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Short Term Solar Irradiation Forecasting using ANFIS and Simulated Annealing ANFIS

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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. Two years data from March 2017 to March 2019 of Sultanpur district has been taken for the forecasting of solar irradiance using the two techniques and the result is compared by calculating the RMSE values.***
Keywords: Solar irradiation, ANFIS, SA-ANFIS.

I. INTRODUCTION

So as to confront atmosphere issues, deciding on renewable sources has become an obligation, as they are the most reasonable and promising solutions. Among these renewable sources, solar energy is the oldest and most reasonable type of energy, which has encountered an expanding exploitation, due to the endeavours of specialists to improve advances and diminishes the overall cost of acquisition.[1]

Discovering energy sources to fulfil the world's developing demand is one of the society's premier difficulties for the next half century. Solar forecasting is a stepping stone to these difficulties. Solar power forecasting relies upon the variables like information of the sun's path, the atmosphere's condition, the scattering procedure and the qualities of a solar energy plant which uses sun‘s energy to create solar power. Solar photovoltaic frameworks change sun oriented energy into electric power. The output power relies upon the incoming radiation and on the solar panel characteristics. Photovoltaic power creation is expanding these days. Forecast information is essential for an efficient use, the management of the electricity grid and for solar energy trading. [2]

In this paper the solar irradiance is forecasted based on preceded data, using ANFIS model we have developed. The purpose of this work is to develop a new approach for predicting solar irradiation from previous recorded values of irradiation and temperature using ANFIS model. This paper is organized as follows: The next section presents the database and parameters used in this simulation study. The section III provides the proposed ANFIS and SA-ANFIS model used in this simulation. Section IV presents a simulation results and discussions.

II. DATA COLLECTION AND PARAMETER SELECTION

Here Sultanpur district, Uttar Pradesh, India has been chosen as a case study area. Solar irradiance level data for station for the period of 2 years has been procured from Central Solar Irradiance Board, Northern Region, Lucknow.

Table 1: Data available for model development

Sl. No.	Data Type	Period	Abbreviations
1	Solar irradiance level	2 years	WL
2	Rainfall	2 years	RF
3	Temperature	2 years	T

Table 2: Structure of Forecasting model both for ANFIS & SA-ANFIS

Model	Input Variables	Output Variable
MI	WL(t-1), WL(t), T(t), RF(t)	WL(t)
MII	WL(t-1), WL(t), RF(t)	WL(t)
MIII	WL(t-1), WL(t), T(t)	WL(t)
MIV	WL(t-2), WL(t-1), WL(t)	WL(t)

where, WL(t, t-1, t-2) is the irradiance power (watts) level at time periods (t), (t-1), (t-2), RF = Rainfall; RH = Relative Humidity; T=Temperature; WL = Irradiance power (watts) Level

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 is trained for 10 epochs.

III. PROPOSED TECHNIQUES

A. ANFIS

The adaptive community fuzzy inference device (ANFIS), a Sugeno type fuzzy system, includes a community that has neural mastering ability [3]. Artificial neural networks (ANN) and fuzzy logic are used in its structure [4]. The mixture of the bushy system with a neural network is called a neuro fuzzy network.

The ANFIS is a fuzzy model that makes use of adaptive structures to facilitate the learning and adaptation process. Such an approach makes it less dependent on experience and systematic [5]. The purpose of ANFIS is to optimise the parameters of the fuzzy logic system by using input-output data sets via a learning algorithm. Parameter optimisation is set as the minimum error between goal output and the actual output [6].

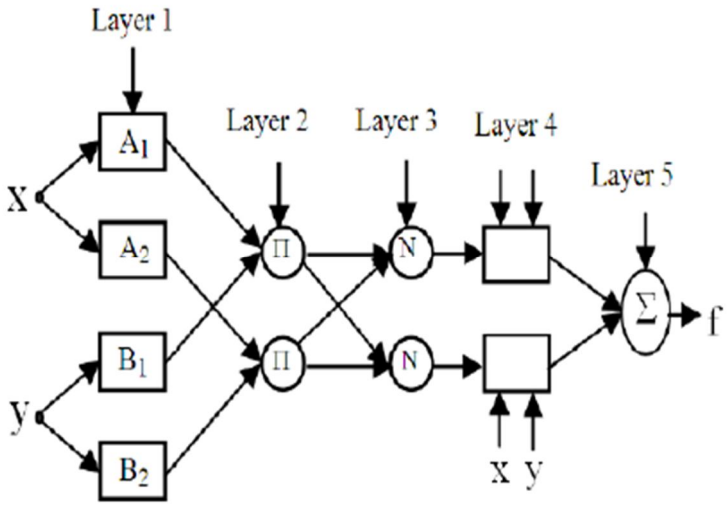

Fig.1: Structure of ANFIS

Layer 1: This layer is called the fuzzification layer.

$$Oi1 = \mu Ai(\ ) \qquad (1)$$

Where x is input and is a linguistic label for the corresponding node.

Layer 2: Rule layer.

$$Oi2 = wi = \mu Ai(x) \times \mu Bi(y), \quad i = 1,2 \qquad (2)$$

Layer 3: Normalisation layer.

$$Oi3 = \bar{w_i} = \frac{wi}{w1+w2}, \quad i = 1,2 \qquad (3)$$

Layer 4: Defuzzification layer.

$$Oi4 = \bar{w}i \times \bar{f}i = w\,i \times (aix + biy + ci) \quad (4)$$

Where $\bar{w}i$ is result of layer 3 and , ci is resultant parameter set.

Layer 5: Sum layer.

$$Oi5 = \Sigma \bar{w}i \times fi = \frac{\Sigma i\, \bar{w}i\, x\, fi}{\Sigma i\, wi} \quad (5)$$

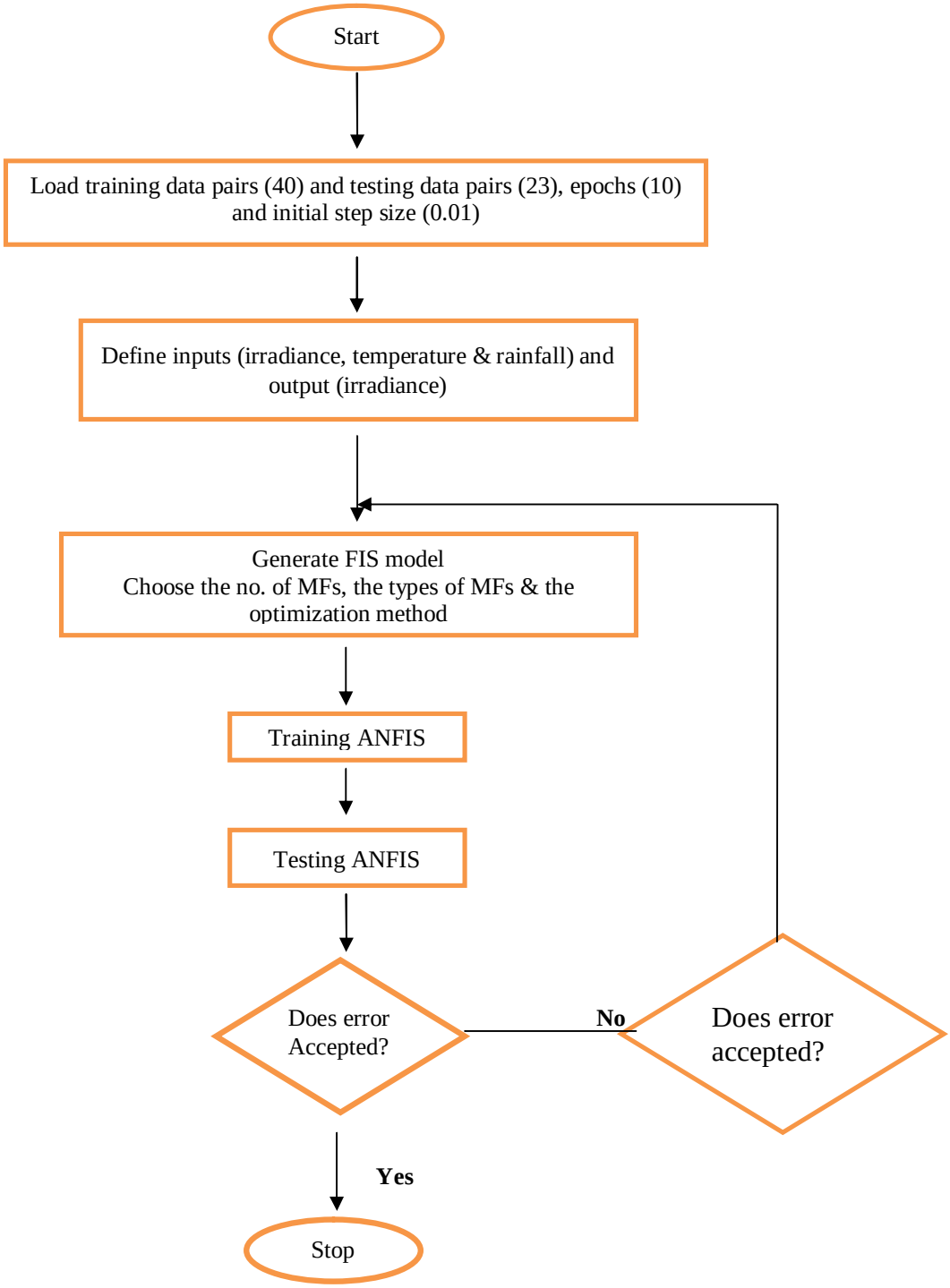

Fig.2 Flowchart for implementing ANFIS technique to the available data

B. The Technique of Simulated Annealing

Simulated annealing [7] 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 [8]. 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.

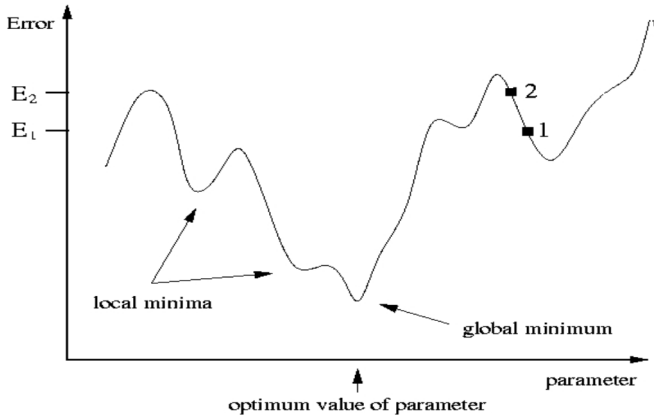

Fig. 3. The Error of a Model's Predictions as a Function of Its One Free Parameter.[10]

C. Simulated Annealing Analogy

The SA is an iterative algorithm which means it reliably attempts to build up a solution that is expressed as a vector of numbers in the arrangement space. It is conceivable to put the significant concepts which ought to be resolved in the execution stage of the SA algorithm to a problem, into two groups: [9]

1) Selections that are specific to the problem

2) Selections that belong to the cooling schedule

Simulated annealing (SA) is one of the most versatile techniques applicable for solving combinatorial problems. 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 way toward presenting a solid to high temperature, with progressive cooling, in order to accomplish top quality crystals [10]. 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 primary highlights of the SA procedure are: (1) the transition mechanism between states and (2) the cooling plan. At the point when applied to combinatory optimization, SA means to locate an ideal setup (or state with least "vitality") of a complex issue. The objective function of an enhancement issue compares with the free vitality of the material. An ideal arrangement is related with an ideal precious stone, though a crystal with imperfections compares with a nearby ideal arrangement. 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.

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

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 [10]. The temperature is accepted to have a rate of variation to such an extent that thermodynamic balance is reached for the present temperature level, before moving to the next level. This ordinarily requires large number of state advances of the Metropolis algorithm. For a combinatory optimization issue to be settled by SA, it is planned as pursues: let G be a finite, perhaps exceptionally large, arrangement of designs and v the expense related with every setup of G. The answer for the combinatorial issue comprises of scanning the space of arrangements for the pair (G, v) introducing the most minimal expense. 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. The entire process is controlled by a cooling schedule that determines how the temperature is decreased during the optimization process.

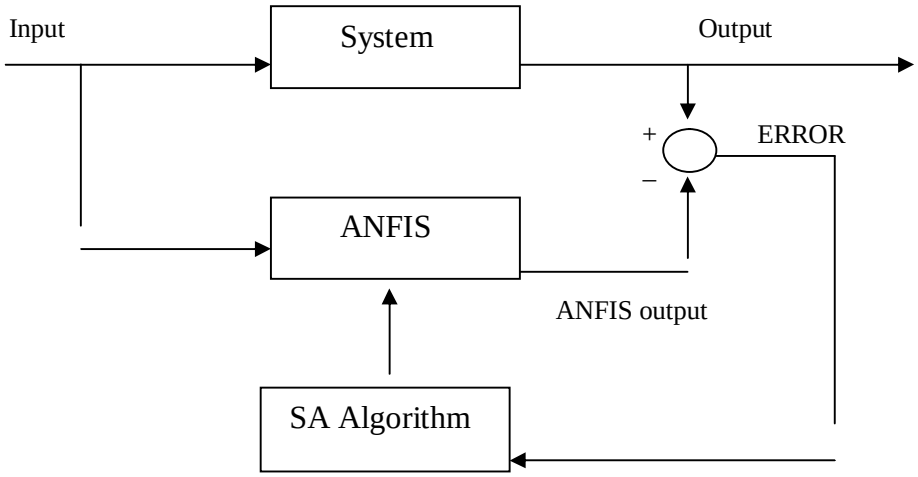

Fig.4. Scheme for training ANFIS to identify a system using the SA algorithm

D. Simulated Annealing Algorithm

Evolutionary algorithms, SA and tabu search are broadly utilized heuristic calculations for combinatorial optimization. The term evolutionary algorithm is utilized to allude to any probabilistic algorithm whose design is propelled by developmental systems found in organic species. One of the most broadly known about heuristic algorithms is SA calculation. SA exploits an analogy between the manner by which a metal cools and freezes into a minimum energy crystalline structure (the annealing procedure) and the search for a base in an increasingly broad framework [8-10]. In the optimization process, the arrangement arbitrarily strolls in its neighbourhood with a probability dictated by Metropolis rule while the system temperature diminishes gradually; when the annealing temperature is shutting zero, the arrangement remains at the worldwide best arrangement in a high probability. [11-13]

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.[14-17]

Algorithm: [18]

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) ≤ 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 present state Si with expense f (Si), a neighbour arrangement Sj, with expense f (Sj) is created by the transition mechanism. The following probability is determined in performing out the acceptance test:

P_T{Accept S_j} = 1, if f(S_j) ≤ f(S_i)

or

exp{(f(S_i)-f(S_j)/Tk)}, if f(S_j) > f(S_i)

IV. RESULTS 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. 5 and 6 below) and their corresponding range of values for all the four models are summarised in table1. The comparative plot of all the four models M-I to M-IV is plotted below in fig. 7.

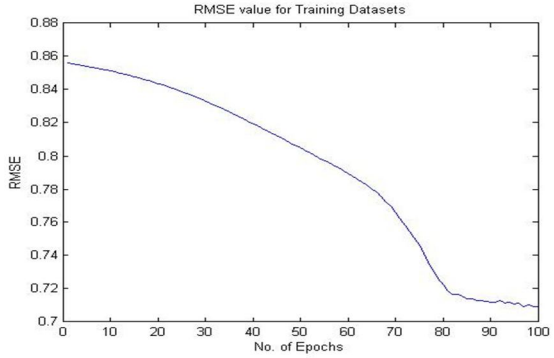

Fig. 5: Graphical plot of RMSE value variation during ANFIS training for training datasets

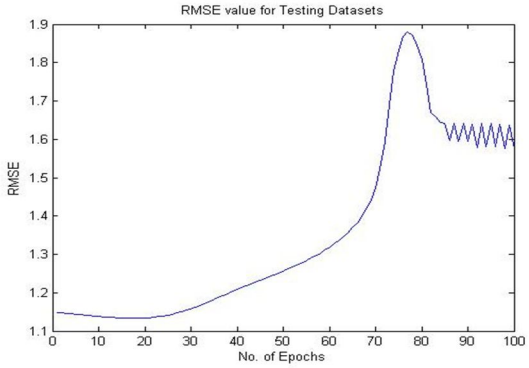

Fig. 6. Graphical plot of RMSE value variation during ANFIS training for testing datasets

From graphical analysis of Fig. 3 and 4 it is inferred that during training phase (Fig. 3), 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. 4) 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 up to 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 3: 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	
	Training data	Testing Data	Training data	Testing Data	Training data	Testing 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

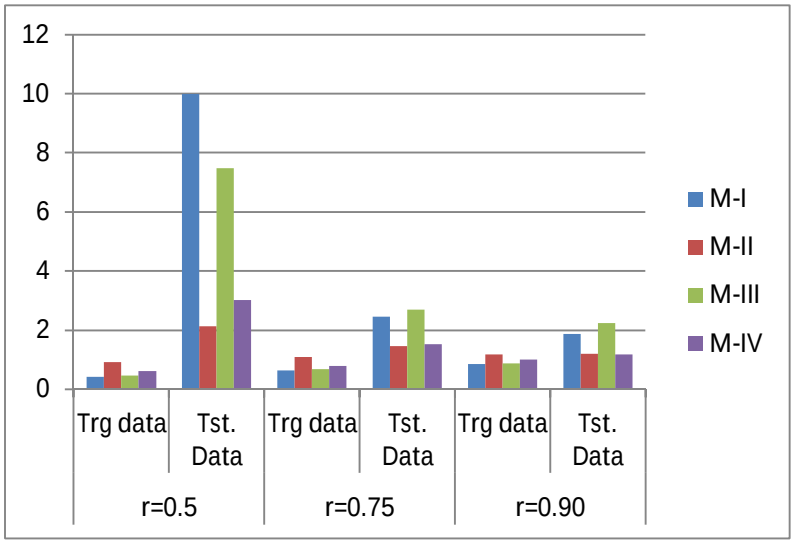

Fig: 7. Graphical plot of Comparative RMSE values for different models

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 3 and Fig. 4. 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 3 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 vice-versa for testing phase.

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.

A. 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 3. 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 3) 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.

1) 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.

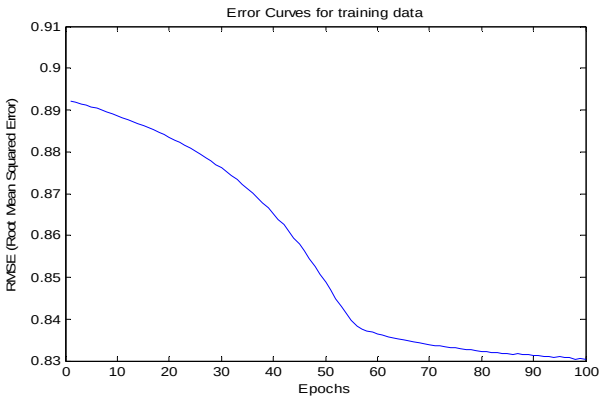

Fig. 8: Graphical plot of RMSE value variation during value SA-ANFIS for training datasets

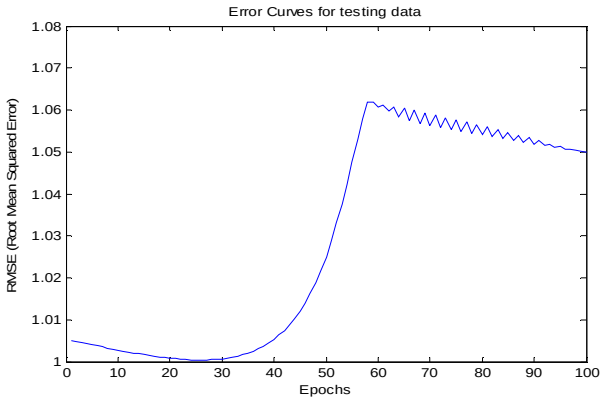

Fig.9: Graphical plot of RMSE variation during SA- ANFIS for testing datasets

The graphs shown in fig. 8 and 9 shows the RMSE values of the datasets in which in fig. 8 there is a sharp decline and at epoch no. 55 the error is reduced and becomes minimum at epoch no. 90. Also during testing phase the minimum RMSE value is obtained at epoch no. 20 and the graph has a zig zag nature from epoch no. 55.

B. Day Wise Prediction

From the 2 years data solar irradiance is predicted for six different days for the dates 12 March 2017, 1 March 2018, 30 September 2017, 19 October 2018, 19 October 2017 and 7 November 2018 respectively. Finally actual and predicted monthly value for 2 years is shown in Fig.10 and Fig.11. and the calculated RMSE values are given in Table 4.

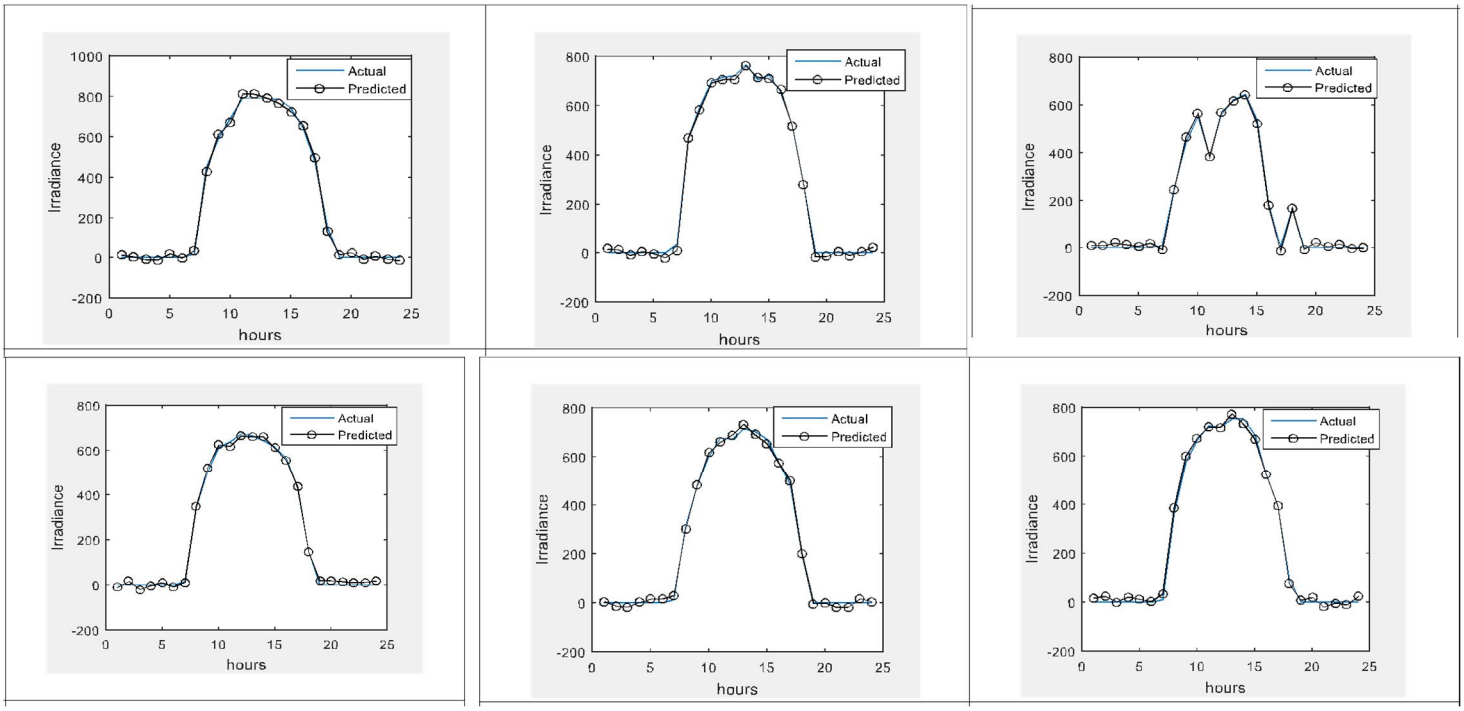

Fig.10: Solar irradiance forecasting on different days using ANFIS

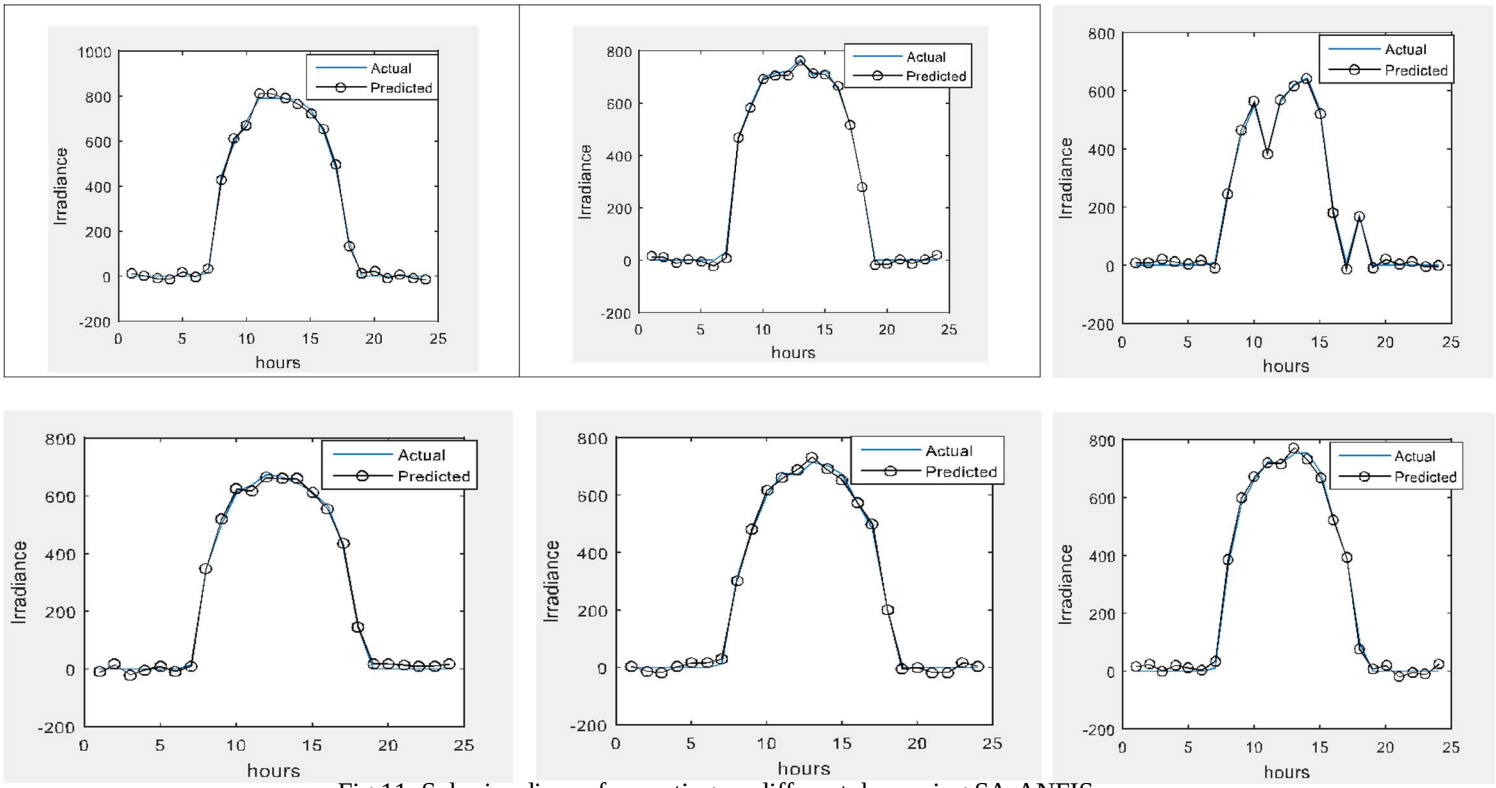

Fig.11: Solar irradiance forecasting on different days using SA-ANFIS

Table 4: RMSE values by ANFIS and SA-ANFIS for different days

RMSE Values (%)	12 Mar 2017	1 Mar 2018	30 Sept 2017	19 Oct 2018	19 Oct 2017	7 Nov 2018
ANFIS	1.8933	0.0879	0.5717	0.6988	0.2291	0.2952
SA-ANFIS	0.4391	0.0532	0.3641	0.3806	0.1444	0.2375

V. CONCLUSION

The solar photovoltaic power forecast could be very vital for the dependable, secure and efficient operation of the grid and the financial functioning of the electricity market. This paper proposes an ANFIS model and SA-ANFIS model for the short-term prediction of solar irradiation, which is the combination of the neural network and the fuzzy inference system. The proposed model is trained and tested using actual measured data from Sultanpur, India and daily solar irradiation forecasts were made using a new dataset from the same region. The error results show that the RMSE values obtained are 1.8933 and 0.4391 from ANFIS & SA-ANFIS respectively. Similarly the RMSE values for other five days has been calculated and it can be seen that from table 2 that error obtained from SA-ANFIS are much less than ANFIS. Therefore the performance of the SA-ANFIS has outperformed ANFIS in terms of forecast accuracy and also the number of iterations also reduced which reduces the time taken by the system in giving outputs.

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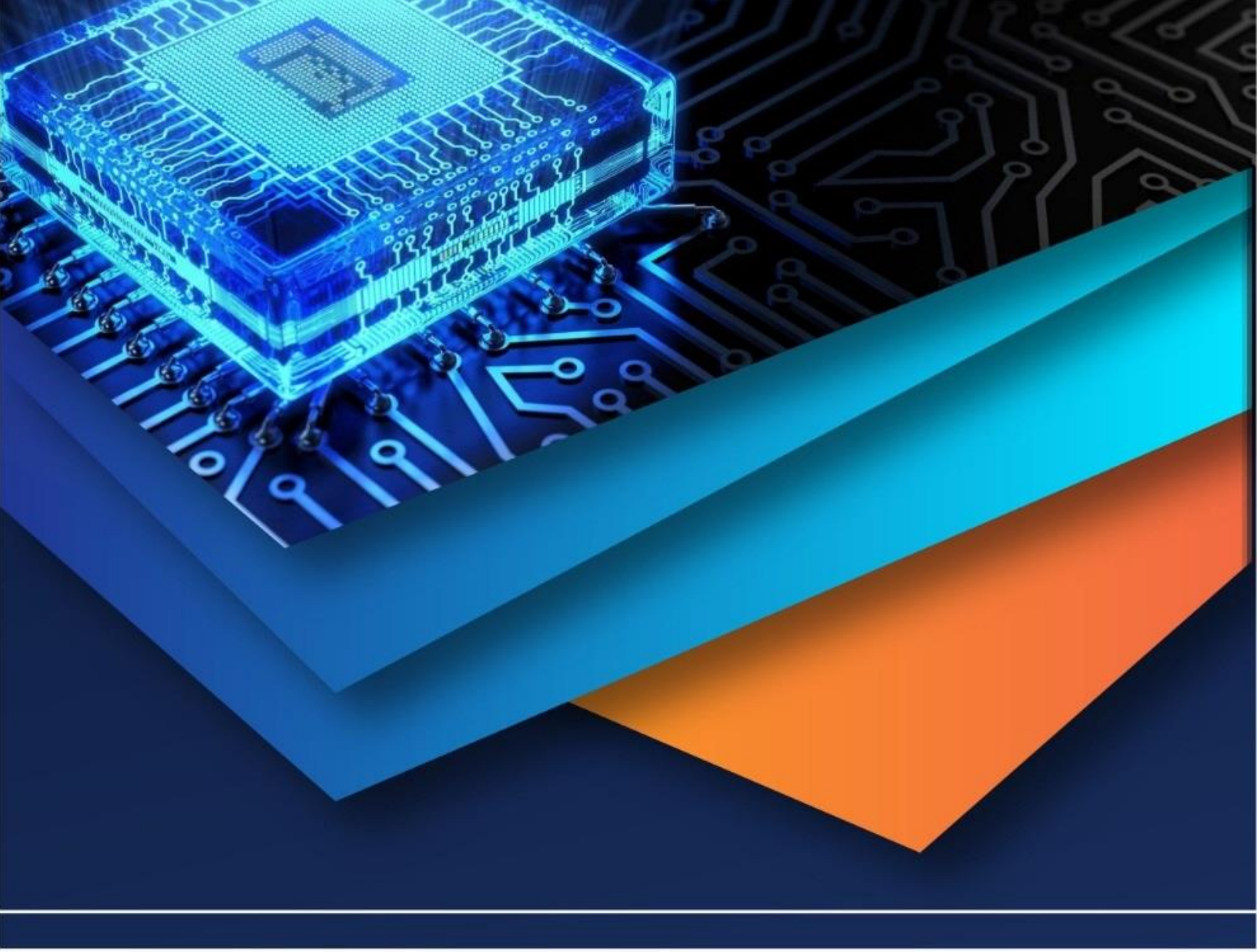

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