International Journal of Scientific & Engineering Research, Volume 5, Issue 1, January-2014 1500
ISSN 2229-5518

Node Level ANN technique for Real Time Power System State estimation

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***Abstract**:* - The growth of modern power system is phenomenal. The increasing demand for quality energy for various purposes, initiated both business and technological transformation. Today's modern hybrid power system is on the lookout of complete SCADA implementation for better, reliable, efficient energy system. The major challenging task here is to solve complicated, non-linear system equations of large power system in very short interval of time. Because the control and security of the power system is being the highest priority and the real time solutions should yield results in mili-second to multi seconds for appropriate implementation. In any SCADA based Energy management system (EMS), real time state estimation is very essential. The conventional state estimation solutions (like NR method) are being slow, many researchers have worked on predictive solutions like AI, tracking, ANN etc. However, the compromise in mathematical modeling for the sake of fast computing is really not acceptable looking at the importance of the power system.

This paper suggests a robust ANN solution which is derived from the intelligent relation observed in the problem domain. Its very complicated to apply ANN to the large power system having hundreds of buses/nodes. The question here is "how to split the network in to smaller network?". Again physical division of the network will result in compromise in it's mathematical model. Hence, a hypothetical division is formed based on the connectivity of the node. This is achieved by two level hybrid techniques. First considering each node as an independent entity along with its connected nodes and then applying centralized NR technique.

Index Terms—ANN- Artificial Neural Network, SE-State Estimation, , NR- Neuron-Rapson, PS- Predicted state variables**,** WLS – Weighted Least Square, NA – Node Area, NL – Node Level, ISE – Integrated State Estimation, IANN – Integrated Artificial Neural Network, NA-ANN – Node Area Artificial Neural Network.

1. INTRODUCTION

1.1 Brief literature review

In 1987 Bruce F. Wollenberg et al. proposed use of Artificial Intelligence in Power System Operations. [2]. V. Leonardo Paucar et al. proposed ANNs for solving the Power Flow (PF) problem of electric power system in the year of 2002. The IEEE 30 bus system is tested successfully to compute voltage magnitudes and angles of the PF problem using multilayer perceptrons NN trained with second order Levenberg Marquardt method [3]. Recurrent neural network was presented, by M. V. Khokhlov in the year 2004, for constrained power system SE. The expensive computation is performed by using Recurrent Neural Network (RNN) so the speed and performance is improved [4]. In the year 2005 uncertainty modeling of PS SE was proposed by A. K. Al-othman et al. It was the two step method; Firstly Static WLS to compute the 'point' SE and then Linear Programming (LP) to obtain the uncertainty Bounds of PS SE [5]. In 2006, Satish Kumar Singh et al. proposed a new method based on Hopfield NN for SE of PS with FACTS devices. It may be employed for real time SE and also with different types of controllers including UPFC [6]. Li Yan et al. developed a new algorithm for distributed PS SE based on Phasor Measurement Units (PMUs). In this approach large system is divided into small systems using bordered block diagonal form (BBDF) and the large PS SE problem is turned into an optimization problem with equality constraints which in turn solved using WLS technique [7]. Bruce A. Grey et al. used Hybrid Kalman Bucy Filter with fuzzy logic approach to solve the PS SE problem [8]. L. Han et al. presented a Hybrid Self-adaptive Dynamic Estimator in 2008. Least Square Support Vector Machine (LS-SVM) was used as filtering technique which founded suitable then ANN in context of its non-linear function fitting performance [12]. A. Karami et al. also worked on neural network (NN) and proposed Radial Basis Function (RBF) NN for PS load flow analysis [13]. In 2011, a regression analysis based state transition model for PS Dynamic SE was presented by Mohmmad Hassanzadeh et al [15]. Jinghe Zhang et al. presented a Lower Dimensional Measurement Space (LoDiM) method for PS SE which was based on extended Kalman Filter. Author used parallel processing technique for real time SE of large interconnected PS [16]. E. A. Zamora-Cardemas et al. proposed an approach to incorporate Flexible AC Transmission Systems (FACTS) devices and synchronized phasor measurements devices into a WLS SE algorithm in 2012. The developed program was found suitable for estimating the FACTS controllers' state variables and also useful for PS SE [17]. Lokman H. Hassan et al. proposed the applications of GA (Genetic Algorithm) in optimization of UPFC (Unified Power Flow Controller) and its location in the PS [18]. In April 2013, Lokman H. Hassan et al. compiled the current state of neural networks application in PS monitoring and control [19]. In Jan. 2013 Sanjeev Kumar et al. presented a paper

ISSN 2229-5518

regarding optimal power flow solution using fuzzy evolutionary and swarm optimization [20]. A new Bus Level State Estimation (BLSE) method for reducing the computational time of the SE was presented in Feb2013 [1] . This paper uses the basic node area with interconnected nodes only and applied the conventional WLS technique of SE [1], a new idea for real time SE is discussed.

1.2 *ANN technique*

The nature of power system network can be related to ANNs. The behavior of each node in the interconnected power system is related to the other connected nodes. Or in other words, the state of a node in the interconnected network depends on the state of the other nodes connected to it and so on. Let us consider a large interconnected power system network having 'n' number of nodes, hence the number of state variables will be equal to (2n-1). These state variables are represented by column vector consisting of voltage and angle at each nodes (δ_i , v_i). The Node which is connected to the surplus power is generally taken as reference node for angle, hence number of state variables corresponds to the angle is (n-1). In state estimation technique, the number of measurements (input) taken is greater than the number of state variables (output). Let 'm' be the total number of measurements taken at a given instant. These measurements may consists of injected real and reactive power (P_i & Q_i), line flow (p_{ij}, q_{ij}) and node voltage and angle measurements; $z^T = (P_i, Q_i, p_{ij}, q_{ij}, \delta_i , v_i)$. The ANN technique can be applied considering these 'm' measurements as input vector and relate it to the output vector (2n-1) which are unknown state variables. The brief description of ANN model for the interconnected power system is given below.

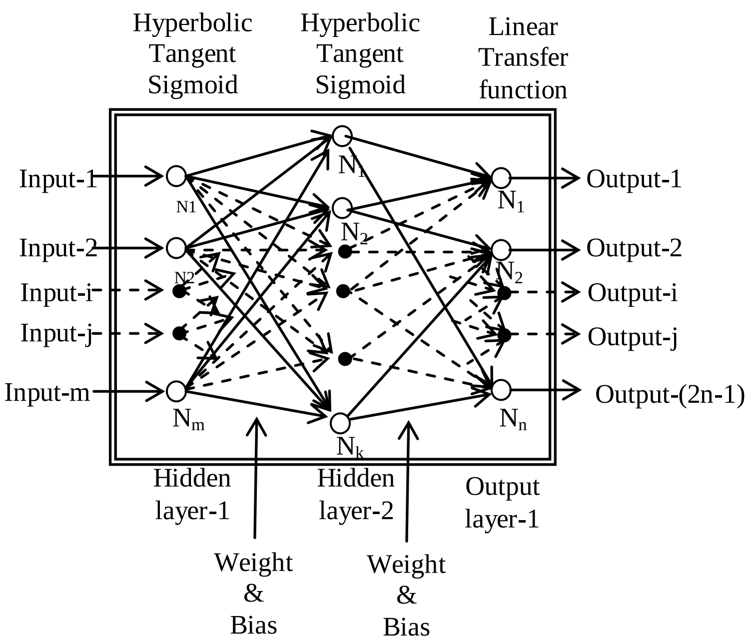


Fig-1: - Typical Architecture of Neural network

The input vector elements enter the network through the weight matrix **W**.

$$\mathbf{W} = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,R} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,R} \\ \\ w_{S,1} & w_{S,2} & \cdots & w_{S,R} \end{bmatrix}$$

Note that the row indices on the elements of matrix **W** indicate the destination neuron of the weight, and the column indices indicate the corresponding source input for that weight. Thus, $w_{1,2}$ say that the strength of the signal *from* the second input element *to* the first (and only) neuron is $w_{1,2}$. Or in other words, '$w_{1,2}$' first subscript the (row), which represents the destination neuron and the second subscript (column) which represents the source input for the corresponding weight.

The *S* neuron *R* input one-layer network also can be drawn in abbreviated notation.

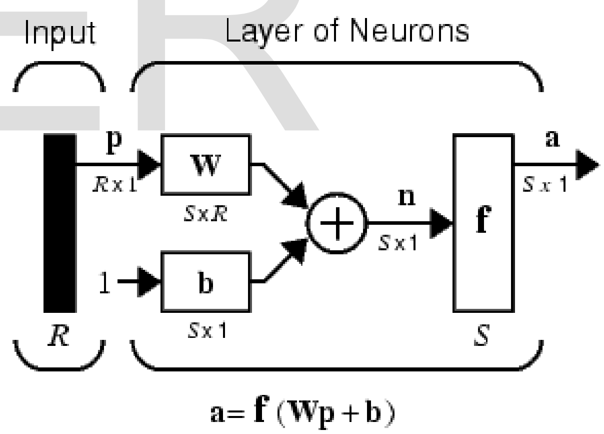
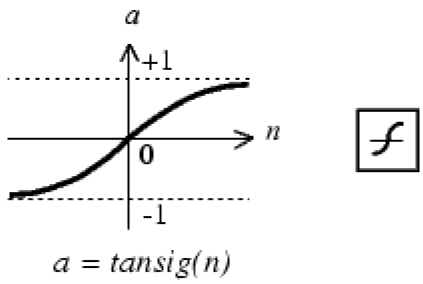


Fig-2: - one-layer network

Where, 'R' represents number of elements in input vector and 'S' represents number of neurons in layer-1. Here **p** is an *R* length input vector, **W** is an *S*x*R* matrix, and **a** and **b** are *S* length vectors. As defined previously, the neuron layer includes the weight matrix, the multiplication operations, the bias vector **b**, the summer, and the transfer function boxes.

Output of a neuron = Transfer Function {∑(Input z Weight)+(Bias)}. In the proposed model the default Transfer function '**Hyperbolic tangent sigmoid' is used for hidden layers** and **'Linear transfer function'** for output layer.

ISSN 2229-5518

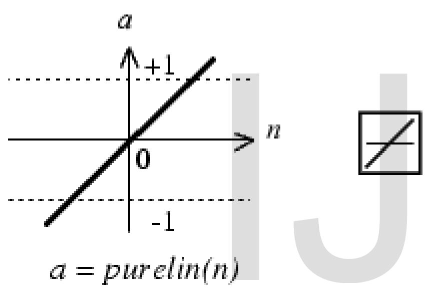


The tan-sigmoid transfer function, also known as the hyperbolic tangent function

$$a = \text{tansig}(u) = \tanh(u) = \frac{2}{1+e^{-2u}} - 1$$

This is mathematically equivalent to tanh(u). It differs in that it runs faster than the MATLAB® implementation of tanh, but the results can have very small numerical differences. This function is a good tradeoff for neural networks, where speed is important and the exact shape of the transfer function is not.

- 'Linear transfer function' for output layer.



Linear transfer function

"purelin" is a neural transfer function. Transfer functions calculate a layer's output from its net input. The Mathematical expression used in MATLAB is a = purelin(n) = n.

ANN Training: - The most common back propagation (BP) algorithm is used for training the network [23],[24]. The BP is nothing but generalization of the least mean squared algorithm that modifies network weights to minimize the mean squared error between the desired and actual outputs of the network. Back propagation uses supervised learning in which the network is trained using data for which inputs as well as desired outputs are known. Once trained, the network weights are frozen and can be used to compute output values for new input samples.

The feed forward process involves presenting an input pattern to input layer neurons that pass the input values onto the first hidden layer. Each of the hidden layer nodes computes a weighted sum of its inputs passes the sum through its activation function and presents the result to the output layer. The point to be noted here is that for interconnected large power system network, the inputs as well as the output vectors are very huge. (For 'n' node with redundancy of 2, the number of inputs 'm' will be equal to 2*(2n-1). The ANN architecture and the training will be quite complex. The Node Level ANN technique for SE is discussed in the following section which results in reduction in Structural and training complexity while providing additional advantage of node level independency.

2. Proposed Node Level (NL) ANN Technique

2.1 Node level NR method [1]

In the paper "Node level SE" [1] is used as the basic model. the three dimensional view of the modified Jacobian relation is shown in fig. 3.

i. First Level ANN technique: -

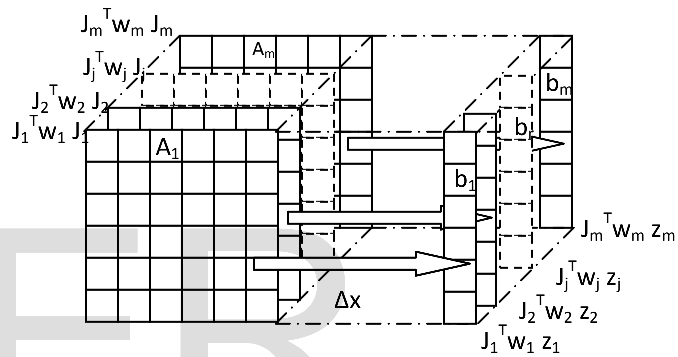


Fig-3: Jacobian 3dimension view

2.2 Node level ANN technique

Using the concept of node area [1], the ANN architecture is remodeled as shown in fig. 4.

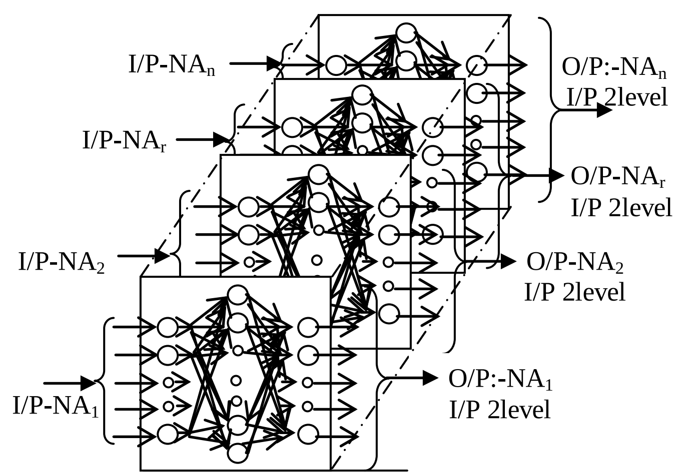


Fig. - 4 : Typical Architecture of Bus-Level Neural Network

Remodeling the large interconnected PS in node level architecture [1] made the computation less complex. In this paper use of ANN in place of basic NR technique [1] made it more effective and provides rapid results which are very important in developing the real time PSSE method. In fig.

ISSN 2229-5518

5 typical architecture of node level neural network is represented.

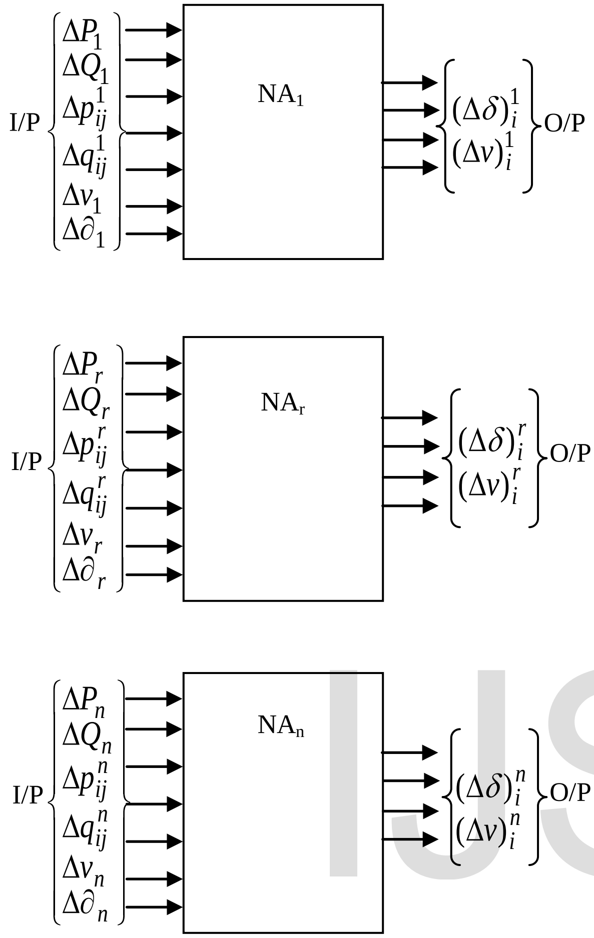


Fig.-5 : Typical Architecture of Node-Level Neural Network, node area wise Block diagram.

Note that the notation 'NA' stands for Node Area and the subscript represents corresponding node area.

It is evident from fig. 5 that the input vectors are clustered on the each node area. The assumption is that the number of inputs at a node area is greater than the number of state variable of the node area under consideration. The other condition is that at a given node area only the major node injected power measurement is considered. The above diagrammatic explanation shows the application of ANN technique at a given node/bus along with its connected node hence it leads to "node Level ANN technique for SE"

2.3 Second Level NR technique

$$\begin{bmatrix}(\Delta\delta)_i^z \\ (\Delta v)_i^z\end{bmatrix} = \begin{bmatrix}[1] & [0] \\ [0] & [1]\end{bmatrix}\begin{bmatrix}\Delta\delta_i \\ \Delta v_i\end{bmatrix}$$

3. Implementation and Results

For implementation of the proposed approach an ANN architecture is developed with 2 hidden layers, having 8 and 10 neurons respectively and one output layer with 6 neurons in case of Node level PSSE while 8 neuron in integrated SE. Hyperbolic tangent sigmoid is used as transfer function of hidden layer while in output layer linear transfer function is used. Supervised training is carried out with 99 training sample (i.e. 99 known input-output sets) and then unknown set of input is presented to find its output from the already trained network.

The output is taken for 2 different states :
1st : Taking whole PS network at once i.e. Integrated SE.
2nd : Considering Node area wise PSSE.

Table-1: - Integrated State Estimation (ISE) and ANN (IANN) result of sample set-1

	Estimated state variable by ISE		Predicted state variable By IANN	
Node	V_i	δ_i	V_i	δi
1	1.0000	0	1.0000	0
2	0.9820	-0.9760	0.9820	-0.9759
3	0.9690	-1.8720	0.9690	-1.8719
4	1.0200	1.5230	1.0200	-1.5232

Table-2a: - Node Area State Estimation (NASE) and ANN (NA-ANN) result of sample set-1

Node	**Node Area 1**		**Node Area 2**	
No.	V(p.u.)	δ (deg)	V(p.u.)	δ (deg)
1	1.0000	0	1.0000	0
2	0.9821	-0.9762	0.9820	-0.9760
3	0.9690	-1.8722	X	X
4	X	X	1.0200	-1.5230

Table-2b: - Node Area State Estimation (NASE) and ANN (NA-ANN) result of sample set-1

Node	**Node Area 3**		**Node Area 4**	
No.	V(p.u.)	δ (deg)	V(p.u.)	δ (deg)

1	0.9999	0	X	x
2	X	X	0.9808	-0.9760
3	0.9690	-1.8721	0.9583	-1.8720
4	1.0200	-1.5229	1.0089	-1.5231

Table-3: - Integrated State Estimation (ISE) and ANN (IANN) result of sample set-2

Node	Estimated state variable by ISE		Predicted state variable By IANN	
	V_i	**δ_i**	**V_i**	**δi**
1	0.9100	0	0.9100	0
2	0.8920	-6.1326	0.8920	-6.1326
3	0.8790	-7.0286	0.8790	-7.0286
4	0.9300	-3.6336	0.9300	-3.6336

Table-4a: - Node Area State Estimation (NASE) and ANN (NA-ANN) result of sample set-2

Node	**Node Area 1**		**Node Area 2**	
No.	V(p.u.)	δ (deg)	V(p.u.)	δ (deg)
1	0.9100	0	0.9100	0
2	0.8920	-6.1326	0.8920	-6.1325
3	0.8790	-7.0286	X	X
4	X	X	0.9300	-3.6335

Table-4b: - Node Area State Estimation (NASE) and ANN (NA-ANN) result of sample set-2

Node Area	**Node Area 3**		**Node Area 4**	
Node No.	V(p.u.)	δ (deg)	V(p.u.)	δ (deg)
1	0.9100	0	X	x
2	X	X	0.8920	-6.1326
3	0.8790	-7.0286	0.8790	-7.0286
4	0.9300	-3.6335	0.9300	-3.6336

Note: - after second level the results obtained is same as that of integrated state estimation.

The results are complied in tabular format. The results are generated for two different sample sets Table-1 and Table 2 (2a & 2b) is for sample set – 1 while Table-3 and table 4 (4a & 4b).

Conclusion

It is clear from the tables (1, 2a, 2b, 3 & 4a, 4b) that the output for integrated as well as node area wise calculations are almost similar. When it compared to the old calculated PS state variables (i.e. the estimated and predicted state variables) then also the results are satisfactory. This is very encouraging and leads to a new era of use of artificial intelligence (AI) in power system for developing a real time State Estimation.

References

[1] H.N. Udupa, Dr. H.R.. Kamath et al., *Node Level Power System State Estimation – A Parallel Processing Technique*, IJAEEE, Vol2; Issue 4, No.67, Aug.2013.

[2] Bruce F. Wollenberg and Toshiaki Sakaguchi, *Artificial Intelligence in Power System Operations*, Proceeding of the IEEE, Vol.75, No.12, Dec. 1987.

[3] V. Leonardo Paucar and Marcos J. Rider, *Artificial neural networks for solving the power flow problem in electric power system,* Electric Power Systems Research 62 (2002) 139_/144.

[4] M. V. Khokhlov, *Constrained Power System State Estimation on Recurrent Neural Networks.*

[21]A.K. Al-Othman and M.R. Irving, *Uncertainty modelling in power system state estimation*,IEE Proc.-Gener. Transm. Distrib., Vol. 152, No. 2, March 2005

[5]A.K. Al-Othman and M.R. Irving, *Uncertainty modelling in power system state estimation*,IEE Proc.-Gener. Transm. Distrib., Vol. 152, No. 2, March 2005

[6] Satish Kumar Singh, and Jaydev Sharma, *A Hopfield Neural Network based Approach for State Estimation of Power Systems Embedded with FACTS Devices, published* 2006 IEEE.

[7] Li Yan, Zhou Xiaoxin, Fellow, IEEE and Zhou Jingyang, *A New Algorithm for Distributed Power System State Estimation Based on PMUs*, 2006 International Conference on Power System Technology

[8] Bruce A. Grey and Ghadir Radman, *Decentralized Power System State Estimation using Hybrid Kalman Bucy Filter Incorporating Fuzzy Logic,* Proceedings of the 38th Southeastern Symposium on System Theory Tennessee Technological University Cookeville, TN, USA, March 5-7, 2006

[9] Hui Xue, Qing-quan Jia, Ning Wang, Zhi-qian Bo, Hai-tang Wang and Hong-xia Ma, *A Dynamic State Estimation Method with PMU and SCADA Measurement for Power Systems,* published in 2007, RPS.

[10] C. Rakpenthai, S. Premrudeepreechacharn, S. Uatrongjit and N.R. Watson, *PMU-based Two Stage State Estimation for Power System with Nonlinear Devices,* published in RPS, 2007.

[11] M. Y. Patel and A. A. Girgis, *Two-Level State Estimation for Multi-Area Power System,* published in IEEE, 2007.

[12] L. HAN, X. S. HAN, F. CHEN and H. ZHA, *An Effective Hybrid Approach for Dynamic State Estimation in Power System,* DRPT2008 6-9 April 2008 Nanjing China

[13] A. Karami and M.S. Mohammadi, *Radial basis function neural network for power system load-flow,* Available online at www.sciencedirect.com Electrical Power and Energy Systems 30 (2008) 60–66

[14] [38]Qinghua Huang, Noel N. Schulz, Anurag K. Srivastava and Tomasz Haupt, *Distributed State Estimation with PMU Using Grid Computing,* 978-1-4244-4241-6/09, IEEE, 2009.

ISSN 2229-5518
[15] Mohammad Hassanzadeh and Cansın Yaman Evrenosoğlu, *A Regression Analysis Based State Transition Model for Power System Dynamic State Estimation,* published in IEEE Transaction.

[16] Soummya Kar and Jos´e M. F. Moura, *Real-Time Adaptive Distributed State Estimation in Smart Grids,* accepted in IEEE, 2011.

[17] E. A. Zamora-Cárdenas, C. R. Fuerte-Esquivel, *Static State Estimation of FACTS containing Synchronized Phasor Measurement Units,* 978-1-4673-2729-9/12, 2012 IEEE

[18] Lokman H. Hassan, M. Moghavvemi, Haider A.F. Almurib and Otto Steinmayer, *Application of Genetic Algorithm in Optimization of Unified Power Flow Controller Parameters and its location in Power System Network,* Electrical Power and Energy Systems 46 (2013) 89–97

[19] Lokman H. Hassan, M. Moghavvemi, Haider A.F. Almurib and Otto Steinmayer, *Current State of Neural Networks application in Power System Monitoring and Control*, Electrical Power and Energy Systems 51 (2013) 134–144

[20] Sanjeev Kumar and D.K. Chaturvedi, *Optimal Power Flow solution using Fuzzy Evolutionary and Swarm Optimization*, Electrical Power and Energy Systems 47 (2013) 416–423

[21]Daniel Graupe, University of lllinois, Chicago, USA, PRINCIPLES OF ARTIFICIAL NEURAL NETWORKS (2nd Edition), Advanced Series on Circuits and Systems – Vol. 6,*Published by* World Scientific Publishing Co.Pte. Ltd

[22] Kishan Mehrotra, Chilukuri K. Mohan and Sanjay Ranka, October 1996, Elements of Artificial Neural Networks, Bradford Books.

[22]Algorithm in Optimization of Unified Power Flow Controller Parameters and its location in Power System Network, Electrical Power and Energy Systems 46 (2013) 89–97

[23] Lokman H. Hassan, M. Moghavvemi, Haider A.F. Almurib and Otto Steinmayer, *Current State of Neural Networks application in Power System Monitoring and Control*, Electrical Power and Energy Systems 51 (2013) 134–144

[24] Sanjeev Kumar and D.K. Chaturvedi, *Optimal Power Flow solution using Fuzzy Evolutionary and Swarm Optimization*, Electrical Power and Energy Systems 47 (2013) 416–423