International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 04 Issue: 09 | Sept -2020 ISSN: 2582-3930

AI Estimating Viable Locations for Onshore Wind Turbine Installations

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Abstract - For a Commercial wind power production, thorough planning and preparation are required. Various geographical, technological, legal, and social aspects are needed to be considered to conclude whether a given location can be viable for wind farm installation which requires extensive labor and research. This at times leads to years of delay. This paper proposes an assistive application that serves the respective authorities in charge of the on-shore topographical survey, to be capable of inspecting the potential installation sites without a physical visit or manual labor. The application uses a deep and complex neural network that feeds on topographical and meteorological data to measure and validate various factors necessary for Wind Farm installation ultimately deeming it viable or non-viable for further analysis.

1. INTRODUCTION

Millions of people suffer from the effects of climate change worldwide. In order to keep further risks of climate change at bay, developing countries need to decrease their CO2 emissions with at least 80-95 % before the year 2050. At the moment, the global energy production by the renewable source is about 25 % (in 2017) out of which 61% is from wind energy. The fossil fuel industry, on the other hand, receives a great amount of subsidy. Contamination is extremely expensive. The costs of contamination caused by fossil fuels – climate change, air pollution are now paid with tax-payers money. Wind turbines deliver immaculate energy from an abundant renewable source. We need to invest in systems channeling the wind energy more effortlessly in order to sustain the future economy on only renewable energy. If we do not make the transition now, future generations would have to cope with the consequences.

Our research project aims to promote the growth and spread of systems exploiting Renewable Resources namely wind, by focussing on one of the costly procedures followed in the process of on-shore wind farm installation. At every potential site, a manual topographical survey is carried out to study the physical characteristics and existing constraints of the wind farm site.

This paper studies two important constraints that affect the manual survey, being the topographical and meteorological factors. We approach these with the help of an architecture consisting of two complex neural networks. The Keras Convolutional Neural Network, using the Kaggle Deepsat-sat6 airborne data[17], helps identify the topography of the potential land area, and the ARIMA (Auto-Regressive Integrated Moving Average) model is utilized to return the average energy generated by a GE 1.5xle wind turbine through predicted wind speeds using bulk historic weather data of the given location. These predictions ultimately contribute to realizing the viability of a land area to host a wind energy harnessing project.

2. PROBLEM DEFINITION

In the current scenario, the survey procedure for wind farm installations and the time required to carry it out are considerably large and labor-intensive making the installations of wind farms a tough, costly, and lengthy task hence causing the delay. Our project aims to Build an assistive AI application to help estimate the best possible locations from the given onshore potential sites, viable for the installation of wind turbines. The selection criteria should be based on the geographical and physical land and surrounding attributes extracted through processing the geo imaging of these locations. The weather factors in the specific area such as wind speed, and pressure that affect the efficiency of a wind turbine. This project aims to significantly reduce the cost of Wind Turbine installation by cutting down the time-intensive process of manual on-site surveys.

3. DATASET

Kaggle Deepsat Sat6 Dataset[17] has 405,000 image patches each of size 28x28 and covering 6 land cover classes - barren land, trees, grassland, roads, buildings, and water bodies. The dataset contains images that have 4 channels which include IR along with the regular Red, Blue, and Green channels.

The dataset for training the ARIMA model is historical weather data of a specific location for a 10-year duration. Daily average value data[19]. The dataset has multiple columns describing the various attributes of weather averaged by day. These attributes include Wind Speed, Visibility, Temperature, Pressure, Wind Direction, Precipitation, etc. For our project, we considered Wind speed only as it is the main contributor to the generation of energy using wind turbines.

4. PROPOSED SYSTEM

The proposed system for our project consists of two pipelines. The first pipeline is for the terrain classification part of the project, we have implemented an image classification

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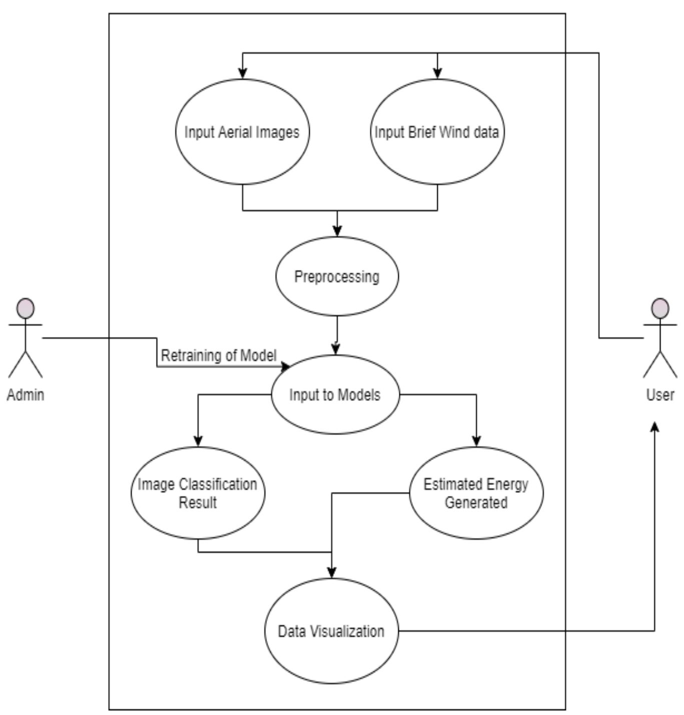
using a Convolutional Neural Network (CNN). The Second Pipeline consists of a Time series analysis model named ARIMA (Autoregressive Integrated Moving Average) which will predict the wind speed for the next few days. Based on this data the power output for a single turbine will be calculated. Based on the power generated for a single turbine we can calculate an average power generated over time for a set of wind turbines in a specific area. Now the return of investment can be decided by the officials considering the estimate for the power generated. If it is profitable they can decide to install wind turbines in the considered area.

The first pipeline of this architecture classifies a given image in one of the 6 land cover classes, which are barren land, trees, grassland, roads, buildings, and water bodies. We are using a convolutional neural network for this image classification task as they are easier to train and have fewer parameters to train than fully connected networks. The images classified to classes water bodies, roads, and buildings will be marked as not viable for wind turbine installation and so we won't have to go through the second pipeline for this case. For the images classified to other classes, the result will depend on time series analysis of the data provided along with the image of the site.

The second pipeline of this architecture consists of a time series analysis model called as Autoregressive Integrated moving average (ARIMA). ARIMA model is a generalization of an autoregressive moving average (ARMA) model. Autoregression (AR) refers to a model that shows a changing variable that regresses on its own lagged, or prior, values. Integrated (I) represents the differencing of raw observations to allow for the time series to become stationary, i.e., data values are replaced by the difference between the data values and the previous values. Moving average (MA) incorporates the dependency between an observation and a residual error from a moving average model applied to lagged observations.

Finding Best available sites for Onshore wind turbine Installation



4.1 COMPARATIVE STUDY: WHY CNN

The number of parameters in a neural network grows rapidly with the increase in the number of layers. This can make training for a model computationally heavy (and sometimes not feasible). Tuning so many parameters can be a very huge task. The time taken for tuning these parameters is diminished by CNNs. CNNs are fully connected feed-forward neural networks. CNNs are very effective in reducing the number of parameters without losing on the quality of models. Images have high dimensionality (as each pixel is considered as a feature) which suits the above-described abilities of CNNs.

There are a total of 6 layers in this CNN model, with 4 convolutional layers and 2 fully connected layers. The output layer is a dense layer with 6 nodes that represent 6 different classes. This 6 layered CNN has a total of 3,31,478 trainable parameters and The model was trained for 4 epochs, with final training loss and training accuracy as 0.0809 and 97.07% respectively. Validation Accuracy is 95.94%.

4.2 COMPARATIVE STUDY: WHY ARIMA

RNNs are complex neural networks and difficult to train. They take more time for implementation and it also requires a significantly larger dataset. Having a larger dataset to train also indicates a large number of input parameters to tune.

ARIMA is a type of linear regression model therefore it has a simpler structure than RNN. Its implementation is more efficient and works adequately on smaller datasets. It is Easier to tune parameters with this model.

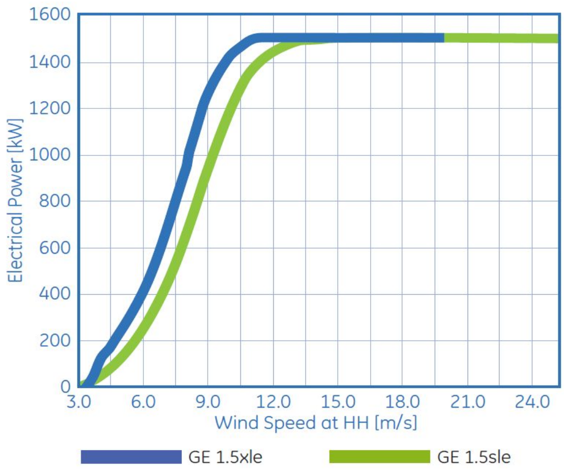
4.3 ENERGY ESTIMATION

Wind generation occurs through the contact of the wind with the blades of the wind device. When rotating, these blades convert wind speed into mechanical energy that drives the rotor of the wind generator, which produces electricity. Wind Energy generated by a Wind Turbine is defined by

$$P = kCp\frac{1}{2}\rho AV^3$$

Where:
P = Power output (kW)
Cp = Maximum power coefficient, (0.25 to 0.45)
ρ = Air density, (lb/ft^3)
A = Rotor swept area, ft^2 π D2/4 (D is the rotor diameter in ft)
V = Wind speed, (mph)
k = 0.000133 A constant in kilowatts.

In the case of wind farms, several turbines (ranging from about 250 kW to 750 kW) are at work together on a grid to generate large amounts of power. Besides the constraints resulting from the number of turbines, any site selection should think over the technical, socio-economic, and environmental aspects. Each aspect uses criteria for its own evaluation. Technical factors are related to the suitability of the potential site for wind energy production. One of the main factors being the average wind speed must be quantified in the area in order to produce wind energy profitably. General Electric 1.5 MW is one of the most common wind turbine models used on-shore and hence its specifications act as constants to our study.

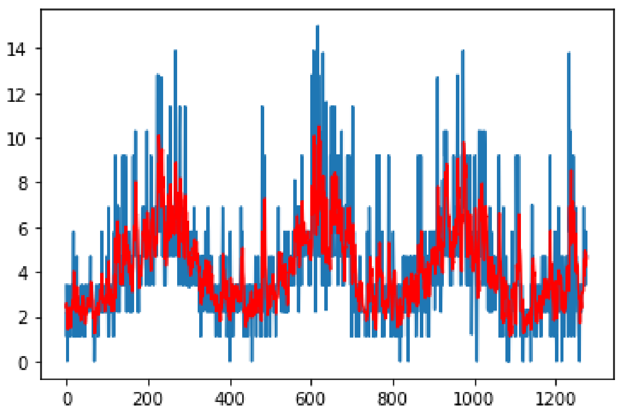


GE 1.5xle Wind Turbine Energy Curve

The wind potential evaluation of a region asks for systematic weather data collection and analysis on wind speed. Generally, a rigorous assessment is required including specific surveys of the on-shore site where the wind farm will be placed. It is established that accurate wind forecasting is decisive to have a reliable power system. However, the intermittent and unstable nature of the wind speed makes it very difficult to predict accurately. Therefore the case study "Different Models for Forecasting Wind Power Generation" works on defining a hybrid system using ARIMA and neural networks. Such a model predicts relatively accurate wind speeds using historic weather data, benefitting in the further prediction of the power generated on-site, and hence is being used in our research for determining the profitability.

5. RESULTS

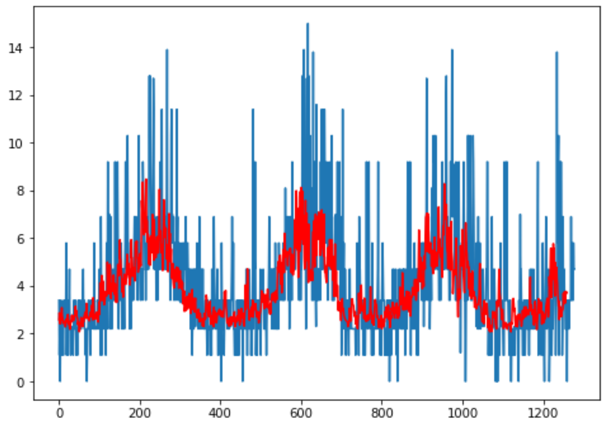
The CNN model for terrain classification trained on the Kaggle DeepSat dataset for 4 epochs, with final training loss and training accuracy as 0.0809 and 97.07% respectively. The validation loss for the model was 0.1061, with validation accuracy as 95.94%.



Wind speed Prediction using ARIMA

Blue - Original Wind Speed
Red - Predicted Wind Speed

The mean squared error for this model on the weather dataset is 3.953. The general trend of the wind speed has been captured by our model and gives promising results. However, fails to predict the extreme wind speeds on a given day. So we can use our model for general wind speed forecasting for a given area, and based on that calculate the power generated for the wind turbine.



Wind Speed Prediction using RNN
Blue - Original Wind Speed
Red - Predicted Wind Speed

The mean squared error for this model on the weather dataset is 4.561. As we can see even though the RNN captures the general trend, it is more rigid in its pattern and fails to generalize towards the outliers very well.

6. CONCLUSIONS

The model developed based on this architecture will be able to predict whether wind turbines can be installed on a certain location or not. The geographical attributes such as terrain, as well as meteorological attributes such as wind speed, turbulence can help us decide which location is best suited for the installation of a wind farm. This will simplify the current methods used for wind farm installations and surveys. The model developed will also be able to predict the total energy that could be generated in that area using the energy x wind speed curve. The two pipeline architecture will be used for this purpose.

7. FUTURE SCOPES

This approach only discusses the potential for wind farms. However, there are various other renewable energy resources available out there and this project can be modified further to fit those energy resources. Our approach takes into consideration some of the conditions to be ideal and taking their real nature into the picture might need some changes to make in the model. Data collected from this project can provide valuable resources for grid monitoring and operation, socioeconomic analysis for wind adoption, and provide insight for energy policymaking.

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