

Solar Power Forecasting

Software Design Specification

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Chapter-1 Introduction

- 1.1 **Overview and issues involved:** Solar power is the conversion of energy from sunlight into electricity, either directly using photovoltaics (PV), or indirectly using concentrated solar power systems. One of the most sustainable and competitive renewable energy sources is the solar photovoltaic (PV) energy.
- 1.2 **Problem definition:** The main objective is to benchmark different forecasting techniques of solar PV panel energy output. Towards this end, machine learning and time series techniques can be used to dynamically learn the relationship between different weather conditions and the energy output of PV systems. Four ML techniques are benchmarked to traditional time series methods on PV system data from existing installations. This also required an investigation of feature engineering methodologies, which can be used to increase the overall prediction accuracy.
- 1.3 **Proposed solution:** The main crucial and challenging issue in solar energy production is the intermittency of power generation due to weather conditions. In particular, a variation of the temperature and irradiance can have a profound impact on the quality of electric power production. Hence, accurately forecasting the power output of PV modules in a short-term is of great importance for daily/hourly efficient management of power grid production, delivery, storage, as well as for decision-making on the energy markets. Solar Power Forecasting basically is predicting the solar generation for future time blocks based on forecasted weather parameters like Irradiance, ambient temperature, humidity, wind speed and other relevant parameters.

Chapter-2 Literature Survey

- 2.1 PV power generation is dependent on many factors, such as weather conditions and PV module temperature. Natural variation in climatic conditions can vary these factors changing the PV power generation. Since PV power generation is variable, intermittent, and nonlinear, an accurate solar power forecasting method is required to operate the power system reliably and stably and to ensure quality power production.

There are three types of solar power forecasting: physical methods, statistical methods, and hybrid methods. The machine learning method also comes under the statistical models. Physical models are numerical weather prediction, sky imagery, and satellite imaging model. Statistical methods are more accurate for a short time horizon (1 to 6 hours), whereas physical models are suitable for the long term.

- 2.2 We are using Python, Machine Learning Techniques, Time Series Modeling, Neural Network, Google Colab, Jupyter Notebook.
- 2.3 Solar Power Forecasting basically is predicting the solar generation for future time blocks based on forecasted weather parameters like Irradiance, ambient temperature, humidity, wind speed and other relevant parameters.

Chapter-3 Analysis

3.1 Software Requirements: -

Following are the software used for the Solar Power Forecasting.

- Language: Python
- Libraries: Scikit Learn, Tensorflow, Keras, Matplotlib, Seaborn, Pandas, Numpy, statsmodel, pmdarima, facebook-prophet, etc.
- Tools: Jupyter Notebook, Google Colab
- Operating System: Windows 10

3.2 Hardware Requirements: -

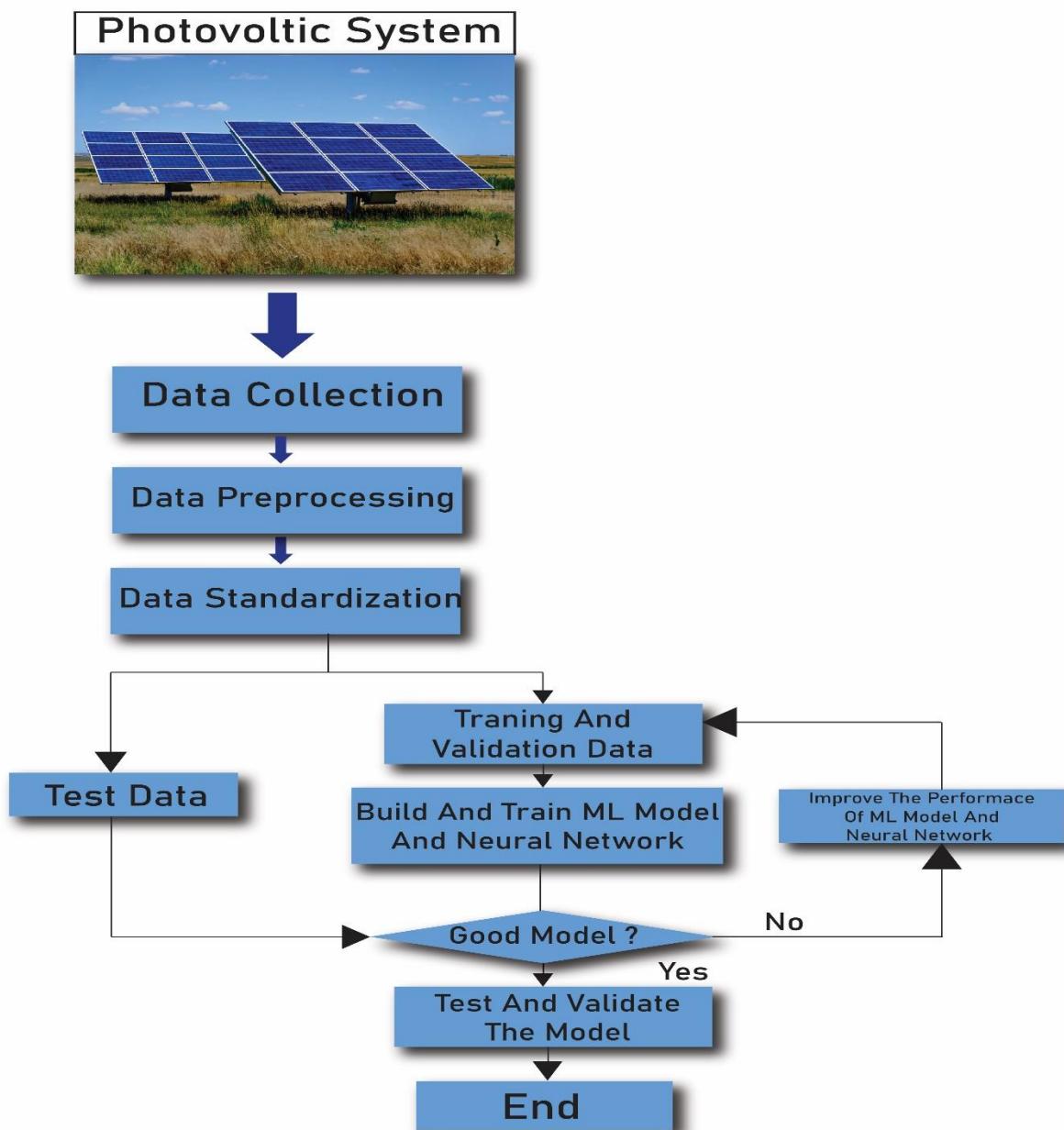
Since the initial version of the software is a Desktop Client, the hardware specifications should be appropriately compatible with the software. The actual application can be installed on a low-end computer as well, but to the implementation of the software consists of processing a large amount of data that require a certain level of hardware requirements.

- **Graphics Processing Unit (GPU):** NVIDIA GeForce 940MX 2GB graphics card would be the minimum required GPU capability for training the machine learning models.
- **Device Storage:** 500 GB HDD. The implementation can take place on ordinary Storage as well but an SSD storage would speed the processing exponentially.
- **Processor:** Dual core.

- **Memory (RAM):** At least 2GB, preferably higher.

Hardware Interface: The interface can either be touch screen or simple keyboard and mouse/touchpad.

3.3 Use Case Model



3.4 As major barriers to solar energy implementation, such as materials cost and low conversion efficiency, continue to fall, issues of intermittency and reliability have come to the fore. The intermittency issue has been successfully addressed and mitigated by solar forecasting in many cases.

Information used for the solar power forecast usually includes the Sun path, the atmospheric conditions, the scattering of light and the characteristics of the solar energy plant.

Generally, the solar forecasting techniques depend on the forecasting horizon

- *Nowcasting* (forecasting 3–4 hours ahead),
- *Short-term forecasting* (up to seven days ahead) and
- *Long-term forecasting* (weeks, months, years)

Many solar resource forecasting methodologies were proposed since the 1970 and most authors agree that different forecast horizons require different methodologies. Forecast horizons below 1 hour typically require ground based sky imagery and sophisticated time series and machine learning models. Intra-day horizons, normally forecasting irradiance values up to 4 or 6 hours ahead, require satellite images and irradiance models. Forecast horizons exceeding 6 hours usually rely on outputs from numerical weather prediction models.

Chapter-4 Design

- 4.1 With the help of Scikit learn's beautiful “Pipeline” functionality to wrap different models for the ease of training, we have used here 7 different Regression algorithms with default parameters including a several layered Neural Network regressor.

Can't forget to standardize. Features have varying scales and algorithms such as linear regression does make assumptions about the data having a Gaussian distribution, it is imperative to **standardize** the data before training. It will also help in reaching the global minimum faster.

Now for finalizing the model.

When it comes to model selection and evaluation, k-fold Cross validation is a good approach. Going one step further, we'll be using Stratified k-folds based on the BINS column. This will help us get the same distribution of bins per fold.

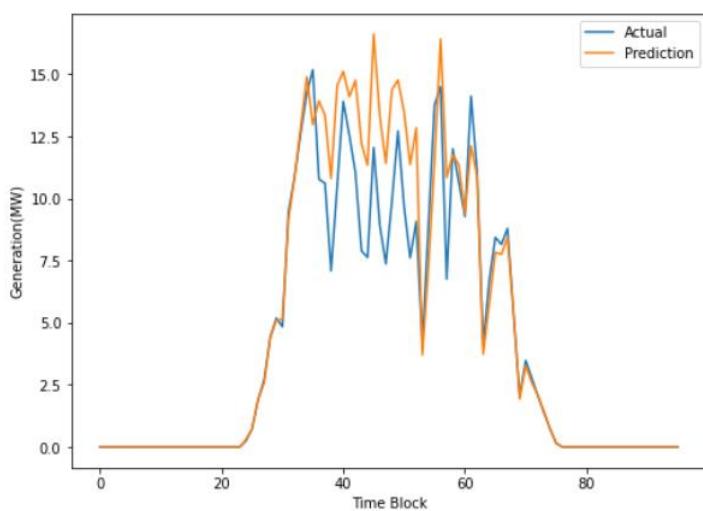
Model Evaluation and Selection using stratified k-Fold Cross validation

1. Split df_train into into 8 folds
2. Use 7 folds for training(xtrain, ytrain), 8th fold for validation(xvalid, yvalid)
3. Standardize the xtrain & xvalid generated in step 2
4. Fit xtrain, ytrain on the model
5. Predict on xvalid, find the RMSE value and store in a list
6. Repeat steps 1–5 for 8 iterations and find mean of the list having RMSE scores to get model mean RMSE for 8 iterations
7. Repeat steps 1–6 for each model in Pipeline list and compare the results

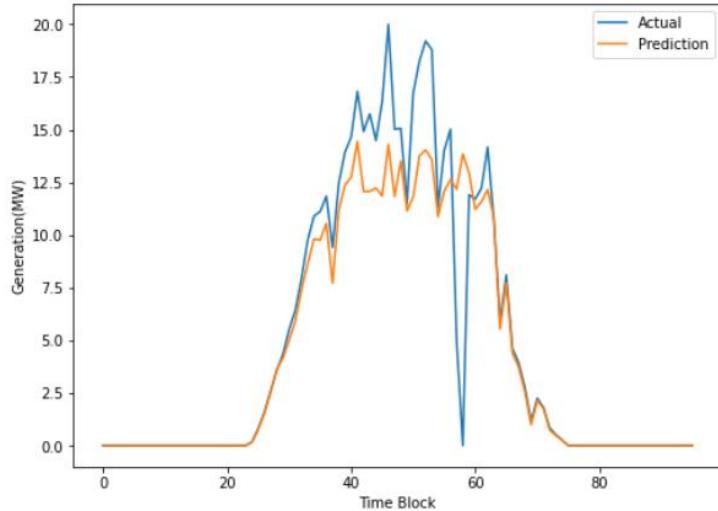
Chapter – 5 Conclusion

the solar PV power forecasting depends upon the unpredictable parameters of weather as well as the intrinsic parameters of solar PV systems themselves such as the temperature of PV modules and the irradiance on the plane of PV array. In this case, the study of the forecasting parameters including both variables of weather and PV system can be considered before the modelling such as the use of similarity algorithm which can help the designer to select the best parameters and fast modelling. At the same time, after a careful analysis of methods used to forecast the PV power, this study ascertains the need for developing more skillful methods and approaches in this area alongside the generalization methods that are capable to generalize the forecasting results. The PV power forecasting is also useful in the cases of microgrids and EVs. It provides the necessary information about the PV power available in the future time horizon and going to join the input of PV inverters. Further recommendation concerning the PV power forecasting modelling consisted on the PV power forecasting model for each time horizon which means, for example, a model for short-term time horizon cannot be used for a time horizon of very short-term.

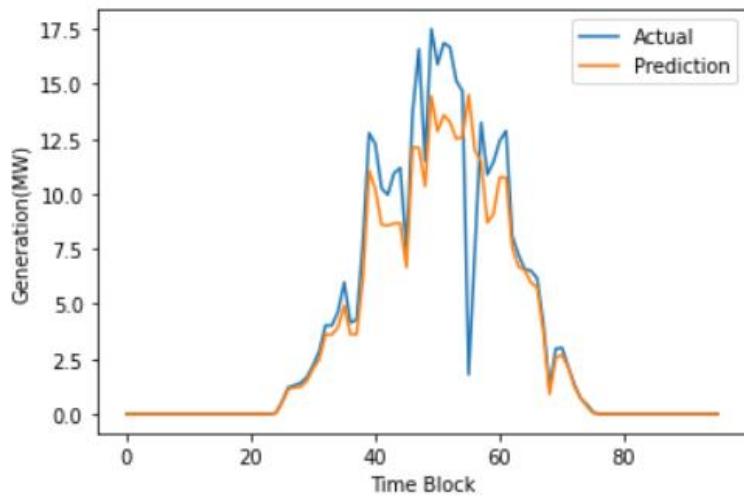
Outcomes



Day 1 Forecast

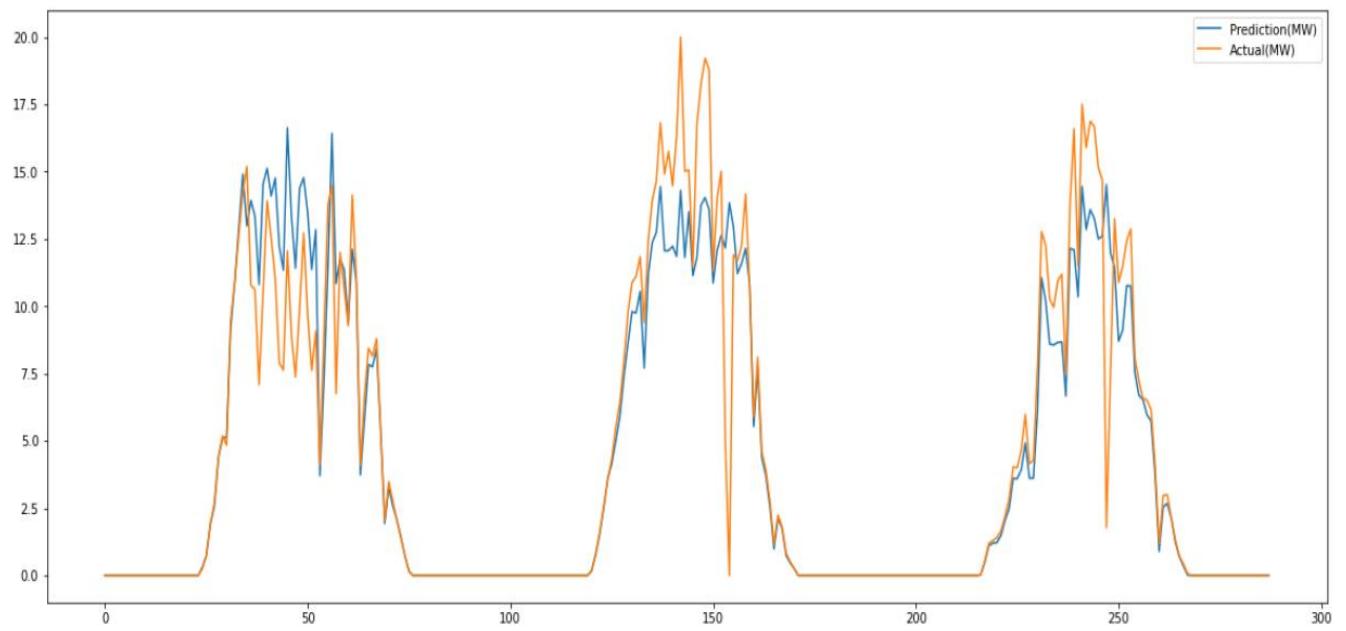


Day 2 Forecast



Day 3 Forecast

High fluctuations in actuals can be observed in all the 3 days. Predictions(Orange) in plot 1 is on the higher side in the middle part, rest is covering well. Forecasts in Plot 2 & 3 are slightly underfitting the actual curve.



3 Days Forecast

Appendix: Glossary

- it covers all the requirements that are actually expected from the system.
- there are no conflicts between any set of requirements. Examples of conflict include differences in terminologies used at separate places, logical conflicts like time period of report generation, etc.
- It exists a specific technique to quantifiably measure the extent to which every requirement is met by the system.

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