ISSN 2347 - 3983
Volume 8. No. 9, September 2020
International Journal of Emerging Trends in Engineering Research
Available Online at http://www.warse.org/IJETER/static/pdf/file/ijeter78892020.pdf
https://doi.org/10.30534/ijeter/2020/78892020

Solar Irradiance Prediction Model design by hybrid of ANFIS with Simulated Annealing Mechanism

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ABSTRACT

The physical interaction between the hydrological variables (such as solar irradiation, evapotranspiration) with solar irradiance is highly nonlinear, stochastic, and complex. The solar power prediction models can be divided into two groups, namely, i) physical and ii) system theoretic. The main drawback of the physical model is the complexity of the models, which increases with increase in model parameters. Further, the development of these models is based on understanding of the physical processes in the system. On the other hand, the system theoretic model is based on data driven techniques, where the mapping or learning of the models is done through data itself. Here, the understanding of the physical process in model building is avoided to a large extent. For this SA and ANFIS, both Artificial Intelligence techniques are used to a great extent.

Key words: Solar irradiation , ANFIS, SA, Solar power.

1. INTRODUCTION

The significance of strength for the life of human society can't be overemphasized. Solar electricity is the essential source of energy in each city and rural India. Besides, it's far an essential source of all electricity assets for the agricultural and the industrial zone. Being an vital and necessary a part of the energy source, its availability depends on the sun irradiation and recharge situations. Till currently it have been considered as a dependable source of uncontaminated energy [12].

Total top off capable sun irradiation useful resource of Uttar Pradesh could be very excessive, out of which present general extraction is ready 30% and the net exploitation is 40% which is 65.9% of total extraction. Thus the sun irradiation aid to be had for destiny exploitation may be very huge. However, this useful resource is unevenly disbursed in area and the existing nation of exploitation has resulted in local solar irradiation imbalances. It is anticipated that for home, commercial and agriculture desires of growing populace, the extent of solar irradiation exploitation will boom i.E. Requirement of solar irradiation can be greater than double the prevailing level. Due to this the variety of over-exploited blocks may growth by using the 12 months 2025. (These represent the blocks where the drawls are more than recharge).

The ever growing demand for enegy has brought about electricity scarcity in many parts of the arena. The situation is annoyed by way of the hassle of pollution or infection. India is heading towards a enegry disaster particularly because of mistaken control of energy sources and environmental degradation, which has lead to a lack of access to strength supply to millions of people. This disaster is already obvious in many elements of India, varying in scale and depth relying mainly on the time of the 12 months [13][14].

Energy crisis is not the result of herbal factors; it has been as a result of human moves. During the past two decades, the electricity level in numerous components of the use of a has been falling swiftly due to an increase in extraction. India's unexpectedly growing population and converting life has additionally multiplied the domestic need for strength. The requirement for the industry also suggests an normal boom. Intense competition amongst customers — agriculture, enterprise, and domestic sectors — is driving the energy supply decrease than the demand. Thus consistent monitoring of the solar irradiation tiers is extraordinarily crucial. The strength ranges if properly predicted properly in advance can assist the management to plot better solar irradiation usage. Also, for an general development of the basin, a non-stop forecast of the sun irradiation stages is needed to efficaciously use any simulation version for electricity control. These fashions based on determined information or theoretical concepts offer a framework for selection making for users and regulators [15].

2. RELATED WORK

It has emerge as a current style in gadget mastering to examine the general performance of SVM and NN, as said. In Rami S. R. Qahwaji, 2006, [1] works it modified into referred to that SVM has outperformed NNs. These packages variety from reputation of sleep spindles in EEG, assessment of hyperspectral records, credit score score assessment and olfactory indicators recognition. On the quick run we purpose to assess each algorithms to decide the splendid studying set of policies for our software.

Henrik Madsen,2009, [2] defined a cutting-edge approach to on line forecasting of electricity production from PV systems. The technique is ideal to online forecasting in masses of applications and in this paper it's miles used to are expecting hourly values of solar power for horizons of as much as 36 hours. The facts used is fifteen-minute observations of sun energy from 21 PV structures positioned on rooftops in a small village in Denmark. The advocated technique is a - degree method where first a statistical normalization of the sun

electricity is received using a easy sky model. The clear sky model is positioned the usage of statistical smoothing strategies.

Jianwu Zeng,2011, [3] proposed a assist vector device (SVM)-primarily based statistical model for wind strength forecasting (WPF). Instead of predicting wind energy right away, the proposed model first predicts the wind tempo, that is then used to are looking ahead to the wind power by using manner of the usage of the power-wind pace traits of the wind turbine turbines. Simulation research are done to validate the proposed model for very quick-term and shortterm WPF by the use of the statistics received from the National Renewable Energy Laboratory (NREL). Results show that the proposed model is correct for terribly quick-term and short-term WPF and outperforms the persistence model similarly to the radial foundation characteristic neural network-primarily based version.

The improvement of a method to forecast as it must be the strength produced by photovoltaic structures may be an crucial device for the dissemination and integration of such structures on the majority electricity grids. Thus, the aim of this observe become to forecast the strength production of a 1-MW photovoltaic energy plant in Kitakyushu, Japan, using a ultra-modern technique based totally on assist vector machines and on using several numerically expected weather variables, collectively with cloudiness. Finally, the use of numerically predicted cloudiness had an important feature inside the accuracy of the forecasts, and whilst cloudiness became not used, the foundation mean rectangular blunders of the forecasts improved extra than 32%, and the propose absolute error elevated more than 42%. The goal of Joao Gari da Silva Fonseca, 2012, [4] paintings changed into to forecast the strength production of a 1-MW PV electricity plant located in Kitakyushu, Japan, the usage of SVMs and numerically anticipated cloudiness.

The growing use of sun power as a source of strength has induced prolonged hobby in forecasting its power output over shorttime horizons. Short-time period forecasts are desired for operational making plans, switching sources, programming backup, reserve utilization, and top load matching. However, the output of a photovoltaic (PV) gadget is stimulated by means of using irradiation, cloud cover, and specific climate conditions. These factors make it tough to behavior brief-time period PV output forecasting. In Yuan-KangWu,2014 [5] paper, an experimental database of solar power output, sun irradiance, air, and module temperature data has been applied. It includes records from the Green Energy Office Building in Malaysia, the Taichung Thermal Plant of Taipower, and National Penghu University.

Precise predictions of wind electricity density play a big role in figuring out the viability of wind power harnessing. In reality, reliable prediction is specifically beneficial for operators and traders to offer a comfortable scenario with minimal monetary risks. In Kasra Mohammadi,2015, [6] paper, a brand new version based totally upon ELM (severe studying device) is offered to estimate the wind power density. Generally, the two-parameter Weibull function has been usually used and identified as a dependable method in wind power estimations for most windy areas.

3. METHODOLOGY

Simulated annealing (SA) is a generic probabilistic meta-algorithm for the global optimization problem, namely locating a good approximation to the global optimum of a given function in a large search space. It is often used when the search space is discrete.

THE TECHNIQUE OF SIMULATED ANNEALING

Simulated annealing [8] is a method for optimisation based on a controlled random walk on the *error surface* (the multidimensional generalisation of the error curve shown in Fig.1). Starting at some random point (1) on this surface, the error, $E1$, is evaluated from the model and data. A nearby point (2) is chosen at random and the error, $E2$, evaluated (see Figure 1). If the new point has a lower error, the search moves there and the process is repeated. However, if it has a higher error (as shown), there is still a chance of moving there. The probability for this is chosen to be $p = e\ (-\Delta E/k\ T)$, as the analogy to statistical mechanics suggests [9]. This probability ranges between 1 and 0 for very small and very large error differences respectively. In other words, 'uphill' moves are permitted, albeit with decreasing probability for larger differences. This has the effect of managing to 'escape' local minima, and hence permits a more comprehensive search of the parameter space. The quantity kT in the equation determines exactly how probable an uphill move of a certain size is: a large kT makes comparatively large uphill moves more likely. The idea behind simulated annealing is to reduce T slowly (for a fixed k) as the search proceeds. This initially permits a large region to be searched. As time proceeds (and T is reduced), large uphill moves become increasingly prohibited, thereby focusing attention on finding what is hopefully the global minimum of the parameter space.

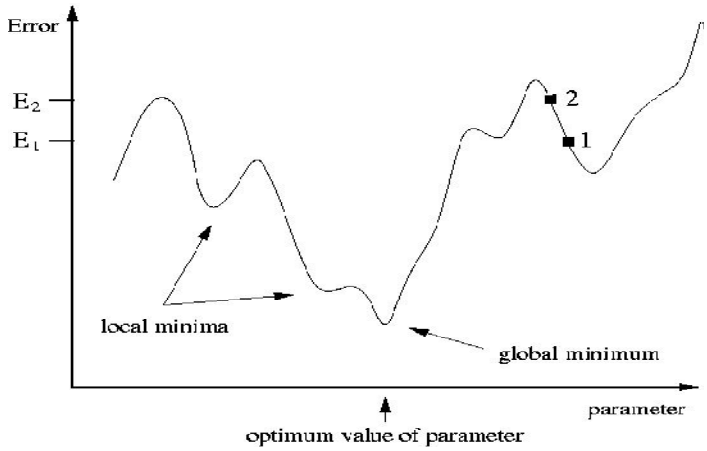

Figure 1: The Error of a Model's Predictions as a Function of Its One Free Parameter. [7]

SIMULATED ANNEALING ANALOGY

Simulated annealing (SA) is one of the most versatile techniques applicable for solving combinatorial problems. Because many real world design problems can be cast in the

form of such optimization problems, there is intense interest in general techniques for their solution. Simulated Annealing is one such technique, rather old, [8]. It is motivated to an analogy of annealing in solids. To understand such a situation, consider how to force a solid into a low energy state. A low energy state is a highly ordered state, such as crystal lattice. To achieve this, a material is annealed, heated to a temperature that permits many atomic arrangements, then cooled carefully, slowly, until the material freezes into a good crystal [16]. SA uses an analogous set of controlled cooling operations for non-physical optimization problems. Interest in such technique is because some optimization problems could be solved in a reasonable time. Simulated annealing is a local search algorithm (metaheuristics) competent enough of escaping from local optima. Its ease of implementation, convergence properties and its use of hill-climbing moves to escape local optima have made it a well-accepted technique. It is normally used to deal with discrete, and to a lesser degree, continuous optimization problems. The main benefit of SA is that it can be useful to large problems regardless of the conditions of differentiability, continuity, and convexity that are normally necessary in conventional optimization methods. Annealing is the process of submitting a solid to high temperature, with successive cooling, so as to achieve high-quality crystals (i.e., crystals whose structure form perfect lattices) [9]. Simulated annealing emulates the physical process of annealing and was originally proposed in the domain of statistical mechanics as a means of modelling the natural process of solidification and formation of crystals. During the cooling process, it is assumed that thermal equilibrium (or quasi equilibrium) conditions are maintained. The cooling process ends when the material reaches a state of minimum energy, which, in principle, corresponds with a perfect crystal. It is known that defect-free crystals (i.e., solids with minimum energy) are more likely to be formed under a slow cooling process. The two main features of the simulated annealing process are: (1) the transition mechanism between states and (2) the cooling schedule. When applied to combinatorial optimization, simulated annealing aims to find an optimal configuration (or state with minimum "energy") of a complex problem. The objective function of an optimization problem corresponds with the free energy of the material. An optimal solution is associated with a perfect crystal, whereas a crystal with defects corresponds with a local optimal solution. The analogy is not complete, however, because in the annealing process there is a physical variable that is the temperature [17], which under proper control leads to the formation of a perfect crystal. When simulated annealing is used as an optimization technique, the "temperature" becomes simply a control parameter that has to be properly determined in order to achieve the desired results. The original idea behind the simulated annealing algorithm is the Metropolis algorithm that models the microscopic behaviour of sets of large numbers of particles, as in a solid, by means of Monte Carlo simulation. In a material, the individual particles have different levels of energy, according to a certain statistical distribution. The possible lowest level of energy, known as the fundamental level, corresponds with the state where all particles stand still and occurs at temperature 0^0 K. For temperatures above that level, the particles will occupy different levels of energy, such that the number of particles in each level decreases as the energy level increases (i.e., the maximum number of particles is found in the fundamental level). The distribution of the particles in the various levels varies with the temperature; for T = 0 K, for example, all particles are in the fundamental level; as the temperature increases, more particles are found in higher energy levels but always as a decreasing function of the energy level. The Metropolis algorithm generates a sequence of states of a solid as follows: giving a solid in state Si, with energy Ei, the next state Sj is generated by a transition mechanism that consists of a small perturbation with respect to the original state, obtained by moving one of the particles of a solid chosen by the Monte Carlo method. Let the energy of the resulting state, which also is found probabilistically, be Ej; if the difference [Ej-Ei] is less than or equal to zero, the new state Sj is accepted. Otherwise, in case the difference is greater than zero, the new state is accepted with probability [18].

$$\exp\left\{\frac{Ei-Ej}{k_B T}\right\}$$

Where, T is the temperature of the solid and k_B is the Boltzmann constant. This acceptance rule is also known as Metropolis criterion and the algorithm summarized above is the Metropolis algorithm [11]. The temperature is assumed to have a rate of variation such that thermodynamic equilibrium is reached for the current temperature level, before moving to the next level. This normally requires a large number of state transitions of the Metropolis algorithm. For a combinatorial optimization problem to be solved by simulated annealing, it is formulated as follows: let G be a finite, although perhaps very large, set of configurations and v the cost associated with each configuration of G. The solution to the combinatorial problem consists of searching the space of configurations for the pair (G, v) presenting the lowest cost. The SA algorithm starts with an initial configuration G_0 and an initial "temperature" T_0 and generates a sequence of configurations $N = N_0$. Then the temperature is decreased; the new number of steps to be performed at the temperature level is determined, and the process is then repeated. A candidate configuration is accepted if its cost is less than that of the current configuration. If the cost of the candidate configuration is bigger than the cost of the current configuration, it still can be accepted with a certain probability. This ability to perform uphill moves allows simulated annealing to escape from local optimal configurations. The entire process is controlled by a cooling schedule that determines how the temperature is decreased during the optimization process.

SIMULATED ANNEALING ALGORITHM

Evolutionary algorithms, simulated annealing and tabu search are widely used heuristic algorithms for combinatorial optimization. The term evolutionary algorithm is used to refer to any probabilistic algorithm whose design is inspired by evolutionary mechanisms found in biological species [9]. One of the most widely known of heuristic algorithms is simulated annealing (SA) algorithm. SA exploits an analogy between the way in which a metal cools and freezes into a minimum energy crystalline structure (the annealing process) and the search for a minimum in a more general system [8]. In the optimization process, the solution randomly walks in its

neighbourhood with a probability determined by Metropolis principle while the system temperature decreases slowly; when the annealing temperature is closing zero, the solution stays at the global best solution in a high probability. [9]

The application of SA in optimization problem is formulated as an NLP problem, expressing the objective function and constraint functions in term of the specified independent variables. The objective function is expressed as

Optimize f(x)

Such that 'x' exists within the n-dimensional feasible region D:

X ı D, where

D = {x | x >=0, $g_i(x)$ <=0, $_{hi}(x)$ = 0, i=1 to n}

In the above equations, f(x), $g_i(x)$ are real valued scalar functions and vector x comprises the n principal variables for which the optimization is to be performed. The function f(x) is called to be objective function, for which the optimal value of x result in the maximum value for f(x), and these optimal values satisfy the given constraints.

Algorithm: [10]

Simulated Annealing
Begin
Initialize (T_0,N_0);
K: = 0;
Initial configuration S_i
Repeat procedure
Do L: =1 to Nk
Generate (S_j from S_i);
If $f(S_i) \leq f(S_j)$ do $S_i = S_j$
Otherwise
If exp{($f(S_i)$-$f(S_j)$/Tk) >random [0,1] do $S_i = S_j$;
End do;
K = K+1;
Calculation of the length (Nk);
Determine control parameter (Tk)
Stopping criterion
End;

From the current state S_i with cost $f(S_i)$, a neighbour solution S_j, with cost $f(S_j)$ is generated by the transition mechanism. The following probability is calculated in performing the acceptance test:

P_T{Accept S_j} = 1 if $f(S_j) \leq f(S_i)$, or
exp{($f(S_i)$-$f(S_j)$/Tk)}, if $f(S_j) > f(S_i)$

4. RESULT AND DISCUSSION

Here the ANFIS model has been trained and tested by ANFIS method and their performance for the best prediction model M-IV for clustering radius r=0.90 are evaluated and compared for training and testing data sets separately. The RMSE performances of the ANFIS model both for training and testing datasets have been plotted separately (shown in Fig. 2 and 3 below) and their corresponding range of values for all the four models are summerised in *table 4.6*. The comparative plot of all the four models M-I to M-IV are plotted below in fig. 4.

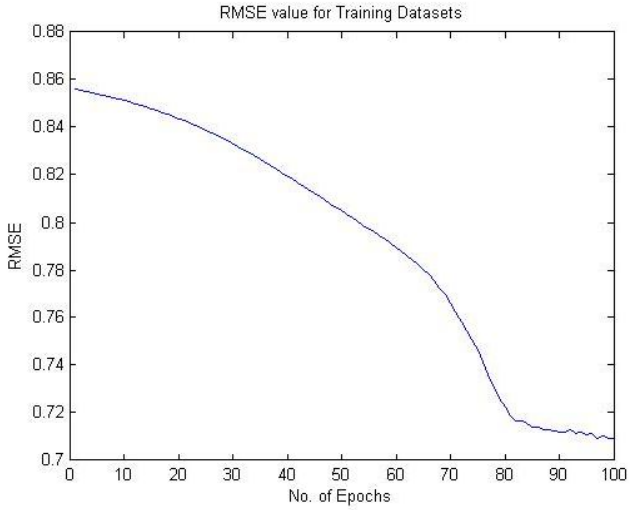

Figure 2: Graphical plot of RMSE value variation during ANFIS training for training datasets

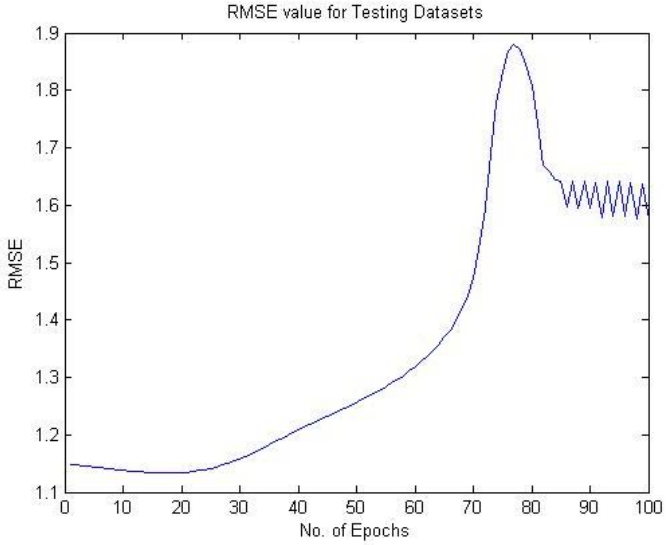

Figure 3: Graphical plot of RMSE value variation during ANFIS training for testing datasets

From graphical analysis of Fig. 2 and 3 it is inferred that during training phase (Fig. 2), there is sharp decline in the RMSE values as the number of epochs increases. Initially it is approximately 0.8560 and smoothens out at epoch number 81 to 0.7187. After that there is a gradual decline in the RMSE value, the minimum being 0.7090 at epoch 99. Hence during training phase there is initially a rise in the RMSE value and then there is a fall at epoch no. 99, after which there is again saturation. On the other hand, during testing phase (Fig. 3) of ANFIS training initially there is a sharp increase in the RMSE values upto epoch 75, then a sharp fall, followed by a zig-zag nature upto the end of the testing phase. The maximum value of RMSE is 1.88 at epoch 77 and the minimum RMSE value of 1.13 at epoch 17. From the above analysis it can be inferred that ANFIS has performed better during training phase than testing phase.

Table 1: Range of RMSE Val. during training and testing phase for different clustering radius for all the four models

Model	RMSE VALUE					
	r=0.5		r=0.75		r=0.90	
	Trg data	Tst. Data	Trg data	Tst. Data	Trg data	Tst. Data
M-I	0.41	10	0.64	2.46	***0.85***	***1.88***
M-II	0.92	2.12	1.1	1.47	1.17	1.21
M-III	0.47	7.47	0.69	2.7	0.87	2.24
M-IV	0.61	3.01	0.78	1.53	1	1.18

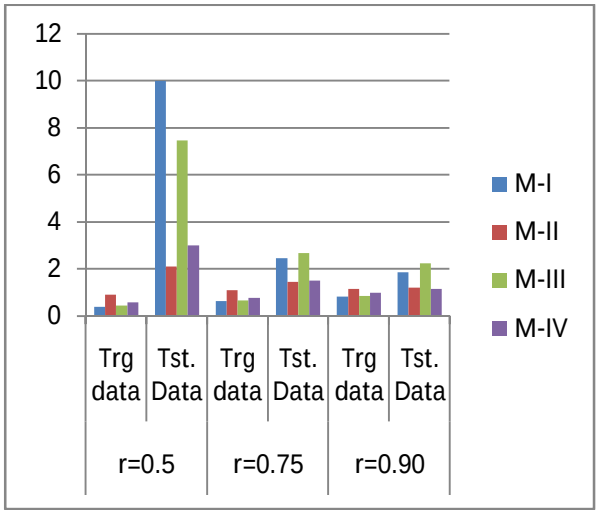

Figure 4: Graphical plot of Comparative RMSE values for different models

Further using the proposed methodology, for the case study mentioned above as related to real world data sets, it was found that ANFIS was able to develop best predictive model M-IV, having only irradiance power (watts) level input variables and irradiance power (watts) level as output variable as compared to other three models. This is clearly evident from the comparative table and graph given in Table 1 and Fig. 4 above. This was followed by M-I, M-II and in the last by M-III model based on RMSE values. M-I model has all the three input variable, viz. irradiance power (watts) level, solar irradiation and temperature, M-II model has irradiance power (watts) level and solar irradiation as input variables and the least developed model, M-III has irradiance power (watts) level and temperature as input variables. Hence, it was seen from the case study that the models that are developed using only irradiance power (watts) level, as input variables (M-IV model) perform very well as far as their prediction efficiency is concerned.

Further from the perusal of the data given in Table 1 it is also evident that the model performance has improved during testing phase as we go on increasing the clustering radius from 0.50 to 0.90 for all the models, whereas during the training phase the trend is just the reverse. This clearly demonstrated that clustering radius has an adverse effect on the performance of the ANFIS during training phase and vise-versa for testing phase. This can be confirmed from the Fig. 4 given above.

Thus, it is clear that proper selection of influential radius which affects the cluster results directly in ANFIS using subtractive clustering rule extraction method , has resulted in reduction of RMSE both for training and testing data sets. Hence, it is seen that for small size training data, ANFIS has performed well.

In order to depict how well ANFIS model has performed, a comparative plot of observed irradiance power (watts) level versus predicted irradiance power (watts) level, both for training and testing datasets using ANFIS technique has been shown in Fig. 5 using data given in Tables 2 and 3. From the graph it is seen that ANFIS model line almost closely follows the observed irradiance power (watts) level line, although the matching is better for training datasets.

Table 2: Comparative chart of Observed and ANFIS ouput WL values for training datasets

OBS. WL	ANFIS OP	OBS. WL	ANFIS OP	OBS. WL	ANFIS OP
3	3.101602	4.32	4.321523	3	3.690055
3.27	2.558733	5.7	5.441232	5.22	5.482093
3.8	3.06208	5.42	4.935216	2.45	2.98788
5.56	5.578889	3.81	4.11208	3.8	3.30865
6.03	4.377033	4.75	4.607641	3.61	4.16183
4.98	4.456122	5.93	5.89957	5.31	5.996201
5.96	5.06968	6.3	4.808206	4.65	3.654653
5.96	5.879401	5.72	5.434501	2.35	3.079244
2.01	3.189785	6.32	6.119223	3.08	3.765223
3.1	3.06201	6.62	6.545403	5.05	5.308596
3.22	3.86224	5.16	4.976374	1.82	2.230871
5.8	5.209993	5.83	5.557632	3.56	3.491151
4.2	4.401861	6.7	5.908139	4.82	4.042466
1.78	2.216577	6.62	6.829228	5.28	5.61417
3.36	4.004685	6.4	5.488647	2.9	4.215859
5.13	5.125159	5.72	6.210226	2.7	2.444321
2.52	3.364637	4.45	6.526844	4.34	3.160084
2.6	3.110817	6.25	5.991027	5.25	5.187266
3.47	3.259289	4.83	5.44044	5.46	3.961166
5.52	5.259987	4.2	3.983264	4.55	4.209965
1.54	3.58498	4.9	5.464421	5	4.88621
3.27	3.404366	6.3	6.022599	5.9	5.698675
		3.66	4.872378	4.58	3.995338
		3.22	3.116067	3.24	2.806226

Table 3: Comparative chart of Observed and ANFIS ouput WL values for testing datasets

OBS. WL	ANFIS OP	OBS. WL	ANFIS OP	OBS. WL	ANFIS OP
3.07	3.936361	6.3	5.753009	5.95	5.058211
5.15	5.036424	6.5	5.359636	6.01	6.67924
3.5	2.976008	6.87	6.447761	4.56	4.759738
4.1	2.784719	7.33	7.39142	**5.14**	3.031368
4.7	4.680095	3.02	5.790728	5.2	5.570331
5.8	5.86551	3.16	4.394051	4.95	6.10015
5.85	4.355382	6.58	4.285836	4.58	3.645836
5.73	5.151408	6.84	5.509316	5.21	2.998457
6.2	5.815523	5.23	5.442607	5.64	5.488742
6.7	6.732107	4.98	4.172076	4.96	6.695673
6.1	5.497515	5.23	5.343047	4.23	3.785678
6.15	5.373019	5.48	6.55633	4.57	2.741664
7.69	6.215645	4.25	3.966875	5.1	4.884588
7.1	7.547512	4.87	2.795949		

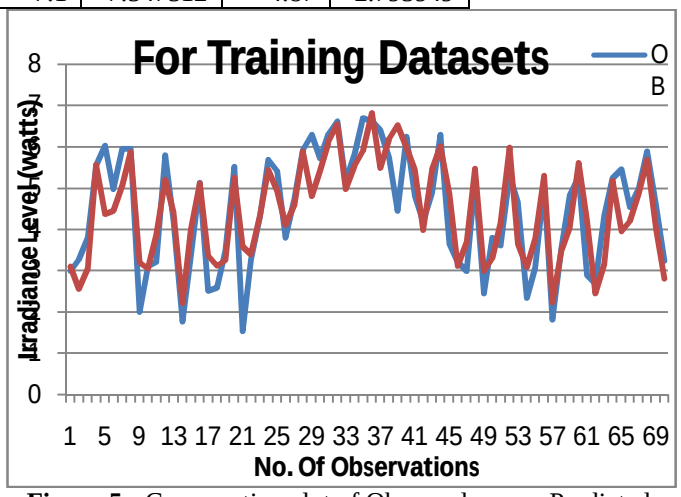

Figure 5: Comparative plot of Observed versus Predicted Irradiance power (watts) Level for Training Datasets

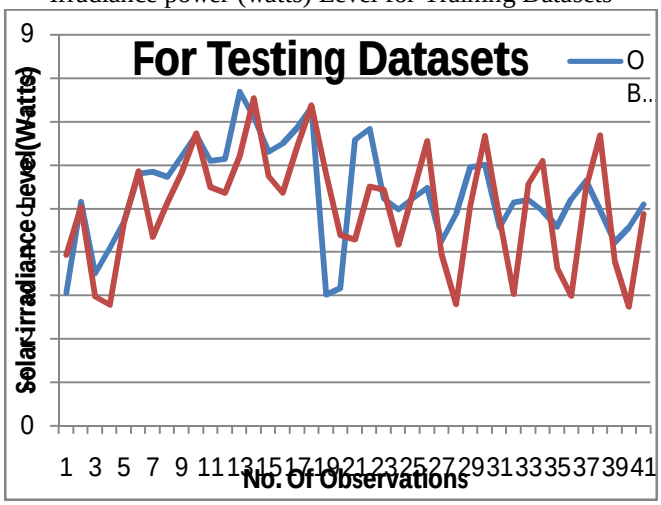

Figure 6: Comparative plot of Observed versus Predicted Irradiance power (watts) Level for Testing Datasets

MODEL PARAMETER OPTIMIZATION USING SIMULATED ANNEALING

In this section we are going to present our results obtained by combining simulated annealing optimization search with the previous section based ANFIS algorithm to accomplish our objective of getting lower prediction error by hybrid of SA and ANFIS. The initial FIS inference system is developed by SA algorithm using the environmental data records as used in Table 1. The SA algorithm generates different FIS structures at different value of cluster range of influence radii and finally we achieves a radii for input vectors at which we get least prediction error in training data set. The lower bound for radii is considered near the vicinity of 0.9 because we are getting least error in prediction at radii of 0.9 (see table 1) and on applying SA at the lower bound 0.9 and upper bound of 1 the results shows minimum prediction error at radii= 0.9741.The fis structure obtained at this radii is described in upcoming section.

A. FIS MODEL GENERATION BY SA OPTIMIZATION

The FIS structure that uses M-I data generates optimized radii of 0.9741 at which the SA algorithm achieves minimum error. This FIS structure has 4 inputs and the respective optimized membership functions for all four inputs are shown in figure 7.

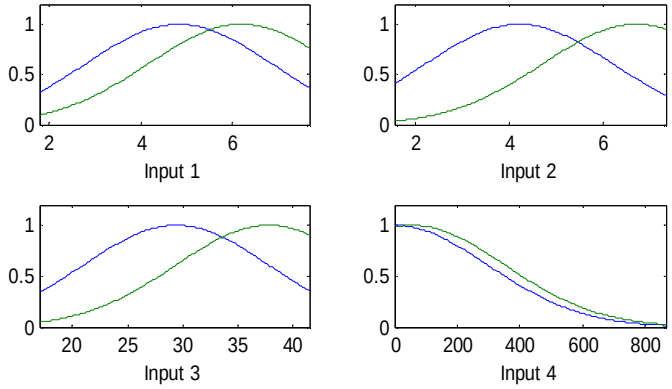

Figure 7: Initial Input Membership function curves for all the input variables at radii =0.9741.

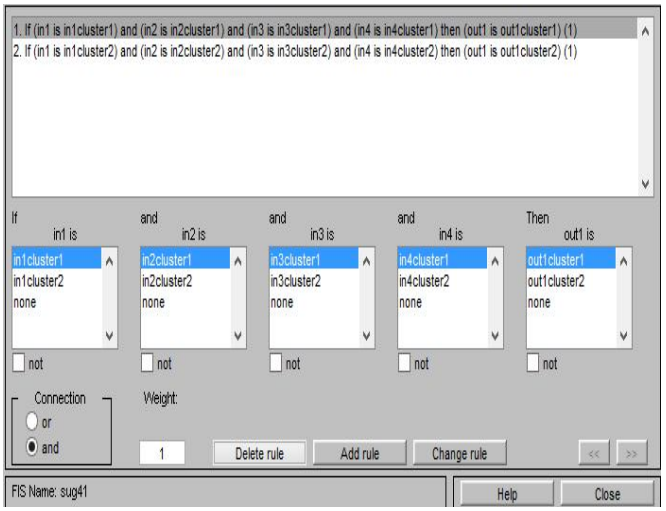

Figure 8: The fuzzy rules at optimized cluster radii of influence are shown for input of figure 4.11.

B. GENERATION OF MODIFIED FUZZY LOGIC PREDICTOR BY ANFIS USING SA FIS STRUCTURE

The initial and the final membership function curves for the input variables for the best fit model based on performance criteria are shown in figure 7 & 8 respectively.

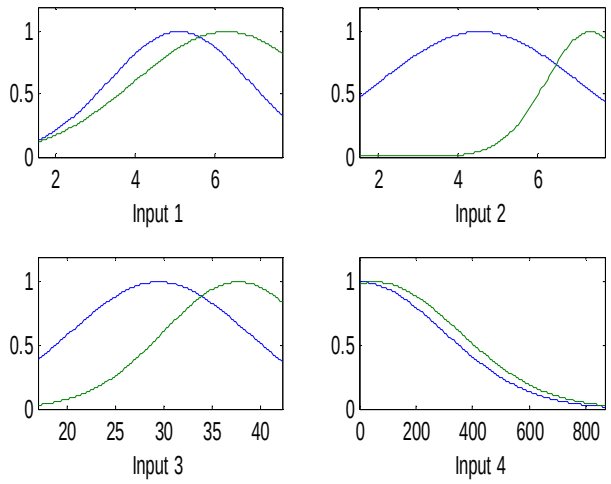

Figure 9: Final Membership function curves for all the input variables by ANFIS using optimized SAFIS fuzzy structure.

Here the SA based generated FIS model has been trained and tested by ANFIS method and their performance for the best prediction model M-I for clustering radius r=0.9741 are evaluated and compared for training and testing data sets separately. The RMSE performances of the ANFIS model both for training and testing datasets have been plotted separately (shown in Fig. 2 and 3 below) and their corresponding range of values for all the four models are summarised in table 3. The comparative plot of all the four models M-I to M-IV are plotted below in fig. 4.

5. CONCLUSION

In this paper, suitability and adaptability of ANFIS techniques for irradiance power (watts) level prediction has been investigated. It is seen that ANFIS models are very robust, characterised by fast computation, capable of handling the noisy and approximate data that are typical of data used here for the present study. Due to the presence of non-linearity in the data, it is an efficient quantitative tool to predict irradiance power (watts) level. The studies has been carried out using MATLAB simulation environment. In all three to four input variable were used, consisting of various combinations of irradiance power (watts) level, solar irradiation and temperature and one output variable as irradiance power (watts) level.

Here the initial parameters of the ANFIS are identified using the subtractive clustering method. Gaussian membership functions (given in earlier section) are used for each fuzzy set in the fuzzy system. The number of membership functions and fuzzy rules required for a particular ANFIS is determined through the subtractive clustering algorithm. Parameters of the Gaussian membership function are optimally determined using the hybrid learning algorithm. Each ANFIS has been trained for 10 epochs.

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