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DEVELOPMENT OF MACHINE LEARNING BASED EMPIRICAL MODEL FOR ESTIMATION OF SOLAR RADIATION

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ABSTRACT

This paper proposes Optimal harvesting of solar radiation is a thrust area since last decades. Machine Learning Techniques are more advocating technology for estimation related cases. This study claims that extreme learning machines (ELM) can be able to estimate solar radiation more accurately than any other system. The proposed technique was evaluated based on data collected in Karaman Province between 2010 and 2018. This evaluation was carried out with MATLAB 2022 under toolbox- Multiprocessing Algebra Data (Mu PAD). It was hypothesized that ELM had shown a better estimating performance than the other method when the data were compared. In addition, ELM was evaluated using a variety of activation functions to find the one that provided the most accurate estimate response. ELM models have minimum RMSE which is 14.02 as compared to other methods. The computed data and the approximation data that are paired together to form the global model have a superior correlation coefficient, which is about 95.67% on standard. This signifies the global model is accurate to a high degree. A comparison between ELM and other training algorithms reveals that it is the most effective strategy for training all sub models based on the data collected in the two rounds of the study. All ELM activation functions performed better than all transfer functions of SCG and RP when compared to the general outcomes of the evaluations. Comparing the accuracy and reliability of the suggested machine-learning algorithm to the current industry standard in predicting solar radiation time series for solar energy system design and management.

Keywords: *Extreme Learning Machines, Solar Radiation, Machine Learning, Artificial Neural Network, Root Mean Square Error, Mean Absolute Percentage Error.*

1. INTRODUCTION

In the recent era, population and economic growth have preceded an ascent in energy utilization. A shift toward non-traditional energy sources has occurred because of the significant rise in global energy demand. An increasing number of people are turning to solar power as an alternate source of energy because of its environmental friendliness and long-term viability [1]. Solar energy is becoming more desirable in the twenty-first century since the environmental consequences of fossil fuel combustion get more severe each year. Through the winter of 2015, pollution enveloped most of the cities in China's central and eastern regions resulting in severe health and lifethreatening consequences [2]. Another reason to value solar energy is the fact that fossil fuels have a finite supply. In the long run, the global shortage of fossil fuels is a major issue that requires work toward the development of renewable and sustainable energy sources [3]. As a result, solar energy is the primary renewable energy resource that has been identified as a potential source of energy for any nation shortly as it is plentiful (easily accessible), cost-free, and clean. Solar energy is the world's most plentiful renewable energy resource accounting for around a quarter of all available energy [4]. Global solar radiation is a foremost source of energy in the ecosystem which includes solar energy systems and architectural designs, snowmelt, and evaporation of open water from the land surface, plant photosynthesis, crop growth, and irrigation water yields as well as the design of irrigation drainage systems and fluctuations in the level of open water. Accurate measurements of solar radiation at a given location enable more realistic plans to be developed, as well as more control over the outcome of these initiatives to be exercised [5].

1.1 SOLAR RADIATION

This section contains a summarized overview of solar radiation which is to be estimated in this study.

Solar radiation is a critical component of the earth-atmosphere system's operation since it provides energy to the systems [6]. There are many ways to quantify solar radiation involving global solar radiation (GSR), diffused solar radiation, and beam solar radiation. Climate change, agriculture, hydrology, meteorology, and climatology all rely on global solar radiation as the most significant characteristic for a wide variety of solar energy implications [7]. The quantity of energy obtained at the exterior of the surface of the earth is dependent on a variety of elements including the height of the sun, the purity of the sky, the slope and part of a landscape as well as the latitudinal position of a location on the axis of rotation of the earth [8]. As a result of these variables, solar radiation varies spatially and temporally over the globe and the ability to quantify and comprehend its spatial-temporal distribution is critical for designing systems that maximize energy reception for various uses [9]. There is very little data available because of the high expense of the instruments needed to collect data on this component of solar radiation at various locations throughout the globe. Extrapolated information obtained from remote sites is used to figure out the value of stations that have no data available [10].

1.2 GSR MODELS

This section introduces the GSR model below:

Solar energy is not only safe, efficient, and cost-effective, but it is also ecologically excellent due to its low carbon footprint. As an added benefit, solar power is one of the most significant and almost limitless sources of energy available under several alternative renewable energy models [11]. The conduct of the surface of the earth about solar radiation helps to explain the significant relationship between ambient temperature and solar emission. The earth' surface soaks up the shortwave electromagnetic radiation that enters the environment from the sun resulting in the increasing the temperature of the surface of the earth [12].

After absorbing energy from the sun and reemitting it as longwave radiation, the heated earth's surface heats the surrounding ambient air causing it to warm up as well. The ambient air is heated up indirectly through contact with the hot earth's surface rather than directly by sun radiation which causes it to become warm [13]. This process is characterized by an inter-cyclic phase lag between the temperature cycles and solar radiation. Generalized radiation balancing and air mass advection are two factors that influence temperature fluctuations in the atmosphere [14]. The quantity of cloud cover and the kind of surface cover all have an influence on the local temperature and radiation balance, in addition to the time of day and year. A substantial correlation between ambient temperature and solar radiation could be seen in the yearly temperature cycle which shows a predictable fluctuation in incoming solar energy throughout the year. As a result, research focuses on calculating various solar radiation-temperature relationships [15].

The objective of the research is to improve the performance of solar radiation estimation models through better design and analysis. This study claims that extreme learning machines (ELMs) can accurately estimate solar radiation. More realistic plans and greater control over the outcomes of these initiatives can be achieved through precise measurements of solar radiation at a given place. It is possible to experiment with the number of ELM neurons and intermediate layer neurons to see how accurate their estimations of sunlight are in future experiments.

2. LITERATURE REVIEW

This section contains a review of literature in the field of approximation of the solar radiation model.

Mughal et al., (2021) [16] discussed that forecasting global solar radiation was critical since it was very changeable. Time series neural networks in MATLAB were used to estimate global sun radiation using actual data gathered over time. Three models were constructed in research: one for daily global solar radiation predictions and two for hourly global solar radiation predictions. Analysis of the data revealed that nonlinear autoregressive models were an effective approach for predicting global solar radiation. There was strong support for the suggested patterns based on the mean absolute error and the root-mean-square error among other performance metrics. Once equated to several time series models, the suggested model had the tiniest root mean square error (RMSE) of 1.28.

Karaman et al., (2021) [17] suggested that extreme learning machines (ELM) were expected to provide superior performance in sun radiation estimates as compared to artificial neural networks (ANN). This technique was evaluated using data collected by the author province between 2010 and 2018. The data collected by the author province between 2010 and 2018 was utilized in the evaluation. According to the findings, ELM had shown superior estimating performance when results were compared. Furthermore, several initiation tasks for the ANN and ELM were evaluated to acquire the optimum estimate response from the models. The ELM attained a RMSE of 0.0297 when measured. The performance of ELM estimation was superior to that of ANN with a 95 percent confidence interval.

Üstün et al., (2020) [8] explained that solar energy played a significant part in the production of clean and emissions-free electricity in comparison to traditional ways. However, a dependable and predictable energy supply was necessary for long-term sustainability. Using a variety of machine learning (ML) approaches, the researcher set out to create more accurate and dependable monthly mean daily forecasts of solar radiation. The first-choice model in research used a simple membership function and fuzzy rule generation technique (SMGRT) which did not need mistake or prosecution for simulation tuning. However, deep learning (DL) and adaptive network-based fuzzy inference systems (ANFIS) have grown more prominent in the study of the resolution of complicated issues. All three models had exceptional outcomes when the models' findings were compared. SMGRT outperformed DL and ANFIS for various input combinations.

Amiri et al., (2020) [18] focused on the use of the weights approach which was employed to evaluate the relative value of input characteristics for calculating global sun irradiation on an arbitrarily inclined plane. Data collected from the satellite with varied inclinations was utilized for learning whereas ground data taken from a radiometric station of Algeria was utilized for testing. It was possible to improve the model performance by removing parameters that were not well connected with the network output using the Weights approach. In the hidden layer, RMSE = 6.37 percent and coefficient of purpose (R_2) = 0.992 were the ideal values for a network with 16 neurons.

Thapar et al., (2019) [19] evaluated that several models were available for predicting solar radiation, no studies had been conducted to determine the influence of these estimates on the energy generation of a photovoltaic (PV) system and its finances. A PV generating system's energy output and economics were evaluated and the recent exploration was completed to analyze the impact of evaluated estimates of solar radiation which were calculated by applying the Sunshine duration technique on these two variables. Consequently, a PV system constructed based on solar radiation estimates would be around 7% to 10% undersized. As a result, it was possible to conclude that areas without access to hourly data on solar radiation estimates based on sunlight hours might be used to estimate energy output and conduct feasibility studies on PV power plants.

Ishola et at., (2019) [20] discussed regional coefficients for calculating hourly global solar radiation using empirical techniques that connect radiation to meteorological and geological characteristics. According to certain chosen error indicators (such as the global index that incorporates all other errors), the models' performances were assessed. The polynomial-based regional calibration coefficients provided by the polynomial technique were shown to be better than other models in terms of accuracy. As a result, the study findings would aid in the design of a different regional or local moderate environment that supports solar energy uses on the microscale.

Karaveli et al., (2018) [21] examined the best methodology, databases, and software to

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accurately estimate solar irradiation for short- and long-term performance and feasibility as well as the best one to utilize to generate the most accurate calculations. New approaches established by the authors were compared against a frequently used database (Meteonorm). For the comparisons, statistical errors were used to determine the quarterly mean diurnal principles of global and diffuse solar irradiation. As a consequence, the diffuse solar irradiation and monthly mean daily global amounts could be more accurately estimated using the new technique.

Karaveli et al., (2018) [22] evaluated an artificial intelligence model (ANN) to improve global and diffuse sun irradiance estimates using ground observations as precisely as feasible. Using such an approach, the most precise estimates of the input into solar energy systems were obtained. A technique was developed to provide the most precise estimates of monthly mean diurnal sun irradiance on the horizontal surface as well as its diffuse and beam components. In both linear and quadratic forms, novel techniques were devised, assessed, and explored for the estimate of global and diffuse parameters in the environment. The study found that the methods yielded very accurate estimates of both diffused and direct sun exposure to horizontal surfaces.

Yaniktepe et al., (2017) [23] conducted a study to determine the predicted solar radiation model with the tangible solar energy generated. There were employed four models to estimate solar duration and temperature. The mean absolute bias error (MABE), measurement of resolve (R2), RMSE and mean absolute percentage error (MAPE) was employed to analyze model performance. Sunlight duration and average temperature were utilized in a linear regression to forecast diurnal global solar radiation on a parallel surface during the month. The five-minute average recorded values of sun radiation were employed to calculate the diurnal and quarterly average values of solar radiation. According to the findings, solar energy had enormous promise as a source of electric power.

Arslan et al., (2015) [24] discussed the Ordinary Least Squares (OLS) approach which was one of the most often applied techniques for determining scattered solar radiation. For the OLS technique to be used in the estimate, the dataset must have specific assumptions that must be satisfied by the approach. An alternative robust approach for estimating diffuse radiation was developed and compared to the OLS approach which was utilized for assessing diffuse radiation in a variety of applications. Finally, the R2 value achieved by the OLS approach was found to be smaller than the estimates achieved by M regression models after the study. In additional words, when the OLS technique was utilized, the explanation of the dependent variable was inadequate.

2.1 Comparative Study Of Literature Review

This section contains the comparative study of the literature review shown in Table-1 given below.

Table 1: Comparative Study of Literature Review

Authors [Ref. no.]	Technique Used	Outcomes	Research Gap
Mughal et al., (2021) [16]	Time Series Neural Network	Nonlinear autoregressive models were an effective method.	The model is expected to outperform all other time-series models in the future.
Karaman et al., (2021) [17]	ELM	ELM estimation was superior to that of ANN.	In the future, improved performance would be achieved by using confidence interval estimates.
Üstün et al., (2020) [8]	SMGRT	SMGRT Model outperformed DL and ANFIS Models.	The models' capabilities and the parameters' efficacy would be assessed in the next research.
Amiri et al., (2020) [18]	Weight Approach	RMSE and R2 were the ideal values for a network.	A sensitivity analysis would be used in the future to determine the most important inputs.
Thapar et al., (2019) [19]	PV System	The model can be used to estimate energy output and conduct feasibility studies on PV power plants.	Sunlight hours would be successfully used for energy predictions in the future.
Ishola et at., (2019) [20]	Polynomial	Findings would aid in the design of different regional or solar energy applications.	The use of ANNs to estimate global sun radiation across the research area would be explored in the future
Karaveli et al.,	Meteonorm	Diffuse solar irradiation and	Prospects would likely be the subject of more

(2018) [21]		monthly mean daily global amounts were accurately estimated.	debate in the future.
Karaveli et al., (2018) [22]	ANN	Methods yielded very accurate estimates.	SOlAR TURnKEY software would include the model's accuracy in the future.
Yaniktepe et al., (2017) [23]	Coefficient of Determination (R2)	Solar energy had enormous promise as a source of electric power.	In the future, the potential of solar radiation would seek opportunities to generate power.
Arslan et al., (2015) [24]	OLS	The model was appropriate for diffuse solar radiation estimation.	In the future, it would be given with the accurate model computation.

3. BACKGROUND STUDY

The most important climatic elements that influence plant development are solar radiation, moisture, and temperature. Although GSR) is seldom measured at climatological stations in underdeveloped nations, it is frequently calculated using data-driven methodologies or empirical calculations. Model trees (MT), adaptive neuro–fuzzy inference system (ANFIS), several experiential equations, support vector regression (SVR), and gene expression programming (GEP) were used in this study to measure the relationships among GSR and several climatological variables such as maximum sunshine hours (N), minimum temperature (T_{min}), sunshine hours (n), corrected clear-sky solar irradiation (ICSKY), relative humidity (RH), maximum temperature (T_{max}), (Ra) and day of year (DOY). The daily GSR determined at the Tabriz synoptic station in Iran's semi-arid areas from the beginning of 2011 to the end of 2013 were utilized for this purpose. The GSR and n were shown to have a direct and strong association. Three distinct statistical indicators were utilized to evaluate the effectiveness of the researched techniques such as RMSE, mean absolute error (MAE), and correlation coefficient (CC). A Taylor chart was also used to examine the comparability of the examined and anticipated GSR levels. The SVR-6 with input parameters of Ra, R_H, T_min, T_max, and n/N performed well in calculating GSR than the other models, with RMSE of 1.656, MAE of 0.990, CC of 0.980, and Willmott's Index (WI) of 0.990. Furthermore, MT-6 was the second-best model for predicting GSR levels. It's worth noting that the empirical equations tested exhibited lesser accuracies when compared to the SVR, GEP, MT, and ANFIS approaches. GSR values, for example, were derived using the best empirical equation, the Angstrom and Prescott equation, with WI of 0.988, MAE of 1.156, RMSE of 1.786, and CC of 0.977. The current study's findings demonstrated that the SVR gave appropriate trends for GSR modelling at the Tabriz synoptic station. The GSR can also be estimated using MT models with linear equations, which are simple to use and have acceptable precision [25].

4. PROBLEM STATEMENT

Compared to traditional ways, solar energy plays an important role in creating clean and pollution-free electricity. However, a stable and predictable energy supply is also required for the sustainable growth of any country. The forecasting of global solar radiation is critical since it is very changeable. Using fossil fuels is becoming more harmful to the environment, and solar power is becoming more appealing as a solution to this issue. To assess a region's potential for solar energy, data on solar radiation from various locations is needed. Deployment of measuring equipment everywhere is impractical due to the high cost and difficulty of the measurement procedures. This study examined alternative ML and experimental models for global solar radiation forecast simply utilizing solar data as input. To forecast daily global solar radiation, experimental temperature-based models and machine learning algorithms were employed in conjunction with each other.

5. PROPOSED METHODOLOGY

In the context of the proposed methodology architecture in figure1 is laid out to predict the solar radiation. Firstly, solar data is collected, and inputs and targets are specified. After specialization of input and target data, data normalization is performed. On the normalized data, two techniques are applied i.e., Machine learning technique and temporary based empirical model. For both the techniques parameters are adjusted and training and testing of model is performed. Methodology to for solar radiation estimation has been explained step by step.

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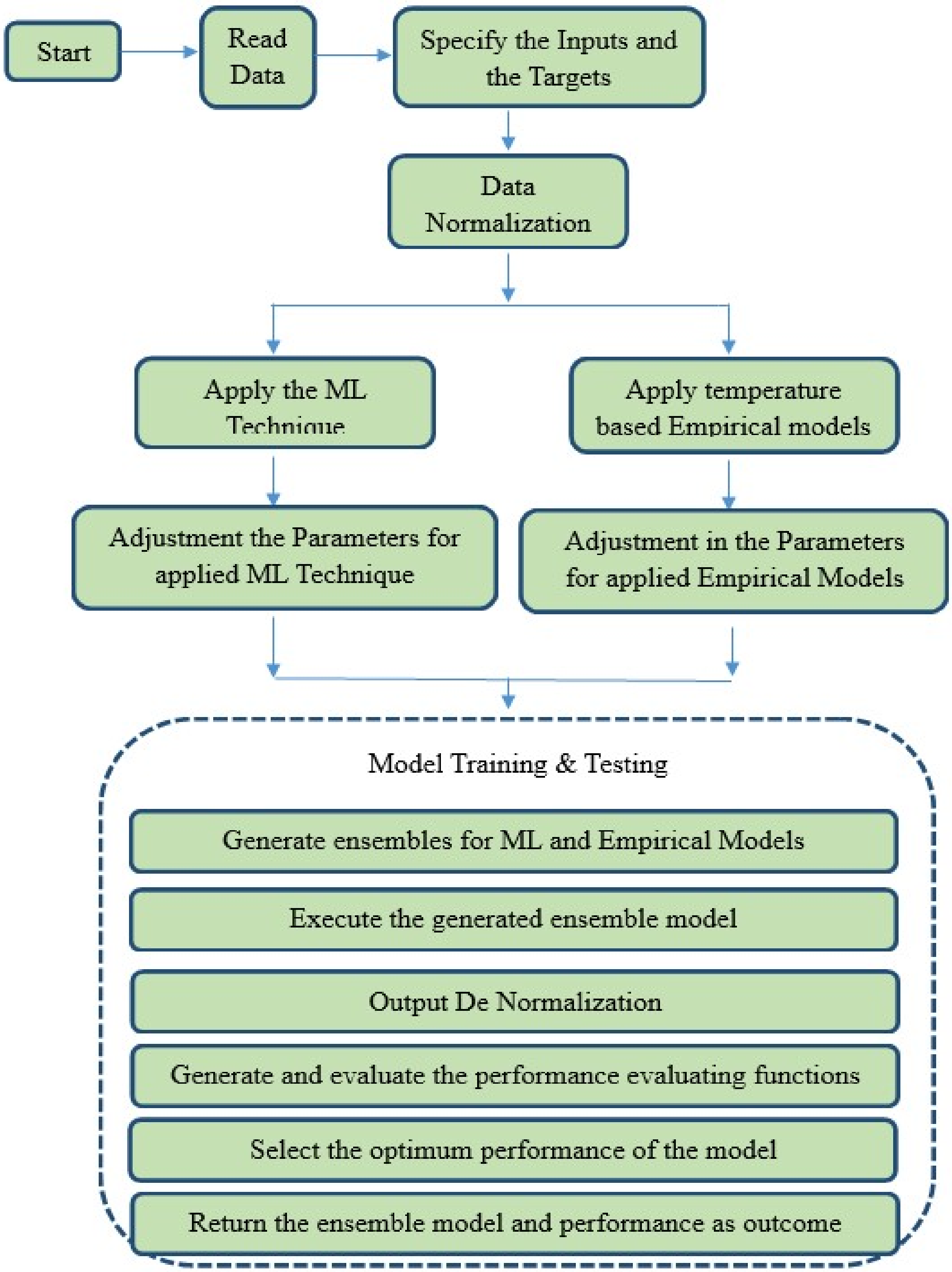

Figure 1: Architecture of Solar Radiation Estimation. Model

Step-1: Read the Data

In the first step of the proposed methodology data is read for solar radiation estimation. Intended for the distribution and assessment of solar energy systems, accurate worldwide solar radiation measurements (data) are essential.

Step-2: Specify the inputs and Targets

In this step, input and target values are specified because no data is ever in a perfect state

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for processing, so that some of the settings are adjusted before running an analysis.

Step-3: Data Normalization

In this step, data normalization is performed after specifying the inputs and targets. Normalization is the act of restructuring data in a database in this manner that it fulfils two fundamental requirements: it is accurate, and it is complete. There is no duplication in the data since it is all kept in a single location. Data dependencies are logical in nature, and all linked data items are kept in the same location.

Step-4: Apply the ML technique

In this step, the ML method is applied to the data set and the efficiency of this approach has emerged when the dataset size is significantly larger. The machine-learning technique is based on an ANN approach and used to increase the precision of the solar radiation estimation. After applying the ML technique parameters are adjusted for the applied technique.

Adjust the parameters for the ML technique; Parameters are adjusted for the ML technique because Machine learning algorithms rely on parameters to function properly. A component of a model that is learnt from past training data is known as a learning component.

Step-5: Apply temperature based empirical models

For the calculation of regular global solar radiation in this step, experimental models based on temperature are utilized in conjunction with temperature data. Empirical models utilizing generally accessible meteorological data as inputs are the most often used models because of their inexpensive computing costs and data requirements.

Adjust the parameters for the applied empirical model

After applying the empirical model for estimation, parameters are adjusted in the same way in the ML technique.

Step-6: Training and Testing the Model

In this step, training and testing of the model are performed via various methods which are discussed below.

a) Generate ensembles of ML technique and empirical model

Assembling, in general, is a strategy for merging two or more algorithms of similar or distinct kinds known as base learners. In order to create a more robust system that combines the predictions from all the basic learners, this procedure is followed.

b) Execute the generated ensembled model

An ensembled model is generated by the combination of both the techniques and in this step, execution is performed of the ensembled model.

c) Output De-normalization

After the execution of generated ensembled model output denormalization is performed. In relational databases, denormalization is the practice of adding redundant data to enhance the database's readability.

d) Generate and analyze the performance evaluating functions

In this step, performance evaluating functions are generated and analyzed. A function evaluation is the process of determining a function's output from a record. The record offers context for the evaluation; all fields mentioned in the function take on the record's value.

e) Select the optimum performance of the model

It is necessary to use metrics indicators to calculate the efficiency of the constructed model. These metrics indicators include the MSE, MAE, the correlation coefficient (R) and the RMSE.

f) Return the ensemble model and performance as the outcome

Two techniques are used for solar radiation estimation i.e., ML technique and empirical model. The presentation of both models is analyzed by using indicators such as RMSE and MAE. After analyzing the performance of both the models, the model with the optimum performance is returned as output.

6. RESULTS AND DISCUSSION

This section of the paper contains implementation done using the proposed methodology. MATLAB 2020 is used as a tool for the implementation of the proposed work. MathWorks created Matrix Laboratory (MATLAB), a computer environment and a multi-paradigm programming language. Matrix operations, data visualization and function, interfacing, and user interface building algorithm implementation with other programming dialects are all possible with MATLAB. Although

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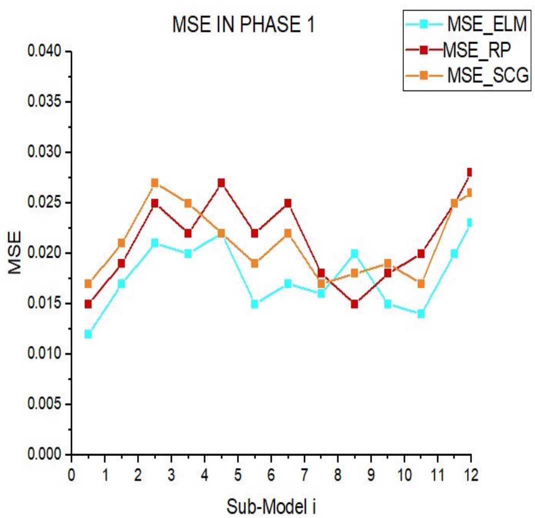
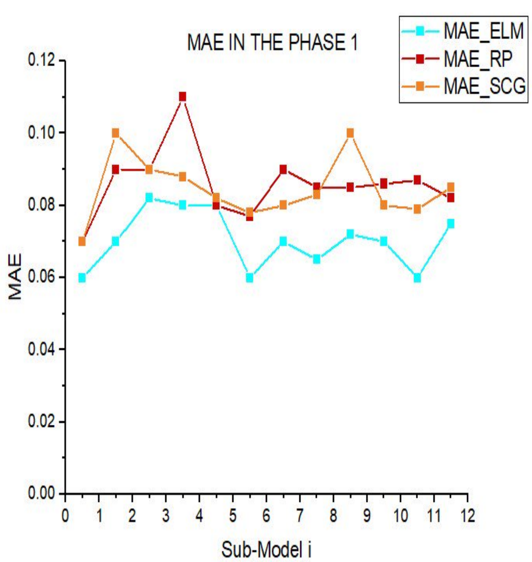
MATLAB is mainly intended for numerical computation, an optional toolbox makes use of the Multiprocessing Algebra Data (Mu PAD) representative engine to give users access to symbolic computation competencies as well. Simulation and model-based design for active and fixed systems are added by Simulink, a third software package [26].

Figures 2 and 3 show the changes in the statistical indicators RMSE, MSE, and MAE, as well as the R, for every sub-model and every training procedure, respectively.



(a)



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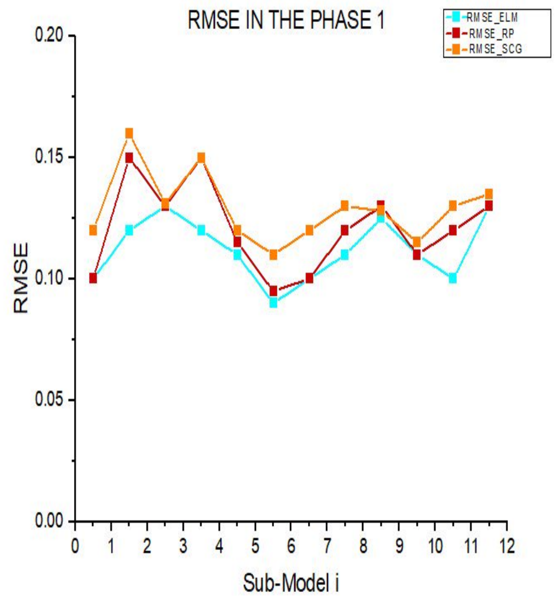

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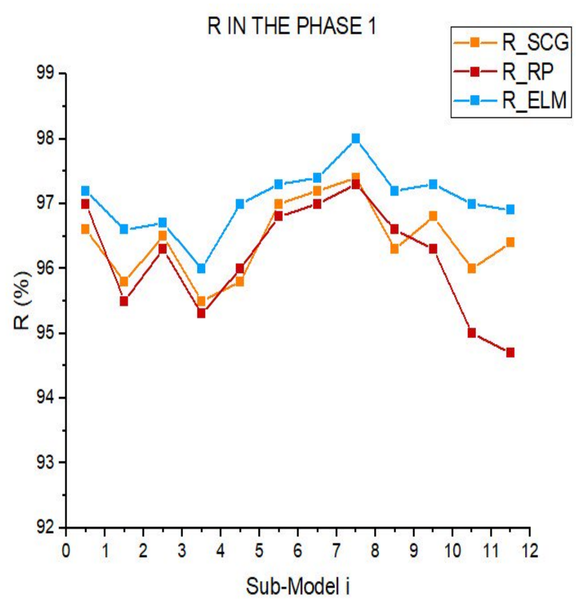

(d)

Figure 2: Changes in the statistical indicators (a.) MSE (b.) MAE, and (c.) RMSE as well as the (d.) R for every sub-model (Phase 1)

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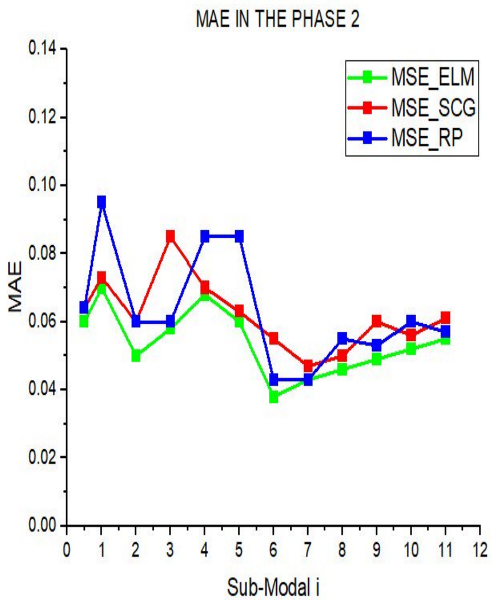
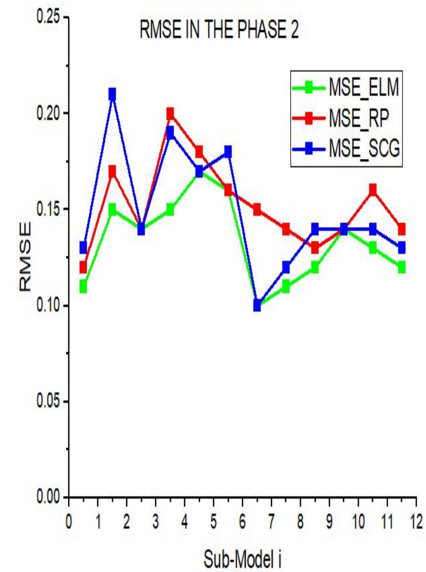


(a)



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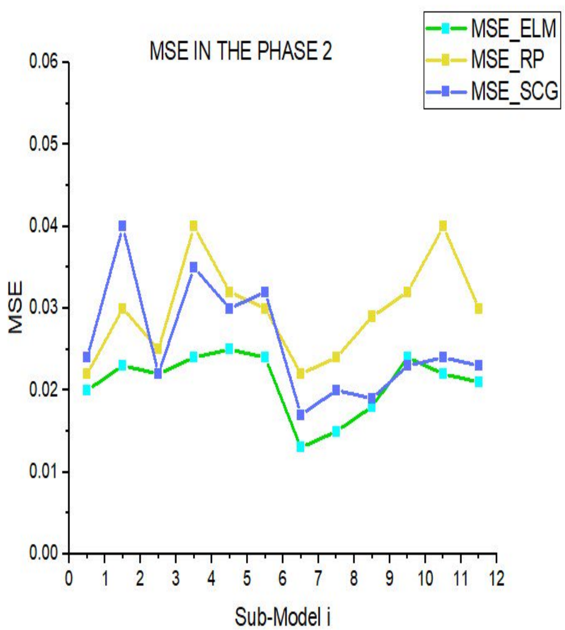

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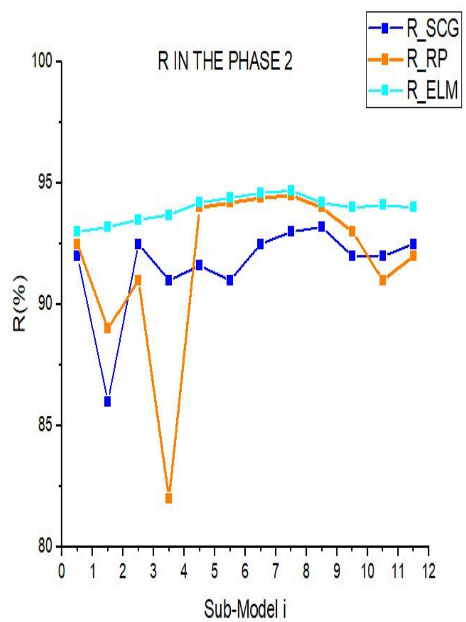

(d)

Figure 3: Changes in the statistical indicators (a.) MAE (b.) MSE, and (c.) RMSE as well as the (d.) R for every sub-model (Phase 2)

Based on the results acquired in the two stages of all sub models with different statistical indicators, it is concluded that the extreme learning machines (ELM) method is the best fit for training all sub models when evaluated to the additional training algorithms. Excluding for some sub-

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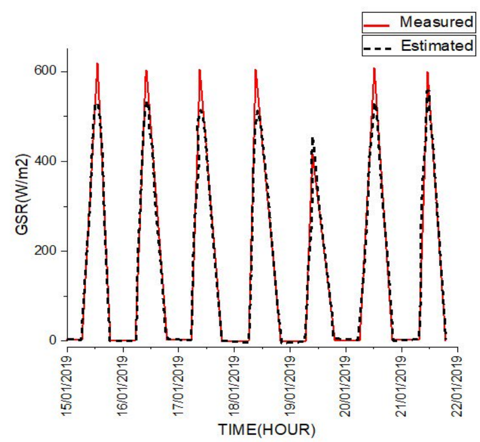
models, as shown in the figures, the resilient backpropagation and scaled conjugate gradient (SCG) preparation processes give high values in standings of the used statistical criteria (MSE, RMSE, MAE) and lower precision in terms of the correlation coefficient R associated to the ELM procedure excluding for some sub-models as the figures exposed, where they give outcomes quicker to those assumed by the ELM algorithm. It is possible to generalize the ELM training method to alter the weights and bias of all produced sub-models based on the outcomes of the study.

Winter, spring, summer, and fall performance of the suggested machine-learning method are shown in Figure 4. The findings show that the suggested method for approximating hourly global solar radiation performs better than additional methods. The pairs of the calculated and the approximate data that make up the global model have a superior correlation coefficient, which is about 95.67% on standard.



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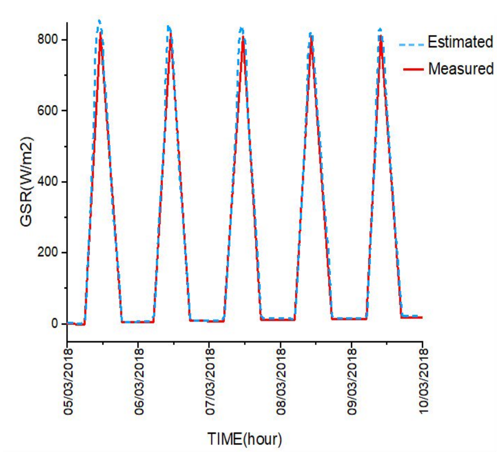

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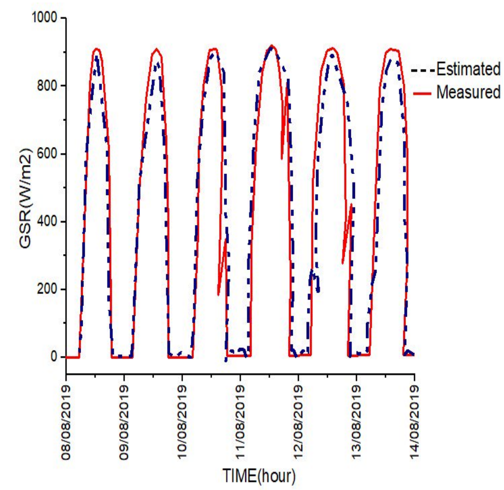

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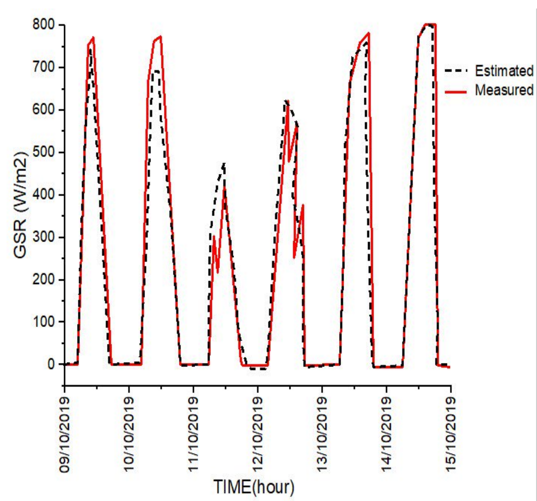

(d)

Figure 4: (a.) Winter (b.) spring (c.) summer and (d.) fall performance of the suggested machine-learning method

Simulation results obtained and incorporated under figure 2-4, are having good similarity with measured values of solar radiation. Also, the values of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Square Error (MSE) & Regression (R) values obtained in phase 1 & 2 are justifying one. These findings advocate to our research objective.

7. CONCLUSION AND FUTURE SCOPE

Setting up solar energy networks at the lowest cost requires accurate estimates of global solar radiation. This study used ELM algorithms to estimate sun radiation. A variety of ELM activation functions were utilized to estimate the data. All ELM activation functions performed better than all transfer functions of SCG and RP when compared to the general outcomes of the evaluations. As per obtained results, proposed ELM models have maximum R variance which is 95% in predicting hourly global solar radiation time series in semi-arid climates. Also, the proposed ELM models have shown minimum RMSE which is 14.02 as compared to other methods. The computed data and the approximation data that are paired together to form the global model have a superior correlation coefficient, which is about 95.67% on standard. This signifies that the global model is accurate to a high degree.

The present simulation is carried out with the data of Karaman Province of Turkey which has andesitic and dacitic volcanism of Pliocene aged calcalkaline character around Karadag in the north of Karaman. Hence, in future the same simulation may also be carried out with stations located near by seashore area or pure plain area and then results may be compared.

Here, solar radiation was estimated using ELM in this investigation. There is a possibility that the data obtained would serve as a guide for the construction of future solar networks. Different assessment criteria must be used to characterize and illustrate the capabilities of each model of solar network, such as RMSE, MSE, R. In future experiments, the amount of ELM neurons and intermediate layer neurons can be adjusted to see how effectively they estimate sun radiation. Physical alterations could be applied to the input neurons and their influence on solar radiation estimate might be evaluated as part of an additional investigation.

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