SMARTINTERNZINTERNSHIP

PROJECTREPORT

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ProjectTitle:PredictingTheEnergyOutputOfWind TurbineBasedOnWeatherConditionsusingIBMcloud.

1.Introduction:

1.1Overview

Category:MachineLearning

SkillsRequired:Python,PythonforDataAnalysis, MachineLearning,IBMCloud,IBMWatson

1.2Purpose

Predictingtheenergyoutputofwindturbinebasedon weatherconditionsUsingIBMcloud.

2.LiteratureSurvey:

2.1ExistingProblem

Windenergyplaysincreasingroleinthesupplyof energyworld-wide.Theenergy-outputofawindfarm ishighlydependentontheweatherconditionspresent atitssite.Iftheoutputispredictedmoreaccurately, theenergysupplierscancoordinatethecollaborative productionofdifferentenergysourcesmore efficientlytoavoidcostlyoverproduction.Inthis paper,wedoenergypredictionbasedonweatherdata andanalysetheimportantparametersaswellas theircorrelationontheenergyoutput.

2.2ProposedSolution:

Ouraimistomapweatherdatatoenergyproduction. Wewishtoshowthatevendatathatispublicly availableforweatherstationsclosetowindfarms canbeusedtogiveagoodpredictionoftheenergy output.Furthermore,weexaminetheimpactof differentweatherconditionsontheenergyoutputof thewindfarms.WearebuildinganIBMWatsonAuto AIMachineLearningtechniquetopredicttheenergy outputofwindturbine.Wedeploythemodel.onIBM cloudtogetscoringendpoint.ItcanbeusedasAPI inmobileapporwebappbuilding.Weare developingawebapplicationwhichisbuiltusing noderedservice.Weusethescoringendpointto giveuserinputvaluestothedeployedmodel.The modelpredictionisthenshowcasedonUser Interfacetopredicttheenergyoutputofwindturbine.

3.TheoreticalAnalysis

WindPowerForecasting(WPF)hasapplicationsin generationandtransmissionmaintenanceplanning, energyoptimizationaswellasenergytrading.WPF modelsexistsatdifferentscalesandtheycanbeused topredicttheproductionforasingleWTtoawholeWind Farm(WF).WPFmodelsaregenerallydividedintotwo maingroupsphysicalandstatistical,buthybridsstate-of -the-artmethodsarealsocommon.Thephysical approachphysicalaspectsintothemodell,such-as informationaboutsurroundingterrainandpropertiesof theWT.Thesemodelstrytogetasgoodestimateof localwindspeedaspossiblebeforefinallyreducingthe remainingerrorwithsomeformofMOS.Statistical approaches,reliesmoreonthehistoricalobservations and theirstatisticalrelation to meteorological predictionsasaswellasmeasurementsfrom SupervisoryControlAndDataAcquisition(SCADA).

SCADAisacontrolsystemthatisusedinindustrial processesandisthemaintooltoevaluatethestateof individualpowerplants.Asthenameindicates,itisnota fullcontrolsystem,butratherasystemforsupervision. Inthecaseofwindturbinesitallowsremoteaccessto onlinedatathathasbeengatheredbysensorsinside andaroundtheplant.Variablesaccessiblethroughthese systemsarethosedirectlyrelatedtothewindflowas wellastheproducedpowergeneratedbytheplant.I.e. thingslikerotorwindspeed,nacelleposition,pitchangle, activepower,etc.

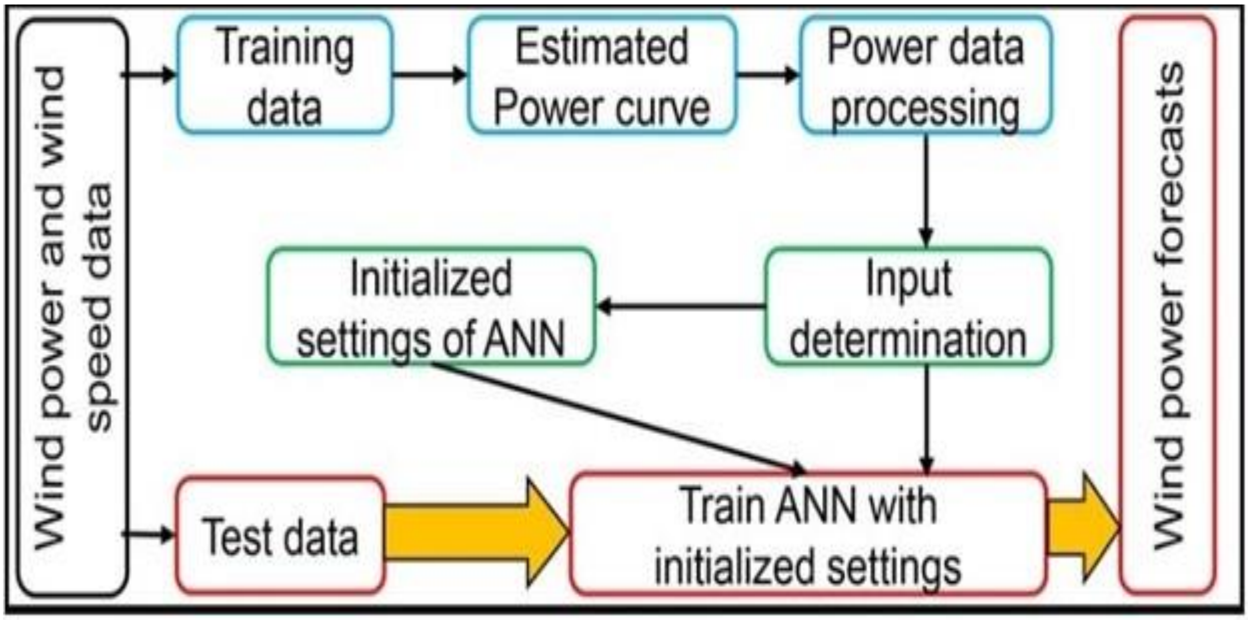
ForecastmodelsthatuseSCADAdataastheirprimaryinput sourceusuallyhaveagodforecastaccuracyatleastforfirst fewhoursbuttheytendtobelessusefulforlongerprediction horizons..SCADAdatacanalsobeusedtodetectproblemin WTsomethingthatcanbehelpfultoimprovethereliabilityof WT.

4.ExperimentalInvestigations

Studyshowsthattheaccuracyofthecurrentpower curvemethodmaydependonthedistributionofwind speed,turbulenceintensity,andshearatthetestsite, comparedtothedeploymentsite.Ifthetestsite conditionsaresimilartothedeploymentsite,the powercurvemethodmaygivegoodresults.The greatestpotentialforerrorwhenusingapowercurve approachcomeswhenthetestsitehashighhub. heightturbulenceandhighshearcomparedtothe deploymentsite.Inthisstudy,thesimulationdatahave beenusedtotrainaregressiontreemodelofthe WindPACT1.5MWbaselineturbine.Theregression treemethodpredictswindturbineenergycapturewith twotothreetimesmoreaccuracythan

1.theindustry-standardpowercurvemethod,andmaybemore usefulforpredictionsofenergycaptureatsitesthatexperience differentconditionsthanthetestsite.Tousetheregression treemodellingapproachtopredicttheenergycaptureofturbine atanewsite,severalstepsarerequired.

5.FlowChart



6.Datasets

ThedatasethasbeencollectedfromKaggle.

Thedata'sinthefileare:

1.Date/Time(for10minutesintervals)

2.LVActivePower(kW):Thepowergeneratedbytheturbine forthatmoment

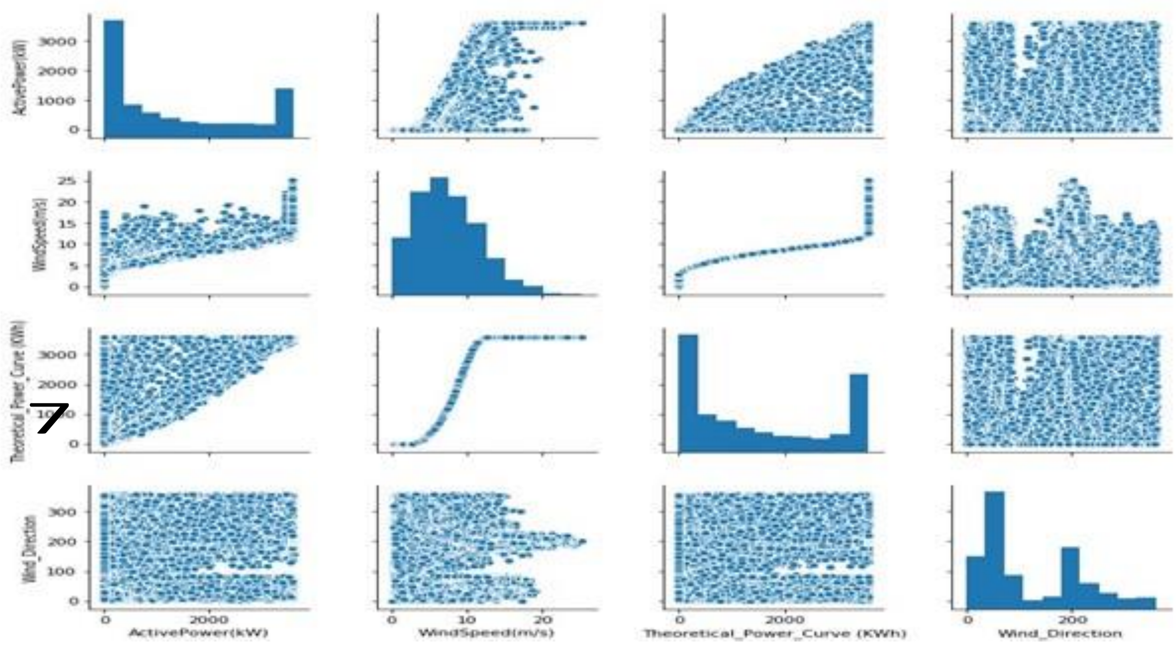
3.WindSpeed(m/s):Thewindspeedatthehubheightofthe turbine(thewindspeedthatturbineuseforelectricity generation)

4.TheoreticalPowerCurve(KWh):Thetheoreticalpower valuesthattheturbinegenerateswiththatwindspeedwhich isgivenbytheturbinemanufacturer.

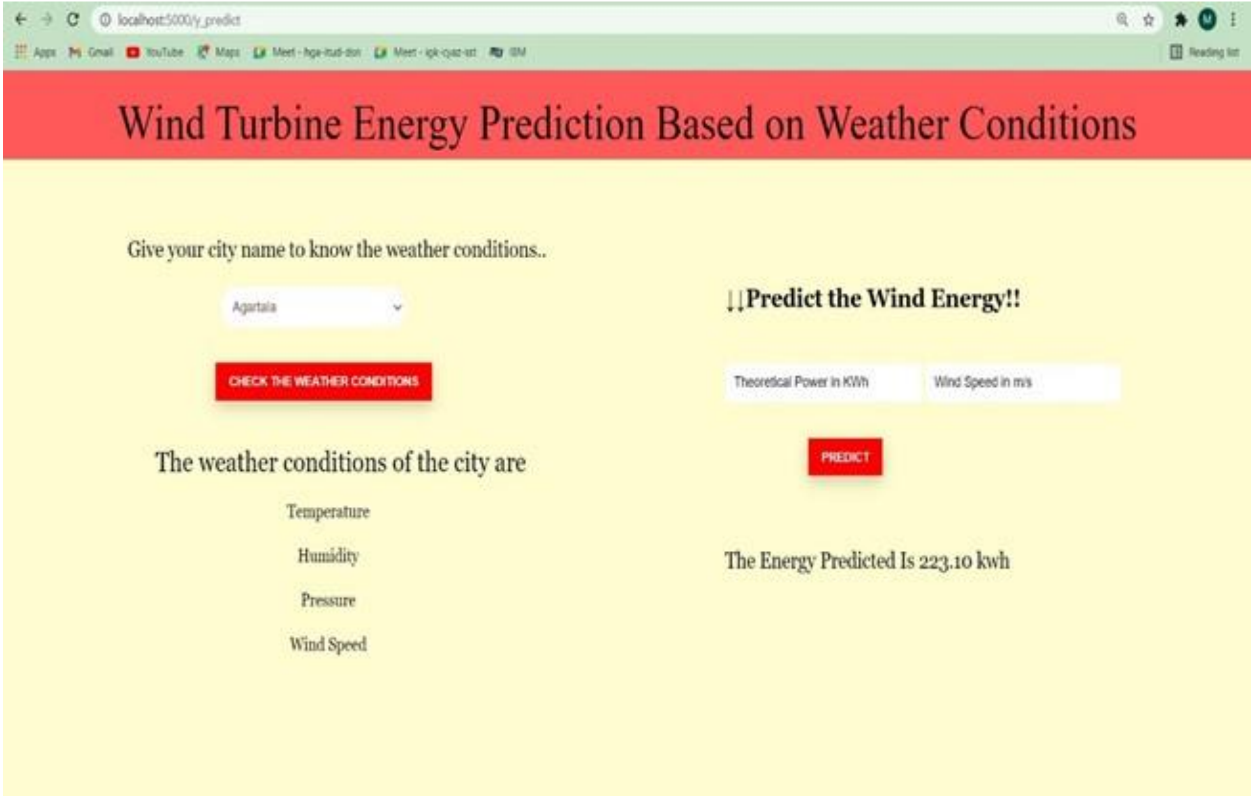
5.WindDirection(°):Thewinddirectionatthehubheightof theturbine(windturbinesturntothisdirectionautomaticaly).

Data Set Flow:

1	Date/Time	LV ActivePower (kW)	Wind Speed (m/s)	Theoretical_Power_Curve (KWh)	Wind Direction (°)
2	01 01 2018 00:00	380.0477905	5.31133604	416.3289078	259.9949036
3	01 01 2018 00:10	453.7691956	5.672166824	519.9175111	268.6411133
4	01 01 2018 00:20	306.3765869	5.216036797	390.9000158	272.5647888
5	01 01 2018 00:30	419.6459045	5.659674168	516.127569	271.2580872
6	01 01 2018 00:40	380.6506958	5.577940941	491.702972	265.6742859
7	01 01 2018 00:50	402.3919983	5.604052067	499.436385	264.5786133
8	01 01 2018 01:00	447.6057129	5.793007851	557.3723633	266.1636047
9	01 01 2018 01:10	387.2421875	5.306049824	414.8981788	257.9494934
10	01 01 2018 01:20	463.6512146	5.584629059	493.6776521	253.4806976



7.ResultandDemo



7.Advantages:-

- Accuaratevalues
- Reliability
- Quickresponse
- Ongivinglocationpermission,anyonecanpredictpoweroutput atyourlivelocation
- itismoreconvenienttouseinworldwide

9.Disadvantages:-

- LimitedAPIrequestesperday
- Androidappcan'tbedeployedonIBMcloud
- NofreeServeravailableonIBMCloudfordeployingBackend

knownpeoplecanoperate

10.Applications:-

AirTraffic

Marine

Agriculture

Utilitycompanies

Privatesectors Militaryapplication

11.Conclusion

Westartedwiththeaimofimprovingthepredictionsofpower generatedusingwindenergyandwehaveachievedthatusing LSTMasmachinelearningmodelandperformingmodel optimizationonit.Wehavealsoobservedthatifthewindspeedis lessthan4m/sthepowergeneratedbythesystemiszero.LSTM isnotabletolearnthispatternasthisisnotthepartwhichitcan understandintimeseriesanalysis.So,ifahybridnewmodelis createdwhichcanworkasthecombinationofDecision. Tree/RandomForestandLSTMwecanimproveuponthese resultsaswell.

12.FutureWork

Mostwindpowerforecastingmodelsstudy‘regular’wind conditions.TheEUfundedprojectcalled‘Safewind’aims toimprovewindpowerpredictionoverchallengingand extremeweatherperiodsandatdifferenttemporaland spatialscales.Developmentactivitiesareon-goingto reduceerrorinthewindpowerprediction,toimprove regionalizedwindpowerforecastingforon-shorewind farmsandtoderivemethodsforwindpowerprediction foroffshorewindfarmsItispossiblethatuseof ensembleandcombinedweatherpredictionmethods togethermayenhanceforecasting.

Iftheerrorinwindpowerforecastingand predictionisreducedtheelectricitymarketscan tradewithmorecertainty.Contracterrorsasa functionoftimeinelectricitymarketscanbeas highas39%foraforecastingleadtimeof4h.

Gubinaetal.presentanewtoolcalledtheWILMARand ANEMOSschedulingMethodology(WALT)toreducethe numberofthermalgeneratorsonstand-byorinreserve usingtheprobabilityofgenerationoutagesandload sheddingaresystem reliabilitycriteriainsteadof generationadequacybasedsolelyongenerationoutage. Thewindandloadforecasterrorsaremodelledusinga Gaussianstochasticvariableapproach.However,in anotherstudyitwasfoundthatthepredictionerrorsdo notsatisfytheKolmogoroveSmirnovtestfornormal distribution.InRamìrezandCarta,itwasshownthat,the useofautocorrelated(andthusnotindependent) successivehourlymeanwindspeeds,thoughinvalidating

alloftheusualstatisticaltests,hasnoappreciableeffect
ontheshapeofthepdfestimated.

13.Bibilography

1.Long-termwindspeedandpowerforecastingusinglocal recurrentneuralnetworkmodelsIEEETrans.Energy Convers.

2.https://smartinternz.com/Student/guided_project_info/2244#.