Chapter 2
Market Power Assessment Using Hybrid Fuzzy Neural Network

Kirti Pal[1], Manjaree Pandit[2], and Laxmi Srivastava[2]

[1] Department of Electrical Engineering, RGGI, Meerut
kirtiglory@yahoo.co.in
[2] Department of Electrical Engineering, MITS, Gwalior, India
{manjaree_p,srivastaval}@hotmail.com

Abstract. Market power assessment is an important aspect of electric market analysis and operation. Market power problems are more complicated in an electric market than those in other markets due to the specific properties of electricity. A comprehensive and dynamic market power assessment has been proposed in this paper to protect and improve the open electricity market. This paper proposes a multi output fuzzy neural network (FNN) for market power assessment and for finding the on line market power ranking status of GENCOS in a competitive power system using a fuzzy composite market index (FCMI). This index is formulated by combining (i) Lerner Index, (ii) Relative market power and (iii) Nodal Cost. In the proposed FNN a trained multi-output neural network is being used as a fuzzy inference engine. The input of FNN consists of real loads and a bipolar code to represent a trading interval while the output consists of the fuzzy values of FCMI. To train the FNN a number of training patterns, covering the full operating range of the power system, are generated using the system data such as offer prices and operating constraints. OPF results are used to compute the above three market power indices and the corresponding FCMI. Once the network is trained it is capable of predicting the FCMI values in five fuzzy classes (GENCO ranking) for any given operating scenario, on line, instantaneously, without bothering about the computational burden of OPF. The computational effort is required only for training the network which is an off line process. Since the training of ANN is extremely fast and test results are accurate, they can be directly floated to OASIS (open access same time information system) and any other web site. An Independent system operator(ISO) and customers can access this information instantly. The performance of the proposed method has been tested on an IEEE 14 bus system.

Index Terms: Generator Market Share (GMS), Lerner Index (LI), market power, Must Run Ratio (MRR), open electricity market, Relative Market Power (RMP), transmission congestion.

1 Nomenclature

FNN	Fuzzy neural network
ISO	Independent system operator

I. Jordanov and L.C. Jain (Eds.): Innovations in Intelligent Machines -3, SCI 442, pp. 15–36.
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GENCO	Generating Company
LI	Lerner index
MRR	Must run ratio
MRS	Must run share
RMP	Relative market power
NC	Nodal cost
FCMI	Fuzzy composite market index
OPF	Optimal power flow
GMS	Generator market share
µ	Membership value of the class to which GENCO belongs
W	Weighting factor
x_i	Input variable
ϕ_{ik}	Input variable fuzzy membership function for x_i corresponding to the data point k.
OASIS	Open access same time information system
ANN	Artificial neural network

2 Introduction

Market power is defined as the ability to alter profitably prices away from competitive level. Market power can be exercised either by withholding the quantity of commodity or by raising the asking price above the competitive price level without affecting the demand of the commodity. In power systems, transmission network provides the infrastructure to support a competitive electricity market, but congestion occurs frequently in weakly connected networks. In a competitive electricity market, the oligopoly structure of the market and the network constraints may produce results far from the perfect competition.

One of the main objectives in the market monitoring process is the analysis of market power issues. The path toward liberalization has been under taken under the belief that the competition would strive for market efficiency [1] and price reduction resembling to the microeconomic model of perfect competition in which the social welfare would be the highest possible and the price will be the lowest. Unfortunately, different reasons may lead the market far from this desirable result. Some papers focus on the congestion impacts also in presence of the demand elasticity representation and the reactive load modeling [2], [3], [4], and provide methods to alleviate congestion impacts. In [5], the transmission congestion cost and locational marginal prices are considered, while in [6], thermal voltage and stability limits are considered to represent the feasibility region for the system. Strategic bidding has been extensively considered according to different approaches such as statically approaches [7], [8], parametric dynamic programming [9], Lagrange relaxation [10], genetic algorithm [11], stochastic procedure [12], fuzzy set theory [13], and game theory [14], [15]. In [16], the oligopolistic competition is examined in the submarkets that are isolated by constrained transmission lines.

The primary objective of this paper is to explore the potential for using an engineering approach to measure the existence of market power in the real time operations of a power grid.

An ISO requires the bid prices of GENCOS to run the OPF. For measuring market power an ISO solves an Optimal Power Flow (OPF) to determine the least cost pattern of dispatch based on the available offers in a uniform price auction. The OPF is determined subject to physical constraints on the power grid, such as thermal limits on transmission lines, and operating constraints, such as maintaining voltage levels.

This chapterproposes a multi output fuzzy neural network (FNN) for market power assessment and for finding the on line market power ranking status of GENCOS in a competitive power system using a fuzzy composite market index (FCMI). This index is formulated by combining (i) Lerner Index, (ii) Relative market power and (iii) Nodal Cost. In the proposed FNN a trained multi-output neural network is being used as a fuzzy inference engine. The input of FNN consists of real loads and a bipolar code to represent a trading interval while the output consists of the fuzzy values of FCMI. To train the FNN a number of training patterns, covering the full operating range of the power system, are generated using the system data such as offer prices and operating constraints. OPF results are used to compute the above three market power indices and the corresponding FCMI. Once the network is trained it is capable of predicting the FCMI values in five fuzzy classes (GENCO ranking) for any given operating scenario, on line, instantaneously, without bothering about the computational burden of OPF. The computational effort is required only for training the network which is an off line process. Since the training of ANN is extremely fast and test results are accurate, they can be directly floated to OASIS (open access same time information system) and any other web site. The ISO and customers can access this information instantly.

The main advantage of this approach is that it requires only the current load information for computing the FCMI and corresponding GENCO ranking without having to run the full OPF for every load variation. The FCMI will be used to analyze the GENCOS behavior in power market for any particular trading interval for any given loading conditions.

The membership values of loads to linguistic classes of low, medium, high, etc. constitute the input vector while the output vector presents the operator with the probability of a GENCO belonging to different market power class. Therefore, the proposed method can accept and analyze data in linguistic as well as in quantitative form. The fuzzy load modeling enables the handling of the uncertainty associated with power system loads and a whole set of scenarios is analyzed at one time.

This chapter is organized as follows. Study on market power is presented in section 3. FNN approach for open electricity market is produced in section 4. Power market assessment based on hybrid FNN is done in section 5. Training and testing detail of proposed FNN used for ranking of GENCOS for power market assessment is described in section 6. Section 7 is the conclusion.

3 Market Power

There are two main reasons why the potential of market power is brought to the electricity market. First there is market dominance and then there are transmission constraints [9]. Market power due to market dominance is a scenario that applies for every imperfect market and not only for the electricity market. On the electricity market, a supplier that is large enough to affect price can exploit market power by either economical withholding or physical withholding. When dealing with economical withholding a seller keeps bidding above the marginal cost of production and thereby driving up the price. Physical withholding simply means that a seller withholds some of its available capacity.

Market power due to transmission constraints makes it necessary to get a full understanding of the topology of the transmission system before starting any plan of detecting the potential for market power [10].

If a supplier is placed within a so called load pocket, this participant will have a local market power. A supplier in this case can find himself in a position of monopoly by intentionally create congestion and limit access of competitors. This means that by getting dispatched at strategic points in the network, a supplier in a load pocket can gain profit even by increasing its generation rather than by withholding its generationcapacity [11]. Conclusively, transmission constraints in the electricity market make it possible even for a small supplier to exploit market power.

In a network loads cannot be accurately forecasted and energy cannot be stored economically. Demand and supply must be balance all the time in order to maintain the system frequency, voltage, stabilization standards; Kirchhoff's laws and impedance of the whole network which determine the power flows in the system [12]. In the congested area generation capacity will be relative scarcity, so congestion results in locational market power and causes invalidation of the optimization of generating resources in the whole network.

Zonal market power has been recognized and analyzed in [17]. The Must-run ratio has been proposed to consider the transmission constraints. The MRR for Group A in a transmission zone is defined [18] as follows:

$$MRR = (Pd - Pl(\sum_{k=1}^{Ng} P_{gk,\max} - \sum_{k=1}^{NgA} P_{gk,\max})) / \sum_{k=1}^{NgA} P_{gk,\max} \tag{1}$$

Where Pl is the import limit of the zone, $P_{gk,\max}$ is the output limit of Generator k in the zone, N_g is the number of Generators in the zone, and N_{gA} is the number of Generators owned by Group A in the zone and P_d is the total load of the zone.

The MRR represents the capacity that must be provided by a generation company (GENCO) to supply a given load in a congestion zone as the percentage of the maximum available capacity of the GENCO. Theoretically, if the MRR of a seller is large than zero the seller is said to have market power. The MRR can provide useful market power signals in a congestion zone, which refers to a simple configuration in which one transmission line (or a set of lines in a "corridor") can be filled to its limit by exporting generation from a low-cost region to a high-cost region. However, the MRR does not clearly indicate the controllability of a GENCO over market price which usually depends on the market share owned by a GENCO to supply a given load in a congestion zone. This can be explained using a specific GENCO with 300 MW installed capacity in the following two different congestion zones. *Congestion zone 1*: the total load is 3000MW, the maximum import from other part of the system is 1000MW, the available generation capacity from other GENCOs in the zone is 1700 MW, and the capacity must be supplied by the specific GENCO is 300 MW.

In this case, the GENCO holds 300/3000=10% Generator market share (GMS) and the MRR=300/300=100 %. *Congestion zone 2*: the total load is 1000MW, the maximum import from other part of the system is 200 MW, the available generation capacity from other GENCOs in the zone is 500MW, and the capacity must be supplied by the specific GENCO is 300 MW. In this case, the GENCO holds 300/1000=30 % GMS and the MRR=300/300=100 %. Obviously, the specific GENCO in both cases has the same MRR but different market power due to different market shares.

Market participants may exercise their market power under certain system operating conditions through financial withholding and quantity withholding. Exercising market power by a supplier can expose customers to the risk of paying high price. Market power may appear in a deregulated power system under contingency states caused by random failures. For example, a random failure in a transmission line may results in network congestion and a generating unit failure may cause inadequate system generation capacity. Network congestion and generation inadequacy may result in local and system market powers. Although the probability of a contingency state is small and the state duration is short (usually from a few minutes to a few hours), the market power possessed by suppliers due to random failure may be quite larger than that in the normal state. If market participants exercise their market power under contingency conditions, the price can be extremely high (price spike). Customers usually use the hedging tools such as long term bilateral contracts, futures and options as risk management instruments to reduce the risk of their paying high prices. A customer has to know the possible risk of paying high price before making the decision to select a suitable hedging tool. It is therefore necessary to evaluate the risk of a customer being exposed to price spikes caused by exercising market power. Market powers caused by random failures and the associated probabilities are rarely considered currently in power market analysis.

4 FNN Approach for Open Electricity Market

A fuzzy neural network is employed for monitoring the power market and ranking the GENCOS. Load uncertainty is dealt with by representing loads as fuzzy variables in different linguistic categories. A fuzzy composite market index is proposed to screen market power and rank the GENCOS on line. This index is fuzzified in different severity classes to get a more informative ranking compared to conventional crisp approaches. The excellent non linear mapping characteristics of an efficient high performance neural network are utilized to map inputs with the expected outputs. Fuzziness incorporated at the input as well as at the output level provides flexibility and insight into the ranking process and a whole set of load scenarios are analyzed at one time. The application of an efficient neural network as a fuzzy inference engine eliminates the complicated process of fuzzy if then rule extraction. Once the fuzzy neural network is properly trained, GENCOS are ranked on the basis of the class membership values of FCMI. It is assumed that the index belongs to the severity class having highest value of membership. Due to the fuzzy approach, its probability of belonging to other classes is also available in the form of membership to other classes.

a. Fuzzy composite market index (FCMI)

A new fuzzy composite index is proposed by [31] for contingency ranking. In this paper same approach is used for screening of market power used by GENCOS in power system. The index is based on combining (i) Lerner Index, (ii) Relative market power (iii) Nodal cost. By including the effect of all three indicators it is ensured that the screening achieved will be more realistic and accurate.

(i) Lerner index

The Lerner index is used to measure the proportional deviation of price at the firm's profit-maximizing output from the firms marginal cost at that output. It is defined as the following:

$$LI_i = \frac{P_i - mc_i}{P_i} = \frac{1}{\varepsilon_i^d} \tag{2}$$

Where LI_i is the Lerner index for firm i, p_i and mc_i are price and marginal cost at the firms profit-maximizing output, respectively, and ε_i^d is the elasticity of demand seen by the firm. The Lerner index takes into the consideration of the effect of demand elasticity on market power. The Lerner index includes the effect of other fringe firm's elasticity of supply in the form of the market clearing price. Theoretically, if the LI of a company in a power system is large than zero it possesses the market power.

(ii) Relative Market Power

In general, one would expect the degree of substitutability between two Generators to be inversely related to how far apart they are on the network. Some Generators have market power in the Actual Experiments. These are the cases that an ISO would observe. Hence, the next question is whether or not Generators are using their market power effectively to raise prices. Seeing prices for Generators substantially higher than the prices paid to other Generators may raise suspicions, but, this situation is neither sufficient nor necessary for exploiting market power. Combining the results for the observed OPF with the high offer and the low offer by the Generators, respectively, it is possible to calculate the following measure of relative market power (RMP):

RMP=100[Competitive price-Low offer price/High offer price-Low offer price] (3)

High values of RMP close to the maximum of 100 indicate that market power has been exploited successfully. Although the RMP works quite well for our examples, it is still not an ideal measure. Developing better measures of the exploitation of market power is one of the ongoing objectives of our current research. It should be noted, however, that the main limitation of the RMP is the inability to discover the true costs. This is a deficiency on the supply side. From the perspective of customers, the prices paid are more important than measuring profits. Hence, the RMP, or, as an alternative, the ratio [Competitive price/Low offer price], provides a reasonably good measure of how well the power system is working for customers in a load pocket.

(iii) Nodal cost

Nodal prices are the price of power, which the supplier are paid and the price which consumers are billed. In order to compute these prices the Pool Operator receives bid plots from market participants for both supply and demand. Fig.1 shows bid plots for both demand and supply. G_m and $H_m$are market clearing price and market clearing volume of electric power respectively in \$/MWh and in MW. The prices shown on y-axis are in \$/MWh.The supply bid plot shows the minimum price at which a generator is willing to produce a certain amount of power, while demand bid plot shows the maximum price, which is accepted by customers to buy a certain amount of power. For, the sake of simplicity it is assumed here that supply and demand bid is a single price not complete plot.

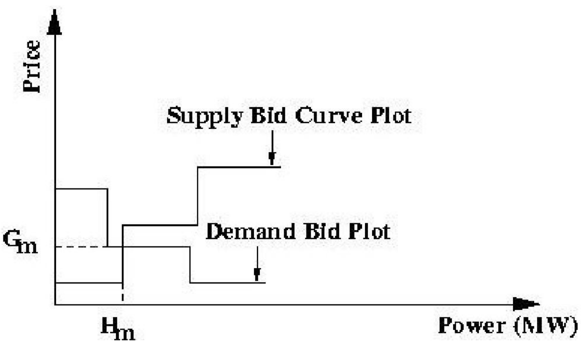

Fig. 1. Supply and Demand Bid Plot

In power market security pricing field, OPF-based approach is basically a non-linear constrained optimization problem. One crucial outcome of this optimization procedure can be nodal congestion prices. This outcome in pool-market operation is achieved through objective-function as Maximization of social welfare i.e. maximizing the generator's income for their power production and simultaneously ensuring that consumers pay cheapest price for their power purchase.

To combine the effect of all three, a composite index is proposed in (31) for contingency ranking the same approach is used here for GENCO assessment. The normalized values of LI, RMP and NC are fuzzified in different classes. Then the proposed index is computed as

$$FCMI = (\mu_{LI} \times W_{LI}) + (\mu_{LI}^{'} \times W_{LI}^{'}) + (\mu_{RMP} \times W_{RMP}) + (\mu_{RMP}^{'} \times W_{RMP}^{'}) + (\mu_{NC} \times W_{NC}) + (\mu_{NC}^{'} \times W_{NC}^{'}) \quad (4)$$

where μ_{LI} , μ_{RMP} and μ_{NC} are the memberships (highest value) of the class to which the market power of GENCOS belongs on the basis of FCMI value, i.e. on the basis of the combined effect of LI,RMP and NC. The memberships of the adjoining severity class (next highest value) are $\mu_{LI}^{'}$, $\mu_{RMP}^{'}$ and $\mu_{NC}^{'}$ and W_{LI} ,$W_{LI}^{'}$,W_{RMP} ,$W_{RMP}^{'}$,W_{NC} and $W_{NC}^{'}$ are the weighing factors.

b. Fuzzy modeling of power system loads

Load uncertainty is modeled by representing it as a fuzzy variable in the range (0–1) with memberships in different linguistic categories, such as, very small (VS), small (S), medium (M), large (L) and very large (VL). The membership value of ith linguistic category (μ_i) is calculated as [19]:

$$\mu_i = \frac{1}{1 + \left[\dfrac{x - a_i}{b_i} \right]^4} \tag{5}$$

where μ_i is the membership value in ith linguistic category, X is the crisp value to be fuzified, a_i and b_i are parameters corresponding to linguistic category i such as a_i determines the center value of the corresponding category, where the membership value is equal to 1.0 and b_i controls the width of the corresponding category. These parameters can be determined by carrying out simulations off-line under various operating conditions covering the possible range of variation. Past experience or operator judgment can also prove effective in setting these values. Non-linear membership functions are found to be most suitable to fuzzify power system variables (loads and FCMI) as they represent a more practical transition of loads from one category to the other compared to the common triangular or trapezoidal functions [19].

For each input variable x_i, the m data points in the x_i-y space are available. For every point in the x_i-y space, a fuzzy membership function ϕ_{ik} can be found, defined by [20]

$$\phi_{ik}(x_i) = \exp\left(-\left(x_{ik} - x_i / b\right)^2\right), \text{(k=1, 2, m)} \tag{6}$$

c. Data normalization

During training of a neural network, the higher valued input variables may tend to suppress the influence of smaller ones. Also the network does not produce outputs close to 1 or 0, as the neural network output governed by the activation or threshold function practically never realizes these values. To overcome this problem the input/output variables (x) are scaled in the range of 0.1–0.9. The normalized value x_n presented to the neural network as the input or target output is calculated using the equation:

$$x_n = \frac{(x - x_{\min})}{(x_{\max} - x_{\min})} 0.8 + 0.1 \tag{7}$$

Where x , $x_{\max}$ and $x_{\min}$ are the actual, maximum and minimum values of the variable which is to be normalized.

5 Hybrid Fuzzy Neural Network Based Power Market Assessment

The steps followed for power market assessment are:

(i) A large number of load patterns are generated randomly by perturbing the real loads at all the buses to cover the complete operating range of the power system under study.
(ii) For each pattern the values of LI, RMP and NC are calculated for each GENCO for each trading period using OPF solution and the offer prices of each GENCO.
(iii) The obtained indices are normalized between 0.1 and 0.9 for each load pattern using expression (7) and then fuzzified for computing the fuzzy composite market index (FCMI) using eq. (4).
(iv) The normalized loads at all buses are fuzzified into different linguistic categories and along with line codes (bi-polar digits used to represent the trading period) are fed to the fuzzy-neural network as training inputs. The first trading period is represented as (0 0 01) and so on.
(v) Computed FCMI in step three is then normalized and fuzzified into different linguistic categories. The membership values of FCMI of each GENCO form the desired output vector.
(vi) A one hidden layer neural network is trained with Levenberg– Marquardt back-propagation algorithm for input–output mapping. Once the network is properly trained, it is subjected to unseen patterns, for testing its performance.
(vii) During testing, a GENCO is assigned to the market power class for which it has highest value of membership.

a. Description of the test system

The hybrid fuzzy neural network was tested for measuring the existence of market power in the real-time operations of a power grid. An IEEE 14 bus system is used for testing and training the hybrid fuzzy neural network. The indices LI, RMP and NC are calculated from OPF solution obtained by MATPOWER [32] which simulate the full AC network, by using equ.(2) and (3). The weighing factors for computing FCMI in equ. (4) were taken equal to 1,2,3,4 and 5 for severity classes I, II, II, IV and V respectively for LI, RMP and NC. The weights were selected in this manner to assign highest weight to the most severe class (i.e. class V) and least weight to the least severe class (class I). Full AC, OPF solution were run for all load scenarios to obtain LI,RMP and NC for each trading period of an IEEE 14 bus system. The normalized LI, RMP and NC values were fuzzified using data given in Tables 1, 2 and 3 respectively. The graphical representation is given in figs 2, 3 and 4 respectively.

The value of FCMI of individual generator for each trading period was computed using membership values of the indices LI, RMP and NC. Table 4 presents the computation of FCMI of individual generator for 10 trading period each period has different load condition. The overall rank (last column) is found using fuzzy values of computed FCMI .Out of the 220 patterns generated 200 (20x10) were used for

Table 1. Fuzzy representation of LI

Linguistic Category for LI	Class V	Class IV	Class III	Class II	Class I
A	0.2	0.35	0.55	0.75	0.9
B	0.2	0.10	0.15	0.10	0.15

Table 2. Fuzzy representation of RMP

Linguistic Category for RMP	Class V	Class IV	Class III	Class II	Class I
A	0.2	0.45	0.65	0.8	0.9
B	0.3	0.15	0.2	0.10	0.2

Table 3. Fuzzy representation of NC

Linguistic Category for NC	Class V	Class IV	Class III	Class II	Class I
A	0.15	0.35	0.58	0.70	0.9
B	0.10	0.15	0.10	0.15	0.2

training the neural network while remaining 20 (2x10) unseen patterns were used to test its performance. Utility derived load compositions may also be employed to train the fuzzy-neural network instead of theoretically generated data. The obtained value of FCMI is normalized in the range of 0.1–0.9. Pattern wise normalization of FCMI ensures accurate ranking under peak as well as off-peak times of the day, because the generators are ranked for the current load based on their relative severity. Table 5 data was used to fuzzify normalized FCMI values into five fuzzy classes. The graphical representation is given in Fig. 5. The flexibility in ranking due to the fuzzy representation can be clearly seen. The operators and planners can set the different parameters to suit their system (as low, medium, high, etc. would have different numerical significance for different systems/variables) and thus flexibility is incorporated in the model.

b. Effectiveness of FCMI

The ranking of GENCOS on the basis of LI, RMP, NC and FCMI is compared in table 4 for 10 trading period. The significance of using FCMI for GENCOS classification becomes clear from table 4 which lists the values of the constituent

Table 4. FCMI and its Constituents LI, RMP, NC for IEEE 14 bus system

Trading period	GENCO	LI values		Rank	RMP Values		Rank	N.C. Values		Rank	FCMI (normalized)	Over all Rank
		Highest μ_{LI}	Next μ'_{LI}		Highest μ_{RMP}	Next μ'_{RMP}		Highest μ_{NC}	Next μ'_{NC}			
1	1	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	3.15 (0.1)	V
	2	0.93,III	0.30,II	III	0.85,III	0.47,II	III	0.91,III	0.35,II	III	10.31 (0.39)	IV
	3	0.83,IV	0.61,III	IV	0.73,III	0.68,IV	III	0.97,IV	0.79,V	IV	17.89 (0.71)	II
	4	1.0,V	0.16,IV	V	1,V	0.16,IV	V	1,V	0.16,IV	V	16.92 (0.67)	III
	5	0.97,V	0.62,IV	V	0.96,V	0.69,IV	V	0.99,V	0.67,IV	V	22.2 (0.89)	I
2	1	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	3.15 (0.1)	V
	2	0.96,III	0.24,II	III	0.9,III	0.37,II	III	0.92,III	0.33,II	III	10.22 (0.39)	IV
	3	0.99,IV	0.70,V	IV	0.99,IV	0.63,V	IV	0.99,IV	0.39,III	IV	19.7 (0.78)	II
	4	0.98,V	0.57,IV	V	0.97,V	0.63,IV	V	1,V	0.16,IV	V	20.19 (0.80)	II
	5	1,V	0.16,IV	V	1,V	0.16,IV	V	0.93,V	0.78,IV	V	19.05 (0.76)	II
3	1	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	3.15 (0.1)	V
	2	0.97,III	0.22,II	III	0.92,III	0.34,II	III	0.73,III	0.68,II	III	10.34 (0.39)	IV
	3	0.99,IV	0.61,V	IV	1,IV	0.54,V	IV	1,IV	0.45,V	IV	19.96 (0.79)	II
	4	1,V	0.16,IV	V	1,V	0.16,IV	V	1,V	0.16,IV	V	16.92 (0.67)	III
	5	0.98,V	0.53,IV	V	0.98,V	0.57,IV	V	1,V	0.24,IV	V	20.16 (0.80)	II
4	1	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	3.15 (0.10)	V
	2	0.99,II	0.19,III	II	0.87,II	0.09,III	II	0.84,II	0.61,III	II	8.07 (0.30)	IV
	3	0.74,III	0.67,II	III	0.99,II	0.36,III	II	0.99,III	0.38,II	II	11.72 (0.45)	III
	4	1,V	0.16,IV	V	1,V	0.16,IV	V	1,V	0.16,IV	V	16.92(0.67)	III
	5	0.9,III	0.38,II	III	0.91,II	0.54,III	II	0.89,II	0.88,III	II	14.87 (0.58)	III
5	1	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	3.15 (0.1)	V
	2	0.84,II	0.61,III	II	0.95,II	0.48,III	II	0.9,II	0.37,II	II	10.29 (0.39)	IV
	3	0.87,IV	0.58,III	IV	0.73,IV	0.69,III	IV	1,IV	0.49,V	IV	17.66 (0.70)	II
	4	1,V	0.16,IV	V	1,V	0.16,IV	V	0.57,IV	0.98,V	V	18.46 (0.73)	II
	5	0.91,V	0.85,IV	V	0.9,IV	0.87,V	IV	1,V	0.16,IV	V	21.54 (0.86)	I
6	1	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	3.15 (0.1)	V
	2	0.97,III	0.23,II	III	0.91,III	0.35,II	III	0.85,III	0.47,II	III	10.29 (0.39)	IV
	3	0.94,IV	0.83,V	IV	0.97,IV	0.79,V	IV	0.73,IV	0.68,V	IV	20.65 (0.82)	I
	4	1,V	0.16,IV	V	1,V	0.16,IV	V	1,V	0.16,IV	V	16.92 (0.67)	III
	5	0.99,V	0.73,V	IV	0.99,IV	0.67,V	IV	0.96,IV	0.69,V	IV	22.48(0.9)	I
7	1	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	3.15 (0.10)	V
	2	0.97,III	0.21,II	III	0.92,III	0.33,II	III	0.90,III	0.37,II	III	10.19 (0.39)	IV
	3	0.99,IV	0.38,V	IV	0.99,IV	0.39,III	IV	0.99,IV	0.63,V	IV	18.1 (0.72)	II
	4	1,V	0.16,IV	V	1,V	0.16,IV	V	0.97,V	0.63,IV	V	18.65 (0.74)	II
	5	0.95,V	0.72,IV	V	0.93,V	0.78,IV	V	1,V	0.16,IV	V	21.04 (0.84)	I
8	1	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	3.15 (0.1)	V
	2	0.85,III	0.47,II	III	0.73,III	0.68,II	III	0.92,III	0.34,II	III	10.48 (0.40)	IV
	3	1,IV	0.53,V	IV	1,IV	0.45,V	IV	1,IV	0.54,V	IV	19.6 (0.78)	II
	4	1,V	0.16,IV	V	1,V	0.16,IV	V	1,V	0.16,IV	V	16.92 (0.67)	III
	5	1,V	0.23,IV	V	1,V	0.24,IV	V	0.98,V	0.57,IV	V	19.06 (0.76)	II
9	1	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	3.15 (0.1)	V
	2	0.76,III	0.63,II	III	0.84,II	0.61,III	II	0.87,III	0.09,II	III	9.06 (0.34)	IV
	3	0.99,IV	0.40,V	IV	0.99,IV	0.38,III	IV	0.99,IV	0.36,III	IV	14.12 (0.55)	III
	4	1,V	0.16,IV	V	1,V	0.16,IV	V	1,V	0.16,IV	V	16.92 (0.67)	III
	5	0.92,V	0.81,IV	V	0.89,V	0.88,IV	V	0.91,V	0.54,III	V	19.25 (0.77)	II
10	1	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	1.0 ,I	0.025,II	I	3.15 (0.1)	V
	2	0.96,III	0.24,II	III	0.90,III	0.37,II	III	0.95,III	0.48,II	III	10.14 (0.39)	IV
	3	1,IV	0.57,V	IV	1,IV	0.50,V	IV	0.73,IV	0.69,III	IV	18.34 (0.73)	II
	4	0.98,V	0.52,IV	V	0.98,V	0.57,IV	V	1,V	0.16,IV	V	19.8 (0.79)	II
	5	1,V	0.16,IV	V	1,V	0.16,IV	V	0.9,IV	0.87,V	V	19.23 (0.76)	II

Table 5. Fuzzy representation of FCMI

Linguistic Category for FCMI	Class V	Class IV	Class III	Class II	Class I
A	0.2	0.35	0.45	0.6	0.9
B	0.3	0.15	0.2	0.15	0.2

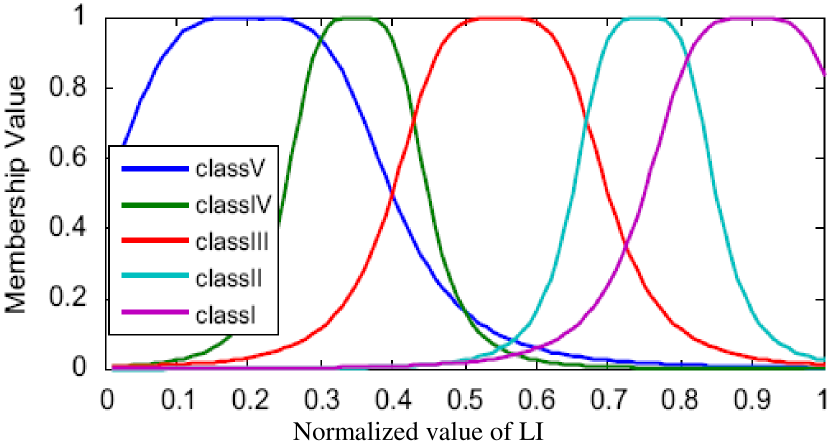

Fig. 2. Fuzzy representation of the LI index

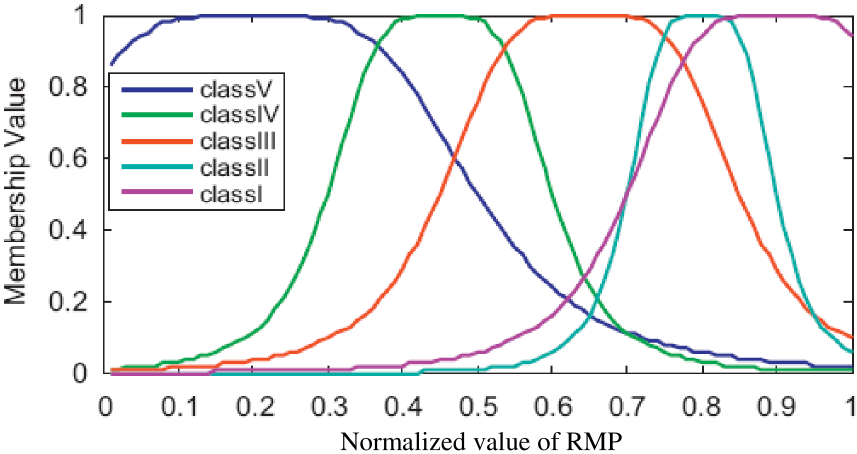

Fig. 3. Fuzzy representation of the RMP index

indices for 10 trading period. It can be observed that for a few trading period the classification remain same for all three indices but in other cases the ranking based on indices LI, RMP and NC is different. The composite index FCMI is hence very useful for ranking of GENCOS as it includes combined effect of all three individual indices. By using a composite index the effect of all three individual indices was effectively

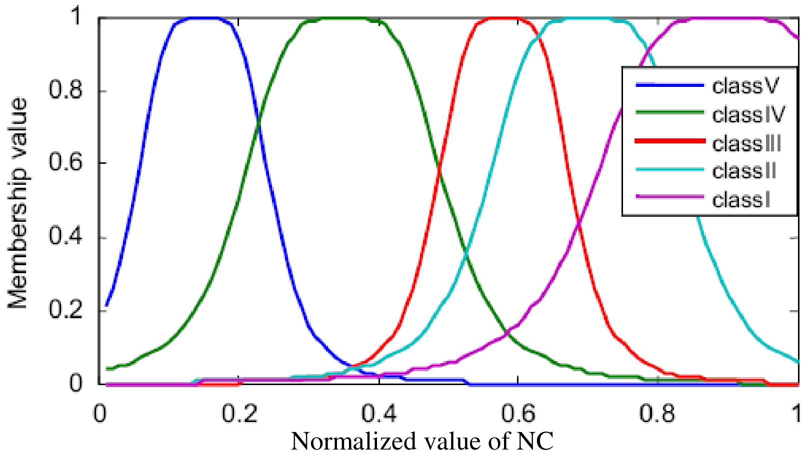

Fig. 4. Fuzzy representation of the NC index

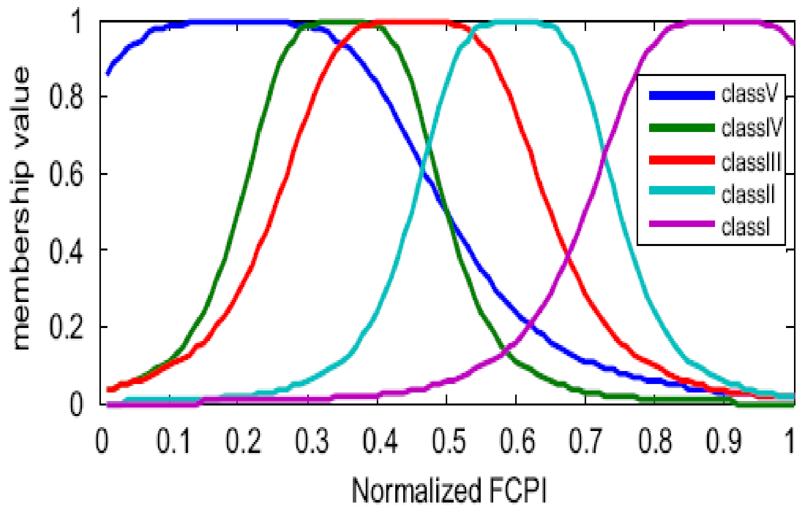

Fig. 5. Fuzzy representation of the FCMI index

included for market power assessment. The FCMI will be used to analyze the GENCOS behavior in power market for any particular trading interval for any given loading conditions.

6 Training and Testing Detail

The Levenberg– Marquardt algorithm [21, 22] was used for training the neural network. It is a variation of Newton's method. The conventional multi-layer perceptron (MLP) networks are usually trained using gradient descent based on back-propagation (BP) algorithm, which is too slow for practical problems. Recently, several high performance algorithms have been developed to train MLP models that converge 10 to 100 times faster than the BP algorithm. These algorithms are based on numerical optimization techniques like conjugate gradient, quasi-Newton and Levenberg–Marquardt algorithms. Out of these, Levenberg–Marquardt (LM) algorithm is found to be the fastest method for training moderate size feed forward neural networks [30]. It also has very efficient Matlab implementation. The proposed fuzzy-neural network is very advantageous as:

(i) No rule formation required and
(ii) Misranking is eliminated.

Hybridization of fuzzy logic with neural network has eliminated the need for deriving complex if-then rules by directly computing the membership values of composite performance index in all five severity classes. The proposed FNN-based method has an edge over conventional methods [23, 24, 25, 26, 27, and 28] that rank a pattern to a particular class based on its severity index because here any possibility of misranking is avoided by giving increased information in the form of membership values to neighboring classes. Simulations were carried out using MATLAB 7.0.1 on a Pentium IV processor, 2.8 GHz with 512GB RAM. The performance of the trained network was tested for 20 unseen trading periods. Market summary for 20 trading period are presented in Table 6.

The GMS represents the capacity that must be provided by a generation company to supply a given load in a congestion zone as the percentage of total load of the congested zone. The MRR represents the capacity that must be provided by a generation company (GENCO) to supply a given load in a congestion zone as the percentage of the maximum available capacity of the GENCO. Theoretically, if the MRR of a seller is large than zero the seller is said to have market power. Table 6 show the GMS and MRR for 20trading period respectively. For increased load demand, at trading period 4, MRR of GENCO 4 is 100% which indicate that GENCO4 used its maximum capacity. From table it can be easily concluded that as the demand is increased GENCO 4 and 5 offer high nodal costs with lowest MRR and GMS values try to exploit the market.

a. Architecture of the FNN for testing

The membership values of loads at all 14 buses along with a four digit topology number representing 20 trading period were used as inputs to the fuzzy-neural network making the number of neurons in the input layer equal to 59 (11X5+4). The first trading period is represented as (0001) and so on. There were five output layer neurons corresponding to the five membership classes of FCMI which reflect the market power assessment for each GENCO. Fuzzy rules for FCMI for five classes are given in table 7. GENCOS belonging to class 1 and 2 represent that they do not use market power. GENCOS belonging to class 3 represent that they partially utilize the market power to make their own profit, but do not exploit the market. GENCOS belonging to class 4 represent that GENCOS create a local market to maximize their profit, but still do not exploit the market. GENCOS belonging to class 5 represent that GENCOS fully utilize the market power to maximize their profit and fully exploit the market.

Table 6. Market summary for 20 testing pattern

Trading Period		GENCO1	GENCO2	GENCO3	GENCO4	GENCO5
1 (Pd=314.2)	MRR	60.34	27.04	00	51.81	35.91
	GMS	63.83	12.05	00	16.49	11.43
	Price ($/MWh)	37.26	38.93	39.94	41.04	40.72
2 (Pd=330.04)	MRR	60.41	27.11	18.96	35.14	49.30
	GMS	60.84	11.49	5.740	10.65	14.94
	Price ($/MWh)	37.28	38.97	40.38	40.70	40.99
3 (Pd=241.89)	MRR	58.81	26.33	00	15.78	3.34
	GMS	80.81	15.24	00	6.52	1.38
	Price ($/MWh)	36.82	38.43	39.69	40.32	40.07
4 (Pd=424.85)	MRR	57.62	27.81	44.62	100	66.74
	GMS	45.08	9.16	10.50	23.54	15.71
	Price ($/MWh)	36.48	39.47	40.89	49.19	41.33
5 (Pd=411.99)	MRR	60.66	27.12	16.19	71.65	48.81
	GMS	55.62	10.47	4.46	19.76	13.46
	Price ($/MWh)	37.53	38.98	40.32	41.43	40.98
6 (Pd=254.81)	MRR	59.18	26.56	2.94	27.57	00
	GMS	77.21	14.59	1.15	10.82	00
	Price ($/MWh)	36.93	38.59	40.06	40.55	39.98
7 (Pd=330.78)	MRR	60.7401	27.28	11.91	54.89	36.70
	GMS	61.04	11.55	3.60	16.59	11.09
	Price ($/MWh)	37.37	39.09	40.24	41.09	40.73
8 (Pd=367.25)	MRR	60.28	26.97	20.09	58.30	54.50
	GMS	55.99	10.55	5.61	16.29	15.23
	Price ($/MWh)	37.25	38.88	40.40	41.17	41.09
9 (Pd=359.69)	MRR	60.01	26.91	22.18	69.88	45.90
	GMS	55.46	10.47	6.17	19.43	12.76
	Price ($/MWh)	37.17	38.84	40.44	41.39	40.92
10 (Pd=331.87)	MRR	60.32	27.11	16.58	38.72	52.06
	GMS	60.42	11.43	4.99	11.67	15.69
	Price ($/MWh)	37.26	38.98	40.33	40.77	41.04
11 (Pd=386.23)	MRR	61.16	27.45	13.21	83.07	63.77
	GMS	52.64	9.95	3.42	21.51	16.51
	Price ($/MWh)	37.50	39.21	40.26	41.66	41.27
12 (Pd=278.48)	MRR	58.66	26.14	00	37.46	22.25
	GMS	70.02	13.14	00	13.45	7.99
	Price ($/MWh)	36.78	38.30	39.49	40.75	40.44
13 (Pd=250.18)	MRR	58.20	25.91	00	12.49	19.11
	GMS	77.3292	14.50	00	4.99	7.64
	Price ($/MWh)	36.65	38.14	39.45	40.25	40.38
14 (Pd=392.38)	MRR	60.50	27.17	29.93	85.02	55.30
	GMS	51.26	9.69	7.63	21.67	14.09
	Price ($/MWh)	37.31	39.02	40.60	41.70	41.10
15 (Pd=194.29)	MRR	51.83	23.00	00	00	00
	GMS	88.68	16.57	00	00	00
	Price ($/MWh)	34.83	36.09	37.42	37.31	38.49
16 (Pd=277.78)	MRR	58.59	26.06	00	37.16	22.15
	GMS	70.11	13.14	00	13.38	7.97
	Price ($/MWh)	36.76	38.25	39.65	40.74	40.44
17 (Pd=362.04)	MRR	60.87	27.40	23.93	50.56	62.16
	GMS	55.89	10.59	6.61	13.96	17.17
	Price ($/MWh)	37.41	39.18	40.48	41.01	41.24
18 (Pd=155.91)	MRR	40.73	17.96	00	00	00
	GMS	86.84	16.13	00	00	00
	Price ($/MWh)	31.65	32.58	33.28	33.58	33.65
19 (Pd=188.51)	MRR	49.70	22.03	00	00	00
	GMS	87.63	16.36	00	00	00
	Price ($/MWh)	34.22	35.42	36.16	37.18	36.81
20 (Pd=200.48)	MRR	52.95	23.58	00	00	00
	GMS	87.79	16.46	00	00	00
	Price ($/MWh)	35.15	36.50	37.15	38.03	38.12

Table 7. Fuzzy rules for FCMI

Class1	Class2	Class3	Class4	Class5
(NMP) GENCOS do not use market power	(NMP) GENCOS do not use market power	(PMP) GENCOS partially utilize the market power	(LMP) GENCOS create the local market	(FMP) GENCOS Fully utilize the market power

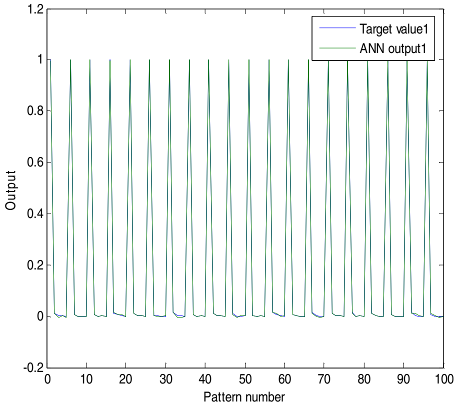

Fig. 6. Testing performance of FNN for Membership value of class 1

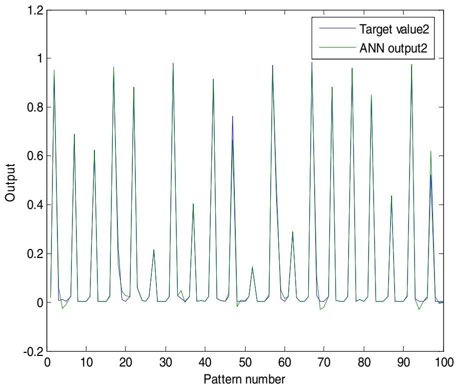

Fig. 7. Testing performance of FNN for Membership value of class2

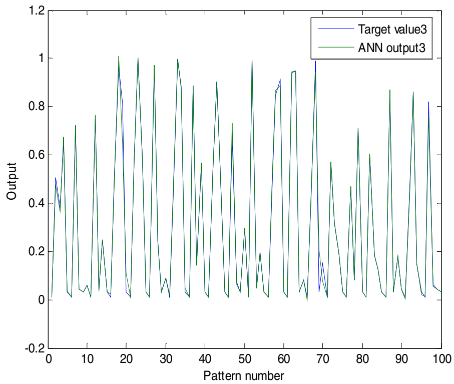

Fig. 8. Testing performance of FNN for Membership value of class 3

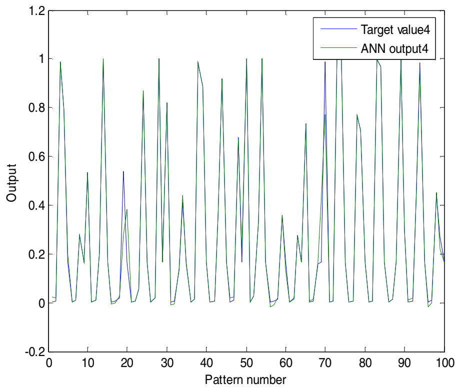

Fig. 9. Testing performance of FNN for Membership value of class4

Test results for all the 20 trading period are presented in Figs. 6–10 and it can be seen that fuzzy-neural network is capable of producing membership values of all the classes quite accurately. A GENCO belongs to the class for which it has highest membership.

Ranking of GENCOS for 20 testing trading period is shown in table 5. For each trading period GENCOS are ranked according to their FCMI values. For trading period 1 load is 314.2MW, the total load is shared by each GENCOS expect

GENCO3, which is clearly indicated by ranking as it belong to class1. However GENCO5 share the least load but exploit the market by offering high nodal cost and maximize the profit which is clearly indicated by ranking and from market summary table. For trading period 15,18,19 and 20 any GENCOS do not use market power as the load is low no congestion will occur and total load is shared by GENCO1 and 2 which is clearly indicated by ranking of GENCOS and also the ranking can be checked from market summary table. For trading period 2, 4, 5, 7, 8, 9, 10, 11, 14 and 17 demand is high congestion will occur, all GENCOS share the load, by offering high cost maximize their profit and exploit the market. It can be easily concluded that as the demand is increased GENCOS MRR will increase and they offer high cost to see the demand and exploit the market. The ranking of GENCO can be easily checked by market summary table which clearly indicate marginal cost, MRR and GMS values for each GENCO for each trading period.

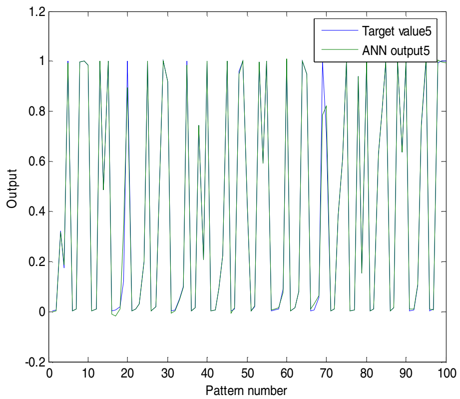

Fig. 10. Testing performance of FNN for Membership value of class 5

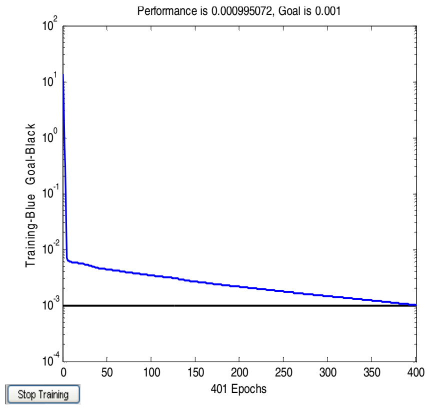

Fig. 11. Convergence characteristic for FNN

b. Market power assessment for each GENCO

The market power assessment of each GENCO for the proposed trading market is shown in figs 12-16. Out of the five GENCOS, GENCO1 always belong to class1 show that GENCO1 never use market power. GENCO2 belong to class2 and 3 show that GENCO2 partially try to utilize the market power but does not exploit the market. GENCO3, 4 and 5 belong to all classes clearly indicate that they use the market power to maximize their profit as per demand. GENCO 4 and 5 always try to use their market power as the demand is increased just because of their location in the system and also without their contribution demand cannot be fulfilled. Hence they raise their prices above the marginal cost. The proposed hybrid Fuzzy-neural network trained with LM algorithm is a model free estimator and its mapping accuracy is dependent on how closely the training patterns resemble the actual operating conditions. Being an intelligent system, it however has considerable fault tolerance and therefore can produce accurate results even for previously unseen operating conditions as long as they are within the same range. The computational time and complexity of conventional

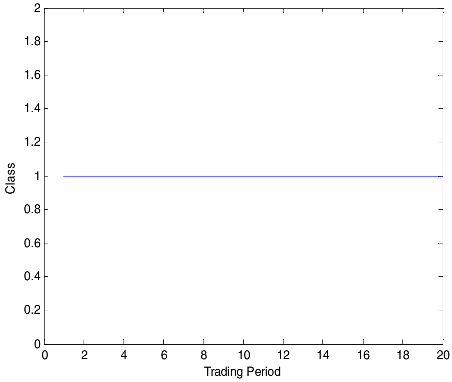

Fig. 12. Classes belonging to Genco1

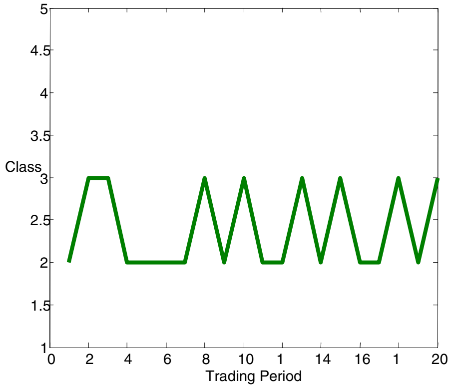

Fig. 13. Classes belonging to Genco2

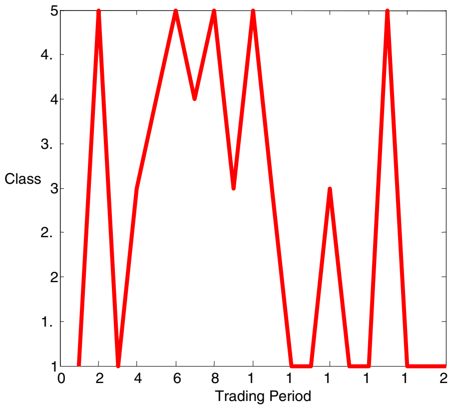

Fig. 14. Classes belonging to Genco3

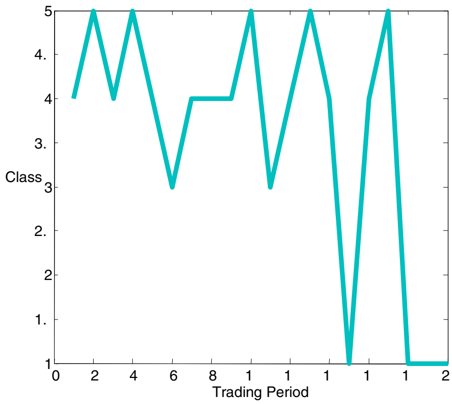

Fig. 15. Classes belonging to Genco4

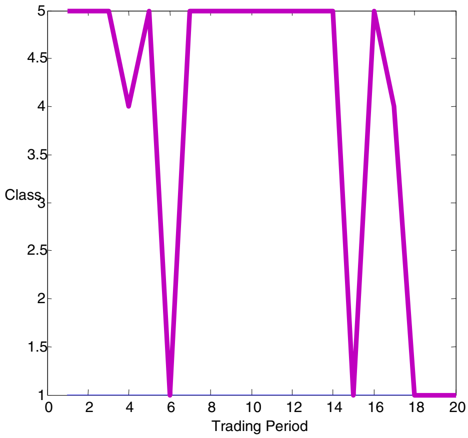

Fig. 16. Classes belonging to Genco5

approaches increase when all AC limits and load compositions are incorporated in the model, but in case of the proposed approach there will be no such effect as once it is trained off-line using data obtained from conventional methods, the results will be produced instantaneously, during the on-line application.

Discussion:

In this paper a multi output fuzzy neural network (FNN) is trained for market power assessment and for finding the on line market power ranking status of GENCOS in a competitive power system using a fuzzy composite market index (FCMI). This index is formulated by combining (i) Lerner Index, (ii) Relative market power and (iii) Nodal Cost. In the proposed FNN a trained multi-output neural network is being used as a fuzzy inference engine. The input of FNN consists of real loads and a bipolar code to represent a trading interval while the output consists of the fuzzy values of FCMI. To train the FNN a number of training patterns, covering the full operating range of the power system, are generated using the system data such as offer prices and operating constraints. OPF results are used to compute the above three market power indices and the corresponding FCMI. Once the network is trained it is capable

Table 8. Ranking of GENCOS for each Trading Period based on FNN

Trading Period	FCMI (Normalized, Rank)				
	GENCO1	GENCO2	GENCO3	GENCO4	GENCO5
1	0.1,I	0.4,II	0.1,I	0.68,IV	0.9,V
2	0.1,I	0.43,III	0.88,V	0.9,V	0.85,V
3	0.1,I	0.44,III	0.1,I	0.75,IV	0.9,V
4	0.1,I	0.38,II	0.59,III	0.9,V	0.78,IV
5	0.1,I	0.41,II	0.73,IV	0.77,IV	0.9,V
6	0.1,I	0.39,II	0.82,V	0.67,III	0.1,I
7	0.1,I	0.40,II	0.77,IV	0.79,IV	0.9,V
8	0.1,I	0.46,III	0.9,V	0.77,IV	0.87,V
9	0.1,I	0.39,II	0.64,III	0.78,IV	0.9,V
10	0.1,I	0.45,III	0.85,V	0.88,V	0.9,V
11	0.1,I	0.4,II	0.49,III	0.65,III	0.9,V
12	0.1,I	0.41,II	0.1,I	0.69,IV	0.9,V
13	0.1,I	0.49,III	0.1,I	0.9,V	0.82,V
14	0.1,I	0.39,II	0.59,III	0.64,IV	0.9,V
15	0.1,I	0.46,III	0.1,I	0.1,I	0.1,I
16	0.1,I	0.4,II	0.1,I	0.69,IV	0.9,V
17	0.1,I	0.42,II	0.83,V	0.9,V	0.74,IV
18	0.1,I	0.50,III	0.1,I	0.1,I	0.1,I
19	0.1,I	0.39,II	0.1,I	0.1,I	0.1,I
20	0.1,I	0.47,III	0.1,I	0.1,I	0.1,I

of predicting the FCMI values in five fuzzy classes (GENCO ranking) for any given operating scenario, on line, instantaneously, without bothering about the computational burden of OPF. The computational effort is required only for training the network which is an off line process.

This proposed technique is applied on an IEEE 14 bus system. All load buses with their demand is taken as input to FNN and FCMI computed after running OPF program is taken as output to FNN. Firstly we train the FNN and then testing is done with unseen load patterns. After testing and training it can be easily analyzed that at low demand GENCOS do not use market power means they do not raise their prices above the marginal price. As the demand is increased due to some reasons some GENCOSin this case GENCO 4 and 5 raise their prices above the marginal price just because of their location in the system. Without their contribution demand cannot be supplied hence they use their market power. By calculating FCMI we can easily identify which GENCO uses their market power and after identification they can be ranked.

Once we train FNN it requires only the current load information for computing the FCMI and provide GENCO ranking without having to run the full OPF for every load variation. The FCMI will be used to analyze the GENCOS behavior in power market for any particular trading interval for any given loading conditions**.** Since the training of ANN is extremely fast and test results are accurate, in future they can be directly floated to OASIS (open access same time information system) and any other web site. The ISO and customers can access this information instantly.

7 Conclusion

A comprehensive and dynamic market monitoring system has been proposed in this chapter to protect and improve the open electricity markets. Several important indices have been proposed as part of the market monitoring system, such as GMS, MRR, LI, RMP and NC all are combined together to give the single index FCMI. With this proposed market monitoring system handy, all participants will be able to have a better understanding of their markets and the policy makers will have a better gauge to measure the market behavior. It is also expected that this analysis will help make better market policies and find more incentives for everybody within the power system to improve the overall system operation and reliability as well as the market performance. It is strongly recommended that market participants and policy makers use this conundrums measurement and indices to locate and mitigate their market problems so that the power system is treated as a whole, not just as generation, transmission, load or other individual components.

In this paper a hybrid fuzzy neural network is developed for online ranking of GENCOS for each trading period. The proposed combined index developed using the effect of individual indexes is found to be very efficient for ranking GENCOS compare to methods which use only one index. Loads are modeled as fuzzy variables in contrast to the conventional deterministic approaches. The complicated task of fuzzy rule framing is not required here because a trained neural network serves as an inference engine. It has been demonstrated that the proposed method is particularly suitable for ranking of GENCOS lying on class boundaries because the fuzzy environment increases amount of information available and provides ranking within a severity class. The main advantage of this approach is that it requires only the current load information for computing the FCMI and corresponding GENCO ranking without having to run the full OPF for every load variation. The FCMI will be used to analyze the GENCOS behavior in power market for any particular trading interval for any given loading conditions.

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