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INVESTIGATION OF EXPERIMENT DATA AND SENSITIVITY COEFFICIENT DATA WITH ARTIFICIAL NEURAL NETWORK IN THE OHMIC HEATING PROCESS FOR SOUR ORANGE JUICE

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ABSTRACT
In this investigation, an ohmic heating system was constructed and applied to the heating process at three voltage gradient inputs (8.33, 10.83, 13.33 V/cm) and three percent weight loss sample (10, 20 and 30%) compared to total weight was selected. During the thermal process, the power consumption, electrical conductivity and coefficient performance system were calculated. All experiments were performed in three replications. An artificial neural network was used to predict experimental data. In this study multi-layer perceptron were selected and radial basic function artificial neural network by 1 hidden layers and 4, 8 and 12 neurons hidden layers, and with two activation function (hyperbolic tangent and sigmoid). The highest R values were for power consumption (0.998), electrical conductivity (0.996) and Coefficient performance systems (0.999) in a MLP network with 8 neuron in hidden layer and sigmoid activation. Also the fastest network with lowest EPOCH was in a network of 12 neuron. According to the results obtained for R, MSE and learning cycle, it can be said that the neural network has ability to predict power consumption, electrical conductivity and coefficient performance systems to an acceptable level for ohmic processing.

1. Introduction

Artificial neural network (ANN) seems very appropriate for the investigation and simulation of the data. ANN is, in fact, a collection of mathematical methods mostly including artificial intelligence and it attempts somehow to imitate human brain. During the past two decades, the neural network has exhibited a very high potential in a great many of the science and engineering areas for its exceptional performance, internal organization and self-learning, overcoming the challenges and high solidity rate. Recently, there has come about an increase in the interests in utilizing neural networks as a modeling tool in agriculture and food industry technologies. Neural networks have been successfully employed in several foodstuff processing technologies such as drying, post-harvest technologies, rheology of the foodstuff, microbial predictions, fermentation and thermal processing (Lu et al., 2010). Artificial neural networks are also considered as most effective tools for processing a large volume of information that was once a big challenge in various respects. The development trend of the neural networks is suggestive of the importance of using them for information processing because they have been proved highly successful in data analysis and they have been capable of undergoing development in various grounds. Moreover, the use of neural networks is promising in food production and foodstuff quality processing and evaluation methods wherein old methods of data processing might not provide us with accurate information or be substantially costly. Two important abilities of neural networks, to wit prediction and classification scales, have drawn a large deal of attention. According to the internal competencies of the artificial neural networks, they can be successfully applied in agriculture sector (Hosu, Cristea, & Cimpoiu, 2014). The artificial neural network is a topic discussed in artificial intelligence and it is an information processor trained using a percentage of input and output data and the system's performance method is stored in its memory(Mazloumzadeh, Alavi, & Nouri, 2008). Artificial neural networks are trained based on calculations on numerical data or examples. One feature of the neural networks is their ability in extracting the relationships between the inputs and outputs of a process with no need to complex environmental conditions. They are capable of connecting a multidimensional space to another space even if the information is imperfect and erroneous. These characteristics have made them appropriate for the problems related to the estimation and prediction in agriculture and industry and the neural network displays a good efficiency when the relations are nonlinear (Beale & Jackson, 1998; Menhaj, 2000). Moreover, the artificial neural network (ANN) modeling is widely used in many fields. This method is of high efficiency in solving the complex and non-linear equations in dryers (Özdemir, Aktaş, Şevik, & Khanlari, 2017). They also researcher used neural network in thermal processes:

Mattar and et al (2004) on modeling thermal conductivity, specific heat, and density of milk with neural network reported that artificial neural networks presented a better prediction capability of specific heat, thermal conductivity, and density of milk than polynomial modeling(Mattar et al., 2004).

Chegini et al. (2007) used predictive process and orange juice from artificial neural network, the results of which showed that the properly trained ANN model was able to produce simultaneously seven outputs, unlike traditional models where one mathematical model was required for each output. Radial Basis Function neural networks were not able well to learn the relationship between the input and output parameters. ANN parameters had a significant effect on learning ability of the ANN models(Chegini, Khazaei, Ghobadian, & Goudarzi, 2008).

The objective of this research is the power consumption, electrical conductivity and Coefficient performance systems analyses of ohmic processing with three ohmic voltage gradient in order to reduce the weight loss sour orange with new processes. For this purpose, the ANN (multilayer perceptron and radial basic function) was applied to verify the accuracy of the numbers obtained. Additionally, the sensitivity coefficient test was applied to relate the power consumption, electrical conductivity and coefficient performance systems factors to voltage gradient and weight loss percentage.

2. Materials and methods

2.1 Preparation of the sample

The oranges were purchased from a garden located in the city of Gorgan, Golestan province. The prepared oranges were washed and split into two halves in the middle and immediately after the purchase in the same condition for all samples (ambient temperature and applied uniform pressure), the manual removal was carried out.

2.2. Method of testing

For this processing was considered one tank and the sample were poured into the ohmic tank and between the two electrodes, and their initial temperature was recorded after stability. After recording the temperature, the voltage was applied to the set and the samples were heated. Three heating gradients of 8.33, 10.83 and 13.33V/cm were selected for the heating process and, using this voltage gradient, 10% (from 90 g to 81 g), 20% (from 90 g to 72 g) and 30% (from 90 g to 63 g), the percentage of the total weight of the samples of sour orange discharged inside the cell is steamed during the heating process. All samples were weighed 90 g and the temperature of all specimens was 26 °C to initiate the heating process. In Figure 1, a schematic representation of the heating process and system components is shown.

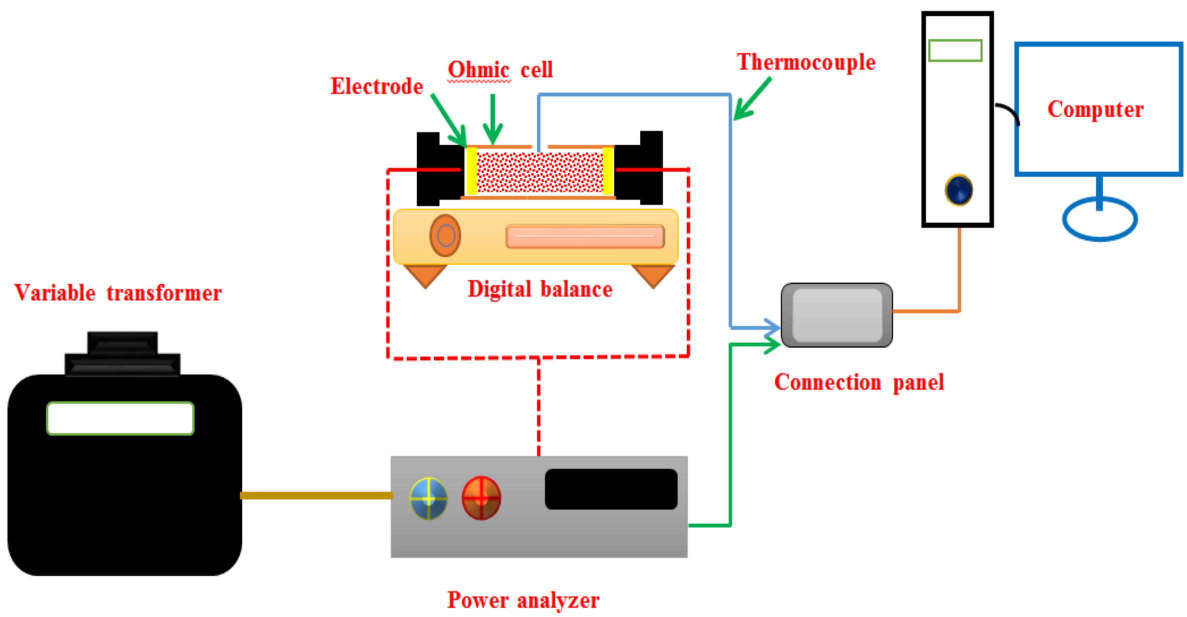

Figure 1. Schematic of equipment used for the ohmic heating process

The experiments were carried out in a home-based heating system. The system specifications used are shown in Table 1. All experiments were carried out at the department of bio systems mechanical engineering, Gorgan University of Agricultural Sciences and Natural Resources

Table 1. The system specifications

Length	6 cm	Distance electrode	6 cm
Width	6 cm	Power controller	(3 kW, 0–300 V, 50 Hz, MST – 3, Toyo, Japan
Height	3 cm	Balance accuracy	0.01 g
Thickness	0.3 cm	Electrode Thickness	0. cm
Electrode	Steel		

2.3. The equations of the heating process of ohmic

Electrical conductivity was calculated using the resistivity of the samples within the cell geometry used in equation (1)(Castro, Teixeira, Salengke, Sastry, & Vicente, 2004)（ Cappato et al., 2017）

$$\sigma = R\frac{L}{A} = \frac{LI}{AV} \qquad (1)$$

In this formula, σ = the electrical conductivity of the sample L: the distance between the two electrodes (m) from each other, A: the cross-sectional area of the plates (m^2), V: the input voltage (V), I: the input current (A)

During the heating, the contact surface between the samples and the electrode decreases due to the vapor output, the contact surface can be calculated using the equation below.（ Darvishi, Hosainpour, Nargesi, & Fadavi, 2015： ）

$$A = \frac{M_t}{\rho_t L} \qquad (2)$$

$$\rho_t = 1340 - 3.26M_t^2 \qquad (3)$$

M_t Humidity content at any moment

Power consumption was also calculated using formula 4（Kanjanapongkul, 2017):

$$P=VI=I^2R \qquad (4)$$

In this equation, P is the power consumption (W)

The energy given to the system in accordance with the relationship provided by icier and Hammers in 2005 is as follows (Srivastav & Roy, 2014)

$$E_{given} = E_{taken} + E_{loss} \qquad (5)$$

$$\sum(VIt) = mc_p(T_f - T_i) + E_{loss} \qquad (6)$$

The energy of the system is equal to the sum of the energy needed to increase the temperature of the cell, the energy dissipated to the environment through the displacement and the electrical energy converted to heat. In the above equations, the volatility value was determined and the amperes and time values were calculated by the software. The initial temperature and final temperature of the orange water were measured by a thermometer and the mass of water in the orange water was calculated by the balance. The system performance coefficient is given by the energy ratio taken by the system to the energy and calculated from the following equation（Darvishi, Khostaghaza, & Najafi, 2013.）

$$SPC = \frac{E_{taken}}{E_{given}}$$
$$SPC = \frac{mc_p(T_f - T_i)}{\sum(VIt)} \qquad (7)$$

In this formula, the energy $_{given}$ to system (j), T_f is the final temperature (C), Etaken energy taken from the system (j), T_i input temperature, E_{loss}, the energy lost in the system (j), t (s), SPC is the coefficient of performance system, m is the mass of the sample (kg).

2.4.Artificial Neural Network Modeling

In this research, the artificial multilayer perceptron (MLP) and radial basic function (RBF) neural network were used for modeling the Investigating sour orange components during voltage and percent decrease mass different to predict electrical conductivity by one hidden layer and 4, 8, and 12 neurons using the Neuro-Solution 5 software. Hyperbolic tangent and sigmoid activation functions (Equation 3,4), which are the most common type of activation functions, were used in the in hidden input and output layer. In this paper, the Levenberg-Marquardt algorithm was used to learn the network(Taheri-Garavand, Karimi, Karimi, Lotfi, & Khoobbakht, 2018). Additionally, 70% of the data were used for training, 10% of them were used for network evaluation (Validating Data), and 20% of the data were used for testing the network (Testing data) (Table 3). The voltage, decreasing mass value, current input and ohmic time as network inputs and power consumption, electrical conductivity and Coefficient performance systems were the considered network outputs. Five repetitions were considered to achieve the minimum error rate and maximum network stability as a mean of 5000 Epoch for the network. Error was estimated using algorithm with back propagation error. Statistical parameters including, Root Mean Square Error (RMSE), R^2, and Mean Absolute Error (MAE) were calculated for inputs and relationships were calculated using the formulas shown in Table 2.

Table 2. Neural Network Relationships

Formula	**Formula Number**	**Reference**
$\text{Tanh} = \frac{e^x - e^{-x}}{e^x + e^{-x}}$	(8)	(Soleimanzadeh, Hemati, Yolmeh, & Salehi, 2015)
$\text{Sig} = \frac{1}{1+e^{-x}}$	(9)	(F. Salehi, Gohari Ardabili, Nemati, & Latifi Darab, 2017)
$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{(P_i - O)^2}$	(10)	(Azadbakht, Torshizi, & Ziaratban, 2016)
$r = \sqrt{1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{(P_i - O)^2}}$	(11)	(Fakhreddin Salehi & Razavi, 2012)
$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(P_i - O_i)^2}{n}}$	(12)	（B. Khoshnevisan, Sh. Rafiee, M. Omid, 2013）
$\text{MAE} = \frac{\sum_{i=1}^{n} \lvert P_i - O_i \rvert}{n}$	(13)	(Azadbakht, Aghili, Ziaratban, & Vehedi Torshizi, 2017)

Table 3. Optimization values for artificial neural network parameters

Number of hidden layers	Learning rule	Type of activation function	The number of hidden layer neurons	Testing data %	Validating data %	Training data %
1	Levenberg Marquardt	Hyperbolic tangent and sigmoid	4	20%	10%	70%
1	Levenberg Marquardt	Hyperbolic tangent and sigmoid	8	20%	10%	70%
1	Levenberg Marquardt	Hyperbolic tangent and sigmoid	12	20%	10%	70%

3. Results and discussions

For to predict power consumption, electrical conductivity and coefficient performance systems, MLP and RBF neural network model were used. As lower error value was obtained by using the hyperbolic tangent and sigmoid activation function, this type of function was selected as the activation function in the hidden layer and the output. Based on the test method, 70% of the data were used for training and the network could learn the relationships between inputs and outputs well and 20 % of the data were used to test the network and 10 % of the data were used to Cross Validation network. The value of Mean squared error, Normalized Mean squared error, Mean absolute error, Correlation coefficient are shown Table 4.The results showed that best neural network for 4 neurons in the hidden layer was in tangent hyperbolic activation function and MLP network for power consumption (R = 0.991-MSE=91.419), and for Coefficient performance systems (R= 0.9832 - 0.0003) and best value for electrical conductivity (R = 0.9164 – MSE=0.0072) was in RBF network with tangent hyperbolic and sigmoid. Also for neural network with 8 neurons in hidden layer, Sigmoid activation function and MLP network have best amount for power consumption (R = 0.99832-MSE=3.5E+1), electrical conductivity (R = 0.9963 – MSE=3.1E-4) and Coefficient performance systems (R= 0.99963 -7.8E-5). In neural network with 12 neuron in hidden layer were best amount R=0.9996, 0.9782, 0.999 for power consumption, electrical conductivity and coefficient performance systems in tangent hyperbolic, respectively and best amount for MSE were 18.800, 0.00089, 0.00001 respectability in MLP network and tangent hyperbolic tangent activation function. In total MLP network with 8 neuron in hidden layer and sigmoid activation function have best amount R and MSE for power consumption, electrical conductivity and coefficient performance systems. The results showed in table 4. According to MSE and R value, network 8 neuron in hidden layer was best network for predication power consumption, electrical conductivity and Coefficient performance systems value, because this network has lowest MSE and highest R. Table 5 shows the best network between input data and the data simulated by the network for each of the neurons in the hidden layer. Smaller epochs suggest that the number of neurons in the layer successfully learned by the neural network compared to other neurons. As shown in table 5, the fastest learning speed network for predicting data with sigmoid activation function and tangent hyperbolic were in network by 12 neuron in hidden layer and RBF network by 795 and 115 EPOCH and RUN 1 for training, respectability. Also according to result in table 5 all network created by RBF has Lowest EPOCH than MLP network. But according to result in table 4, lowest MSE and R was in MLP network, sigmoid and tangent hyperbolic activation in 8 and 12 neuron in hidden layer respectively, so the best EPOCH and RUN are 1093-1 for 8 neuron in hidden layer and 795-1for 12 neuron in hidden layer. In total speed training for tangent activation function is highest than sigmoid activation function. Also result for cross validation showed in table 4 for data experiment. The results of the sensitivity analysis for power consumption, electrical conductivity and Coefficient performance systems are shown in Figure 2, 3, 4. Based on this figures, the highest sensitivity for training data were obtained for the Voltage gradin and weight loss percentage in the hidden layers with 8 neurons and sigmoid activation in MLP network and highest sensitivity process time and input current for electrical conductivity and Coefficient performance systems were in hidden layer 8 , 12 and hyperbolic tangent , sigmoid activitaion function and RBF , MLP, respectivity. overall, the voltage gradient sensitivity was higher than the other three inputs, meaning the voltage had a greater effect on power consumption, electrical conductivity and Coefficient performance systems. Also, the sensitivity coefficient of the process time and the input current are exactly the same for power consumption, electrical conductivity and Coefficient performance systems.

Table 5. Some of the best MLP and RBF neural network topologies to predict test value

Sigmoid							
12		**8**		**4**			
MLP	**RBF**	**MLP**	**RBF**	**MLP**	**RBF**		
795	695	4377	1093	4407	1934	Training	**EPOCH**
7	5	215	73	11	10	Cross Validation	
1	1	1	1	5	1	Training	**RUN**
4	1	1	3	5	5	Cross Validation	
Tangent hyperbolic							
12		**8**		**4**			
MLP	**RBF**	**MLP**	**RBF**	**MLP**	**RBF**		
157	115	4999	457	5000	500	Training	**EPOCH**
32	21	25	6	15	7	Cross Validation	
1	1	1	1	4	1	Training	**RUN**
3	4	3	2	4	3	Cross Validation	

Table 4. Error values in predicting experimental data using optimal artificial neural network

Power consumption													
R			**MAE**			**NMSE**			**MSE**				
12	**8**	**4**	**12**	**8**	**4**	**12**	**8**	**4**	**12**	**8**	**4**		
0.9534	0.99832	0.9815	14.97	4.7526	16.1328	0.1019	8.2E-03	0.0978	481.45	3.5E+01	473.2174	S	MLP
0.91236	0.9690	0.9636	29.65	10.37	17.24	0.863	0.0639	0.0845	580.65	309.14	413.43		RBF
0.99683	0.99288	0.991	2.519	4.84	6.636	0.00649	0.02	0.019	18.800	78.30	91.419	T	MLP
0.9822	0.9827	0.9655	14.01	7.3861	16.2073	0.0812	0.0370	0.0855	279.28	107.7434	388.5924		RBF
Electrical conductivity													
0.8215	0.99633	0.9157	0.0762	0.0117	0.0696	0.3808	1.1E-02	0.1937	0.0116	3.1E-04	0.0077	S	MLP
0.7936	0.9465	0.8258	0.156	0.0579	0.0838	0.456	0.1222	0.3323	0.0793	0.0050	0.0130		RBF
0.97824	0.94909	0.883	0.01512	0.04	0.076	0.04368	0.10	0.227	0.00089	0.0036	0.009	T	MLP
0.5661	0.9088	0.9164	0.2582	0.0589	0.0670	4.7372	0.2098	0.1911	0.0864	0.0059	0.0072		RBF
Coefficient performance systems													
0.97813	0.999750	0.9799	0.01632	0.0059	0.0144	0.04714	7.7E-03	0.0403	0.00044	7.8E-05	0.0004	S	MLP
0.9336	0.9936	0.9832	0.0296	0.0093	0.0143	0.089	0.0133	0.0357	0.00245	0.0001	0.0003		RBF
0.99963	0.98228	0.973	0.00187	0.01	0.020	0.00077	0.04	0.060	0.00001	0.0002	0.001	T	MLP
0.9916	0.9851	0.9375	0.0228	0.0122	0.0265	0.0822	0.0314	0.1229	0.0008	0.0003	0.0010		RBF

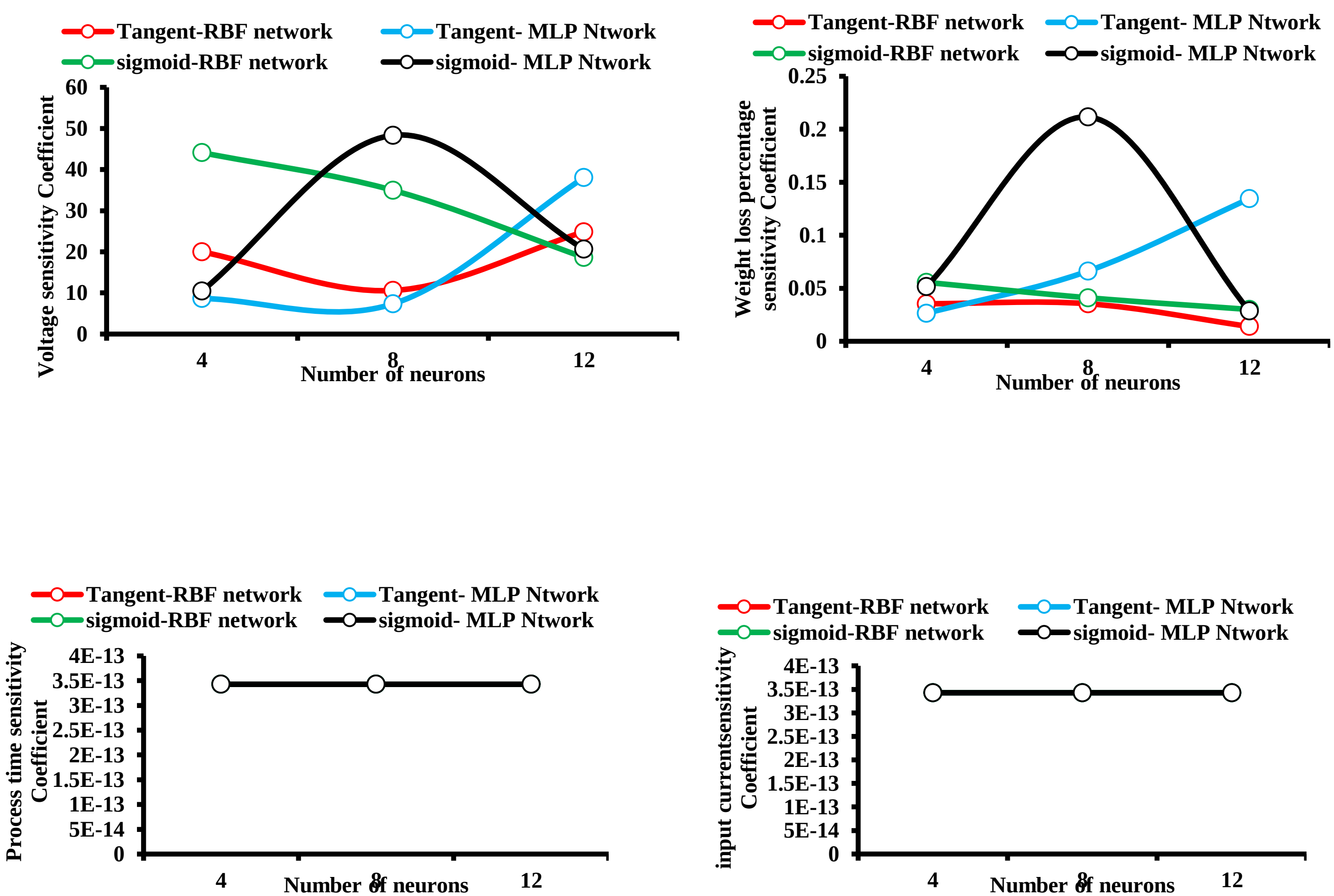

Figure 2. Sensitivity coefficient power consumption

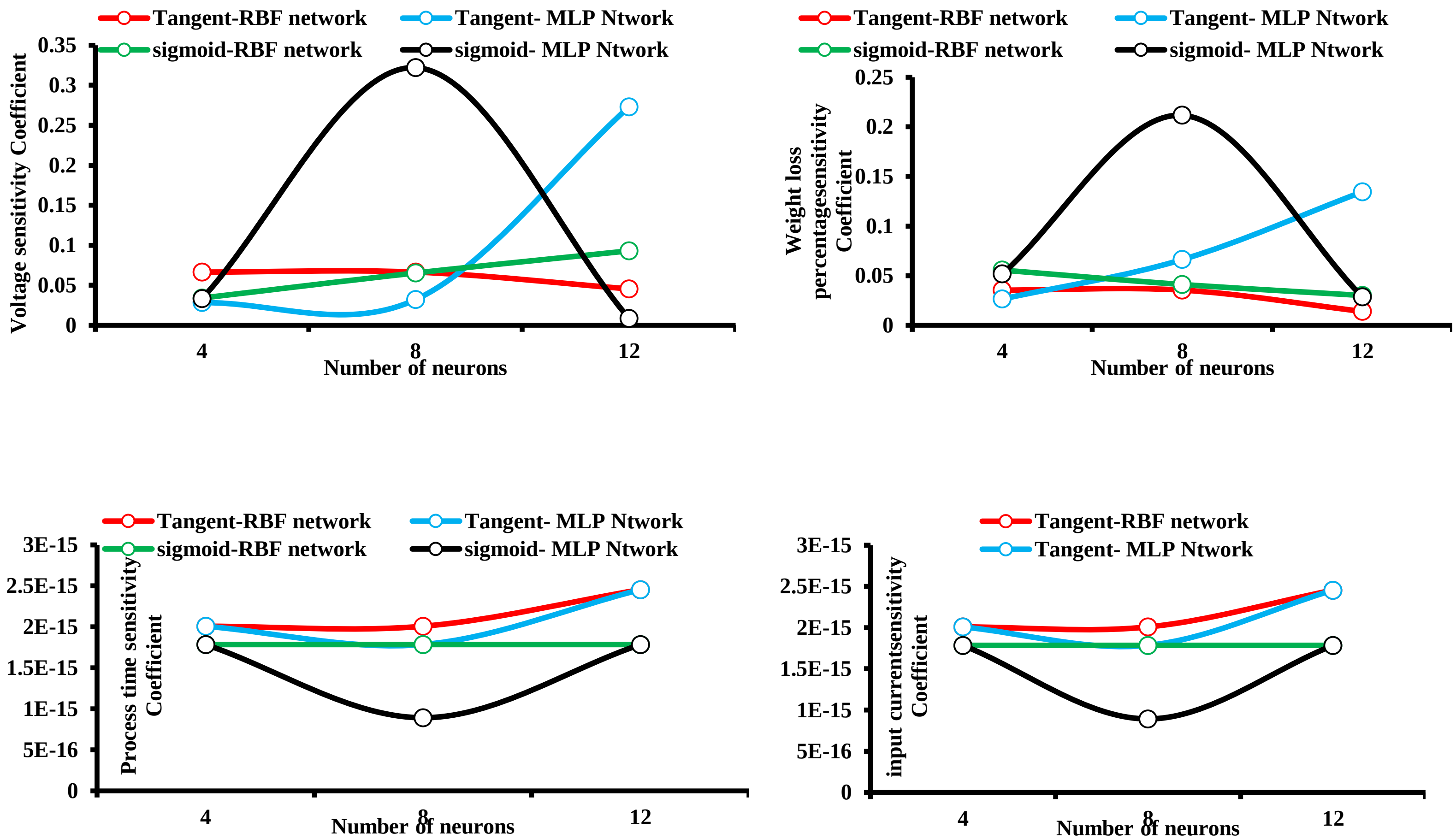

Figure 3. Sensitivity coefficient conductive electrical

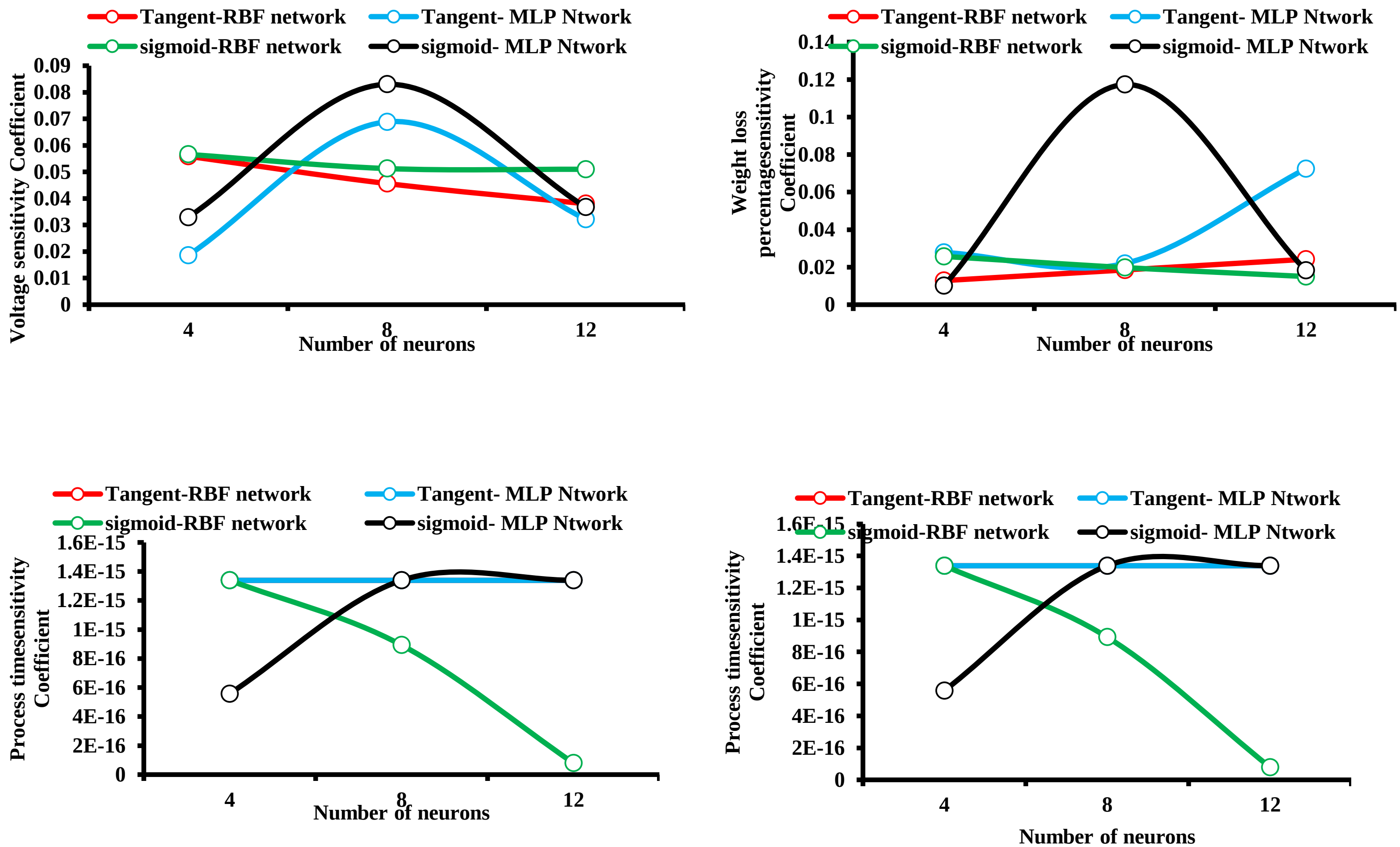

Figure 4. Sensitivity coefficient, coefficient performance systems

4.Conclusion

For power consumption, electrical conductivity and performance system, the best R value in the MLP network with 8 neurons in the hidden layer was the sigmoid activation function, But for power consumption and system efficiency, Sigmoid activation functions and tangent have been able to show R values in RBF and MLP networks, These values were good for all three numbers of input neurons for the network. But for electrical conductivity, the network with 12 neurons, and especially the RBF network, has not shown satisfactory results.

For power consumption, electrical conductivity and performance system were the lowest MSE in a network of 8 neurons, The MSE values for both the hyperbolic and sigmoid tangency activation function were lower for both the MLP and RBF networks than for the two networks with 4 and 12 neurons, which suggests a better formation of the network with 8 neurons.

According to the results of the network learning speed, as the number of neurons in the hidden layer has increased, the speed of network learning has increased to simulate data, and the fastest network with lowest EPOCH was in a network of 12 neuron. Also, the hyperbolic tangent activation function has a faster speed in network training than sigmoid activation function.

The sensitivity coefficient for the Voltage gradient relative to the other parameters of the network input has a greater effect on the power consumption, the electrical conductivity coefficient, and the coefficient performance of the system.

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