PREDICTION OF SOLAR RADIATIONS FOR SOLAR SYSTEM UNDER DIFFERENT CLIMATIC CONDITIONS

By

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Dedicated to

My Parents

&

Wife

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Blessed are those that can give without remembering and receive without forgetting. As we express our gratitude, we must never forget that the highest appreciation is not to utter words, but to live by them. My heart and soul feels greatly honored to find this opportunity to be in thankfulness before **Almighty** for his constant innumerable blessings and also for bestowing the enough strength and courage to complete my thesis work.

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Anand Mohan

THESIS COMPLETION CERTIFICATE

This is to certify that the thesis on *"Prediction of Solar Radiations for Solar System under different Climatic Conditions"* by **ANAND MOHAN** in Partial completion of the requirements for the award of the Degree of Doctor of Philosophy (Engineering) is an original work carried out by him under our joint supervision and guidance.

It is certified that the work has not been submitted anywhere else for the award of any other diploma or degree of this or any other University.

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DECLARATION

"I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text."

Name: Anand Mohan

Date:- 27th April, 2018.

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EXECUTIVE SUMMARY

Energy is a fundamental input for human activities that provide to economic, human and social development of any country. Among all the energy carriers, electrical energy is the most important and sought after energy carrier for its quality, versatility and ability to perform various technology driven end-use activities. Demand for electricity has increased significantly, especially in the developing countries like India, in recent years due to growth in population and economic activities such as agricultural, industrial and domestic activities.

Each year, the sun casts four thousand times more energy on the earth than what is consumed worldwide. German scientists Gerhard Knies and Franz Trieb assert that covering a small part (0.5%) of the earth's hot deserts with solar collectors would suffice to meet the electrical needs of the entire planet. One of the possibilities is to transform this energy into electrical power.

For optimum use of solar energy we should be well conversant with the availability of the solar radiations and their requirement for a particular system. The climate conditions of particular region also play a major role for use of solar radiations. The information regarding same can be obtained from the instruments installed at different weather stations but it is not possible economically to install instruments everywhere. Therefore some suitable model for prediction of solar radiations becomes need of the hour.

Himachal Pradesh state's some districts experience severe cold and windy conditions during November to mid of March requiring electricity for 24 x7. Also the snowfall makes the situation worse at some of the places due to breakage of power supply wires which cannot be repaired overnight and people have to remain without light for several days. The best answer to all these problems can be the solar electrification of these places.

The state government has planned to harness renewable energy to meet the energy requirements at all levels. The data of solar radiations is required not only for evaluation of solar energy plants but also for evaluation of various energy devices like solar water heating, passive solar house technology, solar photovoltaic lights, agriculture studies and meteorological parameters. But data at most of the far flange areas is either not available or its not reliable. Hence a system is to be devised to predict the solar radiations at different places of the state to achieve the solar electrification.

As solar energy systems depend on the climatic conditions, that is why their use requires complex design, planning and control optimization methods. Fortunately, the advances made in computer hardware and software are allowing researchers to deal with these optimization problems using computational techniques, as can be seen in the large number of optimization methods that have been applied to the renewable and sustainable energy field.

A detailed methodology has been devised to predict the solar radiations at different places The first objective was to make the assessment of solar irradiation in particular area by using artificial neural networks (ANN) method. The meteorological data of location has been obtained from Himachal Pradesh power Corporation Limited (HPPCL), Shimla, Himachal Pradesh for training the neural networks and used for testing the estimated values. Different input variables such as temperature data maximum temperature (T_{max}) and minimum temperature (T_{min}), average relative humidity, average rainfall, global solar radiations, pressure for the year 2014 has been used to propose the solar radiations as the output. Three ANN based models have been developed using artificial neural networks tool (nftool). They have been given names as ANN-1, ANN-2 & ANN-3 in the nftool of MATLAB 9.1 (R2016b) Simulink. The three ANN based models have been developed using different input variables. The correlation coefficient (R value) which determines the association between outputs and targets have been found out in all the three models. Hidden layers have been varied between 10 to 20 for all the three models and the MLP model with least MSE have been suggested for the particular ANN based model as it has the least MAPE. The best model out of the three models has been proposed.

Then one model based on adaptive neuro-fuzzy inference system (ANFIS) have also been proposed to predict the global solar radiations taking the inputs of the best model based on ANN. The basic idea behind these neuro-adaptive learning techniques is very simple. These techniques provide a method for the fuzzy modelling procedure to learn information about a data-set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. This learning method works similarly to that of neural networks. The Fuzzy Logic Toolbox function that accomplishes this membership function parameter adjustment is called ANFIS.

Next study has been carried out for the prediction of solar radiations using climatic conditions for the 10 selected cities of Himachal Pradesh. In the three different models predicted maximum number of inputs used is six and minimum is four. The different variables used in this study are temperature (Temp.), humidity (H), rainfall (R), sun shine hours (SH), latitude (Lat.), longitude (Long.) and target average daily solar radiations (SR) for 10 cities of Himachal Pradesh on average basis. It has been suggested in the research conducted that what are the most suitable climatic conditions required for prediction of solar radiations. The errors have been calculated to suggest the most efficient model for solar radiation prediction.

Chapter 1 comprises the basic introduction of the solar energy, its requirements, existing solar technologies, scope and availability of solar energy in context of World, India and state of Himachal Pradesh. In the end it has been discussed that why there is need of solar energy with reference to state of Himachal Pradesh.

Chapter 2 elaborates the extensive literature review carried out to find the different existing prediction models and gap in the research. ANN as a better tool of prediction, its advantages and accuracy for prediction models has also been discussed. In the last of this chapter the objectives of research has been listed.

Chapter 3 deals with the methodology used for the prediction of solar radiations. Methodology has been given in the form of flow chart. Prediction models selection processes using both ANN and ANFIS have been given in this chapter.

Chapter 4 gives the site specific prediction model using ANN. Different meteorological parameters have been selected and data for the same has been collected from HPPCL. The models have been proposed using different inputs from the selected parameters and the model with minimum error has been suggested out of the three. Error has been calculated to check the accuracy of the proposed prediction model.

In chapter 5 ANFIS has been used to predict the one model predicting global solar radiations using six input parameters same as taken in chapter 4 for the ANN model. Rule base have been designed for model based on the training and validation process. Then next year’s prediction has been done based on the proposed model and error has been calculated between actual and predicted solar radiations.

Chapter 6 has the prediction model based on the data collected for 10 cities of Himachal Pradesh. Input parameters for the selected cities are the meteorological parameters and different inputs have been given to all the three proposed models using ANN. Depending upon the calculation of error the model with least error has been taken as the best model for the prediction of solar radiations. Also, the best model input parameters have been taken as the most influential climatic conditions for prediction of solar radiations. Based on these estimations solar radiations have been predicted for the next five years for these selected cities.

In this chapter ANFIS has also been used to propose the model using same inputs used in the best prediction model by ANN. Error calculation and prediction of 2017 has been done based on this model.

Chapter 7 has analysed all the results obtained from the different models. The errors as well as best models with their inputs have been discussed in length in this section. Also the range of solar radiations for the 10 selected cities of Himachal Pradesh for next five years has been predicted. The results from both the models using ANN and ANFIS have been discussed and compared.

Chapter 8 has the conclusion drawn from the obtained results through different models. The conclusions have been drawn qualitatively with comparison to the objective of this research.

The last chapter contains the references and bibliography of the work carried out.

LIST OF ABBREVIATIONS AND SYMBOLS

AI	:	Artificial Intelligence
ANFIS	:	Artificial Neuro-Fuzzy Inference System
ANN	:	Artificial Neural Networks
CSP	:	Concentrating Solar Plant
et al.	:	el alia (and other authors)
etc.	:	et cetra (so on)
FIS	:	Fuzzy Inference System
GUI	:	Graphical User Interface
IMD	:	India Meteorological Department
MABE	:	Mean Absolute Value of Bias Error
MAPE	:	Mean Absolute Percentage Error
MBE	:	Mean Bias Error
MLP	:	Multi Layer Perceptron
MNRE	:	Ministry of New and Renewable Energy
NISE	:	National Institute of Solar Energy
NIT	:	National Institute of Technology
PV	:	Photo Voltaic
RBF	:	Radial Basic Function
RMSE	:	Root Mean Square Error
SH	:	Sun Shine Hours
SR	:	Solar Radiation
$SR_{i(Actual)}$	:	Solar Rediation Actual
$SR_{i(ANN)}$	:	Solar Rediation predicted through ANN
SRPM	:	Solar Rediation Prediction Model
UPES	:	University of Petroleum & Energy Studies
T	:	Temprature
RH	:	Relative Humidity

R	:	Rainfall
Lat.	:	Latitude
Long.	:	Longitude
h	:	Hidden Layers
I_n	:	Number of Inputs
O_n	:	Number of Outputs
S_n	:	Data Samples Used
δ	:	Error Term for each node
θ	:	Solar Zenith angle (degrees)
ω	:	Weight Change
α	:	Activation for each Node
ε	:	Learning Rate
Δ	:	Incremental Change

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1. INTRODUCTION

Energy is a fundamental need for the human being and is the very basis of economic and social development of any region. Of all the available energies, electrical energy, because of its distinct quality, wide range of capability and its unmatched usage is the most needed energy carrier. Due to the perpetual economic activities and the considerable growth in the population, the demand for electricity has been on the rise in developing nations like India. Electricity generation in far off places at the least prices, available potential and the power system sizing plays a vital role.

Solar systems are the most preferred options in the far -flung regions for the different power levels, because of the convenient power sources.

1.1 INTRODUCTION TO SOLAR ENERGY

Each year, the earth receives approximately 4000 times more energy than what is utilised across the globe from the Sun. Mere coverage of 0.5% of the planet’s hot places with solar systems will help meet the electricity requirements of the whole planet as asserted by Gerhard Knies and Franz Trieb. Solar energy is nothing but capturing sun’s radiation on the earth. The biggest advantage of this energy is that it can be converted into electrical power.

Of all the renewable energy resources, the solar energy generation has witnessed the highest percentage growth of late. The researches however show that the solar energy’s contribution towards generation of electricity is still low.

Use of Solar Energy is evident some 2500 years back in which Greeks build their houses and other infrastructures facing towards sun orientation. Greeks and Romans used the solar energy making their architectures south facing. Also the use of wood is evident in ancient literatures but that was mainly limited to the rulers and well to do families of that times. This also made the poor's use sun energy to maximum.

For optimum use of solar energy we should be well conversant with the availability of the solar radiations and their requirement for a particular system. The climate conditions of particular region also play a major role for use of solar radiations. The information regarding same can be obtained from the instruments installed at different weather stations but it's not possible economically to install instruments everywhere. Therefore some suitable model for prediction of solar radiations becomes need of the hour.

Different sectors have different requirements of energy at different levels. The major chunk of the energy is consumed by the buildings. They use almost two thirds of all energy consumptions and to provide energy to such sectors without disruptions is one major challenge. By using only the existing systems it's not possible to fulfil all the requirements of energy consuming sectors including industries. So it's very important to use the renewable energy systems for the same and solar energy is one major renewable system which is available in abundance.

There is a growing concern worldwide regarding conservation of energy and to conserve the environment from the current sources of energy generation. Hence solar radiations use for energy generation addresses both these concerns. Prediction of solar radiations for a particular solar system or specific region would serve as primary model in order to prepare for the future generation technologies. Gradually, newer techniques of solar radiations prediction models/systems for solar generation plants are suggested to improve the overall system. Various analytical as well as simulation techniques have been suggested for the solar radiation predictions in the recent times. Due to its substantial growth, it is believed to be one of the world’s energy pillars in years to come. Weather conditions of any particular area play a very major role in prediction of the solar radiations.

1.2 ENERGY STATUS

The energy status is divided into three broad categories with respect to this particular research study as world energy status, Indian energy status and status of energy in Himachal Pradesh.

1.2.1 WORLD ENERGY STATUS

The ever-increasing growth of energy at world level whether it’s for daily use or for the large technological advancement requirements has risen sharply but it has its disadvantages also. The climate change, ozone layer depletion and global warming etc. are few of its major concerns. Worldwide the use of renewable energy has also started growing due the above said concerns.

The global renewable energy status report 2017 indicates that energy demand has increased around 1.8% annually since 2011 worldwide. The global energy consumption using renewable energy resource is estimated to be 19.3 % as of 2015.The overall chunk on non conventional energy sources has grown miserably of late in spite of the increase in this sector especially in solar and wind power energy. The electrical generation sector has witnessed the greatest increase as far as the renewable sector in concerned [1].

In developing countries, the use of renewable energies can decrease their dependency on the fossil fuel rich nations and ultimately can enhance their living standards and economy. Solar energy can play a major role towards achieving this target of shifting to renewable sources of energy. That’s why the major emphasis of the World is to channelize the different sources of renewable energies.

1.2.2 INDIA ENERGY STATUS

India is undergoing the phase of economic growth. Electrical systems in remote areas can use electricity storage to integrate renewable generation and help meet continually varying electricity demand. Despite many socio economic problems with respect to electrification in India there are innumerable technical glitches.

While the economy globally is experiencing its lowest growth ever, the Indian economy is towards upsurge. Indian economy has seen an exceptional growth in the year 2016-17 and power sector plays major role in it. The Installed capacity has risen to 310 GW in which thermal energy still plays pivotal role as 69.4% of total and renewable only 14.8% of total (The Ministry of New & Renewable Energy, MNRE, as per annual report 2016-17)[2].
The Indian government has increased the target of non conventional energy to 175 GW out of which 100 GW is to be installed from the solar energy which is to be achieved by 2022. 750 GW out of 900 GW is to be achieved from Solar energy only as per the Indian estimation. Technological confidence has given the belief that the non conventional energy can play a vital role in energy sector. Apart from the private sector, all the main government organizations like Aviation, Medical, Railways and PSUs are being solar powered.

1.2.3 HIMACHAL PRADESH ENERGY STATUS

Himachal Pradesh is located in North India with Lattitude 30° 22’ 40” N to 33° 12’ 40”, Longitude 75° 45’ 55” to 79° 04’ 20” E, height 350 to 6975 m (above sea level) and an average rainfall of 1323 mm. This state is hilly having 12 districts and a geographical area of 55,763km^2 with population of 6,856,509 persons. Its terrain is generally divided into four parts: Low hills (altitude up to 1,000 m); Medium hills (altitude between 1,000 -2000 m); High hills (altitude between 2,000-3,000 m); Cold & Dry zone (altitude above 3,000 m). It has very different weather conditions ranging from low to high hills and then to dry zone. Its average temperature ranges between -10° to 35°C and cold desert areas covered by snow 3-5 m with no or very rare vegetation, with in average rainfall of about 25 cm and temperature as low as -40°C. This state has average snowfall of 150 cm. The major sources of energy generation in state are large and medium hydro power plants at different locations of the state on rivers like Satluj, Beas, Chenab and their rivulets. The installed capacity of hydro plants is approximately 25,000 MW.

While the states own requirement of power should be met from clean sources as per state policy of sustainable development and solar fits in that. Solar is much firmer and efficient and compliments hydro. National Institution of Solar energy (NISE) [3] has estimated a potential of 34 GW taking into account 3% of total wasteland and roof top surface area of the consumers for this purpose. HP Solar Power Policy-2016 [4] is also in place which shall be applicable to Solar PV technology. Therefore this state has huge solar potential if the solar radiation predictions can be done at each or every place or some model for the prediction can be used where weather or other data are not available.

1.3 EXISTING SOLAR TECHNOLOGIES

Currently there are two methods of generating electricity from solar radiations. The first is solar thermoelectric technology and the second is known as photovoltaic technology.

1.3.1 SOLAR THERMOELECTRIC TECHNOLOGY

This technology is based upon the solar radiations used for heating of fluid to be used in thermodynamic cycle or generate electricity using a turbine. This concept was first introduced in 1767 by Horace de Saussure, and there after some latest methods are also available.

One of the commonly used example of this method is solar water heaters used on the rooftops, whilst Concentrating Solar Plants (CSP) are found generally in United States South-western states. These CSP concentrate sun light on a small area through large number of mirrors and used to heat the fluid which in turn convert water into steam and used to operate turbine to generate electricity. The disadvantage of this approach is that it requires a large volume of water to operate the turbines and CSP conversion rate is only 20%.

1.3.2 PHOTOVOLTAIC TECHNOLOGY

This photovoltaic (PV) technology is also known as solar photovoltaic conversion. Using photovoltaic effect, the solar energy is converted to the flow of electrons using solar cells which is best method for electric power generation. In this conversion method the materials are used which exhibit the photovoltaic effect.

PV power generators have number of solar panels comprising of solar cells containing a PV material. Solar powered PV panels convert the sun’s rays into electrical energy by exciting electrons in silicon cells using the photons of light from the sun. Solar cells can be classified into first, second and third generations. First generation cells are also called conventional or wafer-based cells. It is considered as the best technology for solar powered electricity generation due to its simple and easy functioning.

Alexandre-Edmond Becquerel was the first researcher who observed this effect in year 1839 using a silver coated platinum electrode in an electrolytic solution. Later in 1876 this effect was also seen in selenium by Adams and Day. But as per literature the first large area solar cell was produced in 1894 by Fritts using selenium in between gold and other metal.

The electronics industry stated widespread use of p-n junctions by 1950s. The first silicon solar cell was developed by Chapin, Fuller and Pearson in 1954 with an efficiency of 6%. It had high cost as Rs.13000 per watt but it opened up the electricity distribution channel for the remote areas. The actual efforts to use the renewable energy and specially the solar energy started in the 2000s and it truly reduced the costs of PV cells due to its high production. Now the silicon based cells manufactured in labs have efficiencies as high as 25% and their cost has been reduced to as low as Rs.64 per watt. Modern solar cells which are silicon based are usually single junction devices and can be classified as mono crystalline (high quality), multi crystalline (lower quality) or amorphous (low efficiency), each with all having their own different methods of manufacturing. Due to silicon's low cost, very good quality and technologically sound materials almost 85% of total available PV cells are of silicon family.

The solitary junction solar cells, despite all the above qualities have the limitations of their performance efficiency. Therefore in recent times a number of other PV technologies have been evolved today based on other than silicon materials. These are generally divided into the following three categories:

1.3.2.1 High Efficiency

These materials use inorganic semiconductors with properties for high absorption of the incoming solar radiations. Its high conversion efficiency has made it popular for space power systems applications where weight is the main consideration.

1.3.2.2 Thin Films

These PV cells are manufactured by depositing thin layers of active semiconductors on a substance, Copper Indium Gallium di Selenide, Cadium Telluride. They have the properties of high performance under low light conditions and also they are cheaper than crystalline silicone.

1.3.2.3 Organic and Dye-Sensitised

In this type flexible solar cells are manufactured with a band gap that can be changed by varying material composition by the use of molecular or organic materials containing carbon. The major disadvantage is that it requires large volume production for low cost and also its performance efficiency is good if used for long periods under illumination. Due to this advantage they are very rarely used commercially.

1.4 EXISTING SOLAR MODELING TECHNIQUES

1.4.1 ANGSTROM MODEL

The original Angstrom [5] is the first model for estimation, which shows relation/equation between daily radiation to clear sky radiation (monthly average) and actual sunshine duration to average probable sunshine hours.

$$\frac{H}{H_c} = \text{a+b}\left(\frac{n}{N}\right) \tag{1.1}$$

Where

H = Month's average daily radiation at surface in hours$(W/m^2/day)$.

H_c = Month's average clear sky radiation.

$n =$ Actual daily sunshine duration in hours.

$N =$ Maximum possible bright sunshine duration in hours.

$a, b =$ Regression coefficients.

Also the ratio $\left(\frac{n}{N}\right)$ is known as Cloudless index and it avail the information regarding atmospheric characteristic and conditions of area under study.

1.4.2 ANGSTROM-PRESCOTT MODEL

In equation (1.1) there is a basic difficulty that lay's with its defining term H_c, as problems arising in finding clear sky radiation precisely. So Prescott [6] has modified above equation (1.1) and named as Angstrom-Prescott model which is commonly used model. Prescott has modified and replaces cloudless sky radiation with extraterrestrial radiation H_o with H_c and is given by.

$$\frac{H}{H_o} = \text{a+b}\left(\frac{n}{N}\right) \tag{1.2}$$

Where

$H_{0=}$ Monthly average extraterrestrial radiation.

Now he termed $\frac{H}{H_o}$ as Clearness index. The value for H_o can be calculated as [7].

$$H_o = \frac{24 \times 3600 \times I_{sc}}{\pi} \times \left[1 + 0.033 \cos\left(\frac{360 \times d}{365}\right)\right] \times \left[\cos\varphi \cos\delta \sin\omega_s + \frac{\pi\omega_s}{180} \sin\varphi \sin\delta\right] \tag{1.3}$$

Where
H_o = Monthly average extraterrestrial radiation.
I_{sc} = Solar constant ($1367wm^{-2}$)
d = Number of days from 1st January to 31st December.
φ = Latitude of location in ($\circ$)
δ = Solar declination angle in ($\circ$)
ω_s = Sunset hour angle in ($\circ$)

Also, Solar declination angle in ($\circ$) and Sunset hour angle in ($\circ$) can be find by following relations.

$$\omega_s = \cos^{-1}(-\tan\varphi\tan\delta) \tag{1.4}$$

$$\delta = 23.45\ \sin\left[360\left(\frac{284 \times d}{365}\right)\right] \tag{1.5}$$

The maximum sunshine duration (N) hours may be given by eqn. [7].

$$N = \frac{2\omega_s}{15} \tag{1.6}$$

Besides Angstrom-Prescott Model equations can further improved to more precise results and used for many application.

1.4.3 LIEU AND JORDAN MODEL

Lieu and Jordan have proposed computational formulae for solar radiation, given as [8].

$$G = I_s.R_b + D_s.\left(\frac{1+\cos\beta}{2}\right) + \left(\frac{1-\cos\beta}{2}\right).\rho \tag{1.7}$$

For Horizontal plane solar radiation is given as:

$$G = G_h = I_s + D_s \tag{1.8}$$

Where
I_s = Direct radiation on horizontal surface.

I_s is given as,

$$I_s = A\ \cos\theta.\exp\left(\frac{-1}{c\sin(\theta+2)}\right) = \frac{I}{R_b} \tag{1.9}$$

Where,

θ = angle of Incidence on horizontal surface.
R_b = Orientation Factor.
I = Direct Radiation.

Sun height angle is calculated as:

$$\sin\theta = \cos\omega\cos\varphi\cos\delta + \sin\varphi\sin\delta \tag{1.10}$$

Where,
ω = Time angle.
φ = Latitude location.
δ = Declination angle of Sun.

Direct radiation is calculated as:

$$I = R_b I_s \tag{1.11}$$

R_b (Orientation Factor) is expressed as:

$$R_b = \frac{\cos(\varphi - \beta)\cos\omega\cos\delta + \sin(\varphi - \beta)\sin\delta}{\cos\varphi\cos\delta\cos\omega + \sin\varphi\sin\delta} \tag{1.12}$$

Where,
β = Tilt angle.

To find amount of diffused radiation D_s, the following relation is proposed:

$$D_s = B(\sin(\theta))^{0.4} \tag{1.13}$$

Generally, diffuse radiation D in terms of tilt angle $\beta$is obtained as:

$$D = D_s\left(\frac{1 + \cos\beta}{2}\right) \tag{1.14}$$

Where,
$A\&B$ = Constant under clear sky and its values are given in Table 1.1.

Table 1.1

Constant's A, B for Lieu and Jordan Model.

State of Sky	Constant Value (A)	Constant Value (B)
Luminous Sky	1300	87
Average Sky	1230	125
Contaminated Sky	1200	187

In Table 1.2 some other models have also been tabulated given in literature [9] for prediction of solar radiation.

Table 1.2

Different Models and Equations considered for Global Solar Radiation.

S.No.	Author Name	Equations/Model Proposed	Reference No.
1.	Jain P.C.	$\frac{H}{H_0} = 0.177 + 0.692\left(\frac{S}{S_0}\right)$ Where S= Month's Daily Average Sunshine Hours S_0= Maximum Probable Month's Daily Average Sunshine Hours	[10]
2.	Glower and McCulloch	$\frac{H}{H_0} = a\cos\varphi + b\left(\frac{S}{S_0}\right)$ $\frac{H}{H_0} = 0.29\cos\varphi + 0.52\left(\frac{S}{S_0}\right)$	[11]

3.	Page	$\frac{H}{H_0} = 0.23 + 0.48\left(\frac{S}{S_0}\right)$	[12]
4.	Dogniaux and Lemoine	$\frac{H}{H_0} = 0.37022 + \left[0.00506\left(\frac{S}{S_0}\right) - 0300313\right] cos\varphi + 0.32029\left(\frac{S}{S_0}\right)$	[13]
5.	Louche A	$\frac{H}{H_0} = 0.206 + 0.546\left(\frac{S}{S_0}\right)$ $\frac{H}{H_0} = a + b\left(\frac{S}{S_{ns}}\right)$ $\frac{1}{S_{ns}} = \frac{0.8706}{S_o} + 0.0003$	[14]

6.	Samuel	$$\frac{H}{H_0} = a + b\left(\frac{S}{S_0}\right) + c\left(\frac{S}{S_0}\right)^2 + d\left(\frac{S}{S_0}\right)^3$$ $$\frac{H}{H_0} = -0.14 + 2.52\left(\frac{S}{S_0}\right) - 3.71\left(\frac{S}{S_0}\right)^2 + 2.24\left(\frac{S}{S_0}\right)^3$$	[15]
7.	Newland	$$\frac{H}{H_0} = a + b\left(\frac{S}{S_0}\right) + c\log\left(\frac{S}{S_0}\right)$$ $$\frac{H}{H_0} = 0.34 + 0.40\left(\frac{S}{S_0}\right) + 0.17\log\left(\frac{S}{S_0}\right)$$	[16]
8.	El-Metwally	$$\frac{H}{H_0} = a^{(1/S/S_0)}$$ $$\frac{H}{H_0} = 0.713^{(1/S/S_0)}$$	[17]
9.	Hargreaves	$$\frac{H}{H_0} = a(T_{Max} - T_{Min})^{0.5}$$ $$\frac{H}{H_0} = 0.16(T_{Max} - T_{Min})^{0.5}$$	[18] [19]
10.	Goodin	$$\frac{H}{H_o} = a\left[1 - exp\left(-b\left(\frac{\Delta T^c}{H_0}\right)\right)\right]$$ $$\Delta T = Tmax - Tmin$$	[21]

11.	Gopinathan	$\frac{H}{H_0} = a + b\cos\varphi + cZ + d\left(\frac{S}{S_0}\right) + eT + fRH$	[21]
12.	Ojosu and Komolafe	$\frac{H}{H_0} = a + b\left(\frac{S}{S_0}\right) + c\left(\frac{T_{Min}}{T_{MAx}}\right) + d\left(\frac{RH}{RH_{Max}}\right)$	[22]

1.5 RELEVANCE FOR SOLAR ELECTRIFICATION IN HIMACHAL PRADESH

Himachal Pradesh state some districts experience severe cold and windy conditions during November to mid of March requiring electricity for 24 x7. Also the snowfall makes the situation worse at some of the places due to breakage of power supply wires which cannot be repaired overnight and people have to remain without light for several days. The best answer to all these problems can be the solar electrification of these places. This will not only provide them electricity round the clock but also decrease the cost of maintenance and distribution for state utility.

The state can also become the carbon neutral state if the renewable energy and especially solar energy potential is effectively utilized. In order to become energy crisis Free State, it has to plan and organize the use of solar energy.

The state government has planned to harness renewable energy to meet the energy requirements at all levels. The data of solar radiations is required not only for setting up of solar energy plants but also for evaluation of various energy devices like solar water heating, passive solar house technology, solar photovoltaic lights, agriculture studies and meteorological parameters. But data at most of the far flange areas is either not available or its not reliable.

Hence a system is to be devised to predict the solar radiations at different places of the state to achieve the solar electrification.

In order to establish a power system for a particular site it is necessary to get down to the nitty-gritty of the particular power demand and the solar energy existing there. This will allow us to design the kind of solar energy system that meets the demands of the utility at its best.

As solar energy systems depend on the climatic conditions that is why complicated design, control optimization techniques and planning is essential. Fortunately, the technological advancements as regards computer software and hardware are permitting researchers to tackle these optimization hurdles using computational methods.

2. LITERATURE REVIEW

2.1 RELATED RESEARCHES

Many researches have been carried out on the prediction of solar radiation. Some relevant researches have been presented as follows.

Yadav et al. [23] has suggested that number of climatic and topographical elements affect the solar radiations. Various inputs such as latitude, longitude, temperature, humidity etc. have been considered to propose 3 different models based on ANN with most valuable inputs for these models. It has been suggested that temperature, altitude and sunshine are most relevant factors whereas longitude and latitude are the as least effecting input variables in prediction of solar radiations for state of Himachal Pradesh.

An empirical model has been suggested by Li et al. [24] for evaluating global solar radiations on daily basis on a horizontal surface. The MAPE, MABE, RMSE and correlation coefficients have been calculated and results show good adjustments to varying conditions.

Data of solar radiations are of great importance for solar systems. Li et al. [25] shows that for prediction of global solar radiations estimation of 8 models can be done using only the sunshine hours. Output shows that the models present fair prediction preferring only Angstrom-Prescott models.

The work proposed by Rahimia et al. [26] has been developed to calculate the Angstrom equation coefficients by making use of sunshine duration hours and solar radiations of Mashhad Synoptic station from 1997 to 2003. To evaluate error and validate the model three statistical parameters such as MBE, RMSE and index of agreement have been employed.

To obtain solar radiation maps, multilayer perceptron application has been used in Spain by Hontoria et al. [27]. To establish solar radiations ANN has been used. Seven different cities have been chosen to draw the conclusions using MLP.

Estimation of daily global solar radiations have been done using ANN based techniques by Benghanem et al. [28]. Different solar data like global radiation, air temperature and humidity has been used to project the model. By using different combinations as inputs 6 ANN models have been proposed and it has been noticed that the methods employed using sunshine duration and air temperature yield accurate results.

Mohandes et al. [29] introduced neural networks technique for Saudi Arabia for estimating the global solar radiations. The 41 locations data has been separated into 31 sites for training and 10 locations for trying and the outcome suggest comparatively fair relation between projected values and the observed ones.

Daily global solar radiations on horizontal surfaces has been measured for three years at Amman City, Jordan for research by Al-Salaymeh et al. [30].The obtained model gives best fit for measured values and has a high value of regression coefficient. Mathematical formula has been used by the paper for predictive model for the duration of sunshine.

Three methods have been employed to determine Angstrom regression coefficients which are used to suggest the daily solar radiations for 8 metrological sites in Egypt by M.T.Y et al. [31]. The first ratio has been taken between monthly sunshine duration and corresponding maximum of daily sunshine, the next between monthly daily global solar radiation and corresponding monthly mean solar radiation on horizontal surface.

To determine the solar-energy prediction in Turkey ANN has been used by Sozen et al. [32]. The inputs used to the system are Latitude, longitude, altitude, mean sunshine duration and mean temperature. Solar radiation has been taken as output layer. The trained and testing models of ANN give accuracy to find the solar radiation potential.

The work purposed by Jemaa et al. [33] the modelling of solar radiation has been done using three approaches namely linear, quadratic and cubic models. Different inputs have been used. To suggest the daily global radiations with measured daily duration of sun on earth data is the prime objective of this study.

The objective of the study given in paper by Hasni et al. [34] has been to test an ANN for evaluating global solar radiation as a dependent of air temperature and relative humidity data. The suggested model can be used at locations where only the above two data are available.

A fuzzy based model for obtaining energy available at the PV cells output which keep varying with solar radiation and temperature by Li et al. [35]. Maximum power point has been obtained using the fuzzy model. During tracking phase the fuzzy control algorithm efficiently enhances the efficiency. It is suggested to be suitable for fast changing environments.

Black et al. [36] proposed model where regression constant 'b' is almost constant and value of 'a' mean proportion of radiation is varying.

Page et al. [37] suggested that clearer the sky; more is the value of solar radiation for given ratio of mean daily duration of sunshine over maximum possible sunshine duration. Ultimately the value of 'b' got affected.

A correlation model proposed for the relation between monthly daily average global solar radiations to the possible sunshine hours by Rietveld et al. [38]. Its correlation at that time was assumed to be applicable everywhere in world.

Flocas et al. [39] suggested that the accurate measurement of solar radiation is of great importance as most of the weather stations are doing the predictions based only on the duration of sunshine hours.

A study based on the Hounman model has been implemented on the 6 Australian stations with monthly values of 458 months of almost 3to 10 years for solar radiation prediction by Hutchinson et al. [40].

Turton et al. [41] established an average regression constant for humid tropical countries. Using this regression constant solar radiations can be predicted for humid regions.

Singh et al. [42] suggested the correlation formula for the solar radiation study of Amritsar and gave the values of regression constants.

The altitude and latitude of the site have been taken into consideration in order to calculate regression coefficients by Chandel et al. [43]. This model suggested results better than other models.

A model has been proposed by Akpabio et al. [44] for the prediction of global solar radiations using the data supplied by International Institute of Tropical Agriculture station at Onne, Nigeria which is a high rainfall station.

Alawi et al. [45] have taken into consideration different climatic conditions like temperature, pressure, relative humidity, mean wind speed etc. to predict solar radiations for area where no measurement of solar data is being done. The MAPE calculated is 7.3 in this study.

Multistage ANN is used in this study to estimate the daily radiations of the next day by Kemmoku et al. [46] using average atmospheric pressure as one of the inputs.

Kalogirou et al. [47] used ANN to suggest the solar radiation. The input to the suggested model has been affected mainly by the availability and magnitude of solar radiation.

Solar radiation data from 13 Indian locations has been trained by ANN to estimate hourly values of solar global radiation and the monthly mean daily by Reddy et al. [48] to propose a prediction model.

Different meteorological parameters and global solar radiation in Sao Paulo City, Brazil are used in this study by Soares et al. [49] to predict hourly values of diffuse solar radiation using perceptron neural-network technique.

Sozen et al. [50] have suggested two different models using ANN. In first model weather data for three years is being used for 17 stations of Turkey. 11 stations have been used for training while 6 have been used for testing. In second model solar radiation potential is predicted for construction of monthly radiation maps in Turkey using ANN.

Solar irradiance has been estimated in this research by Cao et al. [51] using ANN combined with wavelet analysis. Data pre-processing has been done into several time-frequency domains and then back-propagation is being used.

In the proposed model Lopez et al. [52] trained a multi-layer feed-forward perceptron. Bayesian system for ANN has been used for prediction of direct solar irradiance.

Ouammi et al. [53] have suggested ANN model for estimating monthly solar irradiation of 41 sites of Morroco for the years 1998-2010 and longitude, latitude and elevations have been used as inputs to the model.

Khatib et al. [54] used sunshine ratio, longitude, latitude and days number as input values for estimation of clear day sky for Malaysia using feed-forward multilayer perceptron.

Modelling of diffuse and direct normal solar radiation have been suggested in this study by Mohandes et al. [55] using Radial basis function network (RBF) using global solar radiation, ambient temperature and relative humidity as inputs to the model.

Sumithira et al. [56] have proposed ANFIS system for monthly global solar radiation prediction for state of Tamilnadu, India. Inputs used to the system are relative humidity, ambient temperature, atmospheric pressure and wind speed.

Yildiz et al. [57] have suggested two models using ANN for prediction of solar radiation in Turkey. Model 1 used latitude, altitude, longitude and land surface temperature as input whereas model 2 used satellite surface temperature in place of land surface temperature other inputs remaining same. A better estimation result for model 2 has been obtained as compared to model 1.

2.2 GAPS IN RESEARCH DRAWN FROM LITERATURE

- ✓ In this regard, there is essential requirement for estimation of solar radiation before erecting the solar plant. For the applicability of these models for evaluating daily global solar radiations there has been dearth of substantial evidence in literature.
- ✓ Solar radiation models are of immense significance. Most of solar prediction models are of the modified Angstrom-type equation. Few models have used ANN but taking different inputs for different models. Generalization of input parameters is required.
- ✓ Though empirical models appear to be simple yet they invariably lack accuracy and generality.
- ✓ The weather parameters are used randomly for the solar radiation prediction models.

2.3 ESTIMATION OF SOLAR RADIATION POTENTIAL

Climatic data such as ambient temperature, solar radiation, clearness index and relative humidity, sunshine duration, snow fall, are considered as reliable and widely variable resources. That is why it becomes mandatory to formulate prediction and estimation models of these meteorological data. In solar systems a very significant role is played by this data. However, the complexity of instrumentation results in non availability of data. To design and study solar energy conservation devices it is mandatory to have an accurate knowledge of global solar radiations however these are not easily available because of the high cost and technique involved [58].

Angstom was the first one to propose the model for estimation of solar radiation from sunshine duration related to the global solar radiation of the clear day. In order to solve the difficulty of obtaining the clear day solar radiation data, Prescott replaced clear day solar radiations by extra terrestrial radiation which resulted in the modified model commonly known as Ångströme Prescott (Å-P) model, which is said to be the the most convenient and thoroughly used model. Subsequently, extensive studies were carried out regarding modification and general validity of the Å-P model have been extensively studied. The effect of air mass, latitude and water vapour terms on the Ångströme Prescott relation has also been investigated [59-60].

At different locations, measured solar radiations are required for solar potential assessment of that region. From geographical as well as climatical point of view data collection for solar radiations is mandatory from different nearest metrological stations. By collecting these measured data different models are given by various researchers. From the models developed it has been calculated that mean absolute percentage error i.e. MAPE $\leq$ 10% means high prediction accuracy, $\leq$ 10% MAPE $\leq$ 20% means good prediction, 20% $\leq$ MAPE $\leq$ 50% means reasonable prediction, MAPE $\geq$ 50% means inaccurate forecasting [61]. The most preferred parameters for estimation of global solar radiation are sunshine hours duration, ambient temperature, cloudiness, relative humidity, vapour pressure, rainfall for evaluating solar radiation have been suggested and validated at various sites [62-64]. Models based on sunshine duration are very commonly used and yield more accuracy. [65].

2.4 OBJECTIVES OF RESEARCH

1. The main objective of this research is to estimate solar radiation potential.

2. Estimation of the instantaneous and daily averaged solar radiations in terms of direct, diffuse & global radiations by considering different climatic conditions.

3. Identification of most suitable parameters required for predictions based on different models.

4. Assessment of the solar radiation for various seasons during the year.

5. Validating of proposed model by comparing with experimental data.

6. Extending proposed model to predict the solar radiations at other sites.

3. METHODOLOGY USED

The process used for prediction of global solar radiations has been based upon two methodologies. In first method ANN has been used whereas other method used is ANFIS.

3.1 PREDICTION MODEL DEVELOPED USING ARTIFICIAL NEURAL NETWORKS

Following methodology has been adopted for the potential assessment and prediction of most suitable climatic parameters:

3.1.1 POTENTIAL ASSESSMENT USING ANN

The first objective was to make the assessment of solar radiations in particular area by using artificial neural networks (ANN) method. The meteorological data of the proposed location has been used for testing the estimated values. Different input variables such as temperature data, maximum temperature (T_{max}) and minimum temperature (T_{min}), average relative humidity, average rainfall, pressure global solar radiations for the year 2014 has been used to propose the solar radiations as the output.

3.1.2 IDENTIFICATION OF MOST INFLUENTIAL PARAMETERS

Assessment of the three different models ANN-1, ANN-2 and ANN-3 based on ANN using different input parameters has been done. The models have been then compared calculating their MAPE and the most suitable input parameters for solar radiation prediction models have been suggested. It has been found out that the model ANN-1 is the most suitable for the prediction using ANN as the MAPE found out in this is the lowest. It means the prediction is most accurate for this one.

The most accurate model has been employed to predict the solar radiations for the years to come.

3.1.3 ARTIFICIAL NEURAL NETWORK –A BETTER PREDICTION TOOL

Some 50 years back the concept of artificial neural networks was discovered, but its actual inclination due to computer software's and simulation to practically implement it has been taken place in last 25 years. Artificial neural networks (ANN) have established its application in various fields like automobile industry, domestic purpose devices, mathematics, engineering, meteorology, prediction systems, neurology, aerospace etc. They are widely being used in weather, load, market trend forecasting, in robotic and adaptive control and many others [66]. A number of researchers have suggested that ANN is a reliable system for energy consumption and conventional statistical approaches because of their capacity to model non-linear patterns [67].

ANN has been successfully applied to different types of predictions in recent past. It has also been successfully employed to solar radiation estimations by different researchers for different models as perceived in above given literature reviews [23-58]. The ANN models are broadly classified into three types; feed-forward, feedback and auto-associative methods. Feed-forward methods are simplest of all the ANN methods and are used generally for uncertain outcomes. In this type of ANN method data travels in only one direction and that is forward, from input nodes through parallel hidden nodes and then eventually to the output nodes. In feed-forward ANN models, a learning rate, the number of hidden layers in the ANN and number of epochs [68] are the major determining factors. Feedback ANN contains information that travels in both directions. Generally for load prediction models feedback neural networks are being used [69]. Human brain has invariably provided proof of the existence of neural networks in body that are used for cognitive, perceptual and control tasks. Human brain is able to do computational tasks like controlling, recognition and body movements. More than 10 billion inter-connected neurons are there in the human brain. Each neuron is a cell that uses biochemical reactions to receive process and transit information in parallel [70]. The hidden layers decide the result of ANN and getting them in right number is to be achieved by trial and testing for different errors.

Through synaptic weights, every single neuron is connected to all other neurons of a previous layer. The artificial neural network comprises of one input layer, with one neuron corresponding to each input parameter, a hidden layer and one neuron per layer with the output layer. To decide the output of a particular neuron, a neuron performs summation and activation functions.

Through proper adaption of the synaptic weights, the network can be trained as a training set of matched input and output patterns. Output from each of the corresponding input is the variable function. It is necessary to feed the network information as data set which is required for learning. To provide an idea of output value input is feed through the network by initializing randomized weight network. Having read each pattern, the network uses the input data in order to produce an output. If there is error as compared to required output, the connection weights are changed and again same process is repeated till the error is decreased. The network only makes the weights constant when the training of data attains a satisfactory level and uses the trained networks to make decisions.

Many of the solar radiation prediction systems have the exactly same type of the concerns associated with them which can be solved using ANN. ANN has the quality of making better and quicker decision making and more accurate estimations as compared to other existing systems. The performance of a solar radiation prediction system depends upon number of climatic and meteorological parameters. The prediction of solar radiation is one such problem for which ANN has an answer. The extraordinary functions performed by human brain have been tried to simulate with these computational and simulation models for using ANN ability to manipulate the understanding in form of patterns. Depending upon these patterns, input-output functional relationships of neural networks are modelled that can make estimations about the future.

With the help of suitable learning methodology the connection weights can be modified in some orderly fashion which is a training process.The network adopts training mode, where an input is given to the network besides the required output and the weights are tuned so to generate the required output. The weights after learning carry useful information whereas before learning they are arbitrary and have no inference. Fig. 3.1 illustrates how information flows through a single node. Through its incoming connections the node receives weighted commencement of other nodes. First of all, these are summed up. Through an activation function the result is then conceded; the conclusion is the creation of the node. This creation value is multiplied with the particular weight and shifted to the next node, for every departing connection.

By appropriate adjustment of the synaptic weights, a training set is a group of harmonized input and output patterns used for learning of the network. The outputs are the needy variables that the network creates for the subsequent input. The most significant of all is that information the network requires to train is provided as a data set to the network.

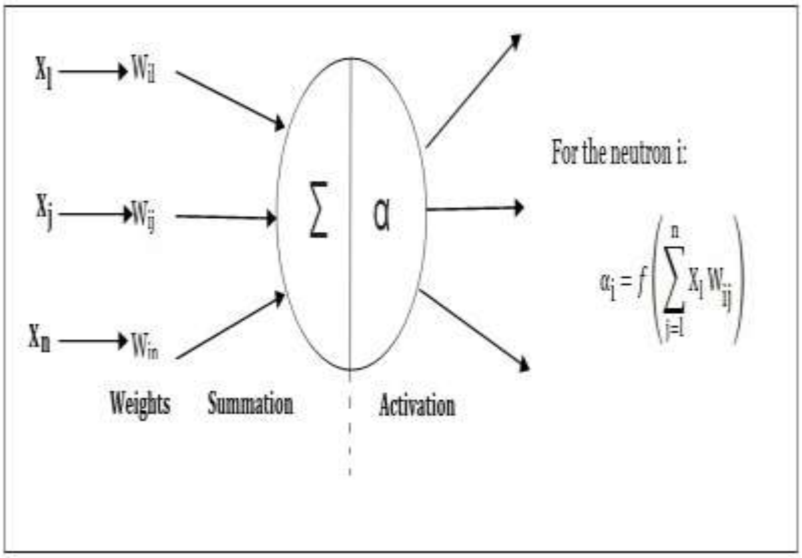

Fig. 3.1 Neural Networks Information Processing System.

The network uses the input data to produce the target, when each pattern is studied, which is then assessed to the learning pattern, i.e. the accurate or required output. The connection weights are changed in such a way that the fault is reduced in case of a difference. When the network has dashed through all the inputs, if the fault is still higher than the upper limit preferred acceptance, the artificial neural network again runs through all the input patterns repetitively until all the errors are within the requisite acceptance limit. The network holds the weights invariable, when the learning reaches a acceptable level. Then the decisions can be made, patterns can be identified using the trained network

The most admired training algorithms are the back-propagation and its hybrid types. An epoch is known as the learning of all patterns of a training data set. The training position must be a courier compilation of input–output examples. Gradient descent algorithm is based on back-propagation training. The performance of the neural network can be raised by dropping the total error by varying the weights alongside its gradient. All the output patterns given by the artificial neural network absolutely match the anticipated values then an error of zero would point out that and the network is well taught. In brief, by originally passing on random values to the weight terms $(\omega_{ij})^2$ in all nodes back propagation instruction is passed. The launching for each node, α_{pi}, is initiated every time a training pattern is offered to the artificial neural network. The inaccuracy term, δ_{pi}, for each node is calculated backwards through the network, subsequent to the output calculation of the layer. This inaccuracy term is the produce of the inaccuracy function, E, and the derived activation function and hence is a calculation of the transformation in the network output formed by the incremental adjustment in the node weight values. The error term for the output layer nodes is calculated as:

$$\delta_{pi} = \alpha_{pi} \ (1- \alpha_{pi}) \ (t_{pi}- \alpha_{pi}) \qquad (3.1)$$

The subscript i expresses the node position in the current layer whereas subscript j shows to a summing up of all nodes in the preceding layer of nodes.

For the hidden layer nodes:

$$\delta_{pi} = \delta_{pk}\ \alpha_{pi}\ (1- \alpha_{pi})\ \omega_{kj} \qquad (3.2)$$

In the concluding expression, the subscript k indicates summing up of all nodes in the route of the output layer. The subscript j indicates each node's weight position. Ultimately, to calculate an incremental alteration to every weight term, the terms α and δ for every node are used as:

$$\Delta\omega_{ij} = \epsilon\ (\delta_{pi}\ \alpha_{pj}) + m\ \omega_{ij}\ (old) \qquad (3.3)$$

For the duration of each training iteration, the term ϵ is said to be as the learning rate and calculates the range of the weight adjustments. Momentum factor is given by the term m, which is useful to the weight alteration used in the preceding training iteration, ω_{ij} (old). To establish the rate and firmness of the network, both of these steady terms are specified at the initiate of the training round.

3.1.4 ARTIFICIAL NEURAL NETWORKS VS REGRESSION

For expressing the reliance of a response variable on a number of self-governing variables regression study is one of the extensively used methodologies. It is of worth significance to find out most excellent amalgamation of these variables to forecast dependable variables while dealing with huge number of independent variables [71]. To explore relationships between variables, regression analysis carries a compilation of methods that are used [72]. As a computing system, an artificial neural network is prepared of a number of plain and well interrelated dispensation elements, which processes data by its vibrant state response to exterior inputs [73]. It is just like brain where information giving out thought is inspired by the mode of biological systems [74]. A model is developed relating the output of network to the accessible real data used as inputs [75]. The concentration on artificial neural networks during the last 15 years has increased. In solving multifaceted problems such as pattern relationship and pattern acknowledgment, and generation of new consequential pattern, artificial neural networks have been fruitfully engaged [76]. One major benefit of artificial neural networks is competent behavior of extremely non-linear associations in data, even when the precise nature of such relationships is unidentified. The performance values of the artificial neural network models have been found out to be superior to the regression models. Artificial neural network models have lower mean absolute percent error (MAPE) as compared to those of the regression models. When compared between the artificial neural network models and regression models, the R values in case of artificial neural networks is much higher which makes it a better estimation tool [77].

3.2 PREDICTION MODEL USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The benefit of using an ANN based establishment of solar power systems is that it good optimization of the data can be done, especially in remote areas where the climate data are not easily on hand, but as far as using the adaptive neuro-fuzzy inference system, it increases prediction accuracy by greater amount and a prediction model based on the number of inputs can be developed.

The researcher has proposed a model using ANFIS wherein by changing the inputs only we can predict the solar radiations for any place. As already discussed ANFIS is far superior a prediction model as compared to other techniques. The best inputs used for ANN model has been used to propose the ANFIS model.

3.2.1 POTENTIAL ASSESSMENT USING ANFIS

ANFIS as its name suggests Adaptive Neuro-Fuzzy Inference System, which uses both neural as well as fuzzy system for training, testing and validation of data. The toolbox function ANFIS prepares a fuzzy inference system (FIS), by means of a specified input and output data set, whose membership functions are accustomed using either a back propagation algorithm alone, or a grouping with a least squares type of technique. The fuzzy systems are allowed to learn from the modelling data they are using. These neuro-adaptive learning techniques work on the very simple idea behind it. To learn information about a set of data, these techniques offer a way for the fuzzy modelling modus operandi that best allow the related fuzzy inference system to follow the given set of data to calculate the membership function parameters. This learning method works similarly to that of neural networks. This membership function parameter tuning in the Fuzzy Logic Toolbox function is accomplished by ANFIS. ANFIS can be used from the command line or all the way through the ANFIS Editor GUI. The Fuzzy Logic Toolbox can be personalized like all other MATLAB toolboxess. One can easily inspect algorithms, modify source code, and add your own membership functions or defuzzification techniques.

The model validation has been done with the ANFIS editor GUI using the testing data set. First of all training data is given to the ANFIS editor which can be given from the selected file or it can be stored in the workspace in MATLAB 9.1 (R2016b). During input of the data to the ANFIS, the model of FIS with minimal testing data error is chosen to connect the parameters for the final modelling of the system.

ANFIS tool is imitative of a universal category of intelligent networks a new Artificial Intelligence (AI) tool known as adaptive networks. The links spell out the relationship between the nodes and every node represents a progression unit. The output of the nodes depends on adjustable parameters pertinent to the nodes and thus all or some of the nodes are adaptive.

To estimate the difference between the actual output and the required output, the learning rules spells out that how these parameters should be rationalized to minimize the approved error. In an adaptive network every node generally may have the node weights or parameters related with them.

The ANFIS based model has been developed for the estimation of solar radiations. With anfis edit of mathslab 9.1 (R2016b) ANFIS based model has been suggested. Some principles of using the file of diverse variables to this tool are employed. For the purpose of training, 75% data has been used and remaining 25% has been given for the purpose of testing. Then with grid separation, the fuzzy inference arrangement is produced. By taking into deliberation the hybrid type of system using different number of epochs and zero error tolerance for different models, the system is trained. After the guidance is full then the ANFIS structure is made. Taking into consideration the output required, the regulation base has been selected.

3.3 DIFFERENT INPUT VARIABLES

Different input variable selection is the first important step for making an acceptable prediction of solar radiations.

ANFIS tool of MATLAB 9.1 (R2016b) is used to train the data set available using hybrid algorithm to obtain the most useful model for solar radiations estimation. The testing of establishes an independent presentation through and subsequent to diverse numbers of epochs are used while validation of data process is complete. Depending upon the error got, the hidden layers numbers selected can be raised or lowered. The performance of the network is described as graph of mean square error (MSE) with respect to epochs.

The proposed work will be carried out by subsequent steps sequentially as depicted in Fig.3.2 as the flow chart and details are as following:

3.3.1 MOST RELEVANT INPUT DATA SELECTION

Most relevant input data selection is one another major step towards achieving most influential parameters for estimation of solar radiation. Various combinations of data are being tried and tested for selection of the different inputs used for the prediction model. From that different set of inputs, errors have been calculated and based on those errors the most relevant input data selection has been done.

3.3.2 DEVELOPMENT OF DATABASE FOR DIFFERENT MODELS

After choice of largely appropriate input parameters, next step is to develop database of different models. For ANN based site specific prediction model, The following flow chart is used to describe the methodology:

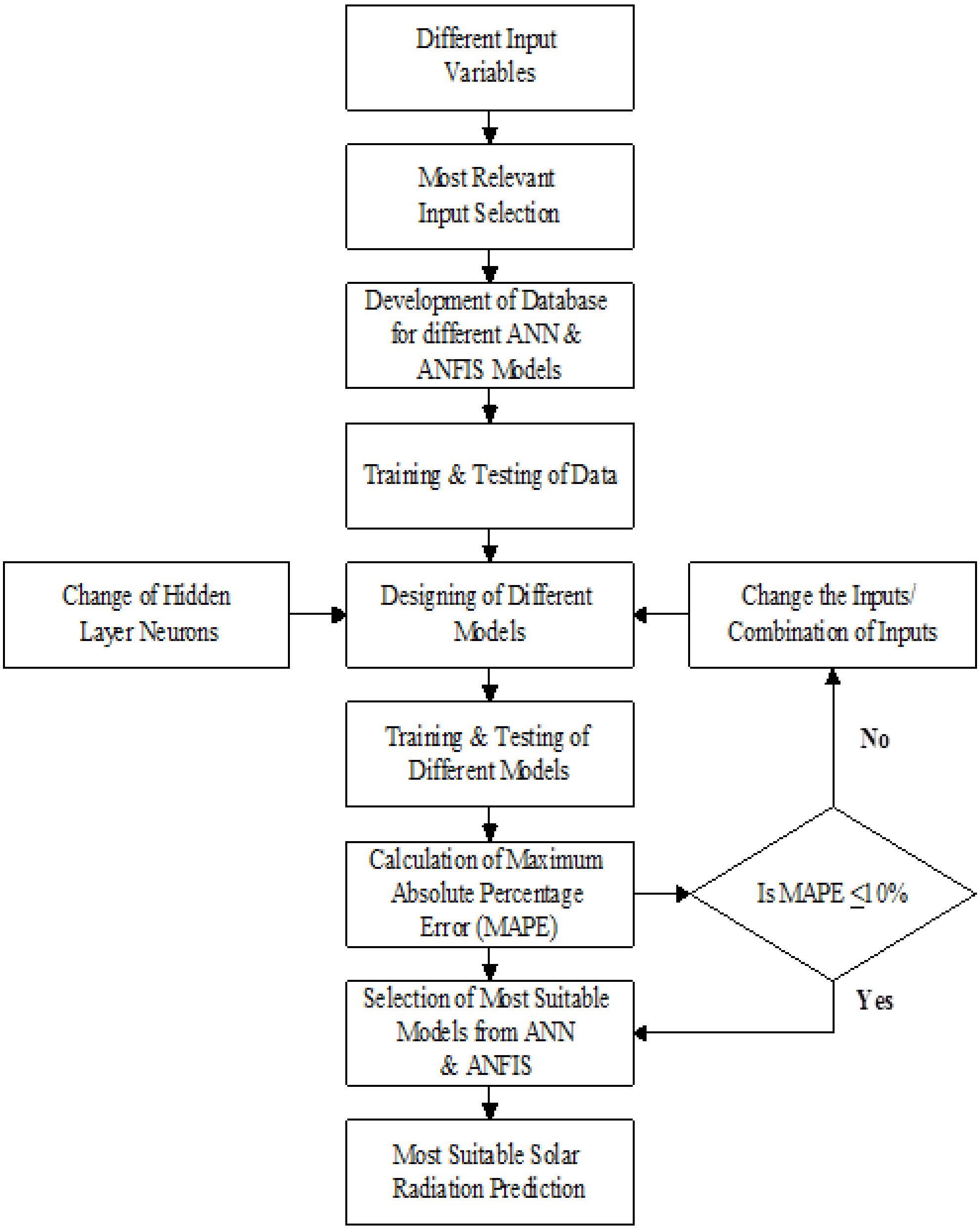

Fig. 3.2 Flow Chart used for Solar Radiation Prediction.

the diverse six key variables and target data base for year 2014 has been established. Then for ANFIS based prediction model same data as for best ANN prediction model has been used. Maximum six inputs and one target have been selected for the different proposed models. Then, data base has been prepared for the ANN based prediction model for ten selected cities of state of Himachal Pradesh for the previous ten years from 2007 to 2016. The different input and output data is separated into testing, validation and training respectively. For the duration of testing, validation and training of data the different numbers of epochs are chosen for the required results.

3.3.3 DESIGNING OF DIFFERENT MODELS

Designing of different models is the step that requires maximum precision as the output of these models will depend upon that. Different models have been the designed taken into consideration the target requirements and by changing the hidden layer neurons. After the designing process is complete models are training and testing of different models for number of inputs to check the efficiency.

3.3.4 CALCULATION OF MAXIMUM ABSOLUTE PERCENTAGE ERROR

Then using the different formulas MAPE has been calculated. As already it has been discussed in literature review that MAPE ≤ 10% is considered to be an accurate prediction model. The MAPE values in case are greater than 10%, the combinations of inputs have been changed and the models have been redesigned until the desired results are obtained.

3.3.5 SELECTION OF MOST SUITABLE MODELS

Then the selection of most suitable models has been done depending upon the MAPE. This research has tried to establish different combinations of inputs to get the key input parameters for estimation of solar radiations prediction models considering different climatic conditions. Based on the most influential input parameters next year’s input has been predicted.

4. ANN BASED PREDICTION MODELS

4.1 INPUTS FOR ESTIMATIONON MODEL

The parameters for the various prediction models are sunshine hours, temperature, humidity, rainfall and barometric pressure. Various inputs have been fed to the same outputs, in the course of their choice for various models suggested for estimation of radiations. The longitude and latitude are taken into consideration for the specific places only so they have not been considered for the inputs taken. Estimation of the solar prediction models have been done on the basis of the above inputs.

When the process of variable selection is complete, subsequently to estimate the prediction schemes using different input variables for ANN estimation models. Maximum six and minimum four number of input variables have been included in the three different prediction models. The different input variables selected are humidity, maximum and minimum temperature (T_{max} and T_{min}), rainfall, sun shine hours (SH), pressure and target solar radiations (SR) for year 2014 have been considered for the site Bara Dol, Bilaspur (HP) from HPPCL, Shimla.

4.2 ANN DEPENDENT SOLAR ESTIMATION MODELS

Three ANN dependent computational models are being suggested using artificial neural networks (nftool)which are named as ANN-1, ANN-2 & ANN-3. Within the nftool of MATLAB 9.1 (R2016b) Simulink software, Levenberg-Marquardt (LM) algorithm with standard two layer feed forward neural networks are used. This type of algorithm is appropriate for static fitting troubles as is required for the predicted solar radiation models. The training is done by ANN based scaled gradient automatically. For training, testing and validation purpose, the input and output data is separated randomly as 70%, 15%, 15% respectively.

The various models are being trained using LM algorithm of ANN. Testing data provides an independent performance during and after training rather than affecting the training. Measurement of generalization ability of the given network is done by validation data as we know that ANN is used for generalization of data and validation stops after completion of generalization. During testing, validation and training of data varying numbers of epochs are achieved. Based upon the error obtained the number of unseen layers chosen are raised and lowered. The performance of the network is defined as graph of mean square error (MSE) pertaining to epochs.

4.3 ERROR EVALUATION OF DIFFERENT ANN MODELS

The three ANN dependant models have been proposed using various input parameters. For all the three models alliance between outputs and targets have been found out by calculating the correlation coefficient (R value) . Hidden layers have been varied between 10 to 20 for all the three models and the multi layer perceptron (MLP) model with least MSE have been suggested for the particular ANN based model as it has the least MAPE. The MAPE is given by Eqn. (4.1) where $SR_{i(NN)}$ and $SR_{i(Exp)}$ are the solar radiations predicted through ANN and the actual or experimental values respectively. ANN model with minimum MAPE has been employed for the estimation of solar radiation.

$$MaxMAPE = \left(\frac{1}{n} \sum_{a=1}^{n} \left| \frac{SR_{i(NN)} - SR_{i(Exp)}}{SR_{i(Exp)}} \right| \right) \times 100 \tag{4.1}$$

The statistical error evaluations for different models have been given in Table 4.1, Table 4.2 and Table 4.3. In ANN-1 model six input variables (temperature {maximum and minimum}, rainfall, humidity, pressure, and sun shine hours) have been utilised for the prediction of solar radiation. ANN-2 model is developed using five inputs (humidity, barometric pressure, maximum and minimum temperature and rainfall) whereas ANN-3 model is tested with only four inputs (maximum and minimum temperature, relative humidity and sunshine hours) for development of solar radiation estimation model.

Table 4.1

Error Evaluation of ANN-1 Model

Inputs, Output and Hidden Layers	MLP Structure	R for training	MSE	Selection of ANN model
Total inputs 6, total outputs 365 (daily global solar radiation) and total samples are 1825. Hidden layer is selected between 10-20.	6/20/2001	79.53	16.8	MLP (6-16-1) where input neurons 6, hidden layer neurons 16 and output layer neuron 1 is best as it has least MAPE.
	6/19/2001	82.97	12.45	
	6/18/2001	86.62	10.78	
	6/17/2001	82.26	12.43	
	6/16/2001	**87.48**	**10.45**	
	6/15/2001	81.72	15.41	
	6/14/2001	87.06	10.72	
	6/13/2001	82.75	12.7	
	6/12/2001	87.73	10.83	
	6/11/2001	82.84	14.37	
	6/10/2001	80.92	14.75	

Table 4.2

Error Evaluation of ANN-2 Model

Inputs, Output and Hidden Layers	MLP Structure	R for training	MSE	Selection of ANN model
Total inputs 5, total outputs 365 (daily global solar radiation) and total samples are 1460. Hidden layer is selected between 10-20.	5/20/2001	82	14.65	MLP (5-15-1) where input neurons 5, hidden layer neurons 15 and output layer neuron 1 is best as it has least MAPE.
	5/19/2001	82.86	14.71	
	5/18/2001	78.18	14.93	
	5/17/2001	81.77	15.05	
	5/16/2001	80.24	16.44	
	5/15/2001	**83.71**	**11.06**	
	5/14/2001	80.83	16.01	
	5/13/2001	82.91	13.7	
	5/12/2001	80.56	16.01	
	5/11/2001	82.11	14.66	
	5/10/2001	82.89	13.06	

Table 4.3

Error Evaluation of ANN-3 Model

Inputs, Output and Hidden Layers	MLP Structure	R for training	MSE	Selection of ANN model
Total inputs 4, total outputs 365 (daily global solar radiation) and total samples are 1095. Hidden layer is selected between 10-20.	4/20/2001	80.39	15.46	MLP (4-18-1) where input neurons 4, hidden layer neurons 18 and output layer neuron 1 is best as it has least MAPE.
	4/19/2001	81.35	15.32	
	4/18/2001	**85.37**	**11.85**	
	4/17/2001	84.95	15.5	
	4/16/2001	76.78	21.02	
	4/15/2001	84.28	12.69	
	4/14/2001	82.6	14.39	
	4/13/2001	81.2	14.4	
	4/12/2001	85.7	11.94	
	4/11/2001	82.53	13.2	
	4/10/2001	79.11	16.93	

4.4. RESULTS AND DISCUSSION

The precision of the estimation is measured with the help of MAPE suggested by Lewis [52]. The MAPE ≥ 50% does not indicate good accuracy of the prediction model. The MAPE in between 20%-50% indicates average forecasting whereas the MAPE between 10%-20% gives good prediction accuracy. The MAPE ≤ 10% predicts high accuracy. The maximum MAPE of the particular testing city for three different prediction models is found out to be 6.33%, 13.25% and 19.60% respectively. Showing that the most accurate model is ANN-1, whereas after removing few variables it has been found out that ANN-2 model is comparatively better than ANN-3 model. Also it has been found out from the above prediction models that sun shine hour is one major input variable for any prediction model. In case of ANN-3 model where sunshine has been removed, the MAPE increased drastically and the accuracy of the model has been decreased.

ANN-1 model's performance plot shown in Fig. 4.1. predicts that the MSE is reduced to the minimum with the increase in number of epochs. The validation and testing set error have the comparable distinctiveness and the best validation performance has happened near epoch 5.

Regression plot of the correlation coefficient (R-value) in Fig. 4.2. shows that association in between outputs and set targets for the model ANN-1.The slope is 0.81and R-value is 0.90 which has been shown in plot and which is very close to perfect fit value of slope i.e.1 and hence indicated the good prediction accuracy of ANN-1 model.

The error plot for ANN-1 model has been shown in Fig. 4.3. It points towards the factor that maximum error has been found out on 207th day of the year for estimation of solar radiations. The annual MAPE calculated in the year 2014 is 2.39% as given in Table 4.4.

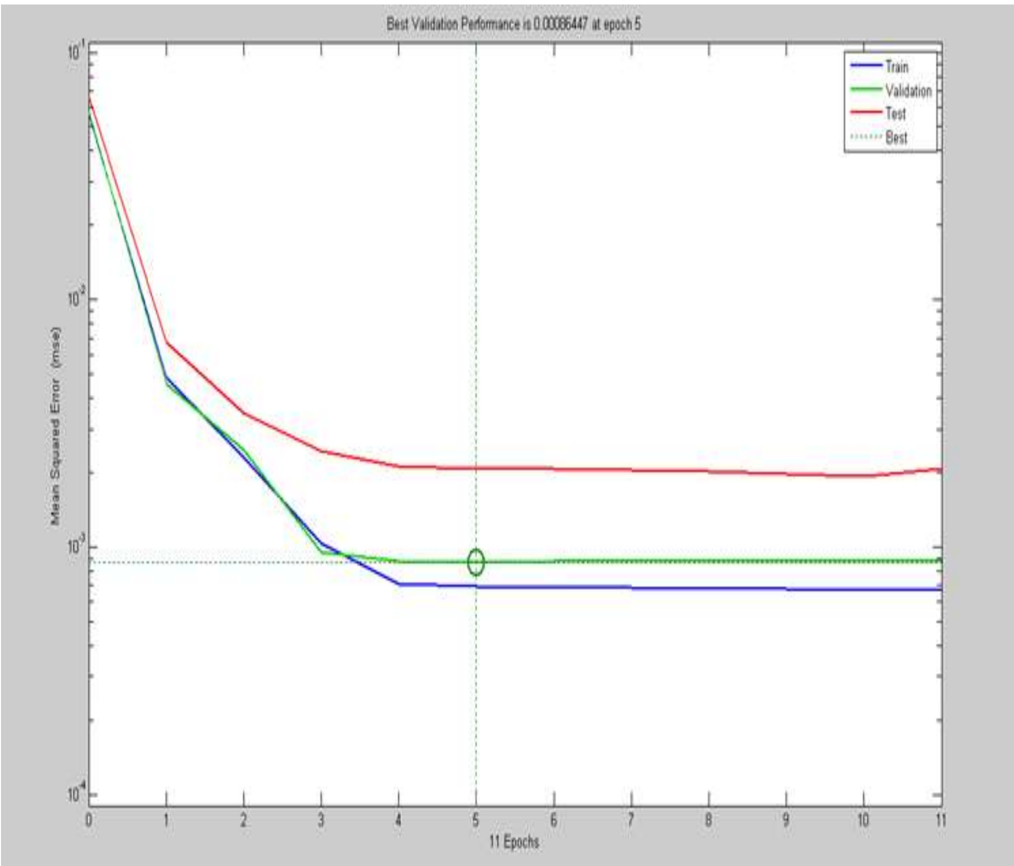

Fig. 4.1 Performance Plot of ANN -1 Model during Training.

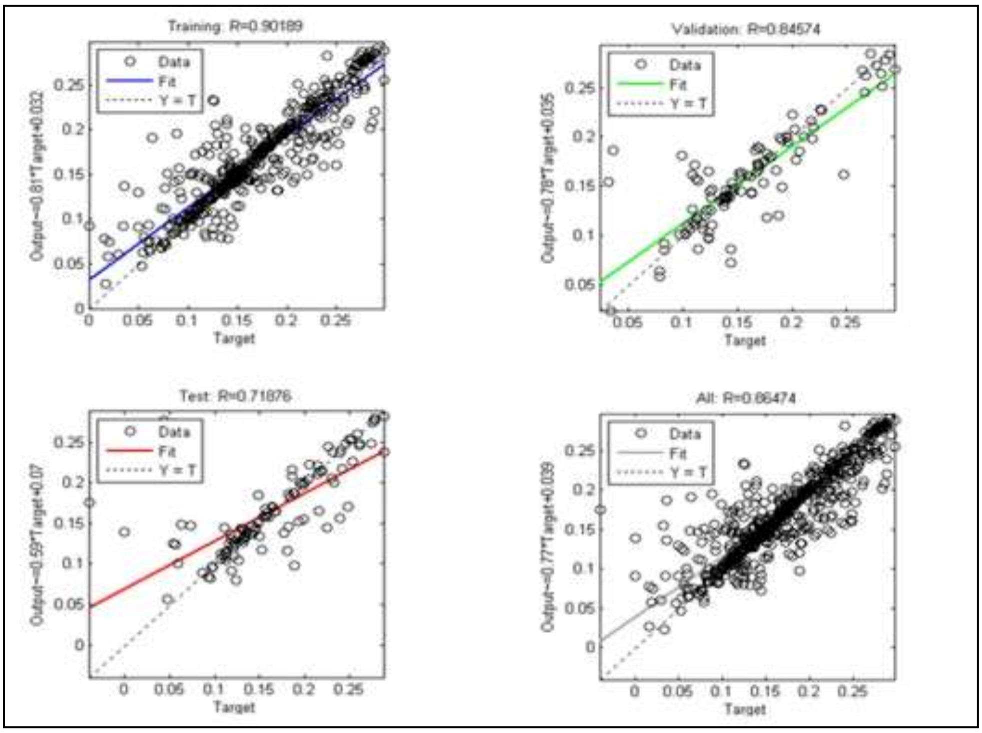

Fig. 4.2 Regression Plot of ANN -1 Model during Training, Testing and Validation.

Table 4.4

Actual and ANN Predicted Values of Solar Radiations for Year 2014.

Sr. No.	Month	Actual SR	Predicted SR	% MAPE
1	**Jan**	2.4	2.66	10.8
2	**Feb**	2.67	3.02	13.1
3	**Mar**	4.97	5.11	2.81
4	**Apr**	5.31	4.76	10.35
5	**May**	6.01	5.89	1.99
6	**Jun**	5.01	5.55	10.77
7	**Jul**	4.45	4.34	2.47
8	**Aug**	4.01	4.23	5.48
9	**Sep**	4.12	4.55	10.43
10	**Oct**	4.32	4.53	4.86
11	**Nov**	3.66	3.71	1.36
12	**Dec**	3.12	2.96	5.12

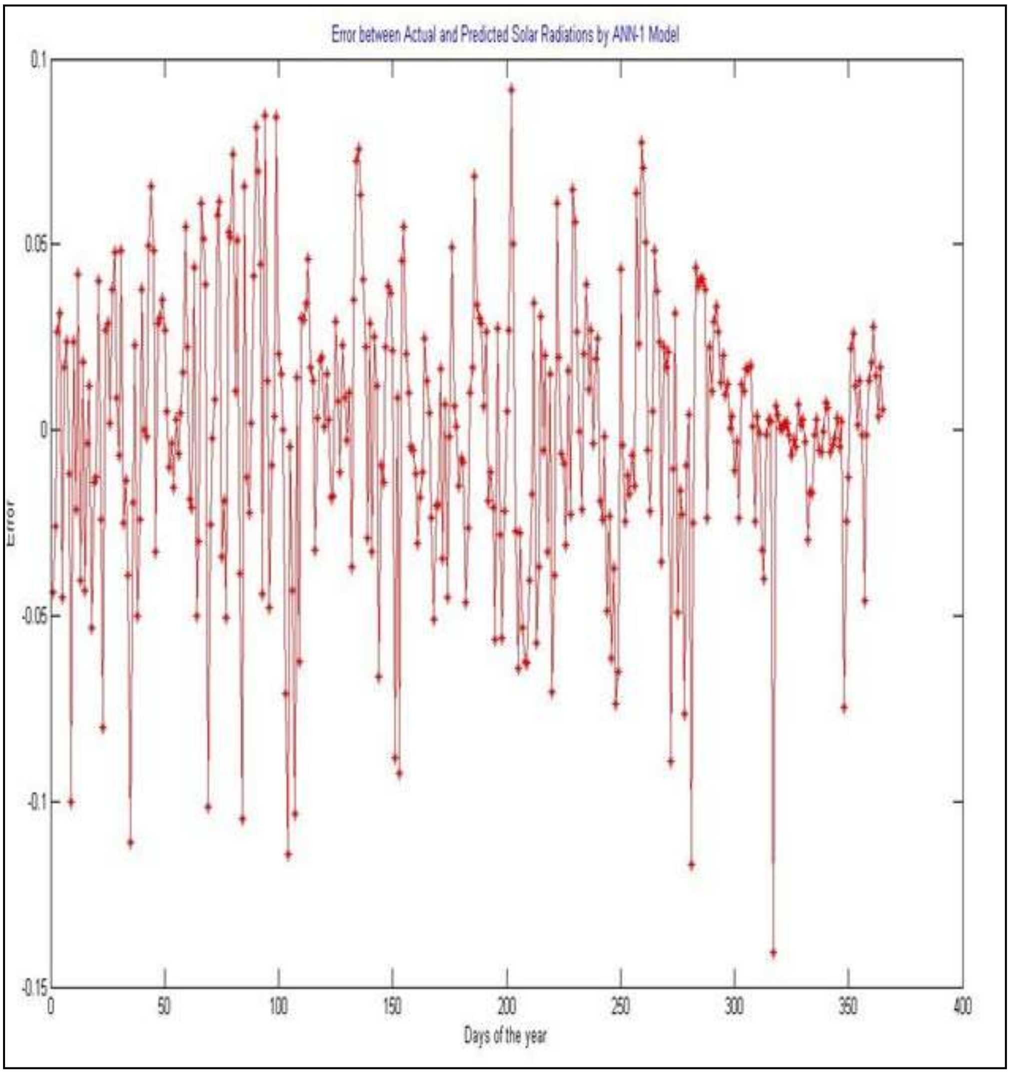

Fig. 4.3 Error Plot between Actual and Predicted Solar Radiations.

4.5. PREDICTION OF NEXT YEARS SOLAR RADIATIONS BASED ON THE ANN SELECTED MODEL

The next year's global solar radiations prediction has been done using the best model based on the error analysis of three proposed models based on ANN. As already discussed in results that ANN-1 model is most accurate with least error, it has been chosen to predict the solar radiations for the next three years i.e. 2015, 2016 and 2017. After prediction of solar radiations for three years errors have been calculated and projected values of the solar radiations with MAPE have been given in the Tables 4.5, 4.6 and 4.7. The plots showing actual and predicted solar radiations have been given in Fig. 4.4, 4.5 and 4.6.

Table 4.5

Actual and ANN Predicted Values of Solar Radiations for Year 2015.

Sr. No.	Month	Actual SR	Predicted SR	% MAPE
1	**Jan**	2.43	2.19	9.05
2	**Feb**	2.87	2.98	3.83
3	**Mar**	4.79	5.01	4.59
4	**Apr**	5.22	4.89	6.32
5	**May**	6.14	5.44	11.4
6	**Jun**	4.95	5.06	2.20
7	**Jul**	4.06	4.56	12.31
8	**Aug**	3.48	3.76	8.04
9	**Sep**	3.98	4.22	6.03
10	**Oct**	4.21	4.79	13.7
11	**Nov**	3.16	3.65	15.51
12	**Dec**	2.85	3.22	12.98
13	**Annual**	**4.01**	**4.15**	**3.49**

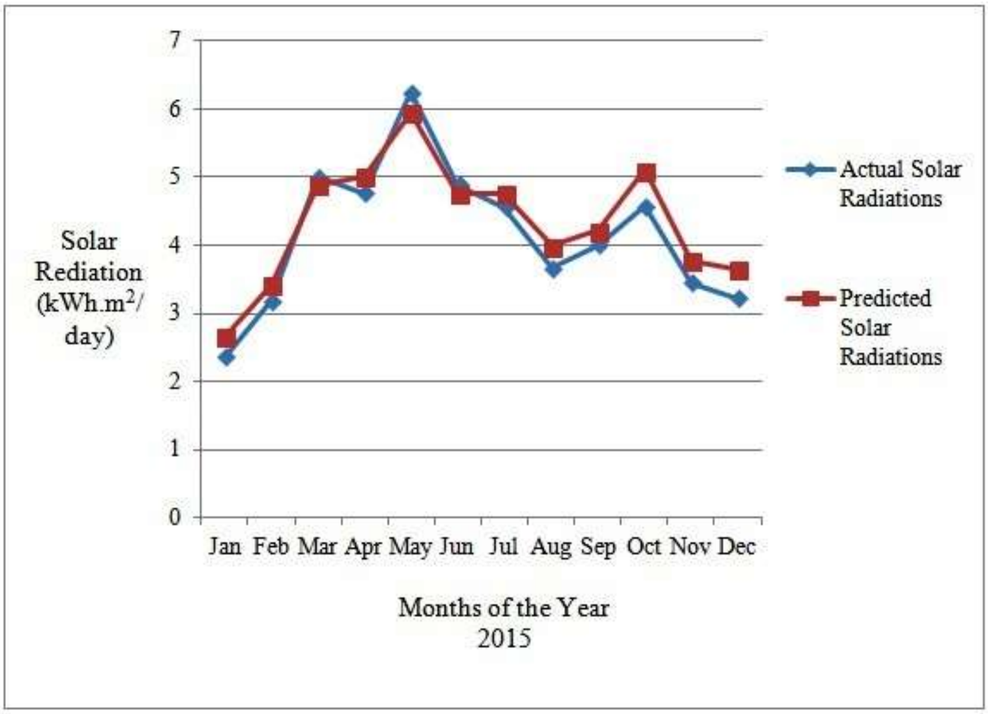

Fig. 4.4 Plot between Actual and Predicted Solar Radiations for Year 2015.

Table 4.6

Actual and ANN Predicted Values of Solar Radiations for Year 2016.

Sr. No.	Month	Actual SR	Predicted SR	% MAPE
1	**Jan**	2.36	2.67	13.13
2	**Feb**	3.19	3.42	7.21
3	**Mar**	5.01	4.89	2.39
4	**Apr**	4.76	5.02	5.46
5	**May**	6.24	5.96	17.15
6	**Jun**	4.89	4.76	2.65
7	**Jul**	4.56	4.77	4.60
8	**Aug**	3.66	3.99	9.01
9	**Sep**	4.01	4.22	5.23
10	**Oct**	4.57	5.11	11.80
11	**Nov**	3.45	3.78	9.56
12	**Dec**	3.22	3.65	13.35
13	**Annual**	**4.16**	**4.35**	**4.56**

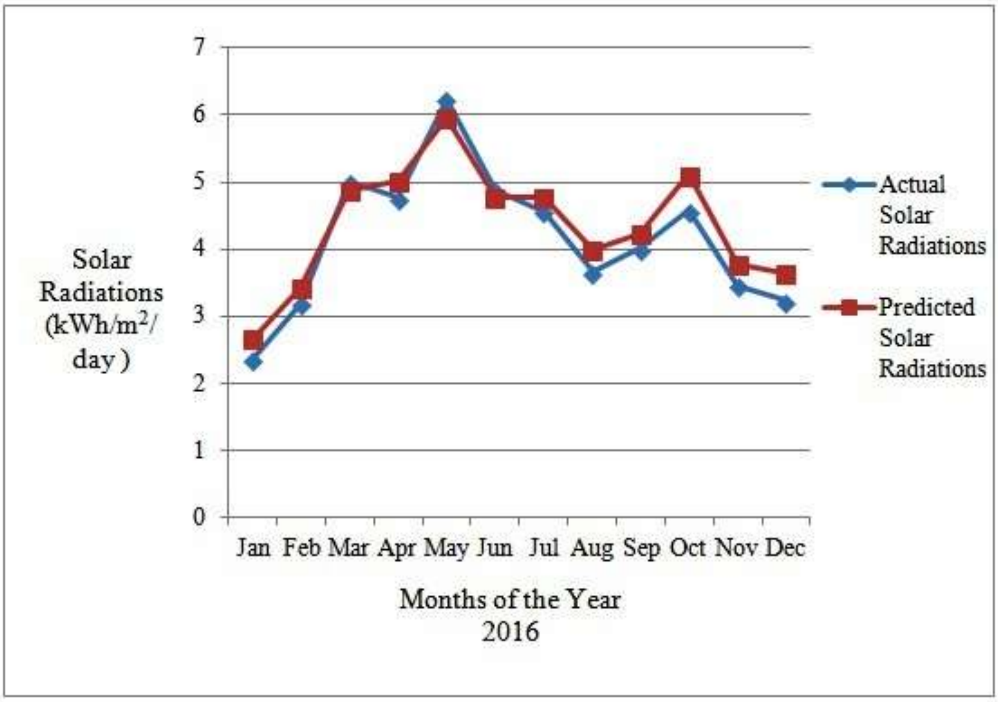

Fig. 4.5 Plot between Actual and Predicted Solar Radiations for Year 2016.

Table 4.7

Actual and ANN Predicted Values of Solar Radiations for Year 2017.

Sr. No.	Month	Actual SR	Predicted SR	% MAPE
1	**Jan**	2.44	2.65	8.60
2	**Feb**	3.93	3.39	13.74
3	**Mar**	4.78	4.89	2.30
4	**Apr**	5.22	5.11	2.10
5	**May**	5.67	5.91	4.23
6	**Jun**	4.88	4.31	11.60
7	**Jul**	4.01	4.55	13.46
8	**Aug**	3.22	3.85	19.56
9	**Sep**	4.12	4.22	2.42
10	**Oct**	4.51	4.41	2.26
11	**Nov**	3.23	3.78	17.02
12	**Dec**	2.99	3.13	4.68
13	**Annual**	**4.08**	**4.18**	**2.45**

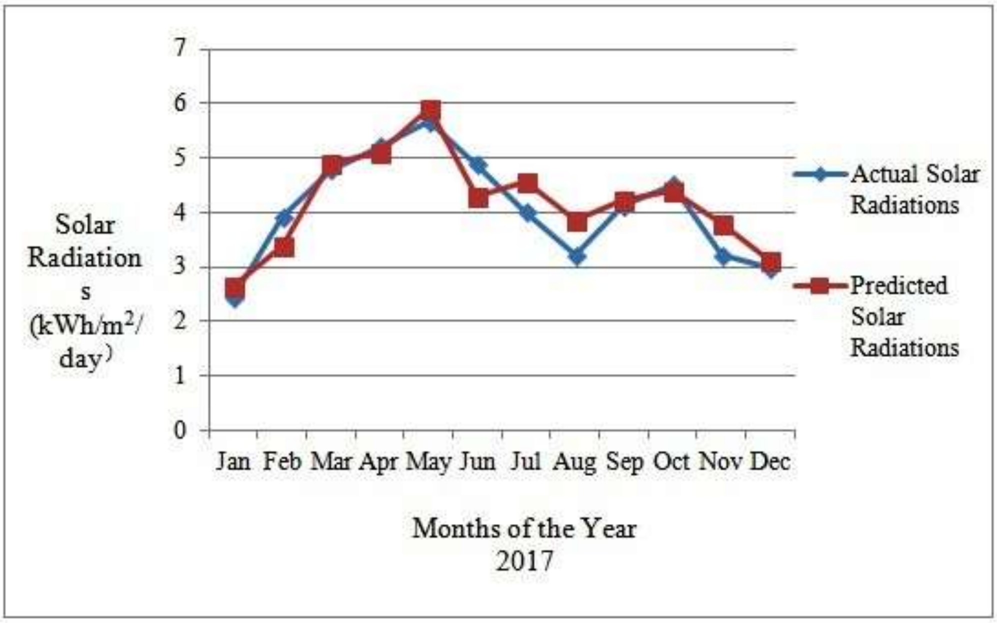

Fig. 4.6 Plot between Actual and Predicted Solar Radiations for Year 2017.

The calculation of MAPE error has been done for all the three years for which prediction has been done. The error results have been changed from the daily average solar radiations to monthly average of solar radiations considering the sunshine hours for that particular day for all the three years predictions. It has been seen that for year 2015 the maximum MAPE has been calculated as 15.51% for month of November and minimum MAPE is 2.20% for June month. The overall annual MAPE for year 2015 is calculated to be 3.49% which is a very low value of any prediction error. The error plot between actual and predicted values has been shown in Fig.4.4 where X-axis shows the months of the year 2015 whereas the values of solar radiations are given by Y–axis.

For year 2016 the annual solar radiation prediction MAPE is 4.56%. The maximum MAPE is calculated for the month of May which is 17.15% whereas minimum MAPE is 2.39% for the month of March. The plot between actual and predicted values of year 2016 has been given in Fig.4.5 to show the difference between actual and predicted values of solar radiations through ANN-1 model.

The annual MAPE for year 2017 is calculated to be 2.45% whereas maximum MAPE has been calculated for the month of August is 19.56%. The minimum value of MAPE for year 2017 is 2.10% for the month of April. Hence all the values predicted based on the best ANN-1 model falls within the permissible limits of a very good prediction accuracy model. Fig.4.6 is used to graphically represent the values of actual and predicted solar radiations for all the months of year 2017.

5. ANFIS BASED PREDICTION MODEL

Hybrid algorithm of ANFIS tool of MATLAB 9.1 (R2016b) has been used to train the model. An independent performance is provided by the testing data rather affecting the training during the course of testing, validation and training. One full cycle of testing, validation and training of data is known as epoch. Depending upon the error the number of unseen layers selection is raised or lowered.

5.1 SUGGESTED METHODOLOGY FOR SOLAR ESTIMATION MODEL

For ANFIS dependent prediction model the methodology used is as shown in flow chart Fig.5.1. This is selected from nftool of mathslab 9.1 (R2016b) software for the proposed methodology used for estimation models.

The input selection to the tool is done from workspace. Three number of membership functions are selected with the grid type partition. The fuzzy inference system is obtained using the different fuzzy rules.

Hybrid type of system is used to train the proposed model. A number of nodes linked by directional links prepare a structure called an adaptive network. The epochs numbers can be altered in between 1 to 20 to get the well-organized and required prediction models based on diverse inputs. In the form of final structure an output is obtained. Using the above said process the rules can be obtained and the surface allocation can also be done.

The validation of model has been completed with the testing data set using ANFIS editor GUI. the ANFIS editor is first fed with the training data which can be obtained from the selected file or the workspace in MATLAB.

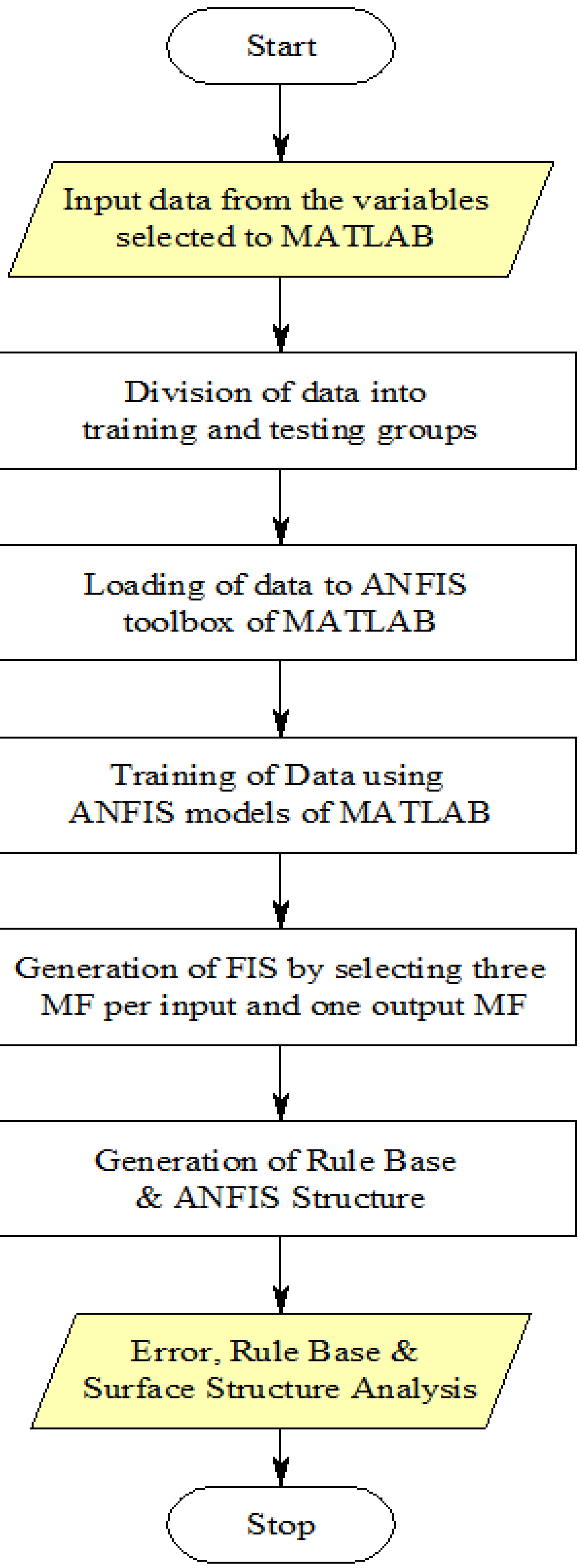

Fig. 5.1 Suggested Flow Chart for Estimation Models.

5.2. ANFIS PREDICTION MODEL

In the suggested model the daily global solar radiations are estimated using relative humidity, rainfall, temperature (minimum & maximum), pressure and sun shine hours as inputs, same data as used for the proposed model using ANN. The same inputs have been considered which have been considered for the ANN model which yielded best results i.e. ANN-1 model. It has been compared in this section that how the MAPE vary by using ANFIS in place of ANN for the same set of inputs.

SUGENO model has been used by the ANFIS editor. The data for the ANFIS model is weighed down from the workspace sheet in the Excel format worksheet. Division of the data into the sets of training and testing is done. The training using ANFIS is shown in Fig.5.2.

By means of the grid partition then the FIS is obtained. Three membership functions are being used by the each input set and the suggested model has used trimf type of membership function. The membership function is kept constant for the output. 3 epochs have been used to train the suggested model. For FIS optimization there are two methods after generation of FIS. First is backpropagation and second is hybrid method which consists of least square evaluation for the values related with the output membership function and back propagation for the values linked to the inputs. The method in which the gradient is estimated for non-linear multilayer networks is referred to as backpropagation. Based on other usual optimization techniques, there exist a lot of changes on the fundamental algorithm. A lot of these variations can be implemented using MATLAB property. It has been told earlier that backpropagation gives very good outcome when offered with inputs never seen before by them. Using this generalization property, it is achievable to train the network on giving a set of input and output targets and getting favorable outputs.This study has used hybrid system for proposed structure optimization as shown in Fig. 5.3.

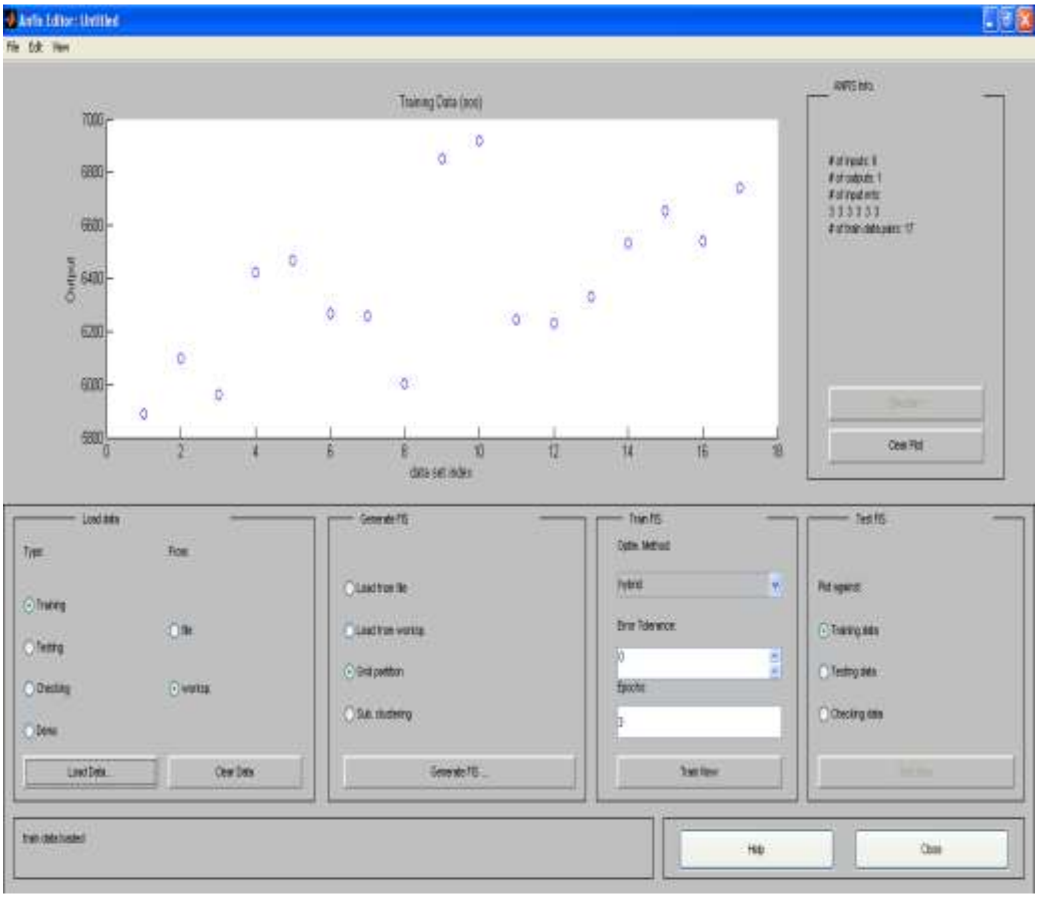

Fig. 5.2 ANFIS Editor Showing the Loading and Training of the Given Data.

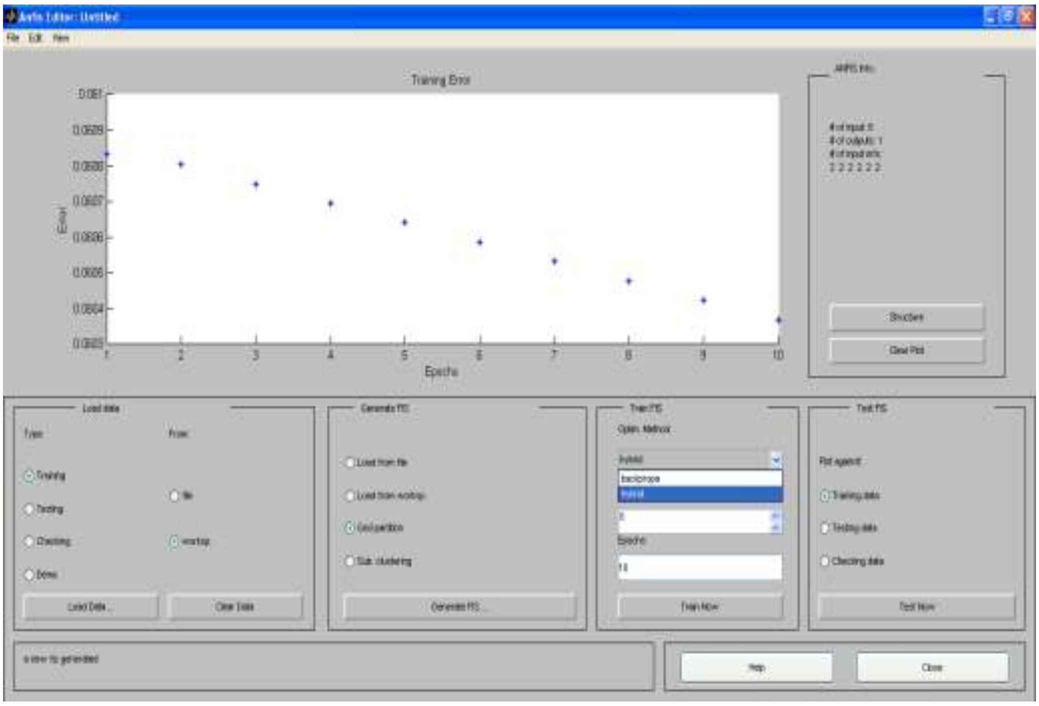

Fig. 5.3 Training of FIS Using Epochs and Hybrid Method.

The grid partition of optimization technique used here showing numeral membership functions for inputs and output and it has been shown in Fig. 5.4.and then structure has been generated for the proposed model which is shown in Fig. 5.5.

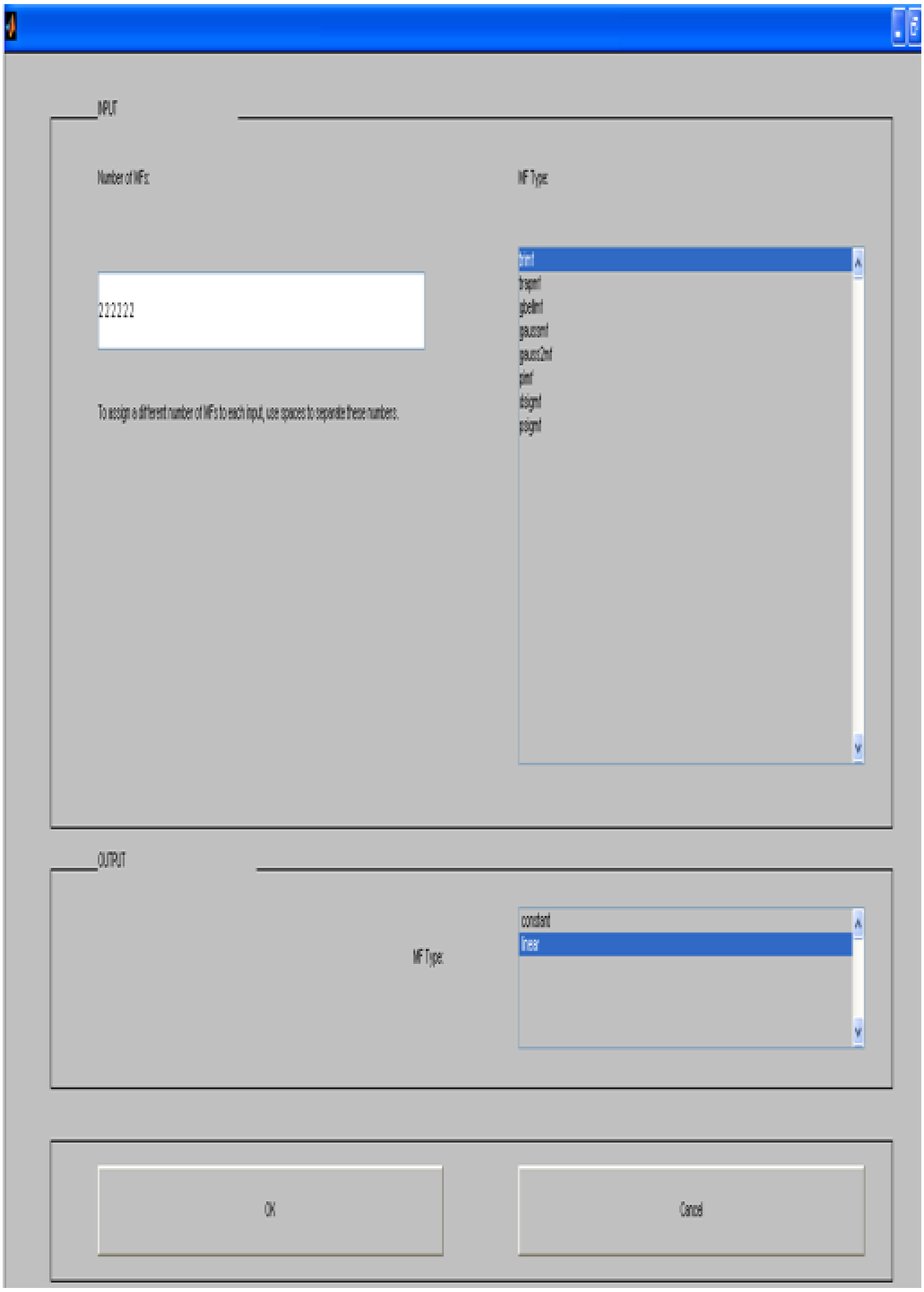

Fig. 5.4 Grid Partition Describing Input and Output Membership Functions.

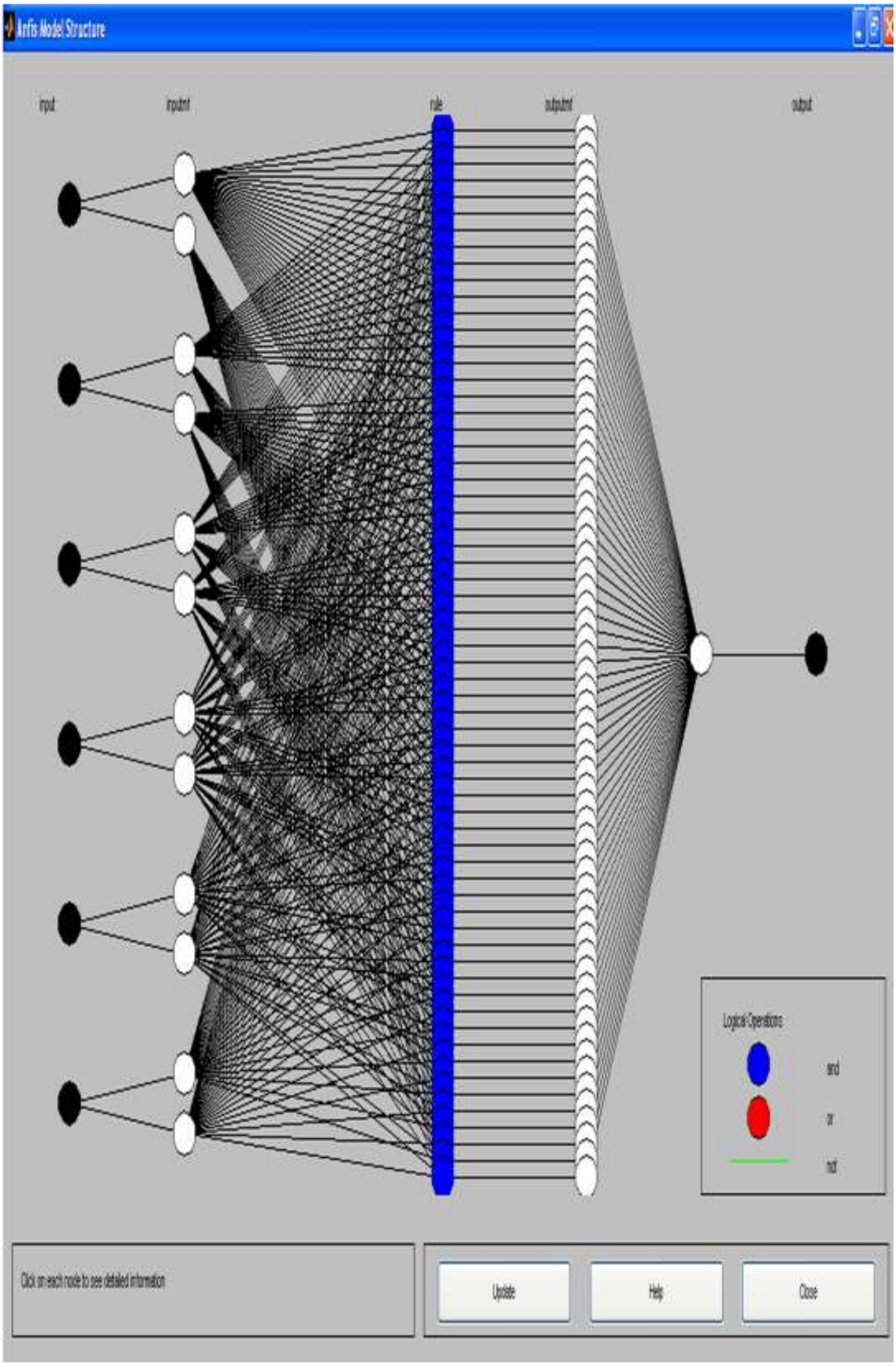

Fig. 5.5 ANFIS Proposed Model Structure.

The proposed model has six inputs as shown in given structure and every input is separated into two membership functions. 64 rules have been formulated, being shown in the given structure. Then output membership function has been assigned to each and every output. To get a single crisp output value the output got from the said rules which was in fuzzified form and was then again defuzzified. This then gives the comprehensive model using ANFIS. The proposed input output model using Sugeno model rules have been given in Fig 5.6. The rules of FIS have been shown in Fig. 5.7.

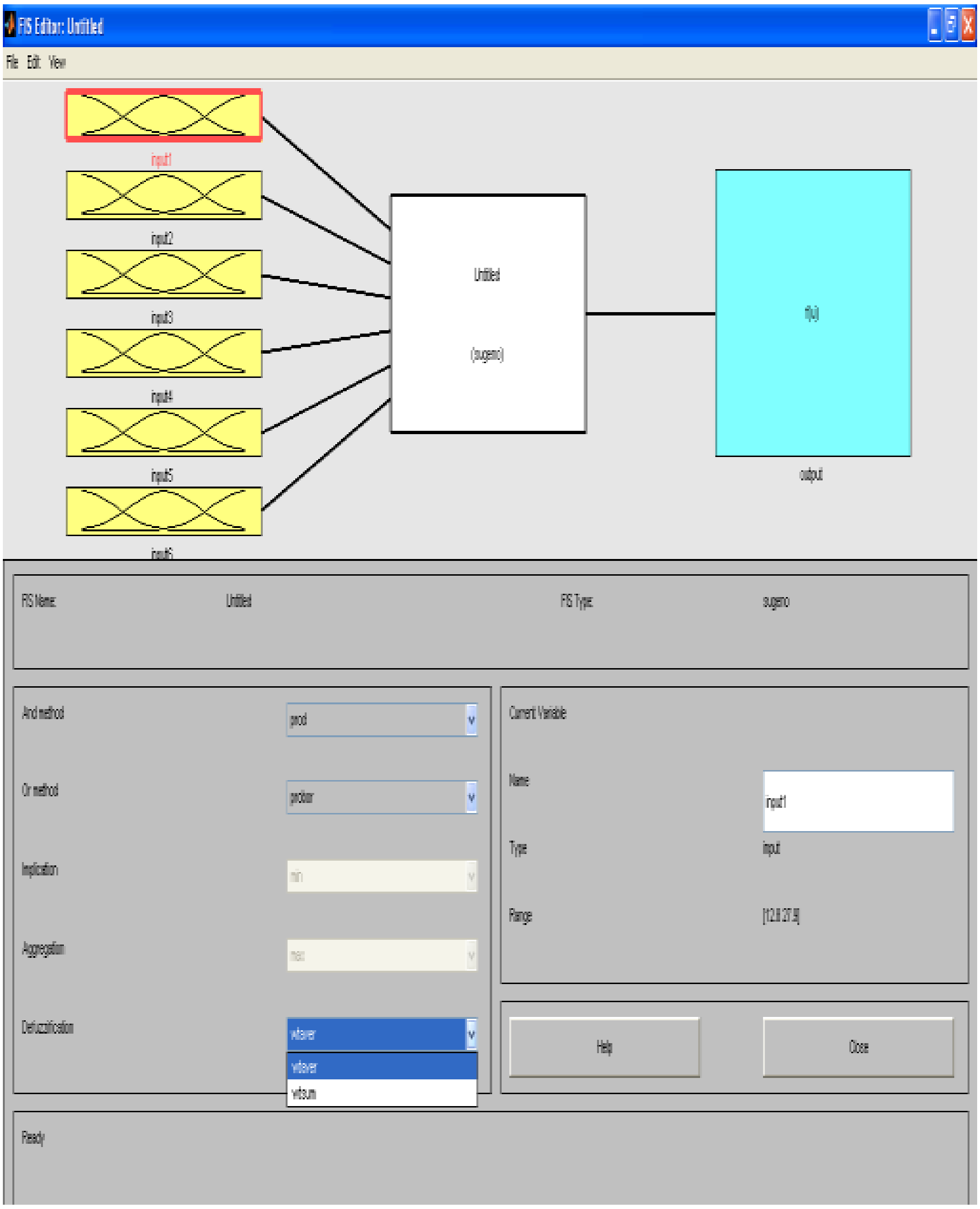

Fig. 5.6 Input-Output Sugeno Model.

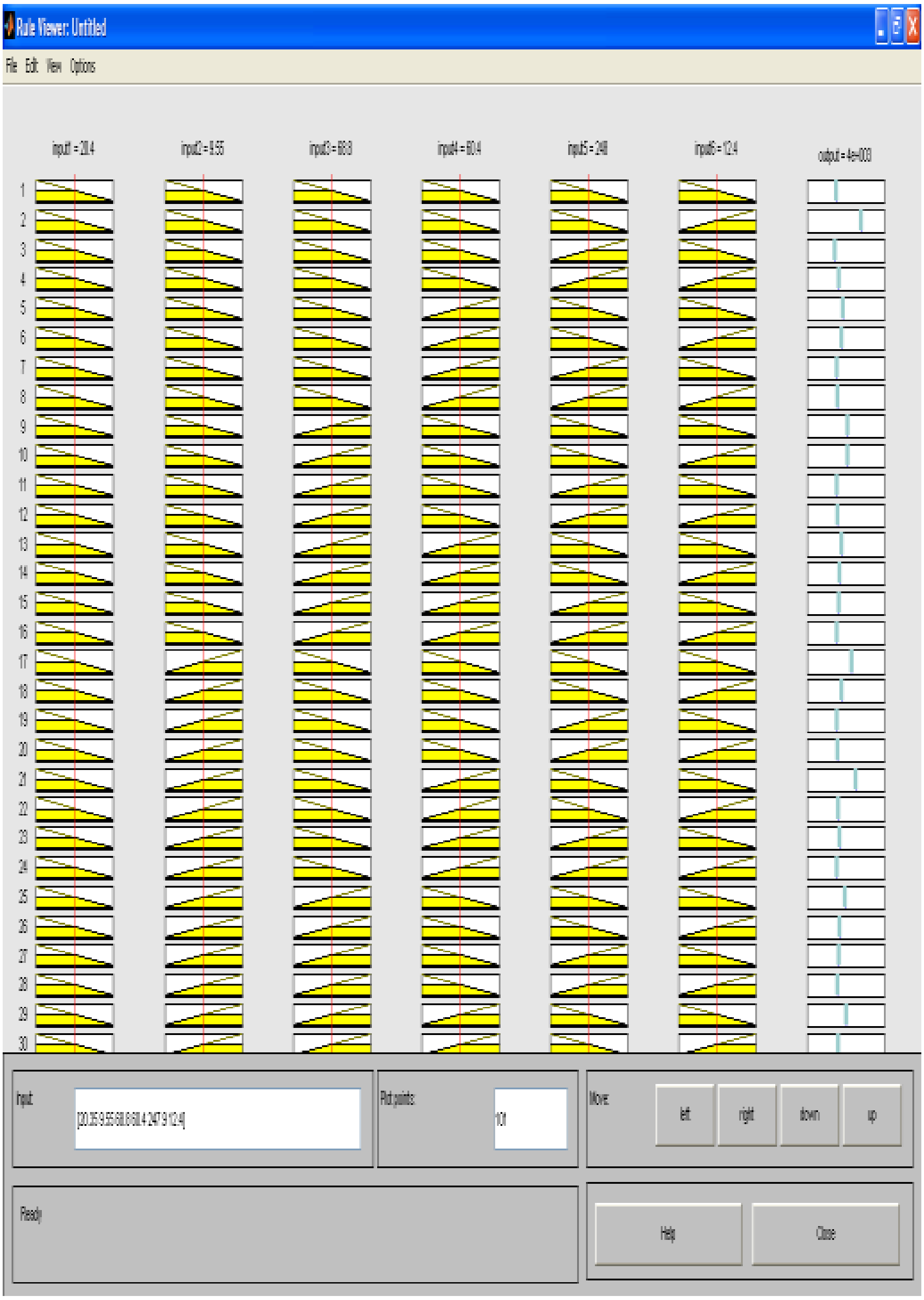

Fig. 5.7 Different Rules Used for the Proposed ANFIS Model.

The error plot as shown in Fig.5.8 has marked the FIS in opposition to the inputs under testing. The indigo are the inputs obtained from the data are cherry are the values obtained after making the model. By the ANFIS proposed model, solar radiations for all the months of year 2014 has been calculated in Table 5.1 using equation (4.1).

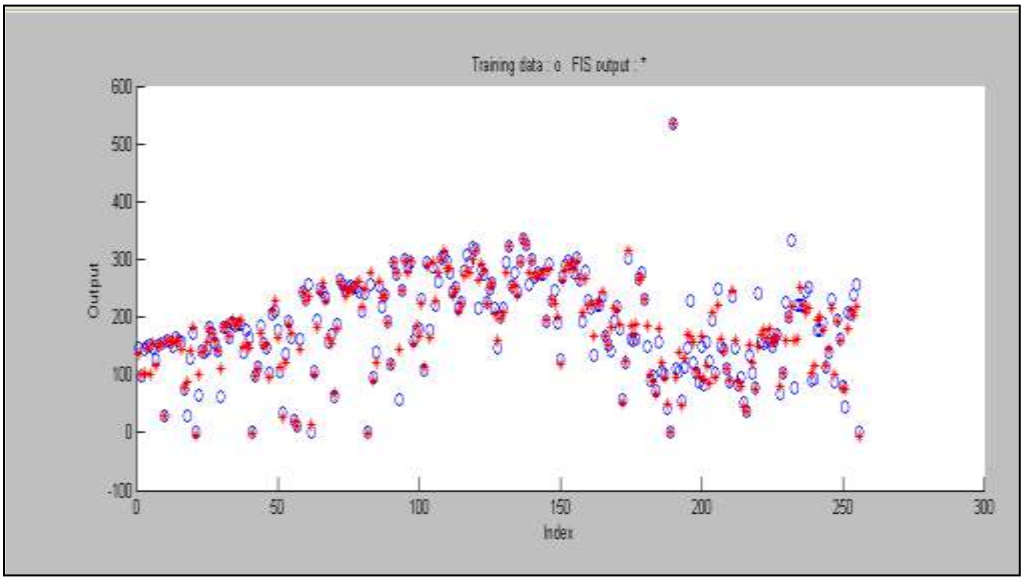

Fig. 5.8 ANFIS Prediction Model Error Analysis between Training Data & FIS Output.

Table 5.1

Actual and ANFIS Predicted Values of Solar Radiations for Year 2014.

Sr. No.	Month	Actual SR	Predicted SR	% MAPE
1	**Jan**	2.40	2.19	8.75
2	**Feb**	2.67	2.98	11.60
3	**Mar**	4.97	5.01	0.82
4	**Apr**	5.31	4.89	7.90
5	**May**	6.01	5.44	9.48
6	**Jun**	5.01	5.06	0.99
7	**Jul**	4.45	4.79	7.64
8	**Aug**	4.01	3.76	6.23
9	**Sep**	4.12	4.22	2.42
10	**Oct**	4.32	4.79	10.87
11	**Nov**	3.66	3.65	0.27
12	**Dec**	3.12	3.04	2.56
13	**Annual**	**4.17**	**4.15**	**0.47**

5.3 RESULTS AND DISCUSSION

It can be concluded that the solar radiations can be estimated much accurately by ANFIS model of prediction. As given in table 5.1, it is clear that the overall annual solar radiation error decreased as compared to ANN. The actual solar radiations annually are 4.17 kWh/m^2/day and predicted is 4.15 kWh/m^2/day. The annual MAPE is 0.47% which is very low and very accurate value of prediction. It means the model prediction is very accurate. The Maximum MAPE is 11.60% for month of February, 2014 whereas minimum MAPE is 0.27% for the month of November.

5.4 PREDICTION OF NEXT YEARS SOLAR RADIATIONS BASED ON THE ANFIS SELECTED MODEL

Prediction of next three years solar radiations has be done based on the model developed using ANFIS. The prediction for the years 2015, 2016 and 2017 has been done based on this developed model. The error results have been changed from the daily average solar radiations to monthly average of solar radiations considering the sunshine hours for that particular day for all the three years predictions. After prediction of solar radiations for three years, errors have been calculated and projected values of the solar radiations with MAPE have been given in the Tables 5.2, 5.3 and 5.4. The plots showing actual and predicted solar radiations have been given in Fig. 5.9, 5.10 and 5.11. The plots have been developed between the twelve months of the respective years and the solar radiations. Both the actual and predicted solar radiations have been shown so that the closeness of the two can be seen.

The calculation of MAPE error has been done for all the three years for which prediction has been done using ANFIS. It has been seen that for year 2015 the maximum MAPE has been calculated as 10.45% for month of October and minimum MAPE is 1.58% for November month. The overall annual MAPE for year 2015 is calculated to be 1.99% which is a very good value of any prediction error. The error plot between actual and predicted values has been shown in Fig.5.9 where X-axis gives the month of the year 2015 and Y –axis gives the values solar radiations values.

Table 5.2

Actual and ANFIS Predicted Values of Solar Radiations for Year 2015.

Sr. No.	Month	Actual SR	Predicted SR	% MAPE
1	**Jan**	2.43	2.66	9.46
2	**Feb**	2.87	2.78	3.13
3	**Mar**	4.79	4.91	2.50
4	**Apr**	5.22	5.1	2.29
5	**May**	6.14	5.97	2.76
6	**Jun**	4.95	5.11	3.23
7	**Jul**	4.06	3.88	4.43
8	**Aug**	3.48	3.56	2.29
9	**Sep**	3.98	4.15	4.27
10	**Oct**	4.21	4.65	10.45
11	**Nov**	3.16	3.21	1.58
12	**Dec**	2.85	3.12	9.47
13	**Annual**	**4.01**	**4.09**	**1.99**

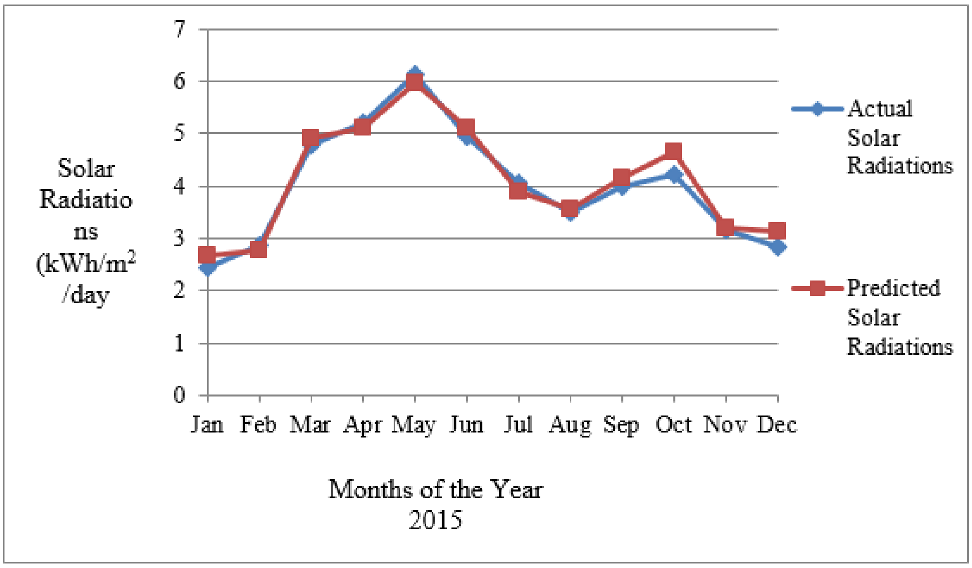

Fig. 5.9 Plot between Actual and Predicted Solar Radiations for Year 2015.

Table 5.3

Actual and ANFIS Predicted Values of Solar Radiations for Year 2016.

Sr. No.	Month	Actual SR	Predicted SR	% MAPE
1	**Jan**	2.36	2.67	13.13
2	**Feb**	3.19	3.42	7.21
3	**Mar**	5.01	4.94	1.39
4	**Apr**	4.76	4.65	2.31
5	**May**	6.24	6.18	0.96
6	**Jun**	4.89	4.65	4.9
7	**Jul**	4.56	4.44	2.63
8	**Aug**	3.66	4.01	9.56
9	**Sep**	4.01	4.16	3.74
10	**Oct**	4.57	5.04	10.28
11	**Nov**	3.45	3.68	6.67
12	**Dec**	3.22	3.43	6.52
13	**Annual**	**4.16**	**4.27**	**2.64**

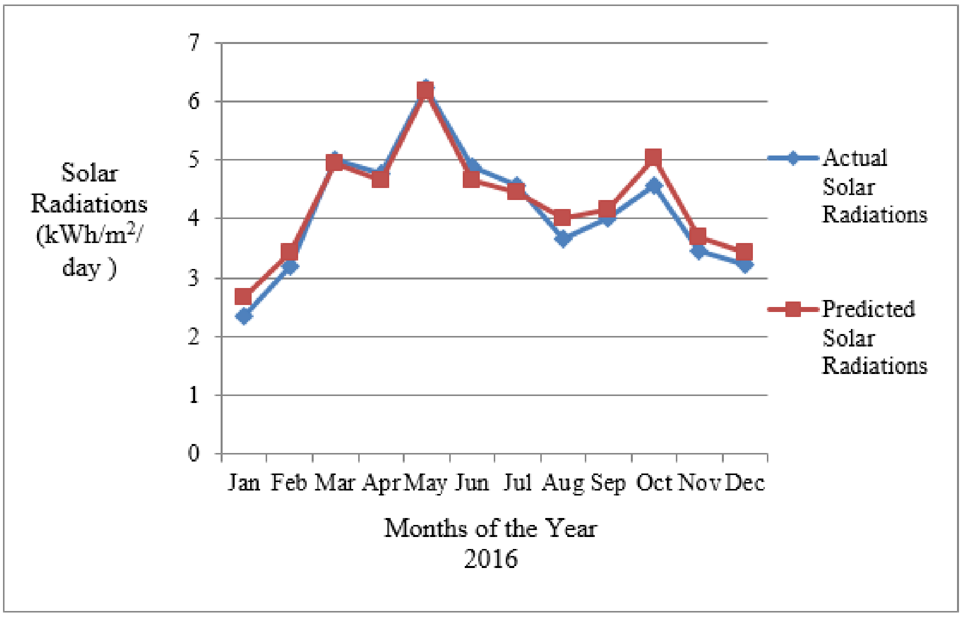

Fig. 5.10 Plot between Actual and Predicted Solar Radiations for Year 2016.

Table 5.4

Actual and ANFIS Predicted Values of Solar Radiations for Year 2017.

Sr. No.	Month	Actual SR	Predicted SR	% MAPE
1	**Jan**	2.44	2.63	7.77
2	**Feb**	3.93	3.75	4.58
3	**Mar**	4.78	4.88	2.09
4	**Apr**	5.22	5.12	1.91
5	**May**	5.67	5.55	2.11
6	**Jun**	4.88	4.77	2.25
7	**Jul**	4.01	4.55	13.46
8	**Aug**	3.22	3.14	2.48
9	**Sep**	4.12	4.01	2.66
10	**Oct**	4.51	4.4	2.43
11	**Nov**	3.23	3.76	16.4
12	**Dec**	2.99	3.12	4.34
13	**Annual**	**4.08**	**4.14**	**1.47**

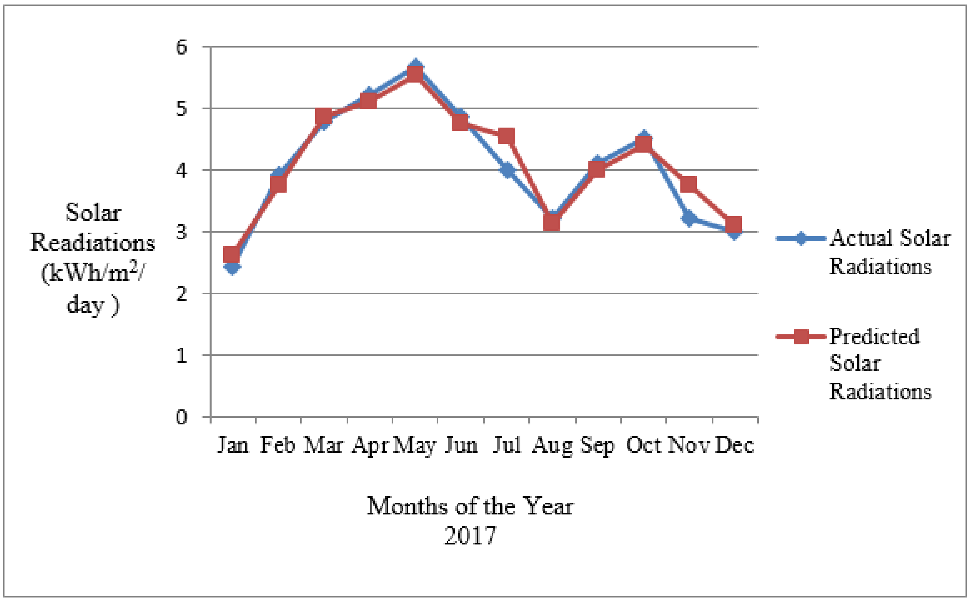

Fig. 5.11 Plot between Actual and Predicted Solar Radiations for Year 2017.

For year 2016, the annual solar radiation prediction MAPE is 2.64%. The maximum MAPE is calculated for the month of January which is 13.13% whereas minimum MAPE is 0.96% for the month of May. The plot between actual and predicted values of year 2016 has been given in Fig.5.10 to show the difference between actual and predicted values of solar radiations through ANFIS model.

The annual MAPE for year 2017 is calculated to be 1.47% whereas maximum MAPE has been calculated for November month as 16.4%. The least value of MAPE for year 2017 is 1.91% for the month of April. Hence all the values predicted based on the best ANFIS model falls within the permissible limits of a very good prediction accuracy model. Fig.5.11 is used to graphically represent the values of actual and predicted solar radiations for all the months of year 2017.

6. PREDICTION MODEL FOR 10 SELECTED CITIES OF HIMACHAL PRADESH

The next model discussed is for 10 selected cities of Himachal Pradesh using ANN as well as ANFIS so that the model can be generalized for a wider region.

6.1 SELECTION OF INPUT VARIABLES USED FOR PREDICTION MODEL USING ANN

For the different prediction models different variables selected as inputs are sunshine hours, temperature, humidity, rainfall, latitude and longitude. In the variable collection process for various models proposed for daily solar estimation variable inputs are fed to the same targets. Three solar estimation models have been proposed using the said inputs in different sets.

Once the process of section of variables is complete, then it is to predict the different prediction models by taking into consideration the different number of inputs using ANN. In the three different models predicted maximum number of inputs used is six and minimum is three. The different variables used in this study are temperature (T), humidity (H), rainfall (R), sun shine hours (SH), latitude (Lat.), longitude (Long.) and target average monthly solar radiations (SR) for 10 cities of Himachal Pradesh on average basis have been given in Table 6.1 and Table 6.2. The data for ten years (1200 samples) has been collected from India Meteorological Department (IMD), Pune [118]. Table 6.1 contains the average daily solar radiations for the selected 10 cities.

6.2 ANN DEPENDENT SOLAR RADIATION ESTIMATION MODELS

Three solar radiation estimation models are being proposed with the artificial neural networks (nftool). They are given names as Solar Radiation Prediction Model (SRPM)-1, 2 and 3. Standard two layer feed forward artificial neural network with Levenberg-Marquardt (LM) algorithm has been used in the nftool of MATLAB 9.1 (R2016b) Simulink. This type of algorithm is used because it is appropriate for static fitting troubles as is the case for prediction of solar radiations in this particular research study. ANN based scaled conjugate gradient training is done automatically. The input and output data is divided randomly as 70%, 15%, 15% for the reason of training, testing and substantiation. The different models have been skilled using ANN tool's LM algorithm. Testing data provides a self-regulating performance during and subsequent to training rather affecting the training. As we know that ANN is used for generalization of data so validation of data are used for capacity of generalization of the given system network and validation stops after completion of generalization. During testing, validation and testing varying numbers of epochs are used.

Table 6.1

Meteorological data and geographical coordinates of 10 selected cities of Himachal Pradesh.

Sr. No.	City	T (°C)	R (mm)	H (%)	SH (hours)	Lat. (°)	Long. (°)	SR (kWh/m²/day)
1	Hamirpur	18.9	1600	62	7.67	31.68	76.52	4.01
2	Nahan	23.8	1100.7	70	9.1	30.55	77.29	5.21
3	Dharamshala	20.8	2050.8	70.9	7.85	32.21	76.32	5.09
4	Bilaspur	32.2	857	65.5	7.5	31.34	76.68	5.2
5	Manali	23.7	1720	85	5.43	32.23	77.18	4.54
6	Mandi	27.8	1389	73.8	7.98	31.58	76.91	4.45
7	Chamba	30.4	1780	85	7.42	32.55	76.12	5.41
8	Sundernagar	29.5	1080	70	7.6	31.53	76.89	5.23
9	Dalhousie	24.9	992	50	6.83	32.53	75.97	5.09
10	Shimla	14.5	810	58	5.98	31.1	77.17	4.63

In hidden layers, the number of neurons is calculated by Eqn. (6.1), as h_n is the number of neurons in hidden layer to be evaluated, I_n is the inputs number and O_n is the outputs number used in different prediction models whereas S_n is the total data samples numbers used for every selected model.

$$h_n = (I_n + O_n) / 2 + \sqrt{S_n} \quad (6.1)$$

Table 6.2
Monthly average solar radiation data (kWh/m^2/day) for the 10 selected cities of Himachal Pradesh.

Sr. No.	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
1	2.43	2.87	4.79	5.22	6.14	4.95	4.06	3.48	3.98	4.21	3.16	2.85	4.01
2	4.38	5.2	6.2	7.03	6.73	5.5	4	3.8	5.2	5.32	4.7	4.57	5.21
3	3.58	4.4	5.47	6.35	6.95	6.06	5.25	4.8	5.32	5.13	4.22	3.53	5.09
4	4.31	5.19	7.03	6.19	6.71	4	5.45	3.72	5.2	5.29	4.69	4.6	5.2
5	3.85	4.63	5.35	5.79	5.1	4.65	4.54	4.13	3.88	4.21	4.34	4.01	4.54
6	3.75	4.35	5.27	5.85	5.73	4.76	4.19	4.32	4.13	4.24	3.84	3.52	4.45
7	4.25	5.11	6.1	7.09	7.25	6.59	5.23	4.8	5.45	5.04	4.37	3.78	5.41
8	4.43	5.33	6.31	6.89	6.78	5.99	4.32	4.29	5.13	5.23	4.55	4.24	5.23
9	3.7	4.55	5.69	6.67	6.77	6.3	5.13	4.99	5.14	4.76	4.01	3.34	5.09
10	4.23	4.67	5.77	6.21	5.89	4.65	3.99	4.01	4.1	4.29	4.12	4.11	4.63

6.3 SENSITIVITY TEST AND ERROR EVALUATION OF SRPM MODELS

The three ANN based SRPM 1-3 models have been developed using different climatic input variables. In SRPM-1 model development all the six input variables (I_n) have been considered. For model SRPM-2 sunshine hours have not been taken into account so the I_n is 5 here. SRPM-3 model has been developed considering 4 input variables where latitude and longitude have not been considered. For the evaluation of sensitivity test to calculate the change in solar radiation prediction error, MAPE is calculated for the each hidden layer neuron as obtained from Eqn. (4.1).

The hidden layer neuron sensitivity tests results have been given in Tables 6.3-6.5 with maximum MAPE for each hidden layer neuron for the three SRPM models. Association between outputs and targets has been found out in all the three models by the correlation coefficient (R value). Hidden layers have been in between 6 to 18 for all the three SRPM models and the MLP structure has been suggested for the particular ANN based SRPM model which has the least value of MAPE.

Table 6.3

Maximum MAPE calculation and SRPM-1 model results evaluation

Sensitivity Test for Neurons in Hidden Layer	Structure for MLP	Training for Regression	% MaxMAPE	ANN based best SRPM-1 Model
The number of inputs I_a is 6, outputs O_a is 12 (average monthly solar radiations of 10 selected cities) and number of samples S_a taken for training are 12. Hence the hidden layers neurons H_a obtained from Eq. (6.1) are 13 and selected layers are ± 5, therefore H_a varies between 8-18.	6/8/2001	95.85	22.14	The ANN based SRPM-1 model with MLP structure 6-10-1 is best which has 6 input neurons, 13 hidden layer neurons and output layer has 1 neuron as it has minimum MAPE value 6.31%.
	6/9/2001	91.41	30.23	
	6/10/2001	**90.73**	**6.31**	
	6/11/2001	90.63	25.34	
	6/12/2001	93.64	29.67	
	6/13/2001	89.19	22.56	
	6/14/2001	90.17	37.24	
	6/15/2001	93.58	23.78	
	6/16/2001	91.77	30.59	
	6/17/2001	88.45	24.1	
	6/18/2001	91.93	29.04	

Table 6.4

Maximum MAPE calculation and SRPM-2 model results evaluation.

<table>
<tr><th>Sensitivity Test for Neurons in Hidden Layer</th><th>Structure for MLP</th><th>Training for Regression</th><th>% MaxMAPE</th><th>ANN based best SRPM-2 Model</th></tr>
<tr><td rowspan="11">The number of inputs I_n is 5, outputs O_n is 12 (average monthly solar radiations of 10 selected cities) and number of samples S_n taken for training are 12. Hence the hidden layers neurons H_n obtained from Eq. (6.1) are 12 and selected layers are ± 5, therefore H_n varies between 7-17.</td><td>5/7/2001</td><td>93.09</td><td>18.29</td><td rowspan="11">The ANN based SRPM-2 model with MLP structure 5-11-1 is best which has 5 input neurons, 12 hidden layer neurons and output layer has 1 neuron as it has minimum MAPE value of 8.01%.</td></tr>
<tr><td>5/8/2001</td><td>86.94</td><td>23.31</td></tr>
<tr><td>5/9/2001</td><td>96.37</td><td>12.34</td></tr>
<tr><td>5/10/2001</td><td>81.6</td><td>17.85</td></tr>
<tr><td>5/11/2001</td><td>92.38</td><td>8.01</td></tr>
<tr><td>5/12/2001</td><td>93.01</td><td>19.45</td></tr>
<tr><td>5/13/2001</td><td>94.33</td><td>25.67</td></tr>
<tr><td>5/14/2001</td><td>84.11</td><td>16.78</td></tr>
<tr><td>5/15/2001</td><td>92.57</td><td>13.76</td></tr>
<tr><td>5/16/2001</td><td>96.42</td><td>19.34</td></tr>
<tr><td>5/17/2001</td><td>89.53</td><td>15.56</td></tr>
</table>

Table 6.5
Maximum MAPE calculation and SRPM-3 model results evaluation.

Sensitivity Test for Neurons in Hidden Layer	**Structure for MLP**	**Training for Regression**	**% MaxMAPE**	**ANN based best SRPM-3 Model**
The number of inputs I_n is 4, outputs O_n is 12 (average monthly solar radiations of 10 selected cities) and number of samples S_n taken for training are 12. Hence the hidden layers neurons H_n obtained from Eq. (6.1) are 11 and selected layers are ±5, therefore H_n varies between 6-16.	4/6/2001	70.39	16.45	The ANN based SRPM-3 model with MLP structure 4-9-1 is best which has 4 input neurons, 11 hidden layer neurons and output layer has 1 neuron as it has minimum MAPE value of 10.99%.
	4/7/2001	88.31	11.1	
	4/8/2001	96.64	25.46	
	4/9/2001	**92.46**	**10.99**	
	4/10/2001	94.22	13.43	
	4/11/2001	82.33	17.89	
	4/12/2001	97.38	21.47	
	4/13/2001	93.73	14.79	
	4/14/2001	84.29	20.98	
	4/15/2001	91.64	35.42	
	4/16/2001	89.28	27.63	

6.4 RESULTS AND DISCUSSION OF ANN MODEL

Three models have been developed as given in Tables 6.3-6.5. The prediction accuracy of each model with the selected MLP structure has been evaluated by calculating Maximum MAPE given by Lewis [52]. The value of MAPE ≤ 10 % is taken as very high prediction, ≥ 10 % and ≤ 20 % gives good prediction accuracy whereas ≥ 20 % indicates reasonable or average prediction. In the three SRPM models developed for the 10 selected cities of Himachal Pradesh, it has been found out that maximum MAPE for SRPM-1, 2 and 3 is 6.31%, 8.01%, and 10.99% respectively. It is also evident from the results that when all the six input parameters are considered then the error is minimum and less than high accuracy percentage of 10% considered for MAPE calculation whereas when some input parameters like latitude, longitude and sunshine are not considered in SRPM 2 and 3 then the prediction accuracy decreases sharply. The prediction accuracy has been decreased by 4.68% for SRPM-3 model where latitude and longitude have not been considered whereas best MAPE results have been calculated for SRPM-1 where the maximum MAPE comes out to be 6.31%. It is also clear from the results that the prediction cannot be done accurately without sunshine hours and latitude longitude of the location.

Thus SRPM-1 model has been proposed for the estimation of solar radiations as it has the least percentage of maximum MAPE. The performance plot for this model has been given in Fig.6.1 from which it is clear that mean square error decreases as the number of epochs is rising. Regression plot shows association among outputs and the intended targets in SRPM-1 in Fig.6.2. The graph also shows that the data is falling along the fit is perfect which means data have to be beside 45° line (slope is very near to 1). Error histogram for the same has been given in Fig.6.3.

The histogram for the output obtained from SRPM-1 has been shown in Fig.6.4. In this it has been shown clearly the 12 monthly average solar radiations for 10 selected cities each by the SRPM-1 model. The prediction for the monthly average daily solar radiations has been given in Table 6.6 for the 10 selected cities based on SRPM-1 prediction model. The monthly average solar radiations predicted are between 4.03-5.42 (kWh/m^2/day) for the 10 selected cities of Himachal Pradesh for year 2017 which are very near to the actual target values.

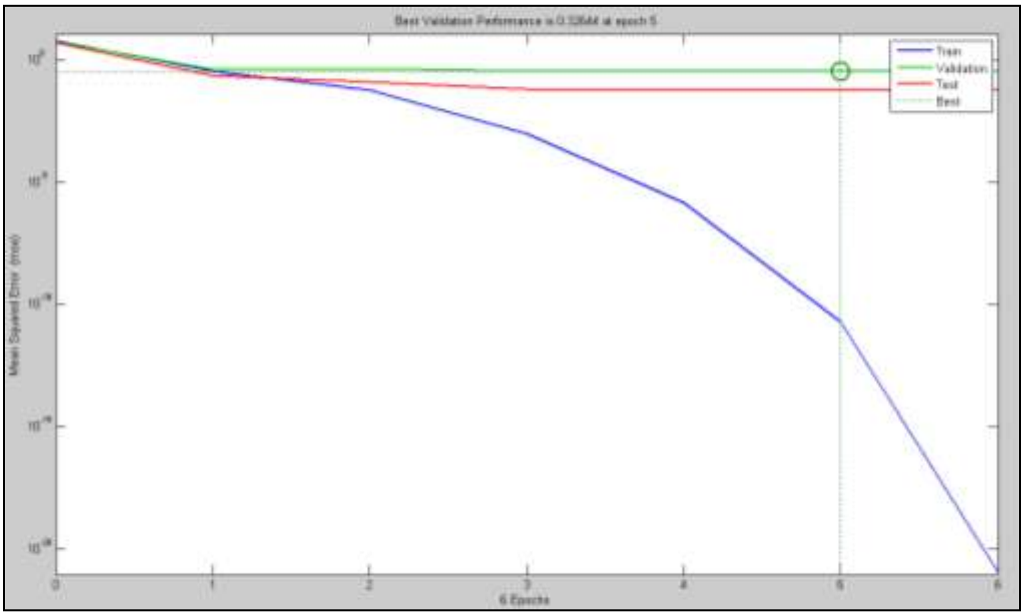

Fig.6.1 Performance plot of SRPM-1 model during training, testing and validation.

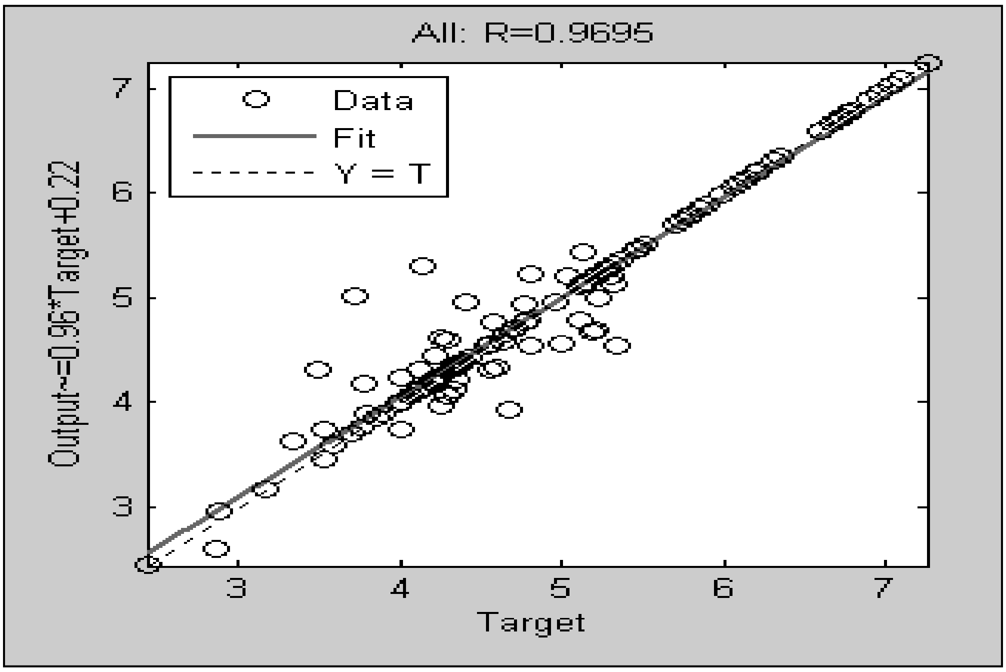

Fig.6.2 Regression plot for SRPM-1.

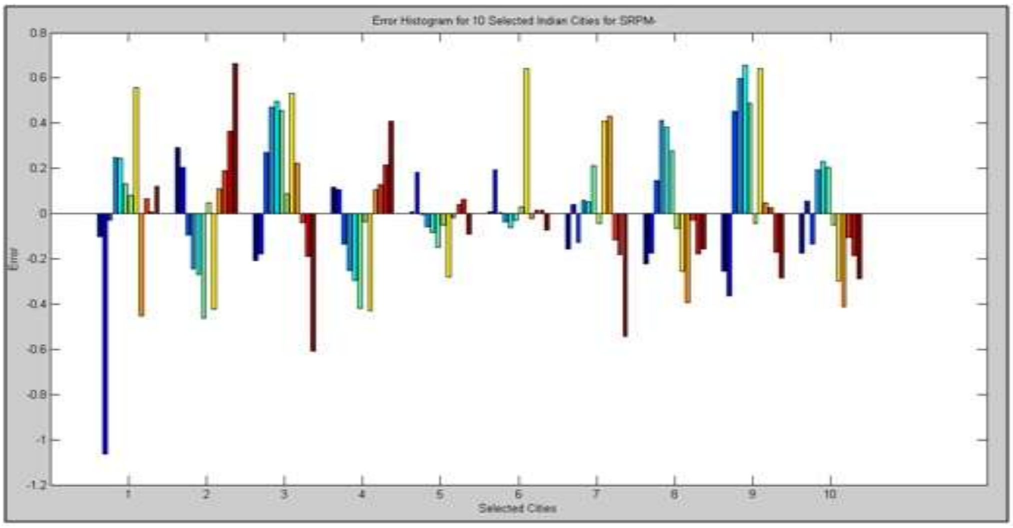

Fig.6.3 Error Histogram between actual and predicted values for year 2017 for 10 selected cities of Himachal Pradesh using SRPM-1.

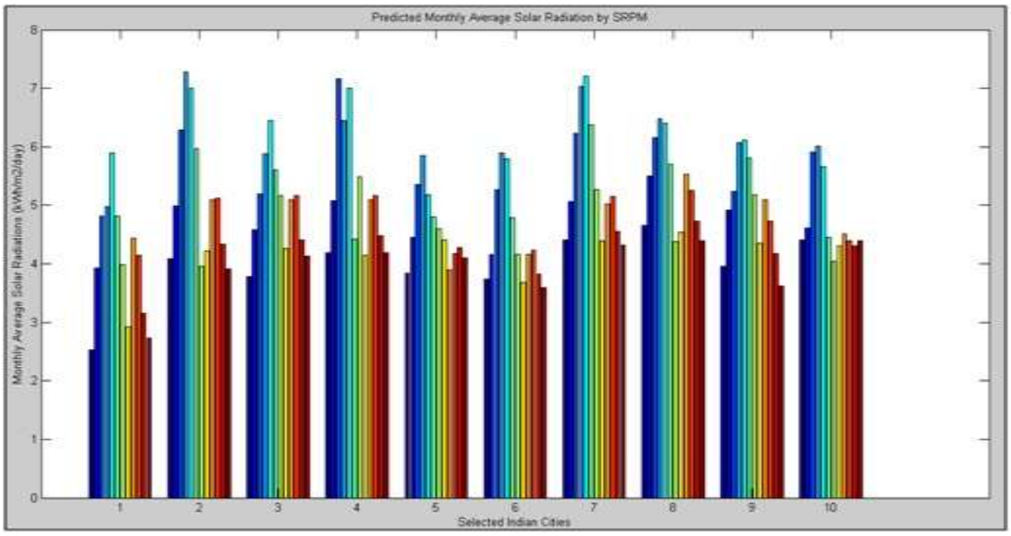

Fig.6.4 Predicted Monthly Average Solar Radiations (kWh/m^2/day) of 10 cities for year 2017.

Using the predicted values for 2017 of annual solar radiations the values for solar radiations are predicted for the year 2018. Similarly by using the values for year 2018 next year's prediction has been done. In this work total prediction of five years have been done from year 2017-2021 taking into consideration the various climatic conditions as used previously. The monthly average solar radiations predicted are between 3.87-5.44 (kWh/m^2/day) for the 10 selected cities of Himachal Pradesh for five years from 2017-2021 as given in the tables below. All these values of solar radiations predicted for 10 cities of Himachal Pradesh have been given in Tables 6.6-6.10.The average MAPE for year 2017 is calculated to be 5.2% as given in Table 6.11 for ten cities.

Table 6.6

Predicted vs actual monthly average solar radiations (kWh/m^2/day) of 10 selected cities of Himachal Pradesh for Year 2017.

Sr. No.	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
1	2.53 (2.45)*	3.93 (2.97)	4.82 (4.65)	4.97 (5.02)	5.9 (5.78)	4.82 (4.24)	3.98 (4.11)	2.92 (3.12)	4.43 (4.08)	4.14 (4.67)	3.15 (3.44)	2.73 (3.11)	**4.03 (3.97)**
2	4.09 (4.21)	4.99 (5.15)	6.29 (6.44)	7.27 (7.01)	7 (6.75)	5.96 (5.45)	3.95 (4.03)	4.22 (4.13)	5.09 (5.31)	5.13 (4.49)	4.34 (4.57)	3.91 (4.13)	5.19 (5.13)
3	3.78 (4.60)	4.58 (4.31)	5.2 (5.54)	5.88 (6.21)	6.45 (6.2)	5.6 (5.94)	5.16 (5.10)	4.27 (4.86)	5.1 (5.36)	5.17 (5.86)	4.41 (4.84)	4.14 (4.41)	4.98 (5.25)
4	4.19 (4.47)	5.08 (5.31)	7.16 (6.87)	6.44 (6.81)	7.01 (7.34)	4.42 (4.96)	5.49 (5.82)	4.15 (4.87)	5.1 (5.68)	5.16 (5.70)	4.47 (5.14)	4.19 (4.01)	5.24 (5.58)
5	3.84 (4.11)	4.45 (4.67)	5.35 (5.82)	5.85 (5.41)	5.18 (5.92)	4.8 (5.32)	4.59 (4.71)	4.41 (4.16)	3.9 (4.27)	4.17 (4.52)	4.28 (4.86)	4.1 (4.49)	4.58 (4.85)
6	3.74 (4.44)	4.16 (4.9)	5.27 (4.89)	5.89 (5.71)	5.79 (5.14)	4.79 (5.17)	4.16 (4.72)	3.68 (4.11)	4.15 (4.55)	4.23 (4.87)	3.83 (4.23)	3.59 (3.88)	4.44 (4.72)
7	4.4 (4.73)	5.07 (5.12)	6.23 (6.79)	7.03 (7.21)	7.2 (6.95)	6.38 (6.99)	5.27 (5.88)	4.39 (4.86)	5.02 (5.62)	5.16 (4.85)	4.55 (5.64)	4.32 (4.88)	**5.42 (5.79)**
8	4.65 (4.15)	5.51 (6.02)	6.16 (6.53)	6.48 (7.14)	6.4 (6.92)	5.71 (5.11)	4.39 (4.84)	4.54 (4.19)	5.52 (6.26)	5.26 (5.87)	4.73 (5.31)	4.4 (3.89)	5.31 (5.52)
9	3.95 (4.27)	4.91 (5.55)	5.24 (5.86)	6.07 (6.42)	6.11 (7.11)	5.81 (6.35)	5.18 (5.83)	4.35 (5.43)	5.09 (5.11)	4.73 (4.34)	4.18 (4.61)	3.62 (4.28)	4.94 (5.43
10	4.41 (4.75)	4.61 (5.25)	5.9 (4.97)	6.02 (6.88)	5.66 (6.55)	4.45 (4.85)	4.04 (4.87)	4.31 (4.11)	4.51 (5.15)	4.4 (4.12)	4.3 (4.88)	4.4 (5.29)	4.75 (5.13)

*: Real time data [118].

Table 6.7

Predicted monthly average solar radiations (kWh/m^2/day) of 10 selected cities of Himachal Pradesh for Year 2018.

Sr. No.	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
1	3.15	3.93	5.67	5.70	6.65	4.65	3.79	3.14	4.23	4.21	3.05	2.24	**4.20**
2	3.78	5.13	6.29	7.43	6.78	5.73	4.05	4.43	5.13	5.07	4.25	3.25	5.11
3	3.79	4.56	5.80	6.02	6.38	5.60	5.15	4.51	5.10	5.25	4.38	4.21	5.06
4	4.19	5.23	7.28	6.52	7.05	4.32	5.45	4.12	5.19	5.76	4.54	3.95	5.29
5	3.83	4.56	5.45	5.90	5.05	4.44	4.45	4.41	4.67	4.74	4.25	3.64	4.61
6	3.74	4.74	5.83	5.87	5.34	4.54	4.46	3.12	4.78	4.04	4.01	3.45	4.49
7	4.43	5.32	6.65	7.10	7.45	6.01	5.04	4.16	5.23	5.06	4.43	4.45	**5.44**
8	4.47	5.60	6.36	6.21	6.15	5.45	4.14	4.52	5.43	5.74	4.23	4.39	5.22
9	4.90	5.03	5.64	6.34	6.65	5.14	5.45	4.31	5.11	4.74	4.10	3.63	5.08
10	4.01	4.60	6.23	5.98	5.43	4.15	4.01	4.31	4.51	4.44	4.26	4.23	4.68

Table 6.8

Predicted monthly average solar radiations ($kWh/m^2/day$) of 10 selected cities of Himachal Pradesh for Year 2019.

Sr. No.	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
1	2.44	3.93	4.92	5.03	5.78	4.63	3.68	2.82	4.14	4.03	3.04	2.64	**3.92**
2	3.98	4.35	5.93	7.09	6.90	5.88	3.86	4.13	4.94	5.03	4.13	3.81	5.00
3	3.57	4.67	5.23	5.73	6.53	5.50	5.14	4.14	5.00	4.91	4.34	4.01	4.89
4	4.05	4.93	7.02	6.05	7.01	4.04	5.41	4.04	5.13	5.03	4.40	4.03	5.09
5	3.56	4.40	5.32	5.73	5.04	4.69	4.57	4.43	3.51	4.01	4.03	4.01	4.44
6	3.74	4.06	5.04	5.82	5.61	5.00	4.01	3.51	4.05	4.13	3.92	3.13	4.31
7	4.42	4.98	6.12	6.92	7.09	6.40	4.94	4.52	5.00	5.03	4.50	4.13	**5.33**
8	4.34	5.34	6.02	6.42	6.26	5.70	4.34	4.1 43	5.34	5.34	4.14	4.13	5,21
9	4.56	5.04	4.98	6.00	5.91	5.72	4.64	4.12	5.45	4.62	4.04	3.53	4.88
10	4.41	4.72	5.82	5.90	5.53	4.40	3.95	4.03	4.35	4.12	4.30	4.13	4.63

Table 6.9

Predicted monthly average solar radiations ($kWh/m^2/day$) of 10 selected cities of Himachal Pradesh for Year 2020.

Sr. No.	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
1	2.32	3.75	4.43	4.85	5.78	4.65	4.00	2.85	4.36	4.09	3.05	2.64	**3.87**
2	4.01	5.07	6.12	7.10	6.90	5.84	3.85	4.11	5.00	5.05	4.41	3.86	5.11
3	3.65	4.60	5.16	5.65	6.54	5.53	5.05	4.17	5.00	5.05	4.33	4.03	4.90
4	4.08	4.07	7.03	6.42	6.95	4.30	5.32	4.05	5.18	5.09	4.41	4.07	5.07
5	3.64	4.34	5.43	5.70	5.04	4.79	4.43	4.40	3.54	4.23	4.64	4.00	4.51
6	3.62	4.05	5.14	5.55	5.64	4.67	4.05	3.57	4.09	4.17	3.87	3.57	4.33
7	4.32	4.88	6.18	7.01	7.05	6.21	5.38	4.31	5.01	5.04	4.38	4.41	**5.34**
8	4.53	5.34	6.06	6.36	6.57	5.65	4.28	4.31	5.32	5.12	4.53	4.21	5.18
9	3.87	4.76	5.31	6.01	6.05	5.74	5.05	4.27	5.31	4.74	4.07	3.53	4.89
10	4.32	4.41	6.04	5.85	5.75	4.37	3.93	4.11	4.54	4.53	4.26	4.41	4.71

Table 6.10

Predicted monthly average solar radiations (kWh/m^2/day) of 10 selected cities of Himachal Pradesh for Year 2021.

Sr. No.	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
1	2.44	3.86	4.65	4.87	5.68	4.80	4.08	2.86	4.40	4.09	3.09	2.68	**3.95**
2	4.01	5.01	6.14	7.15	6.87	5.87	3.86	4.11	5.46	5.29	4.25	3.81	5.15
3	3.44	4.35	5.11	5.67	6.39	5.58	5.06	4.11	4.81	5.09	4.51	4.03	4.84
4	4.01	4.91	7.09	6.32	6.89	4.32	5.38	4.07	4.86	5.08	4.32	4.03	5.10
5	3.65	4.33	5.25	5.81	5.01	4.77	4.47	4.23	4.09	4.15	4.09	4.00	4.48
6	3.68	4.07	5.15	5.77	5.64	4.63	4.09	3.54	4.08	4.08	3.67	3.25	4.30
7	4.31	4.90	6.13	7.01	7.04	6.24	5.22	4.31	4.59	4.98	4.32	4.12	**5.26**
8	4.54	5.43	6.08	6.36	6.26	5.65	4.28	4.46	5.36	5.15	4.86	4.51	5.24
9	4.09	4.85	5.16	5.98	6.07	5.65	5.08	4.27	5.17	4.64	4.10	3.23	4.85
10	4.32	4.52	5.86	6.01	5.47	4.28	3.91	4.41	4.50	4.31	4.40	4.21	4.68

Table 6.11

Actual and ANN Predicted Annual Average values of Solar Radiations for 10 selected cities of Himachal Pradesh for Year 2017.

Sr. No.	Actual SR	Predicted SR	% MAPE
1	3.97	4.03	1.51
2	5.13	5.19	1.16
3	5.25	4.98	5.14
4	5.58	5.24	6.09
5	4.85	4.58	5.56
6	4.72	4.44	5.93
7	5.79	5.42	6.39
8	5.52	5.31	3.80
9	5.43	4.94	9.02
10	5.13	4.75	7.40
	Average MAPE		**5.2 %**

The predicted annual average solar radiations for the years 2017-2021 for the 10 cities of Himachal Pradesh have been given in Fig. 6.5.

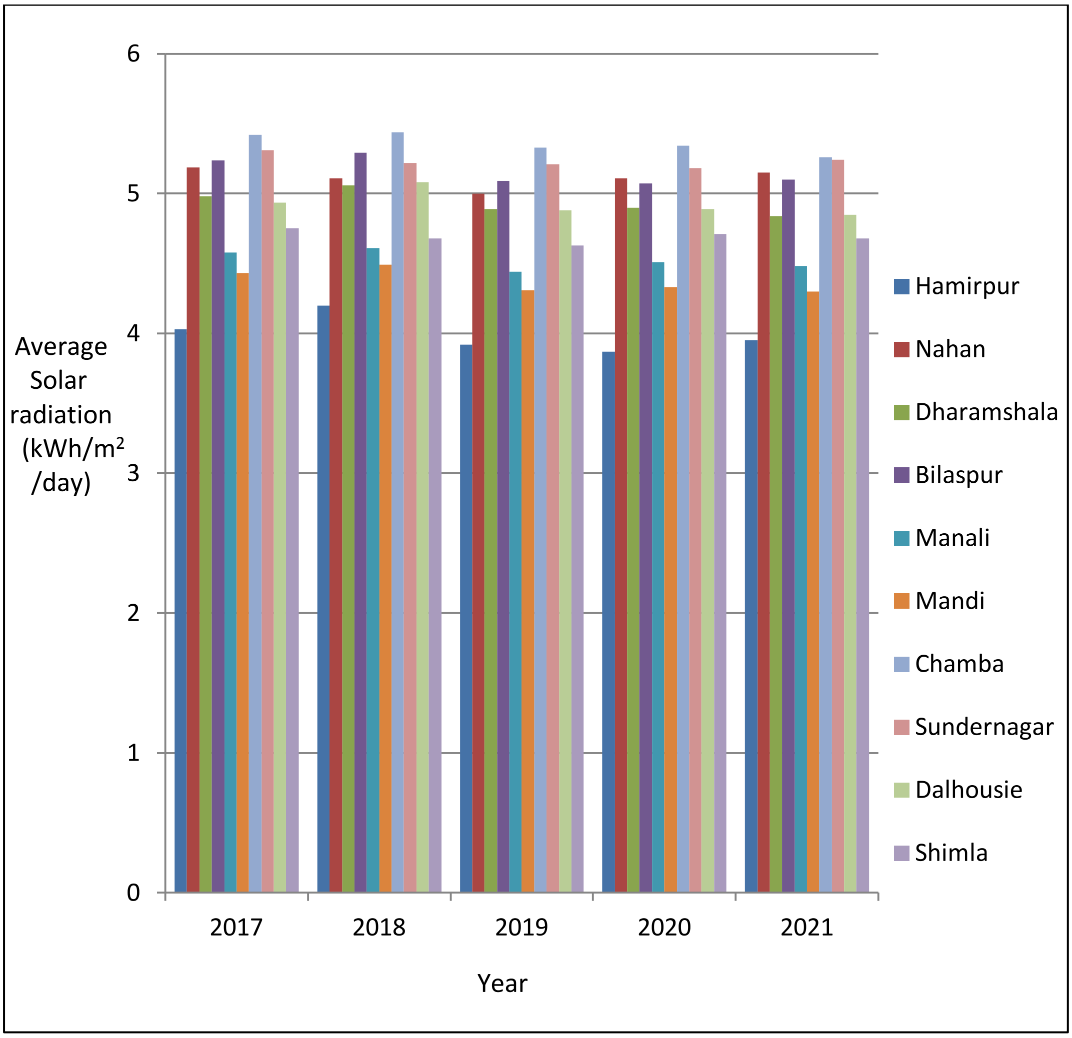

Fig.6.5 Predicted Annual Average Solar Radiations (kWh/m^2/day) for year 2017-2021.

6.5 SELECTION OF INPUTS USED FOR PREDICTION MODEL USING ANFIS

Three solar prediction models have been proposed using the ANN technique. It has been observed that SRPM-1 model is best suited due to its high accuracy and least MAPE. The same six number of inputs given in Table 6.1 used for SRPM-1 has been used for the prediction of solar radiations using ANFIS.

6.6 ANFIS BASED SOLAR RADIATION PREDICTION MODELS

The same process has been adopted to propose the ANFIS model as it has already been proposed in chapter 5. The only difference is that different set of inputs have been taken in this case. As discussed above Table 6.1 input values have been used to propose this prediction model. The estimated model final outcome has been given in Fig. 6.6 which shows six inputs and one target. Every input has been assigned membership functions three in number. Then there are 101 rules framed to get the desired output. Number of epochs used are 10. Fig. 6.7 shows the different rule bases for each of the six inputs. By limiting the inputs as desired, the outputs can be obtained. Fig.6.8 gives the error graph when drawn between the FIS beside the trying values. The indigo dots are the obtained inputs from the data sets and cherry are the estimation got after suggesting the model.

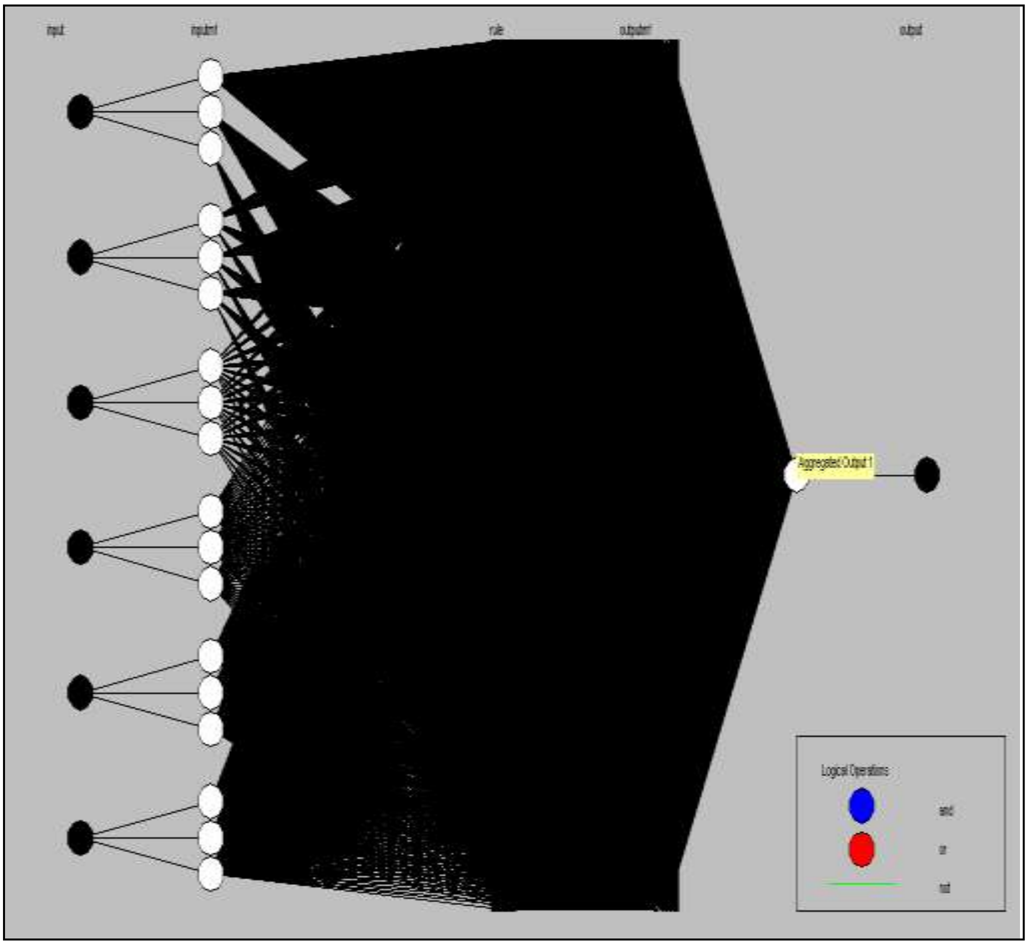

Fig.6.6 ANFIS Predicted Model with Six Inputs and One Output.

6.7 RESULTS AND DISCUSSION OF ANFIS MODEL

To estimate the values of solar radiations for the year 2017 the discussed model has been used. The actual and predicted values of monthly average solar radiations of ten selected cities of Himachal Pradesh for year 2017 have been given in Table 6.12. The maximum MAPE has been calculated to be 10.49% and minimum MAPE is 0.19% as given in Table 6.13. The maximum MAPE is for city Dalhousie whereas minimum MAPE is for city of Dharamshala. The average MAPE is found out to be 3.5% which is lesser as compared to SRPM-1 model. The error plot between experimental and estimatted values of annual average solar radiations of ten cities for year 2017 have been given in graphical representation in Fig.6.9.

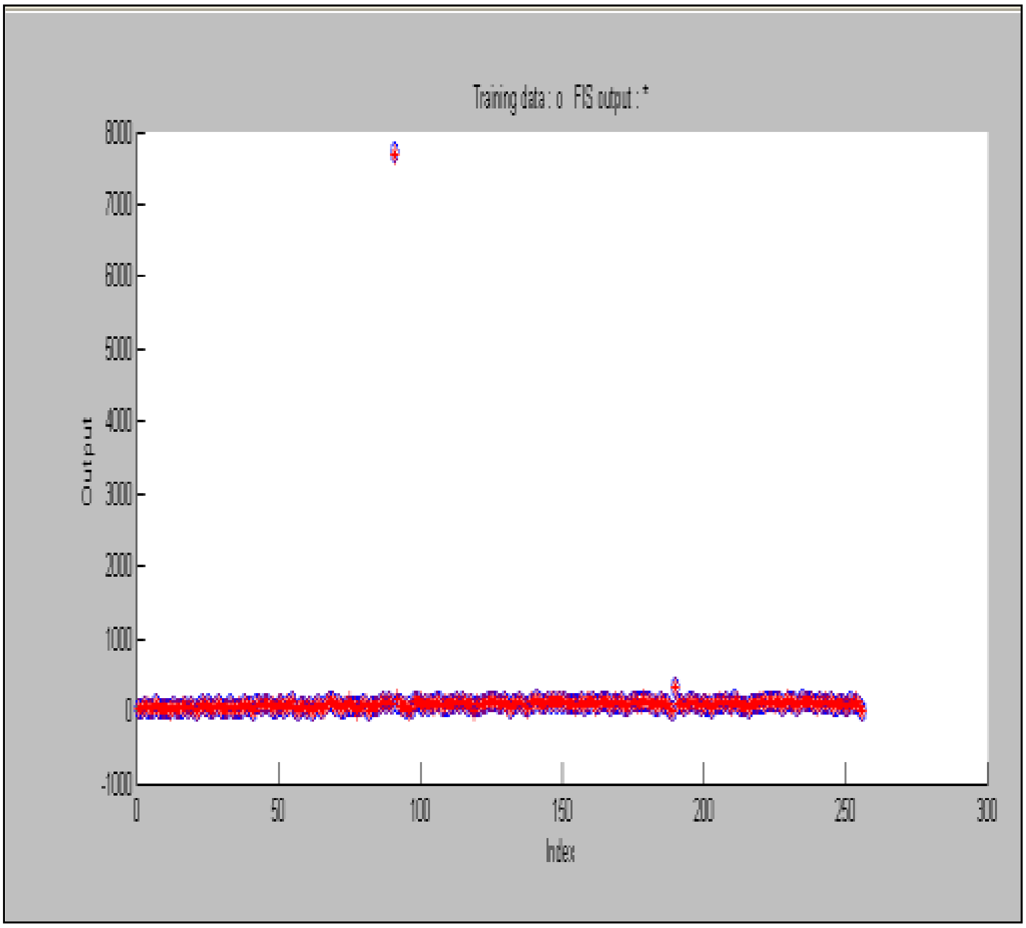

Fig. 6.7 Plot of Error between FIS & Training Output for ANFIS Estimation Model.

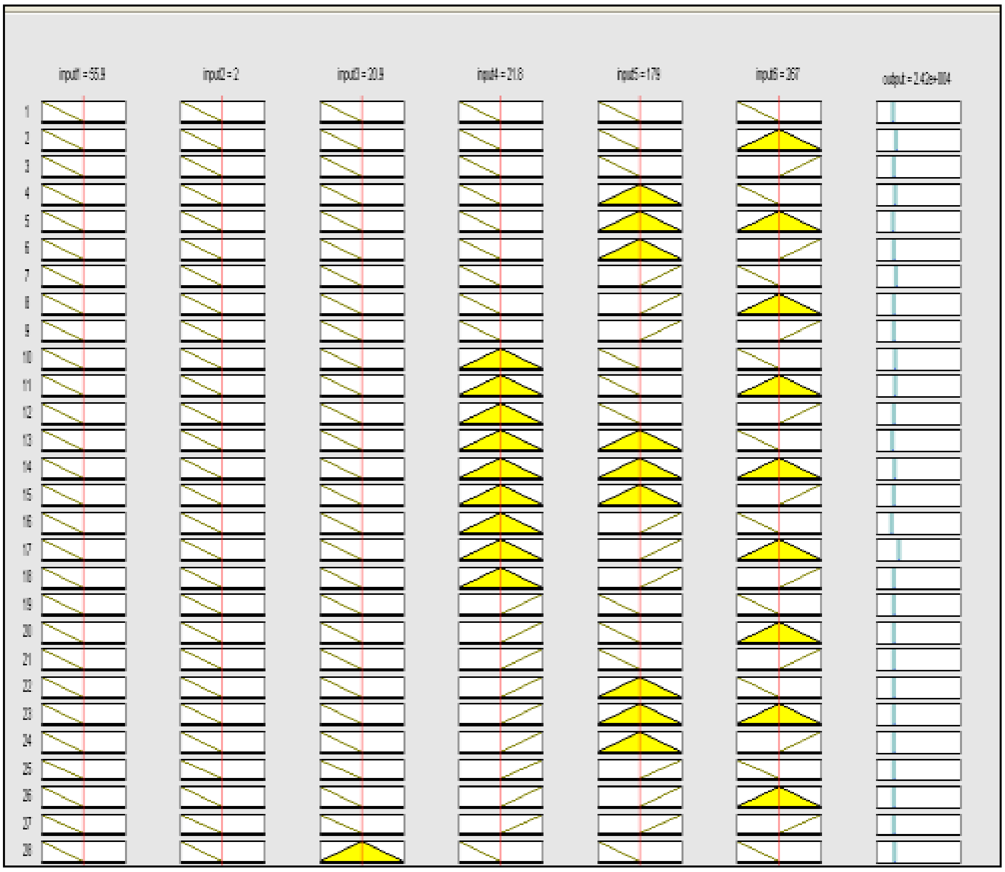

Fig. 6.8 ANFIS Prediction Model Rule Base.

Table 6.12

Predicted monthly average solar radiations (kWh/m^2/day) of 10 selected cities of Himachal Pradesh for Year 2017 using ANFIS.

Sr. No	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
1	2.50 (2.45)*	3.56 (2.97)	4.55 (4.65)	5.11 (5.02)	6.03 (5.78)	4.54 (4.24)	3.99 (4.11)	3.33 (3.12)	4.27 (4.08)	4.50 (4.67)	3.23 (3.44)	2.86 (3.11)	**4.04 (3.97)**
2	4.11 (4.21)	5.24 (5.15)	6.65 (6.44)	7.16 (7.01)	7.04 (6.75)	5.76 (5.45)	4.23 (4.03)	4.55 (4.13)	5.88 (5.31)	4.96 (4.49)	4.88 (4.57)	4.32 (4.13)	5.39 (5.13)
3	4.22 (4.60)	4.16 (4.31)	5.75 (5.54)	5.45 (6.21)	6.05 (6.2)	6.23 (5.94)	5.66 (5.10)	4.66 (4.86)	5.79 (5.36)	6.18 (5.86)	4.55 (4.84)	4.22 (4.41)	5.24 (5.25)
4	4.33 (4.47)	5.65 (5.31)	7.21 (6.87)	6.66 (6.81)	7.15 (7.34)	4.76 (4.96)	6.23 (5.82)	5.27 (4.87)	5.44 (5.68)	5.23 (5.70)	4.79 (5.14)	4.41 (4.01)	**5.59 (5.58)**
5	3.33 (4.11)	4.93 (4.67)	5.21 (5.82)	5.88 (5.41)	5.33 (5.92)	5.88 (5.32)	5.23 (4.71)	4.89 (4.16)	4.75 (4.27)	4.91 (4.52)	4.44 (4.86)	4.86 (4.49)	4.97 (4.85)
6	3.24 (4.44)	4.21 (4.9)	5.87 (4.89)	6.24 (5.71)	5.65 (5.14)	5.54 (5.17)	4.10 (4.72)	3.33 (4.11)	4.98 (4.55)	5.55 (4.87)	4.77 (4.23)	3.34 (3.88)	4.73 (4.72)
7	4.1 (4.73)	4.81 (5.12)	6.1 (6.79)	6.33 (7.21)	7.44 (6.95)	6.48 (6.99)	5.21 (5.88)	4.19 (4.86)	5.07 (5.62)	5.33 (4.85)	4.11 (5.64)	4.10 (4.88)	5.27 (5.79)
8	4.21 (4.15)	5.74 (6.02)	6.19 (6.53)	7.57 (7.14)	6.12 (6.92)	5.31 (5.11)	4.57 (4.84)	4.44 (4.19)	5.11 (6.26)	4.86 (5.87)	4.43 (5.31)	4.18 (3.89)	5.22 (5.52)
9	4.15 (4.27)	4.21 (5.55)	5.29 (5.86)	7.07 (6.42)	6.51 (7.11)	5.55 (6.35)	5.28 (5.83)	4.15 (5.43)	4.84 (5.11)	4.70 (4.34)	4.08 (4.61)	3.55 (4.28)	4.86 (5.43)
10	4.44 (4.75)	4.74 (5.25)	4.76 (4.97)	6.44 (6.88)	5.16 (6.55)	4.40 (4.85)	4.24 (4.87)	4.83 (4.11)	5.86 (5.15)	4.77 (4.12)	4.7 (4.88)	4.38 (5.29)	4.89 (5.13)

Table 6.13

Actual and ANFIS Predicted Annual Average values of Solar Radiations for 10 selected cities of Himachal Pradesh for Year 2017.

Sr. No.	Actual SR	Predicted SR	% MAPE
1	3.97	4.04	1.76
2	5.13	5.39	5.06
3	5.25	5.24	**0.19**
4	5.58	5.59	0.17
5	4.85	4.97	2.47
6	4.72	4.73	0.21
7	5.79	5.27	8.98
8	5.52	5.22	5.43
9	5.43	4.86	**10.49**
10	5.13	4.89	4.76
	Average MAPE		**3.95 %**

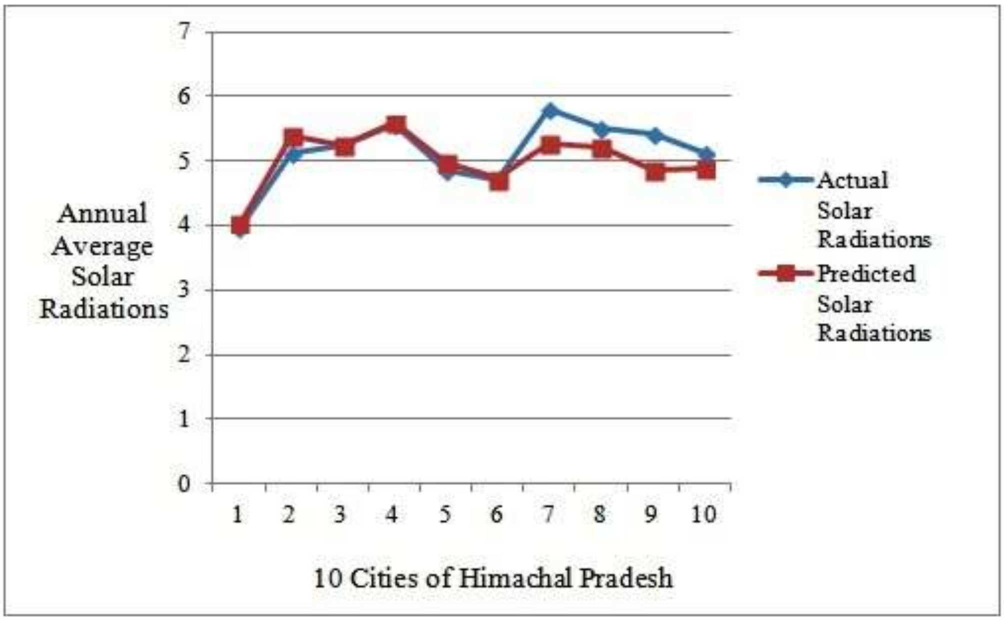

Fig. 6.9 Plot between Actual and Predicted Solar Radiations for Year 2017 using ANFIS.

7. RESULTS AND ANALYSIS

In the present research, two diverse modelling techniques have been proposed to get the predicted solar radiations, first is ANN and second one is ANFIS using different set of input combinations to get the near accurate results.

7.1 RESULTS OF PREDICTION MODELS FOR ONE SITE BASED ON ANN AND ANFIS

In first model the solar radiations prediction is done for a particular site i.e. Bara Dol, Himachal Pradesh and results have been obtained using ANN techniques. Three models suggested are named ANN-1, 2 and 3 using different number of inputs for each model as given in chapter 4. MSE and MAPE calculation has been done from these models and depending upon these parameters, the most influential input variables are being suggested as given in Table 7.1.

Table 7.1

Results of Solar Radiations Prediction Models using ANN having different number of Inputs for Year 2014.

Sr. No.	**MLP Structure**	**R for Training**	**ANN Model**	**Maximum MAPE**
1.	**6-16-1**	**87.48**	**ANN-1**	**6.33%**
2.	5-15-1	83.71	ANN-2	13.25%
3.	4-18-1	85.37	ANN-3	19.60%

For the year 2014 for which the data has been used for prediction, the annual MAPE comes out to be 2.39%. Solar radiations for this site for year 2015, 2016 and 2017 have been predicted using the proposed model. It has been observed from the prediction of solar radiations of these years that prediction values fall very near to the experimental values and within the permissible limits of prediction accuracy error as given in Table 7.2. For year 2015, the annual MAPE comes out to be 3.49% whereas for years 2016 and 2017 it comes out to be 4.56% and 2.45% respectively which is very accurate value of prediction. The solar radiations for these three years vary in between 2.19-5.96 kWh/m^2/day.

Table 7.2

Solar Radiations Predictions using ANN-1.

Sr. No.	Prediction Model	% MAPE for Year 2014	% MAPE for Year 2015	% MAPE for Year 2016	% MAPE for Year 2017
1.	**ANN-1**	2.39%	3.49%	4.56%	2.45%

Based on the best inputs chosen for ANN-1 proposed model, the second type of technique used in chapter 5 is ANFIS for prediction of global solar radiations for the same site for years 2015, 2016 and 2017 as given in Table 7.3. Year 2014 annual MAPE is calculated to be 0.47%. The annual MAPE for year 2015 has been predicted 1.99% whereas for 2016 it has been calculated as 2.64%. For year 2017 the annual MAPE has been calculated to be 1.47% which is again very good prediction as given in Table 7.4. The solar radiations for years 2015-17 vary in between 2.63-6.18 kWh/m^2/day.

Table 7.3

Results of site specific Solar Radiations Prediction Model using ANFIS.

Sr. No.	Name of Prediction	Prediction Model	No. of Rules Formulated	No. of Epochs	% Annual MAPE
1.	Global Solar Radiations	**ANFIS**	64	3	**0.47**

Table 7.4

Solar Radiations Predictions using ANFIS.

Sr. No.	Prediction Model	%MAPE for Year 2014	%MAPE for Year 2015	%MAPE for Year 2016	%MAPE for Year 2017
1.	**ANFIS**	0.47%	1.99%	2.64%	1.47%

7.2 RESULTS OF PREDICTION MODELS FOR 10 SELECTED CITIES OF HIMACHAL PRADESH USING ANN AND ANFIS

In chapter 6, first an ANN based technique for estimation of solar radiations has been suggested for 10 different selected cities of Himachal Pradesh using ten years data taken from IMD, Pune to predict the solar radiations for year 2017. Here also three different models based on ANN are being suggested named as SRPM-1, 2 and 3. The model with least MAPE i.e. SRPM-1 model has been proposed for prediction of solar radiations for 10 cities of Himachal Pradesh. The prediction accuracy of each model with the selected MLP structure has been evaluated by calculating Maximum MAPE. The value of MAPE ≤ 10 % is taken as very high prediction ≥ 10 % and ≤ 20 % gives good prediction accuracy whereas ≥ 20 % indicates reasonable or average prediction. In this research it has been found out that maximum MAPE for SRPM-1, 2 and 3 is 6.31%, 8.01%, 10.99% respectively as given in Table 7.5. It is also evident from the results that when all the six input parameters are considered then the error is minimum and less than high accuracy percentage of 10% considered for MAPE calculation whereas when some input parameters like latitude, longitude and sunshine are not considered in SRPM-2 and 3 then the prediction accuracy decreases sharply. The prediction accuracy has been decreased by 4.68% for SRPM-3 model where latitude and longitude have not been considered whereas best MAPE results have been calculated for SRPM-1 where the maximum MAPE comes out to be 6.31%. It is also clear from the results that the predictions are more accurate with sunshine hours and latitude, longitude of the location.

Table 7.5

Results of Solar Radiations Prediction Models using ANN for 10 selected cities of Himachal Pradesh for year 2017.

Sr. No.	**Hidden Layers Selected**	**MLP Structure**	**R for Training**	**ANN Model**	**Maximum MAPE**
1.	**8-18**	**6-10-1**	**90.73**	**SRPM-1**	**6.31%**
2.	7-17	5-11-1	92.38	SRPM-2	8.01%
3.	6-16	4-9-1	92.46	SRPM-3	10.99%

Thus SRPM-1 model is being proposed for the solar radiations prediction as it has the least percentage of maximum MAPE. The prediction for the monthly average daily solar radiations has been given for the 10 selected cities based on SRPM-1 prediction model. The monthly average solar radiations predicted are between 4.03-5.42 (kWh/m^2/day) for the 10 selected cities of Himachal Pradesh for year 2017 as given in Table 7.6.

Table 7.6

Solar Radiations Predictions using SRPM-1 for 10 cities of Himachal Pradesh.

Sr. No.	**Prediction Model**	**Predicted Solar Radiations (kWh/m^2/day)**	**% Average Annual MAPE for Year 2017**
1.	**SRPM-1**	4.03-5.42	**5.2%**

Using the predicted values for 2017 of annual solar radiations the values for solar radiations are predicted for the year 2018. Similarly by using the values for year 2018 next year’s prediction has been done. In this work total prediction of five years have been done from year 2017-2021, taking into consideration the various climatic conditions as used previously.

The monthly average solar radiations predicted are between 3.87-5.44 (kWh/m^2/day) for the 10 selected cities of Himachal Pradesh for five years from 2017-2021. The average MAPE calculated for SRPM-1 model used for this prediction for year 2017 comes out to be 5.2% when calculated from the actual and experimental solar radiations values.

Depending upon the finest model chosen using ANN i.e. SRPM-1 for estimation of solar radiations for ten cities of Himachal Pradesh the second type of technique used in chapter 6 is ANFIS. To get the required estimation model 101 rules have been suggested. 10 number of epochs are being used. The annual average MAPE for year 2017 is calculated to be 3.5% as given in Table 7.7.

Table 7.7

Solar Radiations Predictions models using ANFIS for 10 cities of Himachal Pradesh.

Sr. No.	Prediction Model	Predicted Solar Radiations ($kWh/m^2/day$)	% Average Annual MAPE for Year 2017
1.	**ANFIS**	4.04-5.59	**3.5 %**

7.3 COMPARISON OF RESULTS BETWEEN ANN AND ANFIS MODELS

An assessment between ANN and ANFIS prediction model has been given in Table 7.8 based on the site specific model. It can be observed that the prediction accuracy in case of ANFIS is superior as compared to ANN-1 prediction model. It is very evident that both the models have high exactness of prediction and can be used to predict solar radiations for solar system.

Table 7.8

Comparison of Solar Radiations Prediction Models using ANN and ANFIS.

Sr. No.	Prediction Model	%MAPE for Year 2014	%MAPE for Year 2015	%MAPE for Year 2016	%MAPE for Year 2017
1	**ANN-1**	6.33%	3.49%	4.56%	2.45%
2	**ANFIS**	0.47%	1.99%	2.64%	1.47%

Table 7.9

Comparison between Solar Radiations Radiations Prediction Models using ANN and ANFIS for 10 cities of Himachal Pradesh.

Sr. No.	Prediction Model	Predicted Solar Radiations ($kWh/m^2/day$)	% Average Annual MAPE for Year 2017
1	**SRPM-1**	4.03-5.42	**5.2 %**
2	**ANFIS**	4.04-5.59	**3.5 %**

For ANN based SRPM-1 model and ANFIS based prediction model as given in Table 7.9, it has been observed that the error in case of ANFIS is less as compared to ANN dependent model. Hence ANFIS can be suggested for highly accurate estimation models. The error in case of ANFIS is 1.7% less as compared to ANN based technique.

When compared with the existing empirical for validation models widely used [5] and [6], it is established that the estimation exactness of suggested models is as good as empirical models. Comparison for Hamirpur city annual average global solar radiations has been given in table 7.10 which is very close to one another. Hence the accuracy of the suggested models has been established.

Table 7.10

Comparison between Empirical and Suggested Models for Hamirpur City.

Sr. No.	ANN Annual Average Prediction ($kWh/m^2/day$)	ANFIS Annual Average Prediction ($kWh/m^2/day$)	Empirical Model Annual Average Prediction ($kWh/m^2/day$)
1.	4.03	4.04	3.92

8. CONCLUSION

The estimation of solar radiations has immense importance to exploit the solar energy utilization for the generation of power. The present research attempts to predict the solar radiations accurately in different cities of Himachal Pradesh by using different soft computational approaches, i.e., ANN and ANFIS. It has been established that Himachal Pradesh is potentially very well situated with reverence to the solar potential. The study also demonstrates that sunshine hours are very important variable for any prediction model, but if it is unenviable at some places ANN-2 model can be used for estimation of solar radiations, however then the prediction accuracy decreases. ANN-1 model is the best model for the prediction of any site specific solar radiations as it has all the variables which are influencing the prediction.

The other aspect of this research focuses upon 10 selected cities of Himachal Pradesh so as to extend the ambit of its study to a comparatively larger region for best estimation of solar radiations with high accuracy. Furthermore, in this research stress has been laid to assess the most dominant parameters for the calculation of average daily solar radiations input parameters using ANN. Out of the given input parameters it has been observed in present research that latitude, longitude and sunshine hours have the maximum effect on the prediction of solar radiations predictions compared to other input parameters. The three SRPM models have been suggested and maximum MAPE for every model has been calculated. The value of MAPE is in the range of $\leq$ 10% for SRPM-1 model which indicates high prediction accuracy of this model. Based on this prediction model the assessment of solar radiations has been done for the next four years. In the course of evaluation it has also been tried to predict solar radiations for the various months of the year. In all the predictions using SRPM-1, monthly predictions have been done for selected 10 cities of Himachal Pradesh for four years.

In another aspect of the study, the solar radiations have been predicted for the same sites cited above using another computing technique ANFIS; it has been proposed that the radiations can be estimated using and mounting only one model at various sites. The same inputs are considered for prediction as in the ANN-1 model and SRPM-1 model. The current study shows the estimation of various parameters for establishing of solar power stations at far-flung in addition to other sites where solar radiations data is not so simply on hand. It can thus be summed up that the preferred outputs can be obtained from the final structures using different available meteorological inputs. The range from minimum to maximum can be fixed for each and every input. Therefore, by using the ANFIS model of prediction global solar radiations can be predicted with high accuracy. It has been seen that the results are more accurate while prediction is done with ANFIS model as compared to ANN model. The MAPE calculated using ANFIS is lesser as compared to the ANN technique. Moreover using these techniques predictions for the next years i.e. 2018, 2019, 2020 and 2021 have also been done based on the models developed.

Thus, in the discussed models, the different parameters for the prediction of solar radiations have been chosen depending upon the error and accuracy of predictions. Next year's predictions have been done and their accuracy has also been calculated which falls within the limits of high accuracy prediction models, depending upon the most influential input parameters,

For validation of proposed model with the experimental data, the experimental data for year 2017 has been taken from HPPCL and Indian Meteorological Department, Pune. The estimated solar radiations have been checked against the experimental solar radiations. It has been found out that the MAPE calculated from the comparison is very less which means that the proposed model lies within the very high accuracy limit. Further it has been compared with the proposed model using ANFIS and it has more accurate results as compared to the ANN based prediction model. It concludes that the prediction model proposed using ANFIS is superior to the ANN proposed model.

Now by selecting these two proposed models, the prediction of solar radiations can be extended to the other sites also. The proposed model is capable of predicting the solar radiations at other places too only by giving the number of inputs. For the best prediction it is required that all the inputs are available but still if some inputs are not there then other models based on ANN where lesser number of inputs have been used can be taken into consideration for prediction of global solar radiations.

Hence would be apt to sum up that solar radiations at any place can be predicted using the discussed models. Therefore, the solar radiations for different seasons of the year can be predicted.

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APPENDIX-A

TERMINOLOGY

Absorber: In a photovoltaic device, the material that readilyabsorbs photons to generate charge carriers (free electrons or holes).

Activation Voltage (s): The voltage (s) at which a charge controller will take action to protect the batteries.

Algorithm: The set of simple instructions that combine to complete a task. Computer codes are algorithms.

Ampere-Hour (Ah/AH): A measure of the flow of current (in amperes) over one hour; used to measure battery capacity.

Angle of Incidence: The angle that a ray of sun makes with a line perpendicular to the surface. For example, a surface that directly faces the sun has a solar angle of incidence of zero, but if the surface is parallel to the sun (for example, sunrise striking a horizontal rooftop), the angle of incidence is 90°.

Azimuth Angle: The angle between true south and the point on the horizon directly below the sun.

Cell (battery): A single unit of an electrochemical device capable of producing direct voltage by converting chemical energy into electrical energy. A battery usually consists of several cells electrically connected together to produce higher voltages. (Sometimes the terms cell and battery are used interchangeably). Also see photovoltaic (PV) cell.

Diffuse Insolation: Sunlight received indirectly as a result of scattering due to clouds, fog, haze, dust, or other obstructions in the atmosphere.

Direct Beam Radiation: Radiation received by direct solar rays.

Direct Insolation: Sunlight falling directly upon a collector.

Gigawatt (GW): A unit of power equal to 1 billion Watts; 1 millionkilowatts, or 1,000 MWs.

Global Horizontal Radiation: Total solar radiation; the sum of direct, diffuse, and ground-reflected radiation; however, because ground reflected radiation is usually insignificant compared to direct and diffuse, for all practical purposes global radiation is said to be the sum of direct and diffuse radiation only.

Global (total) Normal Solar Irradiance: All radiation that strikes a flat surface that faces the sun, while direct normal solar irradiance excludes all radiation that does not come from the direction of the sun in the sky.

Grid-Connected System: It is a solar electric or photovoltaic (PV) system in which the PV array acts like a central generating plant, supplying power to the grid.

Hybrid System: A solar electric or photovoltaic system that includes other sources of electricity generation, such as wind or diesel generators.

Insolation: The solar power density incident on a surface of stated area and orientation, usually expressed as Watts per square meter

Incident Radiation: Incoming radiation; i. e., radiation that strikes a surface.

Irradiance: The direct, diffuse, and reflected solar radiation that strikes a surface. It is usually expressed in kilowatts per square meter. Irradiance multiplied by time equals insolation.

Kilowatt (kW): A standard unit of electrical power equal to 1000 watts, or to the energy consumption at a rate of 1000 joules per second.

Kilowatt-Hour (kWh): 1,000 thousand watts acting over a period of 1 hour. The kWh is a unit of energy. 1 kWh=3600 kJ.

Latitude: The angular distance from the equator to the pole. The equator is 0°, the North Pole is 90° North, and the South Pole is 90° South.

Longitude: The East-West angular distance of a locality from the Prime Meridian. The Prime Meridian is the location of the Greenwich Observatory in England and all points North and South of it.

Mega Watt (MW): 1,000 kilowatts, or 1 million watts; standard measure of electric power plant generating capacity.

Photovoltaic(s) (PV): Pertaining to the direct conversion of light into electricity.

Photovoltaic (PV) Cell: The smallest semiconductor element within a PV module to perform the immediate conversion of light into electrical energy (direct current voltage and current).

Photovoltaic (PV) System: A complete set of components for converting sunlight into electricity by the photovoltaic process, including the array and balance of system components.

Photovoltaic-Thermal (PV/T) System: A photovoltaic system that, in addition to converting sunlight into electricity, collects the residual heat energy and delivers both heat and electricity in usable form.

Solar Energy: Electromagnetic energy transmitted from the sun (solar radiation). The amount that reaches the earth is equal to one billionth of total solar energy generated, or the equivalent of about 420 trillion kilowatt per hours.

Solar Irradiance: The amount of solar energy that arrives at a specific area of a surface during a specific time interval (radiant flux density). A typical unit is W/m^2.

Solar Radiation: The electromagnetic radiation emitted by the sun.

Sunshine: Used interchangeably with the more precise term bright sunshine, when the sun casts an obvious shadow or when a Campbell-Stokes sunshine recorder is recording, usually above 210 W/m^2.

Sunshine Duration: The length of time for which the sun casts an obvious shadow or when a Campbell-Stokes sunshine recorder is recording. The lower limit for bright sunshine (based on a Campbell-Stokes recorder) is between 70 W/m^2 (very dry air) and 280 W/m^2 (very humid air).

Solar Thermal Electric Systems: Solar energy conversion technologies that convert solar energy to electricity, by heating a working fluid to power a turbine that drives a generator.

LIST OF PUBLICATIONS

[1] Mohan A, Kuchhal P, Sharma MG. Effect of meteorological parameters on prediction of daily solar radiations. International Journal of Applied Engineering Research. 2016; 7: 5304–5311.

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BRIEF BIO-DATA

Mr. Anand Mohan is currently serving the Shimla University, Shimla as Faculty in the Department of Electrical Engineering. He has done his Master's of Engineering (M.E.) in Instrumentation & Control from Electrical Engineering Department, NITTTR, Panjab University, Chandigarh. He has played vital role in the implementation of Choice Based Credit System (CBCS), Academic policies and establishing different labs of the department. He is having more than 14 Years of academic, administrative and research experience in the field of Electrical Engineering. His main areas of research are solar, renewable energy and load forecasting. He has published more than 30 research manuscripts in various International & National journals of repute. He has also presented papers in International and National conferences.

He is the member of various International & National professional & academic bodies. He is the part of many international Journals of repute of Electrical & Renewable Energy as Reviewer. He has guided the students in their M. Tech dissertations. He is also the Member of Institution of Engineers (India), Kolkata, India. He is an active participant of various Seminars, Induction and Faculty Development Programmes. He has also been invited for guest lecturers in the Short Term Courses at various institutes like NITTTR etc.