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Use of The GMDH Neural Network to Examine The Oxygen Mass Transfer into The Blood Vessel

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ABSTRACT: In In the essay an partial pressure of oxygen is predicted in blood vessel by neural network. The discussion is selected due to its significance in medical science.By means of GMDH algorithm, a model can be represented as set of neurons in which different pairs of them in each layer are connected through a quadratic polynomial and thus produce new neurons in the next layer.

***Keywords*:** Neural network; Oxygen mass transfer.

INTRODUCTION

Nowadays, mass transfer has an important role to develop vessel obstruction. Arthrosclerosis is a kind of disease that makes disorder in blood carrying system by heart vessel obstruction an oxygen does not reach vessel tissues and the cell will be affected with cell death due to lack of oxygen. Now, different methods are used in order to control the disease. From among these methods we refer to fettering in heart vessels or by passing. Some parameters are considered in this essay such as vessel radius, blood volume rate and vessel septum thickness. In order to compute the oxygen pressure in blood, the speed scope should be determined and then, using it, mass transfer equations should be solved. Continuity equation and movement measure permanency are solving in order to specify speed scope that is as follows (Raoufi et al.,2012), [1].

$$\iint \rho V.dA=0 \qquad (1)$$

$$\int \rho \frac{dV}{dt} d\forall + \iint \nabla\rho\nabla.dA = -\iint Pn.dA + \iint \mu\nabla V.dA \qquad (2)$$

$$\int \frac{\partial(c+\gamma)}{\partial t} d\forall + \iint (c+\gamma)v.dA = \iint D\nabla c.dA \qquad (3)$$

The numerically solving of this equations is difficult and takes our time. Hence, the aim of this study is using GMDH neural network which provide it that could estimate nonlinear multi aspect functions by the higher order functions in order that the answer be possibly close to the real answer.

GMDH neural network

To model multi variable functions that there is no clear function for them could be used several methods, but different part of this function such as experiment is available. Use of different neural networks is one of these methods. Neural networks could estimate a function by training the data that is available. Beforehand, for parts that there is no information about them. GMDH neural network that act on the basis of GMDH data mining method by having $x=(x_1, x_2,\ldots)$ input vector show the effect of each variable by taking part in different equations of neurons which are related to each other,(Garson ,1998),[2].

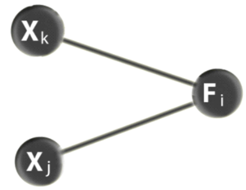

Fig 1. GMDH neural network formed neuron schematic

For the neuron that is shown in figure (1), the general form of neuron equation for both input x_j and x_k are as follows. Input of each layer in neurons will be outputs of next layers. In order to converge the network towards neurons in each layers, the weak neurons will be omitted and cannot take part in the following layers. In order to omit the weak neurons, comparing neurons error is used to complete the amount models output, regarding the empirical output. In order to compute error the following equation is used.

$$\text{Error}=\frac{1}{N}\sum_{i=0}^{N}(P(i)_{Exp}-P(i)_{predicted}) \qquad (4)$$

This process continued until that a neuron to be formed in the last layer. the output of this neuron is the answer. Error of the total neural network is computed by the following relation. This error could be used as criterion to select the best number of neuron and hidden layers. It is better that the neural network error be less than other networks.

RESULTS AND DISCUSSION

The formed neural network is shown in fig (2) in order to model the oxygen partial pressure. The equations of this neural network are as follows.

$F_1 = 3.750e{+}03 - 4.461e{+}03\, x_1 + 2.630e{+}02\, x_2 + 1.304e{+}03\, x_1^2 - 1.570e{+}03\, x_2^2 + 2.698e{+}2\, x_1x_2$
$F_2 = 3.663e{+}03 + -4.371e{+}03\, x_1 + 0.509\, x_2 + 1.305e{+}03\, x_1^2 - 4.102e{-}04\, x_2^2 + 0.216\, x_1x_2$
$F_3 = 5.427e{+}02 + 6.322e{+}02\, x_1 + 1.454\, x_2 + -1.863e{+}03\, x_1^2 + 0.005982\, x_2^2 + -6.064\, x_1x_2$
$F_4 = 22.192 + 14.263\, x_1 + 16.200\, x_2 + 91.052\, x_1^2 + 90.757\, x_2^2 - 1.818e{+}02\, x_1x_2$
$F_5 = 1.289e{+}02 + 1.750\, x_1 + 0.624\, x_2 + 0.00646\, x_1^2 + 6.687e{-}04\, x_2^2 - 1.49667e{-}05\, x_1x_2$
$F_7 = 3.412 + 1.481\, x_1 - 0.652\, x_2 - 0.0447\, x_1^2 - 0.0319\, x_2^2 + 0.0784\, x_1x_2$

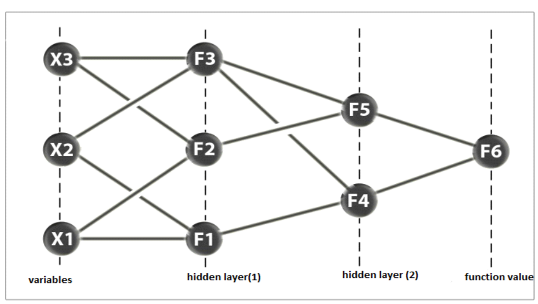

Fig 2. approached neural network for distrbuting insignificant oxygen pressure in the blood vessel

Oxygen partial pressure changes are shown in figures (3) to (7) according to three variables of vessel radius, septum thickness and crossed blood volume rate of vessel and neural network estimate of these testing data.

As it is specified the formed neural network in work limit the border will be seen error relative increasing. Cause of this case is the over fitting phenomenon and of course it does not have any effect on the defined rationalizing problem.

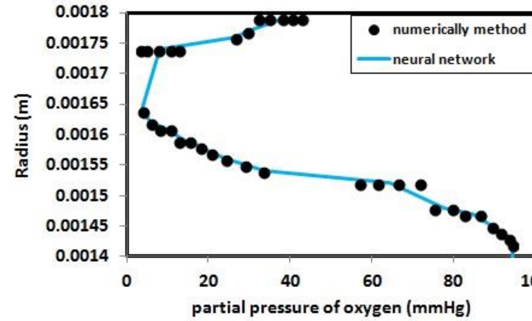

Fig 3. Comparing neural network result by data from numerically method (cross volume rate =50 ml/s, thickness of vessel wall =0.3 mm)

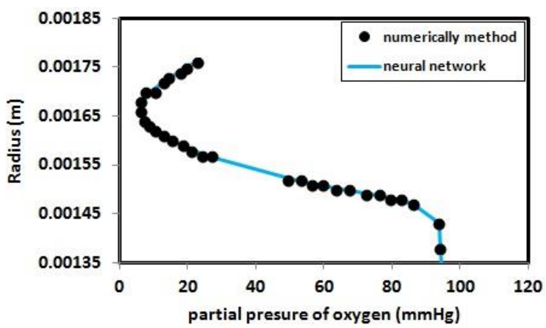

Fig 4. Comparing neural network result by data from numerically method (cross volume rate =100 ml/s, thickness of vessel wall =0.3 mm)

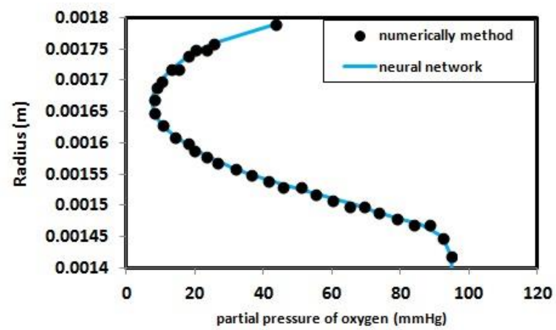

Fig 5. Comparing neural network result by data from numerically method (cross volume rate =180 ml/s, thickness of vessel wall =0.3 mm)

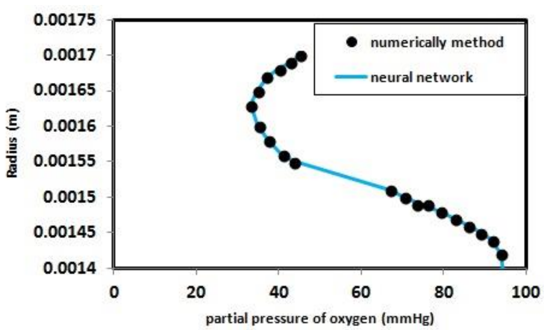

Fig 6. Comparing neural network result by data from numerically method (cross volume rate =180 ml/s, thickness of vessel wall =0.2 mm)

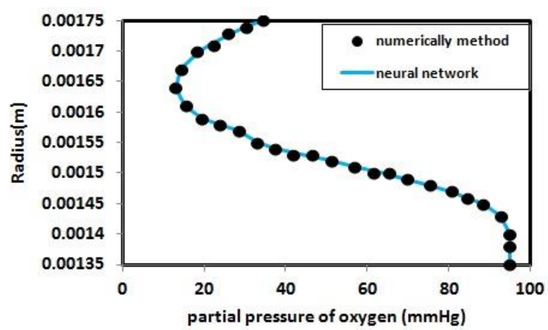

Fig 7. Comparing neural network result by data from numerically method (cross volume rate =180 ml/s, thickness of vessel wall =0.275mm)

Figures

	GMDH neural network formed neuron schematic
Figure 2	approached neural network for distrbuting insignificant oxygen pressure in the blood vessel
Figure 3	Comparing neural network result by data from numerically method (cross volume rate =50 ml/s, thickness of vessel wall =0.3 mm)
Figure 4	Comparing neural network result by data from numerically method (cross volume rate =100 ml/s, thickness of vessel wall =0.3 mm)

Figure 5	Comparing neural network result by data from numerically method (cross volume rate =180 ml/s, thickness of vessel wall =0.3 mm)
Figure 6	Comparing neural network result by data from numerically method (cross volume rate =180 ml/s, thickness of vessel wall =0.2 mm)
Figure 7	Comparing neural network result by data from numerically method (cross volume rate =180 ml/s, thickness of vessel wall =0.275 mm)

Because we already know that the discussed minimal point is located in distance between these border quantities. As it is specified, this neural network estimate the results with a good approximation and the answer of this neural network could be surely introduced to the related rationalizing algorithm as oxygen partial pressure introducer function according to the quantities such as radius, thickness and crossed volume rate from vessel. Error Criterion of this neural network is 0.00024.

Abbreviations

A	area, m^2
C	oxygen concentration
D_b	oxygen diffusion in blood , 10^{-5} (cm^2/s)
D_W	oxygen diffusion in the wall of vessel, 10^{-5}(cm^2/s)
n	Normal vector perpendicular to the plane
P	pressure, (Pa)

CONCULSION

In this text a model of partial pressure was presented using a GMDH neural network. This model can be used to find the minimum partial pressure in a vessel by knowing its properties, radius, thickness and crossed volume rate. The results for the network shows good fitting on the data which previously was used to train the network.

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