Artificial Neural Network Modeling of Blood Flow through Stenosed Artery with Bypass graft

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Abstract

Artificial Neural Network model was designed to describe the behavior of blood flow in which degree of stenosis, flow rate, pressure anastomotic angle are considered as input variable while pressure and flow rate as output. Model predicts higher degree blockage of the stenosed artery with higher drop of blood pressure at the stenosis region. Bypass surgery at optimized anastomotic angle is highly useful for regulating the blood pressure. ANN provides reasonable predictive performance in resemblance to the experimental values. The Levenberg–Marquardt algorithm (LMA) was found best of BP algorithms with a minimum mean squared error (MSE) for training and cross validation.

Keywords: Artificial Neural Network, Stenosis, Anastomotic angle, Pulsatile flow.

Introduction

Coronary Artery Disease (CAD) is one of the top 10 causes of worldwide deaths (WHO, 2008). Bypass surgery has been accepted as the most reliable treatment to restore blood flow in serious blockage of the coronary artery but found to be associated with several complications. About 25% of grafting surgery fails within one to ten years (Papaharilaou et al, 2002) for which abnormal bold flow is believed to be a major cause. The complexity of blood flow in the complete model of arterial bypass has been recently the focus of investigation (Chua et al 2005, Ghista et al 2005, Chen et. al 2006, Qiao and Liu 2007). Bifurcating flow rate through bypass graft in the fully occluded host artery with complete flow- based on anastomotic angle (α) has been pointed out. Wiwatanapataphee et al. (2006) investigated the behavior of blood flow in a stenosed right coronary artery (RCA) with a bypass graft. Shaik et al (2008) analyzed blood behavior in a vessel with bypass graft simulated in a straight tube. Siddiqui et al (2009, 2010) studied blood flow simulated in a single tube with stenotic region. Chuchard et al.(2011) studied blood flow through the system of coronary arteries with diseased left anterior descending.

Neural network provides an approach to obtain accurate numerical values in a computationally less intensive fashion. Arora et al, 2011 has recently reported ANN modelling for the blood flow through tapered artery with mild stenosis. The present paper reports flow fields in a partially stenosed artery with a complete bypass graft having different severity stenosis, occluded area and anastomotic angles.

Materials and Methods

The Fluid Model

Blood is assumed as an incompressible non-Newtonian fluid. The motion of blood flow is governed by the continuity equation and the Navier-Stokes equations, which can be expressed as follows:

$$\nabla \cdot \mathbf{u} = 0 \qquad (1)$$

$$\partial \mathbf{u}/\partial t + (\mathbf{u} \cdot \nabla)\mathbf{u} = 1/\rho \nabla \cdot \sigma \qquad (2)$$

where **u** is the blood velocity, ρ is blood density and σ is the total stress which is given by

$$\sigma = -pI + \eta(\dot{\gamma})[\nabla \mathbf{u} + (\nabla \mathbf{u})^T] \qquad (3)$$

where p is the blood pressure. and denote the viscosity of blood and shear rate, respectively. In this work, the relation between η and $\dot{\gamma}$ are described by Carreau's shear-thinning model,

$$\eta = \eta_\infty + (\eta_0 - \eta_\infty)\,[1 + (\lambda\dot{\gamma})^2]^{(n-1)/2} \qquad (4)$$

where η_∞, η_0, λ, and n are parameters, and the shear rate is defined by

$$\dot{\gamma} = [2\mathrm{tr}(1/2(\nabla\mathbf{u} + (\nabla\mathbf{u})^T)^2]^{1/2}. \qquad (5)$$

considering the pulsatile behavior of blood flow.

The pulsatile pressure p (t) and flow rate Q (t) can be expressed by the truncated Fourier series with the mean pressure and the mean flow rate respectively were measured through power lab (Lab Chart Software). We impose the corresponding pulsatile pressure condition,

$$p(t) = p_0(t), \qquad \eta[(\nabla\mathbf{u} + (\nabla\mathbf{u})^T]^2 \qquad (6)$$

No-slip condition is applied to the outer arterial wall. We find **u** and p such that equations (1&2) and all boundary conditions are satisfied. To investigate the effect of the stenosis severity, we study the pressure distribution along the arterial axis of the stenosed artery. Three different degrees of stenosis including 50%, 75% and 100% are chosen.

ANN Structure

Neural Network Toolbox Neuro Solution6.0 ® mathematical software was used. A single-layer ANN model was designed considering degree of stenosis, flow rate, pressure and anastomotic angle as input while pressure out and flow out as output with sigmoid axon transfer function. Network represents functional relationship between inputs and output, provided sigmoid layer has enough neurons. Levenberg- Marquardt algorithm is fastest training algorithm for network of moderate size, therefore, used in the present study.

Back propagation training algorithm

The back propagation algorithm is a generalization of the least mean square algorithm modifying network weights to minimize the mean square error between the desired and actual outputs of the network. Back propagation uses supervised learning in which the network is trained using data for which inputs as well as desired outputs are frozen and used to compute output values for new input samples. Start with randomly selected weights while MSE is unsatisfactory and computational bounds are not exceeded, do for each input pattern. The input is propagated through the ANN to the output and error e_k on a single output neuron k is calculated as: $e_k = d_k - y_k$, where y_k is the calculated output and d_k is the desired output of neuron k. This error value is used to calculate a δ_k value, which is again used for adjusting the weights .The δ_k value is calculated by: $\delta_k = e_k\, g'(y_k)$, where g' is derived activation function. The δ_k value and δ_j values were calculated for proceeding layers. The δ_j values of the previous layer are calculated from the δ_k values of this layer by the following equation: $\delta_j = ng'(y_j)\mathbf{\Sigma}\, \delta_k W_j K$, where K = 0,1,2……n, where K is the number of neurons and η is the learning rate parameter. Using δ values, the δw values are calculated by: $\delta w_{jk} = \delta_j\, y_k$. The δw_{jk} value is used to adjust the weight w_{jk}, by $w_{jk} = w_{jk} + \delta w_{jk}$ and the back propagation algorithm moves on to the next input and adjusts the weight according to the output. The process goes on until a certain stop criteria is reached. The stop criteria are typically determined by measuring the mean square error of the training data.

Best Networks	Training	Cross Validation
Epoch #	1500	1339
Minimum MSE	1.09372E-05	0.0436217
Final MSE	1.09372E-05	0.04217098

Table 1 Optimized data for applied Neural Network

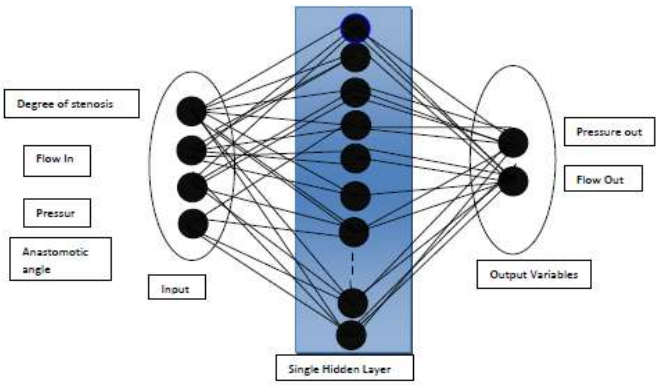

Fig 1. 4,2,1 ANN Structure of of Blood Flow through Stenosed Artery with Bypass graft

The sigmoid axon was considered transfer function with 0.7 momentums. Series of experiment resulted into the evaluation of performance based on 60 % data for training, 20 % data for testing and 20 % data for cross validation at 1500 Epoch with 0.70000 momentums. With 20 neurons the performance of network simulation was evaluated in terms of mean square error (MSE) criterion. The minimum MSE in the group of the variables was determined for training and cross validation are 0.001783209 and 0.006960692 respectively. Fig. 2 shows the result obtained by the Neural Network simulation for training, cross validation and testing data sets.

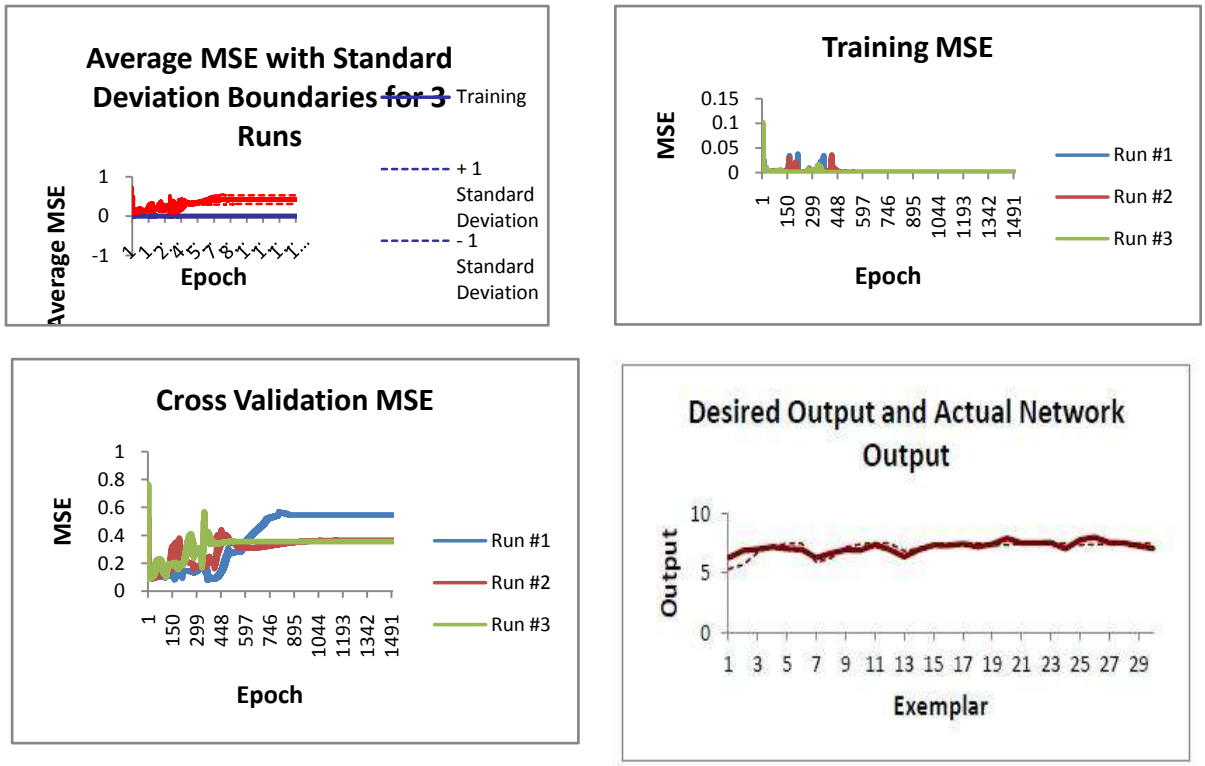

Fig 2. Graphical representation of MSE Value with 1500 EpochTesting and Sensitivity analysis

The developed network model was examined for its ability to predict the response of experimental data not forming the part of the training program. The network was finally tested for training, cross validation and testing data sets. The comparison results of desired outputs and network outputs are shown in Fig.3.

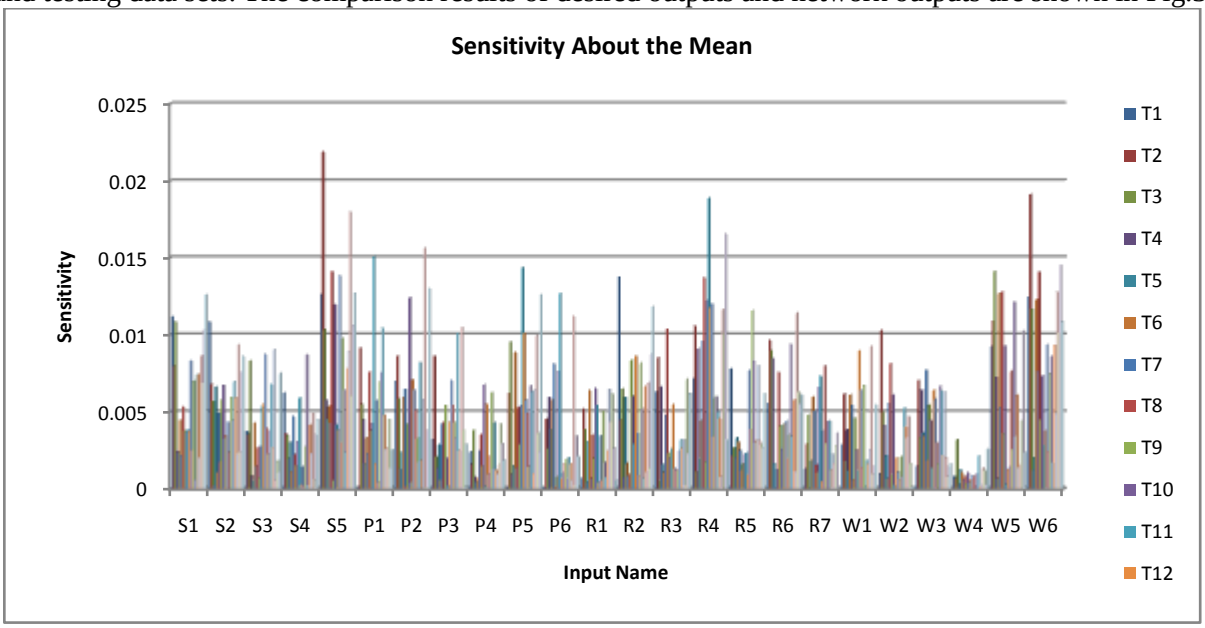

Fig 3. Comparison of desired output and network for training, cross validation, testing

During testing a linear correlation coefficient of (R^2 = 0.987, 0.9587 and 0.9098) were obtained for the training, cross validation and testing data sets. A sensitivity analysis was conducted to determine the degree of effectiveness of variables. Performance of the group of input vectors The blood pressure on the symmetric plane of the three cases with different stenosis severities, including 50%, 75%- and 100%-occluded cases, are considered. It can be seen that the pressure in bypass graft is lesser in more severely occulted cases. Fig 5 shows as the flow rate increases pressure decreases. Fig 6 shows that the blood pressure drops more when the degree of stenosis is higher. The pressure on the symmetric planes of the three cases with α=30°, 50° and 70° respectively are considered. It can be seen that the pressure generally decreases as α increases in all the three cases with different α'_s, the pressure decreases in the constrict region.

Conclusion

The study indicates that stenosis bypass grafting have significant effects on the blood pressure. Higher degree of stenosis severity generated large drop of the pressure, causing the decrease of pressure in stenosed artery bypass grafting at optimized bypass angle. The developed ANN model describes the behavior of the complex interaction process within the range of experimental conditions adopted. The single layer ANN modeling technique was applied to optimize this process. The Levenberg–Marquardt algorithm (LMA) was found best of BP algorithms with a minimum mean squared error (MSE) for training and cross validation as 1.09372E-05 and 0.04217098 respectively.

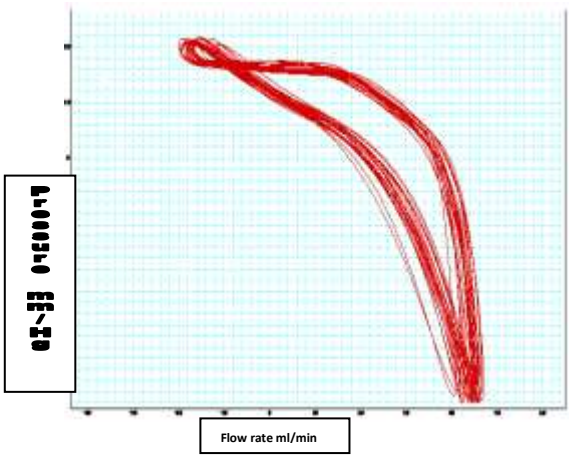

Fig 4. Pressure profile with flow rate

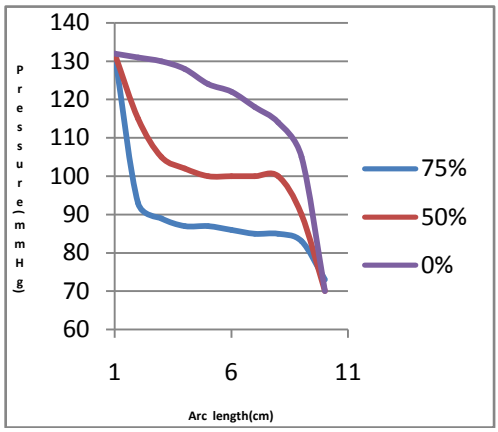

Fig 5. Pressure profile along the stenosis artery

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