Identification of Source to Sink Relationship in Deregulated Power Systems Using Artificial Neural Network

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***Abstract*--This paper suggests a method to identify the relationship of real power transfer between source and sink using artificial neural network (ANN). The basic idea is to use supervised learning paradigm to train the ANN. For that a conventional power flow tracing method is used as a teacher. Based on solved load flow and followed by power tracing procedure, the description of inputs and outputs of the training data for the ANN is easily obtained. An artificial neural network is developed to assess which generators are supplying a specific load. Most commonly used feedforward architecture has been chosen for the proposed ANN power transfer allocation technique. Almost all system variables obtained from load flow solutions are utilised as an input to the neural network. Moreover, log-sigmoid activation functions are incorporated in the hidden layer to realise the non linear nature of the power flow allocation. The proposed ANN provides promising results in terms of accuracy and computation time. The IEEE 14-bus network is utilised as a test system to illustrate the effectiveness of the ANN output compared to that of conventional methods.**

***Index Terms*--Artificial Neural Network, graph theory, load flow, power flow tracing.**

I. Introduction

DEREGULATED power systems are unbundled in the generation, transmission, distribution and retail activities, which are traditionally performed in a vertically integrated manner. Consequently different pricing policies will exist between different companies. With the separate pricing of generation, transmission and distribution, it is necessary to find the capacity usage of different transaction happening at the same time so that a transparent and fair use of transmission system charge can be imposed to individual customers separately. In addition, knowing the capacity usage is important for transmission congestion management. Since tracing the power from each source to each sink through the network help in alleviating the congestion in the system.

Due to non-linear nature of power flow, it is difficult to determine transmission usage accurately. Therefore it is required to use various techniques such as approximate models, tracing algorithms or sensitivity indices for usage allocation. The tracing methods are based on the actual power flows in the network and the proportional sharing principle. A novel tracing method is presented in [1]. But, even though the approach is conceptually very simple, it requires inverting a sparse matrix of the rank equal to the number of network nodes. In [2] graph theory is applied to trace active power and its limited to systems without loop flows. Reference [3] is based on the concept of generator 'domains', 'common' and 'links'. The disadvantage of this method is that the share of each generator in each 'common' (i.e. the set of buses supplied from the same set of generators) is assumed to be the same.

Reference [4] proposed a systematic method based on the basic circuit theories, equivalent current injection and equivalent impedance to allocate the power flow and loss for deregulated transmission system. However arranging payments with counter flows is a difficult process. The method to allocate the power flow and losses based on the electric circuit theories is proposed in [5]. This method assumed that the current at each network injection point may flow through all lines and reach all loads, which may not be true for all system.

A new technique for real and reactive power flow tracing is proposed in [6] to provide a promising way of pricing power wheeling. However the authors did not mention the significant to handle loops flows. Reference [7] proposed a modification of Bialek method in [1]. In the method, the matrix expansion is avoided by introducing matrix decoupling and followed by an introduction of an equivalent model of a line that unites the nodal reactive power with the power produced by shunt admittances.

Reference [8] proposed a vector evaluation particle swarm optimization (VEPCO) in evaluating the contributions of generators to the real power flows. However the experimental result showed that the VEPCO algorithm is slower than analytical methods. The method reported in [9] is based on tracing the current and complex power from individual power sources to system loads. Based on solved load flow, the method converts power injections and line flows into real and imaginary current injections and current flows. This method has a clear physical meaning and its results are unique. However this method is time consuming.

In a related work based on artificial intelligent techniques, [10] proposed a transmission loss allocation method using ANN. The ANN allocates losses with good accuracy and in a

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quick manner. Reference [11] proposed a fuzzy logic as a tool in Available Transfer Capability (ATC) determination to cater the accuracy or the online CPU time requirements in a large-scale power system. Reference [12] proposed computation of ATC for real time applications using three different intelligent technique viz., i) Back Propagation Algorithm (BPA) ii) Radial Basis Function (RBF) Neural Network and iii) Adaptive Neuro Fuzzy Inference System (ANFIS) and compared with the Full AC Load Flow method. From those three different intelligent techniques, ANFIS has minimum error for the base case and line outage case of ATC computations; it can be used in real time application.

From the extensive literature review it can be seen that the proposed methodology is still unique and not being applied directly to the determination of the power transfer allocation. The goal of this research is to incorporate the ANN to identify power source to sink relationship in a deregulated power system. Method based on Graph theory [2] has been chosen as a teacher to train the neural network. Artificial Intelligence has been proven to be able to solve complex process in deregulated system such as loss allocation and ATC. So, it can be expected that the developed methodology will contribute significantly to the knowledge and application of transmission usage allocation for deregulated system.

II. Graph Method as a Teacher

The method assumes that a generator has the priority to provide power to the load on the same bus and is based on the following lemmas of graph theory.

Lemma 1: A lossless, finite-nodes power system without loop flow has at least one pure source, i.e. a generator bus with all incident lines carrying outflows.

Lemma 2: A lossless, finite-nodes power system without loop flow has at least one pure sink, i.e. a load bus with all incident lines carrying inflows.

Based on these two lemmas downstream tracing sequence briefly described the method. The downstream tracing (DSTR) is used for calculating the contribution factors of individual generators to line flows and loads. This process initially requires the formation of intermediate matrices called extraction factor matrix of lines, $\boldsymbol{A_l}$ and loads $\boldsymbol{A_L}$ from total passing power of their upstream buses i.e. $\boldsymbol{P_l} = \boldsymbol{A_l.P}$ and $\boldsymbol{P_L} = \boldsymbol{A_L.P}$ respectively. Where $\boldsymbol{P_l}$ and $\boldsymbol{P_L}$ are the vector of line and load power respectively. $\boldsymbol{P}$ is a vector of bus total passing power in the bus sequence of downstream tracing. Then the nonzero elements in $\boldsymbol{A_l}$ and $\boldsymbol{A_L}$ are calculated with the following equations.

$$\left(A_l\right)_{line\ j,bus\ i} = \frac{line\ j's\ power\ flow}{bus\ i's\ total\ pass\ power\ P_i} \tag{1}$$

$$\boldsymbol{A}_{L_{ii}} = \begin{cases} 0 & i \notin net\ load\ buses \\ \dfrac{net\ load\ power\ on\ bus\ i}{P_i} & i \in net\ load\ buses \end{cases} \tag{2}$$

The next step involves the calculation of contribution factor matrix (**B**) of generators to bus total passing power. Mathematically this can be expressed as $\boldsymbol{P} = \boldsymbol{B.P_G}$. The elements of **B** are calculated using the equation given below.

$$B = \; B_{bus\text{-}i,bus\text{-}k} \begin{cases} 1 & (k = i, k \in net\ gen.buses) \\ 0 & (k = i, k \notin net\ gen.buses) \\ 0 & (k > i) \\ 0 & (k < i, k \notin net\ gen.buses) \\ \sum_{l_j \in i} \left(A_{l_j - m} \cdot B_{m-k}\right) & (k < i, k \in net\ gen.buses) \end{cases} \tag{3}$$

where $k<i$ means k is an upstream bus of bus i, and $k>i$ means k is a downstream bus of bus i. The last expression is for the lower triangular nonzero elements. The term $l_{j\in i}$ means line j is an inflow line of bus $\boldsymbol{i}$. $A_{l_{j-m}}$ is the unique nonzero element corresponding to line j in matrix A_l with bus m as its upstream terminal. B_{m-k} is the element in matrix $\boldsymbol{B}$ already calculated which represents the contribution of generator k to the total injection power of bus.

By substituting $\boldsymbol{P} = \boldsymbol{B.P_G}$ in $\boldsymbol{P_l} = \boldsymbol{A_l.P}$ and $\boldsymbol{P_L} = \boldsymbol{A_L.P}$ contribution of each generator to line flows and loads can be calculated. Exact derivation can be found on [2]. Vector $\boldsymbol{P_L}$ is used as a target in the training process of the proposed ANN.

III. Neural Network Architecture

Artificial intelligence can be broadly defined as computer processes that attempt to emulate the human thought processes that are associated with activities that require the use of intelligence [13]. Mostly, this definition included the fields of automatic learning, vision-image recognition, voice recognition, mathematic problem solving, robotics and expert systems. In recent years, the neural network and other related technologies has become a constituent field of artificial intelligence. An artificial neural network can be defined as a data processing system consisting of a large number of simple, highly interconnected processing elements (artificial neurons) in an architecture inspired by the structure of the cerebral cortex of the brain [13]. The processing elements consist of two parts. The first part simply sums the weighted inputs; the second part is effectively a nonlinear filter, usually called the activation function, through which the combined signal flow. These processing elements are usually organized into a sequence of layers or slabs with full or random connections between the layers. The input layer is a buffer that presents data to the network. The output layer presents the output response to a given input. The other layer is called the intermediate or hidden layer because it usually has no connections to the outside world.

Neural network perform two major functions which are training (learning) and testing (recall). Training is the process of adapting the connections weights to produce the desired output vector in response to a stimulus vector presented to the input buffer. Testing is the process of accepting an input stimulus and producing an output response in accordance with the network weight structure. Testing occurs when a neural network globally processes the stimulus presented at its input buffer and creates a response at the output buffer. Testing is an integral part of the training process since a desired response to the network must be compared to the actual output to create an error function.

A fully connected feedforward ANN as depicted in Fig.1 has been utilised in this project under MATLAB platform.

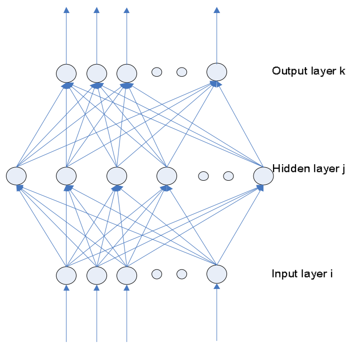

Fig. 1. Simple feedforward neural network.

A. Structure of the proposed neural network

In this research feed-forward networks with one hidden layer and one output layer network have been chosen. The proposed allocation method is elaborated by designing an appropriate ANN for the IEEE 14-bus network. The input samples for training is assembled using the daily load curve and performing load flow analysis for every hour of load demand. Similarly the target vector for the training is obtained from the Graph method [2]. Input data (D) for developed ANN contains independent variables such as real power generation (P_{g1}, P_{g2}), real loads (P_2 to P_{14}), reactive loads (Q_2 to Q_{14}), bus voltage magnitude (V_4, V_5, V_7, V_9 to V_{14}), ,average power for line flows (P_{line1} to P_{line20}) and the target/output parameter, (T) which is real power transfer between generators and loads placed at bus 2 to 14. This is considered as 26 outputs. Hence the networks have twenty six output neurons. The first thirteen neurons represent the contribution from generator 1 to the loads and the remaining outputs neurons correspond to generator 2. Table I summarise the description of inputs and outputs of the training data for the ANN.

TABLE I
DESCRIPTION OF INPUTS AND OUTPUTS OF THE TRAINING DATA FOR THE ANN

Input and Output (layer)	Neurons	Description (in p.u)
I_1 to I_2	2	Real power generations
I_3 to I_{15}	13	Real loads
I_{16} to I_{28}	13	Reactive loads
I_{29} to I_{37}	9	Bus voltage magnitude
I_{38} to I_{57}	20	Average power for line flows
O_1 to O_{26}	26	Real power transfer between gen. and loads

B. Training

Neural networks are sensitive to the number of neurons in their hidden layer. Too few neurons in the hidden layer prevent it from correctly mapping inputs to outputs, while too many may impede generalisation and increasing training time. Therefore number of hidden neurons is selected through experimentation to find the optimum number of neurons for a predefined minimum of mean square error and compromise with the lowest number of epochs in each training process.

To take into account the nonlinear characteristic of input (D) and noting that the target values are always positive, the suitable transfer function to be used in the hidden layer is a log-sigmoid function. Non linear activation functions allow the network to learn nonlinear relationships between input and output vectors. Levenberg-Marquardt algorithm has been used for training the network.

After the input and target for training data is created, it can be made more efficient to scale (preprocessing) the network inputs and targets so that they always fall within a specified range. In this case the minimum and maximum value of input and output vectors is used to scale them in the range of -1 and +1. Next step is to divide the data (D and T) up into training, validation and test subsets. In this case 14 samples (60%) of data are used for the training and 5 samples (20%) of each data for validation and testing. Table II shows the numbers of samples for training, validation and test data.

TABLE II
THE NUMBERS OF SAMPLES FOR TRAINING, VALIDATION AND TEST SET

Data Types	Samples (Hour)
Training	1,6,11,16,21,3,8,13,18,23,5,10,15,20
Validation	2,7,12,17,22
Testing	4,9,14,19,24

The error on the training set is driven to a very small value (to achieve the mean square error (goal)). One of the problems that occurred during neural network training is called overfitting or memorisation. It happens when a new data is presented to the trained network the calculated output error become much larger than acceptable. The network has memorised the training samples, but it has not learned to generalise to new situations. Validation sets is used to avoid overfitting problem.

The test set provides an independent measure of how well the network can perform on data not used to train it. Fig. 2 shows the performance of the training for the ANN with 58 hidden neurons. From Fig. 2, it can also be seen that the training goal is achieved in 6 epochs with a mean square error of 1.13772×10^{-13}. The result is reasonable, since the test set error and the validation set error have similar characteristics, and it doesn't appear that any significant overfitting has occurred.

C. Pre-testing and Simulation

After the networks have been trained, next step is to simulate the network. The entire sample data is used in pre testing. After simulation, the obtained result from the trained network is evaluated with a linear regression analysis. The regression analysis for the trained network that referred to contribution of generator at bus 1 to load at bus 2 is shown in Fig.3. The correlation coefficient, (R) in this case is equal to one which indicates perfect correlation between conventional method and output of the neural network. The best linear fit is indicated by a solid line whereas the perfect fit is indicated by the dashed line. The process to incorporate artificial neural network into real power transfer allocation to the loads can be summarise in the flow chart shown in Fig.4. Required data for the training including daily load curves for every bus and the target patterns along with single line diagram for IEEE 14-bus system is given in Appendix.

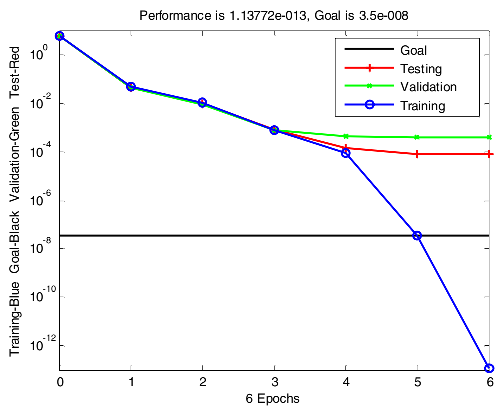

Fig. 2. Training, validation and test curve with 58 hidden neurons.

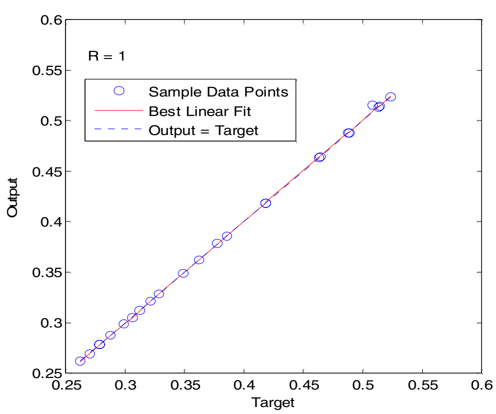

Fig. 3. Regression analysis between the network output and the corresponding target.

IV. Results and Analysis

A number of simulations have been carried out to demonstrate the accuracy of the developed ANN. Two cases have been analysed for the IEEE 14-bus system. The Case 1 scenario is that the real and reactive load increment up to 20% from hour 1 to hour 12 and between hours 20 to 24 from the nominal trained pattern. Besides it also assume that the generation at bus 2 also increases by the same rate to cater for the load demands. Fig. 5 shows the real power transfer allocation results by the proposed method along with the result obtained through to Graph method for loads at buses 3, 6 and 14 within 24 hours.

Results obtained from the Graph method are indicated with lines having circles and the solid lines represent the output of the proposed method. From Fig.5, it can be observed that the developed ANN can allocate source to sink relation with very good accuracy, almost 96 %. In this simulation, ANN computes within 15 msec whereas the Graph method took 360 msec for the same real power transfer allocation. Therefore it can be concluded that the ANN is more efficient in terms of computation time.

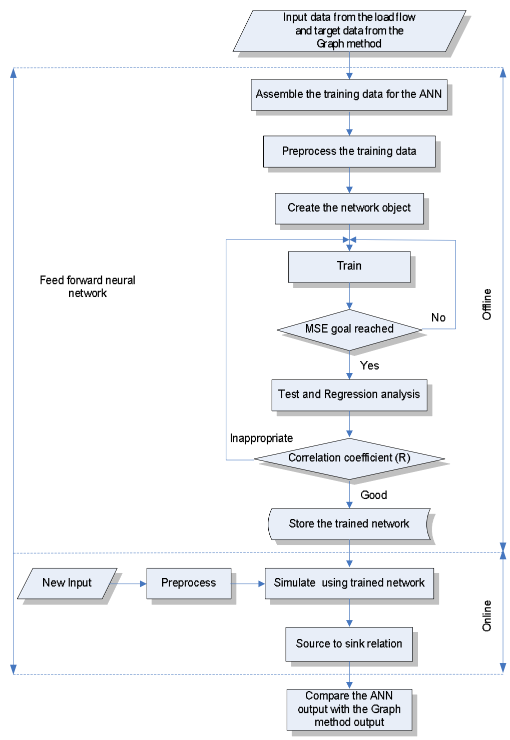

Fig. 4. The flow chart to incorporate artificial neural network into real power transfer allocation to the loads.

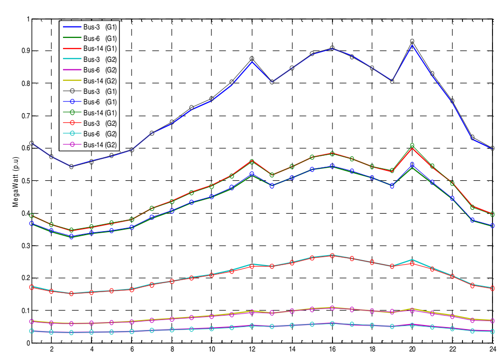

Fig. 5. Real power transfer allocation to loads at bus 3, 6 and 14 within 24 hours. (Case 1)

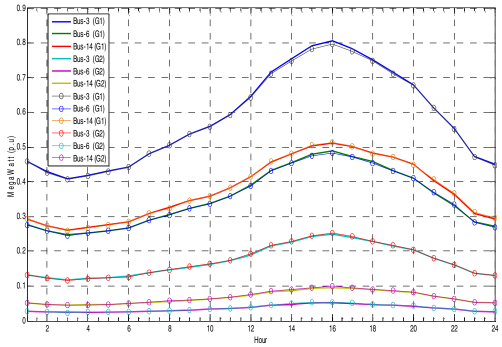

Fig. 6. Real power transfer allocation to loads at bus 3, 6 and 14 within 24 hours. (Case 2)

In Case 2, 10% decrease in load patterns is realised. The real power transfer allocation result referred to Case 2 is shown in Fig.6. Results obtained from the Graph method are indicated with lines having circles and the solid lines represent the output of the proposed method. In this case, the results show that the developed ANN can allocate source to sink relation even with improved accuracy, 2% higher compared to Case 1. From Fig.6, it can be seen that the generator 1 provides more power to the loads at buses 3, 6 and 14 compared to generator 2. Here again, both methods have a similar computation time as in Case 1.

Moreover, the final allocation of real power to loads on hours seven using proposed ANN is presented in Table III along with the result obtained through conventional method. The bus data for the IEEE-14 bus system on hour 7 is also given in Appendix. Note that the result obtained by the proposed ANN in this paper is compared well with the result of Graph method [2]. The difference of real power between generators in both methods is very small which are less or equal than 0.1 MW. The total contribution of generator 1 by using ANN is greater than that computed from Graph method, which is 0.368 MW. For this reason the total branch losses is slightly lower for ANN output than Graph method (see Table III).

TABLE III
ANALYSIS OF REAL POWER ALLOCATION FOR THE IEEE 14-BUS SYSTEM

Bus	Load	Proposed ANN		Graph Method	
number	(MW)	Gen-1	Gen-2	Gen-1	Gen-2
1	0	0	0	0	0
2	36.07	28.04	8.04	28.01	8.06
3	61.90	48.16	13.81	48.06	13.84
4	58.31	48.30	10.02	48.25	10.05
5	23.78	21.69	2.09	21.67	2.11
6	31.78	28.94	2.80	28.96	2.82
7	13.20	10.95	2.27	10.92	2.28
8	13.77	11.40	2.36	11.39	2.37
9	49.27	40.86	8.47	40.77	8.50
10	25.29	20.96	4.26	21.01	4.29
11	18.02	16.48	1.59	16.42	1.60
12	18.59	16.97	1.64	16.94	1.65
13	33.45	30.50	2.96	30.49	2.97
14	36.26	30.92	5.30	30.91	5.35
Loss:	37.91	34.13	3.69	34.50	3.42
Total:	457.59	388.29	69.30	388.29	69.30

V. CONCLUSION

This paper proposes an artificial intelligence technique to identify power source to sink relations. The developed artificial neural network adopts real power allocation outputs determined by Graph technique as a teacher to train the neural networks. The proposed ANN based method provide the results in a faster and convenient manner with very good accuracy. Accordingly, the proposed method has been successfully tested and demonstrated on the IEEE 14-bus system.

The method could be adapted to other larger systems by modifying the neural network structure. This technique can be used to resolve some of the difficult real power pricing and costing issues and to ensure fairness and transparency in the deregulated environment of power system operation.

VI. APPENDIX

TABLE IV
BUS DATA FOR THE IEEE 14-BUS SYSTEM ON HOUR 7

Bus	Voltage		Generation		Load		Shunt
no.	Mag	Angle	P	Q	P	Q	Suceptance
	(p.u)	(deg)	(MW)	(MVAr)	(MW)	(MVAr)	(p.u)
1	1.06	0.00	388.29	-23.53	0.00	0.00	0
2	1.05	-8.107	69.3	97.79	36.07	8.87	0
3	1.01	-16.78	0.00	23.64	61.90	11.14	0
4	0.983	-18.07	0.00	0.00	58.31	5.72	0
5	0.989	-16.26	0.00	0.00	23.78	6.02	0
6	1.07	-32.32	0.00	95.78	31.78	6.53	0
7	1.018	-28.29	0.00	0.00	13.20	2.38	0
8	1.09	-29.55	0.00	47.28	13.77	2.48	0
9	1.004	-31.87	0.00	0.00	49.27	10.50	19.00
10	1.002	-33.17	0.00	0.00	25.29	3.24	0
11	1.023	-33.55	0.00	0.00	18.02	4.55.	0
12	1.031	-34.70	0.00	0.00	18.59	4.28	0
13	1.025	-34.76	0.00	0.00	33.45	6.49	0
14	0.979	-36.18	0.00	0.00	36.26	3.35	0

TABLE V
BRANCH DATA FOR THE IEEE 14-BUS SYSTEM

Line		Series Z		Shunt Y
From bus	To bus	R (p.u)	X (p.u)	Y/2 (p.u)
1	2	0.01938	0.05917	0.0528
1	5	0.05403	0.22304	0.0492
2	3	0.04699	0.19797	0.0438
2	4	0.05811	0.17632	0.0374
2	5	0.05695	0.17388	0.034
3	4	0.06701	0.17103	0.0346
4	5	0.01335	0.04211	0.0128
4	7	0	0.20912	0
4	9	0	0.55618	0
5	6	0	0.25202	0
6	11	0.09498	0.1989	0
6	12	0.12291	0.25581	0
6	13	0.06615	0.13027	0
7	8	0	0.17615	0
7	9	0	0.11001	0
9	10	0.03181	0.0845	0
9	14	0.12711	0.27038	0
10	11	0.08205	0.19207	0
12	13	0.22092	0.19988	0
13	14	0.17093	0.34802	0

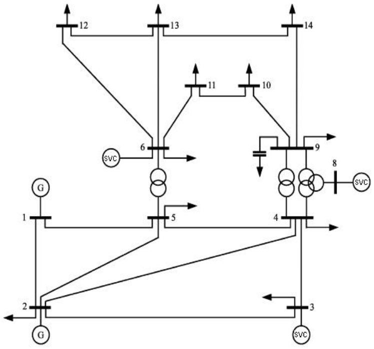

Fig. 7. Single line diagram for the IEEE 14-bus system.

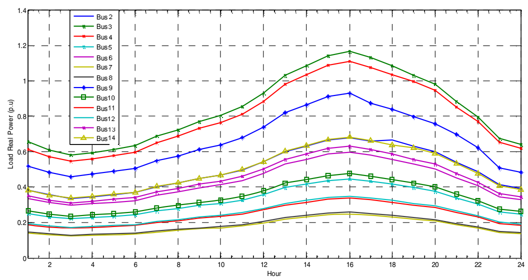

Fig. 8. Daily load curves for different buses.

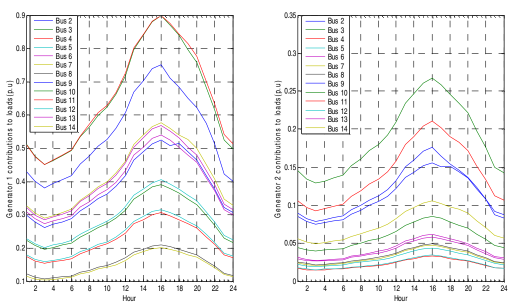

Fig. 9.Target patterns for different buses.

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VIII. Biographies

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