Microstructure, Wear behaviour and Electrical conductivity of Cu-graphite Metal Matrix Composite Prepared by Powder Metallurgy Route

DR. RABINARAYAN BAG, Department of Mechanical Engineering, NM Institute of Engineering &Technology,Bhubaneswar

This paper presents a solar power modelling method using artificial neural networks (ANNs). Two neural network structures,namely,generalregressionneuralnetwork(GRNN)feedforwardbackpropagation(FFBP),havebeenusedtomodelaphotovoltaic panel output power and approximate the generated power. Both neural networks have four inputs and one output. The inputs aremaximum temperature, minimum temperature, mean temperature, and irradiance; the output is the power. The data used in thispaperstartedfromJanuary1,2006,untilDecember31,2010.Thefiveyearsofdataweresplitintotwoparts:2006–2008and2009-2010;thefirstpartwasusedfortrainingandthesecondpartwasusedfortestingtheneuralnetworks.Amathematicalequationisusedtoestimatethegeneratedpower.Attheend,bothofthesenetworkshaveshowngoodmodellingperformance;however,FFBP hasshownabetterperformancecomparingwithGRNN.

1. Introduction

Thesunisoneoftheprimarysourcesofenergyformostof the natural processes such as heat, wind, and rain. Themost effective conversion of sunlight into chemical energycan be seen in photosynthesis procedure. Currently humankind is using fossil fuels as their primary energy source butthe fossil fuels are not an appropriate source of energy. Thisleadstotheusageofsunlightasarenewablesourceofenergy to produce electricity, called solar power. Moreover, solarenergy is green energy and it is environmentally friendly.Photovoltaic panel and solar thermal are the main sourcesforelectricitygenerationfromsolarenergy.Thepredictionofpower generation from solar energy is gaining considerableattentionduetotheincrementofpowergenerationfromsolarenergy [1]. Numerical models have been developed to forecastweather and solar power; however, they require a powerfulcomputingsystem[2,3].

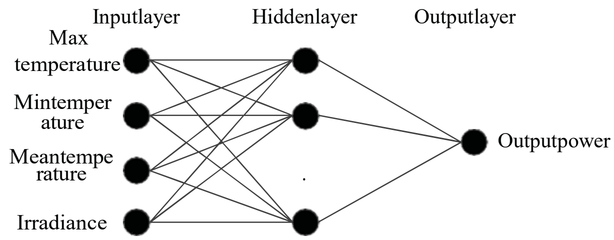
An artificial neural network assimilates human brainlearning system and is able to find an input-output relation-shipforlinearandnonlinearsystemswithlesscomputational effort. This leads to the wide usage of artificial neural net-works to forecast various criteria such as irradiance andtemperature [4, 5]. In general, neural networks are universalapproximators [6]. The original of ANN was introduced byMcCulloch and Pitts [7]. Although there has been researchintothepredictionofsomeparameterssuchastempera-ture and solar radiation, there has not been comprehensiveresearch into the power prediction. A forecasting methodusingANNhasbeenproposedforsolarradiationin[8].Thepower generation of photovoltaic panels depends on solarradiation, temperature, humidity, and so on [9–13]. Theseparameters are naturally variable and nonschedulable; thus,theamountofgeneratedpowerisgenerallyunknown.Feed-forwardbackpropagation(FFBP)andthegeneralregressionneuralnetwork(GRNN)havebeenaffirmedastwoeffectivemethodsinmodellingandpredictionbypreviousresearchers[14]. These two models are employed for the prediction ofPV output power in this research since they have showntheireffectivenesscomparedtostatisticalandautoregressionapproaches. [15]. PV plant modelling has become an activeresearchfieldinthelastfewyears,withthedevelopment

ISSN: 2278-4632
Vol-09 Issue-12 No. 1 December 2019

ofnewmodelsbasedonartificialintelligencetechniques[16].Also,solarradiationforecastingmethodsarepresented in[4,17]andamethodforsolarpowerforecastingisdiscussed in [18]. On the other hand, power planning isnecessary for cost efficiency of power generation in whichpower forecasting is an essential part [14, 19]. Some data isrequired in order to predict a solar panel generated power.However,sometimessuchdataisnotavailableduetothe lack of related databases [8]. Therefore, forecasting is requiredfor sizing and meteorological data prediction [19, 20] toachieveanincreaseintheefficiency[21]andtoscheduletheoperation of the system [18]. The artificial neural network(ANN) is widely used for solar data prediction in previousresearch work. AbdulAzeez [17] evaluated an artificial neuralnetworkforglobalsolarradiationinNigeria.Chenetal. [18] improved the neural network to forecast the power ofPV panels. They mentioned that this method is accurate andefficientintheoperationofaPVsystem.Linares-Rodr´ıguezet al. [20] explained a multilayer perceptron feedforwardneural network. These authors applied a trial process to findasuitablenumberofhiddenlayersforthepredictionofdailyglobalsolarradiation.Theyconcludedthatalthoughtherearesmallchangesintheresultsforadifferentnumberofhiddenlayers, the cost of computing is different and 25 neurons inthehiddenlayersis assumedasthebest number.Paoliet al. [21] used a MLP to develop a methodology for solar radiationprediction.Theauthoremphasizedthattheabilityofan ANNfor prediction is high. The application of ANN has someadvantages such as the following: the mapping function inneural network is very flexible and neural network have theability of generalizing form a limit set of data points andgiving a good results at new data points [22]. Only a fewdescribeforecastingmodelsusedtopredictdirectlythedaily energyproductionofthePVplant[23].

2. BackgroundofResearch

ANN[18,21]anditsrelatedmodelssuchasFFBP[4,18,19,24]and GRNN [8] are shown to be popular methods amongauthors. ANN is a model based on interconnected neuronsto create an output by processing information based on theinput.Therelationshipbetweentheinputandtheoutputisbasedontheweightoftheneuronsandtheinputdatafor which the neurons have to be trained to the system [8].Naini[25]discussedtheapplicationofthreedifferentneural networks structures such as radial basis function network,FFBP,andGRNNforpredictionofthecharacteristicsofthescour hole geometry. Vigneswaran and Dhivya [26] appliedfive accurate neural network models including FFBP andGRNN and concluded that GRNN has better results. Theworkdiscussedin[27]consideredwindspeedforecastingby usingFFBP.Inanotherwork[28],theauthorsusedFFBPtopredict the velocity of crude oil. In [29] the authors appliedFFBP



for temperature forecasting and concluded that thismodelhadtheproperpotentialforcomplexmodellingofthe relation between various factors. The authors in [30]mentioned that FFBP is the best model of neural networkforreal-timeforecastingduetoleasttrainingtimeandfast

FIgURe1:DiagramofpredictionusingFFBP.

response.In[31]theauthorsstatedthatFFBPisoneofthemostp opularconfigurationsofanANN.Theauthorsin[14]undertook loadforecastingusingFFBP.Zhaoetal.
[32] employed GRNN as one of the models employed toforecast wind power density. Some researchers have usedmany types of ANN for comparison and analysis of issuesrelatedtosolarpanels.Khatibetal.[8]appliedfourtypeso f ANN for forecasting solar radiation forecasting. TheirresearchwasbasedonGRNN,FFNN,cascadeforwardba ck propagation neural network (CFNN), and Elman backpropagation (ELMNN) scheme. Based on their research, theGRNN is better than the other models with a high level ofaccuracy and efficiency. One of the major advantages of aGRNN is defined as the effective relation of the model andtheinput[33].

3. ArtificialNeuralNetwork

3.1. FeedforwardBackPropagation(FFBP). Amongthediffer-entformsofANN,feedforwardbackpropagationandgeneralre gressionneuralnetworksareproposedinthisresearch.Afeedfo rwardneuralnetworkisdefinedasasimpletypeof neural network in which the information flow is in theforwarddirection.Corani[34]utilizedafeedforwardneural network (FFNN) for air prediction in Milan. He describedthe structure of the FFNN in different three layers. An inputlayer was used for data collection, a hidden layer for dataprocessing by neurons and the output layer for the results.Back propagation (BP) is assumed as a popular learningtechnique for feedforward [12] neural networks.
ThereforetheFFBPisdefinedasamodelforforecastingparamet ersandthediagramofpredictionusingFFBPshowninFigure1.

The FFNN is defined as a type of MLP network withspecialinputvalues.Thesevaluesthataremultipliedbythe irweight are led to the hidden layer by neurons. In separatework, Khatib et al. [35] developed an artificial neural networkfor solar prediction in Malaysia. He provided a feedforwardmultilayerperceptionmodelwithfourinputsforth ecalcula-
tion.Thetrainingprocessforthebackpropagationalgorithmin cludesafewsteps.First,theweightsareinitializedforthe neurons and the measured output is compared with thedesired value to calculate the error. In the second step theweights are changed based on the error. In this way, theerror is propagated backward to update the weights of thepreviouslayers[19].Kumarietal.[15]usedaneuralnetworkf ortemperaturepredictioninIndia.

ISSN: 2278-4632
Vol-09 Issue-12 No. 1 December 2019

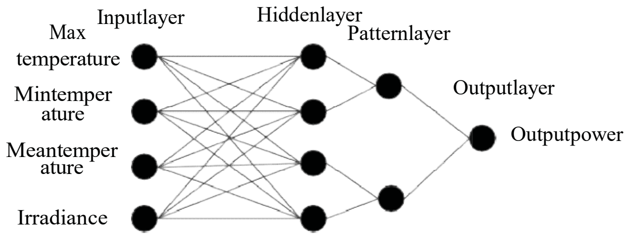


FIGURE2:ArchitectureofGRNN.

TABLE 1: Cell open circuit voltage and maximum power point voltageatdifferentirradiance.

Irr(W/m^2)	$\square_{oc}$(v)	$\square_{mpp}$(v)	$\square_{mpp}/\square_{oc}$
1000	30	23.8	0.793
800	29	22.9	0.789
600	28.56	22.27	0.78
400	27.75	21.6	0.778
200	27	20.8	0.77

Mellit and Pavan [4] provided a feedforward neural networkforsolarradianceforecastinginItaly.Theyproposedamultilayerperceptron(MLP)modelwithabackpropagation trainingalgorithm.Therefore,the24-hoursolarirradiancecanbeforecastedbyusingaMLPneuralnetwork.Ahmedand Adam[24]exploredapredictionmodelforsolarradiationbyuseofanartificialneuralnetwork.TheANNinthatstudywasa feedforward back propagation model. The results provedthat this method is precise and suitable for forecasting solarradiation.

3.2. GeneralRegressionNeuralNetwork(GRNN). AGRNNis defined as a probabilistic neural network that is definitelyuseful for prediction and performance comparison. GRNNis a new kind of neural network that Specht put forward in1991[36].ThenetworkofaGRNNisthesameasanFFNNwith input, hidden, and output layers. The values from thehidden layer are led to a pattern layer. The pattern layerworks as a summation layer with denominator summationandnumeratorsummationneurons.Thevaluesofthe hiddenneurons are added by the denominator summation part andthevaluesfromthemultiplicationoftheweightsoftheactualvalues of the hidden neurons are added by the numeratorsummationpart.Theoutputwillbethedivisionofthevaluesfromthesetwopartsasshownin Figure2.

4. Methodology

Meteorologicaldatasuchasthetemperatureandsolarirradiancewerecollectedfromthe MalaysianMeteorologicalDepartment(MMD)thatincludesthedailyminimum,mean average, and maximum temperature and solar irradiancestarting from January 1, 2006, to December 31, 2010. All datawas collected from the Kuala Lumpur International Airport(KLIA)stationandthesampledataformodellingofPVisshown in Table 4. However, a solar panel was not placed atthis center and therefore the generated power data is notavailable.Thesolarirradiancemeasuredispresentedinunits ofMJ/m^2.Themostcommonlyusedunitforsolarirradiationin photovoltaic system calculations is W/m^2. Thus, these dataareconvertedaccordingtothefollowingequation:

$$\frac{\text{MJ}}{}\times\frac{1000000}{}=\frac{\text{Wh}}{}. \qquad (1)$$

otherwords,thedaylength(DL)isrequiredtobesubstitutedby h inthecalculationwhereDLcanbecalculatedas[8]

$$\text{DL}=\frac{2}{15}\cos^{-1}(-\tan\square*\tan\square), \qquad (2)$$

where□isthelatitudeand□isdefinedasthedeclinationangle.Thevalue□isgivenby[8]

$$\square=23.45\sin\left[\frac{360(284+\square)}{365}\right]. \qquad (3)$$

In(3),□isthenumberofdaysandforthefirstdayofJanuary(□ = 1),thesolardayisconsideredtobe284.

Thenextstepistocalculatethetwoimportantparametersofsolarpanelwhicharetheopencircuitvoltage($\square_{oc}$)andtheshort circuit current [37]. Both of these essential parametersareafunctionofthesolarirradianceandtemperature. However,inthedatasheetofthesolarpanel[38]whichis used in this research, the $\square_{oc}$and $\square_{sc}$are given at twocertainpointsof(Irradiance= 1000W/m^2,Temperature= 25°C) and (Irradiance= 800 W/m^2,Temperature= 20°C).However,inmodellingcalculations $\square_{oc}$and $\square_{sc}$atdifferent irradianceandtemperaturesareneeded.Inotherwords,the mathematical relation betweenthese two parameters andthe environmental factors of temperature and irradiance isrequiredforsolarpanelmodelling.

Accordingly the maximum power point voltage at theoperatingtemperatureandirradianceiscalculatedasfollows:

$$\square_{mpp}=\left(\frac{\square_{oc}\times\square_{T}}{100}\right)\times 0.78, \qquad (4)$$

where $\square_{mpp}$isthevoltageatthemaximumpowerpointand $N_T$isthenormalthermalcoefficient.

Thevalueof0.78isanestimatedcoefficient.Itisestimatedthatthemaximumpowerpointvoltagecanbeconsideredas 0.78 of the open circuit voltage at a different workingpoint.Thisvalueistheaverageratioof $\square_{mpp}$tothe $\square_{oc}$that iscalculatedbasedontheavailabledatainthecelldatasheet. Table 1 shows the cell open circuit voltage and maximumpowerpointvoltageatdifferentirradiance.

Finally, the power can be estimated as in the followingequation:

ISSN: 2278-4632
Vol-09 Issue-12 No. 1 December 2019

m^2 60×60 m^2

In order to convert the Wh/m^{2}to W/m^{2}the data valuesshouldbedividedbythehours(h).Inthiscase$h$isconsidered tobethetimeinwhichthesolarirradianceisavailable.In

$$□=□_{mpp}\times□^2. \quad (5)$$

Thereforethepowerfortheminimum,maximum,andmeantemperaturecanbeestimatedbasedon(5).

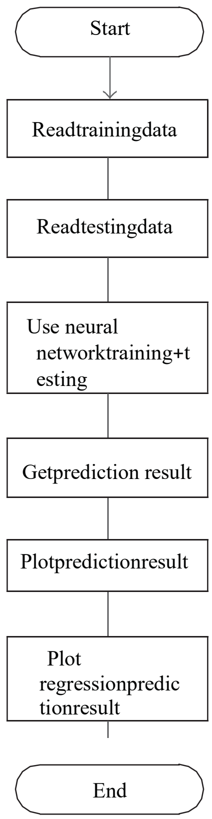


FIGURE3:FlowchartofFFBPmethod.

4.1. *FFBPMethod.* Thefeedforwardbackpropagationmethodisusedasafirstneuralnetworkmodelforthisstudy.TheappliedflowchartofFFBPisshowninFigure3.

AsshowninFigure3,thepredictionresultsarebasedonreadingthetestingandtrainingdataandusingFFBP.

Before the training process, all the data must be normalized. Various normalization methods are used for neuralnetworks to increase the reliability of the trained network[39]. The Min-Max normalization is applied in this researchasfollows:

$$\square=(\square-\square_{\min})\left[\frac{\square_{\max}-\square_{\min}}{\square_{\max}-\square_{\min}}\right]+\square_{\min}, \quad (6)$$

where□isthenormalizedvalueand*b*isanonnormalizedvalue. For thiswork, $\square_{\max}=1$ and $\square_{\min}=-1$.

Afterobtainingtheresult,thenormalizedvaluesmust becomenormalbyusingthefollowingformula:

$$\square=(\square-\square_{\min})\left[\frac{\square_{\max}-\square_{\min}}{\square_{\max}-\square_{\min}}\right]+\square_{\min}. \quad (7)$$

Themeansquarederror(MSE)isusedforevaluationofpredictive powerasfollows[15]:

$$\mathrm{MSE}=\frac{1}{\square}\sum_{t=1}^{N}(\square_t-\square_t)^2, \quad (8)$$

where $\overline{\square}_t$ is a vector of the □ prediction and $\square_t$ is the

TABLE2:MSEforFFBP.

Number of neurons inhiddenlayer	MSEtrain	MSEtest	Regression
3	0.00019	0.000232	0.999157
4	0.000322	0.000278	0.999005
5	0.000364	0.000343	0.998773
6	0.000155	0.000156	0.999427
7	0.000164	0.000187	0.999328
8	0.000136	0.000162	0.999405
9	0.000137	0.000162	0.999408
10	0.000104	0.000141	0.999482

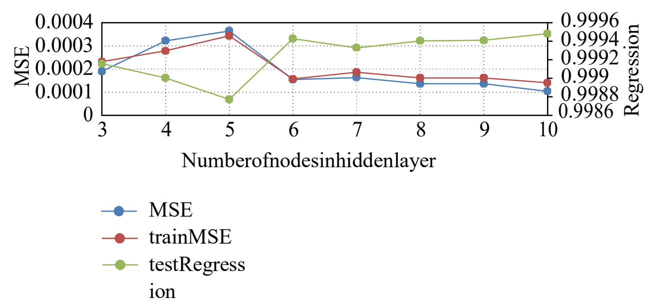


FIGURE4:MSEwiththenumberofnodesinhiddenlayer.

4.2. *GRNNMethod.* GRNNasaprobabilisticmodelcanperformclassificationandregressionfordefiniteandcontinuoustargets [8]. For the purpose of normalization, (6) and (7) areusedinthismodelwithsomedifferences.

The values $\square_{\max}=1$ and $\square_{\min}=0$ are applied in (6) and(7).TheerrorcalculationisthesameasinSection4.1and(8).

5. ResultandDiscussion

Atrialforinvestigationofthenumberofnodesinthehiddenlayerisevaluatedtofindthe MSEoftheFFBPneuralnetwork.Table2representsthetrainingMSE,testingMSE, andregressionvaluefordifferentnumbersofhiddennodes for FFBP. In addition, a graphical visualization of MSE andregression based on the number of nodes in the hidden layerisshowninFigure4.

ThecomparisonbetweenthesimulatedresultsoftheFFBPandtherealdataforthepowerofthesolarpanelin2010 isprovidedinFigures5,6,and7.ThesefiguresillustratethesecomparisonsforJanuary,February,andMarchof2010.TheresultsforthesethreemonthsdemonstratethattheresultsareaccuratefortheFFBPmodel.Thehiddenneuronsandthenumberofepochsinthiscalculationare10and1000,respectively.Thesamecomparisonforoneyear(2010)isprovidedinFigure8withsixhiddenneuronsand1000 epochs.

Figure8showsthatthedifferencesofpredictedpower vectoroftherealvalues.

and real power are very low and a high level of accuracy isachieved by using FFBP. A number of hidden neurons andthe number of epochs are changed to examine the result asshowninFigure9.

ISSN: 2278-4632
Vol-09 Issue-12 No. 1 December 2019

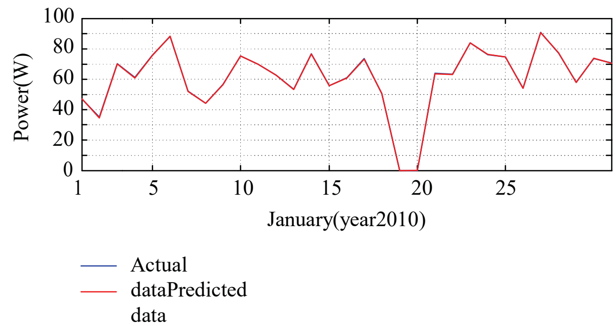


FIgURe5:ResultsforrealdataandFFBPforJanuary2010.

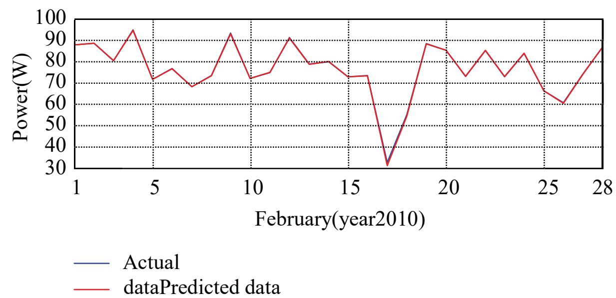


FIgURe6:ResultsforrealdataandFFBPforFebruary2010.

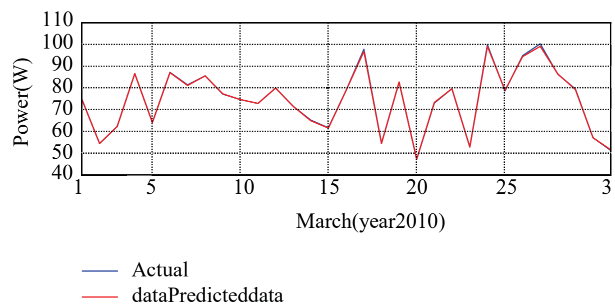


FIgURe7:ResultsforrealdataandFFBPforMarch2010.

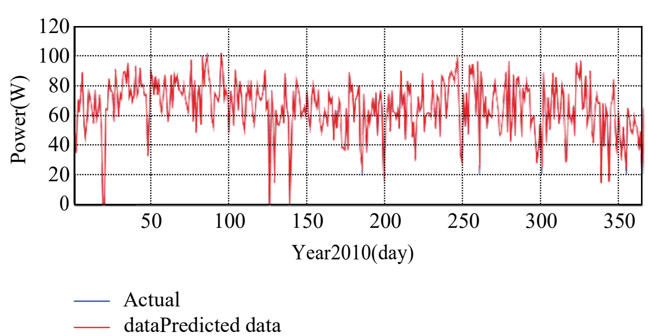


FIgURe8:ResultsforrealdataandFFBPfor2010with6hiddenneuronsand1000epochs.

Althoughthenumberofhiddenlayersisincreasedfrom6hidden neurons to 10 hidden neurons in Figure 9, the levelof accuracy is very close by considering Figures 8 and 9.Figure10presents theregression ofcalculatingdataand the realdata.Asshowninthisfigure,themeasurederrorisverylow.

AccordingtoFigure11thebestvalidationperformanceis 4.4514×10^{-7}atepoch199.

ISSN: 2278-4632
Vol-09 Issue-12 No. 1 December 2019

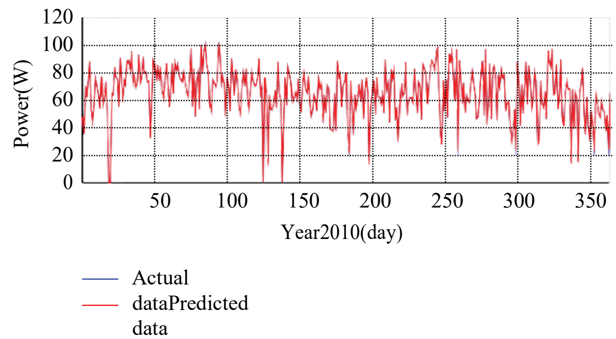


FIgURe9:ResultsforrealdataandFFBPfor2010with10hiddenneurons.

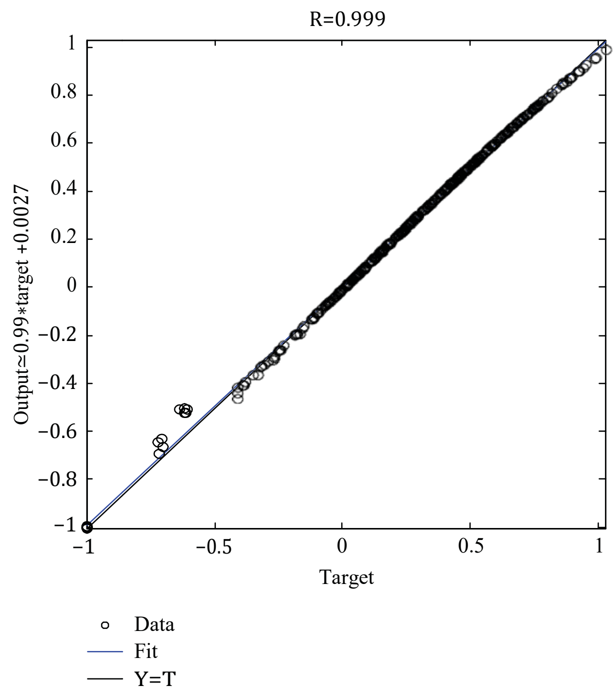


FIgURe10:FFBPregressionoferror.

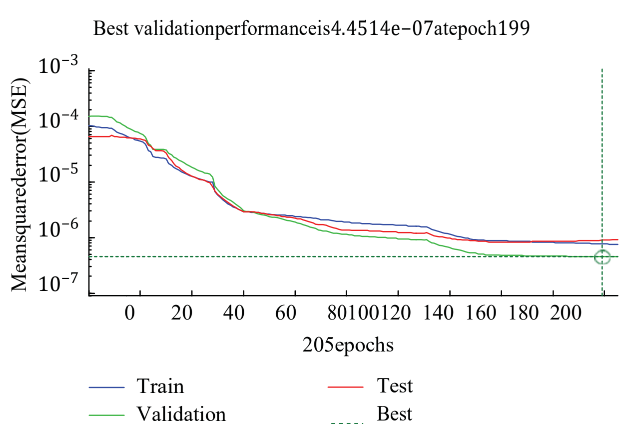


FIgURe11:ThetrainingperformanceforFFBPwith10neurons.

ISSN: 2278-4632
Vol-09 Issue-12 No. 1 December 2019

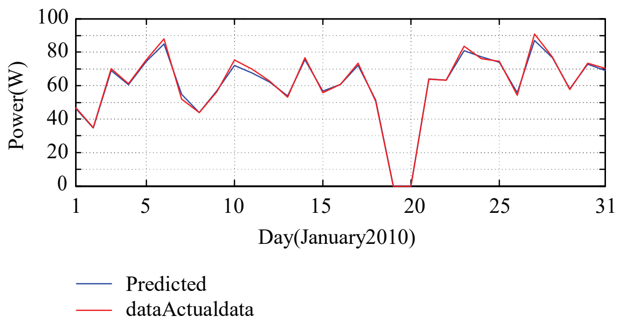


FIgURe12:ResultsofrealdataandGRNNforJanuary2010.

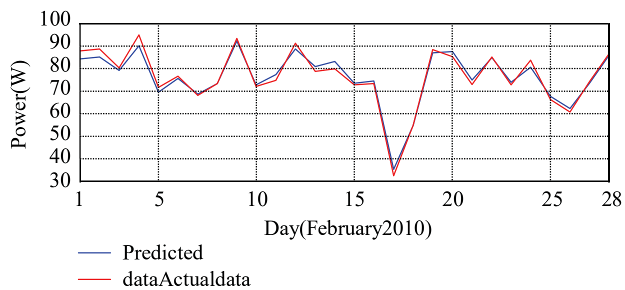


FIgURe13:ResultsofrealdataandGRNNforFebruary2010.

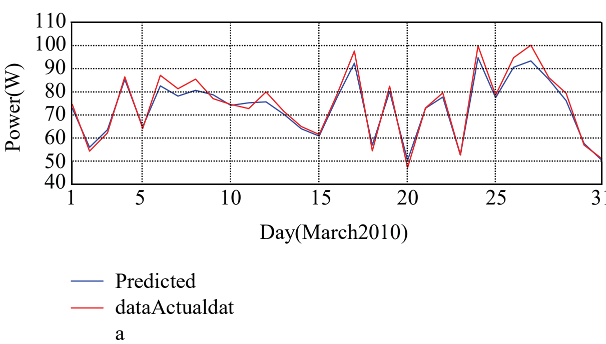


FIgURe14:ResultsofrealdataandGRNNforMarch2010.

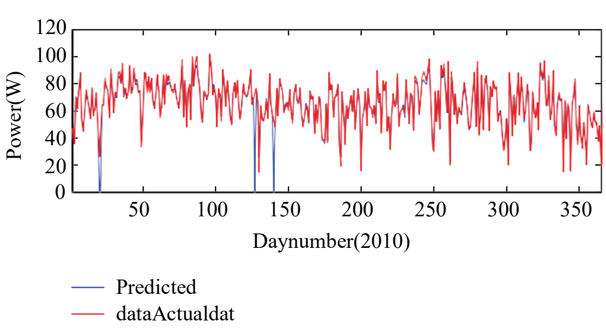
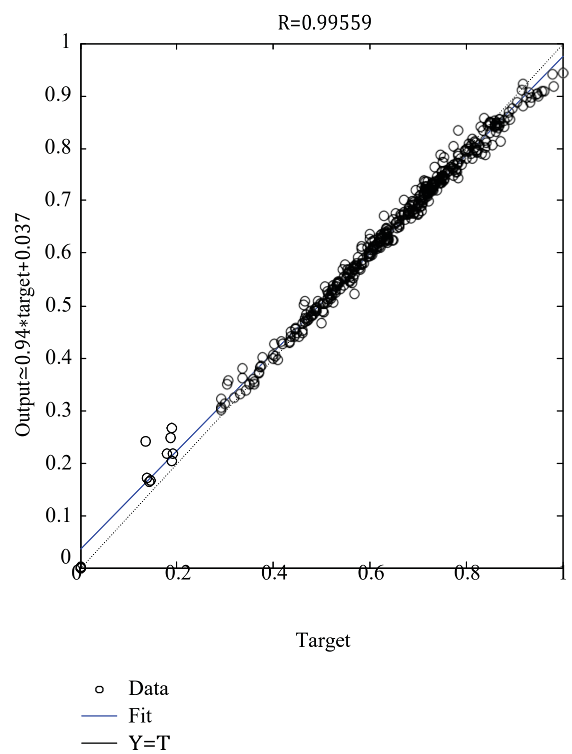


FIgURe15:OverallresultsforrealdataandGRNNfor2010.



GRNN network has only one free parameter as spreadwhichisthedistanceofaninputfromaneuron'sweight[40

].Differentspreadvalueshavebeenexaminedtofindthebest

FIGURE16:Comparisonbetweenmeasuredandpredicteddata.

fitasshowninTable3.Themonthlymeasuredtestingdataarepresentedin Figures12,13,and14basedonaspreadof0.04.Comparingthe resultsofFFBPandGRNNshowsthat FFBPismoreaccuratecomparedwithGRNN.

ISSN: 2278-4632
Vol-09 Issue-12 No. 1 December 2019

TABLe3:TheGRNNcomparisonfordifferentspreads.

Spread	MSEtrain	MSEtest	Regression
0.01	5.16×10^{-8}	0.00072	0.98948
0.02	4.15×10^{-6}	0.00054	0.99238
0.03	2.23×10^{-5}	0.0004	0.99476
0.04	6.80×10^{-5}	0.00039	0.99559
0.05	0.00015	0.00049	0.99505
0.06	0.00029	0.00068	0.99362
0.07	0.00048	0.00094	0.99151
0.08	0.00072	0.00126	0.98882
0.09	0.001	0.00162	0.98575
0.1	0.00131	0.00201	0.98243

TABLe4:SampledataformodellingofPV.

Year	Month	Day	*N*	TotalsolarKW/m^2	□$_{oc}$atIRat25°C	□$_{mpp}$atIRatMaxtemp.	Output power
2006	1	1	**1**	0.274841223	27.181649	0.058270974	*42.6518*
2006	1	2	**2**	0.203071904	26.6355684	0.042189698	*30.7373*
2006	1	3	**3**	0.384548966	27.8008342	0.0833881	*61.5857*
2006	1	4	**4**	0.365065203	27.7040672	0.078887569	*57.9466*
2006	1	5	**5**	0.352615893	27.6396815	0.07602029	*55.6912*
2006	1	6	**6**	0.299843763	27.3408209	0.063944202	*46.9139*
2006	1	7	**7**	0.197615363	26.5869615	0.040981138	*29.8238*
2006	1	8	**8**	0.121888679	25.7392373	0.024471109	*13.5845*
2006	1	9	**9**	0.175552495	26.376727	0.036117902	*18.5403*
2006	1	10	**10**	0.255924153	27.051971	0.054001371	*39.564*
2006	1	11	**11**	0.252152139	27.0250476	0.053152504	*38.9175*
2006	1	12	**12**	0.301336286	27.3499262	0.064283897	*47.1211*
2006	1	13	**13**	0.412130472	27.9302742	0.089785153	*66.1377*
2006	1	14	**14**	0.474875137	28.1969664	0.104442299	*76.9622*
2006	1	15	**15**	0.198878834	26.5983269	0.041260785	*30.0045*
2006	1	16	**16**	0.400291667	27.8757359	0.087035713	*64.3705*
2006	1	17	**17**	0.283381772	27.2374867	0.060205136	*44.1317*
2006	1	18	**18**	0.395752595	27.8544257	0.085982998	*63.4632*
2006	1	19	**19**	0.417949979	27.9565494	0.091138626	*66.9412*
2006	1	20	**20**	0.425391254	27.9896541	0.092871122	*68.2328*
2006	1	21	**21**	0.335214455	27.5460362	0.07202387	*52.8023*
2006	1	22	**22**	0.393920428	27.8457593	0.085558305	*62.935*
2006	1	23	**23**	0.325532825	27.491952	0.069806356	*51.3257*
2006	1	24	**24**	0.287815825	27.26586	0.061210859	*44.8429*
2006	1	25	**25**	0.429558971	28.0079601	0.09384235	*69.3494*
2006	1	26	**26**	0.430434611	28.0117851	0.094046486	*69.4158*
2006	1	27	**27**	0.37166462	27.737372	0.080410199	*59.241*
2006	1	28	**28**	0.468196434	28.1701967	0.102875648	*75.6425*
2006	1	29	**29**	0.438430519	28.0463815	0.095911839	*70.5903*
2006	1	30	**30**	0.356302403	27.6589657	0.076868656	*56.5022*
2006	1	31	**31**	0.413284534	27.9355122	0.090053458	*66.2356*

Figure15demonstratesthattheappliedmethodologyandprocess have been right. There are a few changes betweenmeasured and predicted power. The prediction of powerusing FFBP was more accurate compared to GRNN. Figure 16provides information about variation of measured data andpredictedvalues.Thepredictedvaluesarearoundtherealone andshowthelevelofaccuracy.

6. Conclusion

Powerpredictionforphotovoltaicpanelsisneededforaccu-rate power planning. In this paper, the generated power of asolarpanelhasbeenestimatedusingmathematicalequations. Afterward,themeteorologicaldataandestimatedpowerhaveb eenusedfortrainingGRNNandFFBP.Bothoftheseneural networkshaveshowngoodmodellingperformance;however,FFBPhasshownabetterperformancecomparedtoGRNN.

Conflictof Interests

Theauthorsdeclarenoconflictofinterestsregardingthepublicationofthispaper.

References

[1] L.Mart´ın,L.F.Zarzalejo,J.Polo,A.Navarro,R.Marchante,and M. Cony, "Prediction of global solar irradiance based on timeseriesanalysis:applicationtosolarthermalpowerplantsenergyproductionplanning,"*SolarEnergy*,vol.84,no.10,pp.1772–1781,2010.

[2] D.Heinemann,E.Lorenz,andM.Girodo,"Forecastingofsolar radiation," in *Solar Energy Resource Management for ElectricityGeneration From Local Level to Global Scale*, Nova SciencePublishers,NewYork,NY,USA,2006.

[3] R.Perez,K.Moore,S.Wilcox,D.Renné,andA.Zelenka,"Fore-castingsolarradiation—preliminaryevaluationofanapproachbaseduponthenationalforecastdatabase,"*SolarEnergy*,vol.81,no.6,pp.809–812,2007.

[4] A. Mellit and A. M. Pavan, "A 24-h forecast of solar irradianceusing artificial neural network: application for performancepredictionofagrid-connectedPVplantatTrieste,Italy,"*SolarEnergy*,vol.84,no.5,pp.807–821,2010.

[5] Z.Wang,F.Wang,andS.Su,"Solarirradianceshort-termpre-dictionmodelbasedonBPneuralnetwork,"*EnergyProcedia*,vol.12,pp.488–494,2011.

[6] K.Hornik,M.Stinchcombe,andH.White,"Multilayerfeedfor-wardnetworksareuniversalapproximators,"*NeuralNetworks*,vol.2,no.5,pp.359–366,1989.

[7] W.S.McCullochandW.Pitts,"Alogicalcalculusoftheideasimmanent in nervous activity," *The Bulletin of MathematicalBiophysics*,vol.5,no.4,pp.115–133,1943.

[8] T. Khatib, A. Mohamed, K. Sopian, and M. Mahmoud, "Assess-ment of artificial neural networks for hourly solar radiationprediction," *International Journal of Photoenergy*, vol. 2012,ArticleID946890,7pages,2012.

[9] S.KrauterandT.Depping,"MonitoringofremotePV-systemsvia satellite," in *Proceddings of the 3rd World Conference onPhotovoltaicEnergyConversion*,pp.2202–2205,May2003.

[10] J. D. Mondol, Y. G. Yohanis, and B. Norton, "The effect of lowinsolation conditions and inverter oversizing on the long-termperformance of a grid-connected photovoltaic system," *ProgressinPhotovoltaics:ResearchandApplications*,vol.15,no.4,pp.353–368,2007.

[11] I.Morsy,A.AboulSeoud,andA.ElZawawi,"On-linepredic-tion of photovoltaic output power under cloudy skies by usingfuzzylogic,"in*Proceedingsofthe19thNationalRadioScienceConference(NRSC'02)*,pp.519–526.

[12] A. V. Timbus, R. Teodorescu, F. Blaabjerg, and U. Borup,"Online grid measurement and ENS detection for PV inverterrunning on highly inductive grid," *IEEE Power ElectronicsLetters*,vol.2,no.3,pp.77–82,2004.

[13] E.E.vanDyk,E.L.Meyer,F.J.Vorster,andA.W.R.Leitch,"Long-term monitoring of photovoltaic devices," *RenewableEnergy*,vol.25,no.2,pp.183–197,2002.

[14] R.Mantri,H.Mangalvedhekar,andP.Gupta,"Weathersensitiveshortermloadforecastingusingfullyconnectedfeedforward neural network," *International Journal of Engineering*, vol. 2,2013.

[15] K. A. Kumari, N. K. Boiroju, T. Ganesh, and P. R. Reddy,"Forecasting surface air temperature using neural networks,"*International Journal of Mathematics and Computer Applica-tionsResearch*,vol.3,pp.65–78,2012.

[16] A. Mellit and S. A. Kalogirou, "Artificial intelligence techniquesfor photovoltaic applications: a review," *Progress in Energy andCombustionScience*,vol.34,no.5,pp.574–632,2008.

[17] M. A. AbdulAzeez, "Artificial neural network estimation ofglobalsolarradiationusingmeteorologicalparametersinGusau, Nigeria,"*ArchivesofAppliedScienceResearch*,vol.3,pp.586–595,2011.

[18] C. Chen, S. Duan, T. Cai, and B. Liu, "Online 24-h solar powerforecastingbasedonweathertypeclassificationusingartificialneuralnetwork,"*SolarEnergy*,vol.85,no.11,pp.2856–2870,

2011.

[19] F.O.Hocaoğlu,Ö.N.Gerek,andM.Kurban,"Hourlysolar radiationforecastingusingoptimalcoefficient2-Dlinearfiltersand feed-forward neural networks," *Solar Energy*, vol. 82, no. 8,pp.714–726,2008.

[20] A.Linares-Rodríguez,J.A.Ruiz-Arias,D.Pozo-Vázquez,and J. Tovar-Pescador, "Generation of synthetic daily global solarradiation data based on ERA-Interim reanalysis and artificialneuralnetworks,"*Energy*,vol.36,no.8,pp.5356–5365,2011.

[21] C.Paoli,C.Voyant,M.Muselli,andM.-L.Nivet,"Forecastingof preprocessed daily solar radiation time series using neuralnetworks,"*SolarEnergy*,vol.84,no.12,pp.2146–2160,2010.

[22] W. Chen and S. Varadarajan, "Integration of design of exper-iments and artificial neural networks for achieving affordableconcurrent design," in *Proceedings of the 38th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and MaterialsConferenceandAIAA/ASME/AHSAdaptiveStructuresForum*,pp.1316–1324,April1997.

[23] A.MellitandS.Shaari,"Recurrentneuralnetwork-basedforecastingofthedailyelectricitygenerationofaPhotovoltaicpower system," in *Ecological Vehicle and Renewable Energy(EVER)*,pp.26–29,Monte-Carlo,Monaco,March2009.

[24] E. A. Ahmed and M. E.-N. Adam, "Estimate of global solarradiation by using Artificial Neural Network in Qena, UpperEgypt,"*JournalofCleanEnergyTechnologies*,vol.1,no.2, pp.148–150,2013.

[25] S. Naini, "Evaluation of RBF, GR and FFBP neural networksfor prediction of geometrical dimensions of scour hole belowski-jump spillway," in *Proceedings of the IEEE InternationalConference on Electronics, Circuits, and Systems (ICECS '11)*, vol.19,pp.89–93,IACSITPress,Singapore,2011.

[26] T. Vigneswaran and S. Dhivya, "Analyzing the probabilisticdistributionofthepredictedwindspeed,"*InternationalJournalofComputerandInformationTechnology*,vol.1,pp.88–93,2012.

[27] K. Upadhyay, A. Choudhary, and M. Tripathi, "Short-termwind speed forecasting using feed-forward back-propagationneural network," *International Journal of Engineering, ScienceandTechnology*,vol.3,no.5,pp.107–112,2011.

[28] F. A. Makinde, C. T. Ako, O. D. Orodu, and I. U. Asuquo,"Prediction of crude oil viscosity using feed-forward back-propagationneuralnetwork(FFBPNN),"*PetroleumandCoal*,vol.54,pp.120–131,2012.

[29] C.J.Devi,B.S.P.Reddy,K.V.Kumar,B.M.Reddy,and N. Raja, "ANN approach for weather prediction using backpropagation," *International Journal of Engineering Trends andTechnology*,vol.3,no.1,2012.

ISSN: 2278-4632
Vol-09 Issue-12 No. 1 December 2019