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Analyzing of the Viscosity by Using Artificial Neural Networks

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ABSTRACT

The nano networks with many thousands of devices which are working cooperatively to complete challenging tasks, ultra-responsive to changes in the environment, and self-replicating devices are called nano devices (nano machine). It is thought that the studies in this field will contribute greatly to the developments in the field of nano technology. Many models have been proposed to provide nano or macro-scale systems such as molecular communication, interstitial or inter-neural communication. In these systems, information is carried by the molecules in the diffusion medium and the viscosity of the medium is an important parameter. In this study, some of the system parameters, the viscosity and distance (*d*) between transmitter and receiver are examined detailed by using Artificial Neural Network (ANN) algorithm in Matlab. Viscosity and *d* are simulated and predicted by using ANN and they also compared with results of the proposed system model.

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1. INTRODUCTION

Nanotechnology enables manufacturing by miniaturizing devices in a scale ranging from 1 to 100 nm. Nanotechnology is a new field of research that is intended to revolutionize the industrial, medical, military and environmental fields. At this scale, a nano-device can be considered as the most basic functional unit. Nano devices are small components made up of a series of molecules that can perform very simple computational, sensing and / or actuation tasks [1]. Nano machines can be linked together to execute common tasks in a distributed manner. The resulting nano-networks are expected to expand the capabilities and applications of single nano-machines. Nano-machines can be interconnected to execute collaborative tasks in a distributed manner. Classical communication techniques (eg optical or acoustic waves, electromagnetic fields) cannot be applied to nano-scale networks simply by reducing traditional mesh sizes. [2]. It is the diffusion mechanism that causes molecules to move in nano-sized systems. The process that causes the substance concentrations in a system to equalize or to occur with the distribution of the equilibrium concentration resulting from the random movement of the system elements is called diffusion [3, 4]. Brownian motion refers to the unsystematic movement of nano or micro-sized particles from one part of a mass to another, by remaining in a motionless liquid. In this case, the movement of the particle does not decrease and is independent of the chemical properties of the medium [5]. The diffusion flux relates to the gradient of concentration so the gradient goes from high to low concentration regions in Fick's first law. The general assumption is Fick's law:

$$J = -D\frac{d\varphi}{dx} \qquad (1)$$

where *D, J, φ* and *x* are the diffusion coefficient, diffusion flux, the concentration, and the position of the molecules, respectively [6]. Einstein proved that the diffusion coefficient *D* in an infinitely dilute solution is given by the equation,

$$D = \frac{k_B\, T}{f} \qquad (2)$$

where *f* is the frictional coefficients of the particle. While the value of *f*, commonly is unknown, G. Stokes [7] proved that for the special case of a spherical particle of radius R_B which is moving with an uniform velocity in a continuous fluid of viscosity η, the frictional coefficient f is given by

$$f = 6\pi\eta R_B \tag{3}$$

Information transfer is realized is generally known as the free diffusion motion of molecules in the medium. The property of the transmission medium is determined by the diffusion coefficient; D for diffusion of spherical uncharged particles through a liquid is given below [8]. Einstein [9], this equation can be assumed to be valid for spherical molecules should be pointed out that the diffusion coefficient by the equation,

$$D = \frac{k_B T}{6\pi\eta r} \tag{4}$$

The viscosity constant which is an important part of the environment of the nano-device systems is examined particularly in Matlab in this study. The transmitted molecules are examined at the receiver part by using the hitting probability changing some system parameters such as distance between transmitter and receiver, viscosity constant and receptor deployment on the receiver [10–13]. The hitting probability of a transmitted molecule in 3-D environments is as follow:

$$f_h^{3D}(d, t) = \left(\frac{r_x}{r_x + d}\right) \frac{d}{\sqrt{4\pi D t^3}} e^{\frac{-d}{4Dt}} \tag{5}$$

where D, r_x, and d show the diffusion constant, the radius of the receiver, and distance from the transmitter to the receiver, respectively. The viscosity constant is given as above formulas and the viscosity and the diffusion constant are observed to be inversely proportional. In this study, the viscosity constant and distance which are the system parameters are examined by using Artificial Neural Network (ANN) algorithm in Matlab. The viscosity constant and distance are simulated and predicted by using ANN and they also compared with results of the proposed system model.

The artificial neural network has been developed by researchers in recent years as a mathematical model inspired by the organization and functioning of biological neurons in the brain. There are many artificial neural network variations regarding the nature of the task assigned to the network, and there are many variations in how the neuron is modeled. Some researchers predict that these models are very close to biological neurons [14, 15] and in other cases models differ from biological mechanisms in important ways. An ANN consists of input, hidden layer, and output. A fairly simple and small-sized ANN has some powerful features in information and information processing, even compared because of its similarity to the human brain. ANN is used by researchers for engineering applications increasingly because of the easy ability to learn directly from target outputs. Moreover, ANN can adapt and solve the problem according to new data [16]. Therefore, for engineering applications, ANN can be used as an effective tool [17–20] for molecular communication networks.

- **System Model**

The number of hitting molecules until time t, for 3D environments, are given below,

$$N_{hit}^{3D}(t) = \left(\frac{R_x}{R_x + d}\right) erfc\left(\frac{d}{\sqrt{4Dt}}\right) \tag{6}$$

where $erfc$, d, and R_x refer error function, distance between transmitter and receiver and radius of receiver respectively. The system model includes of a point transmitter, spherical receiver, information molecules, and receptors which are placed on the receiver as shown in Fig.1. The shape of the fixed receiver is chosen as spherical in present study. The transmitter and receiver are both located in a liquid diffusion medium and the medium is assumed to be unlimited, thus extending to infinity in all directions. After the molecules are released into the medium where they are dispersed according to Brownian motion, they reach the receiver within probability. [10, 13].

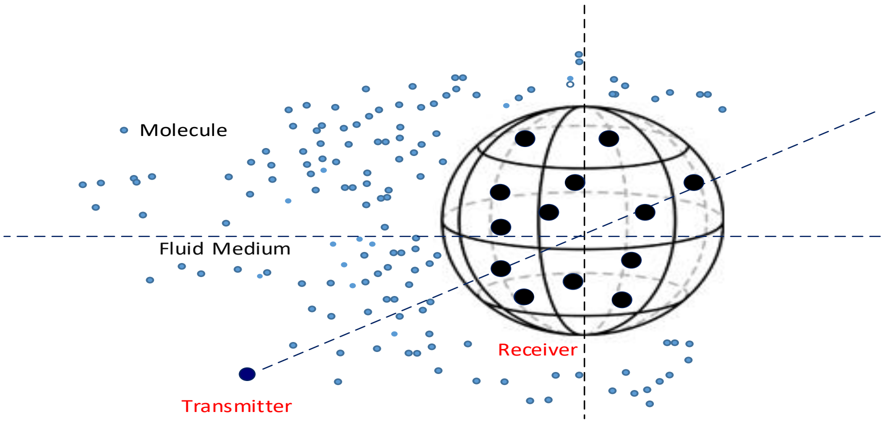

Figure 1. System model

The machine learning techniques which simulate the learning system of biological organisms are commonly used and known as the artificial neural networks [19], [20]. The human's nervous system implicates cells that are referred to neurons. The system that allows neurons to connect is called as axons, dendrites, and the junction areas formed between dendrites and axons which is known as synapses. These systems are illustrated in Fig. 2. In this model, inputs are chosen as η_1 (η =2.7 μg/m.s), η_2 (η =27 μg/m.s), η_3 (η =270 μg/m.s) and time. Outputs are also chosen as FRM η_1 (fraction of received molecules of η_1), FRM η_2 (fraction of received molecules of η_2) and FRM η_3 (fraction of received molecules of η_3).

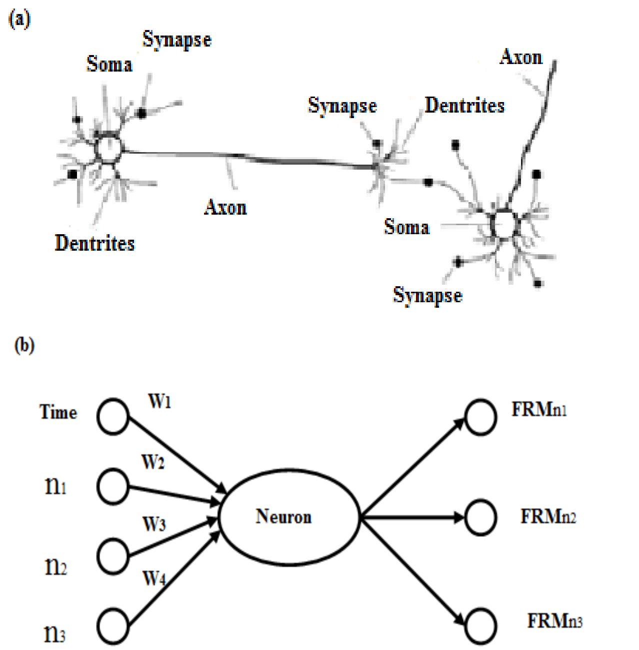

Figure 2. **(a)** Biological neural network, **(b)** Artificial neural network

In the ANN model, network type is chosen as feed-forward back propagation algorithm, and results are obtained with 68 epochs. Levenberg Marquardt is also used for training of the proposed ANN model. The coefficient of determination (*R^2*) and Mean Squared Error (*MSE*) techniques are used to compare obtained results. Formulation of *MSE* and *R^2* are given in the following equations.

$$MSE = \frac{\sum_i (Analytical\ Value_i - Sim_i)^2}{N} \qquad (7)$$

$$R^2 = 1 - \frac{\sum_i (Analytical\ Value_i - Sim_i)^2}{\sum_i (Sim_i)^2} \qquad (8)$$

where Analytical Values, Sim and N refers to the value of analytical data, the value of simulated results, and the number of samples in the proposed model respectively. The coefficient of determination and *MSE* are expected to become around 1 and 0 correspondingly. Although *R^2* values are obtained around 1 for training and testing results of the model, *MSE* values are obtained higher than 0 especially for testing part of the model.

2. RESULTS AND DISCUSSION

The decrease in the fraction of received molecules with the increase of viscosity is an expected result when the equations 4 and 5 are examined. As a matter of fact, in accordance with the analytical results, as the viscosity increases, the diffusion constant decreases, so the fraction of received molecules was decreased. Therefore, the fraction of the received molecule at different viscosity values over time is given in Fig. 3.

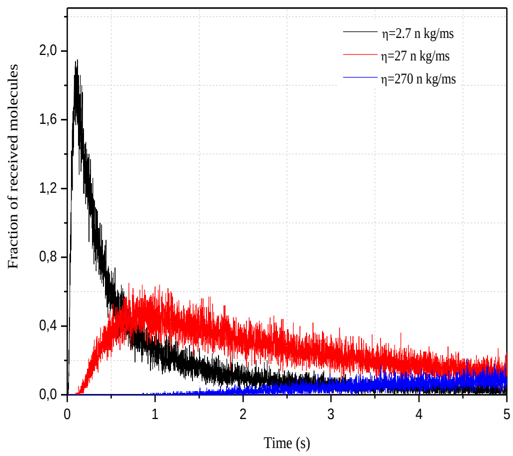

Figure 3. The fraction of received molecules with different viscosity values (η =2.7, 27, 270 *μg/m.s*, r_s =0.01 μm, $N_{receptor}$=14400, d=5 μm, N_{Tx}= 20,000 molecules and the number of simulations = 100).

The distance between fixed transmitter and receiver is an another important parameter for proposed system. As the distance between the receiver and the transmitter decreased, it is expected that the fraction of received molecules increased. Therefore, the variation of distance according to the fraction of received molecules is given in Fig.4.

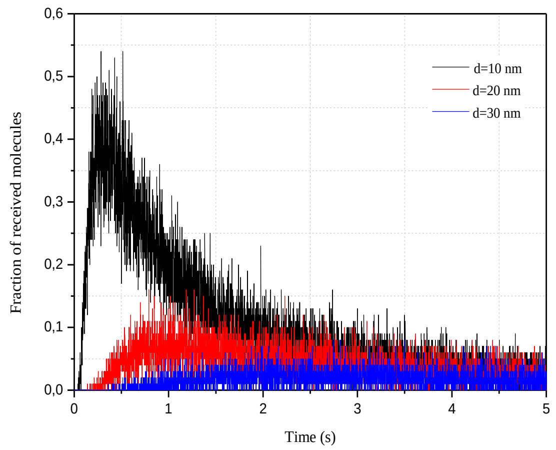

Figure 4. The fraction of received molecules with different distance values (r_s =0.01 μm, $N_{receptor}$ = 14400, N_{Tx}= 20,000 molecules and the number of simulations = 100).

After the studies on the variation of viscosity and the distance between the receiver and the transmitter in the proposed model were completed, it was curious what the result would be when predicted with ANN for other values. The results which are predicted by ANN obtained for the viscosity values of 4.9 and 53.5 μg/ m.s are given in Fig. 5. The reduction in the fraction of received molecules was observed in accordance with the model.

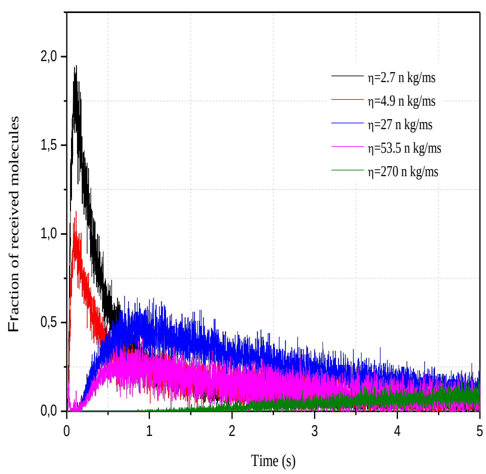

Figure 5. The Prediction and simulation results of fraction of received molecules with time for viscosities.

Different values of the distance between receiver and transmitter were estimated with ANN and the variation was given in Fig.6. The values where the distance between transmitter and receiver is 15 nm and 25 nm have been estimated and the variation according to the other values obtained in the proposed model is seen in compatible with the literature.

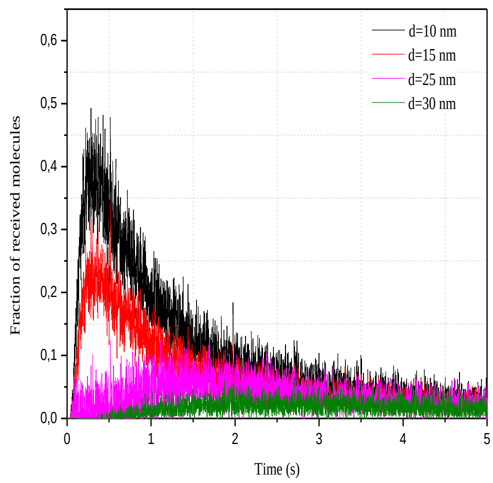

Figure 6. Prediction and simulation results of distance between fixed transmitter and receiver.

3. CONCLUSION

In this paper, it is proposed a new ANN model is proposed to analyze and simulate viscosity and distance between transmitter and receiver. The decrease in the fraction of received molecules with the increase of viscosity. Also, as the distance between the receiver and the transmitter decreased, the fraction of received molecules increased. As a result of analysis, the reduction in the fraction of received molecules with increasing viscosity and distance was observed in accordance with the ANN model as expected. As a future work, it is planned to find new ANN models to increase hitting probability and to decrease effect of viscosity in the environment.

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