Search...

2019 IEEE International Conference on Applied System Innovation

IEEE ICASI 2019

Home Submission Keynote Speakers Registration Organization Participant Q&As Venue Tour Agenda Contact

System Guide FAQ

4/11-4/15 2019 Fukuoka, Japan

IEEE ICASI 2019, April 11-15, 2019, Fukuoka, Japan

Location
Fukuoka, JAPAN

Date
April 11-15, 2019

Speakers
3

Seats
1,200 Available

All accepted papers will be submitted in the proceedings of Taylor & Francis (EI) and IEEE ICASI 2019 (IEEE Xplore®, indexing by EI). Excellent papers selected from IEEE ICASI 2019 will be recommended to be published on suitable 11 different SCI journals after an additional review process and may need extra publication charge.

SUBMIT PAPER NOW!!

Our highlights, in short.

Some times numbers do tell the truth. Perhaps, then, there's no better way to figure out more about us, than checking out these highlights.

5th	4587	3827	43000
year	participants	submissions	returning

Organization

Honorary General Chairs:

Prof. Shoou-Jinn Chang, National Cheng Kung University

Prof. Huann-Ming Chou, Kun Shan University

Prof. Ji-Hwei Horng, Vice President of National Quemoy University

Prof. Ching-Ting Lee, Vice President of Yuan Ze University

Prof. Ying-Chung Chen, Vice President of National Sun Yat-Sen University

Prof. Rong-Fong Fung, Vice President of National Kaohsiung University of of Sci. & Tech.

Prof. Chun-Yen Chang, National Taiwan Normal University

Prof. Chia-Ju Liu, National Kaohsiung Normal University

Prof. Ming-Chung Ho, National Kaohsiung Normal University

Prof. Ming-Chuang Ho, National Yunlin University of Sci. & Tech.

General Chairs:

Prof. Artde Donald Kin-Tak Lam, Fujian University of Technology

Prof. Liang-Wen Ji, National Formosa University

Prof. Kuang-Chyi Lee, National Formosa University

Prof. Te-Hua Fang, National Kaohsiung University of of Sci. & Tech.

Prof. Stephen Prior, The University of Southampton

Prof. Cheng-Tang Pan, National Sun Yat-Sen University

Prof. Tsair-Chun Liang, National Kaohsiung University of Sci. & Tech.

Prof. Shih-Chang Tseng, National Yunlin University of Sci. & Tech.

Prof. Chun-Hung Lai, National United University

Prof. Yue Shen, China University of Petroleum

General Co-Chairs:

Prof. Siu-Tsen Shen, National Formosa University

Prof. I-Tseng Tang, National University of Tainan

Prof. Yaw-Shyan Fuh, National University of Tainan

IEEE Tainan Section Sensors Council

IEEE International Conference on Applied System Innovation

TIKI Taiwanese Institute of Knowledge Innovation

2019 IEEE International Conference on Applied System Innovation

APRIL 11-15, 2019, FUKUOKA, JAPAN

CERTIFICATE OF ORAL PRESENTATION

This Certificate is presented to paper with the oral presentation

J190278
Fault Detection and Classification on Transmission Line using Cascade and Feed Forward Back Propagation Neural Based on Clarke's Transformation

by
Makmur Saini

TIKI President
Prof. Shoou-Jinn Chang
National Chang Kung University

IEEE ICASI General Chairman
Prof. Artde Donald Kin-Tak Lam
Fujian University of Technology

IEEE ICASI General Chairman
Prof. Liang-Wen Ji
National Formosa University

IEEE ICASI Award Chairman
Prof. Ji-Hwei Horng
National Quemoy University

The Taiwanese Institute of Knowledge Innovation

Fault Detection and Classification on Transmission Line using Cascade and Feed Forward Back Propagation Neural Based on Clarke's Transformation

Makmur Saini
Mechanical Eng. Dept.
Politeknik Negeri Ujung Pandang
Makassar, Indonesia
makmur.saini@poliupg.ac.id

A. M. Shiddiq Yunus
Mechanical Eng. Dept.
Politeknik Negeri Ujung Pandang
Makassar, Indonesia
shiddiq@poliupg.ac.id

Ahmad Rizal Sultan
Electrical Eng. Dept.
Politeknik Negeri Ujung Pandang
Makassar, Indonesia
rizal.sultan@poliupg.ac.id

Rahimuddin
Faculty of Engineering
Hasanuddin University
Gowa, Indonesia
rahimnav@gmail.com

Abstract— **This paper proposed a comparative study for detecting and classifying fault on a parallel transmission line using cascade forward and feed forward back propagation. Both calculations were based on discrete wavelet transform (DWT) and Clarke's transformation. Daubechies4 mother wavelet (Db4) was used to decompose coefficients of wavelet transforms coefficients (WTC) and wavelet energy coefficients (WEC) of high-frequency signals. The coefficients were inputs for the training of neural network back-propagation (BPNN). The results showed that the feed forward back propagation approach based on Artificial Neural Network (ANN) models achieved better results than Cascade forward back propagation approach models, particularly in detecting and classifying fault on a parallel transmission line. The results showed that the introduced approach for fault analysis is capable to classify rapidly and correctly all the faults on the parallel transmission line.**

Keywords- Wavelet Transformation; Cascade and Feed forward back-propagation; Fault Classification; Fault detection; Clarke's Transformation.

I. INTRODUCTION

In a power system, transmission lines become a vital part since the electrical energy can only be dispatched from one long distance place to another. However, this transmission line is sometimes situated in impairing condition. Most of the disorder on the power system comes from the interference on the transmission line. Therefore, the speed and accuracy analysis are required in the detection and classification of fault in the transmission line. A parallel transmission line, however, requires more special consideration in comparison with the single transmission line, due to the effect of mutual coupling on the parallel transmission line. It must also comply with the standards of IEEE. STD. 114 2004 [1]. The most advantage of the parallel transmission compared to the single line is the probability of the parallel system to transmit power continuously during and after fault better than the single line, including the parallel transmission lines that are connected with wind turbine generators [2, 3].

This paper proposed a discrete wavelet transform and back-propagation neural network (BPNN) using Clarke's transformation to detect and classify the fault on the parallel transmission line. This study proposes a different approach named Alpha-Beta Transformation (ABT) based on Clarke's transformation; where also is a transformation of a 3-phase system into a 2-phase system [4-6]. The obtained result of Clarke's Transformation is then transformed into Discrete Wavelets Transform (DWT). Recently, wavelet transforms are applied in some applications of in power systems for instance in power system transients, partial discharge, power system protection, transformer protection, and condition monitoring. Among those applications, the power system protection continues to be a main application area of wavelet transform in power systems [7], while the Artificial Neural Network (ANN) has been widely used also in power system protection [8]. In this work, a new algorithm was proposed for some reliable fault detection, classification, and location. The proposed method applied based on ANN scheme. A range of fault types is applied for classification of the faults and location [9]. Currently, the combination of wavelet and ANN has been applied on the researches of the variety of power system operation problems [10, 11], estimating fault location [12], classification using Oscillographic data [13, 14], state estimation, and control system [15, 16]. This paper introduces a new method for classifying a fault in transmission lines using DWT and BPNN. The main concept of the method is to use both the wavelet coefficient and the wavelet energy coefficient of the currents to feed the input patterns. The results then are used to create a simple multi-layer perception network (MLP). To validate this method, the parallel transmission line system with the applied faults is simulated using EMTDC/PSCAD [17]. Additionally, the results of the proposed techniques are compared with and without wavelet transform based Clarke transformation.

II. CLARKE'S TRANSFORMATION

The phase-modal transforms are usually applied to decouple 3-phase systems, relative to Clarke's transform-based phase-modal transformation which adopted in this study. Clarke's transform is formulated as follows [18, 19]:

$$\begin{bmatrix}\alpha\\ \beta\\ 0\end{bmatrix}=\frac{2}{3}\begin{bmatrix}1 & -\frac{1}{2} & -\frac{1}{2}\\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2}\\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2}\end{bmatrix}\text{ X }\begin{bmatrix}a\\ b\\ c\end{bmatrix} \qquad (1)$$

Where a, b, c represent the current values of phase A, B, C respectively; and α, β, 0 represent the modal values. The coefficients of the equation (1) are real numbers; therefore the values of the modal can be obtained from the instantaneous sampling values of the 3-phases. The matrix of Clarke's transformation is a full order matrix. Modal α corresponds to the line modal between phase A and B, while modal β corresponds to the line modal between phase A and C. Modal γ can be proposed for corresponded line modal between phase B and C.

$$\begin{bmatrix}\alpha\\ \beta\\ 0\\ -\\ \gamma\end{bmatrix}=\frac{2}{3}\left[\begin{array}{ccc}1 & -\frac{1}{2} & -\frac{1}{2}\\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2}\\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2}\\ \hline -\frac{2}{3} & \frac{1}{3}(1+\sqrt{3}) & \frac{1}{3}(1-\sqrt{3})\end{array}\right]\text{ X }\begin{bmatrix}a\\ b\\ c\end{bmatrix} \qquad (2)$$

III. BACK-PROPAGATION NEURAL NETWORK (BPNN)

A. Feed Forward Back Propagation Network (BPNN)

A feed-forward back propagation artificial neural network (BPNN) model consists of input, hidden and output layers. The feed forward process calculates the network output and the learning process update the weights using the back propagation. The error between target and network output then reduced by updating the weight from the output, hidden, and input layer. The bias included in the network intended to release the network from the local minimal coefficients [20]. Fig. 1 shows the BPNN model.

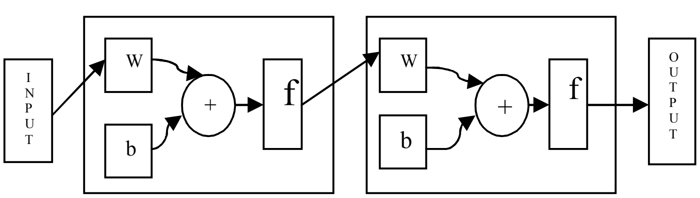

Figure 1. Feed-forward back-propagation network

B. Cascaded Forward Back Propoagation Network (CFBPN)

The cascade forward back propagation network (CFBPN) model is described as that the inputs of the layer feed to each layer and from each layer go to the successive layers. While two-layer feed forward any input-output relationship virtually, feed-forward networks with more layers might learn complex relationships quicker. Both Cascaded Forward artificial intelligence model and feed forward back propagation neural network (FFBPNN) in using the back propagation algorithm for weights updating, but the main indicator of this network is that each layer of neurons associated to all previous layer of neurons [19-21].

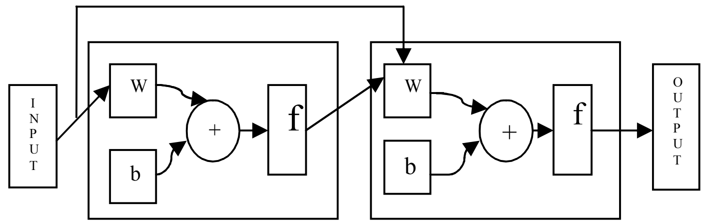

Figure 2. Cascade forward back-propagation network

IV. RESULT AND DISCUSSION

The system under study is shown in Fig. 3. The system is connected with identical sources at both Bus A and B. The simulation of the system under study is carried out using PSCAD/EMTD. The system under study is modeled on a 230 kV parallel transmission line, which is 200 km in length. The parameters of the system can be seen in Table 1.

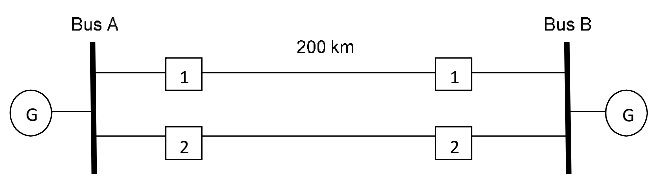

Figure 3. One line diagram of the simulated transmission system

TABLE I. PARAMETERS USED IN THE SYSTEM UNDER STUDY

Sequence Impedance Ohm/km	
Transmission Line	Z_1=Z_2=0.03574 + j0.5776 Z_0 =0.36315 + j1.32647
Source A and B	Z_1=Z_2=Z0=9.1859 + j52.093

In this study, the applied fault is starting at 0.22s and last for 0.15s. After calculating the parameters, the training sample of the detail coefficients wavelet various parameters, called S_0, S_α, S_β, S_γ, Q_0, Q_α, Q_β, Q_γ, and wavelet energy E_0, E_α, E_β and E_γ for various types of faults are set as input variables to build a neural network. The data sets are created by considering different operating conditions, i.e. the different values of inception angles ranging from 0 to 180 degrees, various fault resistances ranging from 0 to 200 ohm and various fault distances ranging between 0 to 200 km. Fault Type: AG, BG, CG, ABG, BCG, ACG, AB, BC, AC, and ABC. Where Fault Location (distance) for training and testing are: 25, 50, 75, 100, 125, 150 and 175 km.

Fault Resistance (R_f) for training and testing are: 0.001,25, 50, 75, 100, 125, 150, 175 and 200 ohm and Fault Inception Angle for training and testing are: 0, 15, 30, 45, 60, 90, 120, 150 and 180 degrees.

A. The result of using DWT and Feed Forward Back Propagation Network

After calculating the parameters, the training sample of the coefficients of wavelet various parameters, namely S_0, S_α, S_β, S_γ, Q_0, Q_α, Q_β, Q_γ, and wavelet energy E_0, E_α, E_β and E_γ for different types of faults are set as input variables to build a neural network. The similar steps of calculation are then applied as the aforementioned steps above. Discreet combination (A-B-C-G) of faults classification obtained by defining 1 for the value of more than 0.6 and 0 for the value less than 0.4. The simulation results error percentage of combination using preprocessing Clarke's transformation compared to without Clarke's transformation calculated as follows:

Percentage of MSE Validity =

$$\frac{MSE(WoTC) - MSE(WiTC)}{MSE(WoTC)} X\, 100\% \qquad (3)$$

Percentage of MAE Validity =

$$\frac{MAE(WoTC) - MAE(WITC)}{MAE(WoTC)} X\, 100\% \qquad (4)$$

Where MSE (WoTC) is Mean Square Error (MSE) without Transformation Clarke's, MSE (WiTC) is Mean Square Error (MSE) with Transformation Clarke's, MAE (WoTC) is Mean Absolute Error (MSE) Without Transformation Clarke's, MAE (WiTC) is Mean Absolute Error (MSE) With Transformation Clarke's. Simulation result of fault detection and classification using DWT and Feed-forward BPPN perform a good result when analysis with preprocessing using Clarke's transformation and architecture combination of 12-12-24-4 (12 neurons in the input layer, 2 hidden layers with 12 and 12 neurons in them, respectively and 4 neurons in the output layer). Fig. 4 and Fig. 5 show the training performance plot of the neural network without and with using Clarke's Transformation.

B. Results of using DWT and Cascaded Forward Back Propagation Network

Similar to the feed Forward Back propagation Network, the parameters of the training of the detail coefficients of wavelet has various parameters, namely S_0, S_α, S_β, S_γ, Q_0, Q_α, Q_β, Q_γ, and wavelet energy E_0, E_α, E_β and E_γ for various types of faults were set as input variables of the neural network. The similar steps on FFBPN are applied in this method. Fig. 6 and Fig. 7 show the training performance plot of the neural network without and with using Clarke's Transformation.

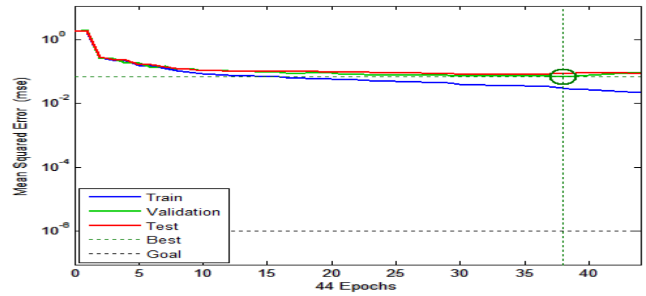

Figure 4. Mean-square error performance of Feed-forward BPPN with configuration (12-12- 24-4) without using Clarke's transformation

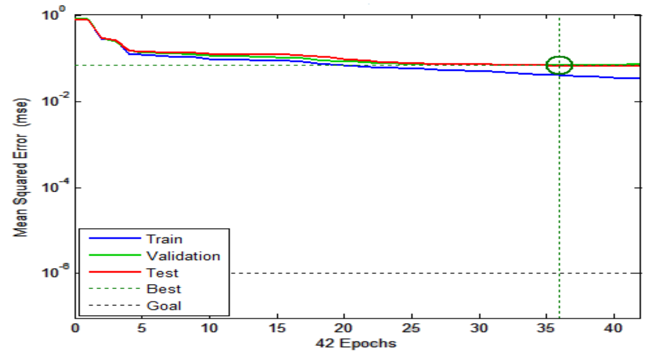

Figure 5. Mean-square error performance of Feed-forward BPPN with configuration (12-12- 24-4) with using Clarke's transformation

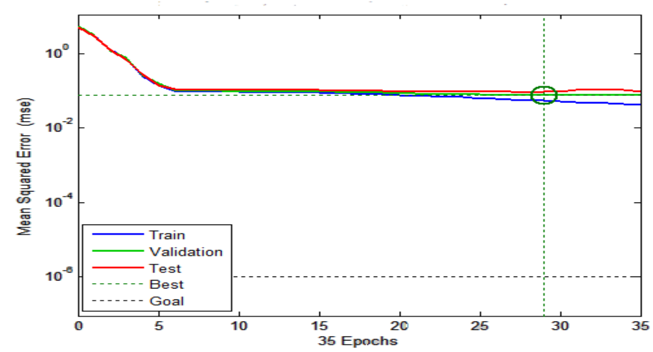

Figure 6. Mean-square error performance of Cascade-forward BPPN with configuration (12-12- 24-4) without using Clarke's transformation

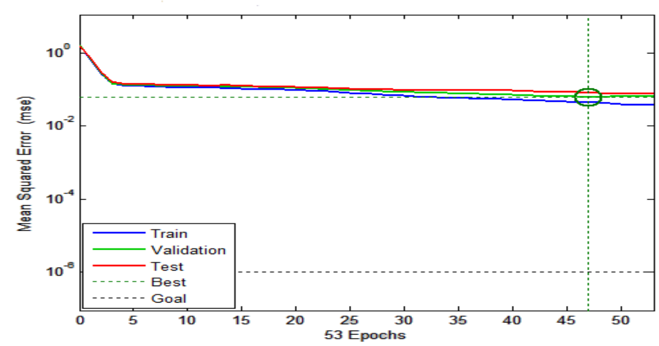

Figure 7. Mean-square error performance of Cascade-forward BPPN with configuration (12-12- 24-4) with using Clarke's transformation

V. CONCLUSION

This paper proposes comparison and exploration the feasibility of Feed Forward Back Propagation Network (FFBPN) and Cascade Forward Back Propagation Network (CFBPN) in ANN models in order to identify and classify fault on parallel transmission lines. The proposed technique applies Daubechies4 (db4) as a mother wavelet. Different types of variation are applied, including distance, the initial angle and fault resistance. Additionally, this study also investigates the comparison of training results of BPPN and DWT with and without Clarke's transformation, where the results exhibit that applying Clarke's transformation in training will yield smaller MSE and MAE, compared without transformation Clarke's. Among the 3-structures 12-24-48-4 is the best structure. The FFBPNN models achieved better performance than CFBPNN models, particularly in detecting and classifying fault on the parallel transmission.

ACKNOWLEDGMENT

This research activity was carried out with funding support from the Directorate of Research and Community Service of the Ministry of Research, Technology and Higher Education of Indonesia.

REFERENCES

[1] IEEE, 'Guide for determining fault location on AC transmission and distribution lines', IEEE Std C37.114. (2004).

[2] A. M. Shiddiq Yunus, M. A. S. Masoum, and A. Abu-Siada," Effects of SMES on dynamic behaviors of type D-Wind Turbine Generator-Grid connected during short circuit", Power and Energy Society General Meeting, 2011 IEEE, Detroit, USA, 24-29 July 2011.

[3] A. M. Shiddiq Yunus, A. Abu-Siada, and M. A. S. Masoum," Effect of SMES unit on the performance of type-4 wind turbine generator during voltage sag", Conference on Renewable Power Generation (RPG 2011), IET, 6-8 Sept. 2011.

[4] Noshad, B., Razaz, M., and Seifossadat, S.G.,: ' A based on Clarke's Transform and Discrete Wavelet Transform for the differential protection of three-phase power transformers considering the ultra-saturation phenomenon', *Electric Power Systems Research.* 2014, 110, pp. 9-24.

[5] Polajzer, B., Tumberger, G. S., Seme, S., and Dolinar, D.,: ' Detection of voltage sources based on instantaneous voltage and current vectors and orthogonal clarke's transformation', *IET. Gener .Transm. Distrib,* 2008, 2,(2), pp. 219–226.

[6] Chaari, Meunier, M., and Brouave F.: 'Wavelet a new tool for the resonant grounded power distribution systems relaying', IEEE *Trans.* on *Power Delivery,* July 1997, 11 , (3), pp. 1301-1308

[7] Kim, C.H., and Aggarwal, R.,: 'Wavelet transforms in power systems', *IET Power Engineering Journal***,** 2001, **15**, pp. 193-200.

[8] Song, Y. H., Johns, A.T., and Yuan, Q.Y.,: 'Artificial Neural Network based Protection Scheme for Controllable Series compensated EHV Transmission Lines', *IEE Proc. on Gener., Transm. and Distr*, November 1996, 143, (6), pp. 2032-2040.

[9] Ezquerra, J., Valverde, V., Mazo´n, I., Zamora, A.J, and Zamora,J.J.,: ' Field programmable gate array implementation of a fault location system in transmission lines based on artificial neural networks, *IET Gener. Transm. Distrib*, 2011, 5, (2), pp. 191– 198.

[10] Cheong, W.J., and Aggarwal, R.K.,: 'Accurate fault location in high voltage transmission systems comprising an improved thyristor controlled series capacitor model using wavelet transforms and neural network', *Transmission and Distribution Conference and Exhibition*, 2002, **2,** pp. 840–845.

[11] Jamian, J.J., Mohd Zin, A.A., Saini, M., Mustafa, M.W., Mokhlis, H 'A Novel TVA-REPSO technique in solving generators sizing problems for South Sulawesi Network', Przeglad Elektrotechniczny, 2013, 89 (2 A), pp. 170-174

[12] Ekici, S., and Yildirim, S.,: 'Fault Location Estimation on Transmission Lines Using Wavelet Transform and Artificial Neural Network', *Conference: Proceedings of the 2006 International Conference on Artificial Intelligence, ICAI 2006*, June 26-29, 2006, Las Vegas, Nevada, USA

[13] Silva, K.M., Souza, B.A., and Brito, N.S.D.,: 'Fault Detection and Classification in Transmission Lines Based on Wavelet Transform and ANN', *IEEE Trans. on Power Delivery*, Oktober 2006, **21,** (4), pp. 2058-2063.

[14] Costa, F. B., Silva, K. M., Souza, B. A., . Dantas, K. M. C and Brito, N. S. D.,; 'A Method for Fault Classification in Transmission Lines Based on ANN and Wavelet Coefficients Energy', *International Joint Conference on Neural Networks*, July 16-21, 2006, Sheraton Vancouver Wall Centre Hotel, Vancouver, BC, Canada.

[15] Yu, I.K., and Song, Y.H.,; 'Wavelet analysis and neural networks based adaptive single pole auto reclosure scheme for EHV transmission systems', *International Journal of Electrical Power & Energy Systems,* 1998, PP. 465–474.

[16] Lai, L.L., Vaseekar, E., Subasinghe, H., Rajkumar, N., Carter, A., Gwyn, B.J., Fault location of a teed-network with wavelet transform and neural networks', *in DRPT International Conference on Electric Utility Deregulation and Restructuring and Power Technologies*, 2000, PP. 505–509.

[17] *PSCAD/EMTDC User's Manual*, Manitoba HVDC Research Centre, Winnipeg, MB, Canada, 2001.

[18] Alfredo, O.F. Luis, I.E. Carlos, R.E.,: 'Three-phase adaptive frequency measurement based on Clarke's Transformation', *IEEE Trans. on Power Delivery*, 2006, 21, (3), pp. 1101-1105.

[19] M.Saini, A.A.Mohd Zin, M.W. Mustafa,A. R**.** Sultan, An accurate fault detection and location on a transmission line using wavelet based on Clarke's transformation, *Przegląd Elektrotechniczny* Vol. 90 (11), pp. 156-161, 2014.

[20] Omaima, N., Al-Allaf, A.,: 'Cascade-Forward vs.Function Fitting Neural Network for Improving Image Quality and Learning Time in Image Compression System', *In Proceedings of the World Congress on Engineering 2012* , London, UK, 4–6 July 2012, **2,** pp.1-7