Impact of Hybrid Intelligent Computing in Identifying Constructive Weather Parameters for Modeling Effective Rainfall Prediction

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Abstract

Uncertain atmosphere is a prevalent factor affecting the existing prediction approaches. Rough set and fuzzy set theories as proposed by Pawlak and Zadeh have become an effective tool for handling vagueness and fuzziness in the real world scenarios. This research work describes the impact of Hybrid Intelligent System (HIS) for strategic decision support in meteorology. In this research a novel exhaustive search based Rough set reduct Selection using Genetic Algorithm (RSGA) is introduced to identify the significant input feature subset. The proposed model could identify the most effective weather parameters efficiently than other existing input techniques. In the model evaluation phase two adaptive techniques were constructed and investigated. The proposed Artificial Neural Network based on Back Propagation learning (ANN-BP) and Adaptive Neuro Fuzzy Inference System (ANFIS) was compared with existing Fuzzy Unordered Rule Induction Algorithm (FURIA), Structural Learning Algorithm on Vague Environment (SLAVE) and Particle Swarm OPtimization (PSO). The proposed rainfall prediction models outperformed when trained with the input generated using RSGA. A meticulous comparison of the performance indicates ANN-BP model as a suitable HIS for effective rainfall prediction. The ANN-BP achieved 97.46% accuracy with a nominal misclassification rate of 0.0254 %.

Keywords

Introduction

Soft computing approaches incorporates efficient computational methodologies stimulated by intrinsic vagueness, intuition and acquaintance of human thinking and real world uncertainty. More ever, the ever growing demand for forecast modeling has led to the emergence of hybrid computing approches. Hybridization of more than one soft computing technique is known as HIS. Usually rough Sets, neural networks; genetic algorithms and fuzzy logic are the widely used for building hybrid architectures to handle uncertainty in real life problems. In this research, rough set based feature selection technique is used for modeling the input data followed by proposed ANN, ANFIS based rainfall models for training the forecast scenario.

Rough set as proposed by Pawlak, has attracted wide range of scientific applications from the time of its introduction. (Pawlak, 1982, 2002, and 2007) stated rough set approach as a suitable model for problem solving in pattern recognition, data mining, machine learning and knowledge representation systems. Rough set based data analysis starts from a data table called as decision table with rows. Attributes of the decision table consists of disjoint groups called condition and decision attributes. Shen and Jensen (2007) have stated rough set as suitable model for handling vagueness and in knowledge discovery for medical and meteorological applications. Yao (2009) reinstated, rough set discernibility matrix based attribute reduction approach as widely adopted reduction approach. Suguna and Thanushkodi (2011) have mentioned that attribute reduction approach based on quick reduct, entropy measure based reduct, hybrid rough set based genetic algorithm, Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) are widely adopted

in attribute reduction. Pradhan and Lee (2010) proposed a neural network technique for assessing landslide susceptibility. Sudha and Valarmathi (2013 and 2014) reinstated that rough set based feature reduction using evolutionary computing as suitable model for rainfall prediction.

Srinivasulu and Jain (2006) have reported the behavior of various training methods existing for training Multi Layer Perceptron (MLP) ANNs for rainfall runoff modeling. Raza and Khosravi (2015) assured that forecast accuracy of ANN could be enhanced using better training input data selection method and optimized neural network architecture. Haykin (2009) has stated neural network as parallel computing processor architecture that consists of collection of nodes capable of storing experiential knowledge for future assessments. Flood and Kartam (1994) described artificial neurons as processing elements arranged as layers that are capable of solving complicated real life and scientific problems. ANN has been a preferred technique for modeling rainfall forecast phenomenon. Tokar and Johnson (1999) used for ANN was modeling daily precipitation. The empirical results showed that ANN model perform better than regression and conceptual models.

Kalteh (2008) developed ANN based rainfall prediction model and compared that with the neural interpretation diagram, garson's algorithm and randomization approach. The investigation showed that ANN provides clear understanding on input and output data relationships within the processes (Solaimani, 2009). Combining computational efficiency with input parameters that describe the atmospheric weather variables has enhanced ANN prediction outcome. Machado et al. (2011) proposed back propagation algorithm for training the neural network. The investigation results proved that the trained ANN has gained good predicting potential. Chen et al. (2013) proposed artificial neural network architecture in rainfall runoff modeling. The investigation illustrated ANN as a suitable methodology for large data. The ANN proved to be optimal computational tool for modeling the complex hydrological processes.

Olaiya, and Adeyemo (2012) stated that artificial neural network, decision tree, genetic algorithms, rule induction, nearest neighbor method, memory-based reasoning, logistic regression and discriminant analysis are extensively applied in predictive data analytics. Indicated Artificial Neural Network and tree pruning techniques as appropriate precipitation predictive models. Lee et al. (2007) proposed a novel fusion method for temperature prediction using fuzzy logical relationships and genetic algorithms. Li (2005) proposed a hybrid rough fuzzy neural network model to work out weather forecasting problems. Wong et al. (2003) described fuzzy rule based rainfall prediction and compared the results of the proposed model with an established radial basis function networks. Experimental results revealed that fuzzy rule based approach as suitable technique for prediction. SLAVE is an evolutionary classification approach that implements iterative approach based on genetic algorithm feature selection to learn fuzzy rules (Gonzalez, Perez, 2001).

Zadeh (1983) described that hybrid intelligent systems as suitable mechanism to handle uncertainty, noisy and incomplete dataset. Nikza and Latif (2014) proposed rainfall prediction model based on adaptive neuro fuzzy inference System for Mashhad meteorological station. Bardossy et al. (1995) described about the evaluation and classification of various atmospheric parameter based on fuzzy approach. Witten and Frank (2005) have explained that classification algorithms included in weka can moreover be applied directly to a dataset from its own interface or used in user defined Java code.
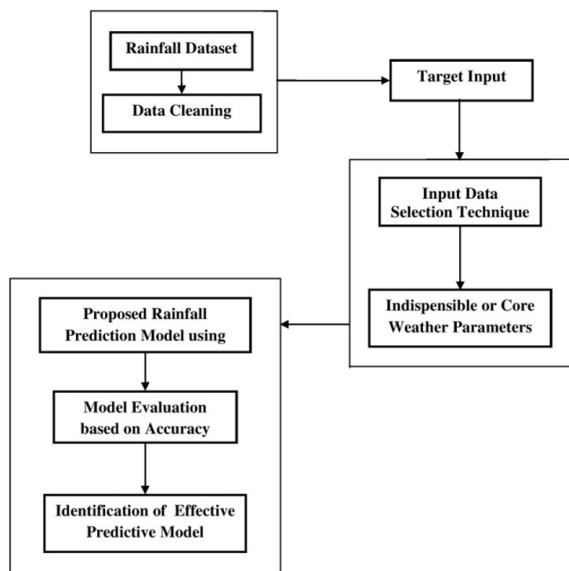
Materials and methods

The day by day rainfall data, measured in millimetre (mm), were obtained from Tamil Nadu Agricultural University (TNAU), Coimbatore, India for 29 years from 1984 to 2013. The observatory dataset consisted of eight atmospheric parameters. The outliers in the raw dataset was identified and removed during data pre-processing phase. The eight conditional variables and one decision variable in the target dataset are Maximum temperature (Wp1), Minimum temperature (Wp2), Relative humidity1 (Wp3), Relative humidity2 (Wp4), Wind speed (Wp5), Solar radiation (Wp6), Sunshine (Wp7), Evapotranspiration (Wp8) and Rainfall (RF). The rainfall (RF) is a binary decision variable; (RF = 0) → no rainfall and (RF = 1) → rainfall occurrence. The sample target dataset used as input for the proposed investigation is represented in Table 1.

Wp1 Celsius	Wp2 Celsius	Wp3 %	Wp4 %	Wp5 Km/ hrs	Wp6 KCalories	Wp7 Hrs	Wp8 mm	RF mm
34.5	23.5	82	43	3.8	221.6	8.4	5	0
36	25.5	78	42	7.4	230.4	7.7	7.4	0
35.8	24.8	87	38	7	201.6	6.9	8.2	0
28.5	18	95	42	7.4	200	8.1	4	0
28	18.5	85	46	7.4	213.6	9.6	4.8	0
28.4	23.2	88	85	7.5	200.2	1.9	3.6	1
32.6	21.8	98	48	4.4	277.2	4.4	3.8	1
31.5	21.8	94	88	5.7	202.5	0	3.1	1
30.8	20.5	96	62	5.7	374.2	7.5	4.6	1

Source: TNAU

Table 1: Daily rainfall observatory record (1984-2012).

Proposed HIS for rainfall prediction

Source: own processing

Figure1: Hybrid Intelligent System for Rainfall Prediction-Architecture.

Input data selection methodology

The complete feature reducts is the target input for RSGA. This rough set based feature selection approach is initially used for finding minimal feature subsets. The significant weather parameters are identified from the complete set of reduct, the complete reduct set contains 105 feature reducts generated using Rough Set Exploration System (RSES 2.3). An average optimal reduct selection algorithm is proposed to find the most optimal feature subset for training the prediction system. Generated reduct sets are subject to evaluation based on a fitness function, the set of subsets that satisfy the fitness criteria are selected as a member of new population for further evaluation. Then crossover and rare mutation operation is applied for determining a random optimal subsets. The set of parameters having relative fitness function higher than or equal to the average relative fitness function will constitute the optimal reduct feature vector.

Reduct Selection using Genetic Algorithm (RSGA)

Genetic Algorithm (GA) based feature reduct selection is implemented for identifying the optimal feature reducts for modeling effective rainfall prediction. Every reduct set is represented as a chromosome and encoded in bit string representation format.

A chromosome here represents the reduct set as collection of 1s and 0s, 1 correspond to the inclusion of particular feature and 0 correspond to elimination of that feature. Actually, complete set consists of the entire eight input features {Wp1, Wp2, Wp3, Wp4, Wp5, Wp6, Wp7, and Wp8}. Wherein a reduct set is a possible subset of complete set. For an example a reduct set: {Min, SS} is then encoded to bit string format to represent as a chromosome {0 10 0 0 0 1 0}. Most important factor of GA is the fitness function; a fitness function has to be effective enough to achieve the desired outcomes.

RSGA Algorithm

1. Begin

2. Let {CF-Red} be the complete feature reducts

3. n = (Total no. of reducts in {CF-Red}(n =105)

4. Encode the input reduct dataset in Bit string format

   a. Initialize the Initial population n =105

   b. Calculate the Fitness function F(X) of a reduct set

   c. Estimate the relative Fitness Function RF(x)

   d. If RF(x)>=Avg RF(x) then include the set in to new population

   e. Perform single point crossover

   f. Perform Mutation

   g. Else ignore

   h. n--

5. Repeat 1 to 5 until desired stopping criteria (n =0) is met

6. Return {OF-Red}

7. End

Input: Initial population with complete set of feature reducts

Fitness function $F(x) = C_{n1}/BS_{len}$ (1)

$C_{n1} \rightarrow$ The number of 1 bit in each chromosome

$BS_{len} \rightarrow$ Complete chromosome length or Bit string length

Relative Fitness function

$RF(x) = F(x) / Avg\ F(x)$ (2)

Output: Optimal Reducts (Table 2)

ANN for Effective Rainfall Prediction

The ANN prediction models used in hydro meteorological applications are feed forward neural networks, which are trained by back propagation algorithm. The ANN models emerged during the last few years have dissimilar architectures and procedures focused to the problem domain. The proposed ANN model is three layer architecture with input, hidden and output layers as shown in Figure 3. Neurons in the input layer act as a buffer to capture the input to pass to the next layer. The neurons in different layers are connected by means of weights. The activation function is used to transfer the received input to the next layer neurons. Neural networks are employed to detect concealed relations in the input in the training phase. The most commonly used training Algorithm is Back Propagation Neural Network (BP-NN).The most significant problem concerning the artificial neural networks implementation is the network architecture. It is well known fact that an insufficient number of hidden nodes may worsen the learning process. (Santosh, et.al., 2010) stated that ANN model can be adjusted to produce relationships among the data for given source. After the completion of training, the neural network can perform classification or prediction on new data of similar source.

Back propagation training

In this investigation, the standard back propagation algorithm is used in training the proposed ANN as in Figure 2. Most of ANN models employed in the field of hydrology used the back propagation algorithm (Coulibaly et al, 2000). Back propagation is a supervised learning method, and is a generalization of the delta rule. It requires a teacher that knows, or can calculate, the desired output for any input in the training set. It is most useful for feed forward networks. Sigmoid transfer function is used in this proposed ANN model for rainfall prediction. The back propagation learning process involves two stages, a propagation phase followed by weight update.

Wp1	Wp2	Wp3	Wp4	Wp5	Wp6	Wp7	Wp8	F(x)	RF(x)	Positive Region
1	1	1	1	1	0	1	0	0.75	1.25	0.976
1	1	1	0	1	1	1	0	0.75	1.25	0.9942
1	0	1	1	1	1	0	0	0.625	1.04	0.9879
0	1	1	1	1	1	0	0	0.625	1.04	0.981
0	1	1	1	1	0	1	0	0.625	1.04	0.9663
0	0	1	1	1	1	1	0	0.625	1.04	0.9658

Source: own survey

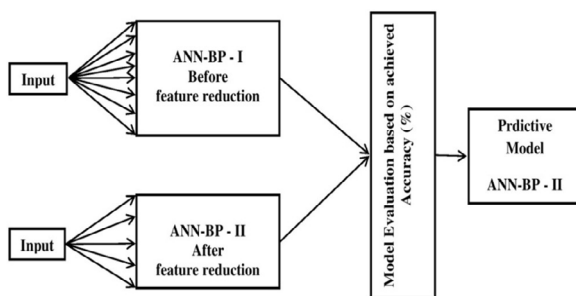Table 2: Optimal Reduct generated using RSGA.

Propagation rule - The propagation rule of a network describes the way the so called net input of a neuron is calculated from several outputs of neighbouring neurons. Typically, this net input is the weighted sum of the inputs to the neuron, i.e. the output of the previous nodes multiplied with the weights in the weight matrix as in equation (3).

$$net(t) = \mathbf{W}.\mathbf{o}(t) \qquad (3)$$

Activation rule - The activation rule frequently called transfer function determines the new activation value of a neuron based on the net input (and sometimes the previous activation value, in case a memory is used). The function $A(F)$, which takes $\mathbf{a}(t)$ and the vectors **net** for each different type of connection, produces a new state of activation. $A(\mathbf{F})$ can vary from a simple identity function, so that $\mathbf{a}(t+1) = \mathbf{net}(t) = \mathbf{W}.\mathbf{o}(t)$. Sigmoid functions adopted by the proposed model as in defined in equation (4) below.

$$a(t+1) = F_{bs}\big(Net\,(t)\big) = (1+x)^n = 1 + \frac{1}{1+e^{-\alpha(net(t))}}$$

$$(4)$$

In Weight update, each weight synapse multiply its output delta and input activation to get the gradient of the weight. Bring the weight in the opposite direction of the gradient by subtracting a ratio of it from the weight. This ratio influences the speed and quality of learning; it is called the learning rate.Momentum is applied for reducing problems of instability while increasing the rate of convergence. Repeat phase 1 and 2 until the performance of the network is trained.
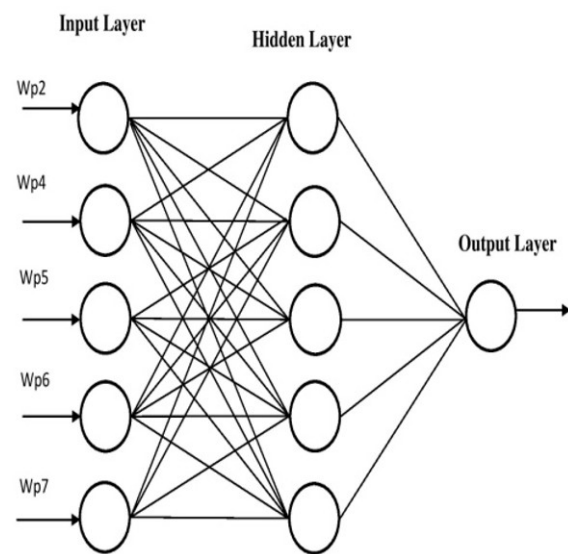

Source: own processing

Figure 2: ANN-BP architecture before reduction.

As represented in Figure 2 and 3, the proposed ANN-BP architectures were trained using entire and optimal parameters identified using RSGA. The input to the nodes (n) in input layer will forward this information to all the nodes of the hidden layer. At any hidden node (h), the data received from all the input nodes and the bias mode of the input

layer are summed up as $i_1 + i_2 + i_3 + ... \; i_n + bias$. A Sigmoid activation function is implemented on neurons. The network is first initialized by setting up all its weights to be small random numbers between –1 and +1. Then in forward pass the input pattern is applied and the desired output is estimated. Then calculate the Error of each neuron: Error = Target – Actual Output. This error is then used mathematically to change the weights in such a way that the error is reduced further. Next, the Output of each neuron is tuned to get closer to its Target in this reverse pass. The process is repeated again and again until the error is nominal.
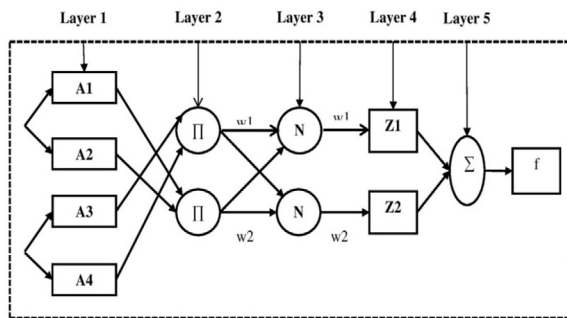

Source: own processing

Figure 3: ANN-BP-II architecture.

BP-NN Algorithm

1. Begin
2. Initialize with randomly chosen weights;
3. While Error is above desired threshold, do for each input pattern x_p,
   a. Determine hidden node inputs;
   b. Determine hidden node outputs;
   c. Determine inputs to the output nodes;
   d. Determine the network outputs;
   e. Determine the error between output and desired output;
   f. Adjust the weights between hidden and output nodes;
   g. Adjust the weights between input and hidden nodes;
4. End-for
5. End-while

ANFIS in modeling rainfall prediction

The proposed ANFIS is implemented using Fuzzy Inference Algorithm (FIA) in which fuzzy rules are used to infer a new approximate fuzzy set conclusion while taking a fuzzy set as foundation. Fuzzy inference systems (FIS) are mainly applied to the cases in which the systems are hard to be designed accurately. Hayati et al. (2011) stated that ANFIS is used to map input characteristics to input membership functions (MFs), input MF to a set of if-then rules, rules to a set of output characteristics, output characteristics to output MFs, and the output MFs to a single valued output or a decision associated with the output. ANFIS usually supports only sugeno type systems that exhibit the following properties. The sugeno type systems used must be first or zeroth order sugeno type. It must have a single output, obtained using weighted average defuzzification.

Source: own processing

Figure 4: ANFIS architecture using FIA.

Dissimilar rules cannot share the same output membership functions. It is expected that the number of rules and the number of output membership functions be equal having unity weight for each rule. To investigate which combination of input parameters can produce the best ANFIS results with the highest accuracy, the subsets of the feature set computed using rough set based maximum frequency weighted feature reduction was developed. The proposed ANFIS model as in Figure 4. is observed with three varying set of input parameters.
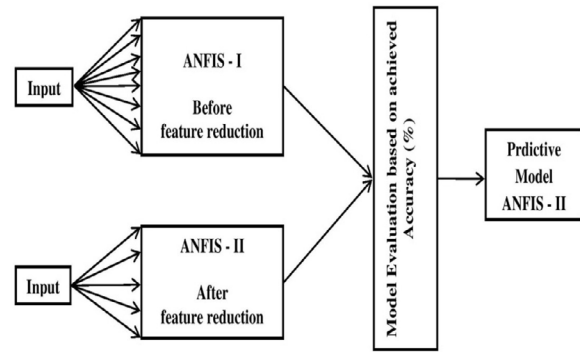
Rule 1:   If *x* is *A1* and *y* is *B1*, then *f1 = p1x + q1y + r1*

Rule 2: If *x* is *A2* and *y* is *B2*, then *f2 = p2x + q2y + r2*

The parameters *p1, p2, q1, q2, r1* and *r2* are linear, whereas *A1, A2, B1* and *B2* are nonlinear. The ANFIS model as in Figure 5. proposed

for rainfall forecast is realized using MATLAb 2012b. The model has five processing layers: fuzzification, production, normalization, defuzzification, and aggregation layer with following input and output relationships for each layer:

ANFIS architecture

Source: own processing

Figure 5: ANFIS architecture for rainfall prediction.

Layer 1 - Fuzzification layer: Let A1, A2, B1 and B2 be the linguistic expressions which are used to distinguish the membership functions (MFs). Each and every node in this fuzzification layer is an adaptive node with a node function. Where x is the input to node i, Ai represents the linguistic label associated with this node function, and O_i^1 denotes the output of the layer 1 and $\mu_{Ai}(x)$ is membership function as given in equation (5) and (6).

$$O_i^1 = \mu_{Ai}(x), \text{ for } i = 1,2 \text{ ..n} \tag{5}$$

$$O_j^1 = \mu_{Bi}(y), \text{ for } i = 1,2 \text{ ..n} \tag{6}$$

The proposed model implements sigmoid membership function with a maximum equal to 1 and a minimum equal to 0 are estimated as in equation (7), f(*x, a, c*) is a mapping on a vector x, and depends on two parameters *a* and *c*.

$$\mu(x) = \frac{1}{1 + e^{-a(x-)}} \tag{7}$$

Layer 2 - Production layer - Every node in this layer is a fixed node represented by the symbol ∏. The nodes in this layer2 act as a simple multiplier. The outputs are *w*1 and *w*2, the weight functions of the next layer are product of the weights and O2,i as in equation (8) is the output.

$$O2,i = \omega1 = \mu Ai(x). \mu_{Bi}(y) \text{ for } i = 1,2,... \tag{8}$$

Layer 3 - Normalization layer - The node labeled as N is an adaptive node. The ith node calculates the ratio of the ith rule's firing strength to the sum

of all rules' firing strengths. The node is marked as **N**, and it is used to normalize the weight functions, The output O3,i as in equation (9) of this layer is a normalized weight functions called as normalized fringing strength.

$$O5,i = \sum \omega i\ 'f_i = \frac{\sum \omega i\ 'fi}{\sum \omega i\ '} \tag{9}$$

Layer 4 - Defuzzification layer - Being an adaptive node of this layer ,$\omega i'$ is the output and $\{pi,\ qi,\ ri\}$ is the parameter set in this layer. The relationship between input and output is

$$O4,i = \omega i'fi = \omega i'(p_i x + q_i y + r_i) \tag{10}$$

The parameters in this layer-4 are referred as consequent parameters.

Layer 5 - Aggregation layer - The single node in this layer is an output corresponding to the aggregate of all inputs so that the overall output is represented as in equation (11).

$$O5,i = \sum \omega i'fi = (\sum \omega i'fi\ )/(\sum \omega i\ ') \tag{11}$$

The model must adjust or tune the premise parameters sets (ai, bi, ci) to enable ANFIS output to match the training data.

Results and discussion

The performance of the proposed ANN-BP developed using C# is implemented using .NET environment. The learning rate and momentum are set for some suitable random value and later tuned to obtain the desired output. The proposed

ANN rainfall forecast model outperformed when trained with optimal feature subsets using novel RSGA algorithm.For the proposed ANFIS model, MATLab 2012b is used to evaluate the performance of the architecture for both complete and optimal feature vectors.The existing models namely, FURIA (Huhn, Hullermeier, 2009) SLAVE and PSO are trained and tested using Weka (Witten, Frank, 2005) and KEEL (Fdez et.al., 2008).

The exixting prediction algorithms were evaluated for various k-cross fold validation settings. However, 10 cross fold validation outcomes were used for the performance comparison. As all the proposed methodology makes use of minimum of two or more soft computing technique it is hybrid in computing. All the models make use of rough set based input data selection approach followed by training proposed rainfall forecast model using BP-NN and FIA.
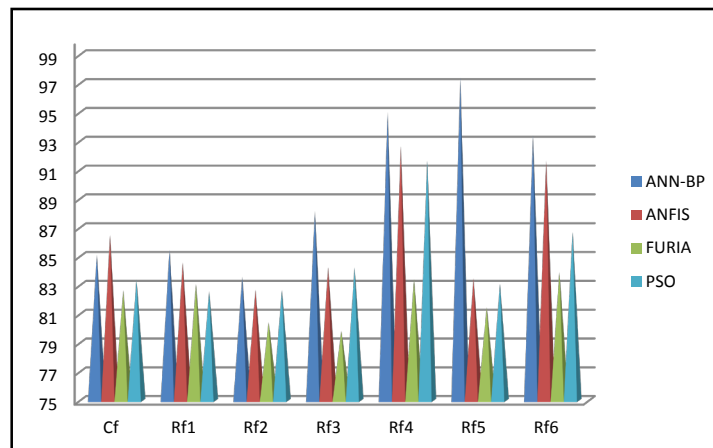
Performance evaluation of proposed HIS's

The HIS's proposed for rainfall forecasting was evaluated under different experimental setups. Although, all the proposed models make use of a common input data selection methodology the improvement in prediction accuracy rate is different for all. Invariably all the architectures have shown some enhancement in prediction rate as shown in Table 3 when trained using the optimal feature vector as input than when trained using the complete feature vector The peak prediction accuracy acquired by ANN-BP model is projected clearly in Graph 1.

Input Data Selection Methodology	Prediction Accuracy Achieved				
Complete feature set before RSGA	ANN-BP	ANFIS	FURIA	SLAVE	PSO
Cf -Wp1,Wp2,Wp3,Wp4,Wp5,Wp6,Wp7,Wp8	85.12	86.5	82.66	80.79	83.4
Optimal Feature set after RSGA	ANN-BP	ANFIS	FURIA	SLAVE	PSO
Rf1- Wp1, Wp2, Wp3, Wp4, Wp5, Wp7	85.47	84.59	83.09	82.3	82.6
Rf2 - Wp1, Wp2, Wp3, Wp5, Wp6, Wp7	83.6	82.68	80.44	87.44	82.7
Rf3 - Wp1, Wp3, Wp4, Wp5, Wp6, Wp7	88.16	84.24	79.84	83.69	84.2
Rf4 - Wp2, Wp3, Wp4, Wp5, Wp6	95.04	92.64	83.44	77.45	91.6
Rf5 - Wp2, Wp3, Wp4, Wp5, Wp7	97.46	83.48	81.48	81.06	83.1
Rf6 - Wp3, Wp4, Wp5, Wp6, Wp7	93.4	91.68	83.92	82.39	86.7

Source: own survey

Table 3: Hybrid intelligent systems rainfall forecast accuracy (%).

Source: own survey

Graph 1: Hybrid intelligent systems prediction accuracy achieved.

Relative study existing and proposed models

Input Selection Methods	Input Reducts	Minimal Reducts	Reduct Selection Strategy	Prediction Accuracy Achived
Exhaustive search based attribute selection (Weka)	1	1	Forward Selection	CART 81.07 %
Information Gain based feature selection (Weka)	1	1	Entropy measure	FURIA 83.92%
PSO based subset search approach (Weka)	1	1	Forward selection	ANFIS 89.75%
Feature selection using Genetic Algorithm (RSES)	105	6	Proposed RSGA	ANN-BP 97.46%

Source: own survey

Table 4: Rainfall prediction accuracy of existing and proposed method.

Conclusions

Experimental results revealed that the proposed ANN-BP model as suitable rainfall prediction model. The model outperformed other proposed and existing models when trained using the feature reducts generated using novel RSGA input selection approach. At the same time, the proposed ANFIS model accquired nominal error rate and prediction accuracy close to ANN-BP after feature reduction than for complete feature input. The performance of FURIA, SLAVE and PSO are not satisfactory when compared to ANN-BP and ANFIS. But the all the prediction models have shown substantial improvement in prediction accuracy after feature reduction. This thorough study on rainfall forecast modeling concludes that irrelevant parameters may affect the performance of learning models and may decrease the efficiency. Consequently, identifying effective input parameters for forecast modeling is an essential task. Empirical results revealed {Wp2, Wp3, Wp4, Wp5, Wp7} as optimal feature reduct for designing effective and reliable rainfall prediction model.

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