Pune Institute of Computer Technology
Dhankawadi, Pune

A SEMINAR REPORT
ON

PREDICTION OF SOLAR INTENSITY FOR SMART HOMES

SUBMITTED BY

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DEPARTMENT OF COMPUTER ENGINEERING

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DEPARTMENT OF COMPUTER ENGINEERING

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CERTIFICATE

This is to certify that the Seminar report entitled

"PREDICTION OF SOLAR INTENSITY FOR SMART HOMES"

Submitted by

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has satisfactorily completed a seminar report under the guidance of Prof. S.S.Sonawane towards the partial fulfillment of third year Computer Engineering Semester II, Academic Year 2019-20 of Savitribai Phule Pune University.

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Place:
Date:

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Abstract

Solar Energy systems are an important source of renewable energy generation. Solar intensity is directly proportional to solar power generation and solar power generation is highly dependent on weather fluctuations. The model is proposed that predicts the amounts of solar power generation using weather data provided using deep learning techniques such as Fully Connected Neural Networks The results allow us to make effective energy consumption plans for smart homes with efficient utilization of solar energy which may provide several economic benefits.

Additionally, accurate forecasts would make users more prepared to switch between conventional and renewable sources as required. A comparison study is performed with various machine learning models to determine the best method for building a model for prediction. The groundwork for constructing models that could be dispatched to various regions is laid out that will incorporate that geographic locations weather data, and output accurate solar intensity predictions for that area.

Keywords

renewable energy; smart grid; solar power generation prediction; photovoltaic power; neural networks; machine learning; deep learning

1 INTRODUCTION

Solar generation capacity is experiencing a dramatic increase in India, with its peak capacity having risen 8 times from 2,650 MW on 26 May 2014 to over 20 GW as on 31 January 2018 and the country's solar capacity reached 31.696 GW as of 31 October 2019.

There exist a different set of challenges that are faced when predicting solar power generation for small or medium scale generators as compared to large scale generators. Large scale plants have various resources at their disposal that can help determine the ideal parameters such as angle of the panel or even dynamically adjust parameters like the tilt in addition to having a much larger area at their disposal. Further, routine maintenance is done of the solar panels in large scale solar farms by expert operators. Custom models for each massive solar farm respectively can be created for prediction of energy generation but the same is not feasible for small scale homes These amenities are not available to the daily consumer and hence there is a different set of challenges for predicting solar energy generation for smart homes.

Since solar energy today only contributes a small fraction of grid energy, currently the lack of effective planning does not pose a significant problem. As dependency on solar energy rises, a need for accurate prediction of solar energy will further increase and this is majorly visible with the ever rising demand of smart homes. The aim is to predict solar energy generation for the next 48 hours at any given time.

The popularity of rooftop solar for homes is evergrowing. However, accurately forecasting solar power generation is critical to fully exploiting the benefits of locally-generated solar energy. Deep learning techniques are compared to machine learning techniques to predict solar intensity from publicly-available weather forecasts.The predicted solar intensity values can be used to calculate solar energy generation under the assumption that solar intensity is directly proportional to the energy generated.

1.1 MOTIVATION

Solar Intensity is directly proportional to solar power generation and hence accurate prediction of solar intensity is useful for a wide range of purposes. Once able to accurately predict future solar intensity given weather prediction data for a specified area, then that area's solar generation output in the near future can be estimated with a higher accuracy.

Half of the solar energy generation capacity is from small scale deployments in homes many of which rely on net metering to transfer excess energy to the grid which eliminate the need for battery based storage systems. With the rise in small scale solar deployments in homes and increasing demand for smart homes, it is a necessity to accurately predict the future generation of solar energy.

Solar energy forecasts have various of applications. For example, smart buildings could employ forecasts for opportunistic scheduling of solar dependent processes, while utilities could use them to estimate aggregate need of energy and further, dynamic allocation of energy could be done and overall excess energy could be predicted that would result in major savings for a large customer base.

A lack of general prediction systems is also a motivating factor towards development of such a system to predict solar intensity for small and medium scale deployments.

2 PROBLEM DEFINITION AND SCOPE

2.1 Problem Definition

Solar Energy is the energy source of the future but there exist no systems for maximizing usage of this energy by smart prediction and dynamic allocation. Create such a system for effective use of small-scale solar panels for Smart Homes.

2.2 Scope

For accurate prediction of solar intensity, proper selection of features is necessary. A relationship between intensity and the various parameters is found and parameters are normalized and selected.

Proper weather data taken from a trusted database along with a proper deep learning model is necessary for avoiding problems like overfitting. These Solar Energy predictions can be used to dynamically recommend distribution and usage of the Solar Energy amongst all Solar Devices in the home.

3 SURVEY OF PAPERS

3.1 Estimating hourly incoming solar radiation from limited meteorological data

A study taking into account parameters like latitude, longitude and elevation was conducted for multiple different locations and predictions were made season-wise by an empirical model. This was conducted for the purpose of maximizing agricultural yield. There was high difficulty in predicting during the occurrence of irregular events such as precipitation. RMSE values varied widely depending on each season hence not giving a generalized prediction model.

3.2 Machine Learning methods for solar radiation forecasting: a review

This paper aims at comparing different machine learning models with the newly popular neural network and SVM models. To improve prediction results, hybrid models and ensemble forecast are being used. Performance ranking of these models is difficult as it varies vastly based on the parameters that are used. It was concluded that SVM, regression trees and random forest were the most promising approaches but were being outperformed by ANNs in most locations.

3.3 Predicting Solar Generation from Weather Forecasts Using Machine Learning

This paper made use of seven weather prediction parameters and compared three machine learning models namely, SVM-RBF kernel with 4 dimensions, cloudy computing model using sky condition forecast, past predicts future prediction model. This paper also made use of feature selection techniques. They concluded that SVM model outperforms most pre-existing models for the given purpose but no comparison was made with ANNs in this study.

3.4 A Cloud-based Black Box Solar Predictor for Smart Homes

This paper shows the most promising results comparing SVM to a black box neural network model. The models were trained on a publicly available dataset and different models that take into account dynamic parameters like solar panel tilt and shade were also tested. Deployed model could predict daily energy generation of a site. It was concluded that best results were given by the black box model with dynamic parameters but limitations such as sporadic events like overcast in a smaller area that may cause errors were still prevalent. Also the reliability of weather prediction values was questioned. This paper was focused on large scale deployments and small scale deployments were not given much weightage.

3.5 A Two-Step Approach to Solar Power Generation Prediction Based on Weather Data Using Machine Learning:

This paper tries to decrease the reliance on external weather predictions by connecting unannounced weather variables i.e. weather observations with announced weather forecasts. That is done in the first step with the help of an auxiliary model. The model used in the second step is a random forest regression as it provides the best results and provides a one day ahead prediction of energy generation. However, the final score is comparatively lower inspite giving a more robust result.

4 FEATURE SELECTION

A variety of features are used for the purpose of prediction. The interrelation between features was studied and the most important ones are selected. NSRDB datasets are used for training and testing purpose. Accuracies (MSE) of various models were analysed and the one with highest accuracy(lowest RMSE) and compared with mse of deep learning model. This model is be used to predict the value of solar intensity 48 hours into the future given input of various features at current time which is the overall goal of the project. Deep learning is used to achieve this particular goal. The terms solar intensity, GHI, solar power and solar energy are used interchangeably as solar energy generation is assumed to be directly proportional to the solar intensity. The dataset had to cleaned and preprocessed before giving it to the model for training. The dataset was split in the ratio of 4:1 (train/test). The features that are present in the dataset are hour, dew point, solar zenith angle, wind speed, precipitable water, wind direction, relative humidity, temperature, pressure. The interrelation between the features was studied and the most important ones were selected. Heat Map was used for the same. The value which is to be predicted is present as 'GHI' column in the dataset.

4.1 Correlation between GHI and feature parameters

Although various features were considered, it was observed that GHI of a particular location has different degree of dependence on these features.

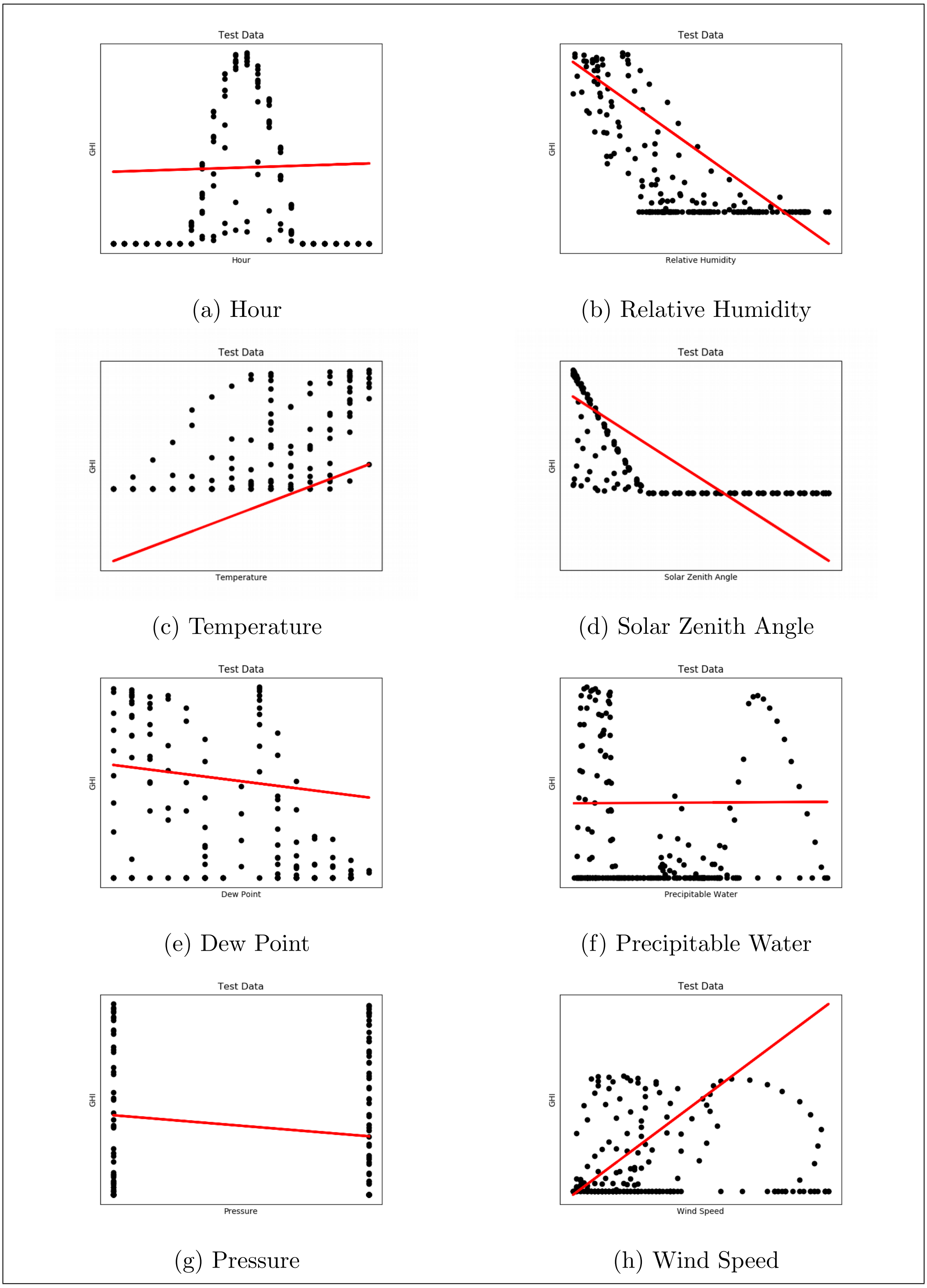
The hours are measured in a 24h clock format ranging from 0-24. GHI is the most in the afternoon hours and shows a symmetric downward parabola with axis of symmetry at Hour=12.

It can be observed from the graph that GHI is inversely proportional to the Relative Humidity of a particular location.

The GHI and Temperature, Wind Speed, Direction and Dew point are directly proportional to each other and show a linear relationship.

The solar zenith angle is the angle that zenith (surface normal) makes with the center of the sun's disc. The plot of Zenith angle vs GHI shows an inverse relationship but it is more to that. It can be observed that the first half of plot along X axis, where solar zenith angle is between 0 to 90, the GHI is inversely related to Solar zenith angle with a linear relationship, but the next half of the plot (90 ¡ Solar Zenith Angle ¡ 180) GHI is constant irrespective of the Solar Zenith angle.

Other features like pressure and precipitable water showed a random relationship with GHI, the same can be observed in the following plots. These features were further tested and it was concluded that these do not make a significant impact on the GHI of a location. All plots are visible in Figure 1 .



(a) Hour

(b) Relative Humidity

(c) Temperature

(d) Solar Zenith Angle

(e) Dew Point

(f) Precipitable Water

(g) Pressure

(h) Wind Speed

Figure 1: Correlation of features with GHI

4.2 Heatmap

The Heatmap [Figure 2] shows the correlation between various forecast parameters giving an idea about which features are highly correlated to intensity and also which features can be combined or removed.

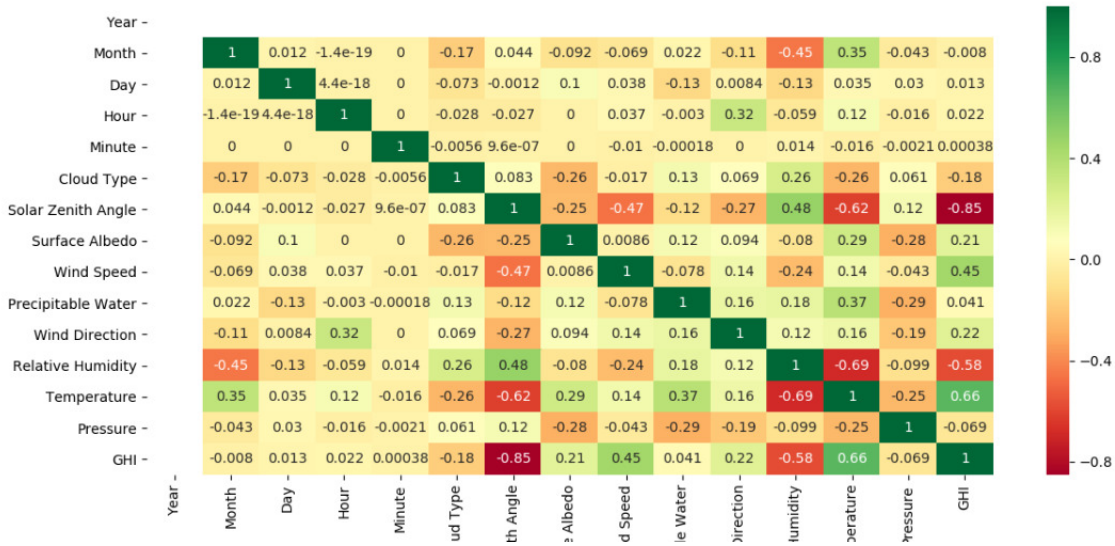


Figure 2: Heat Map

5 EVALUATION METRICS

5.1 Mean Squared Error (MSE)

It is a evaluation metric that measures the average of the squared value of errors. This helps the model give more weight to higher errors and help minimize those first. The measurement unit is different than the output units. The value of MSE is always positive which makes it more accurate.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2. \quad (1)$$

6 DIFFERENT MACHINE LEARNING ALGORITHM USED

6.1 Support Vector Machine (SVM)

Each data item is plotted as a point in n-dimensional space where n is number of features. The value of each feature is the value of a particular coordinate in the space.

6.2 Linear

Simple prediction of a dependent variable based on an independent variable is performed.

6.3 K Nearest Neighbours(KNN)

KNN algorithms use data to classify new data points based on similarity measures such as distance function. Classification is done by a finding number maximum similar neighbors. KNNs are used because they have low computational cost. Similar to SVM, kNNs also plot the points in a space

6.4 Quadratic

Prediction of a dependent variable based on multiple independent variables is performed. It is similar to Linear method.

6.5 Gradient Boosting Machines (GBM)

In gradient boosting, each new tree is a fit on a modified version of the original data set.

6.6 Naive Bayes

Naïve Bayes classifiers are simple probabilistic classifiers that are based on applying Bayes' theorem and they consider strong independence between selected features. Supervised learning model based on the Bayes' Theorem of probability can be used.

7 DEEP LEARNING MODEL

A Fully connected dense neural network model is created having 48,129 trainable parameters and learning rate regularizers at each layer to avoid overfitting. Figure 3. shows the structure of the neural network.

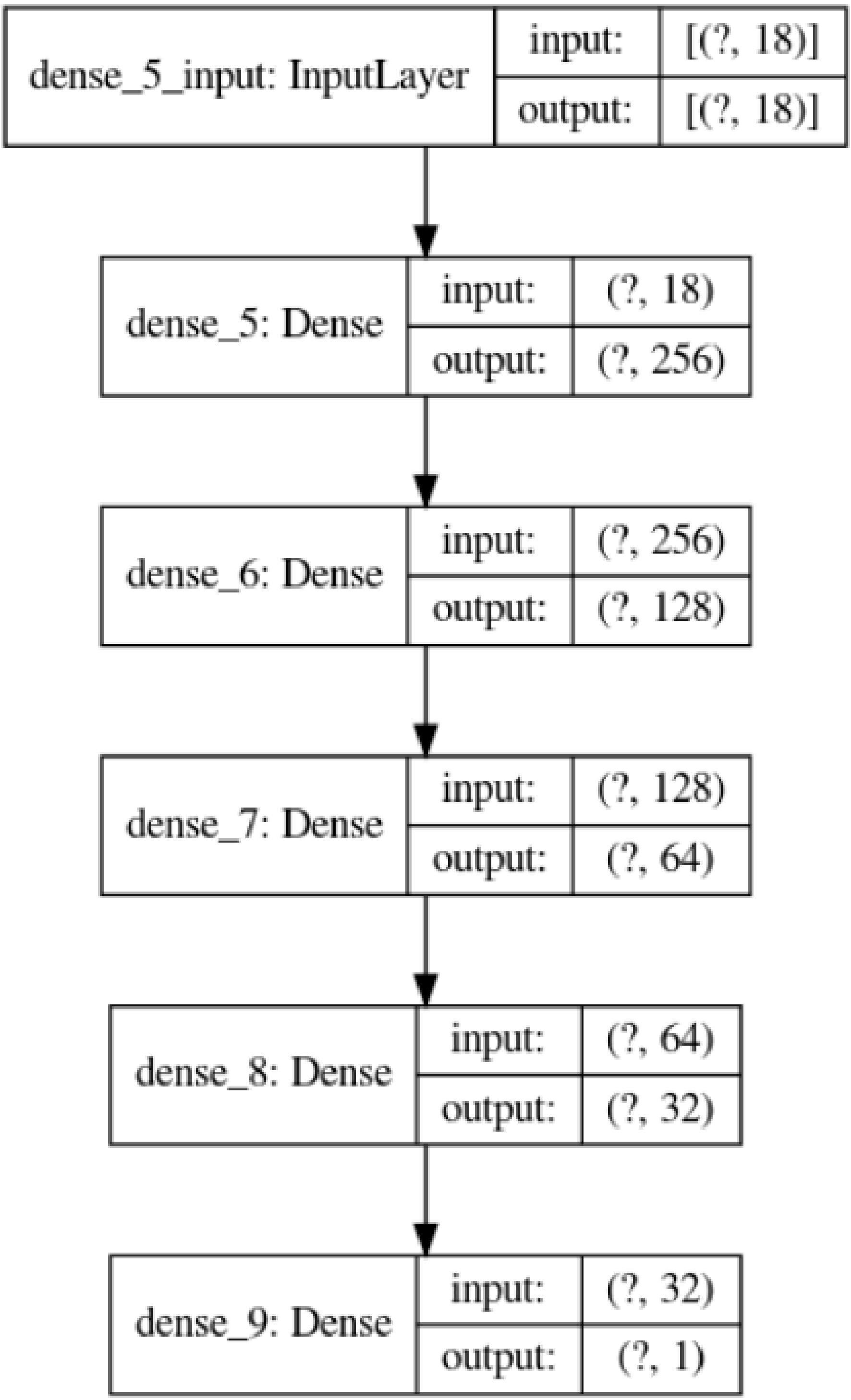


Figure 3: Neural Network Architecture

8 METHODOLOGY

8.1 Workflow

The workflow shows each stop in creation of deep learning model.
Firstly, data is read from the csv files and checked for empty values.
Dataframe is cleaned of empty values and normalized in a range of 0 to 1.
The architecture model of the neural network is defined taking into account learning rate regulizers to avoid overfitting.
Then the model is trained on the dataset which is test-train split in a 1:4 ratio.
Evaluation is done on the test data and model is used for prediction.

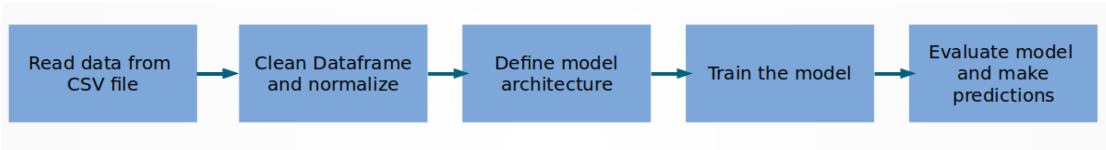


Figure 4: Workflow

8.2 Technologies Used

1. Modules
   - Tensorflow GPU
   - Scikit
   - Matplotlib
   - Numpy
   - Pandas
2. Jupyter Notebook
3. Python 3

9 RESULTS

Results of the different models are shown in this section in the form of tables and bar graphs.

9.1 Mean Squared Error

Table 1: Results Table

S.No	Model	MSE
1	Linear	20037.82
2	Quadratic	6570.13
3	Naive Bayes	13302.69
4	KNN	2587.07
5	SVM	25684.07
6	GBM	5169.35
7	Neural Network	1675.94

9.2 Implementation Results

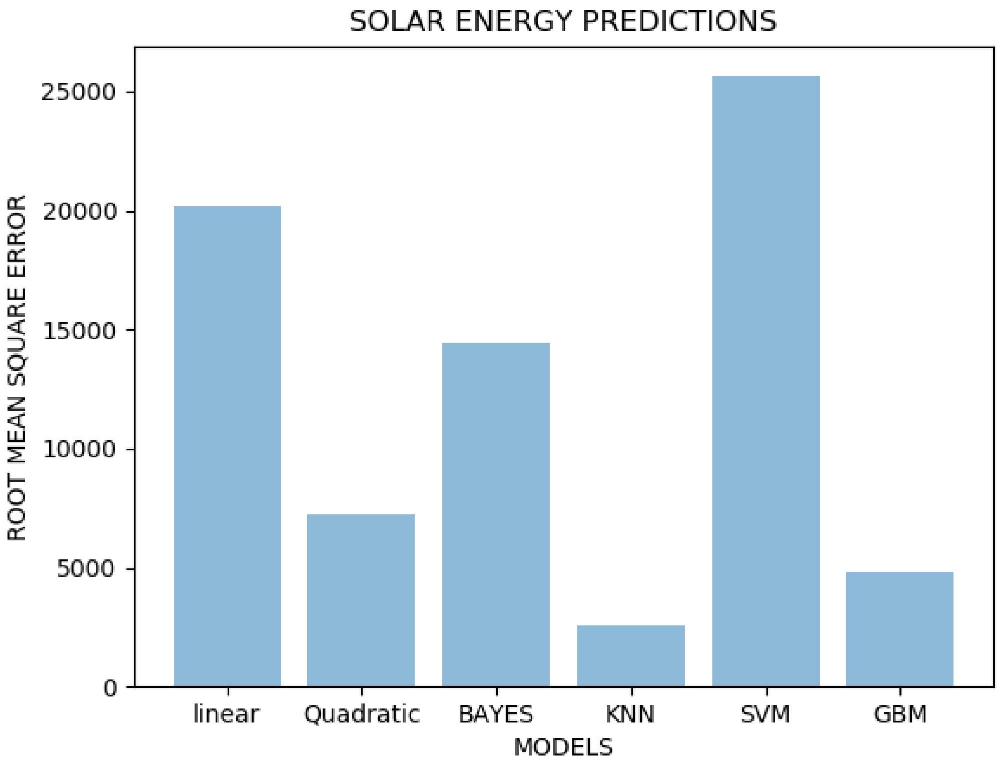


Figure 5: Machine Learning Algorithm MSE

A graph of evaluation metrics against epochs is presented in Figure 6 and Figure 7. We can see the loss decrease over time.

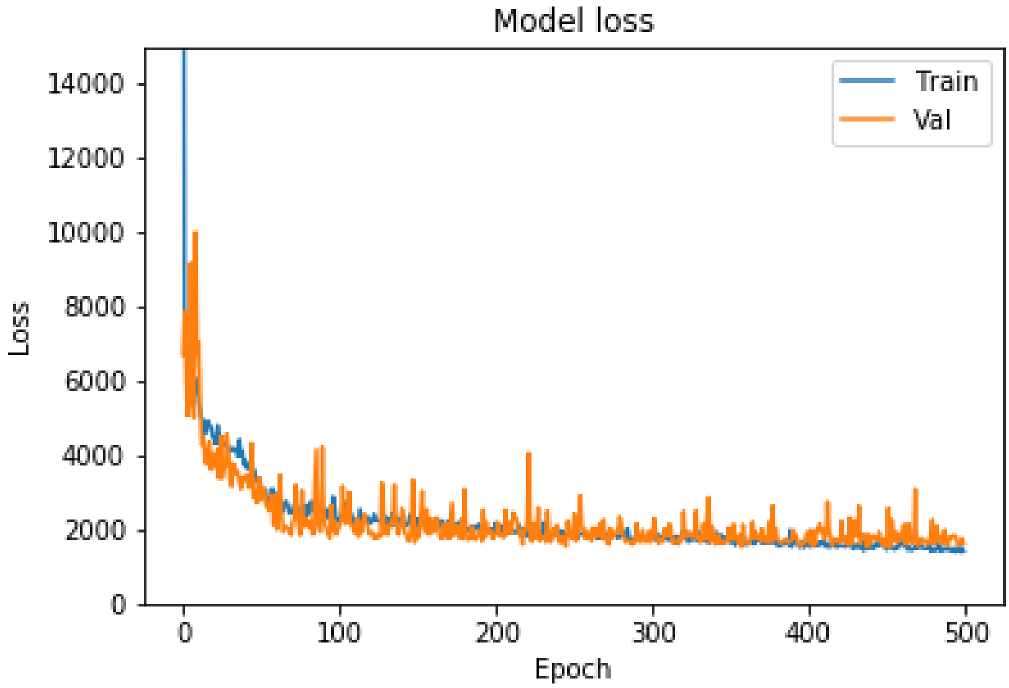


Figure 6: Neural Network Loss (MSE)

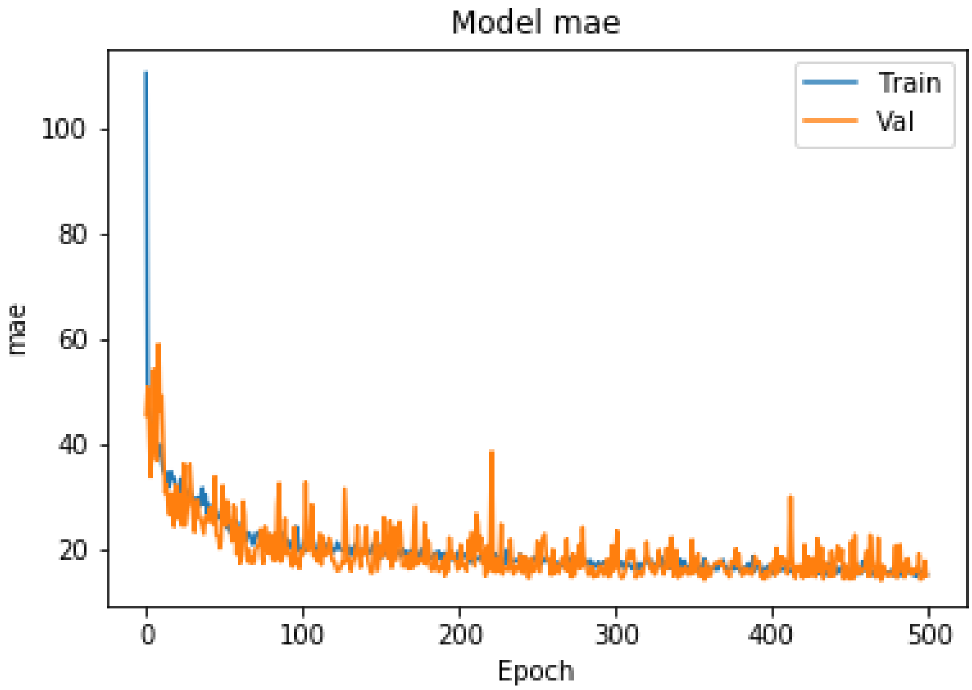


Figure 7: Neural Network MAE

10 CONCLUSION

Comparison of various models shows Neural Network has the lowest mse value which ensures best output. Solar Intensity can hence be predicted using the weather forecast data and can be used for making dynamic decisions for small scale deployments of solar systems. Study of features and correlation helps improve performance and helps avoid overfitting. Smart homes can successfully make use of this method.

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[6] Dataset : https://nsrdb.nrel.gov/about/u-s-data.html

URKUND

Urkund Analysis Result

Analysed Document: 31105_Seminar_Report_Only-content.pdf (D67948385)
Submitted: 4/11/2020 11:55:00 AM
Submitted By: sssonawane@pict.edu
Significance: 1 %

Sources included in the report:

https://www.mdpi.com/2071-1050/11/5/1501
https://www.semanticscholar.org/paper/Predicting-solar-generation-from-weather-forecasts-Sharma-Sharma/1b463b36d1bbccc419954cc28bd28b0108c2ca63

Instances where selected sources appear:

3

Figure 8: Plagiarism Report

APPENDIX – D

Log Book

Roll No. :- 31105
Name of the Student :- Anish Dhage
Name of the Guide :- Prof. S.S.Sonawane
Seminar Title :- Prediction of Solar Intensity for Smart Homes

Sr. No.	Date	Details of Discussion/ Remarks	Signature of guide / Seminar Incharge
1.			
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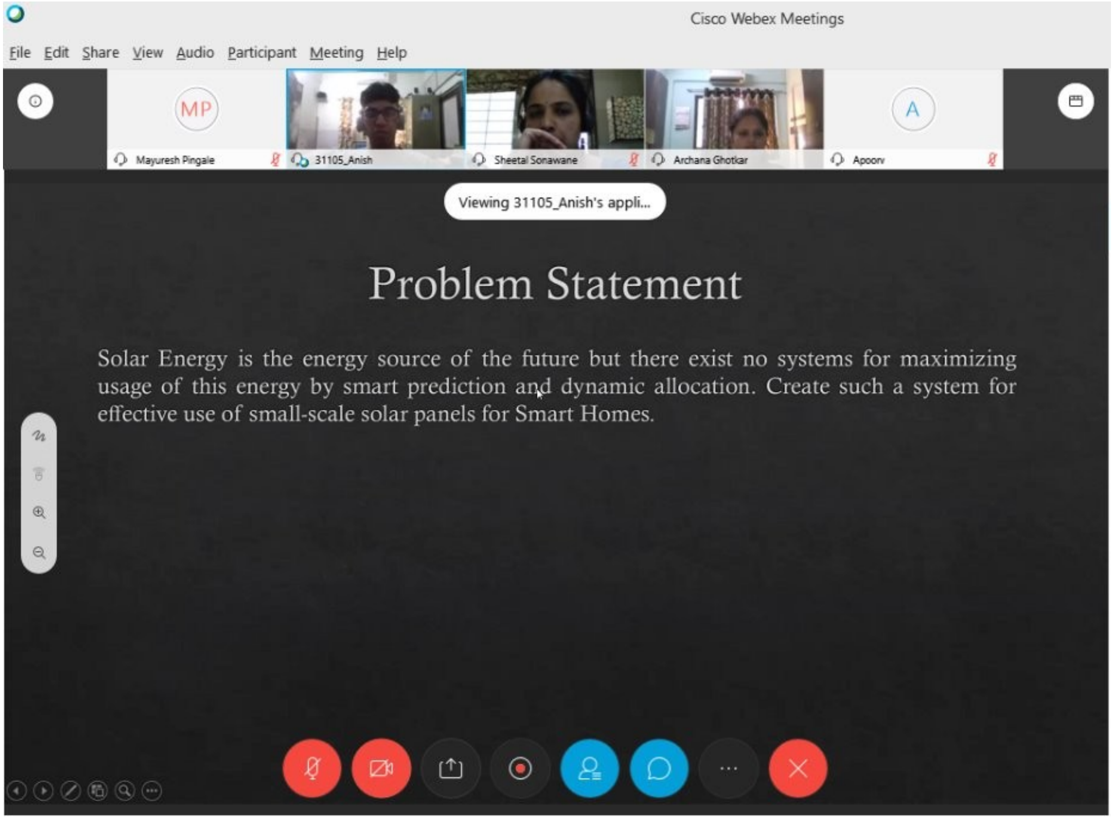
Student Signature **Guide Signature**

Figure 9: Log Sheet


Cisco Webex Meetings
File Edit Share View Audio Participant Meeting Help
MP
Mayuresh Pingale
31105_Anish
Sheetal Sonawane
Archana Ghotkar
A
Apoorv
Viewing 31105_Anish's appli...
Problem Statement
Solar Energy is the energy source of the future but there exist no systems for maximizing usage of this energy by smart prediction and dynamic allocation. Create such a system for effective use of small-scale solar panels for Smart Homes.