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Solar Power Forecasting Using Artificial Intelligence

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Abstract: *Analysingthe Output Power ofaSolar Photo- voltaic Systematthe design stage and atthe same time predictingtheperformanceofsolarPV Systemunder dif- ferentweatherconditionisaprimary worki.e.tobecar- riedoutbeforeanyinstallation.Thelevelofso- larPowerthat can begeneratedbyasolar photovoltaic system dependsupon theenvironmentinwhich itisop- eratedandtwoother important factorliketheamountof solarinsolationandtemperature.Asthesetwofactorsare intermittentinnaturehenceforecastingtheoutputofsolar photovoltaicsystem isthemostdifficultwork.*
Keywords: *SolarPV,MaximumPowerPointTracking, AI- Techniques,Forecasting*

I. Introduction

PowerPlantBasedon RenewableEnergySystemhave draggedtheattentionof Powerresearchersduetoitsscat- teredexpressioninthelastdecade.Largescaleexpansion ofthese sourceshavemade ittomeettheincreaseinde- mandofelectrical energy. Thisexpansion isnotonlyfor economic orpolitical reason but alsoforcreating asuit- ableenvironmentforournewgenerationwherepowerwill beproducedfromcleansources likesolarandwindwith zeroenvironment pollutions. Governmentisalso taking alots ofeffortssuch as carbon credit incentives,subsi- diesforinstallationofsolarphotovoltaicsystem promot- inggreen buildingconcept foreducationalinstituteetc. Fromasurveyitwasfoundthatbyyear2035,outoftheto- talElectricityProducedbythecountry,theResbasedelec- tricitygenerationwillcountonethirdofit.

Forlarge scale interconnectionofsolar photovoltaic system it is requiredto forecast the daily solar insola- tionavailabilityofthegeographicalareawherethephoto- voltaicsystemislikelytooperatefromoperationandmain- tenancepointofview.Itisalsorequiredtoopinethepower engineersaboutdifferentpowerqualityissuesbeingtobe facedthroughoutthedaybecauseofintermittentnatureof solarPVoutput.Unitcommitmentisanotheressentialpa- rameterfordaytypeofpowergeneratingunit.Dayahead unitcommitmentofrenewableenergygenerating system makesitabletoruntheresrvepowergeneration system inamoreefficientmannerwhichnotonlyminimizes both timeandcostandatthesametimeincreasesgridreliabil- itybyinjecting cleanpowertothetraditionalgrid.

Forecasting/unit commitmentforday aheadsystem helpsthegeneratingstationengineertoproperly manage thepowerdemandandtheseby maintainingabalancebe- tween thegenerationand demand.Againduetoinvolve- mentof lotsof environmentalparameterssuchastemper- ature,cloud quantity,dust exact predictionofPVpower outputbecome adifficulttask. A numberofforecasting method havebeenintroducedbymanyresearcherinlast decade.Allthese forecastingareforlongtermprediction ofsolarPVsystem.Fromliteratureitcanbefoundthatba- sically there aretypes ofpower forecastingmethod and they are numericalapproach,hybrid approach,AItech- nique approach,physical approach,numericalapproach isalsoequivalenttostatisticalapproach whichusessome regression analysisinpast historicaldata topredict the outputofforecastedresult. Alittlebitmodificationtosta- tistical approachi.e.Artificialintelligence(AI)usessome backpropagationandforwardalgorithmtoarriveatapar- ticular result. Apartfromallthese methodsphysical pre- diction ofsolarPVdata fromweatherconditionbyusing some numericalmethod and satelliteimages have been used sincelongtime.Combining allthese approachesin asingleunitcanregenerate thehybrid systemwhichhas the capabilityofpredictingthe solar PVoutputbasedandtothatofPVoutputforaparticularsystem.Astandard- isedmodelisalwayshelpfulin predictingtheperformance ofsolarPVofdifferentcapacity under anyenvironmental condition.

2.1 SolarPVplant

DifferentmethodofPVmodellingweredescribedinthelit- eraturelikeonediodemodellingandtwodiodemodelling. Actuallybyincreasingthediodeinthemodellingonecan calculatetheexactlosssoccurringinthesystem.However wolfhasproposedamethod fordescribingthemathemat- icalofsolarcellwithacurrentsource, adiodeconnected inantiparallelandtworesistorsuchasseriesandparallelresistor.AccordingtoWolfontheimagestakenfromthesatellite ,AI-techniquewith somenumericalanalysiscansolvethepredictionproblem.

I_{ph}

(G) {
= Gstc I
ph,stc

+Ki (
T−T
stc)
}
(1)

Apartfromongoing discussedforecastingmethods,some other statisticallyused method usually start withmathe- matical functionwhichdescribe thelinearandnonlinear relationshipbetweenthedatasetsandtheirbehaviourto the environmentalparameterwith an objective tomini- mizethevariationofmathematicalfunction.Inthiscase the analysistakes along time toanalysethe result and thereby making convergenceofthesystem optimizedpa- rameters.Thispaperpresentacomparativeanalysisofall theforecastingmethod mainly used byresearchersover pastdecade.Thepaperdescribesabouttheartificialintelli- gencebased extremum learningalgorithmforforecasting thesolarhiddennetwork suchasanalysingsomekindof weight tothehiddenlayerand arbitraryselectionofhid- denbiaswasselectedby applyingthegeneticalgorithmto themaster realtimedata which arecollected fromopen source data based onmeteorologicaldepartment.Differ- entsection ofthepaper includes theproposedideaisar- rangedinthefollowingmanner.1stsectiondescribesabout brief descriptionofforecastingfollowed by2ndsection which mainly deals withthemodellingofPVcellsalong withdifferentMPPTtechniquewithspecialfocusonincre- mentalconductancemethod.3rdand4thsectiondescribes aboutresultanalysisandcomparisonwithnewtechnique.
5thsection describes about theconclusionalongwithfu- turedevelopment.

2 PVModel

Themain aim ofsolar PVforecastingistoforecast the weatherconditionsuch as temperature,solar radiation Where Grepresentsthe solar radiation,G_{stc} repre- sentsthestandardsolarradiation,$I_{ph,stc}$ representsphoto generatedcurrentduring standardtemperaturecondition (STC),Tand T_{stc} temperatureand temperatureatSTCre- spectively.Similarlythemaximumpowergeneratedbythe solarPVmodule canbewrittenas P_V=ηA[I−0.05(t−25)] (2) Wheretotalconversionefficiencyisrepresentedby‘η’.

This‘η’isfortheentire solarPVarray, totalareacovered bythe solar PVarray representedbyA(m^2).Solarinso- lencefallingonthearrayisrepresentedbyI(kw/m^2)and

‘t’representsthetotalambienttemperatureofPVarrayin (°C).Therealtimemodelwhichwasdevelopedin MATLAB simulinkmodelconsist of72noofcellshaving totalmax- imumoutputpowerof300Wp(p_{max}). Maximumshortcir- cuitcurrent is5.&@Aandaopencircuitvoltageof23.4V. Theshunt and seriesresistancerepresentingthelidcon- nection resistance isof1200ohmando.1miliohmrespec- tively.

3 AspectofPVpowerForecasting

Shortlistingtheinputvariableandeffectofenvironmental aspect affecttheaccuracyofdevelopedmodel.Prediction ofPVgenerationoperatinginanenvironmentdependsin thefollowingmentionedfactor.

a) Historicalorpastdecade dataofPVgeneratingsys- tem.

b) Meteorologicalvariable suchasenvironmentaltem- perature,cloud coverage, windspeed,shadingdue todust, irradianceand global solar insolationetc. Generally four kinds offorecastingare there and theyareasfollows.rithms. Thefunctiondescribingtheobjective canbewrit- tenasfollows

{ XX
$X^{i=m}$
min−
new
$_{i=0}f(x)=$
$X_{max}-X_{min}$ V,u

(1) Intraday Forecasting
Inthecompetitiveenergymarket availabilityofelectrical energyatthepointofdemandisthemostchallengingjob. Intradayforecastingwhich isusually fromsomefewsec tominute could abletoensure theavailabilityofstorage deviceconnectedwithsolarPVsystemonthePVsystem asawhole.Thisincreasestheefficiencyandreliability of gridconnectedPVsystem.

(2) Shorttermforecasting
Economicloaddispatch andtherebyeasydistributionof power isanessentialpart ofanypower distributionnet-work.Shorttermforecastingisactually carriedoutfor2-3 days. Dayaheadforecastingenable thepowerpurchaser andalsodistributioncompanypeopletoallocatetheload accordingtoavailabilityofpowerorenergy.
Where X_{min},X_{max} representmin and maximumvalue of temperature,windspeedbetweentwodata sets.Thispro- cesswillbefollowedinthesubsequentiterationtillitcon- vergeto themaximumonbestpossibleyearseries.Xrepre-
senteachmonth ofthatcorrespondingforwhichanalysis isbeingcarriedout.

(6) DataAnalysis
In this researchpaper different statisticalanalysistool wereusedtoanalyze thepredictedresult. inordertoana-lyzehowfarthepredicteddataisfromthefittestline,root mean square error(RMSE) method isusually used topre-dictthedatasetoriginalityanditsclosenesswithrespect tofittestline.Thisanalysisisgenerallyusedtopredictthe climate conditionand regressionanalysisinordertover- ifyexperimental result. RMSEcanbefound outbyusing equation3.

$$RMSE = \sqrt{\overline{(f-\delta)^2}} \quad (3)$$

(3) Medium termForecasting
Powersystem network always forcessomekindofbreak-downwhichrequiresperiodicmaintenanceofthenetwork. Mediumtermforecastingusually varies from3to7days. Thisenable theoperationandmaintenancepeopletocon-Wherefrepresentstheforecastedvalueonpredictedvalue and δrepresentsthe observed value on base value for whichforecastedwasconducted.Herebarrepresentsthe meanofthatquantity.Equation3canberemodelledas nectthesystemandbringbackthemtothelevelforpower

transmissionanddistribution.

$$RMSE = \left[\sum_{i=1}^{N} \frac{(Z_{f_i} - Z_{o_i})^2}{N}\right]^{\frac{1}{2}} \quad (4)$$

(4) Longtermforecasting
Longtermforecasting usually variesfromweektomonth ontoayearalso.Itinvolvesalotsofparameter andhuge rigorous calculation isusually carried outtoforecast the powerintermsofwatt.
Sofromtheabovediscussionitcanbefoundthatfore-
Where$Z_{f_i}-Z_{o_i}$ representsthedifferencebetweentwo quan- tityandNrepresentthesample sizeofobserved quantity.
Againdifferencebetweentwocontinuousvariablecan berepresentedby meanabsoluteerror.MAEgenerallyrep-resentstheverticaldistancepresentbetweenthepredicted resultandidentityline.Equation5canbeusedtocalculate MAE,casting ofthesolarPVpowerhelpsindecidingthegener-ating commitmentofgeneratingunit, economic loaddis- patch ofpower, realtimeunit commitment,and storage

$$MAE = \frac{\sum^{n} |y_i - x_i|}{} =$$

n
i=1
n
$\sum|e_i|$ (5)
n
i=1system selectionfortheelectricity market. Fromthefour noofforecastingmethod shorttermforecastingisusually carriedoutbythepowerresearcherforsolarPVsystem.

(5) DataSynthesis

Processingand synthesizingalarge sizeofdata alwaysWhere e_i representsthe error presentbetweenthe time varyingquantityandnrepresentthesample quantity.
Meanabsolutepercentage error(MAPE)ormean ab- solute differentiateerror(MADE)isgenerallyused inthe statisticstopredicttheaccuracyofthepredictionvariable. Itisusually representedas

$\frac{1}{}^{n}$ $\frac{A-F}{}$

achallenge.Inoursimulationand analysisworkpriority wasgiventominimize theerrorbetweentwosearch algo-
M=
n
$\sum$

i=1
t t
A_t
(6)

A_t represents the actual value and F_t representsthe forecasted value.”n"representssamplingquantityofthe variables.Combinationofthese three techniquecan be utilised topredict onforecastingtheperformanceofsolar PVsystemunder differentweathercondition.

Introduction

Lonij.etal.[69]intheir paper cloud advectionforecast- inghasdemonstratedaboutthemethod offorecastingusingestimatedcloudmotionvector.TheyhavecollectedthedatafromrooftopPVsystem.Targetlocation arethencal- culatedbased onthemedian oftransposedmeasurement. Acorrelatingapproach wascarriedouttotesttheaccuracy offorecasting.Yargetal.[71]analysethesolution offore- casting using “Lasso”parametershrinkagemethod.The method appliedhere isbased ontrainingonthe recent measurementhistoryandmotionon“upwind”and“down wind” isassumedstatic. Achleitner etal.[76] has intro- duced peakmatchingalgorithmwhich matchesthepeak valueofdata tobemeasuredand PVfarminordertoes- tablishthemomentarytimelaginbetweentheclouds.
rameterforevaluationofobjectivefunctionmaybeeliminat

Figure1: AlgorithmoftheProposedGATechniqueforForecastingofSolarPVACoutput

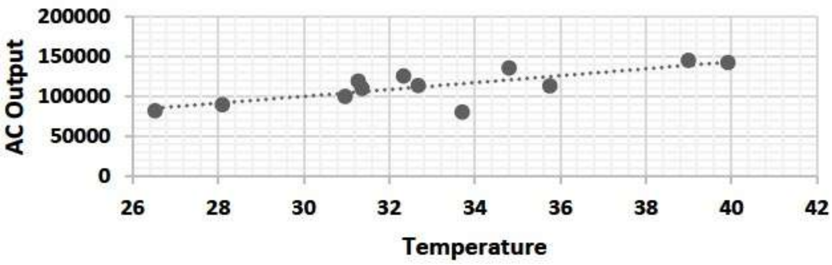


Figure2: PolynomialisationofTemperaturevs.ACOutputCurve

tivefunctionasshownbelow

$$y=3.6169x^2+4077.3x-25301 \qquad (14)$$

Theobjective functionasshown inequation14was de- rivedfromthePolynomialisationofTemperatureand AC output(kWh),whichisshowninFigure

Table1: Observed&CalculatedvalueofEnvironmental TemperatureandSolarPVOutput

Month	**Month**	**ACSystemOutput (kWh)**	**ACSystem Output(kWh)- Calculated**	**Observed Temp.**	**Forecasted Temperature**	**Solar Radiation (kWh/m^2/day)**
1	Jan	82257.875	81609.98438	26.53	26.77	4.2925396
2	Feb	100442.0313	99655.03125	30.97	30.91	5.67678547
3	Mar	135883.5938	134822.3594	34.81	37.95	6.68656969
4	Apr	142563.4375	141450.9688	39.92	40.28	6.84843159
5	May	145573.6094	144436.5625	39	40.23	6.48288298
6	Jun	125976.9844	124990.3047	32.34	37.9	5.53810167
7	Jul	119612.6172	118674.0938	31.28	32.85	4.99226809
8	Aug	114054.0469	113159.0781	32.68	35.56	4.94502401
9	Sep	113528.625	112638.5859	35.76	34.24	5.49704838
10	Oct	110454.2891	109588.3906	31.37	33.34	5.54661322
11	Nov	90045.02344	89337.64844	28.1	29.08	4.85409641
12	Dec	80529.05469	79894.44531	33.71	35.03	4.25716782

Table2:MSEandtheHiddenlayerdetails

NumberofNeurons FirstHiddenLayer	Second HiddenLayer	Train	**MeanSquareError** Validation	Test
10	10	0.0071	0.0198	0.0189
10	15	0.0082	0.0174	0.0192
10	20	0.0001	0.0146	0.0120
10	25	0.0009	0.0180	0.0173
10	30	0.0089	0.0191	0.0175
20	10	0.0023	0.0131	0.0117
20	15	0.0072	0.0171	0.0145
20	20	0.0018	0.0176	0.0169
20	25	0.0010	0.0195	0.0202
20	30	0.0017	0.0216	0.0185

Table3: RegressionStatisticsusingANOVA

ANOVA						
	df	SS	MS		F	SignificanceF
Regression	1	3198110075	3198110075		14.78798	0.003236
Residual	10	2162641479	216264147.9			
Total	11	5360751554				
	Coeflcients	StandardError	tStat	P-value	Lower 95.0%	Upper95.0%
Intercept	−29300.6	37352.97934	−0.784425135	0.450973	−112528	53927.01
XVariable1	4319.441	1123.241284	3.845514379	0.003236	1816.703	6822.178

Figure3showstheSimulationanddatavalidationof ForecastedvaluewithGeneticAlgorithm. Itisfound that theForecastedresultasshown intheTable1isunder the Normalcy. Similar tothe ACOutput Forecast, statistical analysisofTemperatureisshowninthe−5.

Table5and 6shows the StatisticalanalysisofTem- peratureHistogramover18yearsandRegressionanalysis using ANOVAforTemperaturerespectively.Theone-wayanalysisofvariance(ANOVA)isusedtodeterminewhether there areanystatisticallysignificant differences between themeansoftwoormoreindependentgroups.Heredfrep- resentsthedegreeoffreedomwhichis1forRegressionand16forResidual inthispresentstudy. Significance Frepre- sents theratioofMeanSquareErrortoSumSquareError, which isunity inthepresentcase.Thissignifiesthat the forecastedresultforsolarPVisthebestaccurateonewith respect totemperature.TheF-testisused forcomparing thefactors ofthetotal deviation.Inthepresentanalysis ofANOVAF isfoundtobe22.1812whichisinsidethepre- scribedlimitofF.

Table4: ProbabilityOutputVs.PredictedOutput

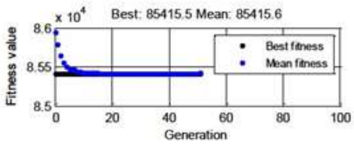
RESIDUALOUTPUT			PROBABILITYOUTPUT	
Observation	PredictedY	Residuals	Percentile	Y
1	85294.14	−3036.265792	4.166667	80529.05
2	104472.5	−4030.425393	12.5	82257.88
3	121059.1	14824.48556	20.83333	90045.02
4	143131.4	−568.0116801	29.16667	100442
5	139157.6	6416.045461	37.5	110454.3
6	110390.1	15586.89424	45.83333	113528.6
7	105811.5	13801.13399	54.16667	114054
8	111858.7	2195.346965	62.5	119612.6
9	125162.6	−11633.95167	70.83333	125977
10	106200.2	4254.056217	79.16667	135883.6
11	92075.66	−2030.63895	87.5	142563.4
12	116307.7	−35778.66894	95.83333	145573.6

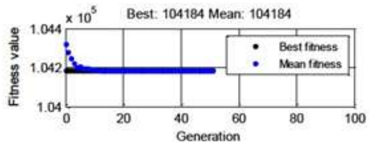
Table5: StatisticalAnalysisofTemperatureHistogramover18Years.

Sl. No.	Year	Average	RMSE	MAE/MAD	MAPE
1	2000	34.86091	1.977964	1.743796296	5%
2	2001	34.43364	1.606435	1.346018519	4%
3	2002	35.45273	2.282671	1.829259259	5%
4	2003	33.81273	0.583844	0.428703704	1%
5	2004	34.46455	1.285657	1.034259259	3%
6	2005	33.90273	0.986355	0.814259259	2%
7	2006	33.39909	1.636352	1.223425926	4%
8	2007	34.19818	1.124786	0.981666667	3%
9	2008	33.57364	1.361213	1.164351852	3%
10	2009	34.62818	1.244886	0.93537037	3%
11	2010	33.33455	1.791018	1.555277778	5%
12	2011	33.06	1.442175	0.97962963	3%
13	2012	32.68273	1.745693	1.461481481	4%
14	2013	32.63	1.279996	1.166944444	4%
15	2014	33.38091	1.11952	0.978518519	3%
16	2015	33.47727	0.854177	0.668333333	2%
17	2016	33.19364	1.66902	1.380092593	4%
18	2017	32.97818	1.398536	1.025925926	3%

Table6: RegressionStatisticsusingANOVAforTemperatureAnalysis

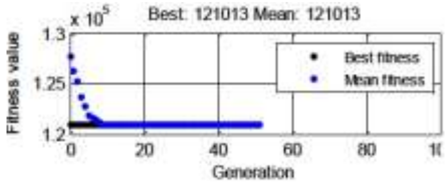
ANOVA					
	df	SS	MS	F	Significance F
Regression	1	6.166595666	6.166595666	23.18126642	1
Residual	16	4.256261451	0.266016341		
Total	17	10.42285712			



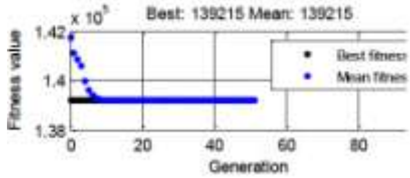


(a) BestFitnessValueorForecastedSolarPV SystemfortheMonthofJanuarry

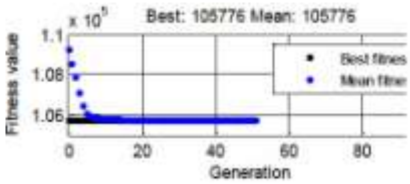
(b) BestFitnessValueorForecastedSolarPV SystemfortheMonthofFebruary



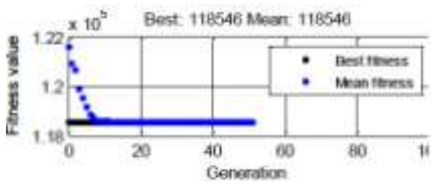
(c) BestFitnessValueorForecastedSolarPV SystemfortheMonthofMarch



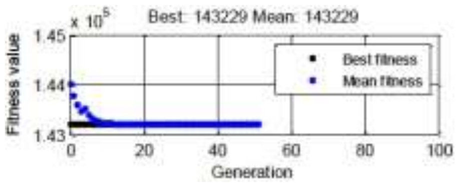
(e) BestFitnessValueorForecastedSolar PVSystemfortheMonthofMay



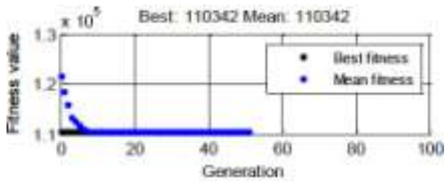
(g) BestFitnessValueorForecastedSolarPV SystemfortheMonthofJuly



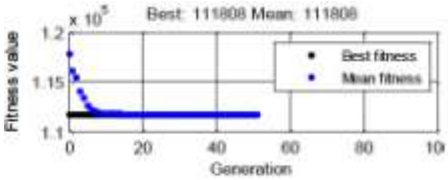
(i) BestFitnessValueorForecastedSolarPV SystemfortheMonthofSeptember



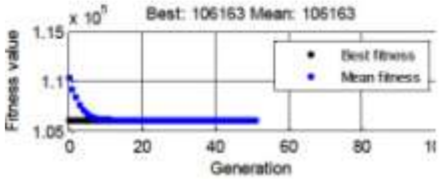
(d) BestFitnessValueorForecastedSolarPV SystemfortheMonthofApril



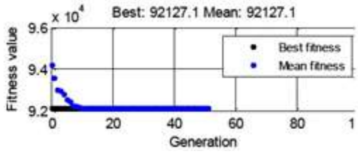
(f) BestFitnessValueorForecastedSolarPV SystemfortheMonthofJune

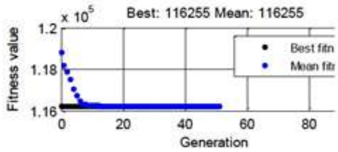


(h) BestFitnessValueorForecastedSolarPV SystemfortheMonthofAugust



(l)BestFitnessValueorForecastedSolar PVSystemfortheMonthofDecember





(j) BestFitnessValueorForecastedSolarPVSystemfortheMonthofOctober
(k) BestFitnessValueorForecastedSolarPV SystemfortheMonthofNovember
Figure3: ShowstheBestFitnessValueorForecastedSolarPVSystemfortheeverymonthofYear

Conclusion

The level ofsolar Power that can begeneratedbyaso- larphotovoltaicsystemd epend supontheenvironmentinwhichitisoperatedandtwootherimportant factor liketheamountofsolarinsolationand temperature. Application of GAto Forecasting of theSolarACoutput systemisdis- cussed inthispaper. Itisfoundthatthe forecastingusing GA ismuchmo reconvenient and accurateascomparedto statisticalmethod of analysis. Inthenextpaperof thisse- riesOptimisation of SolarPV Output withrespect totwo variable such asTemperatureaswellas Solar Radiation will be presented.GridconnectedsolarPhotovoltaicissues based ontheForecastedresult and their mitigationtech- niques willbediscussedinfuturework.

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