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Short Term Irradiation Forecasting Using ANFIS

Authors: Ajay Kumar Ahirwar; Imran Khan
AZAD Institute of Engineering & Technology, Lucknow
ak3365280@gmail.com;pe.imran@gmail.com

Abstract

In a solar power shed basin, the seasonal modelling of solar irradiance fluctuations is very useful in planning and management of both the surface wind and solar irradiance resources. This is important in regions where there is depleting surface solar power resources and increase in solar power demand due to industrialization and urbanization. Further change in climatic trends results in the variation of environmental quantities. Thus, ground solar power resources are becoming an alternate solution to meet the increase in demands. In case of Indian subcontinent, where environmental patterns are changing due to change in climatic conditions, the over exploitation of solar irradiance has become inevitable. The major source of solar irradiance in most of the solar power sheds in India is through recharge from solar power. In this work, the seasonal solar irradiance levels will be predicted using the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) based on previous seasonal solar irradiance levels

1. INTRODUCTION

The importance of solar energy for the existence of human society cannot be overemphasized. Solar energy is the major source of clean energy in both urban and rural India. Besides, it is an important source of solar energy for the agricultural and the industrial sector. Being an important and integral part of the annual cycle, its availability depends on the rainfall and recharge conditions. Till recently it had been considered as a dependable source of uncontaminated solar energy.

Total replenishable solar energy resource of Uttar Pradesh is very high, out of which present total extraction is about 30% and the net exploitation is which is 65.9% of total extraction. Thus the solar energy resource available for future exploitation is large. However, this resource is unevenly distributed in space and the present state of exploitation has resulted in regional solar energy imbalances. It is estimated that for domestic, industrial and irrigation needs of growing population, the level of solar energy exploitation will increase 3 times by 2025 i.e. requirement of solar energy will be more than double the present level. Due to this the number of over-exploited blocks may increase from 14 to 177 by the year 2025. (These represent the blocks where the drawls are more than recharge).

1.1. PRESENT EMERGING PROBLEMS

The ever increasing demand for energy has led to solar scarcity in many parts of the world. This situation is aggravated by the problem of pollution or contamination. India is heading towards a fresh solar energy crisis mainly due to improper management of solar energy resources and environmental degradation, which has lead to a lack of access to safe solar energy supply to millions of people. This clean energy crisis is already evident in many parts of India, varying in scale and intensity depending mainly on the time of the year [1][2].

Energy crisis is not the result of natural factors; it has been caused by human actions. During the past two decades, the solar energy level in several parts of the country has been falling rapidly due to an increase in extraction. The number of wells drilled for irrigation of both food and cash crops have rapidly and indiscriminately increased. India's rapidly rising population and changing lifestyles has also increased the domestic need for solar energy. The solar energy requirement for the industry also shows an overall increase. Intense competition among users — agriculture, industry, and domestic sectors — is driving the solar energy table lower. Thus constant monitoring of the solar energy levels is extremely important. The solar energy levels if properly predicted well in advance can help the administration to plan better solar energy utilization. Also, for an overall development of the basin, a continuous forecast of the solar energy levels is required to effectively use any simulation model for solar energy management. These models based on observed data or theoretical principles provide a framework for decision making for solar energy users and solar energy regulators.

2. ANFIS Model Development

The seasonal modelling of solar irradiance fluctuations is very useful in planning and management of both the surface exposure and solar irradiance resources. This is important in regions where there is depleting surface exposure resources and increase in power demand due to industrialization and urbanization. Further change in climatic trends results in the variation of enviornmental quantities. Thus, solar irradiance resources are becoming an alternate solution to meet the increase in demands. In case of Indian subcontinent, where weather patterns are changing due to change in climatic conditions, the over exploitation of solar irradiance has become inevitable. The major source of solar irradiance in most of the power sheds in India is through recharge from rainfall. The physical interaction between the hydrological variables (such as rainfall, evapotranspiration) with solar irradiance is highly nonlinear, stochastic, and complex. The solar irradiance 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 (Srivastav et al., 2007).

In this chapter Adaptive Neural Fuzzy Inference System Techniques (ANFIS) approach has been applied to develop a model for forecasting solar irradiance levels in Sarojini Nagar Block, district Lucknow, U.P., India, which is characterised by Ganga alluvium of Quaternary age. Irregular rainfall has often led to detrimental effects on the natural and human environment. Increasing dependence on solar irradiance resources has led to a lowering of the solar irradiance table in places where withdrawals have exceeded recharge. The decline in solar irradiance levels has further undermined power security in the region.

2.1. ANFIS Model Develoment

2.1.1 Model Selection

In the present work similar sets of different input parameters have been used for ANFIS model development with Irradiance power (watts) Level as output variable so as to be able to compare it with ANN modelling technique.

2.1.2 Parameter Selection

As discussed earlier, ANFIS is a judicious integration of FIS and ANN, capable of learning, high-level thinking and reasoning and it combines the benefits of these two techniques into a single capsule [3]. Identification of the rule base is the key of a FIS. The problems are (1) there are no standard methods for transforming human knowledge or experience into rule base; and (2) it is required to further tune the MFs to minimise the output error and to maximise the performances. Thus when generating a FIS using ANFIS, it is important to select proper parameters, including the number of membership functions (MFs) for each individual antecedent variables. It is also important to select proper parameters for learning and refining process, including the initial step size (ss). In the present work the commonly used rule extraction method applied for FIS identification and refinement is subtractive clustering. The ANFIS is simulated using the MATLAB Fuzzy Logic Toolbox.

Initial parameters of the ANFIS are identified using the subtractive clustering method. However, the parameters of the subtractive clustering algorithm still need to be specified. The clustering radius is the most important parameter in the subtractive clustering algorithm and is optimally determined through a trial and error procedure. By varying the clustering radius r_a between 0.1 and 1 with a step size of 0.01, the optimal parameters are sought by minimizing the root mean squared error obtained on a representative validation set. Clustering radius r_b is selected as 1.5 r_a. Default values are used for other parameters in the subtractive clustering algorithm.

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.

The parameters used in the model for training ANFIS are given in Table 4.3 and the rule extraction method used are given in Table 4.4. 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 4.4 & 4.5 respectively. Tables 4.5 summerizes the results of types and values of model parameters used for training ANFIS.

Table 1 Parameters used in all the models for training ANFIS

Rule extraction method used	Subtractive clustering
Input MF type	Gaussian membership (‘gaussmf’)
Input partitioning	Variable
Output MF Type	Linear
Number of output MFs	One
Training algorithm	Hybrid learning
Training epoch number	10
Initial step size	0.01

Table 2 Rule extraction method used for training ANFIS

Rule Extraction Method	**Type**
And method	‘prod’
Or method	‘probor’
Defuzzy method	‘wtever’
Implication method	‘prod’
Aggregation method	‘max’

Table 3 Values of parameters used for training ANFIS

No. of nodes	**No. of linear parameters**	**No. of non-linear parameters**	**Total no. of prameters**	**No. of training data pairs**	**No. of testing data pairs**	**No. of fuzzy rules**
1311	646	1216	1862	40	23	38

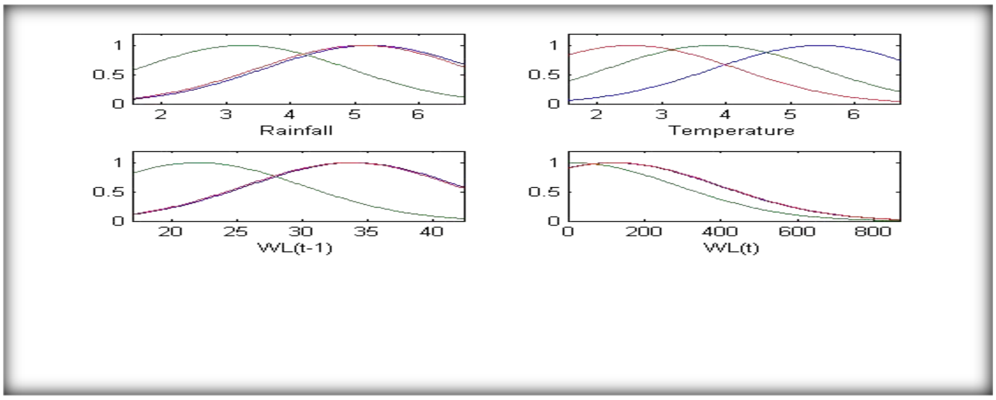

Fig. 1 Initial Input Membership function curves for all the input variables

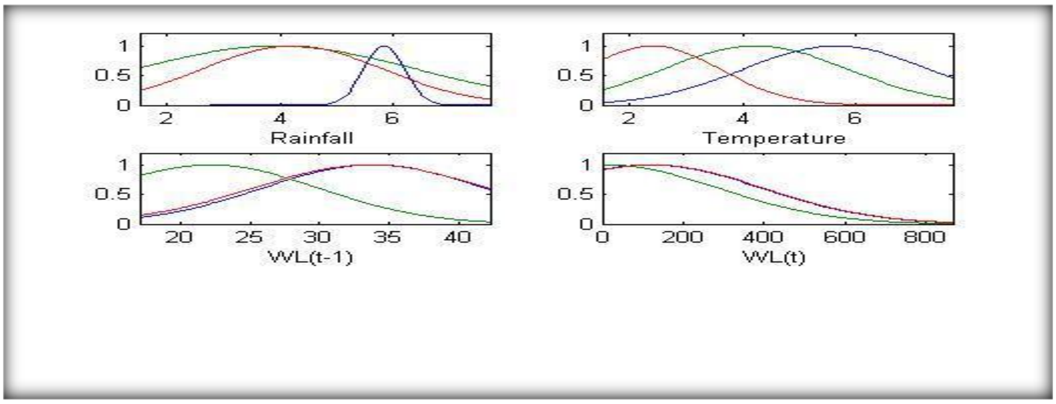

Fig. 2 Final Membership function curves for all the input variables

3. Results and discussions

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. 3 and 4* below) and their corresponding range of values for all the four models are summerised in *table 4*. The comparative plot of all the four models M-I to M-IV are plotted below in *fig. 5*.

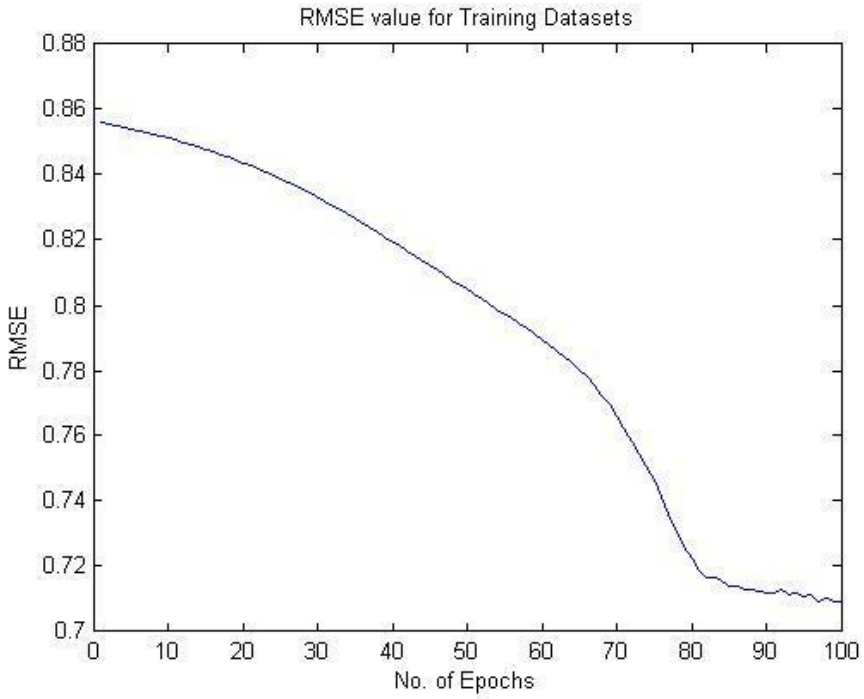

Fig3:- Graphical plot of RMSE value variation during ANFIS training for training datasets

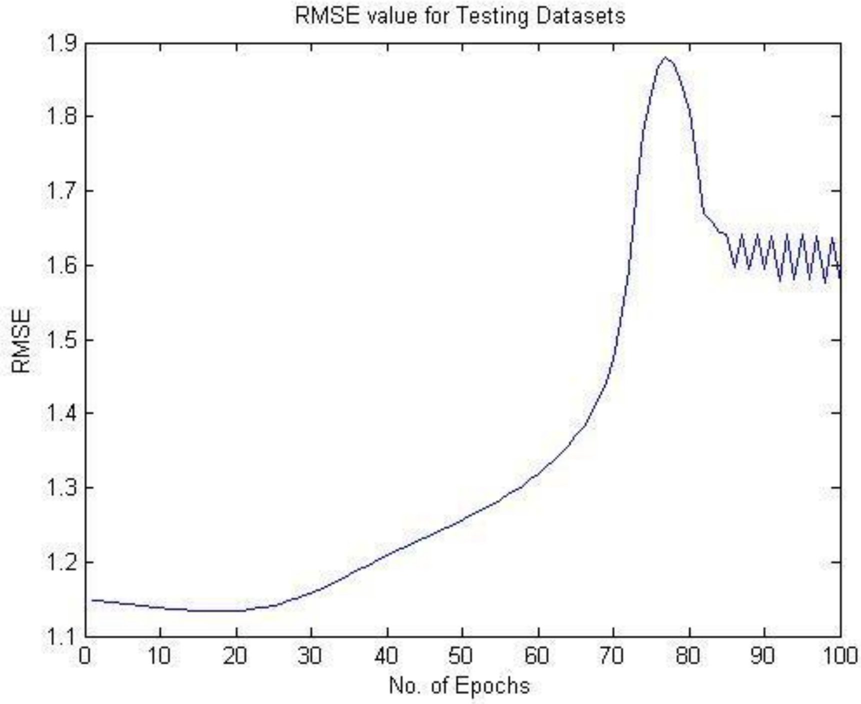

Fig. 4:- Graphical plot of RMSE value variation during ANFIS training for testing datasets

From graphical analysis of Fig. 3 and 4it is inferred that during training phase (Fig.4.6), 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 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.

Table4:- 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

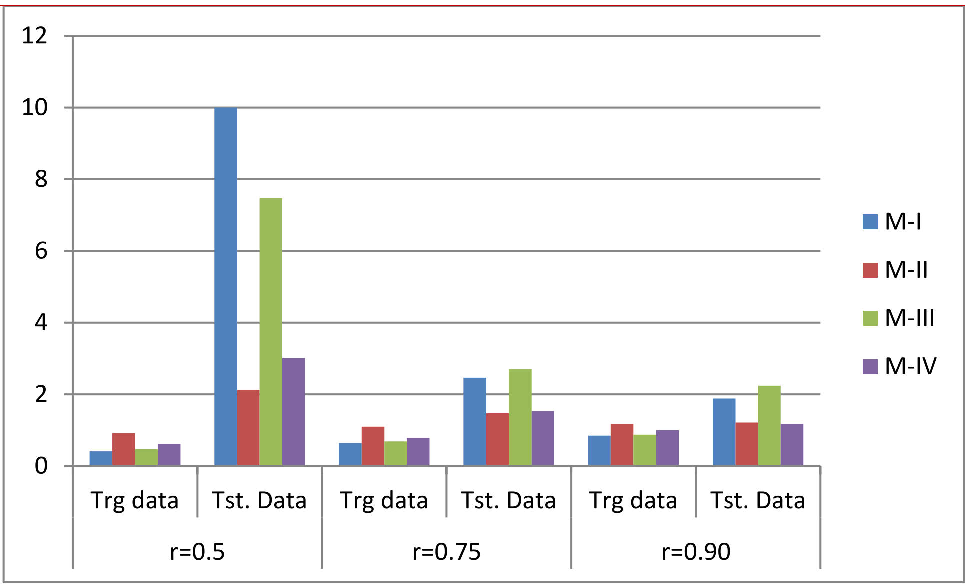

Fig: 5 - Graphical plot of Comparative RMSE values for different models

Fuirther 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. 5 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, rainfall and temperature, M-II model has irradiance power (watts) level and rainfall 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 5 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. 4.8 given above.

Thus, it is clear that proper selection of influential radius which affects the cluster results directly in ANFIS using substractive 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. 6 using data given in Tables 5and 6. 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 5:- 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
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 6:- 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		

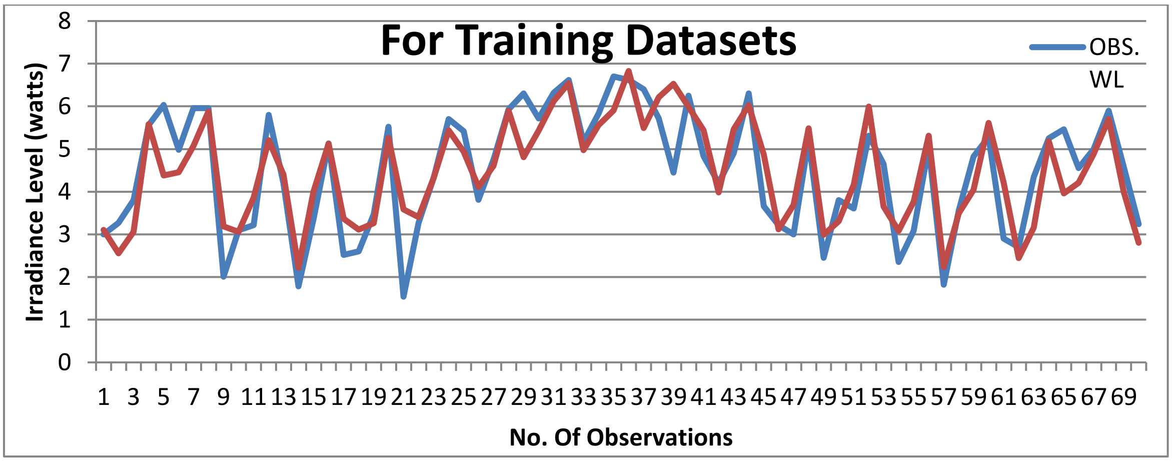

Fig. 6 :- Comparative plot of Observed versus Predicted Irradiance power (watts) Level for Training Datasets

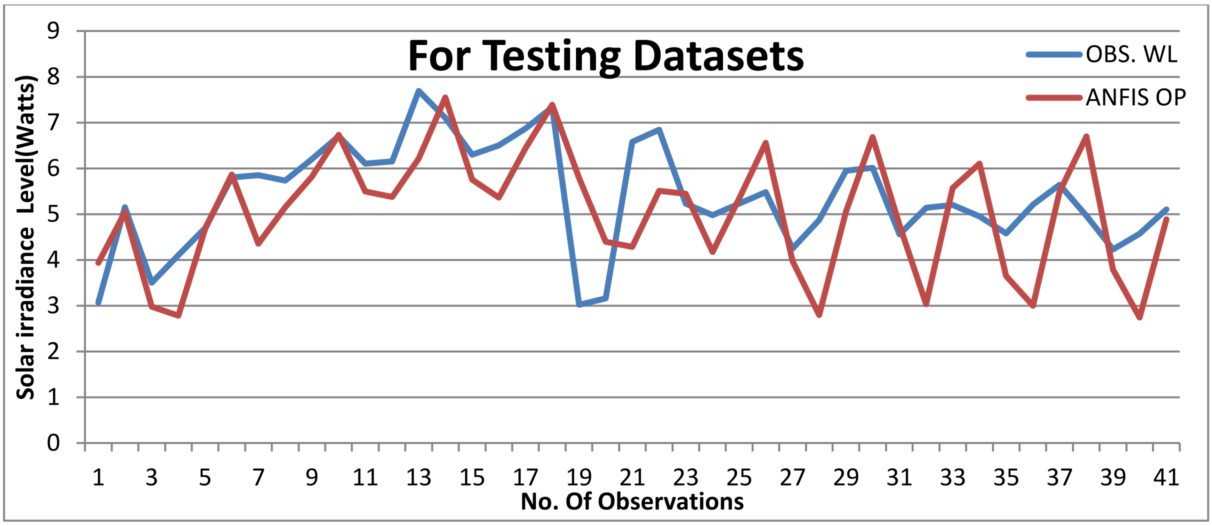

Fig.4.10:- Comparative plot of Observed versus Predicted Irradiance power (watts) Level for Testing Datasets

CONCLUSIONS

Energy crisis is not the result of natural factors; it has been caused by human actions. During the past two decades, the solar irradiance level in several parts of the country has been falling rapidly due to an increase in extraction.

India's rapidly rising population and changing lifestyles has also increased the domestic need for energy. The energy requirement for the industry also shows an overall increase. Intense competition among users — agriculture, industry, and domestic sectors — is driving the solar irradiance table lower. Thus constant monitoring of the energy levels is extremely important. The energy levels if properly predicted well in advance can help the administration to plan better energy utilization. Also, for an overall development of the basin, a continuous forecast of the Solar irradiance levels is required to effectively use any simulation model for energy management. These models based on observed data or theoretical principles provide a framework for decision making for energy users and energy regulators. In this present work, applicability and capability of ANFIS technique for Solar irradiance level forecasting has been investigated.

A step-by-step approach for the successful development and implementation of ANFIS approach for energy level prediction model has been carried out. For this solar irradiance level records of past 2 years along with other meteorological factors (rainfall and temperature) influencing the solar irradiance level of a particular area are selected as input variables. The various approaches include:

- Selection of various input parameters, which have direct or indirect bearings on energy level of that particular area. These data are further subjected to statistical analysis. A graphical plot of meteorological data along with energy level is carried out so as to show the influence of these variables on irradiance level.

- Dividing the data into training and testing subsets using cross validation techniques so that the training data has all the characteristics of the problem in order to get effective model development;

- Selection of model inputs using different permutations and combinations and formation of four model structures;

- In ANFIS model development,
  - For limited database, in order to reduce large computation time and decrease the number of rules, selection of appropriate rule extraction method viz. subtractive clustering is carried out for an effective partitioning of the input space. In case of subtractive clustering, proper selection of cluster radius through trial and error is done.

- Selection of parameterised functions, known as membership functions, is an important step in the development of an optimum model. Here Gaussian and Generalised Bell membership function has been selected for solar irradiance level prediction model development.
- selection of training algorithm, initial step size and training epoch number;
- Four models, viz. M-I, M-II, M-III and M-IV were developed based on different combinations of energy level, rainfall and temperature values.
- All the models were analysed based on RMSE criteria, varying the cluster radius values, viz. 0.50, 0.75 and 0.90.
- Validation and comparison of these ANFIS models.

An analytical study of the technique followed by conclusions drawn regarding the best model developed based on performance criteria.
Initially 4 different models are developed at different combination of database type of irradiance level and rainfall values. For all models ANFIS models are developed using different radius of influence of data clusters. Training and testing errors were calculated at radius values, viz. 0.50, 0.75 and 0.90. Minimum RSMSE observed at model 4.
After checking predictability at ANFIS algo SA ANFIS results are drawn at an optimum radius. The optimum radius observed here is r=0.9741.
On this model data is predicted and error are determined the RMSE in percentage for suny, cloudy and rainy seasons observed here by SA ANFIS is 0.88,063 and 1.111.
Similary another case for prediction error are estimated for three different critical days. The RMSE obtained for these critical days is o.005% by SA ANFIS and it is observed very low as compared to SVM , ANN and ANFIS.

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