IJIREEICE
ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526
INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 4, Issue 4, April 2016

One hour lagged Short Term Electricity Price Forecasting using ANN Algorithm

Mukh Raj Yadav[1], Kishan Bhushan Sahay[2]

M.tech Scholar, Department of Electrical Engineering , MMMUT Gorakhpur, India[1]

Assistant Professor, Department of Electrical Engineering, MMMUT Gorakhpur, India[2]

Abstract: In rebuilt power markets, determining power parameters are most fundamental errands and premise for any choice making. Estimating cost in aggressive power markets is trouble some for customers and makers with a specific end goal to arrange their work in order to accord with price prospect , and it additionally assumes basic role in monetary streamlining of the deallocated power industry. Exact, transient value anticipating is a key instrument which gives vital data to power makers and shoppers to create precise offering procedures so as to boost their benefit. In this research paper artificial intelligence (AI) is being utilized in a connection with fleeting value gauging that is, the hourly lagged forecasted of the power market. Another simulated neural system (SNS) has been utilized to register the estimated cost in Ontario power market utilizing MATLAB R14a.The author used forecasted data are one day and hourly lagged electricity cost of the Ontario electricity market. The reproduction results demonstrates exceptionally exact hourly basis lagged estimates with little mistake in cost estimating.

Keywords: One day and hourly basis lagged electricity price forecast, mean absolute percentage error (MAPE) mean absolute error (MAE) locational marginal price (LMP), short-term price forecasting, neural network (NN).

I. INTRODUCTION

Isolationism of power market causes numerous testing issues. In electricity market, cost and load gauging are the two noteworthy arranging instruments for era, transmission and conveyance frameworks. The aim of electric power industry liberalism is expert propagation, depletion of minimization and electricity in power market. To accomplish these objectives, precise and proficient power load and value anticipating has turned out to be more vital [1]-[2].

But, the crucial ultimatum related with power market in operation &planning of an ambitious market is to analyze the exact participation of power costs as these costs are exceedingly unstable. The erratic cost sums more trouble and convolution of the operational power system, there upon disturbing the role of demand side, transmission, and generation, in power market. Subsequently, a dependable, exceptionally productive and a precise value estimating apparatus are critical as it can grow well-working of force frameworks market and operations. The market operant can assume crucial of forecasted power to determine different symbol and evaluation for market survey [2]-[4].

Value determining gives critical data for power makers and purchasers to create offering systems keeping in mind the end goal to extend profit. It assumes real part in force framework operation and arranging, hazard appraisal and other choice making. Its principle target is to diminish the expense of power through rivalry, and augment productive era and utilization of power. Due to the non-storable nature of power, all created power must be devoured. Therefore, both inventor and purchaser need correct value figures with a specific end goal to build up their own particular systems for advantage or utility amplification [7]-[9].

Price and demand of electricity are generally correlative. Transient burden estimating is for the most part influenced by climate parameters. In any case, in fleeting value anticipating, costs vacillate consistently in light of the variety of the interest. Many factors which influence the electricity price, such as day of the week, month, year month, historical exaction, general demand and prices. In the Ontario power market, it is seen that day by day power request bends having comparative design, yet the day by day value bends are profoundly unstable. In this way, determining of LMPs turn out to be more essential as it markets members not just to decide the offering techniques of their generators, additionally in danger administration.

Distinctive manmade brainpower systems utilized as a part of burden what's more, value anticipating issue are master frameworks, fluffy induction, fluffy neural models, artificial neural network (ANN). Among multiple methods of forecasting, ANN's role for forecasting in power system has claimed much diligence now a day's [8]-[10]. The primary cause of ANN turning out to be so prominent lies within capacity to learn mind boggling and nonlinear connections that could be shown with traditional procedures [11].

In this research paper, another artificial neural system has been exercised to figure out anticipated cost in Ontario power market utilizing MATLAB R14a.Per hour cost and per hour power load, recorded information is being utilized as a part of forecasting. The neural system models are prepared on hourly information from 2010 to 2014 and tried on out-of-test information from 2015.The reproduction results acquired have demonstrated that artificial neural network (ANN) can make exceptionally precise short-term value estimate. The paper has been sorted out in five segments. Segment II shows the review of neural system utilized. Area III talks about the determination of different information and model of ANN for value estimating. After effects of reenactment are displayed in Section IV. Segment V talks about the conclusion and future scope.

II. ARTIFICIAL NEURAL NETWORK FOR PRICE FORECASTING

Neural systems are made out of basic components termed neuron, working in alongside. A neuron is a data handling one that is key of the process to a neural system. The 3 essential components of the neuron perfect are- Maintaining the Integrity of the Specifications.

- A definite of neuron.
- A snake for summing the information signals.

3- Initiation capacities for restricting the adequacy of the yield of a neuron
Artificial neural system is propelled through natural sensory systems. Naturally the associations in the middle components generally decide the system capacity. A neural system may be prepared for the observe a specific capacity through altering the estimations to the associations middle components. The cost and load determining, commonly, numerous information target sets are expected to prepare a neural system.

The neural system proper device comprises of two - layer feed forward system in elliptical shrouded neurons and direct yield neurons. This can fit multi-dimensional checking issues subjectively, obsessed reliable information, full neurons with shrouded layer. The neural network is capable in Levenberg-marquardt back propagation algorithm.

An immaculate able to the information ought to lie on a 45 degree line, where the neural system yields of equivalent into the objectives. On the off chance with the execution of the preparation set is great, however the test set execution to altogether more terrible, with demonstrate upon fitting, and afterward by diminishing the quantity of neurons can give great results [13].

Regression R Values measure the relationship in the middle of' yields and targets. If R value is 0 a random and if 1 means close relationship. In the event that preparation execution is more awful, then build the quantity of neurons.

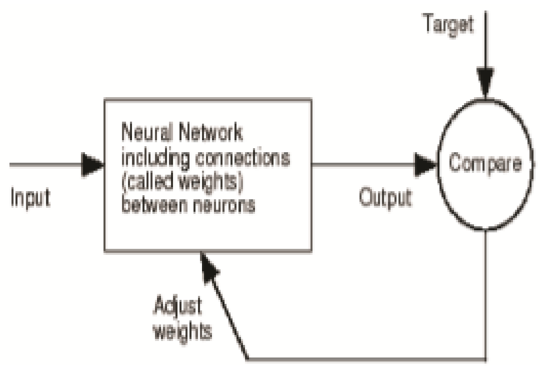


Fig. 1. Working model of an ANN by adjusting it weights

III. DATA INPUTS AND ANN MODEL

The set are prepared on hourly information of Ontario power market from 2010 to 2014 and tried upon the test information from 2015.This information utilized as a part of the ANN model are verifiable information of electricity load and hourly cost.

The ANN model incorporates making of framework to inputs through the verifiable information, choosing and adjusting the picked model and after that running the model. At the cost estimate to the inputs incorporate.

- 1 hour lagged price
- 2 hour lagged price
- 1 hour lagged Ontario demand
- 2hour lagged Ontario demand
- Hour of the day (24)
- 1 hour lagged market demand
- 2 hour lagged market demand

IV. SIMULATION AND RESULTS

In research paper one hour lagged value estimating has been accomplished through test for every month and day, of information of year 2015 utilizing neural system accept kit of MATLAB R14a.The ANNs are prepared to the information from 2010 to 2014 and tried upon the test information from 2015.The test firm are totally different from the preparation firm and are not utilized for model evaluation or fluctuating choice. The model precision upon the era is registered of the Mean Absolute Percent Error (MAPE) measurements. The main measurements recycled to assess the execution of these models, mean absolute percentage error (MAPE), is characterize in eq. 1 below.

$$MAPE(\%) = \frac{1}{N}\sum_{i=1}^{N}\frac{|P_A^i - P_F^i|}{P_A^i} \times 100 \quad \text{eq. 1}$$

Where PF and $_{PA}$ are the forecasted and actual hourly basis prices, I is the hour index and N is the number of hours.
Also, the ANN's precision on out-of-test periods is registered with the Mean Absolute Error (MAE) measurements.. It is showed in eq. 2 below-

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|P_i^{true} - P_i^{forecast}| \quad \text{eq. 2}$$

Where P_F forecast &P_A actual are the forecasted and actual hourly price, i is the hour index and N is the number of hour. MAE and MAPE has been taken as a matrix as a measure of blunder to demonstrate the viability of the ANN over a normal Range of time. The vast majority of time ANN is estimating with least conceivable mistake and high outright blunder at may be a couple examples might happen however viability of ANN stays great the greater part to the time. These blunders might likewise be checked through additional alterations in the ANN.

Different design looking at the hourly real and estimated cost for alternate day of the year 2015 is additionally created. Simulation results are talked about underneath. The ANN firm utilized as a part of the determining is appeared underneath in fig. 1. It has information, yield and one shrouded layer. Shrouded layer have 23 neurons.

Inputs of the information layers recorded upon to value cost. Reproduction results amid preparing state have been

ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526
INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 4, Issue 4, April 2016

appeared in Fig. 2. Fig. 3 demonstrates the plot of relapse acquired from reproduction.

Various arrangement design middle genuine and estimated cost and additionally design of its MAPE by testing year-2015 have been appeared in Fig. 4.Numerous arrangement design middle real cost and determined cost from 1January, 2010 and from 31 December, 2014 furthermore plots of MAPE with 26.052% in year 2015 have been appeared in Fig. 5 and Fig. 6. Numerous arrangement design middle genuine and gauge cost on 1 January, 2010 and 31 Dec, 2014 furthermore designs of its MAPE have been appeared shown below individually.

The Mean Absolute Percentage Error (MAPE) and Mean absolute Error (MAE) in the estimated and genuine cost by one day, one hour slacked has been figured and displayed in the Table I-III individually of the year 2015.

Electricity price forecast Using Levenberg-Marquardt Back Propagation Algorithm:

The Levenberg-Marquardt calculation is generally used to unravel non-direct minimum square issues. These minimization issues happen for the most part in slightest square bend fitting. The fundamental application of the Levenberg–Marquardt is at all squares bend fitting issue and can be given as an arrangement of m information focuses, (xi, yi), parameters β of the model bend f(x,β) so that the total of the squares of the deviations, The Levenberg–Marquardt calculation is an iterative procedure.

The procedure is started by giving an underlying speculation to the parameter vector β. On account of a solitary neighborhood least, the calculation works fine, not withstanding, if there should arise an occurrence of numerous essentials, the calculation meets to the worldwide minima, if the underlying conjecture is near the worldwide least [10]–[11].

The ANN model utilized as a part of the estimating is appeared beneath in Fig. 1. It has data, yield and one concealed layers. The covered up layer has 23 neurons. Inputs to the info layer are recorded as previously through electricity cost estimate.

Fig. 3 demonstrates the execution plot between the execution capacity and the quantity of emphases. The acceptance execution achieved a base on the 43th emphasis. The approval and test bends are fundamentally the same. It is clear from the approval bend that no over fitting happened.

Fig. 4 demonstrates the estimations of various preparing variable amid the preparing process, for example, inclination extent and approval checks. The quantity of approval check being characterized here equivalents to 6 which is accomplished 23 cycle.

After recreation the normal MAPE got is 26.052% for power value anticipating of the year 2015 as appeared in Fig. 5. Different arrangement plots between genuine and estimated power cost from 01January, 2015 and from 31 December, 2015.

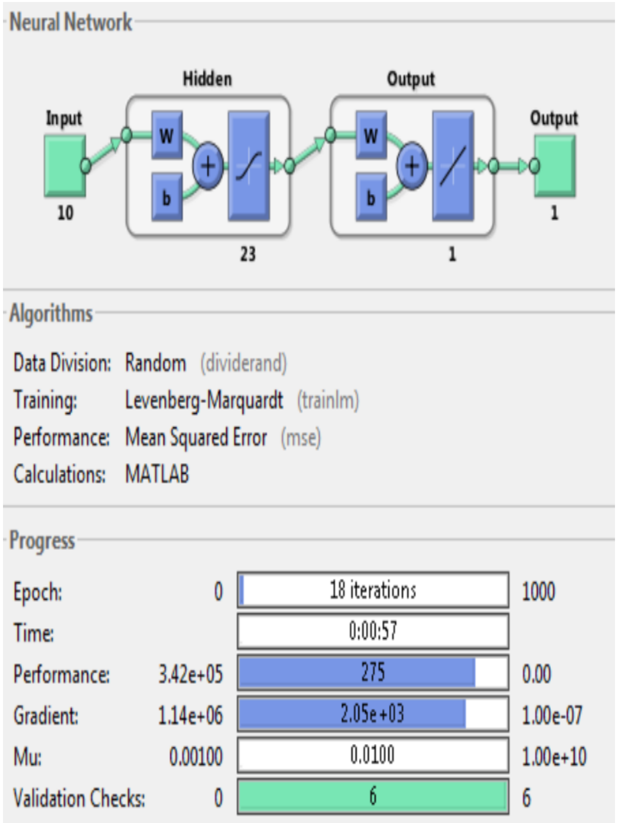
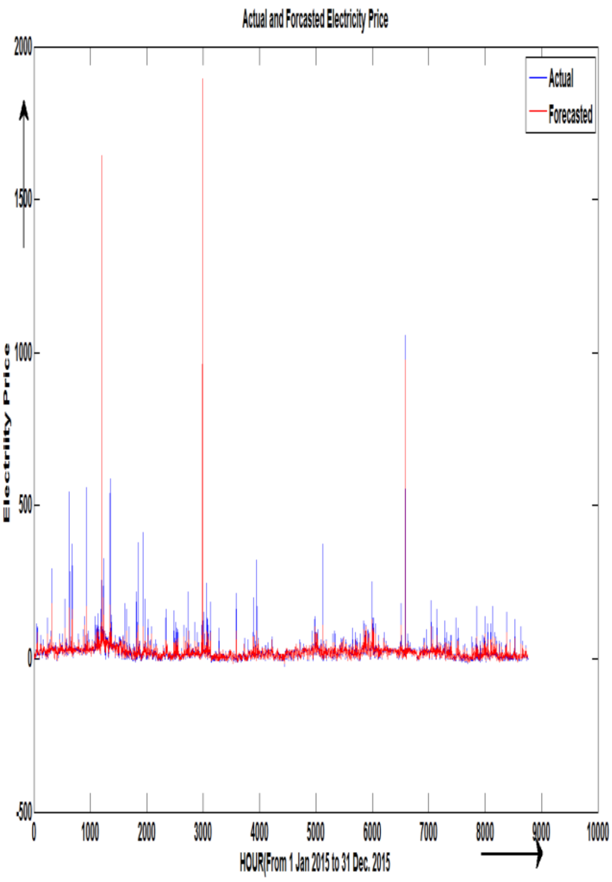


Fig. 1. Displays ten various input data for one target data with 23 neurons in hidden layer.



DOI 10.17148/IJIREEICE.2016.4418

ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526
INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 4, Issue 4, April 2016

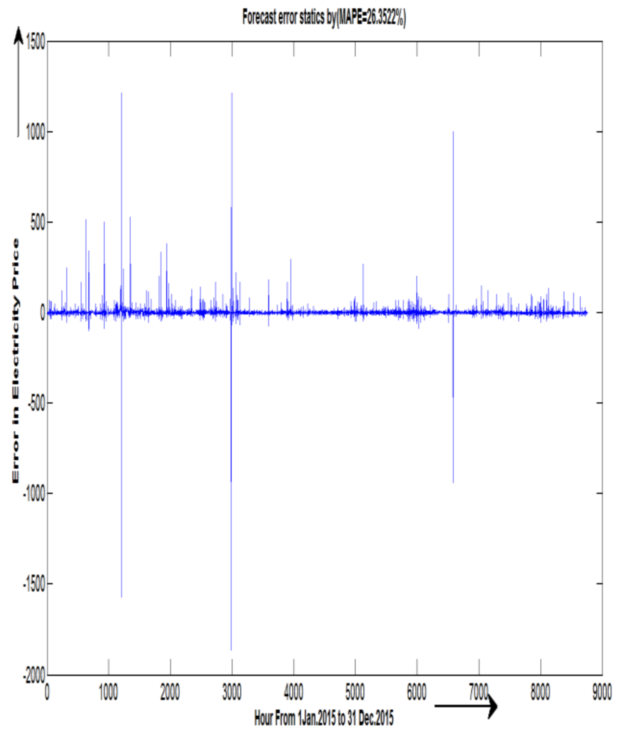


Fig.2- 3. Multiple series plot between actual & forecasted price by using ANN in the year 2015.

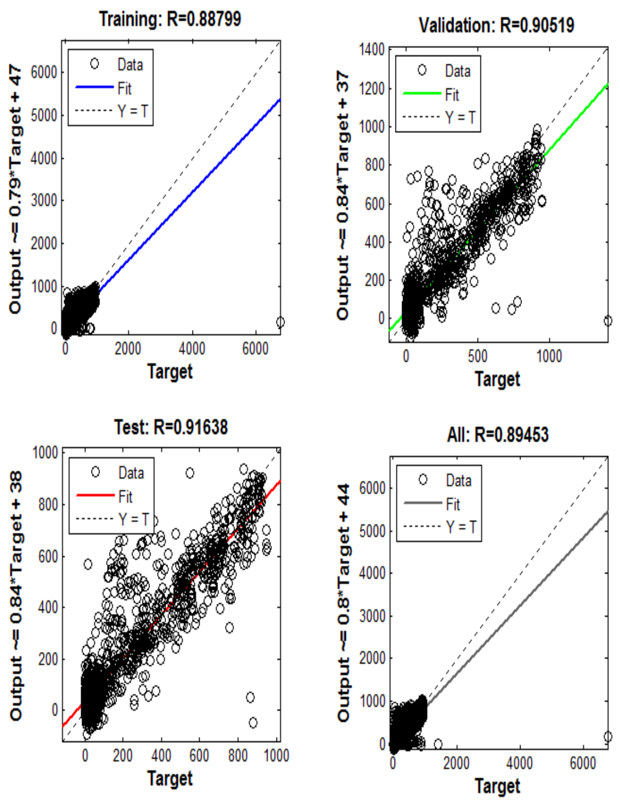


Fig. 4. Regression plot during training, testing & validation.

Elapse "R" values magnitude the connection middle the yields and the objectives. In the event that the estimation of "R" is 1,it implies there exists a cozy relationship, and in the event that it is 0, it connotes an arbitrary relationship. The execution of the neural system can be enhanced by expanding the quantity of neurons. Mean squared mistake with the normal squared contrast middle yields what's more, targets demonstrates the exactness of anticipating. Fig. 08 appears the plot of relapse acquired from recreation.

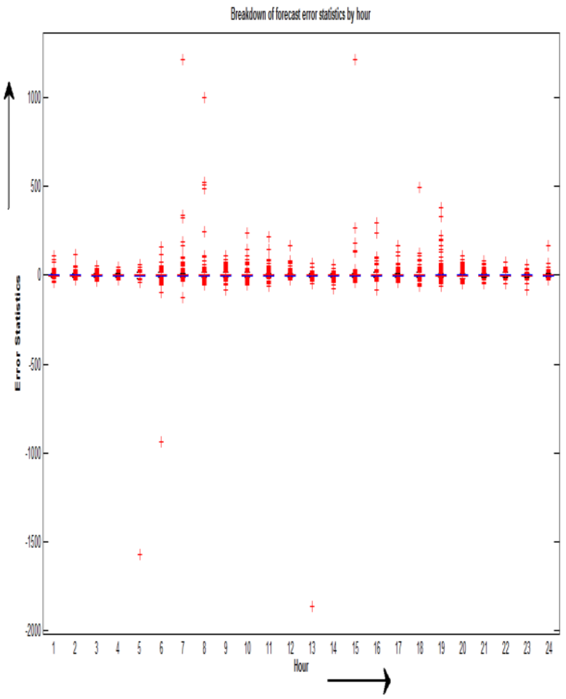


Fig 5 Simulation result of box plot.

Electricity price Forecast Using Bayesian Regularization Algorithm:

In this calculation, regularization is utilized to enhance the system by altering the execution capacity. The execution capacity turns into the entirety of the squares of the mistakes (SSE) and the total of squares of the system weights (SSW) [14]–[15].

$$F = \alpha SSE + \beta SSW \qquad 3$$

Where $SSE = \sum_{i=1}^{n} e_k^2$ *and* $SSW = \sum_{i=1}^{n} w_i^2$

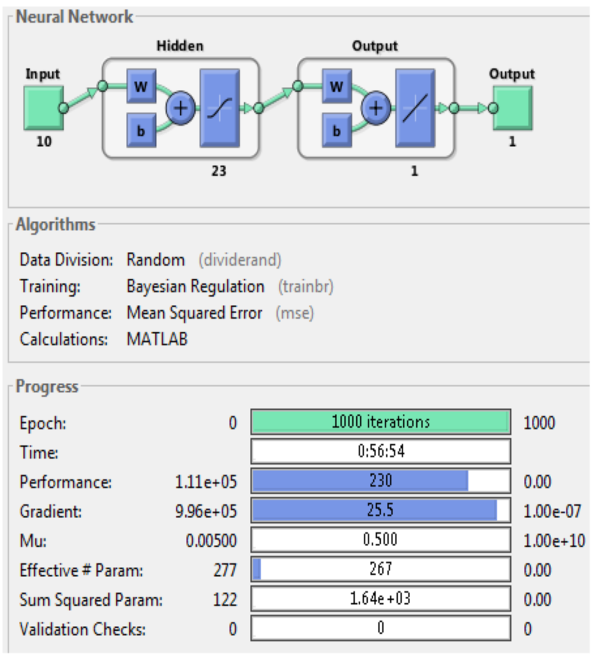
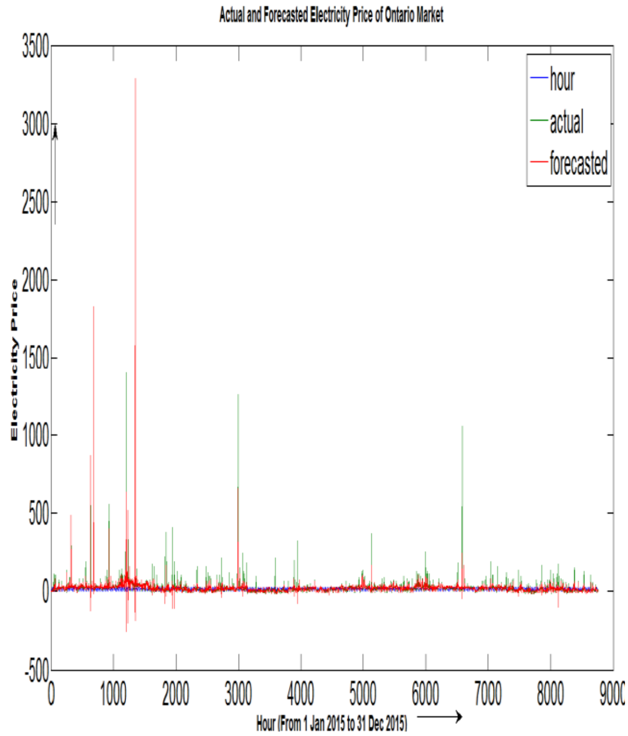


Fig.6.Ann model of Bayesian regulation.

IJIREEICE
ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526
INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 4, Issue 4, April 2016

The ANN model utilized as a part of the determining is appeared beneath in Fig. 9. It has information, yield and one concealed layers. Concealed layer has 23 neurons. Inputs to the info layer are as recorded upon the electricity cost conjecture. After recreation the normal MAPE gotten is 17.015% for Electricity price anticipating of year 2015. Fig. 6,7 demonstrates the execution plot between the execution capacity and the quantity of emphases. The acceptance capacity achieved a base 1000 cycle.



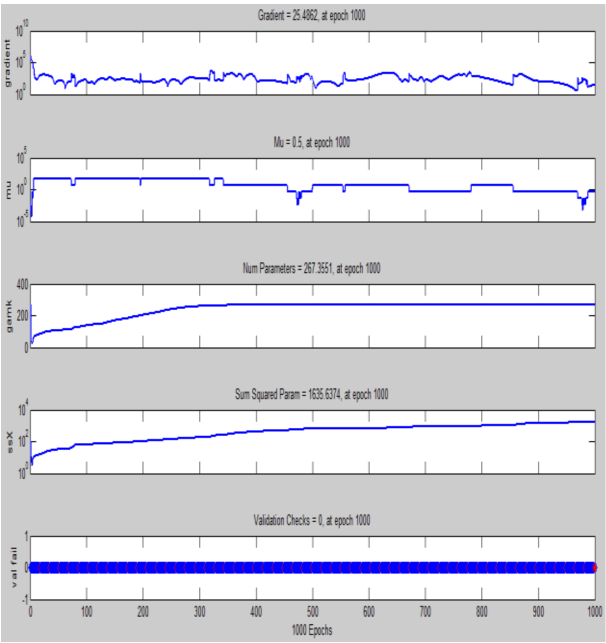


Fig. 7 training status of Bayesian method.

Electricity price Forecast Using Scaled Conjugate Gradient Algorithm:

In the scaled conjugate calculations, a hunt is performed along the heading in which the execution capacity diminishes quickly, while protecting the mistake minimization. At each cycle the stride size is balanced and a hunt is made along the inclination heading to compute the stride size. By and large, the line look calculation is utilized to decide the stride size. This line seek makes the scaled conjugate slope plunge calculations tedious as it is required in all emphases. In any case, the step size can be dictated by utilizing the Levenberg–Marquardt calculation [1]–[5]. The calculation begins toward the steepest drop given by the negative of the slope as

$$p_u = -\nabla v_u \qquad 4$$

$$x_{k+1} = x_k + a_k p_k \qquad 5$$

The ANN model utilized as a part of the determining is appeared underneath shown in below. It has data, yield and one shrouded layers. Concealed layer has 23 neurons. Inputs to the information layers recorded upon the Power value estimate. After reproduction the normal MAPE acquired is 32.2570% for Electricity use anticipating of the year 2015.From this recreation it is clear that a lasting blunder of roughly 1000 mean squared mistake (MSE) is available amid testing, preparing and acceptance. Thusly it must not be considered for fleeting Electricity value estimating. Fig. appears that the calculation neglected to achieve an age esteem in 102 cycles.

The Scaled Conjugate Gradient calculation gives poor execution for fleeting wind speed anticipating when contrasted with Levenberg-Marquardt and Bayesian Regularization calculation, yet it might give better results for long haul anticipating [2].

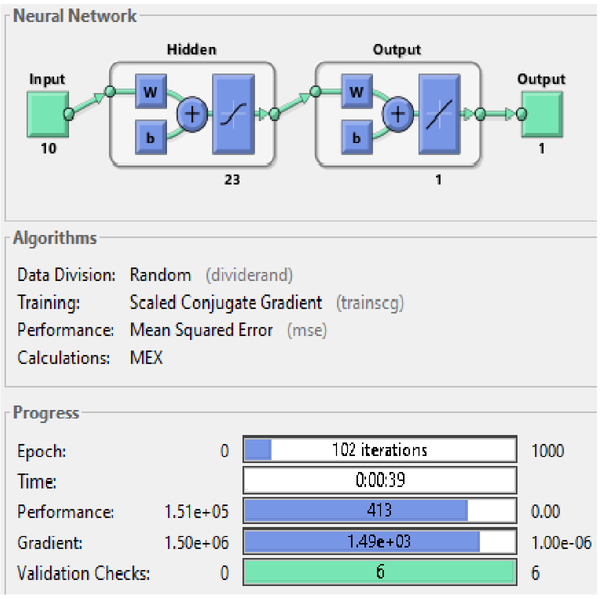
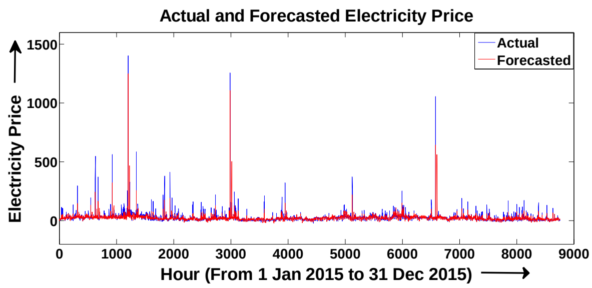


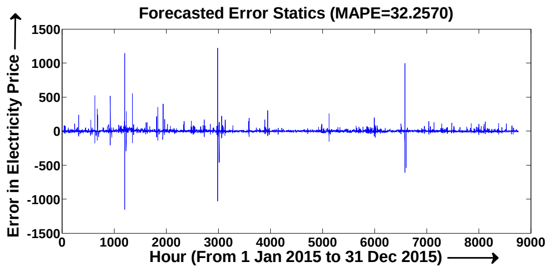
Fig. 8 ANN model of scale conjugate.



IJIREEICE

ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 4, Issue 4, April 2016



The Mean Absolute Percentage Error (MAPE) between the guage and real Electricity cost for test of every day from January-December amid one hour slacked gauge had been computed & introduced in the Table I for the year 2015.

TABLE 1: RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM JANUARY TO APRIL IN YEAR 2015

Day	MAPE % for Each Day of the Month of Year 2015 During One Hour lagged electricity price Forecast of Ontario market							
	Levenberg-Marquardt				Bayesian Regularization			
	Jan	Feb	Mar	April	Jan	Feb	Mar	April
1	97.56	10.9	13.7	34.6	121	8.6	77.5	47.8
2	31.94	17.8	29	5646	32.3	16.8	34.6	5151
3	40.46	19	20.1	1570.7	40.9	16	21	1572
4	28.7	11.9	47.8	686.2	21.7	17.7	54	2071
5	80.13	13.5	27.5	3.7	50	15.7	28.95	9
6	24.87	19.6	33.8	34.8	27.6	23	24.6	35
7	31.34	24.2	120.3	90	25.3	28.2	214.5	86
8	20.3	38.7	24.9	61.8	20.6	36.2	28.7	63.6
9	20.28	28.5	43	40	23	30.8	50	50
10	85.6	11.2	261.7	83.1	80.4	10.8	211.8	57.2
11	18.9	13.1	149	64.3	17.7	13.5	296	49.5
12	26.1	21.8	30.9	220.8	26.3	19	38.6	303
13	22.3	10.6	2523.1	1693	22.6	9.3	3527	2031
14	17.8	12.6	9.8	170.2	28.8	15.7	17.3	424
15	15.6	23.1	13.1	3.4	15.7	22.9	30	23
16	62.0	20	408.1	79.4	69.4	23	680	68
17	29.7	17.8	864.5	29.5	32.3	20.7	445	33.2
18	26.1	14.8	87.4	1005	23.5	12.3	112.8	856.3
19	18.5	38.7	37.25	585.8	21.3	45.4	33.83	878
20	10.7	118	34.8	72.1	14.3	73.2	45	85.4
21	15.9	20.7	61.9	1164	15.5	39	41.7	2140
22	14.5	60.1	36.8	36.4	19.4	69.5	45	38.5
23	22.5	37.4	19.5	59.5	18.9	43.5	18.4	53.7
24	22.6	26.5	37.5	37.5	21.1	17.9	65.1	43.5
25	27.7	43.8	170.6	68.8	25.1	84.3	126	50
26	12.5	18.6	28.2	33.1	11.8	264	32	35.6
27	23.4	11.9	82	25.4	144.5	20.9	82.8	23.8
28	13.9	12.6	21.7	28	13.4	20.5	23.4	30
29	69.6		19.3	40.4	330.6		406	41
30	49.5		91.4	25.5	55.8		86.6	23.6
31	6.6		31.5		6.6		34	

TABLE II RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM MAY TO AUGUST IN YEAR 2015

Day	MAPE % for Each Day of the Month of Year 2015 During One Hour lagged electricity price Forecast of Ontario market							
	Levenberg-Marquardt				Bayesian Regularization			
	May	June	July	Aug	May	June	July	Aug
1	24	40.2	90.5	47.8	23	51	58.4	52.4
2	47	23.8	31.6	138.6	49.1	21.6	4.1	134.4
3	69.4	162	11.6	126.4	83.1	287.4	2.9	79.2
4	329	11.4	388	33.7	69.3	37.9	458	31.6
5	302.7	131.9	26.5	4.5	155.4	162.1	12.7	7.5

DOI 10.17148/IJIREEICE.2016.4418

IJIREEICE
ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526
INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 4, Issue 4, April 2016

6	31.4	20.3	655	14.2	27.7	17.1	1407	23.9
7	14.8	45.5	54.8	19.5	21.3	30.5	73.5	18.7
8	38.3	11	5.9	29.1	48.8	9.2	8.9	34.8
9	78	19.5	26	18	75	20	34	31
10	23.1	64	63	42.1	22.8	80.3	45	45.5
11	33.4	27.7	1367	930	12.7	41	943	846
12	324.7	77	23.4	32.7	316	76.8	20.9	56.6
13	2141	53	22.3	770.5	563	59.4	24.8	650.7
14	288.7	27	19	21.6	123.8	40	15.9	23.8
15	491	31.2	6.1	16.3	-547	30.2	2.9	13.5
16	1.6	822.5	25.3	23.7	0.18	455.3	2.85	22.6
17	32	38.5	64.2	25.6	99.4	77.7	70.6	27.8
18	105	1.87	14.4	10.6	159.5	4.1	13.3	9.9
19	32.2	90.2	31.4	76.4	34.6	83.72	36.5	95.2
20	97.8	23	20	130.6	108.4	19.3	17.6	40
21	63.6	30.4	19.2	3702	101	37.3	20.4	3025
22	71.2	297	2.9	32.9	83.2	331.8	2.2	37.4
23	888.7	62	9.7	32.2	897	57.4	14.2	50.2
24	37.1	92.4	13.4	46.8	92.4	85	12.1	57.1
25	598	13.5	24.2	35.6	1769	15.4	21.7	40
26	57.6	38.4	21.8	33.8	70.4	34	26	46.3
27	49	70	32.3	450	79.3	67	32.7	1096
28	26.5	2.94	20.2	14.2	91	38	18.5	19.6
29	45.5	59.72	14.1	3.5	61.2	37.9	16.6	7.9
30	81	0.25	15.8	0.64	85	19.6	13.6	8.9
31	1575		18.7	17.6	-436		15.2	19.8

TABLE III RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM SEPTEMBER TO DECEMBER IN YEAR 2015

Day	MAPE % for Each Day of the Month of Year 2015 During One Hour lagged electricity price Forecast of Ontario market							
	Levenberg-Marquardt				Bayesian Regularization			
	Sep	Oct	Nov	Dec	Sep	Oct	Nov	Dec
1	26.8	24.7	131.5	72	23.1	19.4	14.3	9.32
2	36.3	158.6	74.9	18.6	34	62.7	13.9	21.4
3	24	147.8	35.8	30.7	20.7	44.25	77.3	30.3
4	26.3	18	41.8	9.4	26.4	9.8	30.2	11.7
5	28.3	11.2	81.2	30.2	30.7	16.8	14.6	9.62
6	166.4	10.2	6.3	24	266	16.77	21.7	35.5
7	84.5	12.4	64.6	26.7	98.1	19.3	15.8	6.7
8	50	10.5	45.6	74.8	41.1	12.19	14.3	11.6
9	29.1	13.6	143.8	2.4	24	12.58	12	14.8
10	46.5	40.2	46.3	219.3	33.2	12.16	8.77	16.9
11	17.9	258.6	169	19	20.3	28	15.8	16.5
12	114.2	34.9	42.4	44.4	141.4	21	15.3	15.5
13	42.8	73.5	170.1	15.2	37.1	13.78	19.4	9.65
14	30.5	19.5	12	0.83	41.4	12.46	13.3	7.54
15	655.5	41.3	50.3	88	657.4	9.64	9.06	6.8
16	22	47.7	39.3	148.4	19	15.95	15.8	13.3
17	11.7	16.6	24.33	52.7	9.1	12.75	23.9	7.36
18	13.3	29.5	12.43	21.7	8.5	24.72	12.1	8.63
19	35.9	16.4	40.4	291.9	32.5	36.46	13.8	7.24
20	19.5	27.4	48	96.84	18	17.06	11.2	10.6
21	16.9	21.7	7.2	71.7	14	12.47	15.4	10.2
22	10.5	82.2	90.2	59.7	8.8	18.08	19.6	14.2
23	7	20.8	10.8	270	9.8	14.72	13.1	13.3
24	7.3	53.5	106.1	25.7	7.5	14.41	7.75	22
25	8.4	489	62.1	3.6	10	7.423	9	11.3

26	20.1	20.3	1113	3.1	29.6	9.98	16	43.2
27	45.1	27.5	20.8765.6	16.8	49.1	10.94	20.7	12.5
28	22.6	73.5	34.2	185	22.1	7.2	14.0	15.7
29	28.1	24.6	42.1	61.7	32	18.3	13.6	15.5
30	58.2	14	78.4	36.8	59.1	8.463	28.1	27.2
31		95.6		110.5		14.44		33.7

V. CONCLUSION AND FUTURE WORK

In this research paper author use different Ann algorithm such as Levenberg-Marquardt ,Bayesian and scale conjugate gradient method and found the Mape in percentage as 26.052,17.015 and 32.570. the data taken from Ontario Electricity market for training from 2010 to 2014 and for testing data taken from 2015.so using Ann method and using this training and testing so compare Mape(%) Bayesian method are more efficient compare to other method.

REFERENCES

1- Paras Mandal, Tomonobu Senjyu, Katsumi Uezato, and ToshihisaFunabashi, “Several-Hours-Ahead Electricity Price and LoadForecasting Using Neural Networks,” IEEE PES Conference, vol. 3, pp.2146-2153, ISBN:0-7803-9157-8 ,June2005.
2- Malliaris ME. Modeling the behavior of the S&P 500 index: a neuralnetwork approach, 1043-0989, IEEE; 1994.
3- M. Shahidehpour, H. YaminandZ.Li, Market Operations in Electric Power Systems:ForecastingScheduling and Risk Management. JohnWiley & Sons, 2002.
4- Smith M. "Neural Networks for StatisticalModelling". Van Nostrand Reinhold. New York 1993.
5- Mandal, P., Senjyu, T., Funabashi, T., 2006, “Neural networksapproach to forecast several hour aheadelectricity prices and loads in deregulated market”, Energy conversion and management , 2128-2142.
6- E. Guresen, G. Kayakutlu, T.U. Daim, Using artificial neural network models instock market index prediction, Expert Syst. Appl. 38 (8) (2011) 10389–10397.
7- Amjady N, Daraeepour A, Keynia F. Day-ahead electricity price forecasting bymodified relief algorithm and hybrid neural network. IET Gener, Transmiss Distrib 2010;4(3):432–44.
8- Yamin, H., Shahidehpour, S., Li, Z., 2004, “Adaptive short-term electricity price forecasting usingartificial neural networks in restructured power markets”, Electrical power and energy systems , 571-581.
9- Areekul, P., Senjyu, T., Urasaki, N., & Yona, A. (2011). Neural-wavelet Approach for Short TermPrice Forecasting in Deregulated Power Market. Journal of International Council on ElectricalEngineering, 1(3), 331–338. doi:10.5370/JICEE.2011.1.3.331
10- Arroyo JM, Conejo AJ. Multi-period auction for a pool-based electricity market.IEEE Trans Power Syst 2002;17(4):1225–31
11- Hong Y-Y, Hsiao C-Y. Locational marginal price forecasting in deregulated electricity markets using artificial intelligence. IEE Proc Generat Trans Distribut 2002;149(5):621–6.
12 M. Stevenson, “Filtering and Forecasting Spot Electricity Prices in the Increasingly Deregulated Australian Elec-tricity Market,” Quantitative Finance Research Centre, University of Technology, Sydney, 2001.
13-Hagan, M.T., & Menhaj, M., (1994) “Training feed-forward networkswith the Marquardt algorithm,” IEEE Trans. Neural Networks, Vol. 5, No.6, pp989-993.
14- E.M. Johansson, F.U. Dowla, and D.M. Goodman, “BackpropagationLearning for Multilayer Feed-Forward Neural Networks using TheConjugate Gradient Method,” International Jouurnal of Neural Systems,vol. 02, issue 04, 1991.
15- Sheela Tiwari, Ram Naresh, and Rameshwar Jha, “Comparative Study ofBackpropagation Algorithms in Neural Network Based Identification ofPower System,” International Journal of Computer Science andInformation Technology (IJCSIT), vol. 5, no. 4, August 2013.