Measurement of Global Solar Radiation data using Raspberry Pi and its estimation using Genetic Algorithm

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Abstract. The demand for more efficient and environmentally benign, non-conventional sources of energy came into picture due to increasing demands for human comforts. Solar energy is now the ultimate option. In this paper, the instruments used to measure the solar radiation at Innovation Centre, MIT Manipal were connected to a Raspberry Pi to access the data remotely. Genetic Algorithms were formulated, so that the monthly mean global solar radiation in Manipal can be effectively estimated. Meteorological data such as humidity, temperature, wind speed, etc. were used as inputs to train the networks. A successful network was made between the data loggers and the Raspberry Pi. The data collected by the data loggers from the devices are transmitted to the Raspberry Pi which in turn sends the data to an internal server. The Raspberry Pi can be accessed using any SSH client such as PuTTY. The meteorological data was collected for the years 2010-2014 in order to formulate the Artificial Intelligence models. The validity of the formulated models were checked by comparing the measured data with the estimated data using tools such as RMSE, correlation coefficient, etc. The modelling of solar radiation using GA was carried out in GeneXpro tools version 5.0.

1 Introduction

Sources of renewable energy have been vital for humans from the start of civilization. The sun is a working fusion reactor that as of now supplies more energy than humans could perhaps require. Solar power is a standout amongst the most encouraging renewable energy sources for being more predictable than wind energy and less vulnerable against changes in regular climate designs than hydropower.

For the advancement of any solar energy project, site-oriented and long term solar radiation information is required right from asset appraisal to design of the system to evaluation and optimization of its performance and transient forecast of solar radiation for operational achievability. Such information is to a great degree fundamental in various field applications, such as climatology, solar energy technologies, architectural and energy saving building designs, illumination, simulation of solar power plant and agricultural research.

Due to high maintenance and calibration costs of solar measurement instruments, the solar radiation data are constricted in many meteorological stations across the globe. This has led to the development of innumerable models for the estimation of solar radiation.

Manipal, located in south-west India has a hot and humid weather condition during the whole year. The obtained solar radiation data can be used for various solar based applications.

The objective of the work is to integrate the existing solar radiation apparatus (pyranometer, pyrheliometer, sunshine duration sensor and UV meter) with a Raspberry Pi so that the data can be retrieved tenuously. to make the assembly water-proof to withstand the rainfall and humidity in Manipal, to utilise historical meteorological data to formulate different models for monthly mean global solar radiation estimation and to validate the models with the real time data obtained from Innovation Center, MIT Manipal. Genetic Algorithm has been relatively less utilised in India for the estimation of solar radiation; it's most utilisation being in Gulf countries. A prediction of the monthly mean solar radiation in Manipal can be made using the formulated Artificial Intelligence models. Genetic Algorithm is used to solve both constrained and unconstrained optimization problems. The genetic algorithm works on the principle of reproduction system by which the data set is repeatedly modified on the basis of the best fit to evolve into best reproduced offspring or data set. This finally leads to the best outcome of data set producing the optimal solution.

Aybar-Ruiz et. al [1] used grouping genetic algorithm to answer optimal solution of features and extreme learning machine algorithm to carry out the prediction and merged them into a novel scheme which uses input of the system and output of the weather meso-scale model.

Haydar and Yasemin et.al [2] researched on the estimation models of horizontal global solar radiation using the weather data of Turkey. They used vigorous coplot technique which lessens the number of covariates and then utilized the monthly and yearly mean daily horizontal global solar radiation prediction models using genetic algorithm. Hongzing et. al [3] proposed an optimal sizing technique made using genetic algorithm, whereby the configurations of a hybrid solar-wind system using battery banks is optimized. The method proved to give good optimization performance and hence achieved minimum annualized cost of system and the required loss of power supply probability.

Will et. al [4] solved the issue of selecting variables to estimate solar radiation through the use of Niching Genetic Algorithm. The algorithm provides a way to predict the input variables for a desired seasonal variable prediction problem and also approximate a given seasonal variable using databases with the aid of missing data. Qin et. al [5] offered a compared the performances of four different shortwave solar radiation models in different climatic conditions and terrain in China. The Yang's Hybrid model was found the most efficient in terms of performance in predicting solar radiation in China than the other three models namely: hourly solar radiation model, efficient physically based model and neural network model.

Ji Wu et. al [6] developed a novel approach to predict solar radiation time series by a genetic way by scrutinizing multi model framework. This model estimates the optimal fragment for the series of solar radiation of Singapore and hence proves to have greater consistency and accuracy than other models such as TDNN, ARMA and hybrid model. The clustering accuracy of the model is to be improved with an improvised capability of obtaining the relationship of data with certain configurations.

Jianyuan et. al[7] performed a critical review on the existing solar radiation estimation models and compared and analysed the models on estimation type as well as from the viewpoint of time scale. By this study they concluded that the artificial neural networks and the sunshine duration fraction models have analogous performances.

Nwokolo et.al [8] made a comprehensive and quantitative review on Africa's solar radiation estimating empirical models and concluded that due to lack of meteorological stations in sites of Africa, models using longitude, latitude, maximum sunshine duration, solar declination, extra-terrestrial radiation and day number of the year inputs for exact measurement should be established. Cano et. al [9] researched on a statistical procedure to evaluate the global solar radiation at ground level with the help of the data extracted from meteorological satellites that provide sufficient ground resolutions and extensive coverage as well. Great precision is obtained for two different time periods using this model for the data obtained by a ground level pyranometers.

Yongbin and Ronghuai et.al[10] created a low cost and portable weather monitoring system for technology rich classroom which is based on raspberry pi. This system allows in the collection, storage and transmission of data. Prediction of global solar radiation should be made as a target for this equipment using soft computing models.

2 Methodology

2.1 Solar radiation monitoring equipment

Solar radiation equipment's record solar radiation data which can utilized further for analysis of solar based applications. Data collection is done using solar radiation instruments such as pyranometer, pyrheliometer and sunshine duration as shown in Figure 1 and Figure 2..

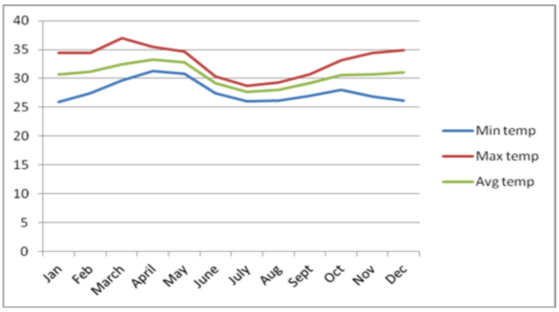

Figure 1. Average Monthly temperature history in Manipal from 2010-2014.

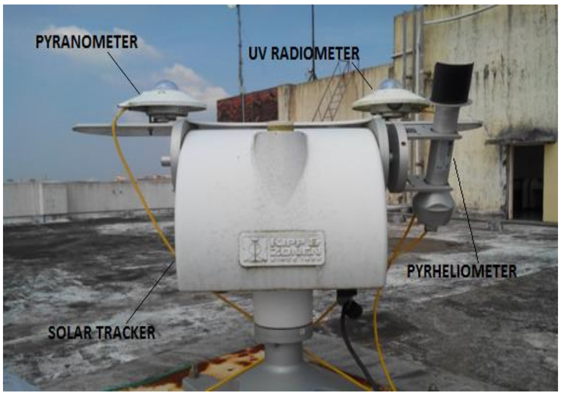

Figure 2. Sun tracker with Pyranometer, Pyrheliometer and Global UV Radiometer installed at Innovation Centre, Manipal.

2.2 Raspberry Pi

The Raspberry Pi as shown in Figure 3, costs only 35$ and about Rs 3000 in India.

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Figure 3. A Raspberry Pi board

The Raspberry Pi is a series of credit card–sized single-board computers developed in England, United Kingdom by the Raspberry Pi Foundation with the intent to promote the teaching of basic computer science in schools and developing countries. The original Raspberry Pi and Raspberry Pi 2 are manufactured in several board configurations through licensed manufacturing agreements with Newark element14. The hardware is the same across all manufacturers. In February 2016, the Raspberry Pi Foundation announced that they had sold eight million devices, making it the best-selling UK personal computer, ahead of the Amstrad PCW.

2.2.1Modifications in the system

- To protect the unit from extreme weather conditions we have replaced with external grid powered voltage adapters.
- The box is placed some centimetres above the ground for better air circulation (cooling) and to prevent direct contact with water in case of heavy rain.
- Silica gel has been kept in the box to prevent humidity.

2.2.2 Working of the Raspberry Pi system

- The data collected by the data loggers are written to RS232 and also to the SD cards inside the loggers(Set interval 1 min).
- Two RS232 to USB adapters are used to connect to the Raspberry pi unit.
- It collects the data and sends it to an internal server. The data can be found at local network.
- To access the data, one must be connected to the institute LAN.
- The Raspberry Pi can be remotely accessed using an SSH client such as Putty.

Figure 4, Figure 5 shows the integration of solar radiation monitoring equipment with Raspberry Pi.

Figure 6 shows the flowchart for the connections of data loggers to the raspberry Pi.

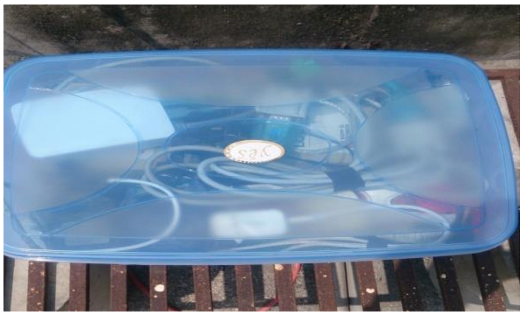

Figure 4. Plastic container integrated with Raspberry Pi and data loggers

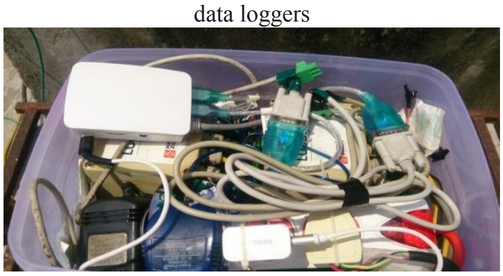

Figure 5. Connections inside the box

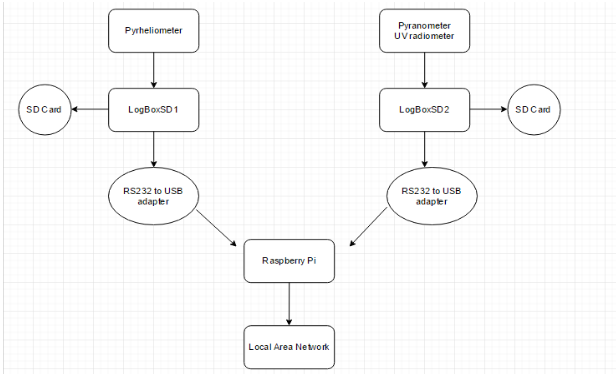

Figure 6. Flowchart deplicting the connections of data loggers to the Raspberry Pi

Table 1. Monthly mean variation in input parameters (for a period 2010-2014)

Month	Humidity	Wind Speed (m/s)	Pressure (Kpa)	Sunshine Duration (hrs)
Jan	51.73	1.91	100.48	9
Feb	44.46	1.66	100.38	9
March	44.95	1.59	100.34	10
April	59.50	1.76	100.23	11
May	72.15	2.46	100.11	11
June	81.49	3.72	100.03	8
July	85.09	4.15	100.07	9
August	85.23	3.64	100.12	9
September	82.86	3.17	100.18	10
October	78.59	2.10	100.25	10
November	73.51	1.94	100.33	10
December	61.81	2.01	100.36	9

2.3 Genetic Algorithm

The Genetic algorithm is based on Darwin's Theory of "Survival of the Fittest". Individuals are created and eliminated based on a fitness function which is determined from the input output relationship.GA used different set of meteorological constraints for the prediction of solar radiation. Different researchers have used different parameters for the prediction of radiation. Based on the literature survey it is found that prediction accuracy of these models get changed with the geographical and meteorological variables as input parameters as shown in Table 1. To select the relevant input parameters one has to use different combinations of input parameters to evaluate prediction accuracy of these models which requires large computational analysis.

Table 2 Input Parameters for different developed models

Model	Input Parameters
GA-1	Mininum Temperature, Average Temperature, Maximum Temperature, Humidity, Pressure and Wind Speed
GA-2	Average Temperature, Maximum Temperature, Humidity and Wind Speed
GA-3	Average Temperature, Wind Speed and Sunshine Duration
GA-4	Wind Speed and Sunshine Duration

3 GSR estimation using GA models

Four Genetic Algorithm models were formulated by using various combinations of input parameters as mentioned in Table 2. Out of the three models which were created, the one with least statistical errors will be chosen as the best model to estimate the monthly mean global solar radiation in Manipal. The modelling was gone in GeneXproTools version 5.0. It can be used to produce dominant predictive models for Time Series Prediction and Regression Predictions, Classification & Logistic Regression and explore Logic Synthesis. The parameter settings for the modelling process is shown in Table 3. 70% of the statistics was used for training the algorithm and remaining 30% was used for testing and validation.

Table 3. Parameter settings

Type	Parameter	Value
General	Chromosomes	30
	Genes	2
	Head Size	3
	Linking Function	Addition
Complexity	Generation w/o change	2000
	No of tries	3
	Max complexity	5
Genetic Operators	Mutation Rate	0.044
	Inversion rate	0.1
	IS transposition rate	0.1
	RIS transposition rate	0.1
	One-point recombination rate	0.3
	Two-point recombination rate	0.3
	Gene recombination rate	0.1
	Gene transposition rate	0.1
Numeric Constants	Constants per gene	2
	Data type	Integer
	Lower Bound	-10
	Upper Bound	10

3.1 GA model I

For this model minimum temperature, humidity, maximum temperature, average temperature, pressure and wind speed were taken as the input parameters. Figure 7 shows the regression plot of the model. The expression tree of the model is shown in Figure 8.

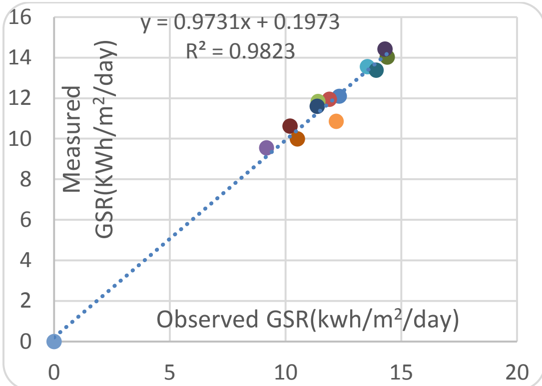

Figure 7.Regression Plot-I

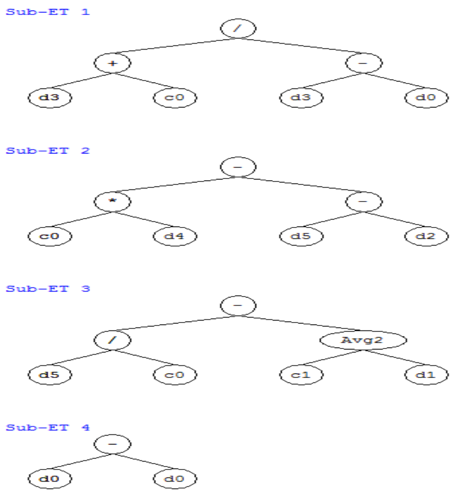

Figure.8 Expression Tree-I

From the expression tree in Figure 8, the model can be explicitly written as:

$$GSR = \frac{d3 + c0}{d3 - d0} + (c0 * d4) - (d5 - d2) + \frac{d5}{c0} - \frac{c1 + d1}{2}$$

Where,
d0 = Min Temp
d1 = Max Temp
d2 =Avg Temp
d3 = Humidity
d4 = Pressure
d5 = Wind Speed
G1C0 = 9.0
G2C0 = -3.674e-04
G3C0 = 4.03596
G3C1 = 4.39120

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3.2 GA model II

For this model maximum temperature, average temperature, humidity and wind speed were taken as the input parameters. Figure 9 shows the regression plot of the model. The expression tree of the model is shown in Figure 10.

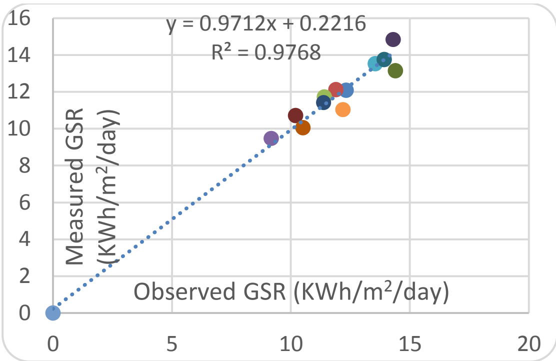

Figure 9. Regression Plot-II

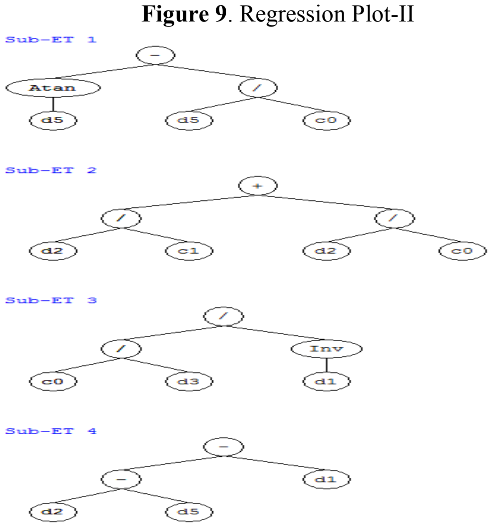

Figure 10. Expression Tree – II

From the expression tree in Figure 10, the model can be explicitly written as:

$$GSR = (a\tan(d5) - \frac{d5}{c0}) + (\frac{d2}{c1} + \frac{d2}{c0}) + \frac{c0*d2}{d3} + (d2 - d5) - d1$$

Where,
d0 = Min Temp
d1 = Max Temp
d2 = Avg Temp
d3 = Humidity
d4 = Pressure
d5 = Wind Speed
G1C0 = 3.5964
G2C1 = 4.3429
G2C0 = 4.1010
G3C0 = 4.1010

3.3 GA model III

For this model average temperature, sunshine duration and wind speed were taken as the input parameters. Figure 11 shows the regression plot of the model. The expression tree of the model is shown in Figure 12.

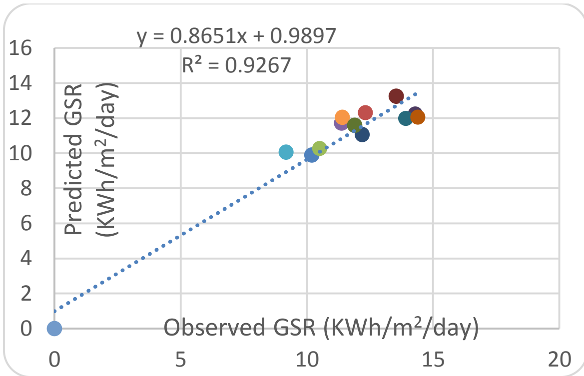

Figure 11. Regression Plot – III

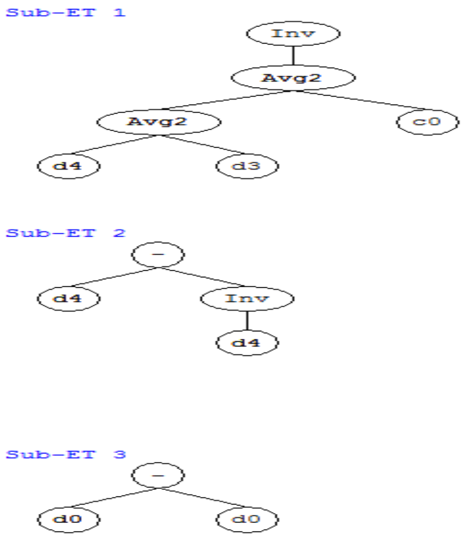

Figure 12. Expression Tree – III

From the expression tree in Figure 12, the model can be explicitly written as:

$$GSR = \frac{4}{d2+d3+2c0} + d2 - \frac{1}{d4}$$

Where,

d0 = Avg Temp
d3 = Wind Speed
d4 = Sunshine duration
G1C0 = -4.870418

3.4 GA model IV

For this model average temperature, sunshine duration and wind speed were taken as the input parameters. Figure 13 shows the regression plot of the model. The expression tree of the model is shown in Figure 14.

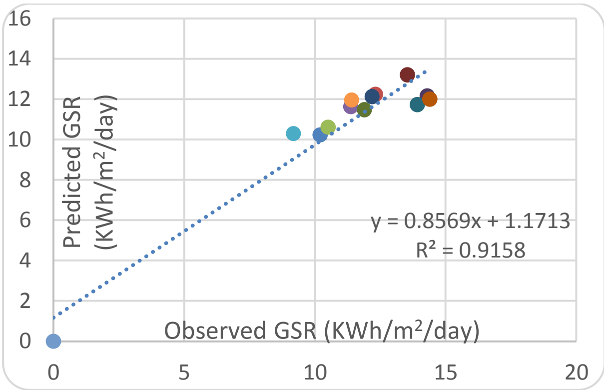

Figure 13. Regression Plot – IV

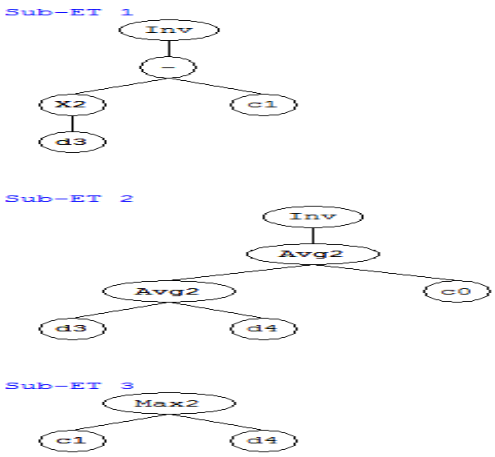

Figure 14. Expression Tree –IV

From the expression tree in Figure 14, the model can be explicitly written as:

$$GSR = \frac{1}{d4^2 - c1} + \frac{4}{d3 + d4 + 2c0} - \max(c1, d5)$$

Where,
d3 = Wind Speed
d4 = Sunshine duration

G1C1 = 9.0

G2C0 = -4.870418
G3C1 = -8.0

Table 4 Validation of the developed models

Model	Parameter	Training	Testing
Model I	MSE	0.297	0.177
	RMSE	0.545	0.42
	MAE	0.384	0.386
	Correl.	0.9	0.99
Model II	MSE	0.237	0.525
	RMSE	0.486	0.724
	MAE	0.353	0.602
	Correl.	0.922	0.932
Model III	MSE	0.35	3.386
	RMSE	0.592	1.84
	Correl.	0.887	0.945
Model IV	MSE	0.219	3.81
	RMSE	0.468	1.95
	Correl.	0.962	0.886

Of the four GA models which were developed using GeneXproTools 5.0, the one which is best suited for Manipal will be determined based on statistical parameters like correlation coefficient, Mean Absolute Error, Root Mean Square Error, etc.From Table 4, it is evident that Model I is the best explicit model to estimate the monthly mean global solar radiation in Manipal. Thus the monthly mean global solar radiation in Manipal can be explicitly expressed as :
GSR = Global Solar Radiation

$$GSR = \frac{H+9}{H-T1} + ((-3.67 * 10^{-4} * \mathrm{P}) - (\mathrm{W} - \mathrm{T3})) + (\frac{W}{4.036} - \frac{4.391 + T2}{2})$$

on (KWh/m^2/day)
H = Humidity
T1 = Minimum Temperature (°C)
T2 = Maximum Temperature (°C)
T3 = Average Temperature (°C)
P = Pressure (KPa)
W = Wind Speed (m/s)

4 Conclusion

The unavailability of solar radiation statistics in many meteorological stations worldwide is mainly due to high cost of maintenance and calibration of the solar radiation measuring devices. The hurdles involved to measure the solar radiation has led to the formulation of various models for its prediction. Four genetic algorithm models were developed in order to predict the monthly mean global solar radiation in Manipal. Solar radiation prediction was made using the developed models and it was found similar to the measured data. The advantage of the GA model is that the output can be explicitly written in terms of the input parameters which is not possible in the ANN model.

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