Hybrid Optimisation and Machine Learning Models for Wind & Solar Data Prediction

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Abstract. The exponential growth in energy demand is leading to massive energy consumption from fossil resources causing a negative effects for the environment. It is essential to promote sustainable solutions based on renewable energies infrastructures such as microgrids integrated to the existing network or as stand alone solution. Moreover, the major focus of today is being able to integrate a higher percentages of renewable electricity into the energy mix. The variability of wind and solar energy requires knowing the relevant long-term patterns for developing better procedures and capabilities to facilitate integration to the network. Precise prediction is essential for an adequate use of these renewable sources. This article proposes machine learning approaches compared to an hybrid method, based on the combination of machine learning with optimisation approaches. The results show the improvement in the accuracy of the machine learning models results once the optimisation approach is used.

Keywords: Renewable Energy· Forecasting · Machine Learning · Optimisation · Wind Speed · Solar Irradiation.

1 Introduction

A considerable proportion of worldwide and especially domestic demand on energy is satisfied by the burning of the fossil fuels [1]. It is broadly recognised that the combustion of fossil fuels such as oil, coal and natural gas emits a great quantity of greenhouse gases (GHG) into the atmosphere, which has very negative effects on the environment [2]. The generation of greener or carbon-free energy can be obtained by exploiting renewable energy sources (RES) such as wind and solar, that have already been developed to satisfy the growing energy needs of the planet [3], trying to minimize the rising product costs. The liberalization of the energy market for electricity, coupled with the growing need for sustainable energy, has pushed policy makers and investors to make greater use of RES to meet the global energy challenge [4]. The injection of these RES into the energy mix needs a large backup generation capacity in order to remove the intermittent nature of such sources. This intermittency causes several problems on the quality of observed power output: voltage fluctuation, power system transients and harmonics, reactive power, electromagnetic interference, switching actions, synchronisation, low power factor, etc. Given technological and economic limitations in current energy storage techniques, it will be difficult to accomplish the current mandates for renewable energy integration.

Moreover, the power generated by wind turbine and photovoltaic systems is strongly influenced by local weather conditions, such as climate temperature, wind velocity, precipitation, relative humidity, solar irradiation and their fluctuations. Consequently, wind and solar energy production is usually rather complex to supervise and forecast, which has rendered the incorporation of both wind and solar energy into electrical networks as a challenge [5].

To address the above challenge, it is crucial to enhance the forecasting capability of wind velocity and solar irradiation in order to mitigate the degree of confidence regarding the potential output of sustainable energy in any operating conditions of the power grid [6]. Given the relationship that exists within solar irradiance and photovoltaic, and the relationship that occurs between wind speed and energy generation from wind turbines, it is necessary to build a forecasting mechanism that will accurately predict solar irradiance on medium and/or short term time scales [7].

The wind speed forecast is classified in the following four time intervals including a few seconds to 30 minutes that is a very short period prediction [8], 30 minutes to 6 hours that is short term prediction [9], 6 hours to 1 day that is mid range prediction [10] and finally a long term that consider more than one day prediction [11]. In parallel, solar irradiation prediction can be separated into four temporal categories: the very short term in minutes to an hour [12], the short term from 1 to 4 hours [13], the medium term considering one day in advance [14] and the long term including more than one day in advance [15].

A variety of techniques have been developed in previous years to forecast wind speed and solar irradiation that can be grouped into three major clusters: physics-based approaches, data-dependent models, and hybrid approaches.

First, physics-based approaches involves measurements of meteorological and topographical data. In literature, Physical methods consist of several approaches, mainly, Total Sky Imagery (TSI) [19], Weather Research and Forecasting (WRF) [20], cloud-moving-based satellite imagery models, and numerical weather prediction (NWP) [21].

The second cluster is composed by the data-dependent models, mainly statistical models and machine learning models, which are the most widely used tools for predicting these time series. In literature, researchers employed statistical approaches including auto-regressive moving average (ARMA) [22], Markov models [23], Lasso [24] and autoregressive integrated moving average (ARIMA) [25]. On the other hand, machine learning approaches are used in term of data driven. The authors employed the support vector machines (SVM) [26], convolutional neural networks (CNN) in [27], artificial neural networks (ANN) in general in [28], feed-forward neural networks (FFNN) in [29], bidirectional long short-term memory neural networks (BLSTM) in [30] and deep belief networks (DBN) in [31]. Ultimately, hybrid approaches [16–18] have been proposed.

By last, to predict the wind speed and solar irradiation values, hybrid methods are widely used in literature, such as, Neural Network models combined with particle swarm optimisation (PSO) in [32]. Duan and al [33] combined error decomposition correction approaches with neural network algorithm. For long term prediction, a combined model including an improved hybrid time series decomposition (HTD) with normal distribution optimisation algorithm for hyperparameter tuning have been employed in [34]. Wavelet transform combined with autoregressive integrated moving average (WT-ARIMA) have been used in [35]. Multi-objective binary backtracking search algorithm (MOBBSA), and an advanced sequence-to-sequence predictor for wind speed forecasting have been provided in [36]. Multiple machine learning methods, including support vector machine (SVM) and back-propagation neural networks (BPNN) used in conjunction with variational mode decomposition (VMD) have been presented in [37]. Artificial neural network combined with Takagi–Sugeno fuzzy inference system (ANFIS) is presented on paper [38].

This paper develops accurate short-term (i.e., next hour) wind speed and solar irradiation prediction models based on hourly real data recorded at the Malviya National Institute of Technology weather station in Jaipur, India. For this purpose, regression-based machine learning models will be used, including linear regression models, regression trees, Gaussian process regression models, support vector machines, kernel approximation, regression tree ensembles and neural network regression models. In order to improve the predictive performance of the regression machine learning techniques, and to achieve better model accuracy for wind speed and solar irradiation prediction, the most efficient model tested will be combined with optimisation approaches, including Bayesian optimisation, grid search and random search.

The main contributions of this paper are:

- Using of Inter Quartil method (IQR) for data perturbation removal.
- Performing correlation study for the correct designation of predictors.
- Using optimisation methods including Bayesian optimisation, Random search, and Grid search for automate and optimal achieving of hyperparametrs.
- Using four regression machine learning models: Regression Trees, Gaussian Process Regression (GPR), Support Vector Machine (SVM) and Ensembles.

The rest of paper is organised as follows: In section 2, the study case and dataset processing and characterization are presented. Section 3 presents the theory behind the proposed regression machine learning approaches combined with optimisation algorithms employed to increase models accuracy. In section 4 the results of the simulation and their discussion are presented. Section 5 summarises the findings of the paper and proposes guidelines for future work.

2 Dataset description and processing

This paper includes a real study case for wind speed and solar irradiation forecasting. As primary step, the used dataset is presented, analysed and processed.

2.1 Dataset Analysis

The dataset employed in this research is obtained from measurements made on the meteorological station of Malviya National Institute of Technology in the Jaipur region located in India (Latitude: 26.8622°N, Longitude:75.8156°E), exported from the online recording platform named: MNIT Weather Data - Live Feed. The weather dataset include the following parameters: temperature, wind speed, solar radiation, and relative humidity recorded at a height of 10 m from the ground. Table 1 provides summary information for solar irradiance and wind speed temperature and relative humidity, including maximumn, minimum, and mean values with standard deviations. Moreover, a dataset composed of 1922 features imported from the platform is presented in Fig.1.

Table 1: Dataset summary: Max, Min, Mean, Std values.

Value / Parameter	Min	Max	Mean	Std
wind speed (m/s)	0.47	20.62	4.71	5.04
Relative Humidity (%)	3.41	80.72	26.14	19.33
Temperature (C°)	21.75	39.97	31.39	4.55
Solar Radiation (W/m^2)	0	1089	233.79	272.25

The profiles are drawn for the month of March (each hour sampling). Dataset densities distribution is represented on Fig.2 for the informal investigation of the data-set properties. A significant value between 0 and 26 W/m^2 classes for solar irradiance represents the repeating pattern of the daily amount during this month, as a result from the night period when there is no sun exposure. It implies that the solar energy yield is low for the deployment of an "efficient" photovoltaic installation, whereas this is irrelevant for a final decision-making process, considering that it is only calculated for one month of measures. The studies of the wind speed represent a very complex operation and must be precise in order to discover the real existing deposit, since an important investment is necessary for the installation of wind turbines farm which the installed generator depend on the characteristics of the wind, therefore, a false analysis of the wind will generate a considerable monetary loss. For this purpose, in addition to the density study, a statistical weibull distribution of the wind speeds was carried out based mainly on two important parameters: the form factor K and the scale factor C. Fig.3 shows the achieved weibull distribution. The characterization values highlighted that this location has a uniform and constant wind variation,

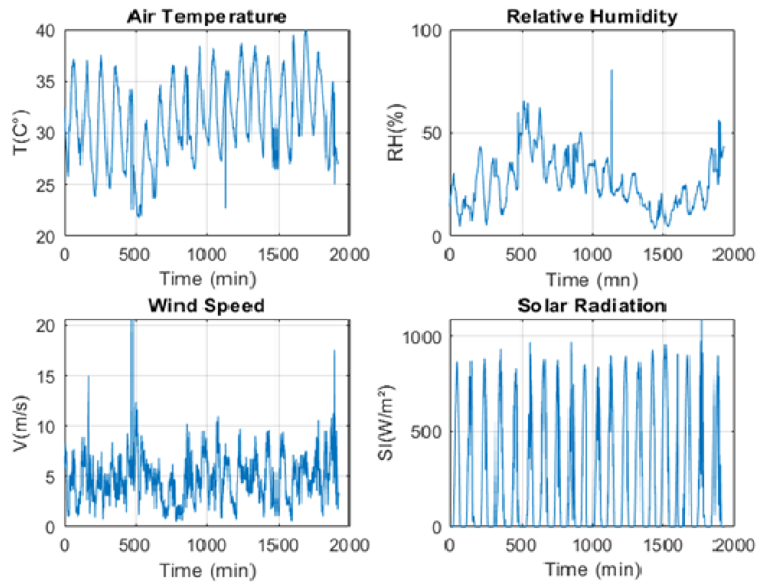


Fig. 1: Dataset.

justified by K=2.53. Furthermore, the concentrated values around 4.66 m/s is justified by the obtained scaling factor. This is also emphasised on the values of the density class between 4 and m/s as presented on Fig.2.

2.2 Data Processing

Sudden wind variability (due to air currents) or lack of solar radiation measurement (due to obstacles) can affect the nature of the data measured. In order to eliminate the inhomogeneities in the measurement and obtain more reliable climate data, more consistent time series should be obtained. To do this, the measurements are first analysed for outliers identification and removing from the measured values. Box and whiskers plots of the original data are presented in Fig.4, where it is shown that the relative humidity and solar irradiation contain outliers.

To clean the dataset from inhomogeneities, the Inter Quartiles (IQR) method have been employed due to the skewed distributions nature of the datasets. Fig.5 illustrate the box and whiskers plot after employing the IQR and removing outliers. The cleaning of the humidity and wind speed measurements is displayed on Figures 6 and 7 showing the data behaviour before and after the removal of outliers by the quartiles method.

It is therefore essential to know the varying relationship between the measured parameters, so that it can be used as a reliable predictor of wind velocity

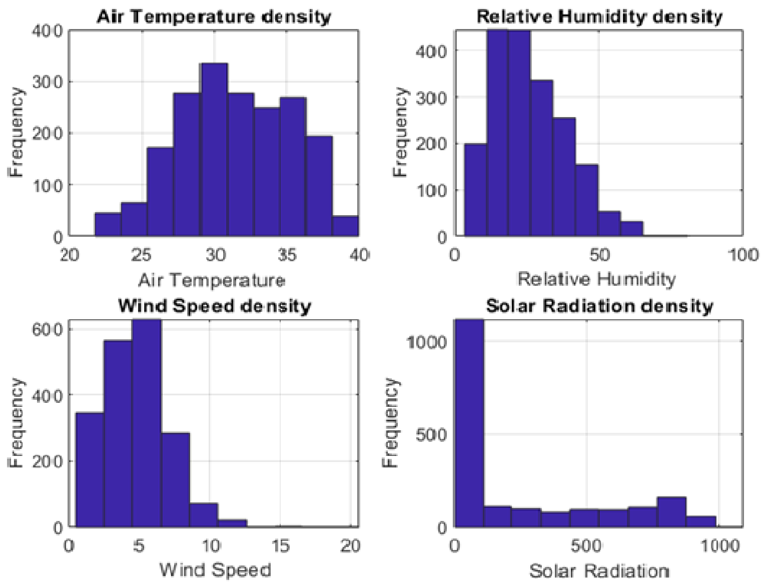


Fig. 2: Weather data density

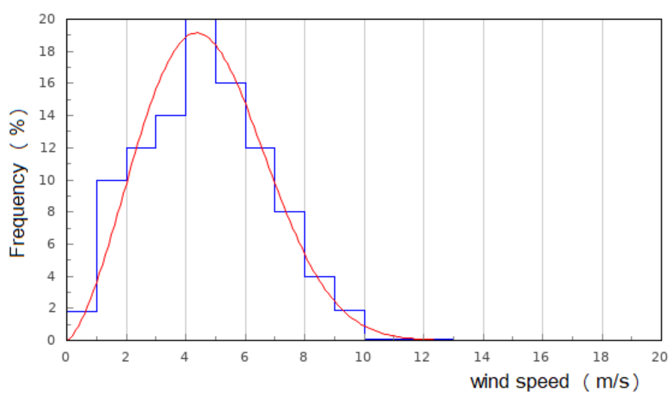


Fig. 3: Weibull distribution

and solar irradiation. For this task, a correlation study is carried out, where each meteorological parameter is related to the other by a pearson correlation coefficient giving a correlation matrix between all the considered variables: wind speed, solar radiation, temperature and relative humidity. Fig. 8 illustrates the correlation matrix showing the scatterplots of a couple of variables with a least squares reference line, having a slope equal to the correlation coefficient. The

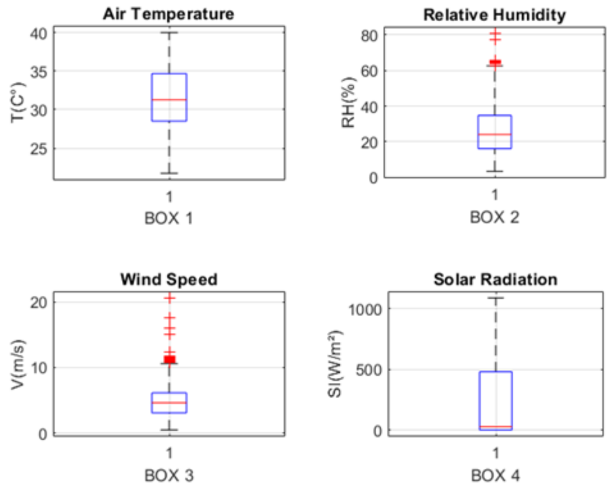


Fig. 4: Box and whiskers plot including data outliers

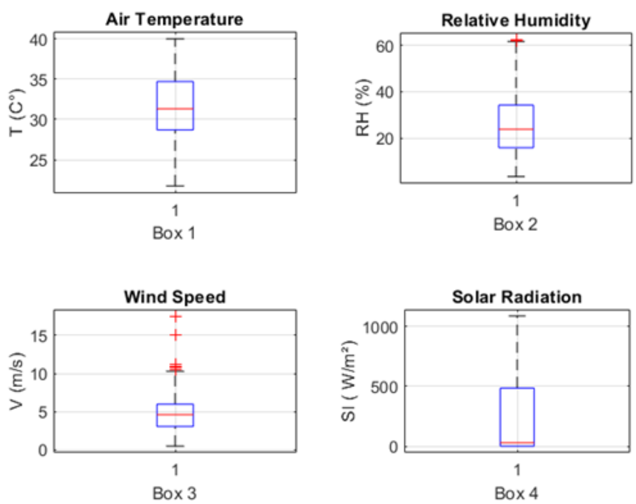


Fig. 5: Box and whiskers plot after outliers removal

diagonal of this matrix is the density distribution of a considered variable. The analysis of the correlation matrix is described [51].

Depending on the degree of linear relationship between each pair of variables obtained from the correlation matrix, it is possible to determine the predictor parameters of wind speed and solar irradiation as shown in the Table 2. It should be noted that according to an already conducted study in the line of short term

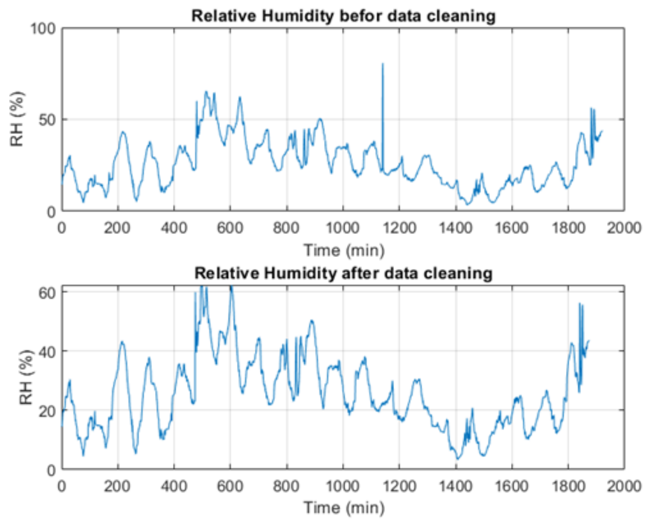


Fig. 6: Humidity data processing

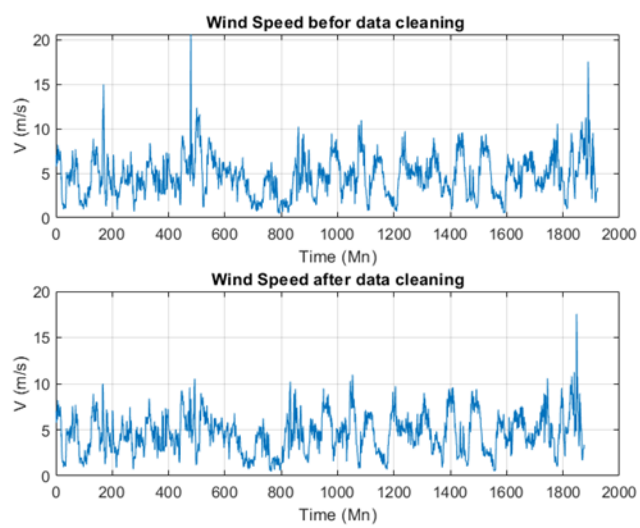


Fig. 7: Wind speed data processing

wind speed forecasting [38], the previous recorded value of wind speed is an important information for predicting this parameter.

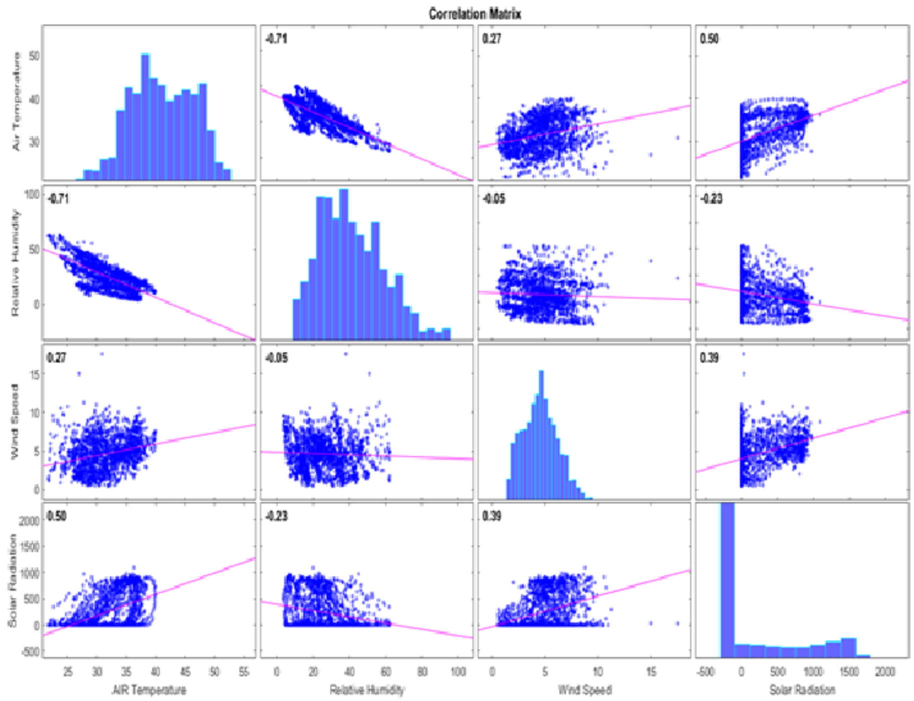


Fig. 8: Data correlation of considered weather parameters.

3 Methodology

As showed in Section 1, machine learning is being one of efficient approaches employed the wind speeds and solar irradiation. Supervised machine learning techniques are used in this paper based on regression, including Regression trees, Gaussian process regression (GPR) models, Support vector machines (SVM) and Ensembles. These methods have been chosen on the basis of the performance that they provide for the same forecasting purpose (i.e, wind speed and solar irradiation) presented in article [51]. In the latest research, the tuning of the hyperparameters was done manually. This approach consisted of using the recommended rules of thumb and then experimenting with a range of values through trial and error. However, it has the drawbacks of being tedious and time-consuming. It is not convenient in situations where there are many hyperparameters with a wide range of values. In this study, in order to automate the tuning process and to obtain a better result in terms of model accuracy, optimisation methods were used including Bayesian optimisation, Grid Search, and Random Search.

Using a set of optimal hyperparameter values for a learning algorithm will ensure that the performance of the model is maximised, by minimizing the loss

Table 2: Predictor parameters.

Wind Speed predictors	**Solar irradiation predictors**
Previous recorded wind speed values (m/s)	Relative humidity (%)
Temperature (C°)	Wind speed (m/s)
Solar Radiation (W/m^2)	Temperature (C°)

function to achieve better accuracy with minimal deviation. The learning algorithm minimises a cost function depending of its data input and attempts to find an optimal solution in the given setting [39–41].

3.1 Optimisation approaches

- **Grid search**: is a kind of rough force method of adjusting the hyperparameters. A grid of potential discrete numbers of hyperparameters is constructed, then the model is tuned with all available combinations. The performance of the model for each set is registered and then the combination that generated the best performance is applied. In a visual way, a grid search based on 2 features can be represented as a sequential way of testing of all combinations. Grid search is an efficient approach in finding the optimal combination of hyperparameters. Nevertheless, it has the inconvenience of being slow. Tuning the pattern using all potential combinations usually involves a large amount of computing power and time, which are not always available. Since it began an initial large-scale grid search, once identifying a particular region of interest in which the models perform well, it began a second grid search in that specific region as explained in Fig.9 [42].
- **Random search**: This method follows the same objective as the grid search. However, it doesn't test all combinations sequentially. Instead, it tries random combinations from the range of values specified for the hyperparameters as shown in Fig.10. Initially it specifies the number of random configurations that it wants to test in the parameter space. The main benefit of this method is the fact that a wider range of hyperparameters can be tested in the same computation time as the grid search, or the same ones can be tested in much less time, there is a compromise between ensuring that the best combination of parameters and the computation time [44].

Grid search and random search are rather inefficient as they often estimate many inappropriate combinations of hyperparameters. They fail to take into account the results of previous iterations when selecting subsequent hyperparameters. Meanwhile, the Bayesian optimisation method takes a different approach.

- **Bayesian**: it treats the search for the optimal hyperparameters as an optimisation problem. When choosing the next hyperparameter combination, this method considers the previous evaluation results [45, 46]. It then applies a probabilistic function to select the combination that will probably yield the

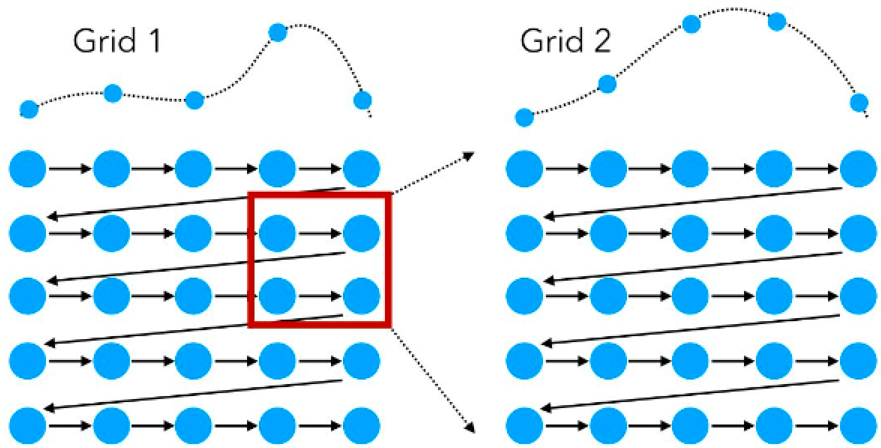


Fig. 9: Grid search hyperparameter tuning method [43].

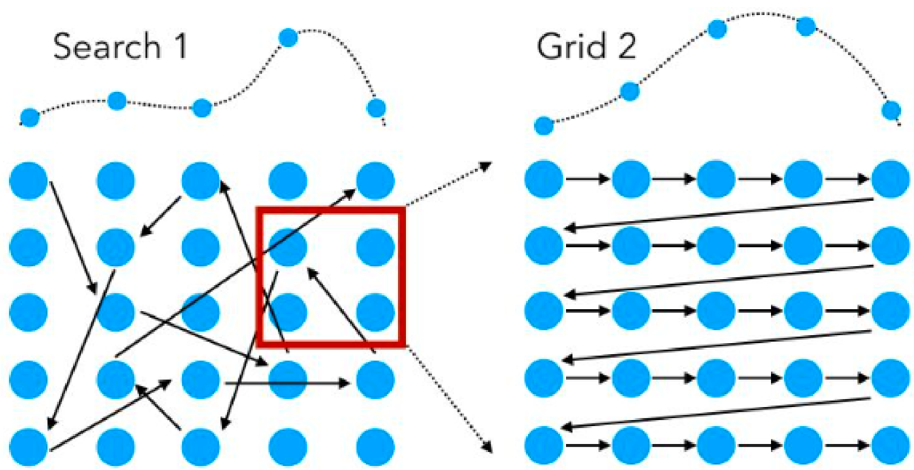


Fig. 10: Random search hyperparameter tuning method [43].

best results [47]. This method discovers a fairly good hyperparameter combination in relatively few iterations [48]. Bayesian optimisation is effective, but it will not solve all tuning problems. As the search progresses, the algorithm switches from exploration trying new hyperparameter values to exploitation using hyperparameter values that resulted in the lowest objective function loss [49]. If the algorithm finds a local minimum of the objective function, it might concentrate on hyperparameter values around the local minimum rather than trying different values located far away in the domain space. Random search and grid search does not suffer from this issue because it does not concentrate on any values [50].

3.2 Combined machine learning and optimisation

This work involves four machine learning models (GPR, SVM and Ensembles) combined separately with three optimisation approaches (Grid search, Random search and Bayesian). The datasets are first separated into two sets, i.e. a training set and a validation set. The preparation phase of the data reorganises the two sets by removing disturbances in the distribution using the quartile method explained in 2.2. The dataset, after being prepared, is used for the training inputs of the model. The tuning of the hyperparameters is done using optimisation methods. A point is a set of hyperparameter values that is a candidate for being the optimal point of the objective function (loss function). In each iteration, the results of the training model are evaluated by the root mean square error (RMSE) (Equation 1):

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(V,S)_{predicted} - (V,S)_{measured}}{n}} \tag{1}$$

where, V and S are wind speed and solar irradiation respectively. If the error results are not satisfactory, for each optimisation approach, the operation make another trial (K+1) to export the best set of hyperparameters for each model using the principle explained in 3.1. The algorithmic principle of the mechanism followed explained in Fig.11.

4 Results and discussions

The paper [51] proposes some regression machine learning models for short wind speed and solar irradiation forecasting based on real measurements collected from meteorological station of Malviya National Institute of Technology. The discussion will present first an overview about the achieved results in this previous work. Then, as a continuation of the proposed future work, the remain part of the discussion is going to be dedicated for the novel contribution of this paper consisting of a combination of optimisation methods with regression machine learning model for extracting a higher accuracy and more precise forecasting models. The predictors used for the forecast are the same presented above.

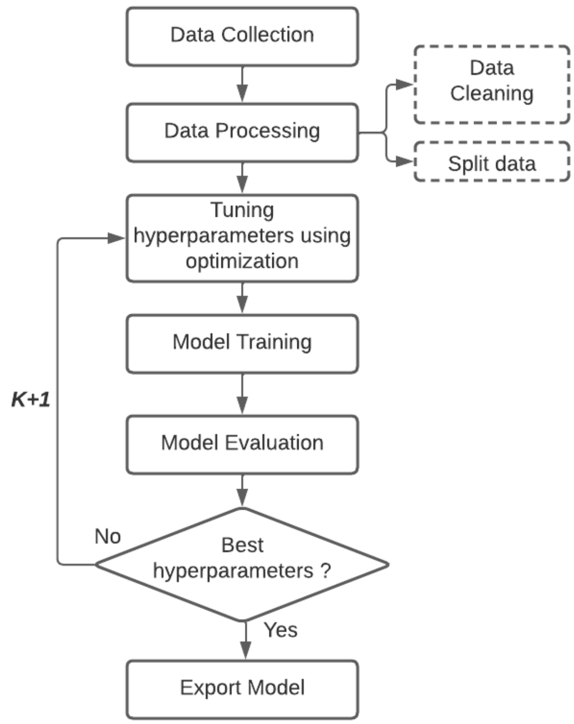


Fig. 11: Model processing flowchart.

4.1 Wind speed and solar irradiation using regression machine learning model: Manual Tuning

Solar irradiation forecasting The best performance, evaluated by the Root Mean Square Error (RMSE), of the regression models for predicting solar irradiance using manual tuning are presented in the Table 3. The previous study focused on the impact of outliers on model performance results. Indeed, the study results showed that by cleaning the data, model performance is increased since treatment of data by removing perturbation ensure a better fitting, so, the results presented in the following are based on processed input data. It is shown that the Gaussian Process Regression (GPR) outperform the other regression models.

Wind speed forecasting Table 4 presents the results of the Root Mean Squared Error (RMSE) for wind speed forecasting based on manual tuning. The Support Vector Machine achieved better results than the other regression models. It was able to solve the non-linear regression on the basis that the SVM algorithm recognises the presence of non-linearity in the data and provides a competent prediction model.

Table 3: Model results performances for solar irradiation (Manual Tuning).

Model	Root Mean Square Error (RMSE)
Regression Trees	61.83
Support Vector Machine (SVM)	57.37
Gaussian Process Regression (GPR)	0.09
Ensembles	77.47

Table 4: Model results performances for wind speed forecasting (Manual Tuning).

Model	Root Mean Square Error (RMSE)
Regression Trees	0.77
Support Vector Machine (SVM)	0.66
Gaussian Process Regression (GPR)	0.80
Ensembles	1.04

4.2 Combined optimisation and regression machine learning models: Automate tuning

Solar irradiation forecasting To further upgrade regression learning models accuracy, hyperparameter tuning of the models is automated based on optimisation approaches, including Bayesian optimisation, grid search and random search, in the purpose of reducing the RMSE values. Table 5 reports the RMSE resulting from hyperparameters tuning models using optimisation methods based on 30 iterations running. The performance of all used regression machine learning models demonstrates that the Bayesian method is better than the other two optimisation methods. The Bayesian optimisation is an integrated approach that uses Bayes' theorem to conduct the search to find the minimum of the objective function (loss function in this case). This approach is most suitable for objective functions that are subject to noise, as in the case of the data presented in this article. Applied to find the optimal values of hyperparameters, Bayesian optimisation computes a probabilistic pattern of the function that relates the values of the hyperparameters to the objective evaluated on a validation set. The difference between Bayesian optimisation and random search and grid search is that Bayesian optimisation is able to boost performance by exploiting past experience of evaluation, whereas the other two optimisation approaches are inconsistent with or independent of previous assessments.

The optimisation results obtained for the optimal hyperparameters tuning considering four the regression machine learning models using Bayesian optimisation method are shown in Fig. 12. The different graphics of the figure illustrate the lowest estimated MSE. calculated by the optimisation process given all the sets of hyperparameter values tested, including the current iteration, is estimated by the blue lines. The best minimum observed MSE calculated by the optimisation process is represented by the dark blue points.

Table 5: Model results performances for solar irradiation (Automated Tuning).

Model \ Optimisation methods	Bayesian	Grid Search	Random Search
Regression Trees	51.50	53.70	51.504
Support Vector Machine (SVM)	169.38	250.72	107.82
Gaussian Process Regression (GPR)	0.09	0.19	0.14
Ensembles	0.65	48.18	36.52

Wind speed forecasting Identical procedure as for solar irradiance was applied to forecast upcoming wind speed values by four regression methods, namely Support Vector Machine (SVM), Gaussian Process Regression (GPR), Ensembles and Regression tree. Hyperparameters have been tuned based on three optimisation methods: Bayesian, Grid Search and Random Search. Table 6 shows the results obtained using the three optimisation methods in the 30 iteration running for hyperparameter tuning considering the four machine learning regression models.

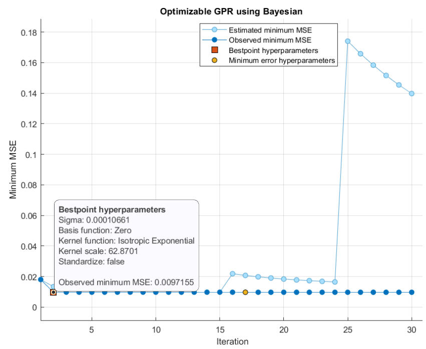
Table 6: Optimisation results for solar wind speed forecasting using bayesian method.

Model \ Optimisation methods	Bayesian	Grid Search	Random Search
Regression Trees	0.66	0.69	0.68
Support Vector Machine (SVM)	0.19	0.58	0.34
Gaussian Process Regression (GPR)	0.48	0.79	0.62
Ensembles	0.16	0.73	0.64

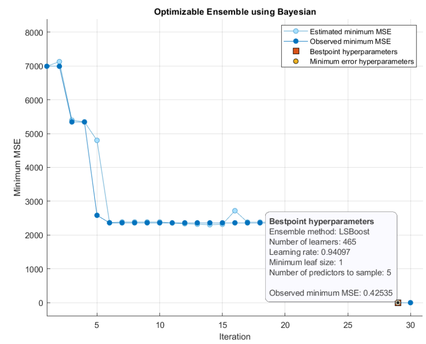
Fig. 13 presents the optimal hyperparameter results concerning the four regression machine learning models using Bayesian optimisation for wind speed forecasting.

4.3 Results comparison of manual and optimized tuning

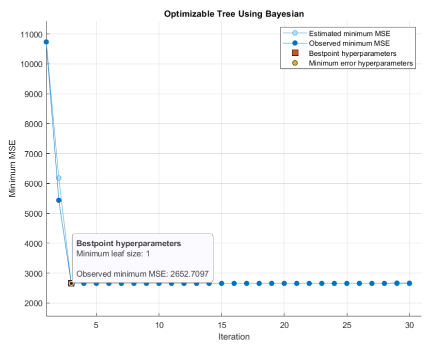
Tables 7 and 8 compare the four regression machine learning models in terms of accuracy based on the root mean square error values (RMSE) of the manually tuned models and the auto-tuned model using Bayesian optimisation. The optimisation process permits to export the best combination of hyperparameters. In fact, the precision of the regression machine learning models has been significantly increased. Automatic tuning eliminates the time-consuming and inconsistent work required to identify better patterns in the hyperparameter space. This feature conserves considerable time and effort in training and tuning machine learning models. Bayesian optimisation is the best approach that can be



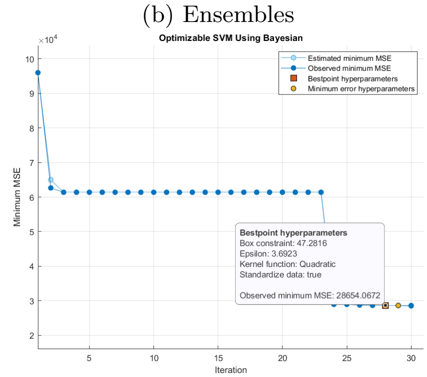
(a) Gaussian Process Regression(GPR)



(b) Ensembles



(c) Regression Trees



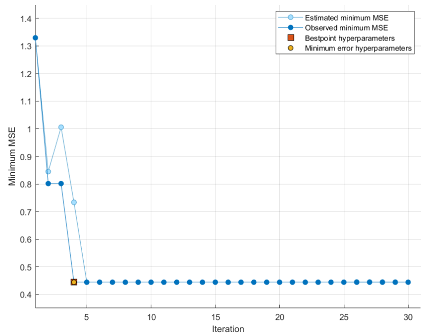
(d) Support Vector Machine (SVM)

Fig. 12: Optimisation model results for solar irradiation forecasting.

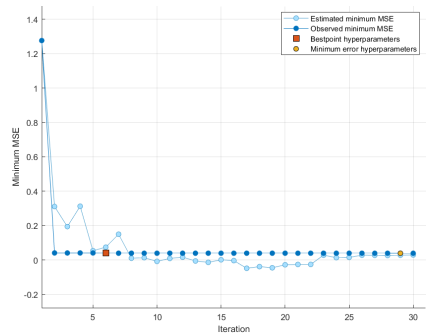
used to automatically adjust the hyperparameters of regression machine learning models. In difference to random search, Bayesian optimisation chooses the subsequent hyperparameters in an informed way, so that mean additional time can be spent on the evaluation of potential values of optimal hyperparameters.

5 Conclusion and future works

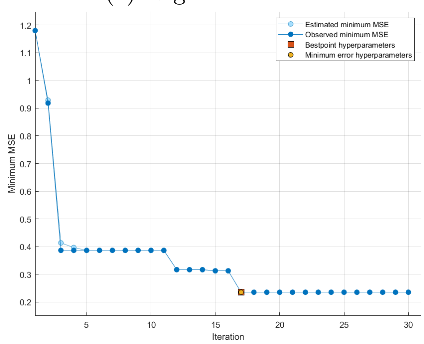
In recent years, most countries have seen an increase in the generation of electricity produced from renewable energy sources and this tendency is anticipated to persist in the foreseeable future. To enhance the successful incorporation of those renewable energy sources, particularly solar and wind, within the established power grid, it is required to address the vulnerabilities caused to grid operations due to their irregular character. The inherent rising of electricity production is a significant issue for system operators in terms of reserve management and energy management. In this sense, having an accurate renewable energies parameters prediction model is important. In this paper, an hybrid machine learning and optimisation procedure has been performed to forecast the future



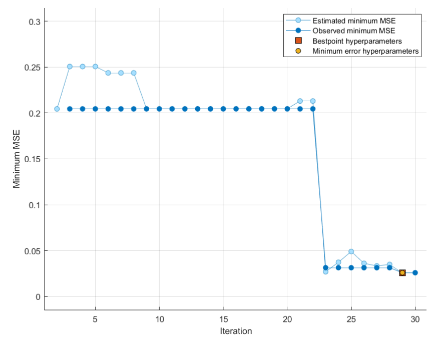
(a) Regression Trees



(b) Support Vector Machine (SVM)



(c) Gaussian Process Regression (GPR)



(d) Ensembles

Fig. 13: Optimisation models results for wind speed forecasting.

values of wind speed and solar irradiation parameters in a short time scale. The dataset employed in this research has been obtained from the National Institute of Technology Malviya metrological station in the Jaipur region of India posted on the online recording platform named: MNIT Weather Data - Live Feed. A dataset of 1922 features have been processed primary by removing outliers using the the inter quartile method (IQR). Based on correlation study, the identification of predictors elements for both wind speed and solar irradiation have been performed using the pearson correlation value of each couple of data resulted from the pearson correlation matrix. Four regression machine learning methods have been used including: Regression Trees, Support Vector Machine (SVM), Gaussian Process Regression (GPR) and Ensembles.

For making an automated tuning of hyperparameters, optimisation approaches using Bayesian, Random search and Grid search have been combined with the four regression machine learning models. Root Mean Square Error (RMSE) has been used to compare the models performances. The best optimisation method for automated tuning of hyperparameters was the bayesian optimisation, considering that the three optimisation method have been compared compared on

Table 7: Manual and optimized tuning comparison for solar irradiation forecasting.

Regression Model \ Tuning method	Manual	Bayesian optimisation
Regression Trees	102.78	51.5
Support Vector Machine (SVM)	202.52	169.38
Gaussian Process Regression (GPR)	0.1	0.09
Ensembles	0.65	0.65

Table 8: Manual and optimized tuning comparison for wind speed forecasting.

Regression Model \ Tuning method	Manual	Bayesian optimisation
Regression Trees	0.77	0.66
Support Vector Machine (SVM)	0.66	0.19
Gaussian Process Regression (GPR)	0.80	0.48
Ensembles	1.04	0.16

a scale of 30 iterations. For the wind speed forecasting, the SVM model gave the best performances. However, the GPR shown a higher accuracy for the forecast of solar irradiation. This paper, is a continuation of performed work for the wind speed and solar irradiation forecasting based on manual tuning [51]. Comparing with the results of this paper, the optimal tuning of hyperparameters using optimisation approaches increased significantly the accuracy of the regression machine learning models. As continuation of this work, it is envisaged to perform wind speed and solar irradiation using deep learning techniques.

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