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Weather Forecasting using Fuzzy Neural Network (FNN) and Hierarchy Particle Swarm Optimization Algorithm (HPSO)

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Abstract

Background: Weather forecasting has become one of the active research areas due to major scientific and technological problems. An analysis is made to utilize of data mining approaches in weather forecast. **Methods:** Fuzzy Neural Network (FNN) and Hierarchical Particle Swarm Optimization (HPSO) are used for predicting the weather changes occur in the atmosphere. The FNN uses biological neurons for exact calculation and the neural network adjust their weights by the practice of training. The HPSO is used here for better optimization of weights, also that to improve the overall performance Adaptive Inertia Weight Algorithm (AWA) is proposed. **Results:** As a result, the total error is reduced with little tolerance which results in accurate weather prediction. The network is trained in such a manner that the model will provide 94% of optimum results. **Conclusion:** The performances of the proposed algorithm were compared with other existing algorithm using other standard performance metrics which gives best results for the mean weather variables. The results show that the proposed approach is efficient in determining weather forecasting and moreover helps in climate change investigations.

Keywords: Fuzzy Neural Network, Hierarchy Particle Swarm Optimization Technique, Network Forecasting, Numerical Weather Prediction, Weather Forecasting

1. Introduction

Weather forecasting is a major problem in today's world. The importance of weather forecasting has been recognized in recent years as population has increased tremendously in the last two decades and moreover, advances in science and engineering has indirectly led to the prediction of weather[1]. Designing an accurate prediction approach is a challenging task as it involves thorough analysis of several prediction techniques. A number of weather prediction algorithms have been developed in the past and each one has their own advantages and limitations[2].

Data mining techniques involved in the weather forecasting applications are focused on determining the hidden patterns from the vague voluminous meteorological data to transform the data retrieved into an exploitable knowledge. Thus, several data mining techniques have been employed in diversified applications such as predicting rainfall, weather, storms and flood. Weather forecasting falls under predictive mining which focuses on the data analysis, formulates the database, and forecasts the features of anonymous data[3].

In recent decades, neural network[4] has become a widespread and efficient approach that could handle and solve complex interrelationships. The impulse for the expansion of neural network is based on the objective to recognize a model that could perform works that are relevant to an artificial intelligent framework.

Similar to Artificial neural network, past two decades have seen an extensive usage of swarm intelligence algorithms in diversified applications. Its significance and efficiency has been justified in various fields of science and

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engineering. It has been used in solving the non deterministic hard polynomial problems.

This research work mainly focuses on solving the weather prediction based NP hard problem through the integrated utilization of Swarm Intelligence (SI) and Artificial Neural Network (ANN). The major contribution of this research work is to formulate an efficient weather prediction model based on the soft computing algorithms. Thus, in order to overcome the limitations of ANN algorithms, this work uses fuzzy neural network wherein the fuzzification model provides better results comparatively. Moreover, among the swarm intelligence algorithms, Particle Swarm Optimization (PSO) is considered as the most widespread approaches and this work utilizes Hierarchy particle swarm optimization algorithm to predict the future weather condition.

2. Related Works

In this section, an analysis is carried out with the existing weather prediction techniques available in the literature based on the diversified concepts of various researchers.

In [5], a weather prediction approach based on Support Vector Machines (SVM) has been presented. Time series information of the day by day maximum temperature has been considered for the analysis of the highest temperature at that spot for a time of prior n days with reference on the input[6]. Experimental result of the approach has been evaluated for different periods of 2 to 10 days with the assistance of optimal values of the kernel function.

In [7] presented an experimental result of Multi Layer Perceptron on dataset which includes 10 years of meteorological data. It indicates that MLP approach has lesser error when compared with the conventional approaches.

In [8], Artificial neural network based prediction model has been presented for the Georgia AEMN data. The main contributions of this work are bigger training set, seasonal input variables, and dynamic hidden layers. Especially, the addition of seasonal variables equivalent to fuzzy membership enhances the performance of the overall system.

Mike ONeill[9] focuses on two main practical aspects which includes the association among the certain amount of training data together with error rate. Other aspect is the transferability of models' proficiency among diverse data sets. In [10,11] schemes based on Back Propagation Neural Network (BPN) has been proposed for the purpose of weather forecasting.

At present, data mining techniques have been widely used in order to effectively predict various climatic variations[12]. Regression tree approach has been used in predicting the interrelationship among the different climatic variations. Independent Component Analysis (ICA)[13] determines the independent component similarity within the spatio-temporal data especially for the case of North Atlantic Oscillation (NAO). Here, neural networks together with nonlinear canonical correlation assessment are proposed for the purpose of determining the association among Sea Level Pressure (SLP) and Sea Surface Temperature (SST).

3. Materials and Methods

In this research work, the approaches like fuzzy neural network and the hierarchy particle swarm optimization scheme is employed to predict future weather condition. The brief explanation about this algorithm is discussed below.

3.1 Fuzzy Neural Network

In fuzzy neural network, the neuron is fuzzily processed which means the input weight value are formulated as the fuzzy measure expressed by membership grade and the output fuzzy sub-collection is diverted to non-fuzzy digital measure. Figure 2 shows the fuzzy neural network model for obtaining the initial forecast. The fuzzy sets for temperature and humidity parameters are given as input. The input to the FNN consists of the membership values to the overlapping partitions of linguistic attributes such as small, medium, and large equivalent to each input feature like rain, temperature, humidity etc. Thus, the linguistic information is integrated in both the training and testing stages of the weather prediction model which increases robustness in handling uncertain input conditions. The output layer consists of the membership values to the overlapping partitions of linguistic attributes small, medium and large equivalent to the forecast load magnitude. At the training phase, FNN back propagates the errors in accordance to the desired membership values at the output nodes. After number of iterations, FNN converges to a minimum error solution through a gradient descent algorithm after the learning phase, when separate weather patterns are presented at the input layer, the output nodes produce the membership values equivalent to the linguistic properties. Thus a centroid defuzzification technique is used in this approach to obtain the initial load forecast from the membership values and the equivalent loads are obtained from the n-functions.

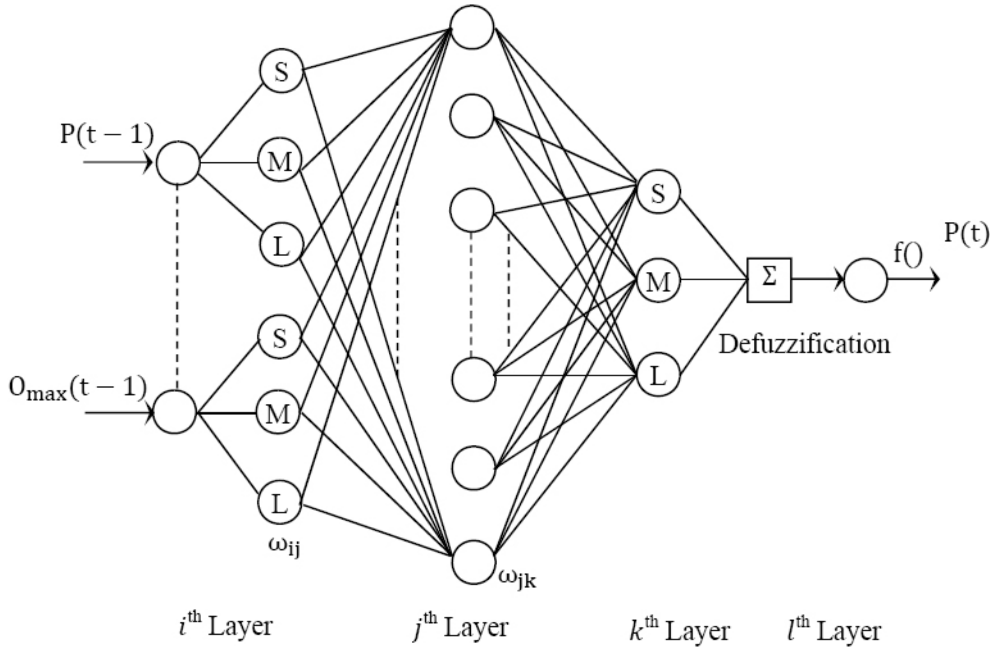


Figure 1. Fuzzy Neural Network for initial weather forecast.

3.2 Hierarchical Particle Swarm Optimization

An efficient HPSO approach has been used in this work to solve hierarchy multiple-objective operation optimizations[14].

The process of HPSO is clearly discussed in the following steps:

In case of multiple-objective functions, optimization of objective function includes logical hierarchy and also priority procedure based on updating process of particle pBest and gBest:

1. Primarily, the objective function vector of the particular j-th particle is calculated, subsequently based on the objective function value of pBest and gBest, sorting is performed. Then, the pBest and gBest of j-th particle value are updated to forecast the weather which adopts an objective value based on the fitness assignment approach wherein fitness is allocated based on the concept of domination.
2. The crowding distance in the objective space is evaluated, which is the 1-norm distance among the two adjacent neighbors of the solution. During the multi-objective optimization formulation, it is modeled that the ultimate solutions take in the entire objective space. Thus, the solutions which have huge crowding distances are taken for consideration for providing efficient solution.

The construction of HPSO is as given below:

Step 1: The constraints are initialized;

Step 2: The preliminary population are created in the suitable locations of particles;

Step 3: The subsequent generation population is created:

for j = 1 to POP_SIZE // where, *POP_SIZE* is population size.
for i = 1 to M

a. Determine the suitable locations of particles $\left\{x_j^i\right\}$. Upper and lower limit of a sequence of particles $\left\{x_j^i\right\}$ (called also limes superior and limes inferior) can be defined and are denoted, respectively as

$$\mathbf{U} := \lim_{\substack{i\to m \\ j\to \text{POP\_SIZE}}} \sup x_j^i \; \mathbf{L} := \lim_{\substack{i\to m \\ j\to \text{POP\_SIZE}}} \inf x_j^i \tag{1}$$

(Some authors use also the notation $\underline{x}_j^i, \bar{x}_j^i$).

b. The velocity of limited region is calculated

$$\mathbf{U} := \lim_{\substack{i\to m \\ j\to \text{POP\_SIZE}}} \sup v_j^i \; \mathbf{L} := \lim_{\substack{i\to m \\ j\to \text{POP\_SIZE}}} \inf v_j^i \tag{2}$$

c. The position $\left\{x_j^i\right\}$ in $t+1$ generation is computed;

d. The objective function vector of j^{th} particle $(f_1, ..., f_N)$; is computed

e. Revise the gBest of population and pBest corresponding to the j^{th} particle in accordance with the first choice among the objective function;

f. Mutate the i^{th} particle;

Step 4: Decide on the convergence of HPSO;

Step 5: Output the *gBest* particle.

3. Accelerating Genetic Operator of HPSO

An essential factor to organize the rate of convergence of the process is the velocity of the particle and also it manages or controls the direction and the exploring process at the time of optimization procedure. There is a possibility that the process may end up in local optima which in turn results in particle oscillation approximately a spot due to the smaller exploration process[15]. If the information about the optimum object is determined, then, it possibly will direct the particles toward the global optimal solution; as a result it results in enhancing the converging speed.

With the individuality of peaking operation, an accelerating genetic operator is formulated to adjust the exploring path of particles by means of the particle's location during the time of optimization procedure. The accelerating genetic operator is thus formulated through the process given below:
Initially, normalize the decision variable of particles, p to [-1, 1]. The absolute value of p are assumed to be greater than a threshold value 0.85 and are positioned at either the peak load (p>0) or valley load (p<0) wherein '**the maximum velocity are fixed to 0'** in case of the previous one and the minimum velocity of particles are fixed to 0 for the following case. With more number of particles p, the dissimilarity limit of velocity would be greater. Hence, the exploration process and the way are altered through restraining dissimilarity limit of velocity. Figure 2 shows the process of the algorithm. In which, $x_j^q = \frac{1}{M}\sum_{i=l}^{M} x_j^i$ indicates the average value of decision variable of the particular j-th particle, R represents an arbitrary number in the range of [0, 1], sgn (·) indicates a sign function, α denotes a real number in the range of [0,1]. The optimization process is repeated until the condition is fulfilled.

3.3 Adaptive Inertia Weight Algorithm (AWA)

Inertia weight w represents the modulus which organizes influence of prior velocity on the existing one, consequently, stabilizing the process of both exploration and exploitation in PSO. This results in the optimal inertia weight which is essential to determine the most favorable solution. So, an AWA algorithm is used in this work to improve the overall searching ability of the algorithm.

When the objective values of particles are closer to local optimal value, there is a rise in the inertia weight or vice versa. Simultaneously, in case of the particles with objective values higher than the mean value, subsequently it will be fixed at lower value to enhance the searching ability, or else, the inertia weight will be fixed a bigger value to investigate the search space.

The algorithm is employed for the purpose of supporting best particles (pairs) in order to transform their exploration step which effects in improved the searching capability. The worst particles are to be modified in the searching space through large step. The algorithm is given below.

$$IW_{i,t} = \begin{cases} IW_{min} + \dfrac{\left(IW_{max} - IW_{min}\right)\left(f_{i,t} - f_{min,t}\right)}{f_{avg,t} - f_{min,t}} & f_{i,t} \le f_{avg,t} \\ IW_{max} & f_{i,t} > f_{avg,t} \end{cases} \tag{3}$$

Where, $IW_{i,t}$ indicates the Inertia Weight of i^{th} particle at some point in t-th iterations, W_{max} and W_{min} indicates the highest and lowest amount of inertia weight, correspondingly. $f_{i,t}$ indicates the objective value of specific i-th particle at some point in t-th iterations, $f_{avg,t}$ and $f_{min,t}$ indicates the average and lowest amount objective values of the entire particles at some point in t-th iterations, correspondingly.

4. Proposed Weather Forecasting using HPSO and FNN

In developing and agro economy based countries like India, weather plays a vital role in economical growth of the nation. So, weather prediction should be more accurate and important. Weather parameters are collected from the various stations of meteorological department, Orissa. The basic parameters are maximum temperature, minimum temperature, rainfall, humidity, pressure and cloudiness. There are many forecasting models is

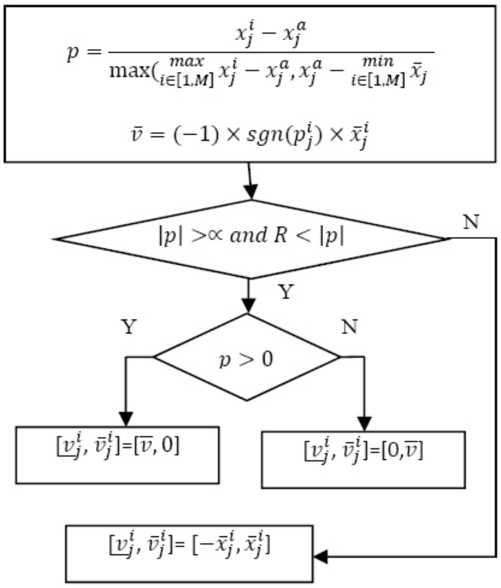


Figure 2. The flow chart of accelerating operator.

presented which uses Fuzzy Neural Network (FNNs). In this work, a model is proposed which uses FNNs and Hierarchical Particle Swarm Optimization (HPSO) technique for accurate prediction.

4.1 Algorithm for Predicting Weather using FNN and HPSO

- The amount of hidden neurons, population size, maximum iterations and model parameters ($c1$, $c2$, m) are initialized
- The weather data are obtained from the respective dataset
- Random generation of population and biases
- for i = 1, ..., *POP_SIZE* Do
- Fitness calculation
- end for
- Gbest and pbest calculation
- for i = 1, . . . , maxIterations Do
- for i = 1, . . . , POP_SIZE Do
- for j = 1, . . . , dimensions Do
- Determine the velocity;
- Determine the Position;
- end for
- end for
- Do step 5
- for i = 1, . . . , POP_SIZE Do
- Determine pbest
- end for
- Determine gbest
- end for
- Finalized Weights and Biases values are attained

In this work, the value of the MSE serves as the objective function for determining the appropriate parameters for use in the HPSO-FNN model.

$$f_{fitness} = \frac{1}{N}\sum_{k=1}^{N}\frac{1}{ON}\left[\sum_{l=1}^{ON}\sum_{i=1}^{POP\_SIZE}\left(TO(x_i)_{kl} - PO(x_i)_{kl}\right)^2\right] \quad (4)$$

Where ffitness indicates the fitness value, TO indicates the target output; PO represents the predicted output in accordance with the xi; N represents the number of training set samples; and, ON indicates the number of output neurons.

5. Results of Rainfall

Simulation of this approach has been carried out in MATLAB. The results are observed for the purpose of assessing the performance of the proposed FNN based HPSO model. The dataset is collected from Puri Zone in the year 2008. The initial step screen shot of the weather forecasting approach is shown in Figure 3. The screen shot of training FNN is given in Figure 4.

The training target output from FNN approach for calculating rainfall of Puri Zone for the year 2008 is shown in Figure 5. The graph shows the actual and the desired

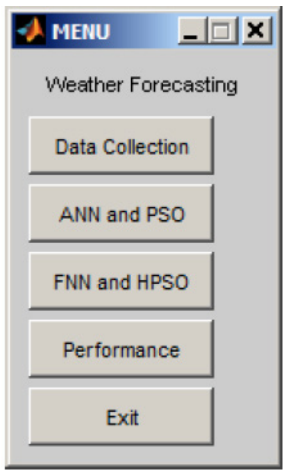


Figure 3. Matlab screenshot of menu list of weather forecasting.

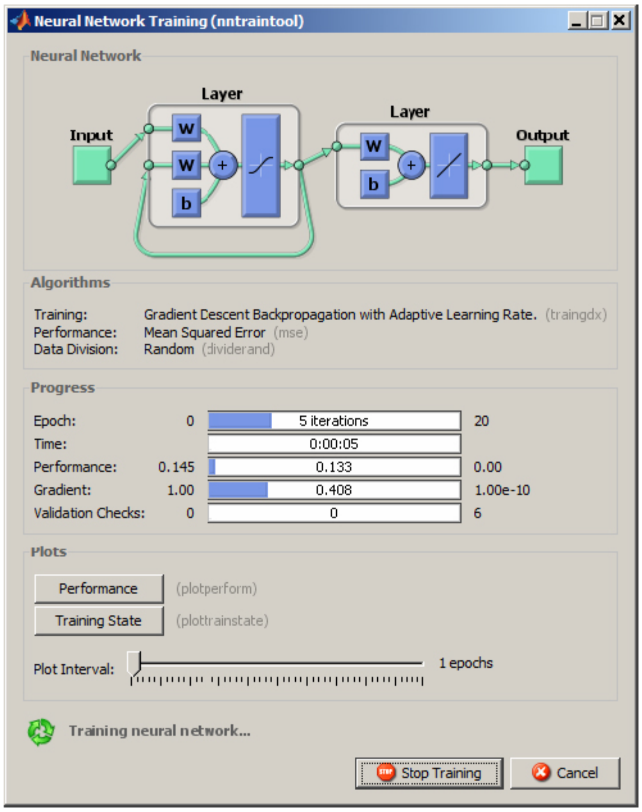


Figure 4. Matlab Screen of training of neural network.

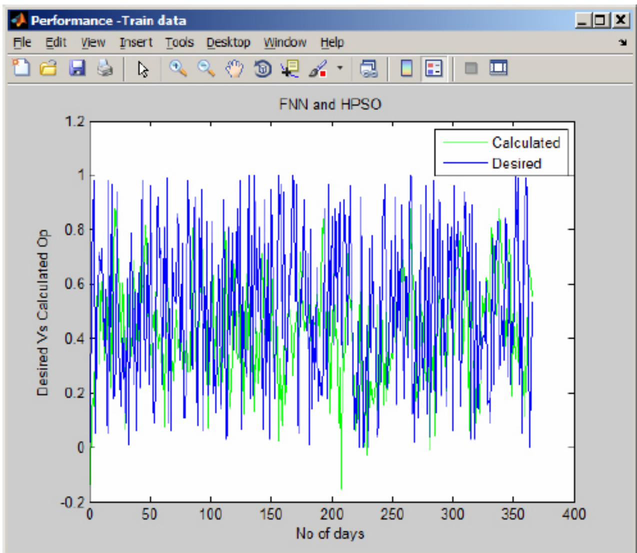


Figure 5. Training target and output of Rainfall of puri.

values obtained from the proposed scheme. It is clearly found that, the calculated and desired curves overlap for most of data values which shows that desired output and target are nearly similar. All outputs are in error range less than 1% at some stage in the training phase.

The mean error rate is computed to evaluate the accurateness of the prediction result. The predicted result is compared with the actual results obtained and an error rate is formulated which is done again for the entire iteration patterns. The normalized error rate is given by equation (5)

$$Err_j = \frac{\sum_i^N |p_i - a_i|}{\sum_i^N a_i} \tag{5}$$

where p_i indicates the predicted rain, a_i represents the actual rain and (N = 100) denotes the number of evaluation patterns. The mean normalized error rate was determined using the following equation,

$$\overline{Err_j} = \frac{\sum_j^L Err_j}{L} \tag{6}$$

Where Err_j represents the error per rain-gauge j computed from the previous eq (6) and L indicates the number of the rain gauges.

Figure 6 demonstrates the testing target and output generated. During testing 94% of estimated data points are closed to desired data values.

Figure 7, Calculation of Error rate. Red Continuous line represents the proposed approach error rate. Blue dotted line represents the existing approach error rate. The black dashed line show the relation between both approaches. In which the proposed FNN with HPSO gives the smallest amount of error rate of 1% when compared with other existing approaches like ANN with PSO.

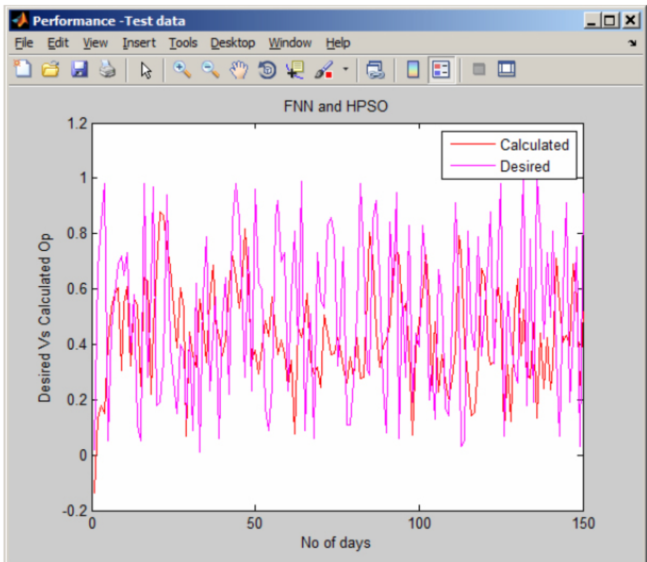
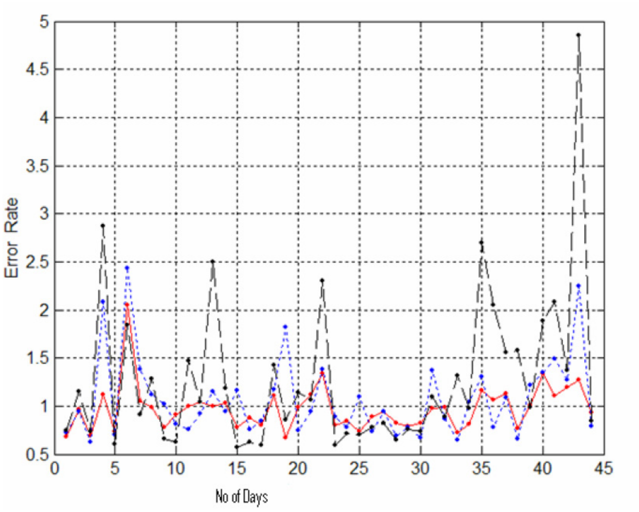


Figure 6. Testing target and output of Rainfall of Puri.



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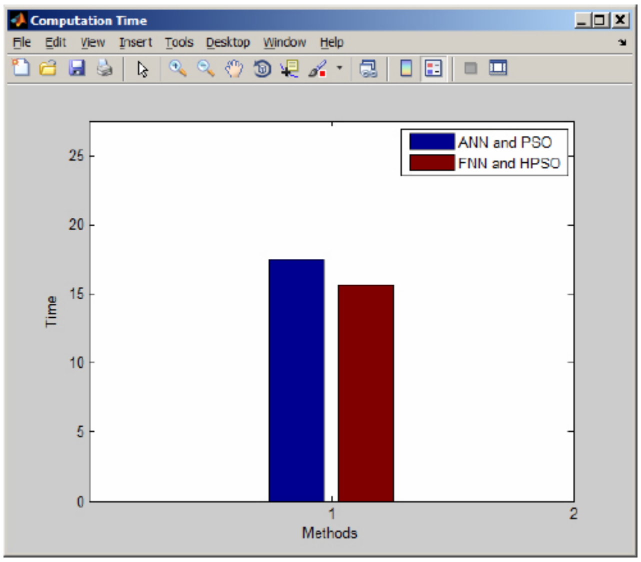

Figure 8. Processing Time comparison. From Figure 8, it can be shown that the proposed FNN with HPSO approach process in less time of 15 sec when compared with the existing method of ANN with PSO.

6. Conclusion

This work proposes an efficient weather prediction model using Fuzzy Neural Network and Hierarchical Particle Swarm Optimization technique. The hybrid HPSO-FNN algorithm is employed to determine the optimum FNN structure, connecting weights and bias values. Furthermore, FNN helps in reducing the size of the network and consequently reduces the training time. The proposed HPSO-FNN method for weather forecasting is observed to produce significant results over the conventional techniques. The working of the proposed method is assessed in accordance with the error rate which revealed that the proposed HPSO-FNN model produces lower prediction error and is better than the ANN and PSO based methods. Thus, this model provided the most optimal forecasting results in comparison against other conventional techniques.

Table 1. Various combination of network parameter

Parameters	Range of value	Increments
Population Size (No of Particles)	10-100	10,20,30,40
No of Neurons in hidden layer	5-50	5,10
No of Iterations	100-1000	100,200,300
No of Runs	5	1

7. References

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