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Mitigation and Prediction of Radiation Effects in Solar power Plants using Neuro Fuzzy and Neural Network

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Abstract-

In the growing energy demand, the renewable energy power generation plays an important role. The most important factor in solar PV system is the estimation of maximum power point calculation. This paper presents Neural and Neuro-fuzzy system-based temperature and solar radiation forecast. In this system the feature values are predicted without the knowledge of the characteristics of the input time-series. Using standard meteorological parameters, the input data used to train the proposed systems with different architectures. After having simulated, many different structures of neural networks are trained using measurements as training data. The best structures are selected in order to evaluate their performance. ANFIS neuro fuzzy system is considered here because it combines fuzzy logic and neural network techniques to get more gain and efficiency which gives best accuracy in performance. Several Error Metrics are considered here to evaluate and compare both the systems according to the resultant predictions.

Keywords: ANFIS, Neural Network , Neuro Fuzzy system, Fuzzy Logic and Error metrics

1 Introduction

Forecasting metrological results is the challenging task to realize better results despite being different scientific efforts are made. Also, solar radiation forecasting constitutes a very crucial issue for different scientific areas which is essential for humans in future. The global solar isolation on inclined surface is predicted by using Adaptive Neural Fuzzy Interference System (ANFIS) method with the input parameters like global irradiance, extraterrestrial isolation, incident angle and zenith angle validated [1]. The electrical parameters of PV system and irradiation intensity which allows the calculation of efficiency during the operation of photovoltaic (PV) grid connected systems are measured [2]. For the making the PV system unreliable especially in the condition of high penetration rates of PV, the power output of grid-connected solar PV is intermittent due to the influences of solar irradiance. Forecasting the solar irradiance and power output of a PV plant problem in an effective way is presented [3].

The neural networks comprise of four inputs and one output. Maximum temperature, Minimum temperature, mean temperature, and irradiance are the four inputs reported [4]. A multi structure feed forward neural networks (Multilayer FF Neural Network) had been proposed and simulated. A large number of simulations have been carried out with different parameters which has resulted at the optimum neural network forecaster structure of daily temperature and solar radiation.[5],[6] The neuro-fuzzy system ANFIS is proposed for this predication whose main purpose is to observe the resultant data from the combination of fuzzy logic and neural networks in the forecasting domain. Having trained and tested with the same data as the neural networks, its forecasting results have been compared with those of the best neural network structures.[7]-[9]. It has to be mentioned that the short-term prediction employs the developed structures [10],[11]. The important features of time-series analysis and more precisely time-series prediction including its advantages are presented [12]- [14]. Brief description of neural networks is given. In addition to this, t several structural training issues of neural network predictors are reported. Subsequently, description of neuro-fuzzy systems and more precisely ANFIS are given, presented and the main results-predictions of temperature and solar radiation are compared after simulating the above systems, utilizing several error metrics [15],[16].

2 Time-series analysis - prediction

The time index of the time series represents either finite or infinite set of values and this process is a stochastic process. These values usually constitute to the physical system measurements which are obtained on specific time delays which could be hours, days, months or years. Time-series analysis includes three basic problems such as prediction, modeling and characterization. This paper concerns the problems on prediction. Time-series prediction is defined as a method which depicts past time series values to future ones. The method is based on the hypothesis that the variation in the values follows a specific model called as latent model. The time-series model can be remarked as a black box which makes nil efforts to retrieve the coefficients affecting its behavior.

Fig. 1. Time-series model block diagram

Input of the model are the past values X_i until the time instance X = t and output Y is the prediction at the time instance X = t + p. The system could be a neural network, a neuro fuzzy system e.t.c

The main advantages of the time series prediction model are:

- What happens, not why it happens are identified in a lot of cases.
- Comparison with other categories of models like the explanatory model shows that the cost of the time series prediction model is least.

Time-series normalization

One of the most frequently used preprocessing methods is constituted by it. Normalization of data results in smoothing of time-series, as the values are limited in a specific range. It is also very suitable for the neural and neuro-fuzzy systems which use activation functions.

3 Neural networks

A neural network is a series of algorithms which successfully recognizes the underlying relationships and connectives in a data set through a process that resembles the human brain operation. An important feature of neural networks is that they adapt to the varying input continuously and generate best possible results without the need of redesigning of output criteria. The activation functions which are being used in every layer node, different architectures of networks, the learning processes that are selected are the important parameters which characterizes the neural networks. Linear, sigmoid and hyperbolic tangent are some of the activation functions used in the Neural Network. Network architectures depends on the learning algorithms used. There are 3 different categorization of Network architectures such as Single-layer feed forward Networks, Multilayer Feed forward Networks and Recurrent Networks. Supervised and unsupervised learning are the two main divisions of Learning processes. They differ in the fact that supervised learning algorithms employ input-output patterns for training purpose whereas the response of the unsupervised learning algorithms is based on the self-organizing ability of the networks.

Application of supervised training manner of Multilayer Networks has successfully solved diverse problems by utilizing the famous Error back-propagation algorithm. This network identifies two kinds of signals such as function signals and error signals. A function signal propagates through the network, and emerges as an output signal at the output end of the network. An error signal originates at the output end of the Neural Network, and propagates backward through the network. Error signal gets its name by the involvement of an error-dependent function in the computation carried out by every neuron of the network. To train network weights with input-output patterns is the main target of the process. The system can generate functional signals with reduced error signal by reducing the error signal of the output node of every training epoch,

The error signal at the output of neuron j at iteration n is defined by:

$$\mathbf{e^{j}(n) = t^{j}(n) - y^{j}(n)} \qquad \mathbf{(1)}$$

The value of the error energy over all neurons in the output layer is defined by:

$$\mathbf{E(n)} = \frac{1}{2}\sum_{j \in C} e_j^2(n) \qquad \mathbf{(2)}$$

The average squared error energy or cost function is defined by:

$$\mathbf{E}_{\mathrm{av}} = \frac{1}{N}\sum_{n=1}^{N} E(n) \qquad \mathbf{(3)}$$

The main objective of the training process is to minimize the cost function by adapting the parameters. Levenberg-Marquardt is a very efficient minimization method due to its small computational complexity.

4 ANFIS (Adaptive Neuro-Fuzzy Inference System)

The combination of Fuzzy systems and Neural network systems constitutes an intelligent system which gives better results. Here proposed a ANFIS which is described as a fuzzy system equipped with a Neural Network training algorithm. ANFIS system is a unique easier and more accurate training result that can be compared to any best neural networks or Fuzzy Systems.

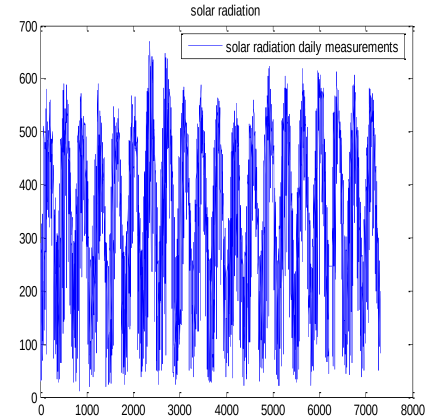
5 Solar Radiation and Temperature Time series

5.1 Solar Radiation

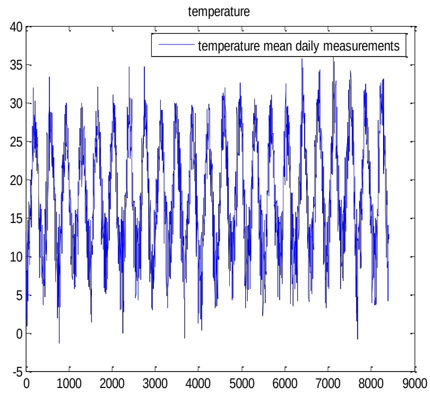
The data referenced from [1][4] hourly measurements and measured in Watt/ m^2. After observing the data with its logical values, there are some Error data during Measurements. This measured data is replaced due to errors during measurement. With the available data the main objective is to create time series of mean day-to-day solar radiation without error measurements, we can use this data for successful prediction process. The description of the process used in order to create the time series is provided.
All the -99.9 values are replaced with zeros. The average value of non-zero hourly values for every 24 hours for all the years is computed. The mean day-to-day values of the time series that are replaced from the average of the previous values if they equal to zero are replaced from the average next values if they are non-zeros or else from first previous non-zero value.

5.2 Temperature

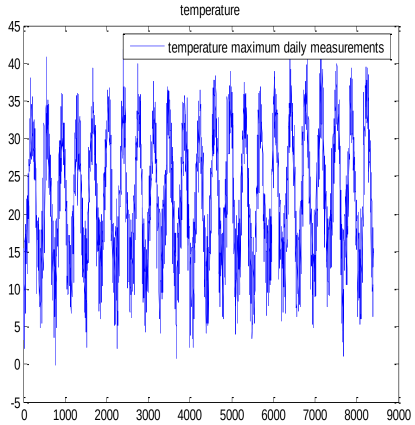
The temperature data for the period 1981-2003 are obtained and are measured in degree Celsius. They error measurements contained in the data collected has to be eliminated. The objective is to create the mean, maximum and minimum day-to-day temperature time series with no errors. The process differs from the previously implemented process in the fact that in the temperature time series. It is also concerned about zero and negative values which is in contrast with the solar time series. The positive non-zero values of solar radiation should be viewed carefully. The day-to-day time series is created in the following curves.



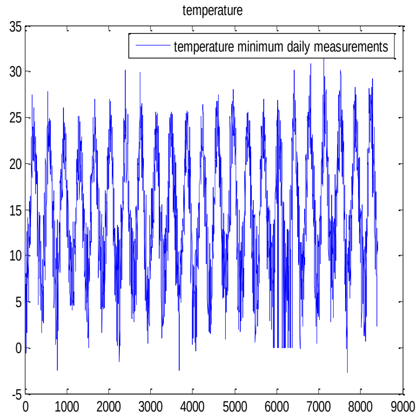
Mean day-to-day solar radiation



Mean day-to-day temperature



Max daily temperature



Min daily temperature

Fig. 2. Mean, minimum and maximum daily solar radiation and temperature

5.3 Normalization

In everyone of the above time series there are used the next two normalizing transformations:

$$Y_k = \frac{X_k - \text{mean}}{\text{std}}$$, normalization with mean=0 , standard deviation=1

$$Y_k = \frac{0.8}{\max - \min} * X_k + 1 \frac{0.1 * \max - 0.9 * \min}{\max - \min}$$, normalization with maximum value equal to 0.9 and minimum equal to 0.1.

6 Neural Network Predictors

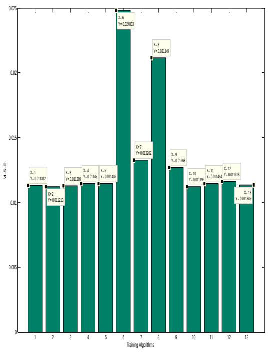
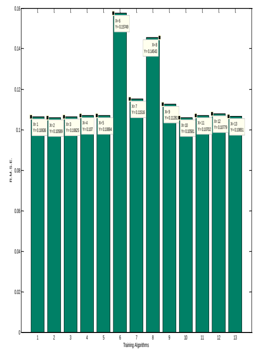
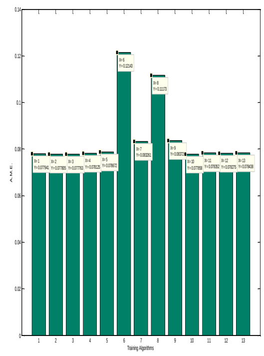
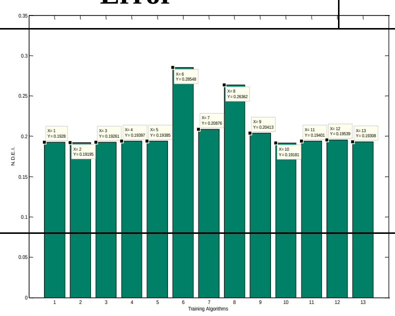
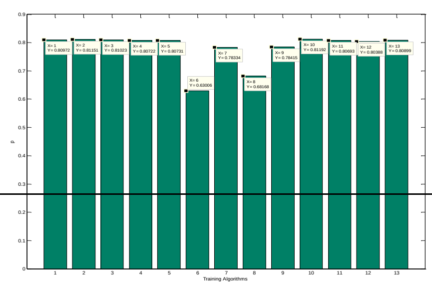
The Neural Network Predictors of different structures are created and trained. Then the network is tested with the meteorological data available and main objective is to achieve the best and more efficient topology for forecasting solar radiation and temperature. Initially it is appropriate to split the data to training and test data. There is not any fixed theoretical model clarifying what percentage of the whole data should be the training or the test data. Usually test data constitute a 20 to 30 percent of the overall data. So, concerning the solar radiation data, they were split in four parts its one consisting of 5 years and the temperature data were split in three parts of 8 years of data each. The question is which part of the data could be used as test data in order to constitute a characteristic sample of the measurements. That's because there may be a part of data that during the training process can cause local minima, which essentially is a destruction of the predictions. In order to solve this problem, multifold cross-validation has been utilized. After implementing this method it was obvious that any part of data can be used as test data as the test error was almost the same for every part. So, it was decided that for the solar radiation the training data are the data of the years 1981 to 1995 and the test data are the data of the years 1996 to 2000, and for the temperature the training data are the data of the years 1981 to 1995 and the test data are the 1996 to 2003 data. Next step is to decide the main structure of the neural network predictors. The main question to this is the number of hidden layers used firstly, and the number of nodes secondly, in order to avoid huge complexity and the over-fitting problem. In forecasting metrological data here it is enough to use single hidden layer is appropriate and enough. The first hidden layer is to find the local characteristics of the variable examined and simulated the following cases of structures of neural networks:

Given Inputs: Day-to-Day measurements for the 12 different time series created (real and normalized data)
Hidden layers: 1 No. of nodes: 5 Output: 1

Activation Functions used in neurons: Hidden layer: sigmoid, line Output layer: linear

The mean square error between the predictions and the real values are minimized using optimization. In order to find training algorithm, a small neural network 3-10-1, with sigmoid activation function of the hidden layer in the nodes is created and it was simulated for normalized data in the region 0-0.9 for 12 different algorithms using Neural Network Toolbox. We have used here five error metrics to choose the most efficient algorithm like:

MSE – Mean Square Error RMSE – Root Mean Square Error
AME – Absolute Mean Error NDEI – Normalized Root Mean Square Error Index
P – Correlation Coefficient.
With the above parameters the following algorithms are considered

		
Mean Square Error	**Root Mean Square Error**	**Absolute Mean Error**
		

Normalized Root Mean Square Error Index	**Correlation Coefficient**

Fig. 3. Mean, minimum and maximum daily solar radiation and temperature

Thus, the above curves prove that the Levenberg-Marquardt Backpropagation algorithm is the most efficient algorithm. Even when Levenbergs algorithm is compared with algorithms whose metrics have close values with, Levenberg is better as it's converging more quickly.

Error Metrics

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(x(k)-\hat{x}(k))^2 \quad \textbf{(4)}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(x(k)-\hat{x}(k))^2} \quad \textbf{(5)}$$

$$AME = \frac{1}{n}\sum_{k=1}^{n}\left|x(k)-\hat{x}(k))\right| \quad \textbf{(6)}$$

$$NDEI = \frac{RMSE}{\sigma} = \sqrt{\frac{\sum_{k=1}^{n}(x(k)-\hat{x}(k))^2}{\sum_{k=1}^{n}x^2(k)}} \quad \textbf{(7)}$$

$$\rho = \frac{\sum_{k=1}^{n}(x(k)-\overline{x})\cdot(\hat{x}(k)-\overline{\hat{x}})}{\sqrt{\sum_{k=1}^{n}(x(k)-\overline{x})^2\cdot\sum_{k=1}^{n}(\hat{x}(k)-\overline{\hat{x}})^2}} \quad \textbf{(8)}$$

Where $\hat{x}$(k) the prediction of the model, x(k) is the real value in time instance k, n the number of test data used for prediction. Correlation coefficient criterion (ρ) is the most characteristic error criterion showing the quality of prediction and it is proved that prediction improves; ρ is getting close to 1.

Neural Networks training and prediction results

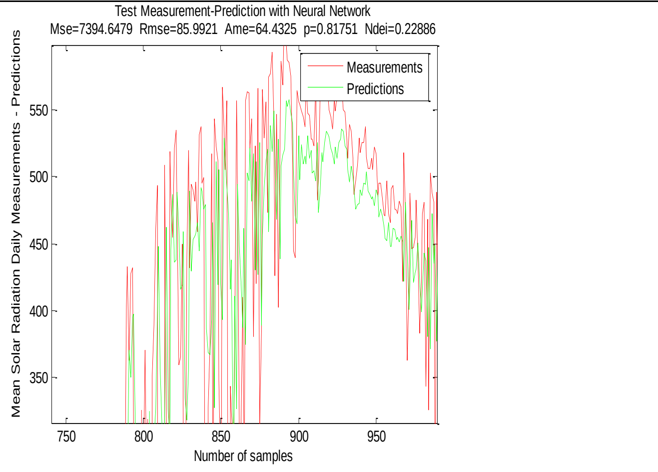
Here, for every different time series, a suitable Neural Predictor structure is chosen according to the discussed error criteria and the selected structure assumed functioning properly with having trained and tested for all the different cases along with the normalization and type meteorological time-series. Finally with the given criteria and Predictors are selected with different time series data. Assume four different type of Normalization and according to the assumed data four Neural Networks are chosen. For every unique type of meteorological time-series, the best four neural network predictors are selected. Finally, the results are compared with ANFIS or any other system created. The best neural network predictors are introduced.

Mean day-to-day solar radiation: normalized in the range 0.1-0.9, using sigmoid activation function.

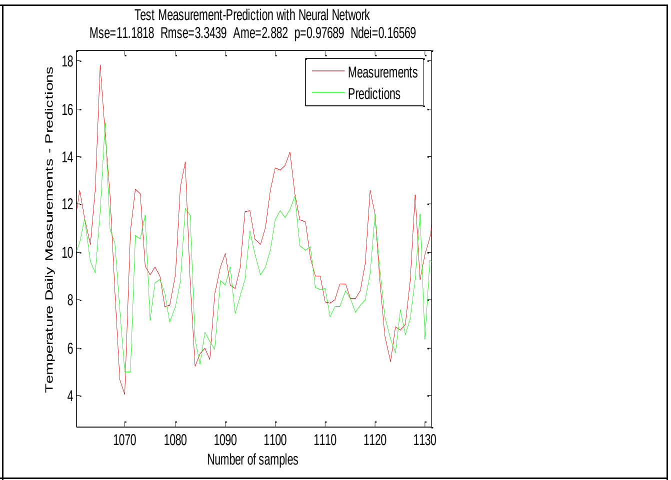
Mean day-to-day Temperature: normalized in the range 0.1-0.9, using sigmoid activation function

Maximum day-to-day Temperature: normalized in the range 0.1-0.9, using sigmoid activation function

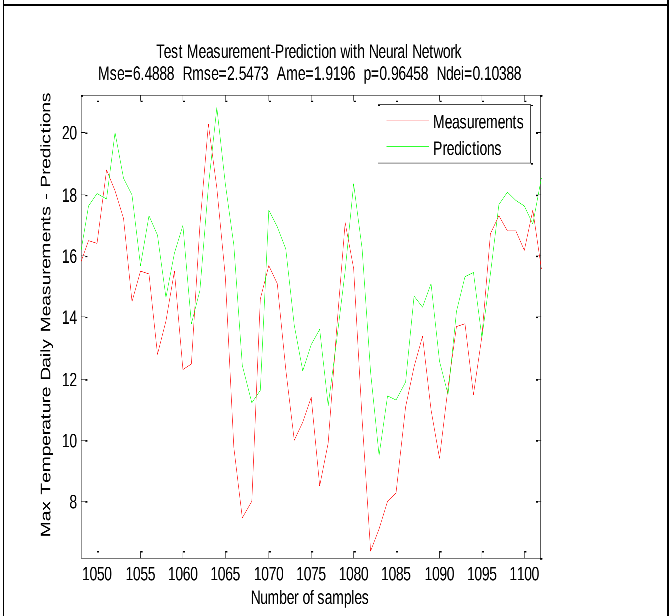
Minimum day-to-day Temperature: normalized in the range 0.1-0.9, using sigmoid activation function



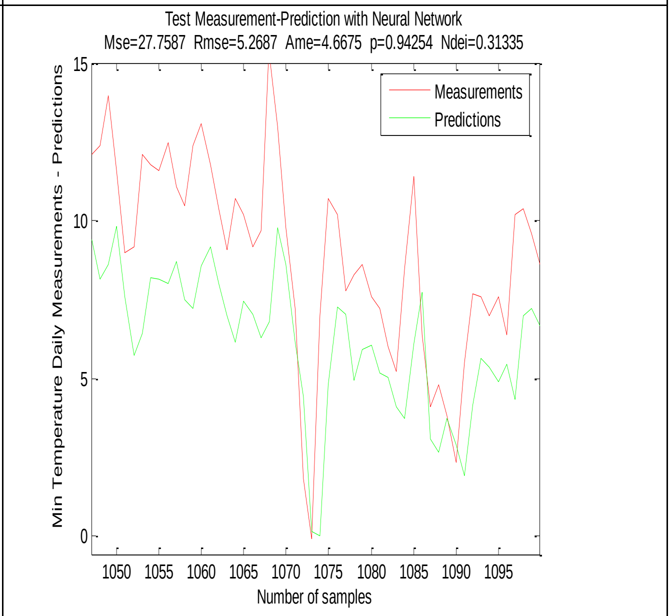
Mean day-to-day solar radiation predictions vs measurements with 5-15-1 N.N. for a small sample of data



Mean day-to-day temperature predictions vs measurements with 5-10-1 N.N. for a small sample of data



Maximum day-to-day temperature predictions Vs measurements with 7-5-1 N.N. for small a sample of data

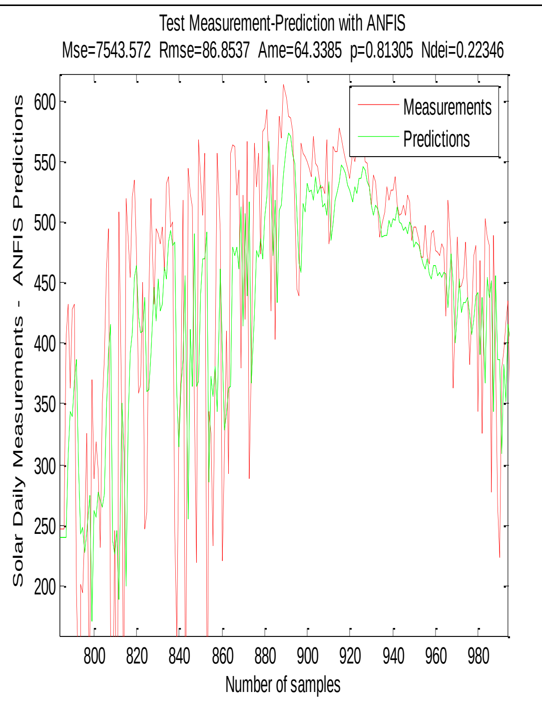


Minimum day-to-day temperature predictions Vs measurements with 2-15-1 N.N. for a small sample of data

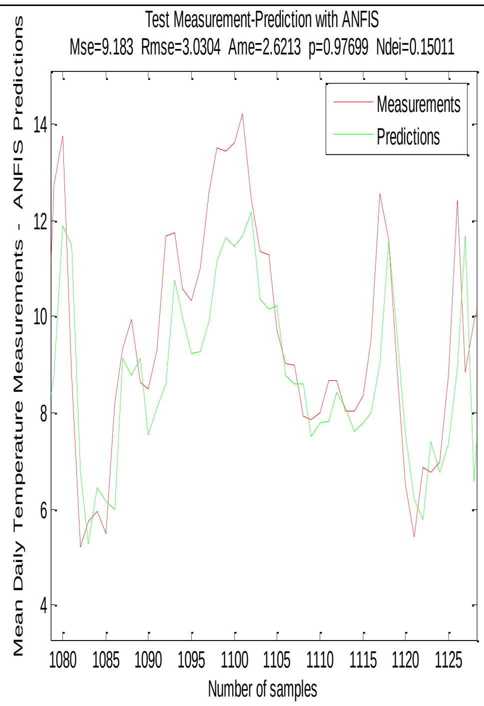
Fig. 4. Mean, minimum and maximum day-to-day solar radiation and Temperature with neural network

7 ANFIS

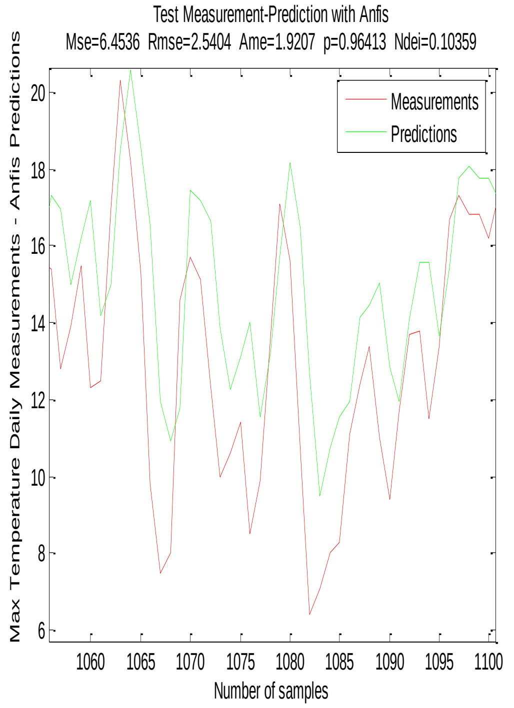
The fuzzy logic combined with neural networks provide very good results in the day-to-day solar radiation and temperature forecasting.



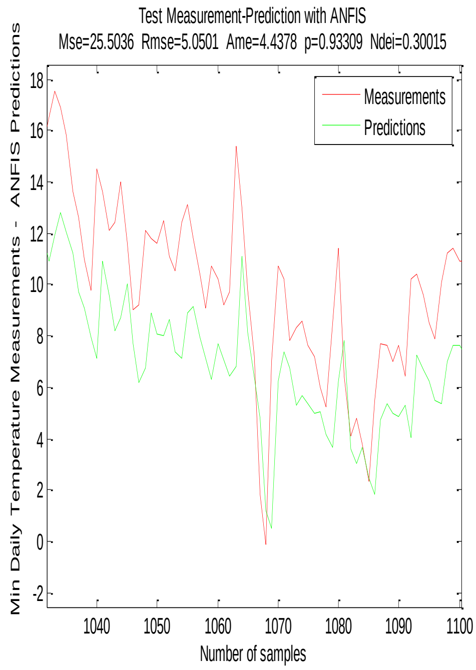
Mean day-to-day solar radiation predictions Vs measurements with ANFIS for a small sample of data



Mean day-to-day temperature predictions Vs measurements with ANFIS for a small sample of data



Maximum day-to-day temperature predictions Vs measurements with ANFIS for small a sample of data



Minimum day-to-day temperature predictions Vs measurements with ANFIS for a small sample of data

Fig. 5. Mean, minimum and maximum day-to-day solar radiation and Temperature with neural network

8 ‘Best’ Neural Network predictors Vs ANFIS

For the four different Time-Series a comparison is made between the ‘best’ Neural Network predictors and ANFIS using correlation coefficient (ρ).

Time-series / Predictors	Mean Daily Solar radiation	Mean Daily Temperature	Maximum Daily Temperature	Minimum Daily Temperature
N.N.→ 5-15-1	ρ = 0.81751	ρ = 0.97689	ρ = 0.96458	ρ = 0.94254
ANFIS	P = 0.81305	ρ = 0.97699	ρ = 0.96413	ρ = 0.93309

9 Conclusions

This paper constructed a hybrid type Neural Network with the following conclusions. Levenberg-Marquardt Back propagation surpasses the others in quality of results and speed thus proving to be the most efficient training. The best type of normalization proved to be the one in region 0.1-0.9 in combination with sigmoid activation function in the hidden layer nodes. The number of nodes used in the hidden layer depends from the type and the complexity of the time series, and from the number of inputs. The combination of linguistic rules of fuzzy logic with the training algorithm used in neural networks contribute to very qualitative prediction results. Thus, proved that the neuro-fuzzy predictors and ANFIS is a qualitative network with very good predications.

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