Solar Radiation Forecasting in Saudi Arabia Using Machine Learning

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***Abstract*—Solar energy is a promising renewable energy source due to its availability and environmental friendliness. The capability to maximize the utilization and efficiency of solar energy remains a difficult task because of the challenges in collecting and analyzing solar radiation data. Therefore, there is a great need to forecast solar radiation to predict the output power. This paper aims to use machine learning methods to forecast solar radiation in Saudi Arabia in Riyadh city. The study compares the forecasted solar radiation using different machine learning models such as Artificial Neural Networks (ANN), Random Forest, and linear regression. The weather dataset was obtained from KACARE. The proposed models were evaluated using root mean square error and direction accuracy. The Random forest has the highest accuracy and the lowest RMSE with an accuracy of 92.8571, and RMSE of 10.3157 compared to ANN (91.3043, 18.4656), linear regression (78.5714, 30.4098).**

***Keywords*—solar radiation, neural networks, GHI, artificial Intelligence, PV Systems, machine learning**

I. Introduction

Saudi Arabia used to base their economy on fossil fuels during the last few decades, and 80% of the present energy used in Saudi Arabia is based on fossil fuels [1]. Fossil fuels generate some environmental concerns, such as the high emissions of carbon dioxide (CO_2) that pollute the atmosphere. They can be overcome by utilizing renewable energy resources such as solar energy [2]. Solar energy is a clean source of energy that has no carbon emissions during its generation. Saudi Arabia lies within the world's solar belt and enjoys clear skies with 3,000 hours of sunshine yearly with high solar radiation [3] [4]. Saudi Arabia developed an ambitious plan to generate more than 50% of its energy demand from renewable energy by 2040 and plan to increase solar energy development in their future electrical power production. Thus, there is a need to forecast solar radiation to predict the power capacity from the solar energy systems accurately. Solar energy projects can vastly benefit from reliable information on solar radiation. Direct global solar radiation measurements are not always readily available for most worldwide locations due to the high installation costs and the difficulty in maintaining the measuring instruments (pyranometer and pyrheliometer) [5]. Accurate prediction of global solar radiation is essential to the design and assessment of solar energy utilization systems. Global solar radiation is a significant parameter in monitoring, simulating, predicting, and sizing solar energy technologies [6]. Since observed global solar radiation data are not always accessible, different techniques have been developed to predict global solar radiation using empirical models [7], machine learning models [8], satellite-based methods [9]. This paper attempts to use machine learning techniques to predict the daily solar radiation in Riyadh city in Saudi Arabia. This prediction is necessary to meet the electricity demand and ensure grid stability. The weather dataset was obtained from KACARE (2017). The machine learning models are trained on historical data to build a prediction model to forecast future solar radiation. The three machine learning techniques used are Artificial Neural Networks (ANN), linear regression (LR), and Random Forest (RF). The models are compared in terms of accuracy and error rate, highlighting the models that provide the highest accuracy rate and lowest root mean square error (RMSE).

II. Saudi Arabia SOLAR ENERGY PLANS

Saudi Arabia's government established the King Abdullah City of Atomic and Renewable Energy (KACARE) to utilize renewable energy resources, act as renewable energy (RE) center, and monitor the strict implementation of RE policies. Since 2007, the government has established the center of research excellence in renewable energy at the King Fahd University of Petroleum and Minerals to conduct solar energy research [10]. Saudi Arabia's solar energy target share in total installed capacity is 54 GW from renewables, including solar technology [11]. Moreover, Saudi Arabia has planned to include 41 GW of solar power by 2032 as an alternative energy source [12]. Since 2010, many solar energy projects have been implemented or in the process of implementation. Many research centers were established, such as the KACST Energy Research Institute KACST (ERI). Saudi research and development actions highlight various practical solar energy applications in Saudi Arabia, such as solar energy in solar furnaces and concentrating collectors [11]. Recently, Saudi Arabia launched the "NEOM" project, one of the largest projects in Saudi Arabia that aims to build a business and industrial zone that operates on 100% renewable energy [13].

III. TYPES OF SOLAR RADIATION

Solar radiation is spread and absorbed by the atmosphere. Solar radiation can take the form of diffused, direct, or reflected radiation. Direct normal irradiance (DNI) is also known as direct solar radiation at normal incidence. It describes the descending

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solar radiation emitted at a solid angle from the disk of the sun. The instrument used to measure DNI is a pyrheliometer with monthly mean daily total radiation being Wh/m2/day. Global horizontal irradiance (GHI) is the total amount of shortwave radiation available from the sky hemisphere on a horizontal surface. GHI is the sum of DNI x cosine (solar zenith angle) and diffuse horizontal irradiance. An unshaded pyranometer is used to measure the horizontal rays, and the units are in Whm2/day. Ground-reflected radiation is not considered to be part of the GHI. It is to be included in the Global Tilted Irradiance (GTI). GHI and GTI data are useful for flat plate collectors. The GHI of Saudi Arabia is presented in figure 1, and the equation of GHI is as follow:

$$GHI = DHI + DNI(\cos \Theta) \tag{1}$$

There are two types of solar power systems: photovoltaic (PV) and concentrated solar power (CSP) systems. Photovoltaic (PV) systems convert sunlight directly to direct current electricity. Concentrating solar power (CSP) systems concentrate the sunlight using reflective devices such as mirror panels to produce heat used to generate electricity. DHI is absorbed through PV panels while the CSP absorbs DNI.

IV. ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Artificial Intelligence and Machine Learning Artificial Intelligence (AI) is a discipline that employs complex algorithms and networking tools to solve multidimensional problems by imitating human brainpower allowing machines to perform computational tasks. The designed models learn through continuous repetitive operations that are constantly refining the models' computing abilities. Some of the advantages of using artificial intelligence and machine learning techniques in forecasting are:

- The ability to make complicated models and nonlinear correlations between input and output features without former assumptions.
- Artificial intelligence leverages numerous human cognitive traits, identification, selection, prediction, and inspection.
- Machine learning handles big datasets with high reliability to deliver relevant correlations and patterns and handle noisy and incomplete data.
- The model can be trained to handle repetitive tasks in a shorter time and with fewer errors than humans.
- Machine learning models provide more accuracy for linear and nonlinear multiple regression predictions than physical and empirical models.
- Machine learning is cost-effective in the short and long term, and it is flexible in handling various types of problems.
- Machine learning and deep learning algorithms can implicitly discover nonlinear correlations between dependent.

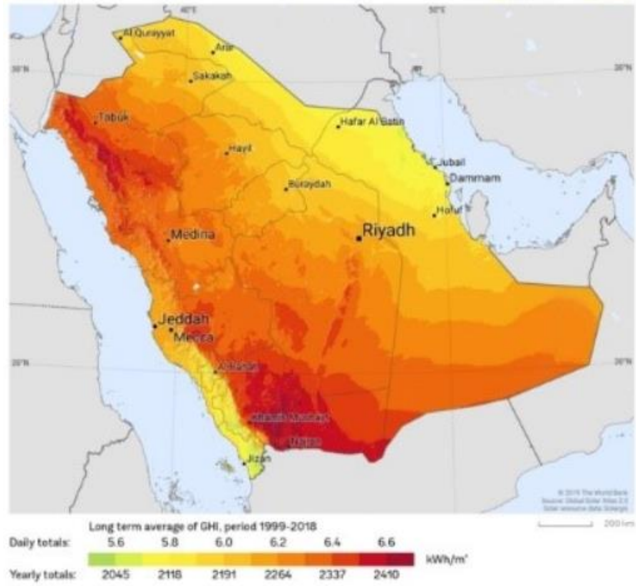

Fig. 1. Saudi Arabia global horizontal irradiance (GHI) [14]

A branch of artificial intelligence, concerned with the design and development of algorithms that allow computers to evolve behaviors based on empirical data. Machine learning can be applied to labeled, semi-labeled, or unlabeled data. The phases of machine learning are as follow:

- Preprocessing phase is concerned with removing noise, segmentation, scaling, remove white space from the dataset.
- Feature selection and extraction: this phase focuses on reducing the dimensionality and selecting useful features.
- Model Selection: this phase selects proper learning techniques if supervised, unsupervised and semi-supervised model.
- Learning or training phase: in this phase, the model is trained using a training dataset.
- Evaluation: this phase is concerned with testing the performance of the model on the testing set.

V. LITERATURE REVIEW

Solar energy is considered the most promising source of renewable energies due to its availability [15]. Consequently, there is an increase in solar energy technologies. However, the capability to maximize the utilization and efficiency of solar energy remains a difficult task because of the challenges in collecting and analyzing solar radiation data. Empirical and machine learning models are more commonly used in practice due to their low computational costs and high prediction accuracy [16]. Although empirical models have been widely employed for predicting global solar radiation, they are difficult to handle complex and nonlinear relationships between independent and dependent variables. Machine learning models are a type of artificial intelligence capable of dealing with nonlinear function approximation, pattern recognition, optimization, clustering, and trend detection. With the advancement of computer technology, many machine learning models have been proposed to predict global solar radiations. Such machine learning algorithms are artificial neural networks (ANN), support vector machine (SVM) [17], tree-based assemble models [18], random forest (RF) [19], adaptive neuro-fuzzy inference system (ANFIS) [20], Gaussian process regression (GPR) [21] and fuzzy logic models [22]. Data mining is an inductive machine learning (ML) technique for prediction and description that works by looking for patterns in a data set. The data set is utilized for training and learning a model of interest by determining relationships among variables and extracting meaningful patterns for accurate prediction [22]. Random forest is an ensemble learning technique that is consists of a large number of decision trees that operate as an ensemble. Each decision tree in the random produces a class prediction, and the class with the most votes becomes the model's prediction. Artificial neural network (ANN) models are efficient computational machine learning models that simulate the biological brain and solve different large-scale complex problems. The ANN models typically have three layers: the input, hidden, and output layers. The input layers are linked to the hidden layers, where the data processing is performed through weighted connections. Each neuron in the hidden layer interconnects to all neurons in the output layer [23].

A. Related Work

Several works investigated solar radiation prediction using machine learning algorithms. Mohandes [24] used Particle Swarm Optimization (PSO) to optimize the artificial neural network (PSO-ANN) for estimating monthly mean daily global solar radiations at 41 sites in Saudi Arabia. It was found that the ANN-PSO model outperformed the neural network trained by the classic backpropagation (BP-ANN). Yacef et al. [25] estimated the daily global solar irradiation in Al-Madinah city in Saudi Arabia using two neural networks models. They found that the Bayesian Neural Network (BNN) performed better than the classical Neural Network (NN). The features selected in their models are air temperature, relative humidity, sunshine duration, and extraterrestrial irradiation. Ramli et al. [26] investigated the performances of SVM and ANN models for predicting daily global solar radiation on PV panel surfaces with particular tilt angles. The Estimation was carried out at two sites in Saudi Arabia. The SVM model showed significantly higher accuracy, robustness, and computational efficiency in predicting daily global solar radiation than the ANN model.

Fan et al. [27] comprehensively reviewed and evaluated 12 existing empirical models and 12 machine learning models for predicting the daily global solar radiation from sunshine duration in different climatic zones of China as a case study. The work concluded that the machine learning models outperformed the empirical in terms of prediction accuracy. Mubiru and Banda [28] proposed a method for predicting the monthly mean daily global solar irradiation at several locations in Uganda by using the ANN technique. Jiang [29] proposed an ANN model to estimate monthly mean daily global solar radiation in eight different cities of China. The proposed ANN model provided a good prediction of solar radiation compared to other empirical regression models. The proposed model was validated using mean percentage error (MPE), mean bias error (MBE), and root mean square error (RMSE). Moeini et al. [30] proposed a hybrid approach for estimating solar irradiation using fuzzy and hidden Markov models. The work revealed that the predictions of the proposed model are close to the training data set. Mohammadi et al. proposed a new hybrid approach by coupling the SVM model coupled with the Wavelet Transform (WT) algorithm for estimating daily horizontal global solar radiations in Bandar Abass of Iran. Their results revealed the superiority of SVM-WT over the ANN models.

Torabi et al. [31] presented a Cluster-Based Approach (CBA) that utilizes the support vector machine (SVM) and an artificial neural network (ANN) to predict the daily horizontal global solar radiation. They conducted clustering analysis and divided the global solar radiation data into clusters to maximize the homogeneity of data within the clusters and the heterogeneity between the clusters. The proposed work compared with ANN and SVM techniques using mean absolute percentage error (MAPE), which was lower in the proposed work than those of ANN and SVM. Azeez [32] proposed an ANN prediction method for global solar radiation that used the maximum ambient temperature, Sunshine duration, and relative humidity as the required input parameters studied.

Chen et al. [33] proposed a prediction model of daily solar radiation during sunshine duration using a Support vector machine (SVM). Seven SVM models using different features and five empirical sunshine-based models are validated using meteorological data at three stations in China. All the SVM models outperform the empirical models. Guermoui et al. [34] evaluated the utility of two support vector regression (SVR) models to predict monthly mean daily global solar radiation. One model is based on the radial basis function, and the other is based on the polynomial basis function. They found that SVR based on the polynomial basis function has higher precision than SVR based on the radial basis function [17].

Halabi et al. [35] proposed a hybrid approach by integrating simulated annealing (SA) and genetic programming (GP). Using the sensitivity analysis, they found out that the suggested model provides accurate predictions. Quej et al. [36] evaluated the performances of three machine learning models, which are support vector machine (SVM), artificial neural network (ANN), and adaptive neuro-fuzzy inference system (ANFIS), to estimate daily horizontal global solar radiations based on measured meteorological variables for a warm sub-humid environment in Mexico. It was concluded that the SVM technique had better performance whereas, ANFIS and ANN models showed similar results.

Bouguerra and Benslimane in [37] performed a prediction analysis of the distinct components of solar radiation using different Artificial Neural Network structures. They found that the Bidirectional LSTM model has the highest accuracy and the least RMSE compared to other tested models such as random forest, gradient boosting machine, and deep neural network (DNN).

El-kenawy et al. in [38] proposed preprocessing and training ensemble phases for an improved solar radiation forecasting ensemble model. The advanced sine cosine algorithm (ASCA) is used in the training ensemble phase to simulate Newton's equations of gravity and motion for objects (agents). The k-nearest neighbors (KNN) regression is then used to create the training ensemble model.

Hemavathi et al. in [39] used machine learning methods such as Random Forest (RF) and SVM to predict solar radiation and found out that the results were positive and provided comparable error statistics.

Ağbulut et al. in [40] used different machine learning methods to forecast daily global sun radiation data for four provinces in Turkey: SVM, ANN, kernel, and nearest-neighbor (k-NN). They discovered that all machine learning methods they examined in their study could accurately predict GHI; however, the ANN algorithm had the best performance of all the techniques.

VI. METHODOLOGY

The King Saud University dataset used in this work was collected from KACARE. The dataset is composed of hourly data of global solar radiation from May 2014 to July 2016. The features selected from the datasets are date and time, air temperature, wind direction and speed, barometric pressure, relative humidity, and global horizontal irradiance (GHI).

Figure 2 presents the hourly distribution of GHI for the city of Riyadh, King Saud University Station (KSU, longitude 21.49604, latitude 39.24492) from May 2014 to July 2016. It demonstrates the maximum and the minimum GHI intensity distribution highlighting the high value of GHI in Riyadh city that can reach more than 1000 Wh/m2, which encourage the utilization of this solar energy to generate electricity; taking into consideration that the PV produced output power is increasing with the increase of the solar intensity.

The sun intensity or the irradiance affects the module performance, with a reduction of sunlight resulting in a reduction in current and, consequently, a reduction in the output power.

As temperature increases, the current increases, the voltage decreases, and the produced output power decrease. Thus, the produced power from the PV systems can be reduced with the cumulative increase of temperature. The open-circuit voltage of a PV module varies with cell temperature. As the temperature increases, the open-circuit voltage (Voc) decreases. This, in turn, reduces the power output.

Figure 3 shows the average monthly temperature and maximum monthly temperatures for King Saud University Station.

Table 1 demonstrates some data from the GHI calculating its maximum, minimum, mean, and standard deviation.

To start forecasting the GHI, we used Weka software version 3.8, the time-series forecast module. We selected three different machine learning algorithms to train three different predictive models.

The algorithms used in this study are the Artificial Neural Network, the Random Forest, and the Linear Regression. More details are presented in the following section of results and discussions.

TABLE I. GHI STATISTICS OF KSU DATASET FROM 2014-2016

Statistic GHI W/m^2	***Value***
Minimum	0.1
Maximum	1068.7
Mean	465.962
StdDev	327.201

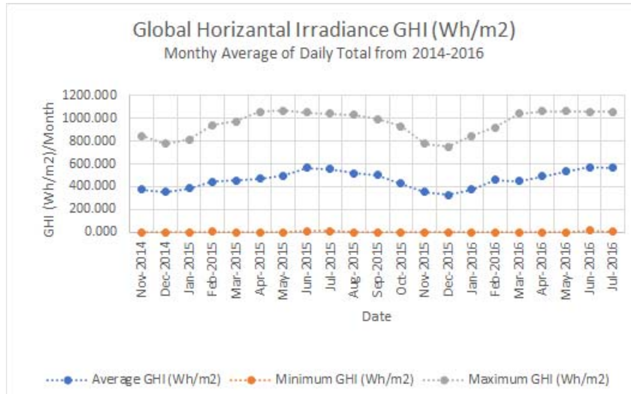

Fig. 2. The global horizontal irradiance.

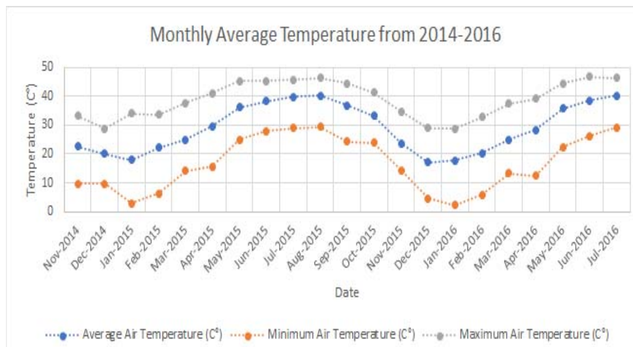

Fig. 3. Monthly temperature distribution.

VII. RESULTS AND DISCUSSION

The dataset used in this study was obtained from KACARE, and it is for Riyadh city, Saudi Arabia (King Saud University, longitude 46.61639, latitude 24.72359). The models were trained on 70% of the dataset and tested on 30%. The features selected in training the models were wind speed, wind direction, GHI, date and time, humidity, and pressure.

The generated machine learning models designed to predict solar radiation are Artificial Neural Network, the Random Forest, and the Linear Regression (ANN, LR, and RF). The predictive models were evaluated in their root mean square error (RMSE), the direction accuracy, and the mean absolute error (MAE). The smaller the RMSE, the better is the predictive model. The root means square error evaluation function is presented in equation 2.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(GHI_i^{actual} - GHI_i^{predicted})^2} \ (2)$$

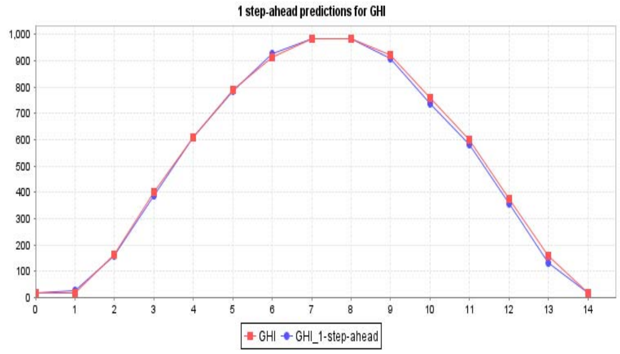

Fig. 4. Actual and 1-step predicted GHI of KSU using random forest

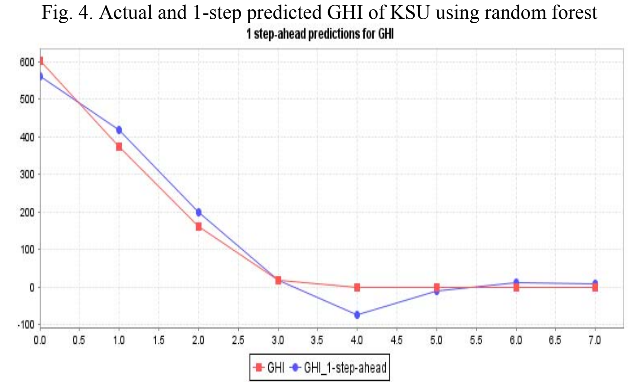

Fig. 5. Actual and 1-step predicted GHI of KSU using linear regression

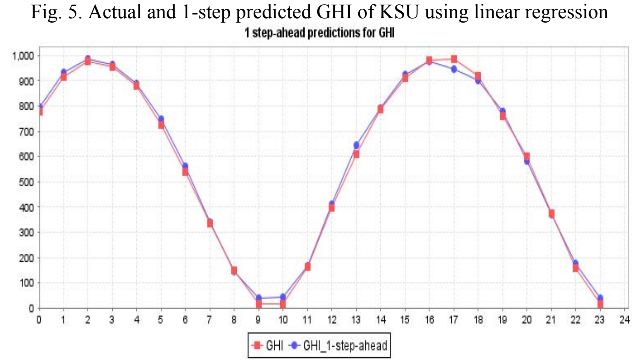

Fig. 6. Actual and 1-step predicted GHI of KSU using ANN

For the artificial neural network (ANN) models, the number of neurons and the hidden layers kept changing till we reached to satisfying prediction rate.

Table 2 summarizes the evaluation metrics of the generated predictive models. Our findings demonstrated that the machine learning models provided good GHI prediction; however, random forest RF outperformed the other models in solar radiation prediction with a direction accuracy of (92.8571) and a root mean square error of (10.3157). Figures 4,5, and 6 demonstrated the actual and predicted GHI using the three models random forest, linear regression, and ANN, respectively.

TABLE II. THE EVALUATION RESULTS OF THE PREDICTIVE MODEL

Evaluation Metric	ANN	RF	LR
Root Mean Squared Error	18.4656	10.3157	30.40981
Mean Absolute Error	15.5477	13.6747	24.6008
Direction Accuracy	91.3043	92.8571	78.5714

I. CONCLUSION

Integrating solar energy with the grid is very demanded to meet the rapid increase in electricity. The accuracy of forecasted solar radiation can directly affect the predicted output power of a grid-connected photovoltaic system that is significant for power planning, management, and operation. Solar radiation plays an important role in the generated power from solar energy systems. Therefore, forecasting solar radiation has becomes very important to predict the output power. This paper investigated three machine-learning models based on ANN, linear regression, and random forest. The prediction result of each model is compared with regarding the accuracy and the mean square error. The results revealed that machine learning models positively predicted the GHI; however, the random forest provided the highest accuracy compared with other models with an accuracy value of 92.8571 and a root mean square error of 10.3157. Different techniques can be used to forecast solar radiation for future work, such as using fuzzy logic.

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