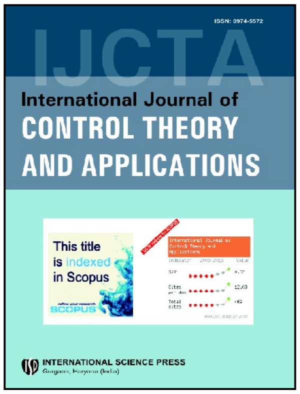

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Oppositional PSO based Optimized RBF Neural Networks for Estimating Daily Rainfall in Kanyakumari District

[1]Balamurali A, [2]Siva Balan R V, [3]Anu Meera B and [4]Karthika B

[1]*Fishing Harbour Project Division, Fisheries Dept, Govt of Tamilnadu, India, E-mail: balamuralia0765@gmail.com*
[2]*Noorul Islam University, Tamilnadu, India*
[3]*Anna university, Guindy campus, Chennai, India*
[4]*Tata consultancy Services, Bangalore, Karnataka, India*

Abstract: Rainfall prediction is most challenging problem around the world. To overcome the difficulty present in the rain fall prediction, in this paper, we develop a novel method to rainfall prediction using oppositional particle swarm optimization (OPSO) , is utilized to regulate the components of radial basis function neural networks (RBF-NN) (number of neurons, their corresponding centers, radii and weight) spontaneously. Initially, the input dataset is given to the RBF-NN. To calculate the parameter of the RBF-NN (radii, weights, amount of neurons and their corresponding centers,), in this approach we used OPSO algorithm. In this OPSO, the oppositional based learning (OBL) is hybrid with the PSO, where OBL is improving the performance of the PSO algorithm while optimizing the parameters of RBF-NN. Using real datasets congregated from pechiparai and perunchani regions the performance of the algorithm is investigated. At last, from comparative study it is recognized that the anticipated prediction produces better solution if associated with other tactics.

Keywords: Rainfall prediction, PSO, RBF, neural network, weather forecasting, parameters, pechiparai, perunchani.

1. INTRODUCTION

Appropriate administration of water resources includes arranging, advancement and circulation of water assets. These exercises are specifically or in a roundabout way connected with expectation of precipitation or spatial examination of hydrologic cycle [1]. Along with the key affecting segments of the hydrological cycle, precipitation forecast has an amazing part in overflow demonstrating and, thus, water asset administration [2, 3]. An exact amount of rainfall prediction can recognize the probable for over whelming precipitation and conceivable related blaze flooding, and in addition giving data to hydrologic interests [4]. Likewise, rainfall perseveres through different human nature collaborations, for example, horticulture, warm solace, and vanishing [5]. Rainfall is difficult to foresee, in light of the fact that it relies on upon the space and time scales. These days, environmental change influences the example of rainfall. The effect of these impacts incorporates great event of flooding and dry seasons [7]. Besides, the forecast of rainfall with great and exact strategy is vital keeping in mind the end goal to foresee the effect [8]. Analysts consider rainfall as a stochastic procedure [6]. In this manner, precise rainfall anticipating is one of the best difficulties in operational hydrology, in spite of numerous advances in climate determining in late decades [9].

The appearances of both stochastic and deterministic precipitation estimate models [12] are influenced as precipitation is being a standout amongst the most convoluted parts of the hydrological cycle to gauge, and gigantic dubious. In each spot precipitation is not a typical occasion. It has a couple regularity results. Consequently, the precipitation figure issue is not comparable as other common barometrical parameters like temperature, mugginess, and so on. Precipitation is more over a period arrangement records like barometrical weight, temperature, vapor weight, relative dampness, radiation, and so on [13]. At nearby and across the country levels a broad exhibit of precipitation estimate strategies are utilized as a part of climate anticipating. There are two ways to deal with conjecture precipitation essentially. Observational and dynamical methods are the two methodologies. Over different parts of the world the observational methodology depends on the investigation of authentic records of the precipitation and its relationship to a scope of barometrical and maritime variables. In light of techniques for conditions in compelling methodology, gauges are delivered by physical models that estimate the development of the worldwide atmosphere strategy in answer to first air conditions [10] [11].

A few experimentations have demonstrated that they are still off base techniques to estimate precipitation and climate since climate information are non-direct [14, 15]. Be that as it may, now and again, precipitation expectation measurable strategy is additionally ready to create great and exact forecasts [16]. In addition, Neural system (NN) methods have been perceived as more helpful than routine factual determining models since they can outline non-direct capacity without comprehension the physical laws and any uncertainties of expected measurable methodologies needed [17, 18]. Several kinds of NN have been projected for precipitation assessing, amongst that two in general used classes are back proliferation neural system (BPNN) [19] and also outspread evidence capacity neural system (RBF-NN) [20]. Back proliferation based preparing calculation has extended much enthusiasm for climate gauging [21] among unique sorts of ANNs. In any case, back proliferation calculation is very little effective in educating for the real time issues. In like manner, the fruitful outlining of showing calculation can demonstrate the best approach to try and enhanced results in ANN models.

We have established a new rainfall prediction method with the help of the actual optimization algorithm along with RBF-NN in this work. One among the main objective of this work is to, improve an actual optimization approach Oppositional Particle swarm optimization for the finest constituents of the RBFNN, specifically RBF-OPSO, to imprecise a performance on behalf of a rainfall prediction. The association of this paper is as follows: rain fall prediction based literature review is presented in Section 2. The proposed rainfall prediction model is detailed in Section 3. The performance evaluation and experimental results are delivered in Section 4. Finally, the conclusions are given in Section 5.

2. RELATED WORKS

Numerous investigators have elucidated the rainfall prediction methodology. Amongst them a few of the research works enlightened in this segment; Abdusselam and Tewodros Assefa [22] have illuminated the two systems termed joined season-multilayer perceptron (SAS-MP) and also mixture wavelet-season-multilayer perceptron (W-SAS-MP) were twisted to improvement forecast exactness and augment anticipation lead duration of every day precipitation up to 5 days with the help of utilizing data from two places as a portion of Turkey. The developing RBF neural schemes for precipitation forecast using hybrid particle swarm optimization (HPSO) and also genetic algorithm (GA) was put forward by Jiansheng Wu *et al.* [23]. Here, the was utilized the rain fall prediction passed on hybrid optimization algorithm with (RBF-NN) that challenges a predefined problem, recognized along with precipitation expecting for this condition. Discrete in additional epoch were completed via three methods to covenant with improve the global streamlining implementation that were elitist organization, PSO method and GA process.

The Assortment of meteorological parameters manipulating precipitation approximation using neuro-fuzzy computing methodology was described by Roslan Hashim *et al.* [24]. For this, they utilized five data components: wet day frequency, vapor weight, and also most extreme and also least air temperatures and additional to overcast spread. Moreover, The Expert System for Rainfall Prediction was described by Indrabayu *et al.* [25]. This technique combines the Support Vector Machine (SVM) and also Fuzzy Logic approaches. The implementation of the approach was compared with the Neural Network (NN)–Fuzzy. The atmosphere reliable data was contracted from PT LAPAN Bandung. Moreover, Discerning models to antedate downpour power (mm/day) in Athens, Greece, using Artificial Neural Networks (ANN) models has been elevated with the help of P.T. Nastos *et al.* [27]. The ANNs solutions stress the plotted mean, most exciting and least month to month downpour power intended for the subsequent four progressive months in Athens. A bearably steady foreknow of the downpour power intended for the subsequent four months was performed with the help of the influences of the produced and connected ANN models. Similarly, A Forecast Model by mode for Artificial Neural system has been associated by Kumar Abhishek *et al.* [26]. This documentation implemented one among those dimensions using building inculcating and testing data sets and detecting the number of enclosed neurons in these layers.

3. PROPOSED RAINFALL PREDICTION MODEL

The main objective of this study is to generate a rainfall prediction model using OPSO and RBF-NN. The rainfall prediction is mainly used for agricultural development. The complete block diagram of projected rainfall prediction model is portrayed in figure 1.

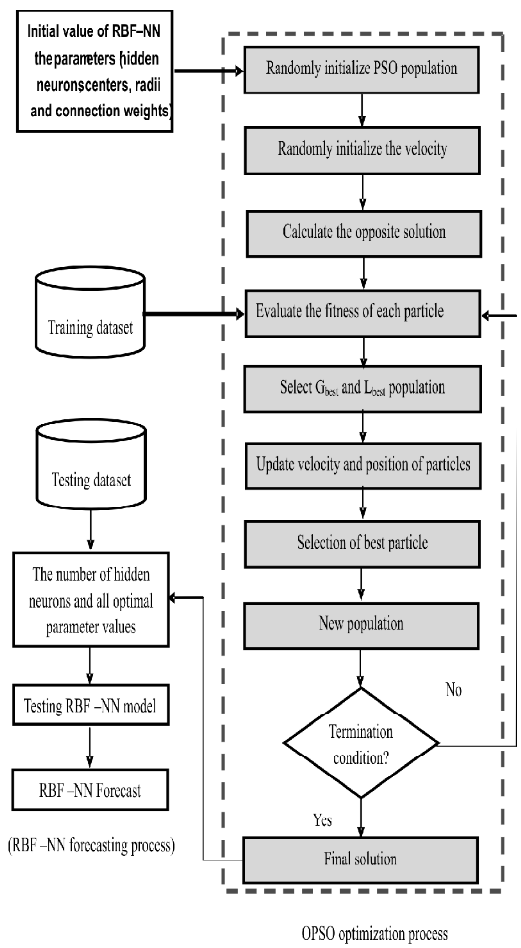


Figure 1: Complete structure of proposed rainfall prediction system

3.1. Prediction based on Radial Basis Function Neural Network

We enlightened a well-organized future rain fall prediction on the basis of hybridization of Oppositional particle swarm optimization and radial basis function neural network (OPSO+RBFNN) in this section. At this point, on the basis of the Particle swarm optimization algorithm, the parameter utilized in the RBFNN (amount of neurons, their respective centers, radii and weight) is enhanced. The elementary architecture of a three-layered RBF-NN is demonstrated in Fig. 2.

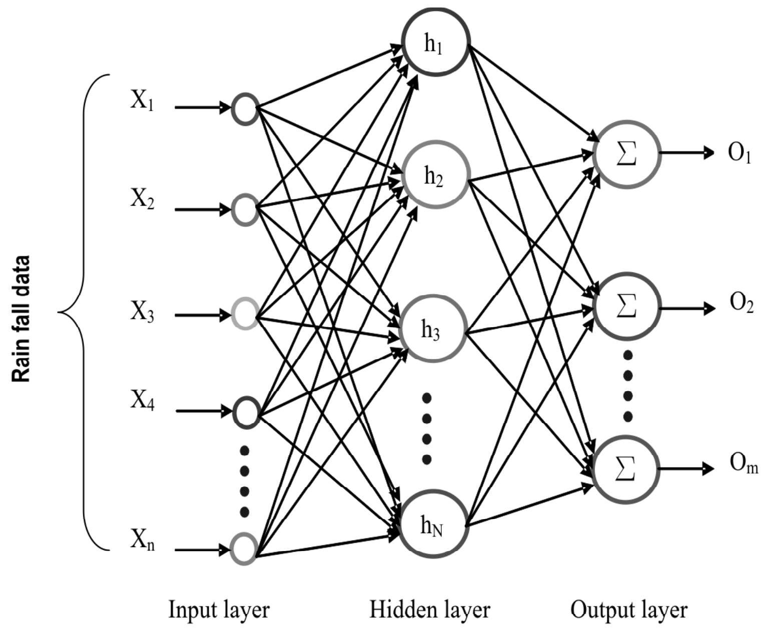


Figure 2: working structure of RBF-neural network

The network is normally consisting of three layers: an input layer, a single unseen layer and an output layer. The output of the RBF-NN is intended conferring to

$$\begin{aligned} Y^s &= \sum_{i=1}^{N} W_{si}\, h_i\,(x, o_i) \\ &= \sum_{i=1}^{N} W_{si}\;\, h_i\left(\|x - o_i\|_2\right), \qquad s = 1, 2, \ldots, m \end{aligned} \tag{15}$$

Where,

$x \in R^{n \times 1}$ → input vector,

$h_k(.)$ → radial basis function

$\|\cdot\|_2$ → Euclidean norm,

W_{si} → Weights of output layer,

N → Number of neuron

O_i → Center

A standardized Gaussian function characteristically is used as the radial basis performance as follows:

$$h_i\left(x, c_i\right) = \exp\left(\frac{-\left\|x - c_i\right\|_2}{R_i^2}\right) \tag{16}$$

In which R_i indicate the radius of the i^{th} node. It has been established that when enough units are distributed, a RBF-NN can vague any multivariate continuous performance as expected [28]. In this paper, a OPSO algorithm is used to determine the best ingredients of the RBF-NN that vague performance on board of a rainfall time series in this analysis.

3.2. Hybrid of OPSO and RBF-NN design

Step 1: Population initialization

The population initialization is the significant phase in the entire optimization algorithm. Here, we arbitrarily modify the RBF-NN parameters with the size of 4*N* individuals. Here, the optimized parameters are how much of hidden neuron needed, the center of the RBF C_i, radii R_i and weight W_i. The initial solution is represented as Y_i.

Step 2: Generate opposite solution

Rendering to opposition based learning (OBL) familiarized by Tizhoosh in 2005 [13], the current particle and its opposite agent are measured instantaneously to acquire a better estimate for current agent result. It is specified that an opposite agent result has an improved chance to be nearer to the worldwide optimal result than random agent result. The opposite agent's positions (OY_i) are entirely well-defined by constituents of Y_i.

$$OY_i = \left[oy_i^1, \ldots, oy_i^d, \ldots, oy_i^D\right] \tag{2}$$

Where $oy_i^d = L_i^d + U_i^d - y_i^d$ with $oy_i^d \in \left[L_i^d, U_i^d\right]$ is the position of i^{th} opposite agent OY_i in the d^{th} dimension of opposite population.

Step 3: Fitness calculation and ranking

The selection of the fitness is a vital feature in OPSO algorithm. It is utilized to assess the aptitude (goodness) of candidate population. Here, Prediction error value is the main criteria used to design a fitness function. The fitness computation is executed for each solution. Suppose that we have a training set $TR = \left\{\left(x_t, y_t\right), t = 1,2,\ldots m\right\}$, where, y_t is the output. The fitness function is defined the equation (17).

$$Fit = \min\left(E_i\left(x\right)\right) \tag{17}$$

$$E_i(x) = \frac{1}{m}\sum_{i=1}^{m}\left(y_i - o_i\right) \tag{18}$$

Where;

$y_i \rightarrow$ Target output

$o_i \rightarrow$ Obtained output

Step 3: Position and velocity updation using PSO

After the fitness calculation, we update the solution based on PSO algorithm. The PSO is a Population based search algorithm. It is formed to pretend the manners of birds in hunt for food on a cornfield or fish school. The technique can competently discover finest or near finest solutions in extensive search spaces. There are two dissimilar kinds of versions are employed according to PSO. The first is "individual best" and the second is "global best". The velocity and position updation is based on Eq. (19) and (20).

$$V_i^d = V_i^d + c_1.r_1.(pb_i^d - x_i^d) + c_2.r_2.(gb^d - x_i^d) \tag{19}$$

$$x_i^d = x_i^d + \delta V_i^d \tag{20}$$

Where,

c_1, c_2- constants with the value of 1

r_1, r_2 - random numbers generated between [0.1]

V_i^d - Velocity of i-th particle

x_i^d - Current position

pb_i^d -particle Best fitness value

gb^d - Global Best fitness value

Step 4: Termination criteria

The algorithm discontinues its execution only if highest number of iterations is achieved and the solution which is holding the best fitness value is selected and it is specified as best Parameters for prediction. Once the best fitness is attained by means of OPSO algorithm, selected solution is allocated for RBF neural network.

3.3. Testing phase

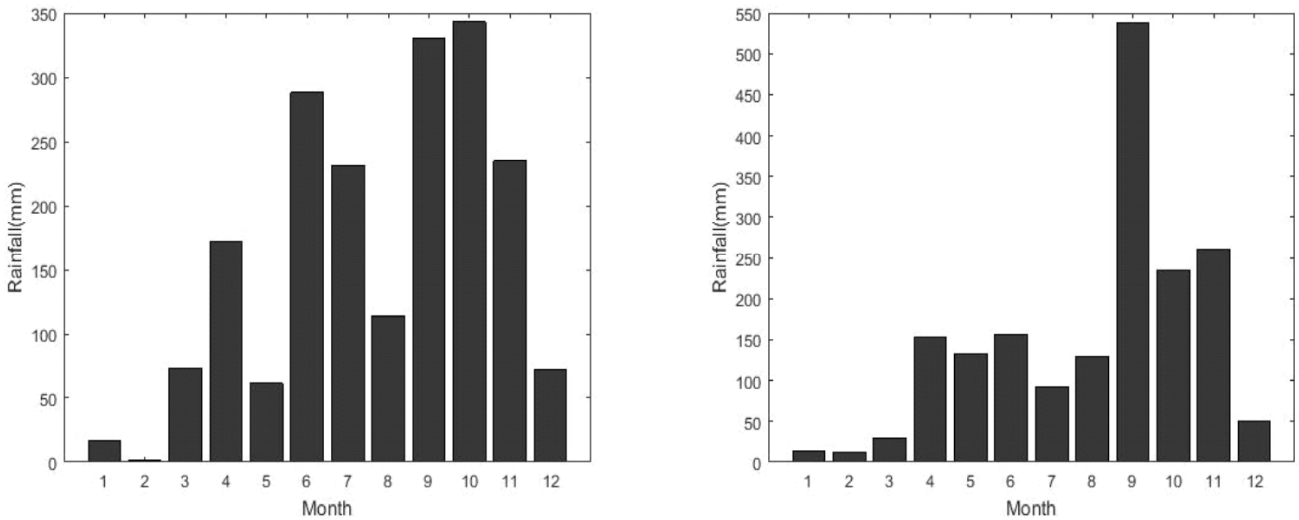
After the training process, the data's are given to the RBF-Neural network. Here, the weight obtained from the training stage is given to the testing process. Then, we get the predicted output for the given input data.

4. RESULT AND DISCUSSION

The platform modified to progress the RBF-OPSO method is a PC with the subsequent features: inter (R) core i3 processor, 3.20 GHz, 4 GB RAM, a Windows 7 Operating system and the mat lab version 7.12 development atmospheres. Furthermore, this segment enlightens the experimental solutions of projected rainfall expectation method with the help of real datasets.

4.1. Dataset description

The experimental results are analyzed with the help of real dataset which are taken from pechiparai and perunchani in kanyakumari district. The monthly rainfall data's are collected from the period of 1966-2014. After investigating perunchani data, total of 192 illustrations were designated to sequence OPSO-RBFNN, total of 96 samples were chosen to test PSO-RBFNN. Similarly, in pechiparai data, aggregate of 392 specimens were selected to train OPSO-RBFNN, aggregate of 189 samples were chosen to test OPSO-RBFNN. The average monthly rainfall prediction taken over a period of 1966 to 2014, in Pechiparai and perunchani is shows in figure 3. In figure 3(a) one crests of precipitation amid a year in September.



(a) **(b)**

Figure 3: Average monthly rainfall (a) pechiparai and (b) Perunchani

4.2. Criteria for evaluating model performance

To evaluating the performance of the proposed rainfall prediction, in this approach we used four types of measures such as Mean Absolute Percentage Error (MAPE), Mean squares error (MSE), mean absolute error (MAE) and also Pearson Relative Coefficient (PR).

- Mean squares error (MSE)

$$MSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(E_t - R_t\right)}$$

- Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{E_t - R_t}{E_t}\right|$$

- Mean absolute error (MAE)

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|E_t - R_t\right|$$

- Pearson Relative Coefficient (PR)

$$PR = \frac{\sum_{t=1}^{N}\left(E_t - \bar{E}_t\right)\left(R_t - \bar{R}_t\right)}{\sqrt{\sum_{t=1}^{n}\left(E_t - \bar{E}_t\right)^2}\sqrt{\sum_{t=1}^{N}\left(R_t - \bar{R}_t\right)^2}}$$

Where;

$E_t \rightarrow$ Predictable value for period t

$R_t \rightarrow$ Real value of period t

$\bar{E}_t \rightarrow$ Expected mean value

$\bar{R}_t \rightarrow$ Actual mean value

$N \rightarrow$ Total number of test data

4.3. Experimental result analysis

The main objective of this paper is to rainfall prediction based on OPSO-RBFNN. The system is mainly used for predict the future rainfall. In this work, at first the input data's are given to the RBF neural network. The parameters used in the RBFNN are optimized based on the OPSO algorithm. Finally, we predict the rainfall in testing process. The parameters utilized in proposed system are specified in table 2. The performances are evaluated based on the assessment metrics value. Table 3 to 4 displays comparative investigation of projected against available method for two dataset.

Table 2
Parameter used in PSO+RBF neural network

Algorithm	*No of iteration*	*Error*	*Number of hidden layers*	*Number of neuron in h1*	*length of population*	C_1	C_2	r_1	r_2
RBF-NN	1000	0.98	1	10	20	0.1	0.2	0.1	0.2

Table 3
Comparative analysis of proposed against existing for pechiparai dataset

Approaches	*MSE*	*MAPE*	*MAE*	*PR*
RBF+FA	0.053988	0.641203	0.041844	0.311752
RBF+GA	0.057003	0.694908	0.044375	0.202904
RBF	0.060802	1.101749	0.049748	0.032566
RBF+OPSO	0.049671	0.623017	0.035684	0.426819

Table 4
Comparative analysis of proposed against existing for perunchani dataset

Approaches	*MSE*	*MAPE*	*MAE*	*PR*
RBF+FA	0.057036	0.549994	0.040037	0.101193
RBF+GA	0.061948	0.563382	0.034129	0.080879
RBF	0.069697	0.903112	0.042183	0.084211
RBF+OPSO	0.064497	0.591523	0.038758	0.070463

The above table 3 illustrates the comparative analysis of proposed against existing for pechiparai dataset. As a consequence, poor performance indices in terms of MAPE, RMSE, MAD, and MSE can be observed in RBF model than other two models. When analyzing table 3, the projected rainfall prediction model is obtain the results of MAPE =**0.623017**, MSE=**0.049671**, MAE=**0.035684** and PR=**0.426819**. Likewise, table 4 shows the

Comparative analysis of proposed against existing for perunchani dataset. From table 4, the projected rainfall prediction technique is MSE=**0.064497**, MAPE=**0.591523**, MAE=**0.038758** and PR=**0.070463**.

5. CONCLUSION

In this paper, we explained rain fall prediction method with the help of the hybrid algorithms. The RBF-NN neural network parameters are optimized using oppositional PSO algorithm.

The amount of unseen neurons, the center, the radii and also the weights are optimized. The function of the algorithm is investigated by an actual datasets occupied from pechiparai, and perunchani regions in Tamil Nadu. Finally, from relative investigation the anticipated method displays improved solutions when associated with other methods.

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