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Original Article

Precise prediction of radiation interaction position in plastic rod scintillators using a fast and simple technique: Artificial neural network

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ABSTRACT

Precise prediction of the radiation interaction position in scintillators plays an important role in medical and industrial imaging systems. In this research, the incident position of the gamma rays was predicted precisely in a plastic rod scintillator by using attenuation technique and multilayer perceptron (MLP) neural network, for the first time. Also, this procedure was performed using nonlinear regression (NLR) method. The experimental setup is comprised of a plastic rod scintillator (BC400) coupled with two PMTs at two sides, a ^{60}Co gamma source and two counters that record count rates. Using two proposed techniques (ANN and NLR), the radiation interaction position was predicted in a plastic rod scintillator with a mean relative error percentage less than 4.6% and 14.6%, respectively. The mean absolute error was measured less than 2.5 and 5.5. The correlation coefficient was calculated 0.998 and 0.984, respectively. Also, the ANN technique was confirmed by leave-one-out (LOO) method with 1% error. These results presented the superiority of the ANN method in comparison with NLR and the other methods. The technique and set up used are simpler and faster than other the previous position sensitive detectors. Thus, the time, cost and shielding and electronics requirements are minimized and optimized.

1. Introduction

The position sensitive detectors based on the scintillator have a vast application in industrial tomography and planar scanning such as cargo scanners [1–3]. Since the materials and objects in an industrial application have large dimension and high density for scanning such objects, we require large detector and the gamma source with high energy or a dense detector in order to detect the transmitted photon from the object. The inorganic scintillator detectors with dense materials such as NaI(Tl) were used vastly in the industry [3,4]. But, for the large objects, several detectors should be used which each detection system requires a complex hardware. Such detection systems are very time-consuming and expensive. Thus, for scanning the large object, a unique of the detector as a position sensitive detector with low cost and fast response is required. The organic scintillators such as plastic scintillator can be a good selection for precise event timing and maximizing gamma detection count rate due to the fast response ($\cong$2.5 ns) and short decay time [5]. Also, they can fabricate into the large dimension with the lowest cost and these characteristics reduce the plastic properties such as low density ($\cong$1 g/cm^3) and low atomic number for industrial scanning [5].

Thus, the goal of our studies is to design a position sensitive detector based on a rod plastic scintillator (without coincidence electronic) and determine the incident position of the gamma rays (position sensitive feature) by using the proposed ANN and NLR techniques, for the first time.

The different groups used the plastic scintillator with different, complicated and expensive designs as a position sensitive detector for industrial applications.

H.S. Jung et al., determined interaction position based on two detectors which each detector was arrayed with five plastic scintillating rods [6]. Also, C. H. De Mesquita et al. simulated an industrial CT using Monte Carlo code. In the developed system, the interaction position was estimated using a sensitive plastic scintillator together with two photomultipliers set up in coincidence [7].

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In all followed works, some detectors together with some pixelated PMTs and coincidence electronic have been used to estimate the interaction position [6,7].

Also, some groups used the soft-computing and machine learning techniques such as artificial neural networks, computational intelligence and etc in a wide variety of data processing and data management applications such as predictions, nonlinear problems, and real time data analysis [8–12].

Kalantari et al. studied computational intelligence approaches for classification of big data in the medical applications. The results showed that on the one hand Support Vector Machine (SVM) and Artificial Immune Recognition System (AIRS) as a single based computational intelligence approach were the best methods for faster performance and a higher level of accuracy in detection [10].

Alansari et al. presented Internet of Things (IoT) in the healthcare sector to achieve sustainable development. Their study is an applied descriptive research according to data collection [11].

Also, Gholipour Peyvandi et al. used the ANN method for prediction and data analysis in the industrial applications to determine precisely the volume fraction percentage in water-gasoil-air three-phase flows [12].

In this research, a plastic scintillator which was coupled to two PMTs (two sides) without coincidence electronic was designed for fabricating a position sensitive detector. The radiation interaction position was predicted precisely in plastic scintillator by using gamma ray attenuation technique and multilayer perceptron (MLP) neural network, for the first time. The MLP neural networks were trained and tested using acquired data from an experimental setup. Also, NLR technique was used in order to estimate the incident position of the gamma rays. The experimental setup and designs used in the previous papers were fairly complicated whereas our design and proposed technique are really very simple, inexpensive and fast and electronics requirements are minimized and optimized.

2. Materials and methods

2.1. Experimental set-up

An experimental setup comprised of the detection setup and the nuclear electronic system was designed and developed at Parto Tajhiz Besat (PTB)-Co, R&D Division in order to provide the required data for the ANN and NLR methods and estimate the radiation interaction position in the plastic scintillator. In the detection system, a rod plastic scintillator (BC400) with a diameter of 5 cm and length of 150 cm was used as a crystal which two photomultipliers were coupled at the ends of two rod sides of the crystal. Also, a source ^{60}Co with 50 μCi activity was placed on side of the rod detector with a distance of 3 cm according to Fig. 1. Seventy-one points with a step size of 2 cm were selected for placing sources to record the related count rates for each point with 100 s time intervals (Fig. 2). A lead collimator was used to make a pencil beam. The details of the experimental setup were listed in Table 1. In the nuclear electronic system, as followed, two PMTs (Model CR-169 BEIJING Hamamatsu, China), two high voltage (HV) power supply modules (CC228-01Y BEIJING Hamamatsu, China), two pre-amplifiers, two amplifiers and two counters (G.G.104 PTB- CO. Iran) were used to record count rates due to the transmitted gamma rays. The experimental setup is shown in Fig. 1.

The source position affects the recorded count rates using counters and these count rates can produce sufficient information about the radiation interaction position (position of the gamma source). Seventy-one arrays having different positions of the gamma source were used to obtain the recorded count rates from the ^{60}Co source. Sixty samples were used for training the ANNs according to Table 2 (training by 70%, validation by 15%, testing by 15%), and 11 samples were used for the assessment of this research. In order to more accurately evaluate the ANN method, ten count rates of samples previously used for ANNs training were used as evaluation samples. Thus, the recorded and attenuated gamma ray count rates from two counters modules together with a multi-layer perceptron neural network can determine radiation interaction position, precisely. Also, the NLR technique was used in order to determine the position of radiation incident.

2.2. ANN training data

ANN models are useful in investigations and complex systems for their ability to solve problems stochastically. They used the acquired experimental data for training and applying to predict output responses of systems. The simplest and smallest recognized division of processing elements in ANNs are neurons which play an important role in solving problems [13,14]. In this research, the position sensitive feature was evaluated in plastic scintillator due to the prediction of radiation interaction position using multilayer perceptron neural networks (MLP) which they are the most widely used ANNs. The most of MLPs have a connection structure with connections from all neurons of one layer to all neurons of the next layer. The MLP is consists of three layers: input, output and hidden layer. These layers were illustrated in Fig. 3. The inputs are registered count rates in the two counters and the outputs are the predicted radiation interaction positions. In this paper, the number of neurons for the MLP neural network in the input, hidden and output layers and the characteristics of the MLP neural network were listed in Table 3.

The activation functions for the training of the proposed ANN model were tan-sigmoid and pure line functions in the hidden and output layers, respectively. The required data set for training the network was obtained from the experimental data described. The inputs are registered count rates in two detectors as the Y ($m \times n$) matrix represents the obtained count rates from the detectors, with n positions and m counters (left and right). Thus, the dataset for ANN consisted of a matrix ($Y_{2\times 60}$) in which the rows correspond to the two detectors and columns corresponded to recorded count

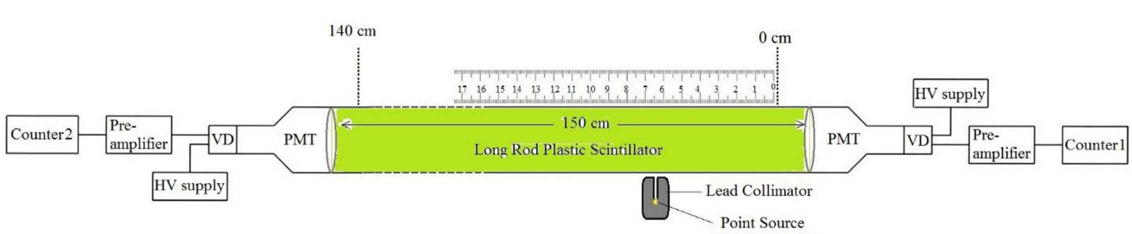

Fig. 1. The arrangement of the source and nuclear electronic system (experimental set-up).

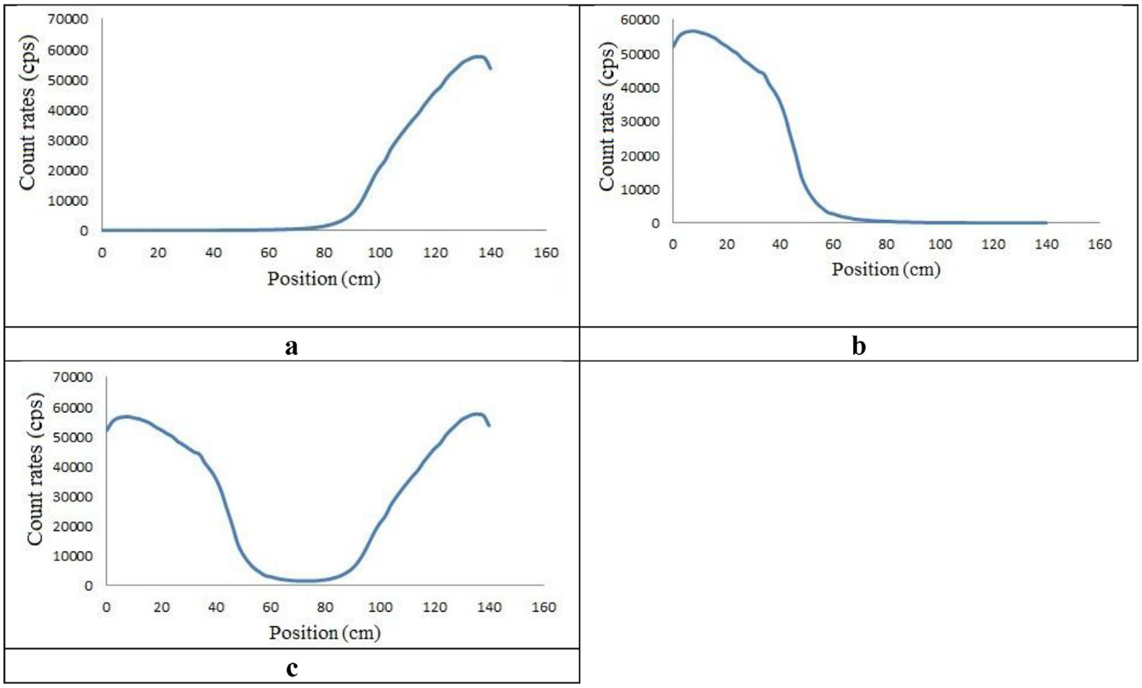

Fig. 2. The recorded count rates for different distances from the end of a rod side of the crystal for (a) counter 1 (b) counter 2 (c) two counters.

Table 1
The details of the experimental setup.

Specifications of the experimental set-up	
Source	^{60}Co
Source activity	50 µCi
Distance from the source	3 cm
Measuring steps	71
Aperture of collimator	0.5 cm
Length of detector	150 cm
Diameter of detector	5 cm
Measurement time	100 s
Lower level	200 mV
Step size	2 cm

rates with different positions of the source.

The Bayesian regularization algorithm trained the presented ANN networks which training function updates the weight and bias values according to Levenberg-Marquardt optimization [13–16]. The number of 77 iterations in epochs were done for achieving the best results. MATLAB 8.3.0.532 was used for training the ANN model.

2.3. Nonlinear regression method (NLR)

In order to analyze data in machine learning, support vector machines (SVM) as supervised learning models together with learning algorithms were used for regression analysis and classification [17]. NLR is a type of regression analysis in which the acquired data are modeled using a nonlinear function such as exponential, logarithmic, trigonometric and etc [18]. In this paper, the radiation interaction position was predicted using NLR analysis. Both of the detector 1 and detector 2 represents the same radiation positions. Thus, the recorded count rates from detector 1 were used only to estimate the incident position of the gamma rays (Fig. 2c).

The transmitted count rates from the end of a rod side of the crystal (detector 1) with different distances were plotted. Then, the best logarithm function was fitted to data points (Fig. 4). This function is:

$$y = a + b\ln x \tag{1}$$

Which x is the recorded gamma ray count rates for detector 1 and y is the real position. Also, a and b are constant quantities 1.66×10^2 and -1.34×10^1, respectively.

2.4. Evaluation of the proposed methods (ANN and NLR)

In order to evaluate precision the proposed methods (ANN and NLR), the predicted results were compared with experimental data with three types of errors composed of the mean absolute error (MAE), mean relative error percentage (MRE%) and Correlation Coefficient (R). The errors relations were calculated by:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|X_i - \widehat{X}_i\right| \tag{2}$$

$$MRE\% = 100 \times \frac{1}{N}\sum_{i=1}^{N}\left|\frac{X_i - \widehat{X}_i}{X_i}\right| \tag{3}$$

$$R = \frac{\sum_{i=1}^{n}\left\{\left(X_i - \overline{X}\right)\left(\widehat{X}_i - \overline{\widehat{X}}\right)\right\}}{\left\{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2 \sum_{i=1}^{n}\left(\widehat{X}_i - \overline{\widehat{X}}\right)^2\right\}^{1/2}} \tag{4}$$

which X_i and $\widehat{X}_i$ are experimental and predicted quantities, respectively. Also, $\overline{X}$ and $\overline{\widehat{X}}$ are mean of experimental and predicted quantities [19]. N is the number of all data. Also, the linear regression between the real and predicted data (in plots) was used to describe the predictive ability of the ANN and NLR.

Table 2
The acquired data set (count rates) from 60 source positions for training the ANNs.

ID Sample	Distance (cm)	Det1 (cps)	Det2 (cps)
1	0	52058	15
2	2	54922	7
3	4	56112	9
4	6	56492	11
5	8	56602	11
6	12	55782	12
7	14	55122	26
8	16	54312	20
9	18	53032	12
10	20	52112	23
11	24	49968	26
12	26	48232	26
13	28	47142	28
14	30	45862	35
15	32	44682	44
16	36	40892	51
17	38	38602	53
18	40	35692	59
19	42	31382	75
20	44	25502	80
21	48	13792	101
22	50	10102	115
23	52	7616	131
24	54	5660	144
25	56	4327	171
26	60	2712	250
27	62	2154	278
28	64	1757	314
29	66	1472	374
30	68	1182	436
31	72	857	664
32	74	722	758
33	76	612	922
34	78	532	1156
35	80	469	1448
36	84	322	2392
37	86	287	3111
38	88	256	4160
39	90	217	5578
40	92	191	7640
41	96	137	14132
42	98	116	17798
43	100	103	20821
44	102	92	23183
45	104	80	26833
46	108	70	32047
47	110	58	34359
48	112	46	36630
49	114	39	38664
50	116	48	41309
51	120	28	45869
52	122	32	47501
53	124	21	50145
54	126	30	52179
55	128	18	53851
56	132	20	56507
57	134	12	57332
58	136	14	57456
59	138	17	56947
60	140	9	53625

Table 3
Characteristics of the presented MLP.

Number of neurons in the input layer	2
Number of neurons in the hidden layer	10
Number of neurons in the output layer	1
Number of epochs	77
Activation function of each neuron in the hidden layer	tansig

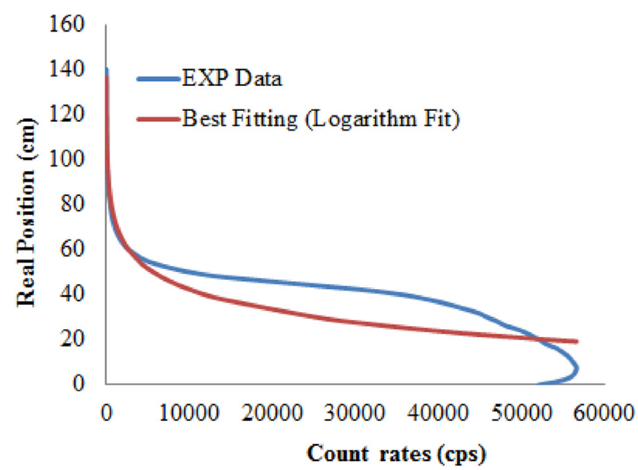

Fig. 4. The fitted logarithm function to data points (detector 1) using NLR technique for the prediction of the radiation interaction positions.

2.5. *Neural network error using leave-one-out (LOO)*

The Leave- one- out (LOO) is one of the most widely used methods to validate the ANNs model. Based on this method, a sample from the set containing 60 samples was removed and a prediction was made for the omitted sample. In order to predict the properties of all the samples, this procedure was repeated [20].

3. Results and discussion

In this research, we used the transmitted gamma ray count rates together with a multi-layer perceptron neural network in order to predict the radiation interaction position. Also, this prediction was performed using the recorded count rates and NLR technique. In these experiments, the ^{60}Co source was placed with selected different distances from the end of a rod side of the crystal (with a step size of 2 cm). The recorded count rates for each PMT as inputs were used for training of ANN to predict source position. Also, these inputs were used for the NLR technique. Table 4 shows the predicted and experimental radiation interaction positions for different distances the ^{60}Co source from the PMTs (the highlighted samples are related to count rates previously used for training of ANNs). The experimental and predicted results were compared with errors of MAE, MRE% and Correlation Coefficient (R). In the

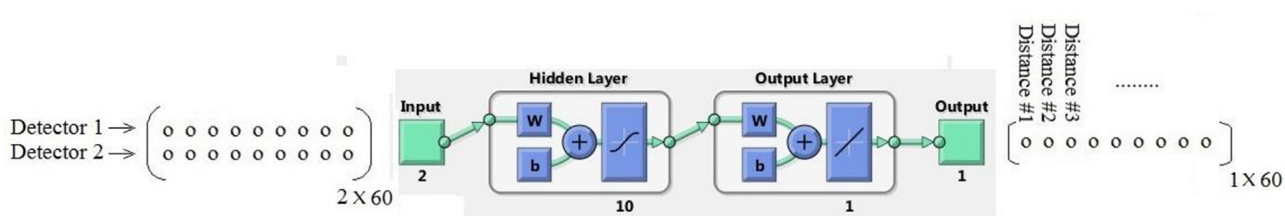

Fig. 3. The multilayer perceptions (MLP)-feed forward network.

Table 4
Comparison of real (experimental) and predicted data (ANN and NLR) for prediction of radiation interaction position (source position).

Sample ID	Real Position (cm)	ANN Prediction (cm)	NLR(cm)
1	10.0	11.2	19.3
2	22.0	20.5	20.8
3	26	23.7	21.3
4	34.0	32.7	22.6
5	38.0	36.1	24.3
6	42.0	39.2	27.1
7	46.0	48.2	33.1
8	50	54.3	42.3
9	58.0	62.1	58.1
10	62.0	63.8	63
11	70.0	70.8	73.1
12	76.0	73.5	79.9
13	82.0	79.3	85.3
14	88.0	84.2	91.5
15	94.0	91.0	97.7
16	100.0	97.5	103.7
17	106.0	107.0	108.5
18	112.0	115.0	114.5
19	118.0	121.9	116.8
20	122.0	125.5	119.4
21	130.0	132.0	120.7

ANN and NLR methods, MAE quantities for prediction of source position were calculated less than 2.5 and 5.5%, respectively. The MRE% values were measured 4.6% and 14.6%, respectively. The Correlation Coefficient (R) quantities for ANN and NLR techniques were obtained 0.998 and 0.984, respectively. The comparison between real and predicted results using the presented ANN and NLR models in regression diagrams have been shown in Fig. 5. Also, the LOO cross-validation error was applied resulting in a 1% error.

These results showed that ANN method has superiority in comparison with NLR and the other methods. Thus, ANN technique is a rapid and accurate method for the prediction of radiation interaction position according to the transmitted gamma-ray count rates of plastic scintillator.

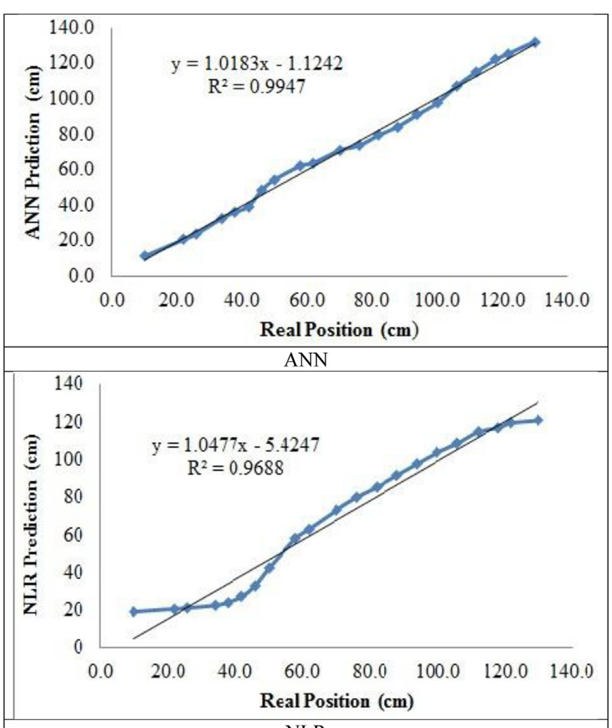

Fig. 5. Comparison of experimental and predicted source position (the graphic of linear regression) with a ^{60}Co source for ANN and NLR techniques.

4. Conclusion

In this paper, a plastic rod scintillator (BC400) coupled with two PMTs at two sides (left and right PMTs) as a position sensitive detector was designed. In this design, the coincidence electronic (TOF method) was not used in order to determine the precise position of radiation incident and this procedure was performed with the attenuation technique and multilayer perceptron (MLP) neural network for the first time. In addition, NLR technique estimated the radiation interaction position. The performance of ANN, NLR and the relationship derived from empirical data were compared with different errors. The results revealed that ANN can more accurately predict the position of radiation incident. The proposed set up and technique reduced cost and electronics for producing position sensitive characteristic. Consequently, we can use rod plastic scintillator as a fast and position sensitive detector for the industrial tomography system application.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.net.2018.06.005.

References

[1] M. Marisaldi, C. Labanti, A. Bulgarelli, A. Andritschke, G. Di Cocco, G. Kanbach, F. Gianotti, A. Mauri, E. Rossi, A. Traci, M. Trifoglio, A position sensitive gamma-ray detector based on silicon drift detectors coupled to scintillators for application in the MEGA Compton telescope, in: Nucl. Sci. Sym. Conf. Rec, IEEE, Rome, Italy, 2004.

[2] S.Z. Islami rad, R. Gholipour Peyvandi, M. Askari Lehdarbolni, A.A. Ghafari, Design and performance evaluation of a high-resolution IRI-microPET preclinical scanner, Nucl. Instrum. Meth. A 781 (2015) 6–13.

[3] H.C. Boston, J. Gillam, A.J. Boston, R.J. Cooper, J. Cresswell, A.N. Grint, A.R. Mather, P.J. Nolan, D.P. Scraggs, G. Turk, C.J. Hall, I. Lazarus, A. Berry, T. Beveridge, R. Lewis, Orthogonal strip HPGe planar Smart PET detectors in Compton configuration, Nucl. Instrum. Meth. A 580 (2007) 929–933.

[4] G. Barouchi, C. Marriette, Description de lélectronique du systéme de tomographie SPECT à detection linéaire, CEA, 2003. DIMRI/SIAR/RAP/03–084.

[5] M.M. Hamada, P.R. Rela, F.E. Costa, C.H. Mesquita, Radiation damage studies in optical and mechanical properties of plastic scintillators, Nucl. Instrum. Meth. A 422 (1999) 148–154.

[6] H.S. Jung, J.H. Lee, Y.K. Kwon, J.Y. Moon, C.C. Yun, C.S. Lee, Position sensitivity and gamma-ray separation of a plastic scintillator for a neutron camera based on electric collimation, J. Kor. Phys. Soc. 56 (2010) 728–732.

[7] C.H. De Mesquita, S. Legoupil, M.M. Hamada, Development of an industrial computed tomography designed with a plastic scintillator position sensitive detector, in: Nucl. Sci. Sym. Conf. Rec. (IEEE), Fajardo, Puerto Rico, 2005.

[8] A. Gani, A. Siddiqa, Sh. Shamshirband, F. Hanum, A survey on indexing techniques for big data: taxonomy and performance evaluation, Knowl. Inf. Syst. 46 (2016) 241–284.

[9] S. Al-Janabi, I. Al-Shourbaji, M. Shojafar, Sh. Shamshirband, Survey of main challenges (security and privacy) in wireless body area networks for healthcare applications, Egypt. Inform. J. 18 (2017) 113–122.

[10] A. Kalantari, A. Kamsin, Sh. Shamshirband, A.T. Chronopoulos, Computational intelligence approaches for classification of medical data: state-of-the-art, future challenges and research directions, Neurocomputing 276 (2018) 2–22.

[11] Z. Alansari, S. Soomro, M.R. Belgaum, Sh. Shamshirband, The rise of Internet of Things (IOT) in healthcare data: review and open research issues, in: Progress in Advanced Computing and Intelligent Engineering, Springer, Singapore, 2017, pp. 675–685.

[12] R. Gholipour Peyvandi, S.Z. Islami rad, Application of artificial neural networks for prediction of volume fraction using spectra of gamma rays backscattered by three-phase flows, Eur. Phys. J. Plus 132 (2017) 511–519.

[13] A.R. Gallant, H. White, On learning the derivatives of an unknown mapping

with multilayer feed forward networks, Neural Netw. 5 (1992) 129–138.
[14] M.T. Hagan, M. Menhaj, Training feedforward networks with the Marquardt algorithm, IEEE Trans. Neural Netw. 5 (1994) 989–993.
[15] H. Demuth, M. Beale, M. Hagan, Neural Network Toolbox TM 6, User's Guide, 2008. The Math Works, Massachusetts.
[16] A. Zaknich, Neural Networks for Intelligent Signal Processing, World Scientific Pub Co. Inc, Toh Tuck Link, 2003.
[17] N.G. Polson, S.L. Scott, Data augmentation for support vector machines, Bayesian. Anal. 6 (2011) 1–23.
[18] K. Schittkowski, Data Fitting in Dynamical Systems, Kluwer, Boston, 2002.
[19] D.C.S. Bisht, A. Jangid, Discharge modeling using adaptive neuro-fuzzy inference system, Int. J. Adv. Sci. Tech. 31 (2011) 99–114.
[20] E.G. Hadaji, M. Bourass, A. Ouammou, M. Bouachrine, 3D-QSAR models to predict anti-cancer activity on aseries os protein P38 MAP kinase inhabitors, J. Taib. Uiv. Sci. 11 (2017) 392–407.