimated by trial and error. The mean square error (RMSE), mean absolute error (MAE) and correlation coefficient (R) were applied to select the best model. The artificial neural networks were considered an effective technique to estimate incoming and outgoing blood. This is a very helpful tool for those working in this important field.

Key words: *forecasting, Artificial Neural Networks (ANNs), blood bank, Nasiriyah.*

Introduction

Blood is an elixir of life. It is responsible for many vital processes in the human body, including respiration, transportation, excretion, regulation and defence. The body's volume of blood ranges from 4.7 to five litres, varying from person to person. In special cases, a person needs to compensate for blood losses or conditions, increasing or reducing the amount of blood, due to illness, injury or surgery, etc. This procedure is usually performed in hospitals, clinics and specialised health centres, as blood is a vital, complex substance consisting of a number of ingredients. The demand for blood is often urgent and patients' lives depend on it. To allow for rapid response, blood is usually collected in establishments – known as blood banks – which specialise in its collection and preservation. These are usually part of, or close to, hospitals and/or health centres. Blood banks usually follow advanced systems and methods when circulating and preserving blood stocks, ensuring the best use of the biological material, as well as relying on several methods to predict the supply and demand of blood.

Forecasting is one of the most widely used concepts in contemporary science, from forecasting weather conditions, to predicting coffee prices, to predicting demand for blood bags. Forecasting is defined as “predicting or anticipating what will happen in the future” (Russell and Taylor, 2011). It is defined by both Schroeder and Goldstein (2018) As “the art and science of anticipating future events.” A forecast is also known as “an estimate of future demand, based on past demand” (Kumar and Suresh, 2008). The forecasting process permeates nearly all functional areas of many organisations. Organisations rely on expectations for the formulation and implementation of their plans. Predictions are important for business plans, annual plans, and budgets. Human resources management relies on forecasting to anticipate or predict recruitment and training needs. Operations managers and supply chain managers also use forecasting when planning production levels, procurement of materials, labour force shifts, production schedules, inventory, capacity, etc. In marketing, finance and other business functions, managers forecast on many variables that affect future demand, such as competitors' strategies, organisational changes, technological changes, processing times, quality losses, etc. (Krajewski et al., 2013). There are many methods of forecasting, and organisations often use qualitative forecasting techniques, based on past opinions and experience to come up with the best possible forecasts. There are also a few quantitative forecasting methods available to assist managers in making planning decisions, assessing trends and predicting the future. A technique that does not lead to accurate forecasting can still be utilised in providing reliable guidelines or principles in decision making (Slack et al, 2010). According to Stevenson (2018), there are six basic steps in the prediction process:

1. Determine the purpose of the forecasting process, how it is used and what is being used. This step provides an indication of the level of detail required when forecasting, the amount of resources (personnel, equipment, money) to be used, and the level of accuracy required.
2. Determine a time horizon. Forecasts should indicate a period, considering that accuracy decreases as a time horizon increases.
3. Obtain, filter and analyse appropriate data. Access to necessary data often involves considerable effort. It then needs to be filtered to eliminate extreme values and incorrect data before analysis.
4. Determine the method of prediction.
5. Create forecast/s.
6. Monitor forecasts for errors. Errors should be monitored to determine whether the projections are operating satisfactorily and, if not, the method and assumptions should be re-examined, and the data should be validated.

Artificial Neural Networks (ANNs)

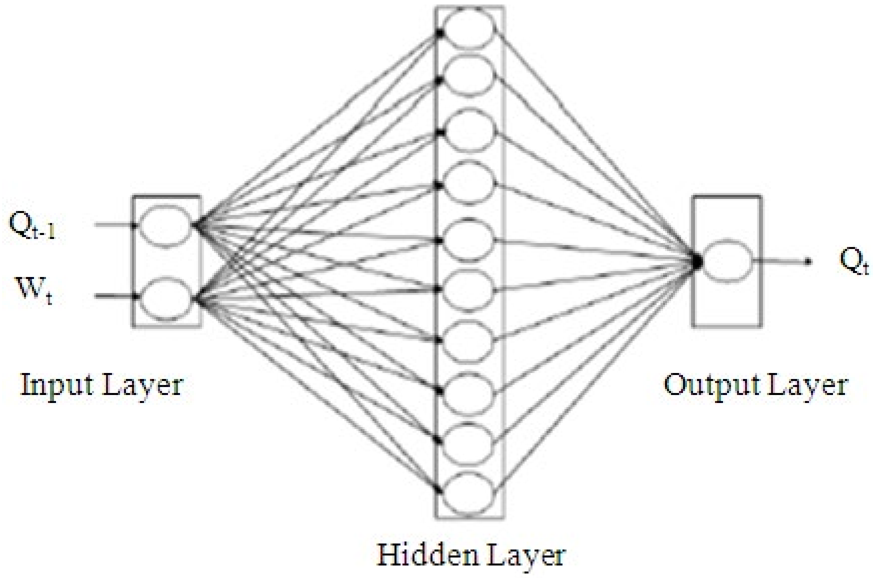
Artificial Neural Networks (ANNs) are a collection of artificial neurons , inspired by the biological systems of living creatures. ANNs are massive parallel-distributed information processing systems that have certain performance characteristics resembling biological neural networks of the human brain (Suresh and Kumar, 2008).

These parallel distributed processors have a natural propensity for storing experiential knowledge and making it available for use. They resemble the human brain in two respects: knowledge is acquired by the network through a learning process, and inter-neuron connection strengths, known as synaptic weights, are used to store knowledge.

ANNs have been applied successfully in the fields of mathematics, engineering, medicine, economics, neurology and many others. Some of the most important applications include use in pattern, sound and speech recognition, analysis of electromyography and other medical signatures, identification of military targets, and the identification of explosives in passengers' suitcases. They have also been used in weather and market trend forecasting, in the prediction of mineral exploration sites, electrical and thermal load prediction, adaptive and robotic control and in many other areas. Neural networks are used for process control, as they can build predictive models from multidimensional data, routinely collected by sensors.

The model of an ANN is showed in Figure 1. The most efficient neural network training algorithm is the back propagation algorithm (BP) (Krajewski et al., 2013). In this study, the back propagation algorithm was used to calculate nonlinear multilayer networks. The ANNs' parameters (weights and biases) can be adjusted to minimiae the sum of the squares of differences between the actual values and network output values (Suresh and Kumar, 2008).

Figure 1: Architecture of multilayer perception of Artificial Neural Networks [Modification from (Suresh and Kumar, 2008)]



In any ANNs there are several data processing elements called neurons, which are gathered in layers (Ali et al., 2017). Neurons of the first layer, called the input layer, receive the input vector and transfer values to the next layer nodes or neurons through connections. This process is continued until the output layer is reached. ANNs can be classified into two types according to the number of layers: single bi-layer and multilayer networks. These can be categorised into feed-forward and feed-backward networks, according to the direction of the information and processing (Heizer et al., 2017). During training, the contact weights are adjusted to reduce the squared difference between the wanted output and the processing elements' response. The optimal weights are the product of the inverse of the input autocorrelation matrix (R^{-1}) and the cross-correlation vector (P) between the input and the desired response. This problem's analytical solution is equivalent to a search technique that obtains the minimum of the quadratic performance surface (wi), using gradient descent by adjusting the weights of each epoch (Krajewski et al., 2013):
$w_i(k+1)=w_i(k)-\eta\nabla Ji(k) \quad \nabla Ji=\partial J\partial wi$(1).

Where:

η: coefficient of learning rate.

∇(k): gradient vector of the performance surface at iteration (k) for the i^{th} input node.
Performance surface (J) is calculated by equation (2): $J=\Sigma_p(d_p-y_p)^2 and \quad \min J\rightarrow w_{opt}=R^{-1}P$ (2).

Where:

w_{op}: optimal weight „p: target output, y_p: calculated output of the p^th output neuron.
Three layer feed-forward neural networks were used in this study, which have been widely used for modelling, because these layers are sufficient to generate arbitrarily complex output signals (Russell and Taylor, 2011). The output value of multilayer perception is calculated as follows Schroeder and Goldstein (2018):

$$y_k = f_{\circ}[\sum_{i=1}^{M_N} W_{Kj} \cdot f_h\left(\sum_{i=1}^{N_N} W_{ji} X_i + W_{j^\circ}\right) + W_{K^\circ}](3)$$

Where:

W_{ji}: a weight in the hidden layer connecting the i^th neuron in the input layer and the j^th neuron in the hidden layer.
W_{jo}: the bias for the j^th hidden neuron.
f_h: the activation functions of the hidden neuron.
W_{kj}: a weight in the output layer connecting the j^th neuron in the hidden layer, and the k^th neuron in the output layer.
W_{ko}: the bias for the k^th output neuron.
f_o: the activation functions for the output neuron.
X_i: i^th input variable for input layer.
y_k: computed output variable.
$M_N and N_N$: the number of the neurons in the input and hidden layers, respectively.

Study Area and Data Set

Nasiriyah represents the centre of the province of Dhi Qar, located in the south-east of Iraq on the Euphrates River. It is the fourth largest city, in in terms of population size, after Baghdad, Basra and Mosul. It is located between the latitude 29.5° and 31.5° north and the longitude of 46.4° and 47.65° east, and is to the north of the province of Wasit, south of Basra and to the west of Maysan, Qadisiyah and Muthanna provinces (Heizer et al., 2017).

Initial statistical data for this study were collected from the blood donors of the blood bank in Nasiriyah city. Monthly data was collected during the period of five years (January 2013 to December 2017). Table 1 shows a statistical summary of the raw data.

Table 1: Summary statistics of the raw data for the blood bank

	Standard Deviation	Skewness Coefficient	Excess Kurtosis	Median (litre)	Minimum (litre)	Maximum (litre)	Average (litre)
Expense of Blood	361.6013	-0.30321	-0.2396	2261.5	1189	2996	2221.95
Donor of Blood	300.8423	-0.7344	0.001639	2090	1163	2562	2026.017

Methodology

In this study, training of ANN models of different architectures applied an automatic performance analysis of the networks, based on the correlation coefficient (R), mean squared error (MSE) and root mean squared error (RMSE) analyses were performed (Ali, 2017: 2647)

$$R = \frac{\sum_{j=1}^{n}[(Y_j-\bar{Y})(\hat{Y}_j-\bar{\hat{Y}})]}{\left[\sum_{j=1}^{n}(Y_j-\bar{Y})^2 \sum_{j=1}^{n}(\hat{Y}_j-\bar{\hat{Y}})^2\right]^{1/2}} \& R = \sqrt{R^2} \quad (1)$$

$$\mathrm{MAE} = \frac{\sum_{j=1}^{n}|Y_j-\hat{Y}_j|}{n} \quad (2)$$

$$\mathrm{RMSE} = \left(\frac{\sum_{j=1}^{n}(Y_j-\hat{Y}_j)}{n}\right)^{1/2} \quad (3)$$

Where:

$Y \& \hat{Y}$: the observed and estimated values respectively.
n: the number of observations.
$\bar{Y} \& \bar{\hat{Y}}$: the mean of observed and estimated values.

Three layers of feed-forward network, with sigmoid hidden neurons and linear output neurons, were used in this study. Several networks, with different numbers of hidden layer nodes (1-20) and with different transfer functions, were developed. The network was trained with Levenberg-Marquradt’s back-propagation algorithm. The data set was scaled using the mapminmax function, according to this scale and range of the input lies inside the range (-1 ≤ x ≤ 1). Hence, the total number of observations is 120 samples for each model, divided into three statistical parts. This included 70% (84 samples) for training, presented to the network during training, with the network adjusted according to error. Then, 15% (18 samples) was used as validation – these were used to measure network generalisation, and to halt training when generalisation stopped improving. The last element of the data set was the 15% (18 samples) that had no effect on training, and provided an independent measure of network performance during and after training. The early stopping method was selected to overcome the over-fitting problem. A trial and error procedure, based on root mean square error (Eq. 3), mean absolute error (Eq. 2) and coefficient of correlation (Eq. 1) are used to select the best network architecture and performance of ANNs for predicting the expense of the blood bank.

Results and Discussion

To predict the expense of blood value is used preceding donor of blood value. There are four models adopted for selecting the best method. Each model is described as follow:

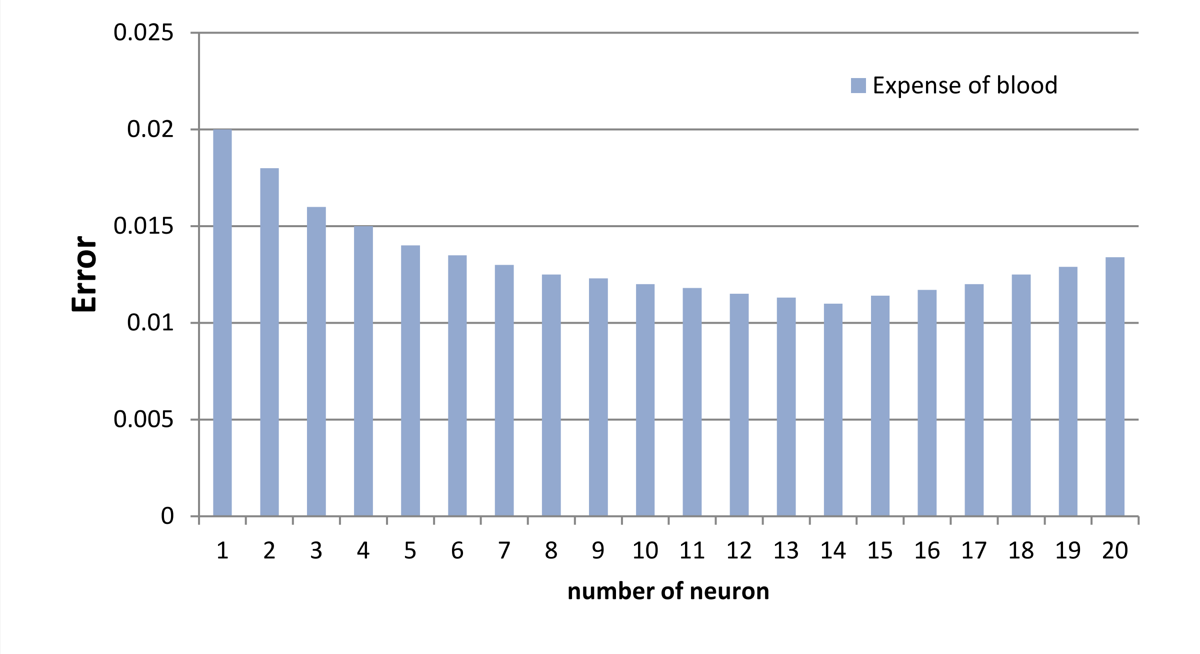
$$M1: EX_t = f(D_t) \quad (7)$$
$$M2: EX_t = f(D_t, EX_{t-1}) \quad (8)$$
$$M3: EX_t = f(D_t, D_{t-1}, EX_{t-1}) \quad (9)$$
$$M4: EX_t = f(D_t, D_{t-1}, D_{t-2}, EX_{t-1}, EX_{t-2}) \quad (10)$$

Where:

EX_t: expense of blood at a specified time.
EX_{t-1} &EX_{t-2}: expense of blood at t-1 and t-2 respectively.
D_t: donor of blood at a specified time.
D_{t-1}&D_{t-2}: donor of blood at t-1 and t-2 respectively.

Root mean square error (RMSE), mean absolute error (MAE) and coefficient of correlation (R) were used to evaluate the performance of models. The ANN models were trained utilising different numbers of neurons in the hidden layer, for training, testing and validation. The results showed the error values obtained for expense of blood, when compared with observed data, is shown in Figure 2, for the validation data set.

Figure 2: Variation of error values with hidden layer neurons for the validation data



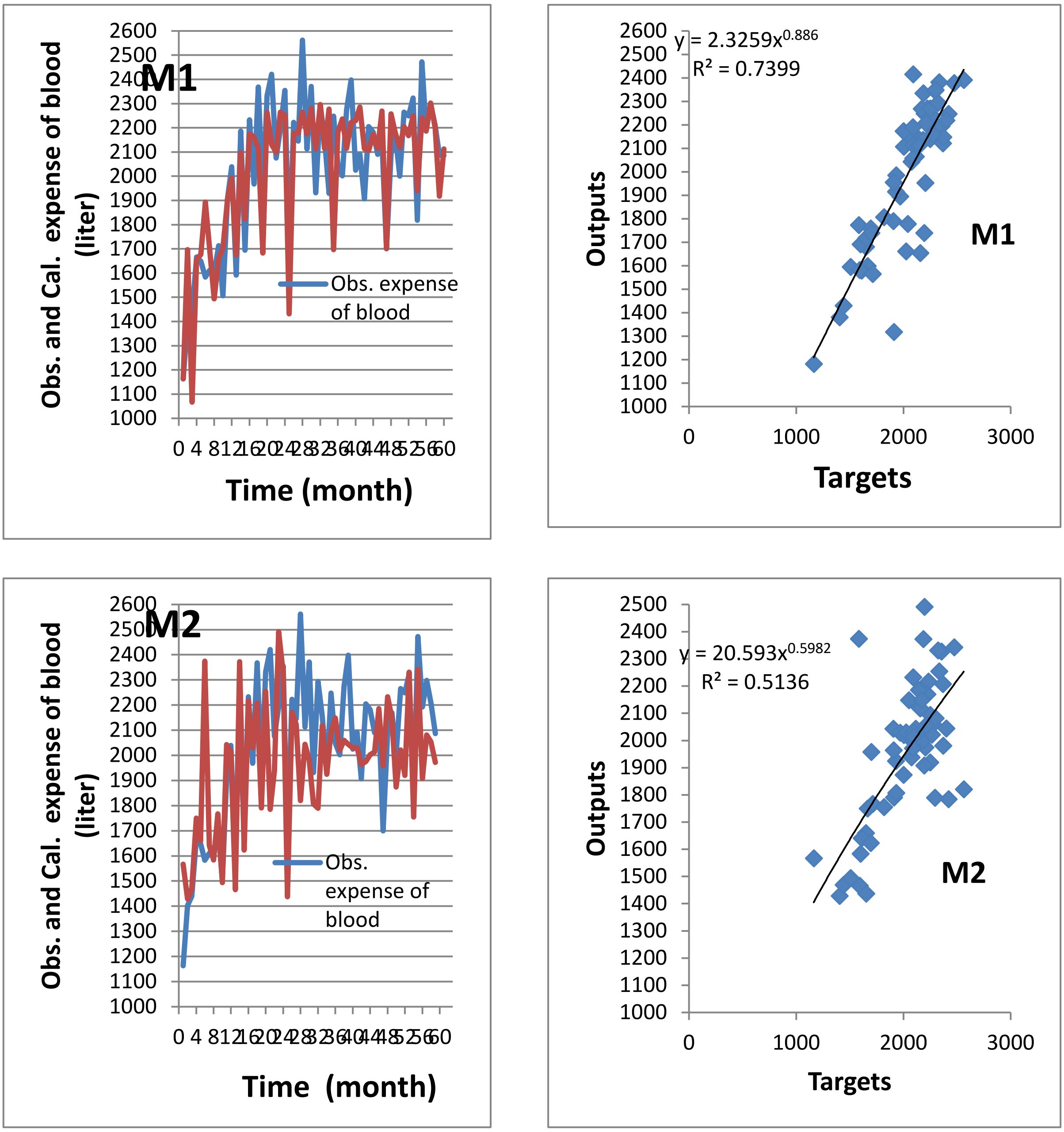
As evident in Figure 2, the minimum error in the expense of blood has been obtained with 14 neurons in the hidden layer for all models. Table 2, shows the comparison of models computed over the test dataset, with marked values corresponding with best performance, according to the criteria in each column. Model one is the best, in terms of performance in the testing stages, compared to the other models, having the lowest RMSE and MAE values, while having the highest R value.

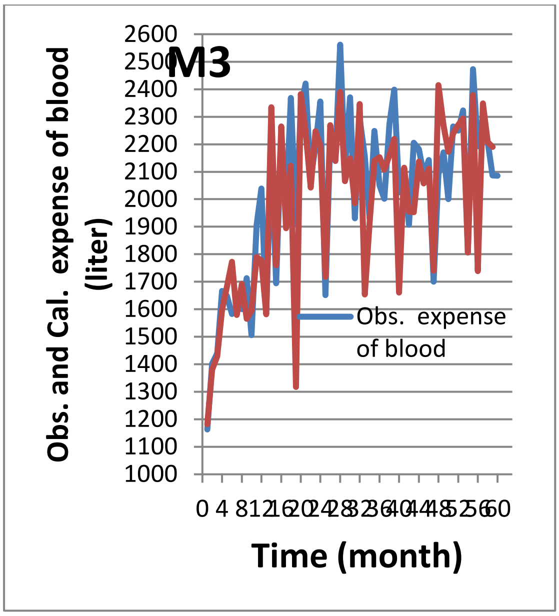
Table 2: Performance parameters of the artificial neural network models in the testing period with 14 nodes

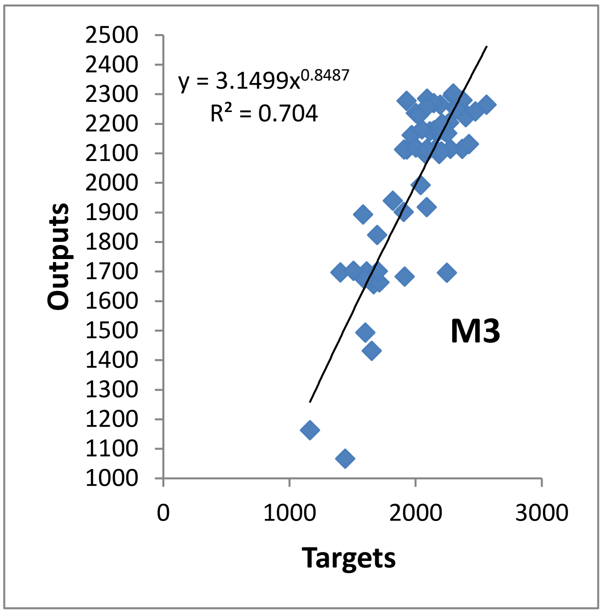
Number Of Model	R	RMSE	MAE
1	0.860174	108.8187	81.35443
2	0.716659	175.3731	148.8976
3	0839047	157.4312	102.0028
4	0.612781	262.519	195.8108

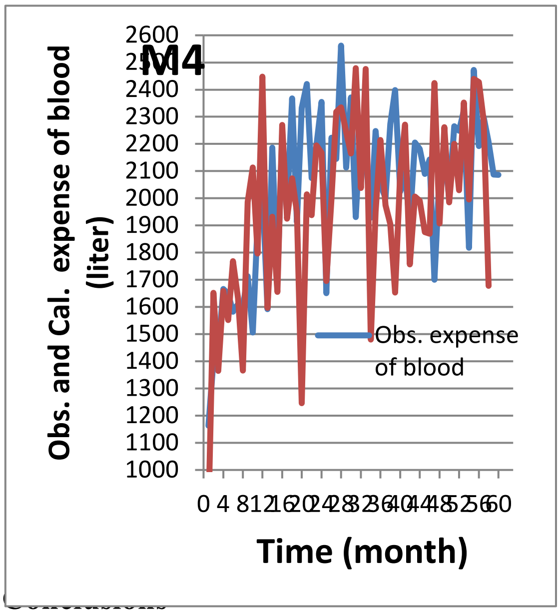
The application of ANNs for prediction of expense of blood is demonstrated in Figure 3, in the form of a hydrograph and scatterplot. The figure also shows an analysis between network outputs and corresponding targets for the test dataset. Also, the figure shows the ability of ANNs as a powerful tool to predict. The performance of the neural networks could be improved using additional information relating to the variable under consideration, such as blood type.

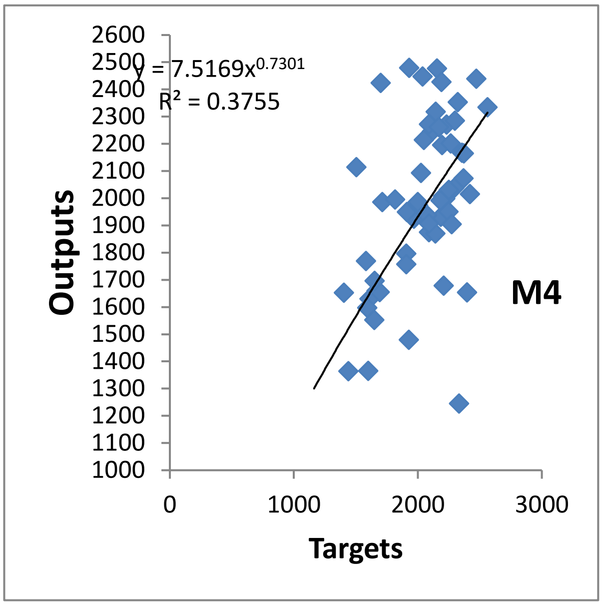
Figure 3: Comparison artificial neural network models for blood bank











Conclusions

In this study, an application of artificial neural network models was developed to predict monthly expenses of blood in blood banks in Nasiriyah city. It used data, which included the monthly expense of blood and the number of donors of blood over five years. The data was spilt into three data sets for training, validation and for testing (using the ratio 70:15:15), respectively. A three layer feed-forward network with sigmoid hidden neurons and linear output neurons was used. The back-propagation algorithm gave a prescription for changing the weights in any feed-forward network, learning a training vector of input-output pairs. The output showed that an artificial neural network, using a back-propagation algorithm, is a powerful technique for predicting the expense of blood. The best numbers of neurons in the hidden layer was 14. Also, results showed the efficiency of ANNs begins to decrease when the length of the forecasting period is increased. The study illustrates practical application of ANN approaches, when combined with other frequently used blood inventory systems planning and management tools. It can be concluded that this is a model which is viable for future applications, competing with existing techniques. The study recommends using hybrid systems developed from various artificial intelligence methods, in order to get more accurate predictions.

REFERENCES

Ali, H., Ahmed, A. & Husham, T. (2017). Comparison of data-driven modelling techniques for predicting river flow in an arid region. International Journal of Applied Engineering Research, 12(11): 2647-2655.

Heizer, J., Render, B. & Munson, C. (2017). Operations management: Sustainability and supply chain management.12th Ed, New York: Pearson Education, 3(82): 82 – 91.

Krajewski, L. J., Ritzman, L. P., & Malhotra, M. K. (2013). Operations management: Processes and supply chains.10th Ed, New Jersey: Pearson Education, 2(71): 173 – 184.

Russell, R.S. & Taylor, B. W. (2011). Operations management creating value along the supply chain.7th Ed, John Wiley and Sons, 7(81): 173 – 186.

Schroeder, R. G. & Goldstein, S. M. (2018). Operations management in the supply chain: Decision and cases. 7^{t}h Ed, New York: McGraw-Hill Education, 1(73): 202 – 215.

Slack, N., Chambers, S. & Johnston, R. (2010). *Operations management*. Pearson education. 6th Ed, London, Pearson Education Limited, 5(13): 172 - `85.

Suresh, N. & Kumar, S. A. (2008). Production and operations management (with skill development, caselets and cases). 2th Ed, New Delhi: New Age International (P) Ltd, 8(17): 172 – 179.