TRANSMISSION USAGE ALLOCATION IN BILATERAL ENERGY TRANSACTION USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

This paper proposes a method to allocate transmission usage for simultaneous bilateral transactions using artificial neural network (ANN). The basic idea is to use supervised learning paradigm to train the ANN, utilising conventional circuit theory method as a teacher. Based on solved load flow and followed by a procedure to decouple the line usage on the basis of transaction pairs, the description of inputs and outputs of the training data for the ANN is obtained. The structure of artificial neural network is designed to assess the extent of line usage by each generator while supplying to their respective customer. Most commonly used feedforward architecture has been chosen for the proposed ANN based transmission usage allocation technique. Almost all the system variables obtained from load flow solutions are utilised as an input to the neural network. Moreover, tan-sigmoid activation functions are incorporated in the hidden layer to realise the non linear nature of the transmission usage allocation. The proposed ANN provides promising results in terms of accuracy and computation time. A 6-bus and also the IEEE 30-bus network is utilised as test systems to illustrate the effectiveness of the ANN output compared to that of conventional methods.

I. INTRODUCTION

Recent trends in the bulk power consumer have been towards into bilateral transactions service with electric power utilities to avoid price fluctuations of energy market in a deregulated environment. Electric power utilities need to know the actual cost of providing unbundled services in order to make correct economic decisions that they should promote or curtail while considering their service obligations. As part of these trends, the emphasis on the knowledge of providing unbundled transmission service has been important and increase steadily. The concept of bilateral transactions allows the consumers and utilities to work according to their policy and does not make them dependent on everyday bid like in a pool model. Bilateral transactions enable consumers to make their best price deals for generation supply with whoever in the competitive market is most effective to meet their load demand. Allowing supplier to transact directly with consumers creates competition in terms of pricing, contract duration, payment terms, type of generation and type of electric service on both sides of the transaction. Generators compete among themselves to supply this demand. This gives consumers a full range of choices among generator. Thus, bilateral transactions will provide a wide range of choices to meet various customer needs.

Typically, the transactions are executed through independent market operators or independent system operators. Therefore, each supplier has to produce enough power to meets its transacted powers with individual customers and system losses. One of the most crucial ‘technical’ data needed about a transaction is the actual usage and path of the power follow from each generator or load across the interconnected system. For that reason it is vital to determine the impact and flow path of the simultaneous transaction taking place in the system accurately and efficiently [1].

This knowledge of the transmission usage is also essentially important in the implementation of usage-based cost allocation methods. Due to non-linear nature of power flow, it is difficult to decouple the actual line flows into components associated with individual transaction pairs accurately. Therefore it is required to use various techniques such as approximate models, tracing algorithms or sensitivity indices to estimate the contribution to actual line flows from individual customers. The tracing methods [2-5] based on the actual power flows in the network and the proportional sharing principles are effectively used in transmission usage allocation, but it is only suitable for pool based market model.

In [6], line power flows are first unbundled into a sum of components, each corresponding to a bilateral transaction. The scheme then proposes ways in which the coupling terms among the components appearing in the line losses can be allocated to individual bilateral transactions. In [7] a process is used whereby individual bilateral transactions are gradually incremented along a given path of variation. Once the path of variation and the loss suppliers are specified, the incremental contract loss allocations and their sums are uniquely determined. Reference [8] proposed a distributed slack bus scheme for transmission and ancillary services pricing associated to bilateral transaction market. A circuit approach to allocate transmission losses for simultaneous bilateral transaction is proposed in [9]. Reference [10] introduced current adjustment factor to allocate real and reactive power losses in bilateral market. In addition, a new voltage participation index is proposed to measure reactive power supports participation.

Reference [11] 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 [12]. 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. Reference [13] introduced the transaction pairs based on circuit concept to calculate associated losses for bilateral transactions in an interconnected system. However this method does not demonstrate the application of line usage allocation.

Counter flow is the component contributed by a particular transaction that goes in the opposite direction of the net flow [1]. In the novel MW-mile formulation as well as some usage-based allocation-pricing rules, impact of each transaction on the flows is measured by the magnitude so that all transmission users are required to pay for the use of path-provision service, irrespective of the flow directions. However, in view of the contributions of counter flows in relieving the congested transmission lines, any usage-based tariff that charges for counter flows need to be carefully reviewed [14]. In this regard, the zero counter flow pricing methods suggests that only the transactions that use transmission facility in the same direction of the net flow should be charged in proportion to their contributions to the total positive flow.

In [15], sensitivity factors are proposed for pricing transmission costs which depend on a base load flow case. However, it can be inaccurate for a large transaction, thus additional corrective scheme need be considered. Reference [16] proposed the actual use of transmission facilities, by a product of power due to a particular transaction times the distance travels in the network.

In a related work based on artificial intelligent techniques, [17] proposed a transmission loss allocation method using ANN. The ANN allocates losses with good accuracy and in a quick manner.

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 line usage allocation. The goal of this research is to incorporate the ANN to calculate line usage associated to bilateral transactions between purchasing and selling entities. Method based on Circuit theory [13] has been chosen as a teacher to train the neural network. This method is very suitable for line usage allocation under bilateral contracts based model. This algoritm is self balancing and dependent only on defined transaction pairs regardless of slack bus assignment. Moreover, real and reactive transactions losses are taken into account in the calculation of power flow solution. Artificial Intelligence has been proven to be able to solve complex processes in deregulated system such as loss allocation. So, it can be expected that the developed methodology will contribute significantly in knowing transmission usage allocation for deregulated system in a faster and accurate manner. A short description of the Circuit method is described next as it has been used as a teacher of developed ANN methodology.

II. CIRCUIT METHOD FOR UNBUNDLING LINE USAGE

Transaction pair encompasses of a sending bus and associated receiving bus. Each transaction pair corresponds to a bilateral energy transaction. An ideal transaction pair is self-balancing, i.e., its net real generation should equal to the sum of its active demand and associated transmission loss. The method assumes that each sending bus, is only associated with a single or multiple transactions. The following notations are used in this paper.

ns : Set of sending buses in the system;

nb : Set of sinking buses in the system;

nl : Set of all branches in the system;

nt : Set of bilateral transactions in the system;

T_k : k^{th} bilateral transaction (transaction pairs);

V_i: Complex voltage value at bus i , $V_i = V_i e^{j\theta_i}$

I_i , $I_{branch(ij)}$: Complex injected current value and branch current value of bus i and branch (ij).

$S_i = P_i + jQ_i$: Net complex power in term of bus i

$y_{ij} = g_{ij} - jb_{ij}$: The admittance of the branch (ij);

PROBLEM FORMULATION

Based on net real power generation, it should be equal to the sum of its active demand and associated transmission loss to form a transaction balance equations [13].

For each $T_k \in nt$;

$$\begin{cases} P_k = \sum P_m + P_{loss}^{(T_k)}, k \in T_k \cap ns \text{ and } m \in T_k \cap nb \\ P_{Loss}^{(Tk)} - \text{transaction loss of } T_k; \end{cases} \quad (1)$$

All power injections are translated into complex injected currents to bypass non-linear coupling between real and reactive power flow equations as follows:

$$I_i = \frac{S_i^*}{V_i^*} = \frac{P_i - jQ_i}{V_i e^{-j\theta_i}}, i \in ns \text{ or } I_i = \frac{-S_i^*}{V_i^*} = \frac{-P_i + jQ_i}{V_i e^{-j\theta_i}}, i \in nb \quad (2)$$

Complex branch current components imposed by individual transaction can be calculated using the equation given below.

For each $T_k \in nt$, and $k \in ns \cap T_k, m \in nb \cap T_k$

$$I_{branch(ij)}^{Tk} = y_{ij} \times \left\{ \frac{P_k - jQ_k}{V_k e^{-j\theta_k}} \left(Z_{ik} - Z_{jk} \right) + \sum_{m \in Tk \cap nb} \frac{-P_m + jQ_m}{V_m e^{-j\theta_m}} \left(Z_{im} - Z_{jm} \right) \right\} \quad (3)$$

Where

y_{ij} – the admittance of the branch (ij);

Z_{ik},et al – means ik^{th} entries of the nodal impedance matrix

Notice that the decoupled branch current vectors are exact solutions from Kirchoff Laws. Accordingly, both real and reactive losses $P_{Loss}^{(Tk)}$ and $Q_{Loss}^{(Tk)}$ incurred by T_k can be calculated by,

$$P_{Loss}^{(Tk)} = \sum_{ij \in nl} P_{Loss(ij)}^{(Tk)} = \sum_{ij \in nl} \operatorname{Re}\left\{ I_{branch(ij)}^{(Tk)} \times (V_i^* - V_j^*) \right\}$$
$$Q_{Loss}^{(Tk)} = \sum_{ij \in nl} Q_{Loss(ij)}^{(Tk)} = -\sum_{ij \in nl} \operatorname{Im}\left\{ I_{branch(ij)}^{(Tk)} \times (V_i^* - V_j^*) \right\} \quad (4)$$

Substituting $P_{Loss}^{(Tk)}$ from (4) into (1), it is possible to get expanded power flow equation which can be solved using Newton-Raphson method until transaction balance is reached. Once the transaction balance is obtained, real power flow components (denoted by $P_{branch(ij)}^{(Tk)}$) in branch (ij) contributed by a transaction T_k can be identified by,

$$P_{branch(ij)}^{(Tk)} = \operatorname{Re}\left\{ I_{branch(ij)}^{(Tk)} \times V_i^* \right\} \quad (5)$$

Finally, the actual real power flow in branch between bus i and j can be represented in terms of transaction pairs as,

$$P_{branch(ij)} = \sum_{k=1}^{nt} P_{branch(ij)}^{(Tk)} \quad (6)$$

The proposed usage allocation technique is applicable for all general networks. An iterative scheme based on classical AC power flow technique can be summarised in the flow chart shown in Figure 1. Vector $P_{branch(ij)}^{(Tk)}$ is used as a target in the training process of the proposed ANN.

III. NEURAL NETWORK ARCHITECTURE

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 [18]. 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 organised 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 has been utilised in this project under MATLAB platform.

STRUCTURE OF THE PROPOSED NEURAL NETWORK FOR 6 BUS SYSTEM

In this work 3 feedforward neural networks are utilised. Each network corresponds to a single contracting generator in the test system and each consists of one hidden layer and a single output layer. This realisation is adopted for simplicity and to reduce the training time of the neural networks. All discussions on designing of each of these ANN below is for the six bus test system as shown in Figure 2 [19]. This system consists of 3 generators located at buses 1, 2, and 3 respectively. They deliver power to 3 loads, through 11 lines located at buses 4, 5, and 6 respectively. For the purpose of analysis it is assumed that each generating bus or load bus is associated

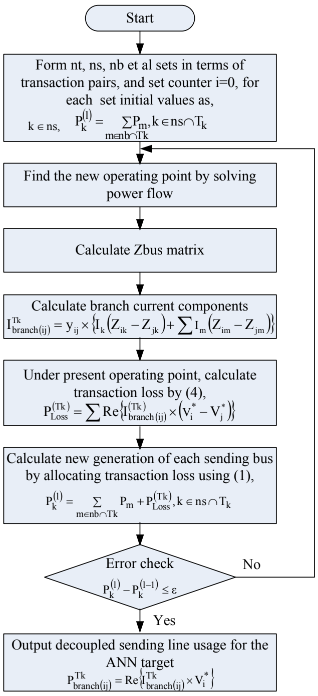

Figure 1. The flow chart of line usage allocation

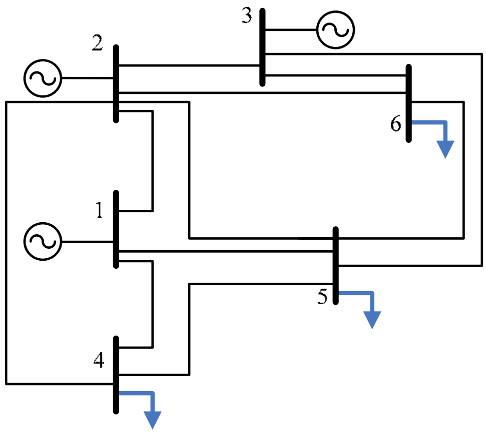

Figure 2. Single line diagram for the 6-bus system

with a single transaction and load patterns of each sinking buses remain constant for a particular hour. This means that this system can have six different combinations of 3 transaction pairs for every hour as shown in Table I. With this initialisation, the input samples for training is assembled by obtaining the operating point of the system that reflects the transaction balance equations (1) for particular combination of 3 transaction pairs for that hour. In the meantime, target vectors that resembles the line usage of each transacting generator is also obtained using the method discussed in section II. This procedure is repeated for all six combinations in duration of 24 hours with different load patterns.

Input data (D) for developed ANN contains independent variables such as real power generation *(P_{g1} to, P_{g3})*, reactive power generation *(Q_{g1} to, Q_{g3})*, real power demand *(P_4 to P_6)*, reactive power demand *(Q_4 to Q_6)*, bus voltage magnitude (V_4 *to* V_6), real power for line flows *(P_{line1} to P_{line11})*, reactive power for line flows *(Q_{line1} to Q_{line11})* and the target/output parameter, (T) contains generator contribution to all line flows which corresponds to 11 output neurons. Table II summarise the description of inputs and outputs of the training data for each ANN.

TABLE I
DIFFERENT POSSIBLE COMBINATIONS

Combination	Transaction	Pairs	(MW)
1	From gen. at bus 1 to load at bus 4 P^{g1}_{d4}	From gen. at bus 2 to load at bus 5 P^{g2}_{d5}	From gen. at bus 3 to load at bus 6 P^{g3}_{d6}
2	From gen. at bus 1 to load at bus 4 P^{g1}_{d4}	From gen. at bus 2 to load at bus 6 P^{g2}_{d6}	From gen. at bus 3 to load at bus 5 P^{g3}_{d5}
3	From gen. at bus 1 to load at bus 5 P^{g1}_{d5}	From gen. at bus 2 to load at bus 4 P^{g2}_{d4}	From gen. at bus 3 to load at bus 6 P^{g3}_{d6}
4	From gen. at bus 1 to load at bus 5 P^{g1}_{d5}	From gen. at bus 2 to load at bus 6 P^{g2}_{d6}	From gen. at bus 3 to load at bus 4 P^{g3}_{d4}
5	From gen. at bus 1 to load at bus 6 P^{g1}_{d6}	From gen. at bus 2 to load at bus 4 P^{g2}_{d4}	From gen. at bus 3 to load at bus 5 P^{g3}_{d5}
6	From gen. at bus 1 to load at bus 6 P^{g1}_{d6}	From gen. at bus 2 to load at bus 5 P^{g2}_{d5}	From gen. at bus 3 to load at bus 4 P^{g3}_{d4}

TABLE II
DESCRIPTION OF INPUTS AND OUTPUTS OF THE TRAINING DATA FOR EACH ANN

Input and Output (layer)	Neurons	Description (in p.u)
I_1 to I_3	3	Real power generations
I_4 to I_6	3	Reactive power generations
I_7 to I_9	3	Real power demand
I_{10} to I_{12}	3	Reactive power demand
I_{13} to I_{15}	3	Bus voltage magnitude
I_{16} to I_{26}	11	Real power for line flows
I_{27} to I_{37}	11	Reactive power for line flows
O_1 to O_{11}	11	Real power flow in line

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 either positive or negative, the suitable transfer function to be used in the hidden layer is a tan-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 86 samples (60%) of data are used for the training and 29 samples (20%) of each data for validation and testing. Table III shows the numbers of samples for training, validation and test data.

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

Data Types	Number of Samples (Transaction Pairs)
Training	86
Validation	29
Testing	29

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. Figure 3 shows the performance of the training for the ANN with 50 hidden neurons. From Figure 3, it can also be seen that the training goal is achieved in 20 epochs with a mean square error of 3.36157×10^{-10}. 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. The same network setting parameters is used for training the other 2 networks.

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 line flow (P_{1-2}) caused by each transaction pairs is shown in Figure 4. 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 steps to incorporate artificial neural network into line usage allocation can be summarise as follows:

Step 1: Get input data from the load flow and target data from the Circuit method.

Step 2: Assemble and preprocess the training data for the ANN.

Step 3: Create the network object and train the network until condition of network setting parameters are reached.

Step 4: Test and regression analysis.

Step 5: Stored the trained network. Steps (1-5) are offline processes. Next the network is ready to test with the new input which is an online process.

Step 6: The new input have to preprocess before they are simulated using selected trained network. Finally, the line usage allocations are determined and compare with the Circuit method output.

Daily load curves for every load bus and the target patterns for P_{d4}^{g1} as depicted in Table I, are given in Appendix.

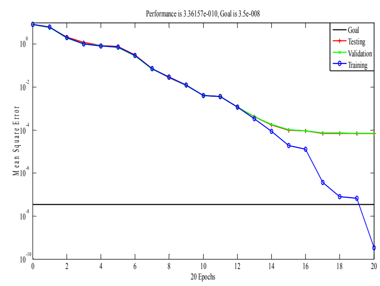

Figure 3. Training, validation and test curve with 50 hidden neurons

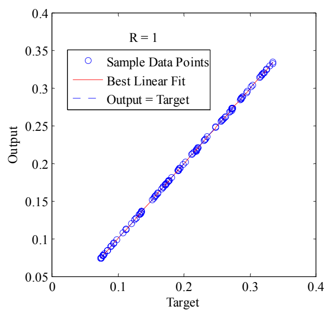

Figure 4. Regression analysis between the network output and the corresponding target

IV. RESULTS AND ANALYSIS

The case scenario is that the real and reactive power at each load to increase up to 10% from hour 1 to 24, from the nominal trained pattern. Figure 5 shows the line usage allocation results for P^{g1}_{d4} by the proposed method along with the result obtained through to Circuit method for line flows $P_{1\text{-}2}$, $P_{1\text{-}4}$, $P_{1\text{-}5}$, $P_{2\text{-}4}$, and $P_{4\text{-}5}$ within 24 hours.

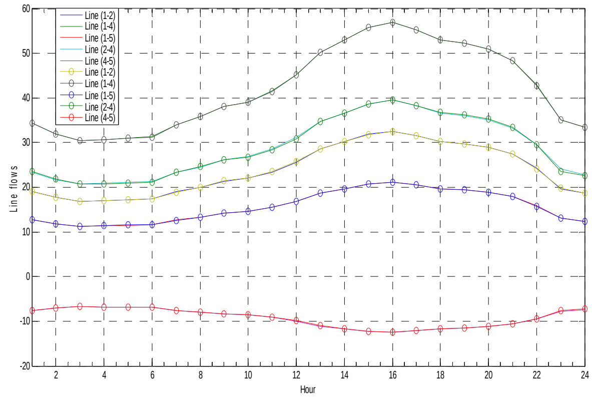

Figure 5. Line usage allocation result for P^{g1}_{d4} within 24 hours

Results obtained from the proposed method are indicated with lines having circles and the solid lines represent the output of the Circuit method. From Figure 5, it can be observed that the developed ANN can allocate line usage to generator involved in transactions with very good accuracy, almost 100%. In this simulation, ANN computes the output within 7.85 msec whereas the Circuit method took 3713 msec for the same combination of transaction pairs for 24 hours. Therefore it can be concluded that the ANN is more efficient in terms of computation time. From Figure 5, it can be seen that the generator 1 use more power in line $P_{1\text{-}4}$ compared to the other line due to this transaction, P^{g1}_{d4} .

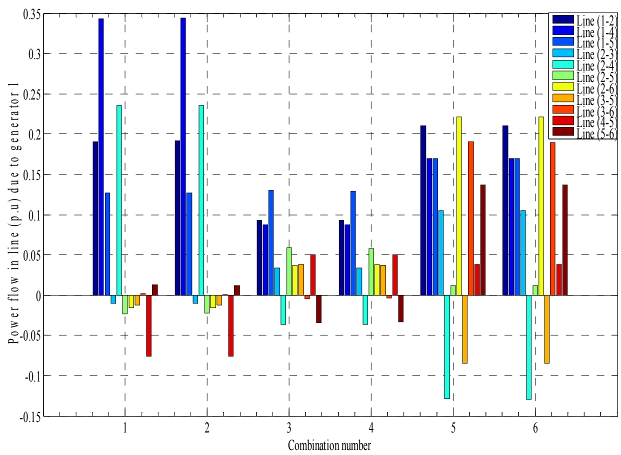

Figure 6. Effect of change of transaction pairs on line usage due to generator 1

Figure 6 shows the effect of change of transaction pairs on decoupled line flows for generator 1. From Figure 6, it can be observed that the line usage of this generator shows similar pattern when it transacts power to the same load. For example, no much variation is observed in line flow in combination number 1 and 2. In these cases generator 1 always transacts power to load at bus 4 while the other 2 loads changes its supply generator to either to generator 2 or 3.

However, when the generator 1 changes its customer, a large variation in decoupled line flow due to this generator is observed. For instance, when generator 1 changes its customer from load 4 to load 5, the flow direction in most of the lines corresponds to this generator reverses it direction. Finally, allocation of real power to line flows using proposed ANN on hour 8 is presented in Table IV along with the result obtained through load flow solutions. Note that the result obtained by the proposed ANN in this paper is compared well with the result of actual power flow. The total line flows from the proposed method are evaluated by summing each of decouple line flows due to transaction pairs. The difference of total line flows of the proposed method with the actual flow is very small which are less or equal than 0.019 MW. Note that, in Table IV there are some transactions that creates counter flows in some lines. For example, transaction pair P^{g1}_{d5} produces opposite flows in line $P_{1\text{-}2}$, $P_{2\text{-}3}$, $P_{2\text{-}4}$, $P_{3\text{-}6}$, and $P_{4\text{-}5}$. This helps to improve the line capacity use in the system.

TABLE IV
ANALYSIS OF LINE USAGE ALLOCATION ON HOUR 8 FOR THE 6-BUS SYSTEM

Line flows		Actual flow	P^{g1}_{d5} =	P^{g2}_{d6} =	P^{g3}_{d4} =	Total
From	To	(MW)	30.839 (MW)	57.618 (MW)	67.37 (MW)	(MW)
1	2	-0.396	9.339	-3.432	-6.300	-0.393
1	4	22.107	8.753	-1.311	14.678	22.119
1	5	9.123	12.895	4.722	-8.502	9.115
2	3	-6.622	3.340	14.742	-24.693	-6.611
2	4	41.920	-3.590	4.932	40.581	41.923
2	5	9.117	5.828	7.573	-4.292	9.108
2	6	13.124	3.757	27.358	-17.975	13.140
3	5	17.189	3.750	-5.001	18.421	17.170
3	6	45.286	-0.436	19.769	25.965	45.298
4	5	-4.371	5.028	3.527	-12.933	-4.379
5	6	-0.278	-3.351	10.867	-7.780	-0.265

The proposed method has been extended to the IEEE 30-bus system to demonstrate the strength of the method. This system has 6 generator buses and 41 branches. The six simultaneous bilateral transactions are obtained by allowing six generators to transact directly with six bundled consumer groups. Table V shows the details of transaction pairs between market participants for the IEEE 30-bus system. In this case study as well, structure and description of input and output of each ANN is considered similar to that of the 6 bus system. In the simulation of trained ANNs, 10% decrease in load patterns is realised. The real power allocation to line flows using proposed ANN on hour 1 out of 48 hours is shown in Table VI along with the result obtained through load flow solutions. For this 48 hours (samples) simulation, ANN computes the output within 234 msec whereas the Circuit method took 38563 msec for the same six simultaneous bilateral transactions. From the Table VI, it can be seen that the result obtained by the proposed ANN in this paper following the same way as the result of actual power flow. The total line flows from the proposed method are evaluated by summing each of decouple line flows due to transaction pairs. The difference of total line flows of the proposed method with the actual flow is very small which are less or equal than 0.0054 MW. A close look at the both test system shows the ANN output provides a close result between the actual power flows (target). Daily load curves for every load bus for 2 days and selected target patterns for the IEEE 30-bus system are also given in Appendix.

TABLE V
TRANSACTION PAIRS FOR THE IEEE 30-BUS SYSTEM

Transaction Pairs		From generator	To load
T1	P^{g1}_{d7}	1	7
T2	$P^{g2}_{d3,4,8}$	2	3,4,8
T3	$P^{g22}_{d10,21}$	22	10,21
T4	$P^{g27}_{d24,26,29,30}$	27	24,26,29,30
T5	$P^{g23}_{d18,19,20}$	23	18,19,20
T6	$P^{g13}_{d12,14,15,16,17}$	13	12,14,15,16,17

V. CONCLUSION

This paper proposes an artificial intelligence technique to allocate transmission usage for simultaneous bilateral transactions. The developed artificial neural network adopts line usage allocation outputs determined by Circuit 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 6-bus system and also on the IEEE 30-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.

TABLE VI
ANALYSIS OF LINE USAGE ALLOCATION ON HOUR 1 FOR THE IEEE 30-BUS SYSTEM

Line flows From-To		Actual flow (MW)	T1 (MW)	T2 (MW)	T3 (MW)	T4 (MW)	T5 (MW)	T6 (MW)	Total flow (MW)
1	2	5.18	9.52	-4.4	-0.06	-0.04	0.01	0.17	5.18
1	3	8.42	4.09	4.4	0.093	0.04	-0.01	-0.2	8.42
2	4	9.21	2.07	7.34	-0.04	0.09	-0.03	-0.2	9.21
3	4	6.97	4.06	2.99	0.067	0.04	-0.01	-0.2	6.97
2	5	8.01	4.19	3.74	-0.03	-0.03	0.01	0.13	8.01
2	6	11.7	3.24	8.19	0.056	-0.09	0.03	0.23	11.7
4	6	13.1	5.75	5.46	0.408	-0.77	0.25	1.99	13.1
5	7	7.97	4.17	3.74	-0.04	-0.03	0.01	0.13	7.97
6	7	5.51	9.3	-3.7	0.056	0.03	-0.01	-0.1	5.51
6	8	14.7	0	15.3	-0.09	-0.47	-0.09	0.09	14.7
6	9	2.92	-0.2	-0.1	0.531	0.96	0.49	1.25	2.92
6	10	1.67	-0.1	-0.1	0.304	0.55	0.28	0.71	1.67
9	11	0	0	0	0	0	0	0	0
9	10	2.92	-0.2	-0.1	0.5	0.97	0.49	1.27	2.92
4	12	-1.46	0.36	0.36	-0.42	0.9	-0.29	-2.4	-1.5
12	13	-22.4	0	0	0	0	0	-22	-22
12	14	3.22	0.04	0.05	-0.13	0.18	-0.2	3.29	3.22
12	15	5.75	0.15	0.17	-0.28	0.58	-0.7	5.84	5.75
12	16	5.4	0.16	0.15	0.002	0.15	0.6	4.34	5.4
14	15	-0.45	0.04	0.05	-0.13	0.18	-0.2	-0.4	-0.5
16	17	3.31	0.16	0.15	-0.01	0.15	0.6	2.26	3.31
15	18	5.32	0.09	0.08	0	0	4.74	0.41	5.32
18	19	3.4	0.09	0.08	-0.01	0	2.84	0.41	3.4
19	20	-2.21	0.09	0.08	-0.01	0	-2.76	0.4	-2.2
10	20	3.52	-0.1	-0.1	0.012	0	4.09	-0.4	3.52
10	17	2.01	-0.2	-0.1	0.028	-0.14	-0.6	3.06	2.01
10	21	-1.84	0	0.03	-0.79	1.04	-1.69	-0.4	-1.8
10	22	-2.52	0	0.02	-1.9	0.63	-1.01	-0.2	-2.5
21	22	-12.2	0	0.03	-11.1	1.05	-1.7	-0.4	-12
15	23	-4.87	0.1	0.14	-0.43	0.76	-5.64	0.2	-4.9
22	24	-0.69	0	0.05	0.991	1.69	-2.73	-0.6	-0.7
23	24	3.98	0.1	0.14	-0.42	0.76	3.19	0.21	3.98
24	25	-1.876	0.07	0.186	0.528	-2.69	0.477	-0.44	-1.88
25	26	2.078	0.00	0.000	0.000	2.078	0.000	0.000	2.078
25	27	-3.96	0.07	0.185	0.514	-4.76	0.475	-0.43	-3.96
28	27	-3.20	-0.07	-0.18	-0.52	-2.39	-0.47	0.437	-3.20
27	29	3.605	0.00	0.000	0.000	3.605	0.000	0.000	3.605
27	30	4.155	0.00	0.000	0.000	4.155	0.000	0.000	4.155
29	30	2.161	0.00	0.000	0.000	2.161	0.000	0.000	2.161
8	28	-3.04	-0.01	-2.45	-0.10	-0.47	-0.09	0.089	-3.04
6	28	-0.147	-0.06	2.278	-0.40	-1.92	-0.37	0.341	-0.15

VI. APPENDIX

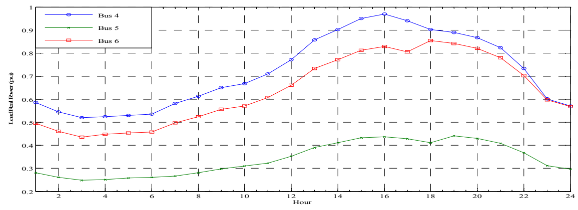

Figure 7. Daily load curves for different buses

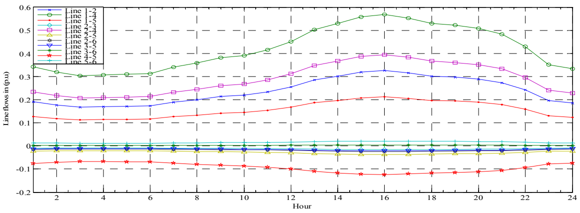

Figure 8. Target patterns of generator 1 for first combination within 24 hours

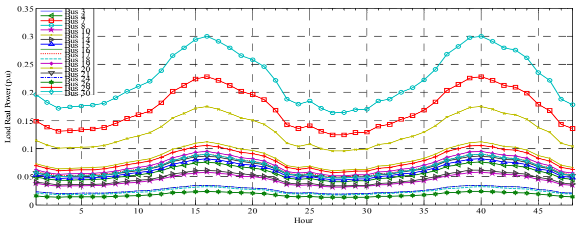

Figure 9. Daily load curves for different buses for 2 days

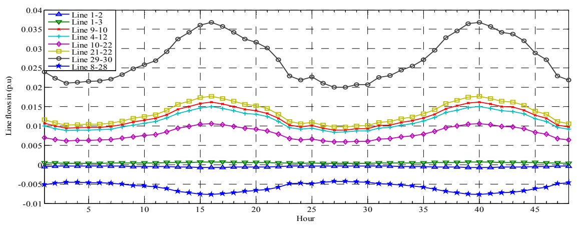

Figure 10. Selected target patterns of generator at bus 27 within 48 hours

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