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Different ANN Models for Short Term Electricity Price Forecasting

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Abstract*: *In a deregulated electiricity market, price forecasting is gaining demand with application of Artificial Neural Network (ANN). The paper deals with price forecasting with different ANN models.like Back Propagation Neural Network(BPNN), Radial Bias Function Neural Network (RBFNN) and Genectic Algorithm based Neural Network (GANN). A contextual investigation is made with the downloaded data of the day-ahead pool market prices of the California Pool Market using the above four different ANN models and the results are compared.

Keywords*: *ANN, genetic algorithm, electricity markets, market clearing price

I. INTRODUCTION

Since the start of deregulation in power showcases around the globe, power market changes into a focused market. In such deregulated markets, showcase players should be educated regarding future power costs to have fixed position; accordingly power value determining has turned out to be one of the most significant assignments. Power industry is reforming day by day by increasing the competitive framework in the market which leads to the introduction of new mechanisms by replacing the old methods. This lay a path for reduction in prices with most secured and reliable power supply to the end level. In the region of Power System checking and control, PC based Energy Management Systems are presently generally utilized in vitality control focuses. Power System examination projects and anomaly application projects are utilized in Energy Management Systems for the reasons for researching and anticipating the conduct of intensity frameworks under consistent state tasks. In spite of the fact that these projects are incredible assets, their capacity to help activity specialists to settle on productive choices is restricted when impromptu or startling methods of framework activity happen. The irregular methods of framework activity might be brought about by system shortcomings, dynamic and receptive power awkward nature, or recurrence deviations. A spontaneous activity may prompt a mal activity or a total framework power outage. Under these crisis circumstances, control frameworks are reestablished back to the typical state as indicated by choices made by experienced activity engineers. For effective finding of system flaws, assurance of operational procedures for system reclamation, and adjusting dynamic and receptive forces, there is obviously a need to grow new PC strategies and techniques to assemble programs where the valuable information of experienced activity specialists can be represented notwithstanding the customary power framework application programs. There is also a need to develop fast and efficient methods for the prediction of abnormal system behavior.

Power has its unmistakable attributes from different wares. For instance, power can't be put away financially and transmission clog may counteract free trade among control regions. In this way, power value development indicates exceptionally extraordinary, really, the best, unpredictability among all items [1]. Individuals in power industry know about burden determining as foreseeing power burden has turned into a significant undertaking for the correct arranging and activity of intensity framework [2]. With presentation of deregulation into power industry, cost of power has been the key of all exercises in the power advertise. Accurately and efficiently forecasting electricity price becomes more and more important [3]-[5]. The power market guidelines is that the hourly power costs depend incredibly on the interest . The power request displays hourly, every day and occasional motions, being likewise affected by the financial action and the (GDP) of the nation. The atmosphere impact and other related elements are basic so as to decide the last power value that may vacillate contingent upon the season and day and hour [6, 7]. Besides, power value development indicates extraordinary unpredictability among all products [4] . Value determining strategies in power frameworks are generally ongoing systems [6]-[9].

Artificial Intelligence (AI) has provided techniques for encoding and reasoning with declarative knowledge. The advent of neural networks provides neural network modules, which can be executed in an online environment. Many ANN based piece forecasting models were proposed [10]-[12]. Numerous Artificial Intelligence frameworks and Expert Systems have been worked for taking care of issues in various regions inside the field of intensity frameworks. Electric price foresting using GA technique is proposed in [13]-[14] These new techniques supplement conventional computing techniques and methods for solving problems of Power System planning, operation and control.

This paper presents the uses of Artificial Intelligence and Neural Networks in Power Engineering. It first reports territories in Power Systems that Artificial Intelligence has been applied to. It at that point outlines the man-made consciousness systems, which have been utilized, and makes recommendations for the improvement of existing man-made brainpower devices.

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Following this, the venture work focuses on neural systems and their applications to control frameworks. The multi-layer feed forward system is presented and the issues in building up neural system methodologies dependent on this system for power framework applications are talked about.
Future subjects for further advancement in Artificial Intelligence and neural system applications in power frameworks are proposed.

As power frameworks have complex structures and muddled choice issues, man-made consciousness instruments and master frameworks shells are expected to meet the different necessities in speaking to control framework parts and structures and to control the derivation components. For advancement work, existing devices can offer advantageous and supportive programming improvement conditions to power engineers for the improvement of man-made brainpower frameworks and master frameworks. Further developed programming apparatuses are required if Artificial Intelligence innovation is to be received generally, in actuality, control frameworks.

The pricing mechanism can affect the competition, efficiency, consumer surplus, and total revenue of the players in the electricity markets. This paper is focused on the Price prediction in the uniform pricing structure, which is the most commonly accepted structure of the electricity markets around the world for next coming day(s)/ weeks/ month(s).

Short term Price Forecasting(STPF) is achieved by three various models of ANN. They are Back Propagation Neural Network model (BPNN), Radial Basis Function Neural Network model (RBFNN), Genetic Algorithm based Neural Network (GANN) with the data taken from California pool market. Section II illustrates the various models and their flowcharts a used for STLF. Section III presents the outcomes got from the contextual analysis utilizing the three unique models. Perceptions produced using the test outcomes are outlined as ends in Section IV.

II. VARIOUS ANN MODELS

i) BPNN Model:

The neurons are orchestrated as certain layers in BP organize. The BP system is made by one information layer and at least one shrouded layers and one yield layer. The learning procedure of system incorporates two courses, one is the information data transmitting forward way and another is the mistake transmitting in reverse heading. In the forward activity, the information data goes to the concealed layers from info layer and goes to the yield layer. On the off chance that the yield of yield layer is distinctive with the unrealistic yield result then the yield blunder will be determined, the mistake will be transmitted reverse way then the loads between the neurons of each layer will be changed so as to make the blunder as least as could reasonably be expected. At that point the system is said to be prepared for the given information or application.

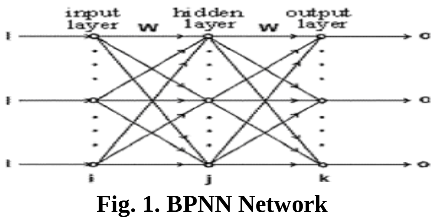

Fig. 1. BPNN Network

A three layers BP system is appeared as pursue Fig. 1. It might be noticed that the numbering of info layer is I, the numbering of shrouded layer is j, and the numbering of yield layer is k.
At that point the contribution of the jth neuron of concealed layer is:

$$net_j = \sum_i w_{ji} o_i \quad ; i = 1 \text{ to } N \qquad \text{---------} (1)$$

The output of the j^{th} neuron is:

$$o_j = g(net_j) \qquad \text{---------} (2)$$

The input of the k^{th} neuron of output layer is:

$$net_k = \sum_j w_{kj} o_j \quad ; j = 1 \text{ to } NH \text{ ---------} (3)$$

Corresponding output of the k^{th} neuron is:

$$o_k = g(net_k) \qquad \text{---------} (4)$$

Where, g is Sigmoid function,

$$g(x) = \frac{1}{1+e^{-x}}$$

The key of BP system is the error Back Propagation during the learning procedure. The learning procedure is practiced through minimization of an item work, which is the aggregate of squares of the mistakes between the genuine yield of system and the objective yield. Inclination plunge calculation is utilized to determine the registering equation.
In the adapting course, target yield of the k^{th} neuron of yield layer is t^{pk} the comparing real yield of system is o^{pk}, then the normal of the aggregate of the squares of the mistake of framework is

$$E = \frac{1}{2p} \sum_p \sum_k (t_{pk} - o_{pk})^2 \qquad \text{---------} (5)$$

Where, p is the quantity of preparing tests utilized in preparing the system.
So as to the express the above advantageously, discard the subscript p and the recipe (5) progresses toward becoming as beneath:

$$E = \frac{1}{2} \sum_k (t_k - o_k)^2 \qquad \text{--------} (6)$$

Where, E is the object function.
As indicated by the slope plunge calculation, we determine the augmentation or change estimation of each weight as pursue:

$$\Delta w_{kj} = \eta (t_k - o_k) o_k (1 - o_k) o_j$$
$$\Delta w_{ji} = \eta \delta_j o_i \qquad \text{---------} (7)$$

Where, η is the rate of learning and δ_j & δ_k are given by

$$\delta_j = o_j (1 - o_j) \sum_k \delta_k w_{kj}$$
$$\delta_k = (t_k - o_k) o_k (1 - o_k) \qquad \text{---------} (8)$$

On the off chance that the pace of learning η is more, the modification or addition estimation of each weight will likewise turn out to be more and this can quicken the preparation procedure of system, however this outcome can

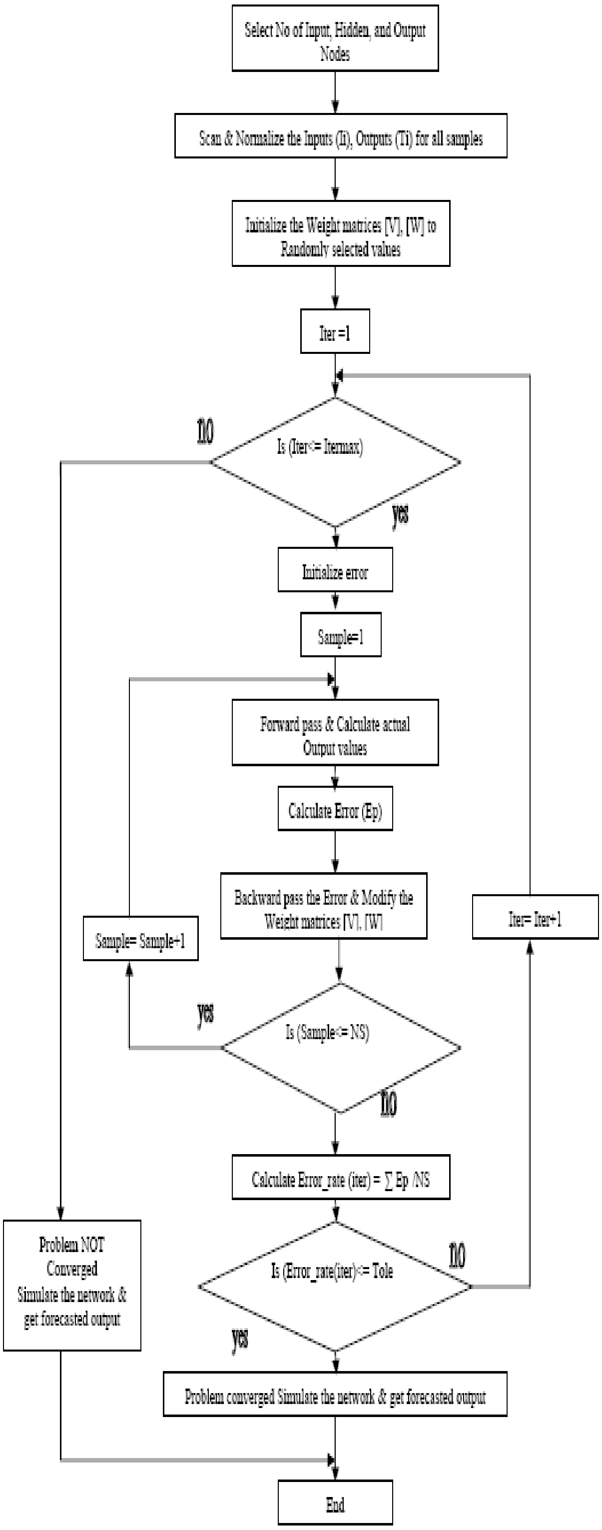

Fig.2. Flow chart for Back Propagation Neural Networks (BPNN)

produce motions. So as to maintain a strategic distance from the motions because of the expanded pace of learning η, a force term is included the recipe (7) and (8), to be specific

$$\Delta w_{ji}(n+1)=\eta\delta_j o_i+\alpha\Delta w_{ji}(n)$$

Where, α is the proportionality consistent or force factor. Through the BP system preparing (as appeared in Fig. 2.), when the exactness necessity is fulfilled, at that point the interconnect weighing between each hub are found out or put away. This finishes the preparation part of BPNN. At that point the prepared system can be utilized to distinguish the obscure example. This part is typically named as testing.

.Radial Basis Function Neural Network Model:

The Radial Basis Function Neural Network (RBFNN) model comprises of three layers viz. the info layer, concealed layer, and yield layer. The hubs inside each layer are completely associated with the past layer. The information factors are alloted to every hub in the info layer and are passed straightforwardly to the concealed layer without loads. The shrouded hubs (units) contain the spiral premise works, and are undifferentiated from the sigmoid capacity generally utilized in the Back Propagation (BP) neural systems. The Radial Basis Function (RBF) is like the Gaussian thickness work, which is characterized by an inside position and a width parameter. The width of the RBF unit controls the pace of reduction of capacity. The association between the concealed units and the yield units are weighted wholes

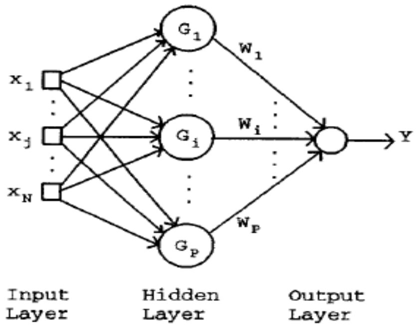

Fig.3 RBFNN structure

Training itself has two stages. At first stage the centre and width of each hidden neuron must be evaluated from the input data elements, as explained in next section, and then the

Fig.3 RBFNN structure

Training itself has two stages. At first stage the centre and width of each hidden neuron must be evaluated from the input data elements, as explained in next section, and then the weight matrix [*W*] must be trained. These loads are balanced by administered preparing strategy; subsequently a preparation set is required. This set is made out of information vector, target vector sets, where the info vector will be alluded as [X] and target vector as [T].

K-means clustering"requires a lot of beginning conditions for the focuses. These can be doled out indiscriminately, anyway this is only occasionally ideal as focuses may frequently fall in a district where there are no information vectors. It is smarter to find the focuses just where there is information close by. Some bunching "calculations may incorrectly characterize a group focus where no group exists.

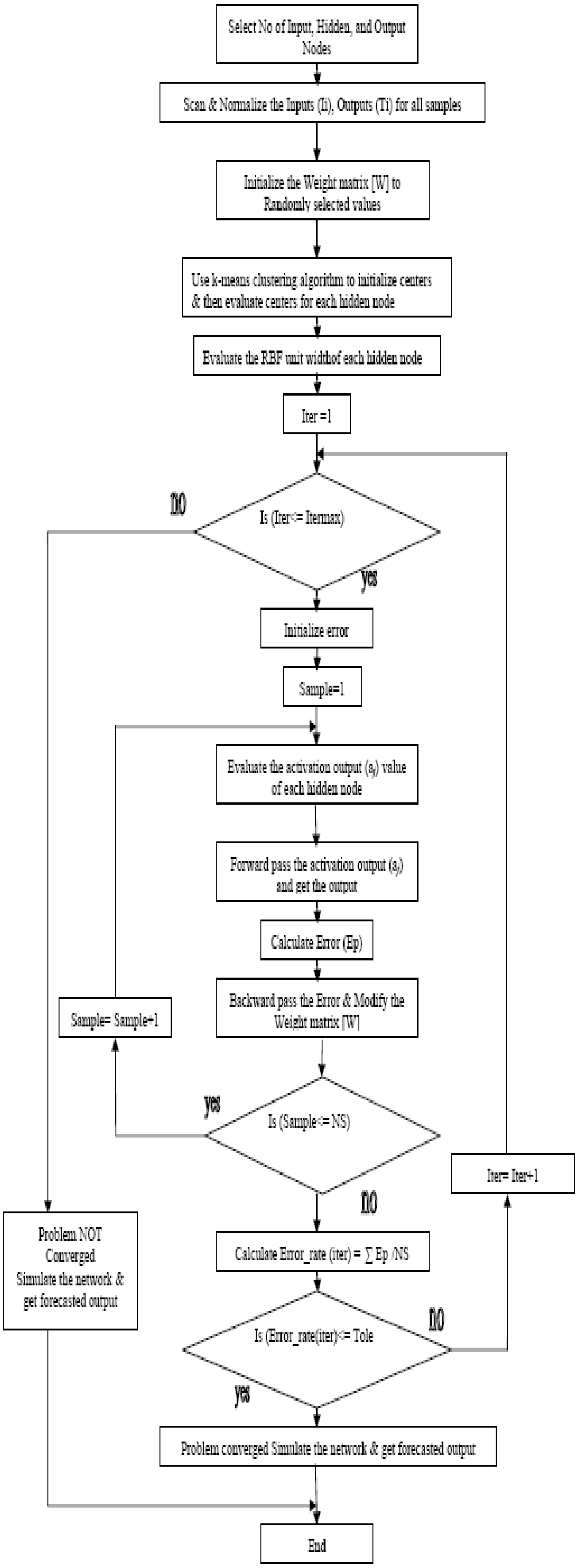

Fig. 4. Flow chart for Radial Basis Function Neural Networks (RBFNN)

This can make it difficult to prepare the yield loads related with the significant shrouded layer neuron. In the event that a group focus is characterized where no information vectors are close by, the yield of that concealed layer neuron will be basically zero for all info vectors.

The distance across of the open locale, dictated by the estimation of 'σ' can have a significant impact upon the precision of the framework. The goal is to cover the info space with responsive fields as consistently as could be allowed. On the off chance that the separating between focuses isn't uniform, it might be fundamental for each concealed layer neuron to have its own estimation of 'σ'. For concealed layer neuron whose focuses are generally isolated from others, 'σ' must be enormous enough to cover the hole, though those in the focuses of a group must have a little 'σ' if the state of the bunch is to be spoken to precisely.

While there are many methods to provide an optimal value for σ the following heuristic will often given good results.

1. For each hidden layer neuron, find the RMS distance between its center and the center of its N nearest neighbors.
2. Assign this value to σ.

III. Genetic Algorithm Based Neural Network Model

Neural systems and Genetic calculations are two strategies for learning and streamlining each with its own qualities and shortcomings. The two have by and large advanced along isolated ways. Be that as it may, as of late there have been endeavors to consolidate these two methods. It is well known that there are different learning techniques for training a NN i.e. supervised, unsupervised and reinforcement learning. Here, we use reinforcement learning to train a NN i.e. a hereditary calculation has been utilized to look through the weight space of a multilayer feed forward neural system without the utilization of any slope data. The essential idea driving this method is as per the following. A total arrangement of loads (V_{11}, V_{12}, V_{13}…W_{11}, W_{21}, W_{31}….) are coded in a string, which has an associated fitness finding the optimal weights.

The assurance of the loads of a multi-layer perceptron is in a general sense a multi-dimensional inquiry issue. In reverse mistake spread and its variations are as of now the most widely recognized strategies for scanning for an ideal point in weight space. Be that as it may, hereditary calculations give an elective technique to actualizing search. The hereditary methodology includes encoding potential arrangements as bit stings of "chromosomes", setting up an underlying populace of chromosomes and afterward utilizing the hereditary administrators of choice, hybrid and transformation to determine another populace. In principle these administrators take the best potential arrangements from the present age and join them to shape another populace, which ought to be superior to the past one. The calculation of new ages proceeds until the best arrangement is 'adequate' by some rule. The procedure requires a 'wellness' work, which returns a numerical incentive for every chromosome.

In using the genetic search for the determination of the optimal set of weights for a Neural network, we have represented the network weights and biases in a chromosome. Each chromosome represents the entire weight set of network and is an individual member of a population.

The members of the population are subjected to the standard genetic operators of selection, crossover and mutation. After each new generation of chromosomes has been computed, the weights of the neural net are determined from each chromosome and the error on the training set is calculated. The error measured is used as the fitness of the chromosome.

Procedure for GANN:

Chromosome Encoding: A noteworthy test in utilizing hereditary calculations to advance the loads of a fixed system is the encoding of the loads onto the chromosome.

The loads of a neural system are commonly genuine esteemed and unbounded, while a chromosome in a hereditary calculation is typically a series of bits of some self-assertive length as appeared in Fig. . Encoding genuine qualities onto such a chromosome presents issues both in the accuracy of the portrayal and the resultant length of the chromosome. The length of the chromosome impacts upon the size of the inquiry space of the hereditary calculation, and the effectiveness of the hunt.

An example chromosome portrayal utilized in this work as shown in Fig 5

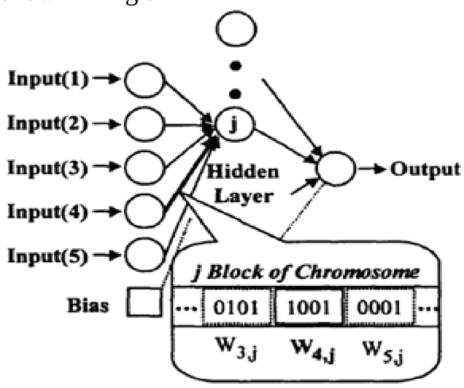

Fig 5. Coding method of GANN

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Chromosome = [V_{11}, V_{12}, ….V_{21},V_{22},…V_{31},V_{32},.….W_{11}, W_{21}, W_{31}….]

where V_{ji} = weight between i^{th} neuron of input layer and j^{th} neuron of hidden layer

W_{kj} = weight between j^{th} neuron of hidden layer and k^{th} neuron of output layer

Evaluation Function: Assessment Function: Assign the loads on the ith chromosome to the connections in a system of a given design, run the system over the preparation set of models, and return the whole of the squares of the errors.

Mean square error of p^{th} sample is calculated as

$$E^p = \frac{\sqrt{\sum (t_k - O_k)^2}}{NO}$$

In the present case, output is a single price hence $NO = 1$

Then

$$error - rate(i) = \sqrt{\frac{\sum_{P=1}^{NS} E^P}{NS}}$$ and

$$fit(i) = \frac{1}{error - rate(i)}$$

a) *Reproduction :* Selection of people which will have some piece of their hereditary material engendered through to the up and coming age of potential arrangements is done using Roulette wheel method. Every individual in the present populace has a space on the roulette wheel corresponding to that induvidual's wellness. The Roulette Wheel is spun once for each parent required, with the triumphant individua being matched for proliferation. Since by this technique people with a low wellness still get an opportunity, yet little, of being chosen for multiplication, the decent variety of the populace is somewhat held.

b) *Crossover:* Many crossover operators have been developed such as single point, two point, and uniform crossover. In this work, uniform hybrid is actualized by producing a piece cover equivalent long to the chromosome being controlled, with the estimation of each piece being resolved with some self-assertive likelihood. On the off chance that the bit of the veil equivalents to "1", the comparing bit of the parent chromosomes is swapped (or traversed) before proliferation to the posterity; and for each cover bit on the off chance that it is "0", the relating guardian bits are engendered to the posterity unaltered. Fig.6 is an pattern of uniform crossover. Probability of crossover is taken as 0.8.

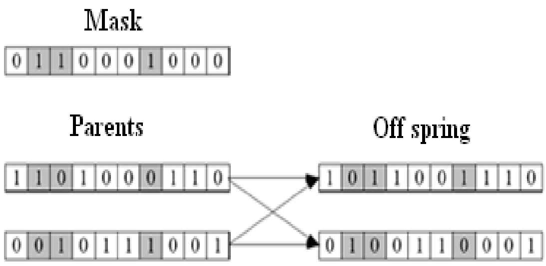


Fig. 6 Pattern of uniform crossover

Since each bit on the chromosome has some likelihood of being traded, uniform hybrid doesn't experience the ill effects of positional inclination.

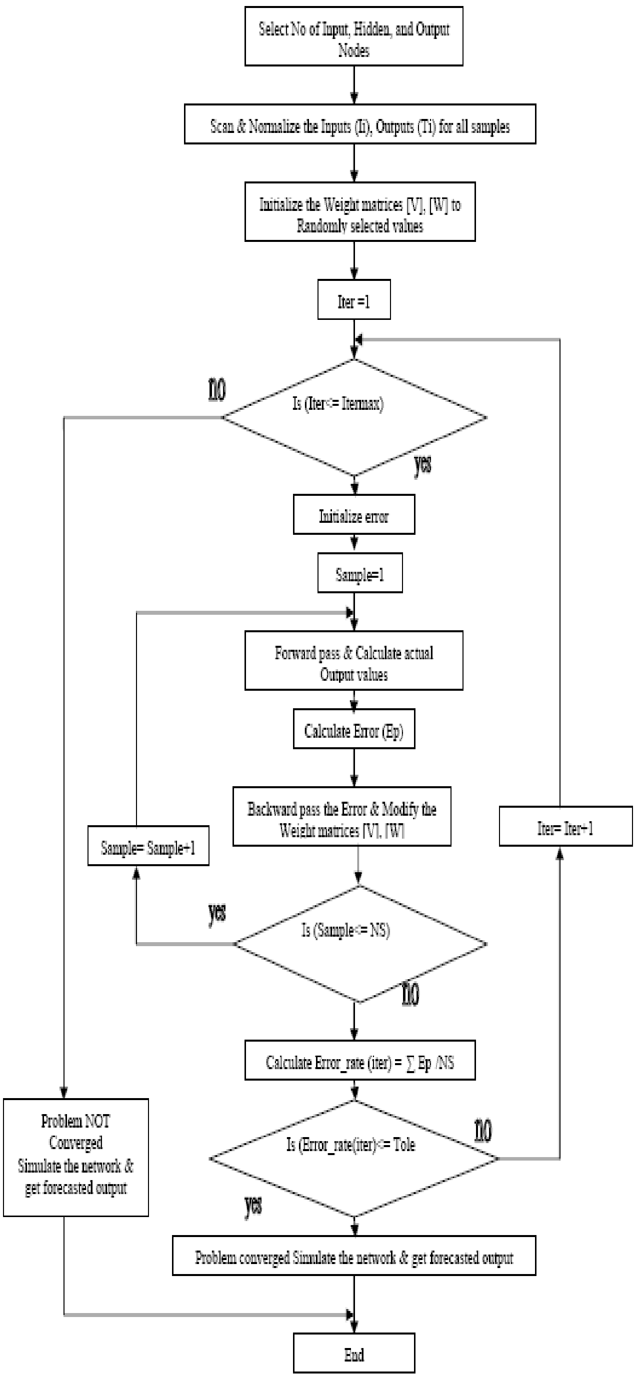


Fig 9. Flow-chart of GANN Model

c) Mutation : Mutation, which keeps up decent variety in the populace, is the irregular adjustment of people. Fig 2.9 demonstrates a case of a solitary bit change

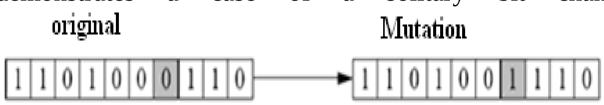


Fig 10 Example of single bit mutation

d) *Elitism:* Elitism guarantees that the best arrangement found so far is never lost when moving starting with one age then onto the next. The best arrangement of every age replaces a haphazardly chosen chromosome in the new age. Likelihood of Elitism is taken in this work as 0.2.

e) Gene Copy Operator (GCO) : This administrator chooses the most noticeably terrible fitted chromosome and replaces that with best fitted chromosome so as to increase the improvement procedure. This procedure expands the pursuit speed and enables the GA to get ideal arrangement,

IV. RESULTS

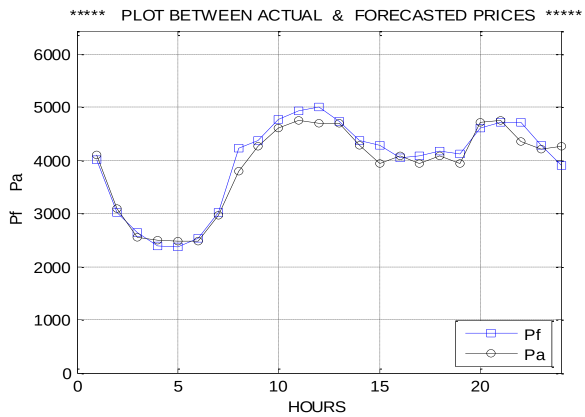
A quarter of a year information (April, May and June of 2011) is downloaded from the California pool market. A contextual analysis with the downloaded information of the day-ahead pool market costs of California is made with the over three distinctive ANN models and cost for 24 hours (from third hour of 29th June 2011 to second hour of 30th June 2011) is guage and the outcomes are demonstrated graphically in Fig.11. Day by day mean mistake is determined for the outcomes got utilizing the three models. Studies are performed by programming in

The real and estimated estimations of costs alongside MAPE for the determined period are arranged in Table 1 given beneath

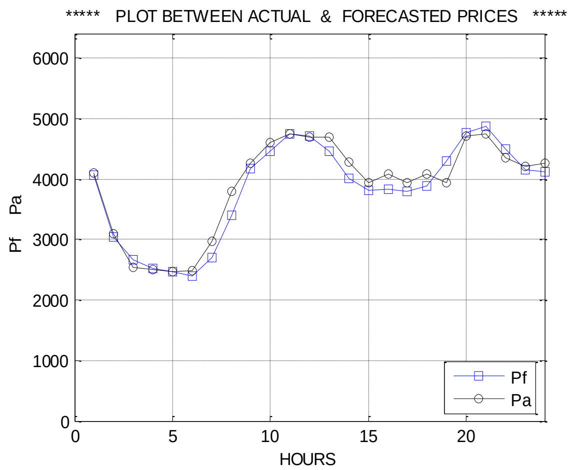
Table 1: Daily Mean Error & Training Time Of 4 Models

	BPNN	**GANN**	**RBFNN**
Daily mean error	4.9198	7.24679	4.72254
TrainingTime (sec)	75.172	175.984	85.953

BPNN



RBFNN



GANN

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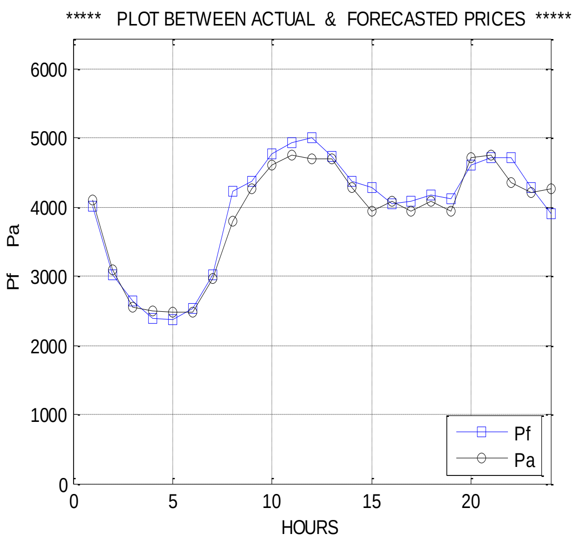

Fig.11. Actual Price and forecasted price using various models

Table 2: Actual, Forecasted Prices and MAPE (30th june 2011)

Forecasted Price				MAPE		
Actual Price	**BPNN**	**GANN**	**RBFNN**	**BPNN**	**GANN**	**RBFNN**
41	40.11	44.76	40.69	2.170	3.82	0.75
30.89	30.15	36.74	30.37	2.40	7.89	1.69
25.44	26.5	30.05	26.59	4.08	7.55	4.52
25.02	23.87	31.19	25.19	4.61	10.28	0.68
24.78	23.78	30.52	24.72	4.046	9.65	0.23
24.86	25.26	29.28	23.94	1.60	7.41	3.70
29.75	30.13	36.53	27.08	1.27	9.50	8.97
38	42.4	42.67	34.05	11.49	5.12	10.40
42.7	43.66	45.01	41.83	2.25	2.25	2.03
46.13	47.75	51.73	44.68	3.52	5.06	3.15
47.5	49.42	42.03	47.53	4.035	4.80	0.05
47.03	50.04	42.87	47.23	6.41	3.69	0.42
47.03	47.33	46.13	44.57	0.64	0.80	5.24
42.92	43.76	47.37	40.11	1.96	4.32	6.54
39.47	42.84	45.83	38.10	8.54	6.71	3.47
40.93	40.53	45.28	38.32	0.98	4.43	6.38
39.47	40.87	55.09	37.99	3.54	16.49	3.75
40.93	41.73	44.81	38.94	1.96	3.95	4.86
39.47	41.20	44.28	42.97	4.37	5.08	8.87
47.21	46.05	50.33	47.73	2.45	2.75	1.11
47.5	47.10	45.37	48.83	0.84	1.87	2.81
43.59	47.23	45.89	44.96	8.36	2.20	3.13
42.1	42.79	49.15	41.59	1.65	6.98	1.22
42.66	39.03	47.55	41.22	8.51	4.78	3.36

V. CONCLUSIONS

Three unique models of ANN are utilized for transient value guaging utilizing the downloaded information of the California pool showcase . The following 24 hours costs are determined and the test outcomes are looked at. Comparision of Daily mean mistake and the preparation time taken for preparing the system obviously sets up the matchless quality in RBFNN method and might be utilized.

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