Solar Irradiation Forecasting using Genetic Algorithms

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Abstract:
Renewable energy forecasting is attaining greater importance due to its constant increase in contribution to the electrical power grids. Solar energy is one of the most significant contributors to renewable energy and is dependent on solar irradiation. For the effective management of electrical power grids, forecasting models that predict solar irradiation, with high accuracy, are needed. In the current study, Machine Learning techniques such as Linear Regression, Extreme Gradient Boosting and Genetic Algorithm Optimization are used to forecast solar irradiation. The data used for training and validation is recorded from across three different geographical stations in the United States that are part of the SURFRAD network. A Global Horizontal Index (GHI) is predicted for the models built and compared. Genetic Algorithm Optimization is applied to XGB to further improve the accuracy of solar irradiation prediction.

Introduction:
Renewable energy usage across the world has increased manifolds during the past few years. Although several renewable energies from sources such as the sun, wind, tidal waves and the sea are available, solar energy has a vast potential to be the most significant renewable energy. Due to the abundance of solar energy, there is an increase in the efficiency of solar photovoltaic cells with constant technological developments and there is a decrease in the cost of manufacturing [1-3]. Accurate forecasting of solar irradiation gains significance due to its impact on solar power generation to ensure efficient power management to the grids, and to look for alternative power sources during the unavailability of solar power. Recently, several Machine Learning (ML) models have been used for the prediction of solar irradiation that include Artificial Neural Networks [4,5], Probabilistic Models [6], Bayesian Methods [7], Deep Learning Models [8,9], and Support Vector Machines [10, 11].

In this work, we study and validate ML algorithms such as Linear Regression (LR) and Extreme Gradient Boosting (XGB) [11-13], together with Genetic Algorithm (GA) [14-17] Optimization. The data used is obtained from three meteorological stations (Bondeville, IL, Desertrock, NV and Pennstate, PA) in the United States, that are part of the SURFRAD network [18,19]. The three stations are chosen for their diverse climatic conditions throughout the year. The current study investigates the ability of Genetic Algorithms (GA) to improve the accuracy of global solar irradiation prediction, where Global Horizontal Index (GHI) is the primary output variable.

Data preprocessing:
From the SURFRAD network, the solar irradiation data acquired by measurements through pyranometer is available for the last 20 years from seven stations located at different states in
the United States. However, data from three stations, which have varying climatic conditions all throughout year that are different from each other, are selected, namely Bondville, IL, Pennstate, PA and Desertrock, NV. The data chosen is from three consecutive years from 2018 to 2020, where the data from 2018-2019 is used for training, and the data from 2020 is used for validating and testing the developed models. The choice of these stations is to show the variability in the solar radiation based on the geographical location. The data recorded during the daytime (between 7 AM and 4 PM) is considered for the study since the solar irradiance is weak during the nights and early mornings. Hence, GHI for nine hours during the day is used for training and testing the models. The output of the model is the next minute GHI value and the parameters included are temperature, pressure, wind speed, wind direction, relative humidity, solar zenith angle, net solar radiation and time, with information in minutes, hours and months. Furthermore, the data is normalized to obtain normalized distribution, removing outliers and cleaning the data. A few of the processed normalized distribution plots such as, dw_solar, temperature and relative humidity can be seen in Figure 1. The data used for training is split into 70/30, for training and testing, respectively.

**Outlier Detection:**
The outliers from the data have been removed as they severely impact the functionality of the model. For example, values such as -9999.90 are recorded for at least 11 variables in the data. If replaced by mean, median, mode or the minimum value, these values impact the results significantly. None of the four mentioned replacements work and hence were removed from the data. The fundamental statistics obtained from the data can be seen in Table 1.

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**Figure 1:** Data preprocessing to obtain normalized distribution of data, removing outliers and cleaning the data: dw_solar (*top*), temperature (*middle*) and relative humidity (*below*).
Nomenclature:

| Feature | Description                               |
|---------|-------------------------------------------|
| dt      | Decimal time                              |
| zen     | Solar zenith angle (degrees)              |
| dw_solar| Downwelling global solar                 |
| uw_solar| Upwelling global solar                   |
| direct_n| Direct-normal solar                       |
| diffuse | Downwelling diffuse solar                 |
| dw_ir   | Downwelling thermal infrared             |
| dw_casetemp | Downwelling IR case temp. (K)   |
| dw_dometemp | Downwelling IR dome temp. (K)          |
| uw_ir   | Upwelling thermal infrared               |
| uw_casetemp | Upwelling IR case temp. (K)          |
| uw_dometemp | Upwelling IR dome temp. (K)         |
| uvb     | Global UVB                                |
| par     | Photosynthetically active radiation       |
| netsolar| Net solar (dw_solar - uw_solar)           |
| netir   | Net infrared (dw_ir - uw_ir)             |
| totalnet| Net radiation (netsolar + netir)         |
| temp    | 10-meter air temperature (°C)            |
| rh      | Relative humidity (%)                     |
| windspeed| Wind speed                               |
| winddir | Wind direction (degrees, clockwise from north) |
| pressure| Station pressure (mb)                    |

Feature Selection:
Feature selection eliminates irrelevant features to enhance the model’s performance by reducing the complexity and computational time of the model. This process also helps get rid of highly collinear variables. In the current work, the selection of features is performed by obtaining the importance of the parameters using the Random Forest method. A total of eight parameters with high relevance with the dependent variable are selected among fifteen variables for training the model. The features with high importance can be seen in Figure 2.

Machine Learning Algorithms
LR is one of the methods used in this study, where the dependent variable is continuous. LR is fitted on the data whose response variable is continuous. The relationship between the dependent variable and one or more independent variables is derived. The LR model predicts the global irradiation taking variables that are both continuous and discrete. A simple LR equation with prediction $y$ and input $x$ is given by:

$$ y = mx + b $$
Figure 2: The importance of features used in feature selection process by using Random Forest method. The top eight features are taken into consideration for the model.

Extreme Gradient Boosting (XGB) is a ML technique for regression and classification problems, which produces a prediction model in an ensemble of weak prediction models, typically decision trees. It builds the model in a stage-wise fashion as other boosting methods do, and generalizes it by allowing optimization of an arbitrary differentiable loss function [2]. The XGB node uses a partitioning algorithm in search of an optimal partition of the data for a single target variable. XGB is an approach that resamples the data several times to generate results that form a weighted average of the resampled data set. Tree boosting creates a series of decision trees that form a single predictive model. Similar to decision trees, boosting makes no assumptions about the distribution of the data. Boosting is less prone to overfitting the data than a single decision tree. If a decision tree fits the data reasonably well, then boosting often improves the fit [11-13].

Genetic Algorithm (GA), first proposed by John Holland, is a type of meta-heuristic search and optimization algorithm. It is inspired by Charles Darwin’s theory of natural selection, where the fittest survives. The best is selected from the population to produce offsprings and continue to mutate and get even better offsprings. A similar approach is applied in the current study to select parameters from every level aiming to get the best parameter. The ‘population’ refers to the solutions to the given problem. While XGB is less prone to overfitting, in selecting the hyperparameters, at times, it is humanely impossible to come up with an exemplary configuration to know if the models will hold good for future prediction and at times, may end up with weak prediction. GA effectively addresses this problem by eliminating the need for blind hyperparameter selection and naturally improving the accuracy of the model without overfitting the results.

The error rate is calculated by using the mean square error (MSE), which is given by:
\[ MSE = \frac{1}{N} \sum_{i=1}^{n} (y_i - (mx_i + b))^2 \]

Where:
- \( N \) is the total number of observations (data points)
- \( y_i \) is the actual value of an observation
- \( mx_i + b \) is the prediction

**Results and Discussion**

The models LR, XGB and GA are used to predict solar irradiation, where 2018 and 2019 data are used for training and testing. In the XGB, four sets of parameters are utilized to identify the best performing set with accurate results. Similarly in GA, three models are used with different
numbers of generations. From the three models, it can be seen that LR has the least accuracy of about 95.5%, with a high MAE of 14.73. Further, XGB offers roughly 3% better accuracy than LR, but still falls short with 98.5% accuracy. Although it is relatively good accuracy, the minimum accuracy in GA model is higher than 98.5% from the test set. The GA model with 10 generations obtained an accuracy of 99% from the tests with a MAE of 2.74. This reinforces that the GA model outperforms the traditional models. This is also proven by the validation set, where it can be seen that the best accuracy is achieved by the GA run for ten generations. The accuracy here is about 97.75% and the MAE is 7.45. In addition to having the best accuracy and the least MAE, this also is the most effective for higher computational efficiency.

Table 2 lists the parameters that were used. The parameters used for the GA run for ten generations have been highlighted. The parameters were generated and determined automatically and recommended by the algorithm to process the ten generations. Obviously, this would be very difficult for a human to do and impossible for humans to do in this period.

The results for the GA run for ten generations have been summarized in this table. As can be seen, the accuracies are 98.64% and 97.74% and the MAE is 4.64 and 7.45 for the test and validation sets, respectively. Finally, the models have been compared against different stations to verify if the GA returns consistent results across the stations. In both the test and validation sets, it can be seen that GA consistently outperforms both XGB and LR. XGB generally performs better than LR, but in Pennstate PA, LR outperforms XGB by 0.2%. XGB consistently outperforms LR and GA outperforms XGB in all stations in the validation set. The best performance of GA can be observed in Pennstate PA results, where the accuracy is 98.33 and the MAE is 5.42. A summary of the results is shown in Table 2.

Table 2: Summary of the accuracy, MAE and variance or the three stations

| Model Comparison | Bondville-IL | DesertRock-NV | PennState-PA |
|------------------|-------------|---------------|-------------|
|                  | LR | XGB - 100 | GA 10 | LR | XGB - 100 | GA 10 | LR | XGB - 100 | GA 10 |
| Train-Test MAE   | 14.73 | 5.39 | 4.64 | 12.09 | 5.3 | 4.58 | 3.89 | 3.69 | 3.08 |
| Train-Test Variance | 88.19 | 97.93 | 98.42 | 90.13 | 98 | 98.47 | 98.94 | 95.01 | 99.28 |
| Train-Test Accuracy | 95.55 | 98.41 | 98.64 | 96.16 | 98.32 | 98.55 | 98.81 | 96.61 | 99.09 |
| Validation MAE   | 14.18 | 7.69 | 7.45 | 13.03 | 12.68 | 12.92 | 6.07 | 5.51 | 5.42 |
| Validation Variance | 88.23 | 95.7 | 95.95 | 89.85 | 89.43 | 88.81 | 97.01 | 97.01 | 97.96 |
| Validation Accuracy | 95.63 | 97.67 | 97.74 | 95.95 | 96.04 | 95.96 | 98.15 | 98.3 | 98.33 |
Figure 4: The (top) test and (bottom) validation plots for the three stations depicting the test, validation data sets compared with the predicted values from LR, XGB and GA models for Bondville IL, Desertrock NV and Pennstate PA during May.

Conclusion
In summary, the data from three meteorological stations, with diverse climatic conditions is used to evaluate the ability of genetic algorithms in improving the accuracy of global solar irradiation prediction. ML algorithms like LR, XGB and GA are used to predict the global solar irradiation and the prediction results from each of these algorithms are assessed. The results clearly show that GA is better than the other ML techniques applied to predict solar irradiation. To reinforce this conclusion, the data from all the three centers were again compared with the solar irradiation prediction results from all the three ML techniques and for all the three stations, the prediction results provided by the GA were superior to the results from the other ML techniques used. This study aims to assess which ML Technique would provide better prediction results for the global solar irradiation. Although the sample size used in this study is small, it provides a basis for comparison that can be leveraged for larger sample sizes in future. For future studies, the number of centers, based on the climatic conditions could be increased. Also, the number of parameters used can be increased by including other centers data and the existing parameter set can be fine-tuned based on the results of the new centers.

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