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Application and evaluation of the neural network in gearbox

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ABSTRACT

We developed old designed of a Back-Propagation neural network (BPNN), which it was designed by other researchers, and we made modification in their structure. The 1st velocity ratio was discriminated by lowest speed, and highest twist. The 6th velocity ratio was discriminated by highest speed, and lowest twist. The aim of this paper is to design neural structure get best performance to control an electrical automotive transportation six-speed gearbox of the vehicle. We focus on the evaluation of the BPNN to select the suitable number of layers and neurons. Experimentally, the structure of the proposed BPNN are constructed from four layers: eight input nodes in the first layer that received data in binary number, 45 neurons in 1st hidden-layer, 25 neurons in 2nd hidden-layer, and 6 neurons in the fourth layer. The MSE and number of Epochs are the main factors used for the evaluation of the proposed structure, and compared with the other structures which was designed by other researchers. Experimentally, we discovered that the best value of Epoch and MSE was chosen when the BPNN consisted of two hidden-layers, 45, and 25 neurons in the 1st and 2nd hidden-layer respectively. The implementation was applied using MATLAB software.

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1. INTRODUCTION

The transportation gearbox can be acquainted as a tool utilized for moving the mechanical movement for the vehicle's engine and assigning it to the wheels, and this occurred by connecting to the flywheel that was located at the back end of the engine. The aim of using this tool is increasing torque and decreasing the round per hour of the crankshaft of the motor engine to be suitable speed according to speed of the driving wheels [1]. The transportation gearbox consists of several serrated shafts, and number of gears of various velocity ratio, each of one able to control and change the rotation velocity to different velocity ratio. In any vehicle, there are two kinds of gear, automotive and manual gear, and in this paper, we concerned at the automotive gearbox type [2, 3].

The automotive transmission gearbox consists of a specified number of gear wheels, and the appropriate wheel is selected for each speed automatically and without the intervention of the driver, providing the comfort of driver. There are numerous kinds of automotive transmission gearbox: semi-automatic transmission, hydraulic and continuous change [4, 5]. The hydraulic gearbox used a fluid coupling instead of friction clutch, which was used in manual (traditional) gearbox type. The semi-automatic and continuously variable gearbox technique changes the speed ration depending on an intelligent computer program not as the traditional hydraulic type. The system detect the speed of driving wheels and choosing the appropriate velocity ratio of gearbox, which suitable with this speed [6, 7]. Experimentally, the BPNN was the best choice as intelligent system between classification manners for the recognition processes.

The BPNN used gradient descent as optimization method in the training method, it detect and sum the loss function of gradient of all weights in the neural net, and the gradient is reused to update the weights for attempting to minimize the error function [8-10]. BPNN is classified as a supervised learning, thus, it need to supply required output to each data entry for computing the error function. It was multi-layer feed forward nets and used chain rule in iterative manner for calculating the gradient function for each layer. It important to call a suitable activation function for each layer [11-14].

The work of BPNN is summarized as follows: when data of learned object is applied the output node is computed by activation function for the weighted sums multiplied with input nodes, then the comparison between computed output and desired output was calculated to get the error value, and this value of error is used to update the weights again for optimizing the new result of output computations [15-18]. The BPNN is constructed from at least three layers, which they are: input layer (first layer), hidden layer(s) (second or more layers), and finally, output layer (the last layer). The first layer consists of determined nodes (neurons), the hidden layer is constructed of single or more layers, where each layer utilizes a specified activation function to supply its output the next layer, and the last (output) layer contains at a specified number of nodes and utilizes an activation function [19-24].

Yazdani M. & Rassafi A. A., [25] presented the study about evaluation of the warning application map, and the satisfaction of the driver to these applications. The study was implemented using 32 driers in the two-way road in the north-west in Iran. The study shows that the drivers were pleased with alarming from car speakers, but they not with alarms from mobile speakers. Kalistratov D. [26], presented a global mathematical model to deal with digital images coming from the traffic control site in the traffic congestion within large cities, where this model can overcome the problem of noise on the transmitted signal, the Fourier series can also separate transmitted signal variables and use them with computer simulation.

Omidi A, et. al., [27] used ADS software to design the low noise amplifier circuit within the low frequency band. This circuit was designed and implemented in wireless networks and GPS systems and proved to be efficient and effective. Khotbehsara E. & Safari H. [28,] used a tree matrix containing pre-fed data about where to build a hospital, and use a smart data collection method to determine the best location for a hospital building depending on the psychological state of the patients in that area as well as the availability of materials and equipment necessary in the treatment.

Gamil Y. & Rahman I. A., [29] presented a study showing the negative impact on the lack of communication on the industry and after several questionnaires show that the industry pretends and offers something excellent when there is communication among the owners of the project. Our work is to design a simulation software of BPNN and to download this software in FPGA, the work of this simulation is depending on the speed of driving wheels of vehicle the suitable value of ratio speed for transmission gearbox are selected. For illustration purpose, the software chooses the speed ratio (1) if the entered data value at range (00000000– 00010100), where the real velocity of the vehicle is ranged (00–20) km/h, if the real velocity of the vehicle is ranged (21–40) km/h, the entered data to the software is ranged (00010101–00101000), then the it chooses the velocity ratio number (2), and so on.

The proposed BPNN of the system constructed from four layers: the input layer consists of eight neurons, the first layer composed from forty-five neurons, second hidden layers consist of twenty-five neurons, and the forth (last layer) consists of six neurons. The MATLAB software has been utilized to design and implement the proposed system. The results are obtained by using Trainlm() Matlab function for training the BPNN. Using Satlins function as activation functions for hidden layers, and Satlin function was used for linear function for the Last layer. The performance of the proposed software has been evaluate by the number of epoch of training networks and the MSE for the training and testing phase.

2. THE PROPOSED SIMULATION SYSTEM DESIGN

The proposed system depended mainly at the BPNN which was designed by Azaad B. [30], and we make some modification at the neural structure, the structure of the proposed BPNN has been illustrated in the Figure 1, as depicted bellow. The design of the proposed BPNN structure has passed through several stages to the final design status and is accepted experimentally. There is no problem in determining the neurons count in the input layer or in the output layer, but the problem is in the neurons count to be provided in the hidden layers as well as the hidden-layers count themselves.

The structure consists of four layers, the first layer named input layer where it composed from eight neurons (nodes), it received the real velocity of vehicle wheels in binary number style as presented in Table 1, and the eight entries of BPNN receive its data from the driver wheel speed, which was encoded into eight bits binary number. The last layer name was output layer, it composed from six neurons, each on represent the speed ration of the gearbox, for example, the first neuron devoted for number (1) ratio speed of gearbox, the second neuron for number (2) ratio speed of gearbox, and so on. For each execution there must be one neuron is activated to one and all the other deactivated to zeros, the Satlin function used as linear function.

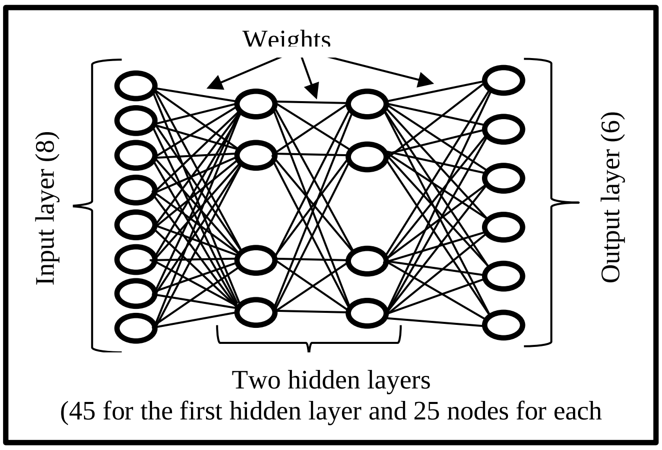

Figure 1. Structure of the proposed BPNN

Table 1. Codes of the proposed structure

Velocity Ratio	Real Velocity km/h	Input data	Proposed Simulation Software Outputs					
			A	B	C	D	E	F
1	00-20	00000000 -00010100	1	0	0	0	0	0
2	21-40	00010101 - 00101000	0	1	0	0	0	0
3	41-60	00101001 - 00111100	0	0	1	0	0	0
4	61-100	00111101 - 01100100	0	0	0	1	0	0
5	101-130	01100101 - 10000001	0	0	0	0	1	0
6	>=131	10000010 - 11111111	0	0	0	0	0	1

At first, the design was experimentally based on the composition of the network consisting of one hidden layer and then each experimental stage, the number of cells forming that layer is selected from the cell to 70 cells. At each stage, the evaluation is based on the value of MSE and the number of epochs, see Table 2. Then the proposed BPNN was reconstructed from two hidden layers, and revaluated to determine the most appropriate number of neurons depending on the value of MSE for the training and testing samples and the number of epochs in each training phase is selected, see Table 3. At last, the suitable structure of BPNN was chosen, and consisted of four layers, the first and last layer was mentioned above and it is not our problem in our research. The first hidden layer composed from forty-five neurons, the second hidden layer constructed from twenty-five neurons, and used Satlins function as linear function for each hidden layer.

3. THE IMPLEMENTATION OF THE PROPOSED SIMULATION SYSTEM

The proposed BPNN implemented using MATLAB software, we used Trainlm function (Levenberg-Marquardt training) as training algorithm. When we implement the proposed software in a computer, the block of the proposed simulation BPNN will be shown and illustrated in Figure 2, it has eight input buttons that represent the velocity of vehicle, the data can be entered to the simulation system by activating (clicking at) the button for 1 entry, and deactivating (releasing) the button for zero entry. The simulation has six output buttons, where only one button will be active (set to one) for the required velocity and the other buttons will be deactivate (reset to zero). When the simulation complete, the result will be one of output buttons set to one and the other reset to zero. To begin the simulation, we select the desired input buttons, for instance, we want to enter the velocity value (00111100), which it equal to (60 km) as a real velocity value in decimal representation, click at the buttons 3, 4, 5 and 6, then click at the BPNN Simulation Button, see Figure 3.

New block of simulation will be appear on the computer screen, see Figure 4, this block illustrates the connection of BPNN layers, by clicking at the first hidden layer button, the summation of multiplication weights by inputs values started, and the results will be the entries values for the second hidden layer. Now, we click at the second hidden layer button, the result will be activation of button C, that means the gearbox speed ratio is 3, see Figure 5.

Table 2. Results of epoch and MSE for implementing the BPNN consists of single hidden layer with many neurons number

No. of Neurons in first hidden layer	Epoch	MSE in training phase	MSE in testing phase
1	8	0.327	0.3507
2	6	0.308	0.2991
3	54	0.236	0.2521
4	8	0.234	0.2798
5	35	0.226	0.2481
6	45	0.226	0.2676
7	16	0.220	0.2619
8	17	0.224	0.2533
9	16	0.228	0.2570
10	15	0.232	0.2644
11	15	0.220	0.2559
12	16	0.224	0.2718
13	11	0.212	0.2505
14	14	0.240	0.2651
15	11	0.210	0.2400
16	11	0.218	0.2630
17	12	0.218	0.2508
18	14	0.224	0.2615
19	12	0.212	0.2511
20	11	0.218	0.2462
21	13	0.212	0.2707
22	13	0.216	0.2803
23	11	0.228	0.2744
24	6	0.216	0.2495
25	12	0.211	0.2606
26	12	0.212	0.3079
27	10	0.214	0.2488
28	15	0.218	0.2743
29	10	0.244	0.3047
30	14	0.211	0.2470
31	10	0.220	0.2503
32	12	0.218	0.2434
33	11	0.212	0.2646
34	10	0.211	0.2398
35	10	0.214	0.2453
36	11	0.214	0.2521
37	13	0.212	0.2603
38	12	0.214	0.2768
39	11	0.212	0.2527
40	12	0.216	0.2584
45	**5**	**0.210**	**0.220**
50	9	0.214	0.2472
55	14	0.214	0.2466
60	8	0.216	0.2341
65	9	0.214	0.2428
70	11	0.218	0.2627

Table 3. Results of epoch and MSE for implementing the BPNN consists of double hidden-layers, 1st hidden-layer fixed at 45 neurons, and with many neurons number for the 2nd hidden-layer

No. of Neurons in second hidden layer	Epoch	MSE in training phase	MSE in testing phase
1	52	0.0982	0.1422
2	44	0.0877	0.1787
3	52	0.0502	0.1599
4	84	0.0414	0.1268
5	38	0.0472	0.1695
6	40	0.156e-32	0.1319
7	47	1.64e-33	0.1246
8	31	7.36e-33	0.1960
9	27	9.12e-33	0.1130
10	58	7.12e-22	0.1357
11	53	8.20e-32	0.1116
12	20	1.03e-32	0.0936
13	26	1.03e-32	0.1950
14	35	8.51e-33	0.1024
15	30	1.51e-32	0.1512
16	17	1.49e-32	0.1287
17	18	7.34e-33	0.1433
18	23	6.87e-33	0.1540
19	18	1.09e-32	0.1407
20	19	1.14e-32	0.1969
21	19	1.75e-32	0.1204
22	23	1.00e-32	0.0992
23	19	1.13e-32	0.1538
24	23	9.42e-33	0.1187
25	**12**	**1.85e-32**	**0.0182**
26	15	1.62e-32	0.1195
20	19	1.06e-32	0.1061
28	16	1.86e-32	0.1320
29	18	1.52e-32	0.1298
30	20	1.94e-32	0.1558
31	16	2.00e-32	0.1394
32	15	1.86e-32	0.1263
33	16	1.63e-32	0.1181
34	17	1.65e-32	0.1018
35	17	2.03e-32	0.1073
36	18	2.65e-32	0.1323
37	20	1.68e-32	0.1213
38	21	1.59e-32	0.1804
39	16	2.05e-32	0.1412
40	16	2.78e-32	0.1132
45	15	2.31e-32	0.1115
50	15	2.88e-32	0.1596
55	24	2.91e-32	0.1368
60	17	3.75e-32	0.1254
65	15	3.59e-32	0.1508
70	17	3.37e-32	0.1728

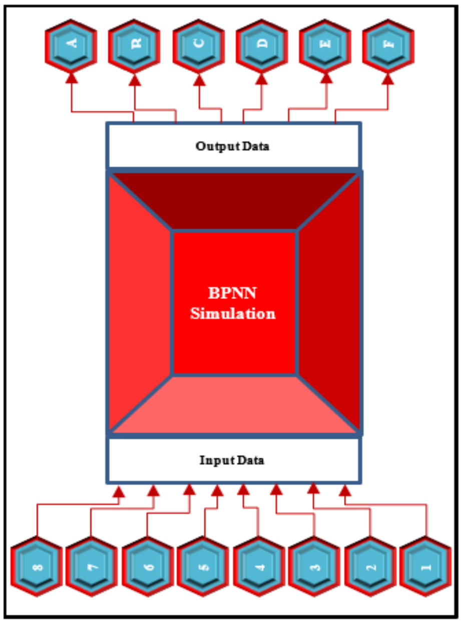

Figure 2. Block of the proposed simulation system

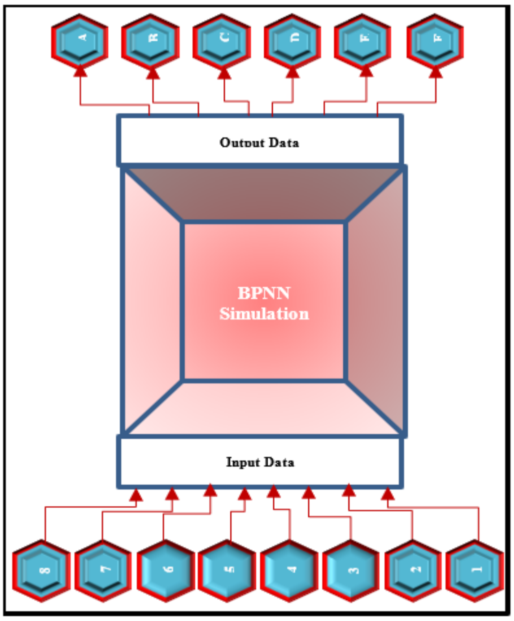

Figure 3. The simulation block after clicking the desired input and BPNN simulation buttons

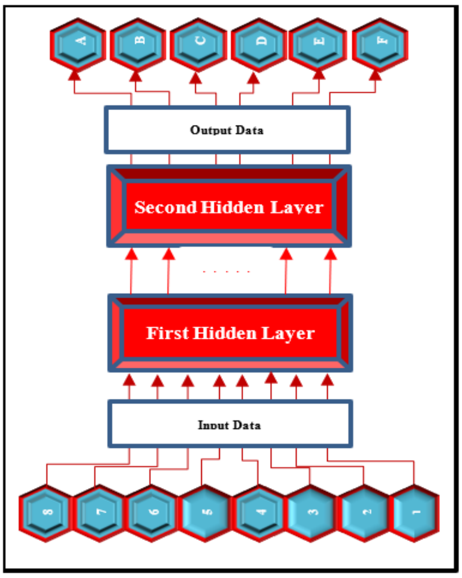

Figure 4. Block of simulation shows the BPNN layers

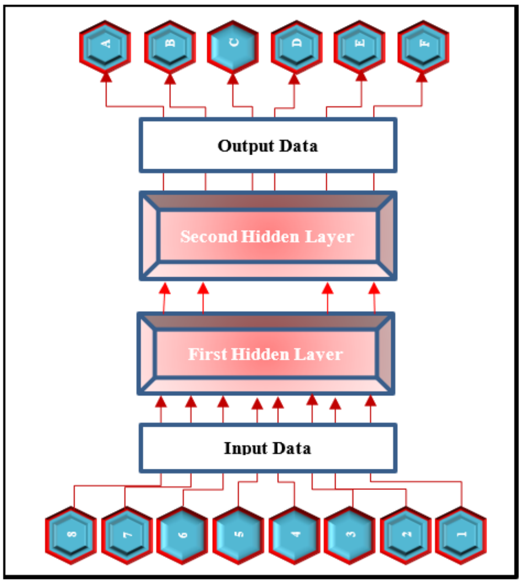

Figure 5. Block of simulation after the execution completed

4. RESULTS AND DISCUSSION

As we mentioned at the previous section, the structure of the proposed BPNN constrained at the selecting the count of hidden-layers as well as the count of its neurons. The proposed network was trained at 31 input samples, tested at 151 input samples, and the evaluation of the proposed structure depended on the value of MSE for the trained and tested samples in addition to the number of epoch of the training phase. We used two phases of designing prosesses, the first one implemented the structure of neural consists of one single hidden layer only, and in the second phase we implemented the structure of neural net consists of two hidden layers. Experimentally, in the first phase, we selected forty-five neurons for the first hidden layer, and the epoch and SME for the training and testing samples were the best value at that number of neurons. See Figure 6, to notice the structure of the proposed BPNN with single hidden layer and the epoch value for using 45 neurons at the first hidden layer.

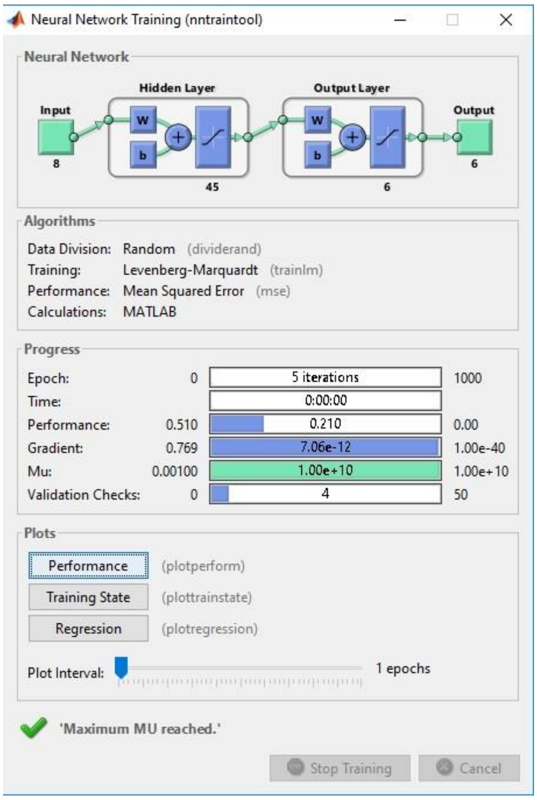

Figure 6. Menu shows the value of epoch at training phase for BPNN consists of single hidden layer with 45 neurons

Figure 7 illustrate the plot of Gradient, Momentums and validation checks when training the BPNN with single hidden layer of 45 neurons. Figure 8 illustrates the plot of training performance for the BPNN with single hidden layer of 45 neurons, and the best validation performance value was at the 1st epoch. Figure 9 shows show the plot of regression during the training of the BPNN of singled hidden layer with 45 neurons.

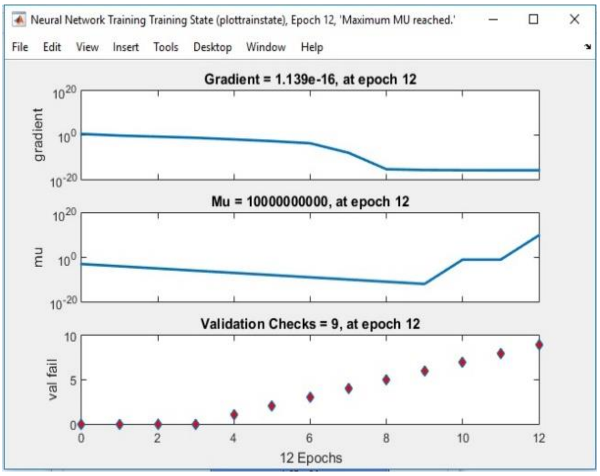

Figure 7. Plot of gradient, momentum and validation checks for the training BPNN consists of single hidden layer with 45 neurons

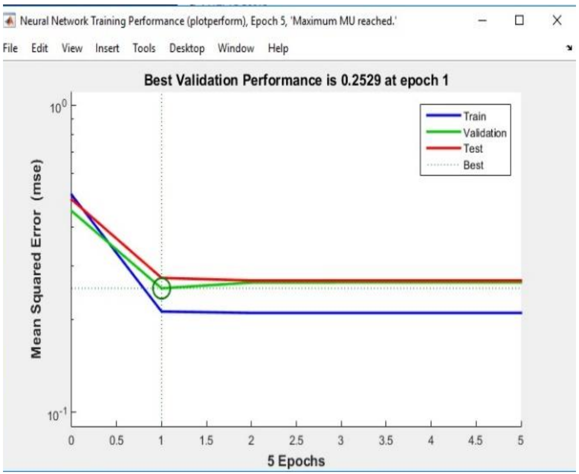

Figure 8. Plot of performance for training the BPNN with single layer of 45 neurons

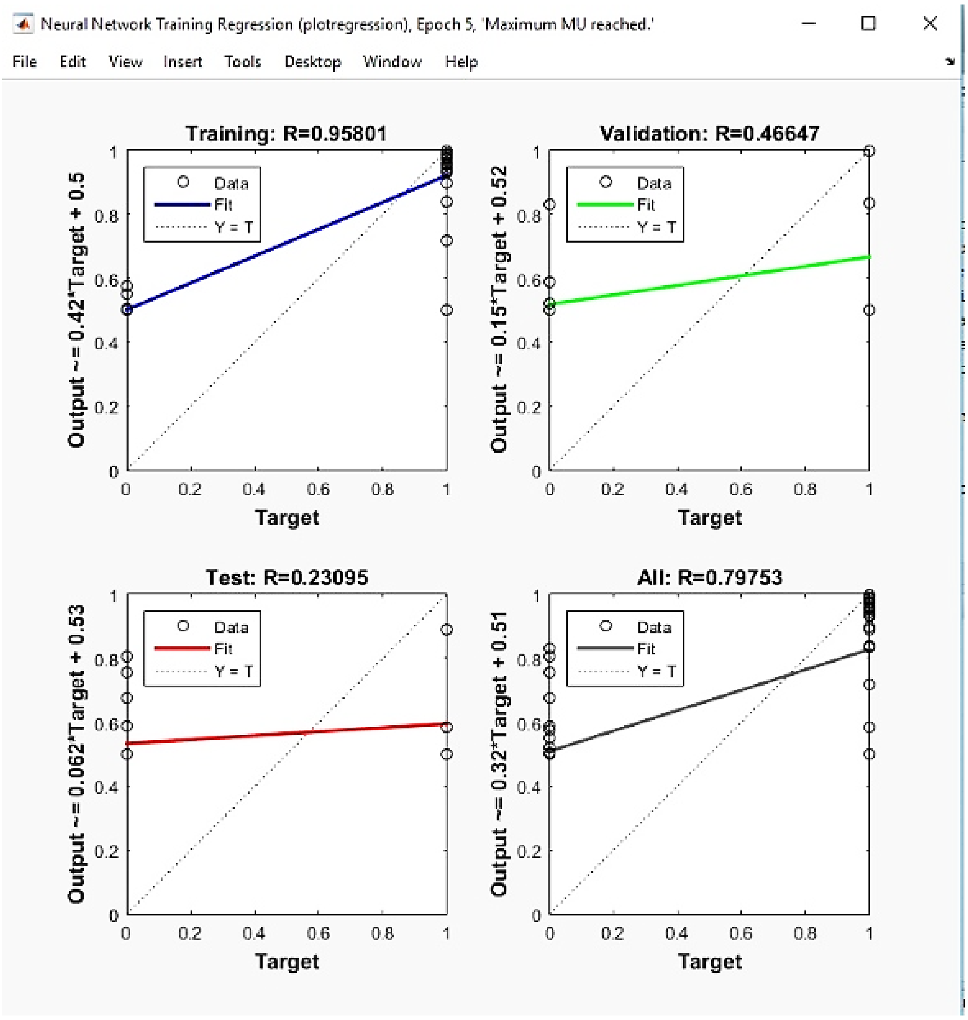

Figure 9. Plot of regression for training BPNN with single hidden layer with 45 neurons

All the above three figures of ploting, shown the 45 neurons in the BPNN is the best choice, where the value of the training epoch was 5, and the value of MSE for the training and testing performance was 0.210 and 0.220 respectively. Then toward more enhancing the network, began to the second phase of the designing process, we reconstructed the structure of the neural net by adding another one hidden-layer to be the network consists of two hidden-layers. Experimentally, we discovered that the best neurons counts was 25 neurons in the second hidden layer, as illustrated by the best value of Epoch and MSE was chosen when the BPNN consisted of two hidden-layers, 45, and 25 neurons in the 1st and 2nd hidden-layer respectively, see Figure 10, which it shows menu that displays the structure and the epoch value equal to 12 when training the proposed BPNN consisted of two hidden-layers, 45, and 25 neurons respectively.

Figure 11, shows the plot of Gradient, Momentum and validation checks for the training BPNN consists of two hidden layer, 1st hidden-layer fixed at the 45 neurons, and the 2nd hidden-layer set to 25 neurons, and the best values was at the 12th epoch. Figure 12, shows the plot of performance for training the BPNN with two hidden-layers, 45 and 25 neurons for the first and second hidden-layer respectively, and the best validation performance value was 0.15258 at the 3rd epoch. Figure 13, shows the plot of regression for training BPNN with two hidden-layers, 45 and 25 neurons for the 1st and 2nd hidden-layer respectively.

Finally and experimentally, from all the above three mentioned figures of ploting, we notice that the best values for epoch equal to 12, and value of MSE for training and testing performance was equal to 1.85e-32 and equal to 0.0181respectively, were exist in the BPNN which structured from two hidden layers (45 and 25 neurons in the 1st and 2nd hidden-layer respectively). Comparing with previous work of other researchers, for instance, Azzad B. Saeed [30], has designed and presented a simulation system as illustrated in Figure 14, as shown in this figure, the best value of MSE equal to 3.9392e-25 is reached at Epoch 15.

Ramya J. et al [31] and Wei L. et al [32] have designed and gave a simulation system as illustrated in Figure 15 and Figure 16 respectively, which they shown that the best value of MSE equal to 4.3515e-14 and equal to 1.3205e-15 were reached at the epoch 24 and 36 respectively. Thus, from the other previous works, we conclude that our proposed BPNN gets the best results in the training testing performance value, where the best SME value was equal to 1.85e-32 at the 12th epoch of training.

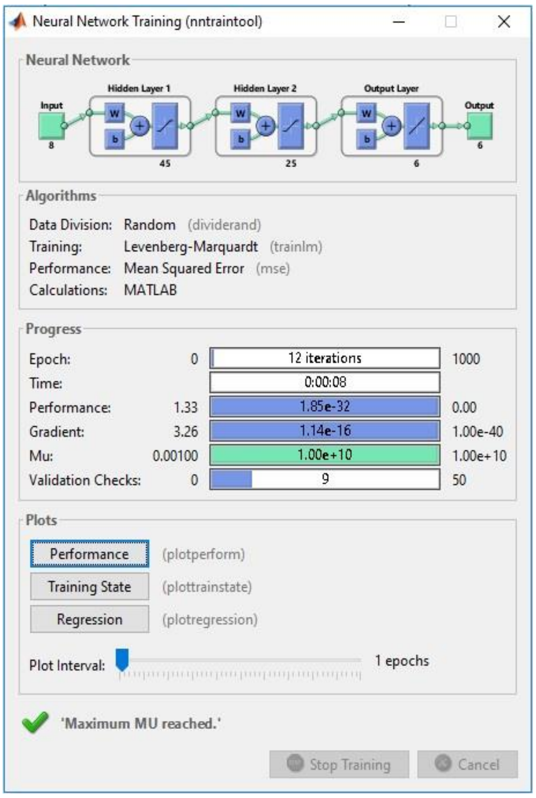

Figure 10. Menu displays the value of epoch at training phase for BPNN consists of two hidden layers with 45 and 25 neurons for the first and second hidden layers respectively

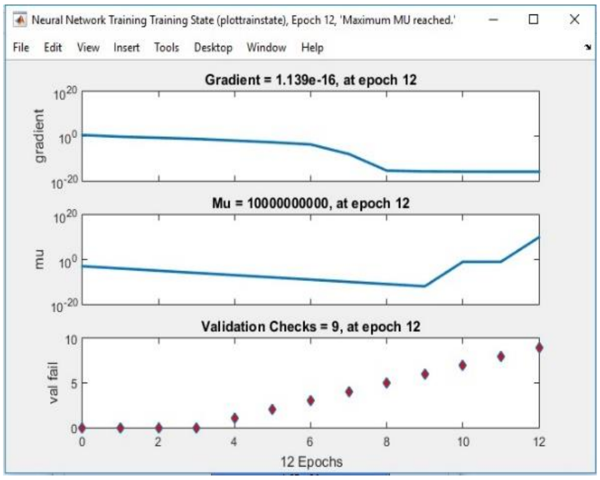

Figure 11. Plot of Gradient, Momentum and validation checks for the training BPNN consists of two hidden layers, 1st hidden-layer fixed at the 45 neurons, and 2nd hidden-layer set to 25 neurons

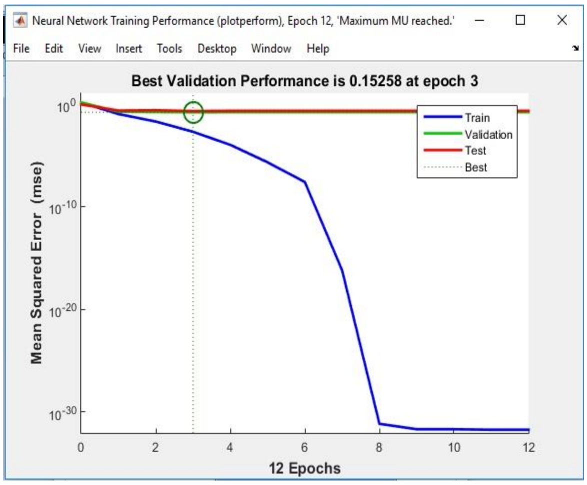

Figure 12. Plot of performance for training the BPNN with two hidden-layers, 45 and 25 neurons for the 1st and 2nd hidden-layer respectively

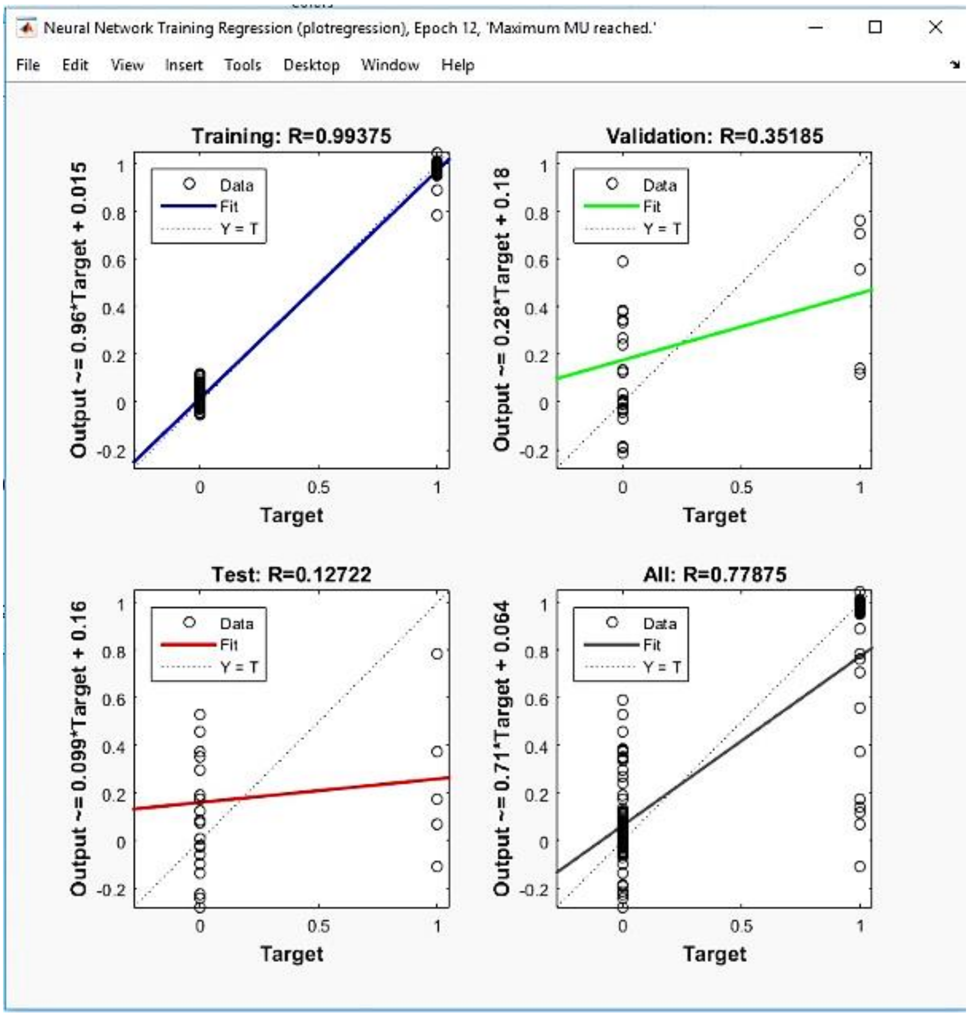

Figure 13. Plot of regression for training BPNN with two hidden-layers, 45 and 25 neurons for the 1st and 2nd hidden-layer respectively

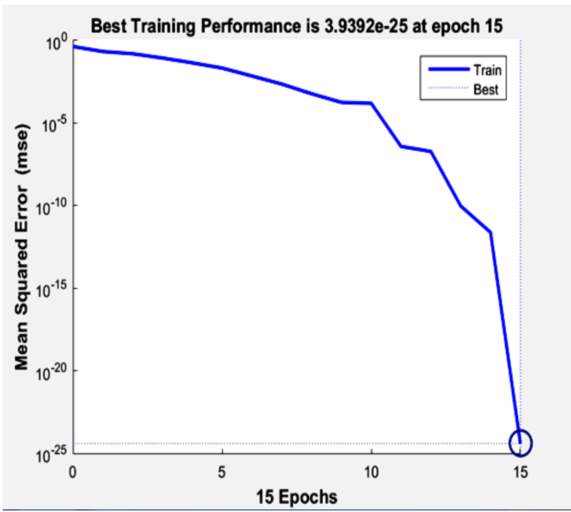

Figure 14. Plot of azzad B. Saeed performance SME results

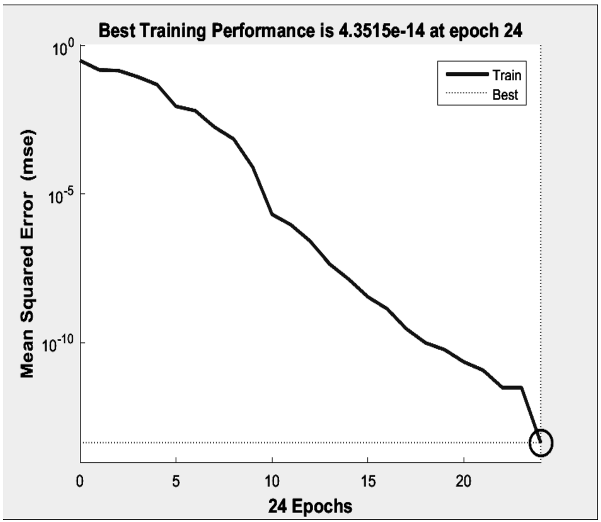

Figure 15. Plot of Ramya J. et al. performance SME results

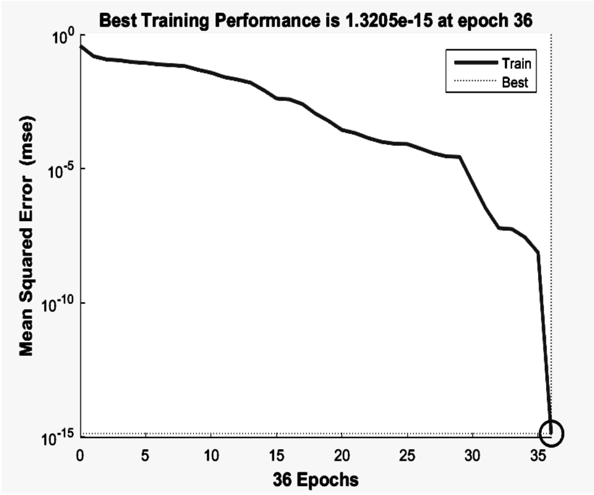

Figure 16. Plot of Wei L. et al. performance SME results

5. CONCLUSION

The main role of the intelligent systems of programed automatic transmission gearbox is base on the performance of the software results that installed for that purpose, and in the neural networks, the performance depends on the MSE training and testing performance results, and on the time of training which represented in epoch of training. In our proposed system, the BPNN was constructed with determined number of hidden layers and number of neurons that able the system reached the best performance results. The experimental results show the best performance SME values are 1.85e-32 and equal to 0.0181 for training and testing performance respectively with epoch number at 12. In the future, I prefer to use some methods of AI in the intelligent system such as genetic algorithm instead of neural networks that may shows new good performance results.

REFERENCES

[1] Bagameri N., Varga B. & Moldovanu D., “Comparative Analysis of Automatic Transissionn and Manual Transission Behaviour on the Worldwide Harmonized Light Duty Test Cycle,” *MATEC Web of Conferences*, vol. 184, no. 12, January 2018.

[2] Darko Stanojevi, Vladimir Spasojevi, Igor Stevanovi, and Aleksandar Nedi, "The Contemporary Automatic Gearboxes- review of the current state and interpretation of advantages and disadvantages of their use with respect to vehicle performance and terrific safety," *Journal of Applied Engineering Science*, vol. 11, no. 2, pp. 89-97, 2013.

[3] Andrew Moskalik, Aaron Hula, Daniel Barba, and John Kargul, "Investigating the Effect of Advanced Automatic Transmissions on Fuel Consumption Using Vehicle Testing and Modeling," *SAE International Journal of Engines*, vol. 9, no.3, pp. 1916-1928, 2016.

[4] Ngo V. D., Hofman T., Steinbuch M. & Serrarens A., “Gear Shift Map Design Methodology for Automative Transissions,” in *Proceedings of the Institution of Mechanical Engineers Part D Journal of Automobile Engineering*, vol. 228, no. 1, pp. 50-72, January 2013.

[5] Wenchen Shen, Huilong Yu, Yuhui Hu, and Junqiang Xi,"Optimization of Shift Schedule for Hybrid Electric Vehicle with Automated Manual Transmission," *Energies Journal*, vol. 9, no. 3, pp. 1-11, March 2016.

[6] Jian Yao, Li Chen, and Fengyu Liu, "Experimental Study on Improvement in the Shift Quality for an Automatic Transmission Using a Motor-Driven Wedge Clutch," *Proceedings of the Institution of Mechanical Engineers Part D Journal of Automobile Engineering*, vol. 228, no. 6, pp. 663-673, April 2014.

[7] Long-Chang Hsieh, and Hsiu-Chen Tang, "The Innovate Design of Automatic Transmission for Electric Motorcycle," *Transactions-Canadian Society for Mechanical Engineering*, vol. 37, no. 3, pp. 741-753, September 2013.

[8] Jing Li, Ji-hang Cheng, Jing-yuan Shi, and Fei Huang, "Brief Introduction of Back Propagation (BP) Neural Network Algorithm and Its Improvement," *Advances in Computer Science and Information Engineering*, vol. 169, pp. 553-558, January 2012.

[9] Chih-Yao Lo, "Back Propagation Neural Network on the Forecasting System of Sea Food Material Demand," *Communications in Computer and Information Science*, vol. 202, pp. 147-154, January 2011.

[10] Dheyaa Shaheed Sabr, “Review on Challenges in Building Knowledge Based Societies Through E-Governance Framework: Technology and Management Issues from Global Perspective,” *Indian Journal of Science and Technology*, vol. 10, no. 28, pp. 1-7, August 2017.

[11] Jyh-Woei Lin, Chun-Tang Chao, and Juing-Shian Chiou," Back-propagation Neural Network as Earthquake Early Warning Tool using a new Elementary Modified Levenberg–Marquardt Algorithm to minimise Back-propagation Errors," *Geoscientific Instrumention, Methods and Data Systems Dicsussions*, vol. 7, pp. 235-243, 2018.

[12] Bin Lin1, Gaotong Lin, Xianyun Liu, Jianshe Ma, Xianchuan Wang, Feiyan Lin, and Lufeng Hu, "Application of back-propagation artificial neural network and curve estimation in pharmacokinetics of losartan in rabbit," *International Journal of Clinical and Experimental Medicine*, vol. 8, no. 12, pp. 22352-22358, Febuary 2016.

[13] Taufik Ari Gunawan1, M. Syahril Badri Kusuma, M. Cahyono, and Joko Nugroho, "The application of backpropagation neural network method to estimate the sediment loads," *MATEC Web of Conferences*, vol. 101, no. 05016, pp. 6, 2017.

[14] Dheyaa Shaheed Sabr, and Mustafa Raheem, "Comparative Analysis Study on Network Performance of VoIP and Data Trafic Pattern using Queuing Algorithms in Wired Network Environment: An Implementation using OMNet++ Simulator," *Indian Journal of Science and Technology*, vol. 10, no. 36, pp. 1-19, September 2017.

[15] Amit Ganatra, Y. P. Kosta, Gaurang Panchal, and Chintan Gajjar, "Initial Classification Through Back-propagation in a Neural Network Following Optimization Through GA to Evaluate the Fitness of an Algorithm," *International Journal of Computer Science and Information Technology (IJCSIT)*, vol. 3, no. 1, pp. 98-116, Feb 2011.

[16] Ali Hossain, Mijanur Rahman, Uzzal Kumar Prodhan, and Farukuzzaman Khan, "Implementation of Back-Propagation Neural Network For Isolated Bangla Speech Recognition," *International Journal of Information Sciences and Techniques (IJIST)*, vol. 3, no. 4, pp. 1-9, July 2013.

[17] Rashmi Amardeep, and K. Thippe Swamy, "Training Feed forward Neural Network with Back-propogation Algorithm," *International Journal of Engineering And Computer Science*, vol. 6, no. 1, pp. 19860-19866, Jan 2017.

[18] Dheyaa Shaheed Sabr, "Points Descriptor in Pattern Recognition: A new Approach," *Iraqi Journal for Computer and Informatics (IJCI)*, vol. 43, no. 2, pp.23-29, 2017.

[19] Kamil Dimililer, "Backpropagation Neural Network Implementation for Medical Image Compression," *Journal of Applied Mathematics*, vol. 2013, no. 1, pp. 1-8, December 2013.

[20] Rama Kishore, and Taranjit Kaur, "Backpropagation Algorithm: An Artificial Neural Network Approach for Pattern Recognition," *International Journal of Scientific & Engineering Research*, vol. 3, no. 6, pp. 30-37, June 2012.

[21] Omaima N. A. AL-Allaf, "Improving the Performance of Backpropagation Neural Network Algorithm for Image Compression/Decompression System," in *Journal of Computer Science*, vol. 6, no. 11, pp. 1347-1354, January 2010.

[22] Dheyaa Shaheed Al-Azzaw, "Recognition and Diagnosis Perspectives for Cancer Patterns in the Medical Digital Images," *Journal of Advanced Research in Dynamical and Control Systems*, vol. 11, no. 2, pp. 1090-1098, 2019.

[23] Astaneh, A. A & Gheisari, S., "Review and Comparison of Routing Metrics in Cognitive Radio Networks," *Emerging Science Journal*, vol. 2, no. 4, pp. 191-201, August 2018,

[24] Moayedi, M., Kheyroddin R. & Shieh I., "Determining the Role of Pedestrian-Orientation, Concerning the Public Places: Improvement of Urban Social Capital Quality," *Civil Engineering Journal*, vol. 5, no. 4, pp. 901-912, April 2019.

[25] Yazadi, M. & Rassafi, A. A., "Evaluation of Drivers' Affectability and Statisfaction with Black Spots Warning Application," *Civil Engineering Journal*, vol. 5, no. 3, pp. 576-586, March 2019.

[26] Kalistratov D., "Wireless Video Monitoring of the Megacities Transport Infrastructure," *Civil Engineering Journal*, vol. 5, no. 5, pp. 1033-1040, May 2019.

[27] Omidi A., Karami R., Emadi P. S. & Moradi H., "Design of the Low Noise Amplifier Circuit in Band L for Improve the Gain and Circuit Stability," *Emerging Science Journal*, vol 1, no. 4, pp. 192-200, December 2017.

[28] Khotbehsara E. M. & Safari H., "A Systematic Review of Affective Factors on Locating Specialized Hospital," *Civil Engineering Hospital*, vol. 4, no. 9, pp. 2210-2217, September 2018.

[29] Gamil Y. & Rahman I. A., "Identification of Gauses and Effects of Poor Communication in Construction Industry: A Theoretical Review," *Emerging Science Journal*, vol. 1, no. 4, pp. 239-247, January 2018.

[30] Azzad B. Saeed, "Simulation Design of an Intellegent System for Automotive Transmission Gearbox Based on FPGA," *EMITTER International Journal of Engineering Technoloy*, vol. 6, no. 2, pp. 395-411, December 2018.

[31] Ramya J., & B. Parvathavarthini, "Feed Forward Back-propagation Neural Network Based Character Recognition System for Tamil Palm Leaf Manuscripts," *Journal of Computer Science*, vol. 10, no. 4, pp. 660-670, April 2014.

[32] Wei Li, Lijuan Cui, Yaqiong Zhang, Zhangjie Cai, Manyin Zhang, Weigang Xu, Xinsheng Zhao, Yinru Lei, Xu Pan, Jing Li, and Zhiguo Dou, "Using a Back-propagation Artificial Neural Network to Predict Nutrient Removal in Tidal Flow Constructed Wetlands," *Water Journal*, vol. 10, no. 1, pp. 83, January 2018.