Artificial Neural Network modelling for the System of blood flow through tapered artery with mild stenosis

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***Abstract*— ANN model was designed to study the effect of blood flow and cross sectional area through tapered artery with mild stenosis , considering blood flow as a two-fluid model with the suspension of all the erythrocytes in the core region as Herschel-Bulkley fluid and the plasma in the peripheral layer as Newtonian fluid. Different ANN architecture were tested by varying network topology, resulting into an excellent agreement between the experimental data and the analytical values. Various experimental parameters i.e. stenosis height, peripheral layer thickness, yield stress, viscosity ratio, angle of tapering and power law index were used for ANN modelling and their effect on the velocity, wall shear stress, flow rate and the longitudinal impedance are analysed. It is reported that the velocity and flow rate increase with the increase of the peripheral layer thickness and decrease with the increase of the angle of tapering and depth of the stenosis. It is observed that the flow rate decreases nonlinearly with the increase of the viscosity ratio and yield stress. The estimates of the increase in the longitudinal impedance to flow are considerably lower for the two-fluid Herschel-Bulkley model compared with those of the single-fluid Herschel-Bulkley model. Hence, it is concluded that the presence of the peripheral layer helps in the functioning of effected arterial system. The findings indicate that the ANN provides reasonable predictive performance in resemblance to the analytical 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; Wall shear stress; tapered artery; mild stenosis.

Introduction

Many cardiovascular diseases, particularly atherosclerosis, blockage of arteries are the main cause for deaths in developing countries. The factors which influence the development of this type of disease are not yet exactly answered. An abnormal growth, formed due to deposits of atherosclerotic plaques in the lumen of an artery is usually called stenosis (atherosclerosis) and, its subsequent and severe growth on the artery wall results in serious circulatory disorders [1,2]. Stenoses developed in the arteries pertaining to brain can cause cerebral strokes and the once developed in the coronary arteries can cause myocardial infarction which leads to heart failure [3]. It has been reported that the fluid dynamical properties of blood flow through non uniform cross-section of the arteries play a major role in the fundamental understanding and treatment of many cardiovascular diseases [4]. The Rheology of circulation was deeply discussed by Whitmore [5]. The analysis of blood flow through a symmetrically stenosed artery has been studied by Singh et al. [6]. Sanyal and Maji [7] investigated the unsteady blood flow through an indented tube in presence of stenosis. Young [8] observed the effect of time-dependent stenosis on flow of a Newtonian fluid through a tube. Chakravarty and Datta [9] performed rheological study on the effect of mild stenoses on the flow behaviour of blood in a stenosed arterial segment. Chaturani and Ponnalagar Samy [10] and Sankar and Hemalatha [11] have mentioned that, for tube diameter 0.095mm, blood behaves like H-B fluid rather than power law and Bingham fluids. Iida [12] says, “The velocity profile in the arterioles having diameter less than 0.1mm are generally explained fairly by the Casson and H-B fluid models. However, the velocity profile in the arterioles whose diameters less than 0.065mm does not conform to the Casson fluid model, but, can still be explained by the H-B model.” Furthermore, the H-B fluid model can be reduced to the Newtonian fluid model, power-law fluid model, and Bingham fluid model for appropriate values of the power-law index and yield index . Since the H-B fluid model’s constitutive equation has one more parameter than the Casson fluid model, one can get more detailed information about the flow characteristics by using the H-B fluid model. Moreover, the H-B fluid model can also be used to study the blood flow through larger arteries, since the Newtonian fluid model can be obtained as a particular case of this model. Hence, it is appropriate to represent the fluid in the core region of the two-fluid model by the H-B fluid model rather than the Casson fluid model. Thus, in this paper, we study a two-fluid model for blood flow through narrow tapered arteries with mild stenosis at low shear rates, treating the fluid in the core region as H-B fluid and the plasma in the peripheral region as Newtonian fluid (Fig. 1).

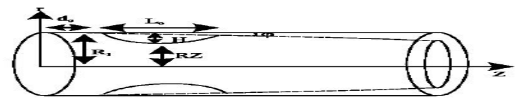


Fig. 1: Geometry of tapered arteries with mild stenosis

The finite-element method is employed to solve the resulting nonlinear system of partial differential equations with the appropriate boundary conditions. Neural networks are useful when a mathematical relationship is not available to describe a phenomenon to be modelled. If the property in question can be modelled by very complex and highly demanding computational techniques, neural networks provide an alternative approach to obtain accurate numerical values in a computationally less intensive fashion. Because of reliable, robust and salient characteristics in capturing the non-linear relationships of variables in complex systems, application of Artificial Neural Network (ANN) has been successfully employed in environmental engineering [13-15] and The study of blood flow through a stenotic artery is important due to nature of blood movement and behaviour of vessel walls are causes of many cardiovascular diseases. [16] bioprocesses [17-20]. Keeping these views in mind, an attempt has been made to find the effect of stenosis height, peripheral layer thickness, yield stress, viscosity ratio, angle of tapering and power law index parameters on the velocity, wall shear stress, flow rate and the longitudinal impedance for Newtonian fluid flow through the tapered artery with mild stenosis are analysed.

Materials and Methods

The Fluid Model

The flow is assumed to be laminar, Newtonian, viscous, and incompressible. The Navier–Stokes (N–S) equations in curvilinear generalized cylindrical coordinates are used as the governing equations. No-slipping boundary condition is assumed between the fluid and the wall. Uniform pressures at the inlet and outlet of the tube are prescribed to match experimental setup. Using the arbitrary Lagrangian–Eulerian formulation [21] we have

$$\frac{\partial}{\partial \xi_i}[J g^{ij} h_j v(j)] = 0,$$

$$\frac{\partial}{\partial t}[J\rho v(k)] + \sum_{i=1}^{3} \frac{\partial}{\partial \xi_i}\left(J g^{ij}\left\{ \rho h_j [v(j) - w(j)] v(k) - \mu \frac{\partial v(k)}{\partial \xi_j} \right\} \right) + \frac{J}{h_k}\frac{\partial p}{\partial \xi_k} = 0, \text{ no sum for } k,$$

$$\mathbf{u}|_{\Gamma} = d\mathbf{x}/dt, \quad \partial \mathbf{u}/\partial z|_{\text{inlet,outlet}} = 0,$$

$$p|_{\text{inlet}} = p_{\text{in}}, \quad p|_{\text{outlet}} = p_{\text{out}},$$

where (k) is the kth component of the fluid velocity in curvilinear coordinates, $w(k)$ is the kth component of the mesh velocity, p is the pressure, p_{in} and p_{out} are the inlet and outlet pressures, ρ is fluid density (ρ= 1 gcm^{-3}), μ is viscosity [μ=0.04 dyn s cm^{-2} (poise)], Γ stands for the inner wall of the tube, (ξ_1, ξ_2, ξ_3) = (r, θ , z) are curvilinear generalized cylindrical coordinates defined inversely by

$$x_1 = r\cos\theta + d(z), \quad x_2 = r\sin\theta, \quad x_3 = z.$$

Other notations related to the curvilinear coordinate vectors and tensors can be found from Tang [22] and are omitted here to avoid unnecessary details.

ANN Model

Neural Network Toolbox Neuro Solution 6.0 ® mathematical software was used to predict output efficiency. Network structure has significant effects on the predictive results. As per the network topology the neural network employed has six input nodes corresponding to the process variables namely stenosis height, peripheral layer thickness, yield stress, viscosity ratio, angle of tapering and power law index and for output nodes corresponding to the velocity, wall shear stress, flow rate and the longitudinal impedance . However, the optimal number of hidden layers and the optimal number of nodes in each layer are case dependent and there is no straight forward method for the determination of them. A Single layer ANN with sigmoid axon transfer function was used for input and output layers. The data were divided into input matrix and desired matrix. The single layer sigmoid 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 Algorithm (BPA)

The back propagation network is a multilayer feed forward network with a different transfer function in the artificial neuron and a more powerful learning rule. The learning rule is known as back propagation, which is a kind of gradient descent technique with backward error (gradient) propagation. The training instances have been set in order to interconnect weights between the neurons to settle into a state of correct classification of input patterns. Once the network is trained with different architectures, it has the ability to generalize over similar features found in different patterns. The four steps in the training processes viz assemble the training data, create the network object, train the network and simulate the network were used to respond to new inputs.

Levenberg – Marquardt Approximation (LMA)

Considering the serious drawbacks of slow convergence and inability to avoid local minima, BP with LMA is used to get better performance. This technique is relatively faster but requires more memory. The LM update rule is:

$\Delta W = (J^T J + \mu I) -1 J^T e$

Where J is the Jacobean matrix of derivatives of each error to each weight, μ is a scalar and e is an error vector. If the scalar is very large, the above expression approximates the Gradient Descent method. The Gauss Newton method is faster and more accurate near error minima. Hence, the aim is to shift towards the Gauss-Newton as quickly as possible. The μ is decreased after each successful step and increased only when the step increases the error.

Results and Discussion

Optimization of the ANN Architecture

ANN model based on double layer recurrent back propagation algorithm for the experimental data, generated from the experimental data from [23] was applied to train the Neural Network. During training, the output vector is computed by a forward pass in which the input is propagated forward through the network to compute the output value of each unit. The output vector is then compared with the desired vector which resulted into error signal for each output unit. In order to minimize the error, appropriate adjustments were made for each of the weights of the network. After several such iterations, the network was trained to give the desired output for a given input vector. The double layer network structure included ten hidden neurons, for each layer describing the dynamics of blood flow through the **tapered artery with mild stenosis** (Fig. 2).

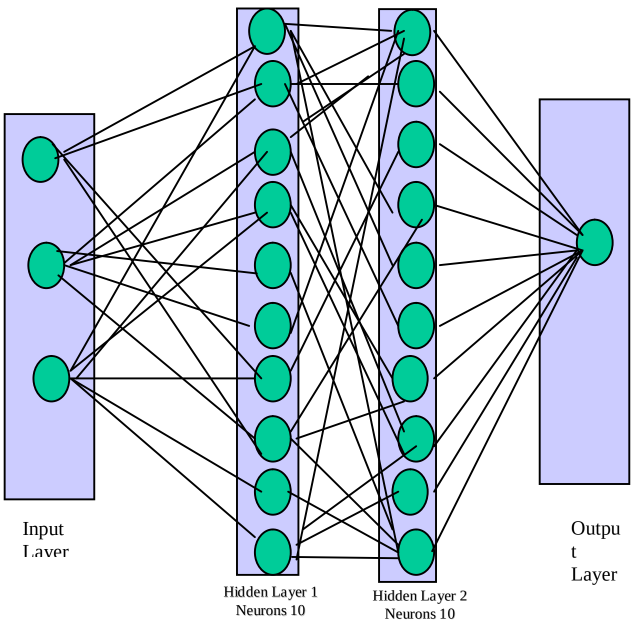


Figure 2: Double layer Neural Network structure for the simulation and prediction of the biosorption efficiency.

Best Networks	Training	Cross Validation
Ekpoch #	1000	983
Minimum MSE	0.001783209	0.006959115
Final MSE	0.001783209	0.006960692

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 1000 Epoch with 0.70000 momentums. The performance of network simulation was evaluated in terms of mean square error (MSE) criterion. The minimum MSE in the group of six variables was determined for training and cross validation are .001783209and 0.006960692 respectively. Fig. 3 shows the result obtained by the Neural Network simulation for training, cross validation and testing data sets.

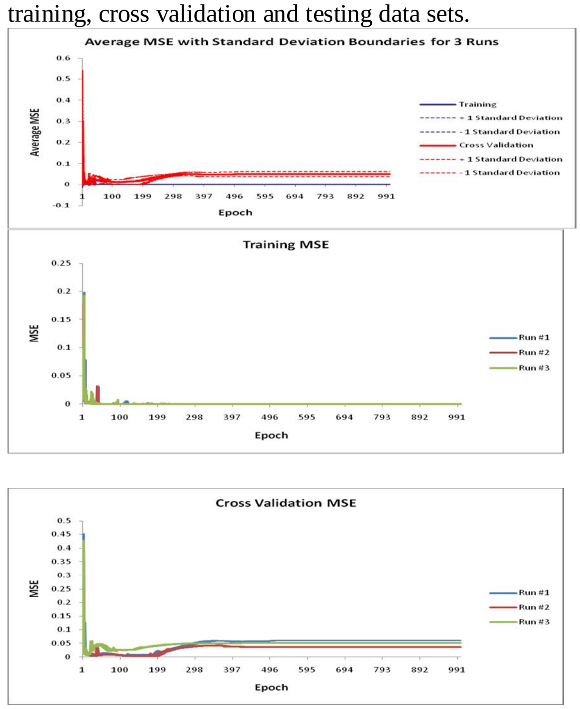
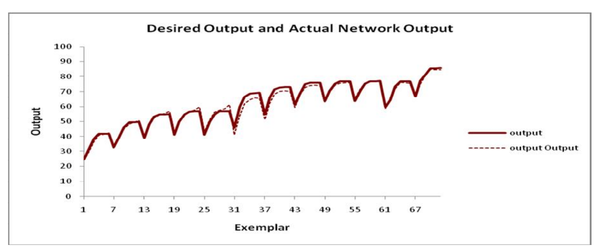
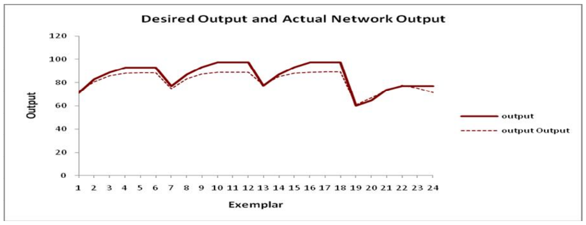


Figure3: Graphical representation of MSE value with 1000 Epoch

Testing 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.4.





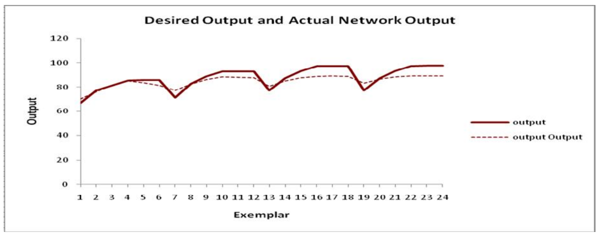


Figure 4: Comparison of Desired output and Network output for: Training; Cross validation; Testing.

During testing a linear correlation coefficient of (R^2 = 0.99, 0.96 and 0.91) 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 velocity and flow rate are higher for the two-fluid H-B model compared to those of the single-fluid H-B model, whereas the wall shear stress and longitudinal impedance to flow are considerably lower for the two-fluid H-B model compared to those of the single-fluid H-B model.

Conclusion

The results indicate that the velocity and flow rate increase with the increase of the peripheral layer thickness and decrease with the increase of the angle of tapering and depth of the stenosis. It is also noted that the flow rate decreases nonlinearly with the increase of the viscosity ratio and yield stress. It is found that the longitudinal impedance to flow increases with the increase of the stenosis height, angle of tapering, and viscosity ratio. It is further noticed that the velocity and flow rate are higher for the two-fluid H-B model compared to those of the single-fluid H-B model, whereas the wall shear stress and longitudinal impedance to flow are considerably lower for the two-fluid H-B model compared to those of the single-fluid H-B model. It is of importance to mention that the estimates of the increase in the longitudinal impedance to flow are considerably lower for the two-fluid H-B model compared with those of the single-fluid H-B model. Thus, the results demonstrate that the present model is capable of predicting the hemodynamic features most interesting to physiologists and, thus, it is concluded that the presence of the peripheral layer helps in the functioning of the diseased arterial system. The developed ANN model could describe the behaviour of the complex interaction process within the range of experimental conditions adopted. The single layer ANN modelling 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.001783209 and 0.006960692 respectively.

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