International Journal of Computer Science and Business Informatics

IJCSBI.ORG

Agronomic Disaster Management using Artificial Intelligence - A Case Study

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ABSTRACT
Artificial Intelligence has become an essential tool in various hydrological data-driven forecast scenarios. The existing needs of farm management activities have witnessed the necessity of an intelligent decision support for strategic planning and implementation. This case study reports the benefits of application of neural network based short range precipitation prediction model in agronomic disaster management (ADM). This investigation describes the benefits of data-driven decision support systems for agronomic sustainability. Neural Network Architecture emerged recently have heterogeneous network design thereby suits for solving complex problems. The methodical evaluation conducted on agronomic disaster management framework designed using rough, genetic and neuro computing approach reported peak prediction accuracy of 97.21 % while the learning rate of the network was set to 0.7 for a fixed momentum of 0.5 producing a nominal error rate of 02.79%.

Keywords
Artificial intelligence, Agronomic disaster management, Daily precipitation prediction, Data-driven computing.

1. INTRODUCTION
As a recent trend rapid proliferation of computers and developments in the area of information technology has increased the applications of computational intelligence in meteorological aspects. Computational intelligence approach has exposed a significant amendment in the advancement of new hybrid data-driven techniques in modeling the wide range of weather data [1], [2], [3] and [4]. Data-driven models are simple to understand and require no prior experience or expertise. Decision making is an execution of an activity that is more or less a human quest. A decision support system is a computer-based information system that help decision maker to deal with the problems through direct interaction with data and analysis model [5]. Soft computing approaches incorporate efficient computational methodologies stimulated by intrinsic vagueness, intuition and acquaintance of rational thinking and real world uncertainty. The intelligent systems designed to handle uncertainty in real life problems

usually make use of rough set theory, neural network, evolutionary algorithms, and fuzzy sets approaches [6] and [7] Fuzziness and uncertainty exist almost everywhere, it is inevitable in atmospheric dynamics.

2. RELATED WORKS

A systematic review was conducted to assess the applicability of data mining, artificial neural network, fuzzy inference system and evolutionary approaches in the modeling hydrological forecast. The review of the presented literature revealed that more often than rare the models have shown average performance in modeling hydrological predictions when compared with techniques that employ the concept of assimilating one or more intelligent approaches. From the following detailed review, it is clear that there is a necessity of much better hybrid soft computing approach which can handle weather parameters more intelligently rather than a black box model. In [8] it has been reported ANN as a superior method for modeling precipitation forecast scenarios. In [9], ANN has been applied for modeling daily precipitation forecasting in the Mashhad synoptic station.

In [10] they have applied ANNs to predict the month wise maximum precipitation, minimum precipitation, average and total cumulative precipitation during a period of the next four consecutive months. [11] compared the performance of General Regression Neural Network (GRNN), ensemble neural network, BPNN, Radial Basis Function Network (RBFN), GA, MLP and fuzzy clustering for precipitation prediction. [12] applied ANN models and decision tree algorithm to forecast maximum temperature, precipitation, evaporation and wind speed at Ibadan city located in Nigeria. The results concluded ANN as a suitable tool for meteorological predictions. ANN and Fuzzy Logic (FL) algorithm for forecasting the stream-flow for the catchment of Savitri River Basin using 20 years (1992–2011) precipitation and other hydrological data. While comparing both ANN and FL algorithms the investigation and empirical results reported that for prediction of hydrological scenarios ANN performance is quite superior to FL[8].

Assimilating the features of ANN and FIS has attracted the rising attention of researchers due to the growing requisite of adaptive intelligent systems to solve the real world requirements [13]. [14] ANFIS models are widely used in modeling daily precipitation prediction. [15] Developed a Modified ANFIS for modeling the nonlinear dynamic characteristics of precipitation events at the Klang River basin; Malaysia. [16] developed two different models for forecasting weather at two separate regions, Amman airport and Taipei, China using artificial neural networks and fuzzy logic. The prediction accuracy achieved by proposed models was satisfactory. [17]

stated that ANFIS based models developed were configured and evaluated for six major dams of South Korea having high, medium and low reservoir capacity. The results showed significant improvement for categorical precipitation forecast using ANFIS. [18] applied ANFIS for forecasting drought, the quantitative value of drought indices and the Standardized Precipitation Index (SPI).

In [6], a neuro-fuzzy model was developed to predict the monthly precipitation of the Daejeon Station in Korea. Choubin et al. (2014) developed a neuro-fuzzy model to forecast annual drought conditions in the Maharlu-Bakhtegan watershed, located in Iran. The study reported neuro-fuzzy model as a suitable method to analyze the influence of independent variables on dependent variables in hydrological applications. An ANFIS model has been applied to forecast of the groundwater level of Bastam Plain in Iran [19]. [20] Developed ANFIS for modeling long-term streamflow forecasting in Dez basin, Iran. The results reported ANFIS as a suitable method for streamflow forecasting, and K-fold cross validation method could increase the model reliability. [14] Reinstated that the performance of fuzzy inference system and artificial neural network based soft computing techniques are better than the L-moments approach used for flood forecasting. [21] Stated that ANFIS perform groundwater level prediction more accurately when compared to artificial neural networks and Bayesian neural networks.

3. CASE STUDY REGION

Western-Ghats region of Tamil Nadu State (Coimbatore zone) in India is the case study region for the assessment of precipitation prediction. This region serves as Manchester of South India lying in the extreme western part of Tamil Nadu This district's total area covers 746,800 hectares, and 43% of the region is bound to agricultural cultivation. The cotton, sugarcane, peanut sorghum, maize, rice, and pulses are the primary crops in this area. The study region is one of the most important agricultural and industrial areas in the country. Fast and independent industrial development projects have caused climatological changes in past years, hence raised necessity to conduct the assessment of factors influencing the current weather prediction.

4. MATERIALS AND METHODS

The day wise observatory record of eight atmospheric parameters for precipitation prediction, measured in millimeter (mm), for 29 years from 1984 to 2013. The target sample data set used as input for this study is represented in Table 1, the dataset having 10,000 records with no missing values and outliers after pre-processing phase is subject to experimental evaluation. The decision attribute (Pp) is a binary decision variable, Pp =

'no' denotes no precipitation (rainfall) otherwise if Pp = 'yes' indicates precipitation (rainfall) occurrences. The parameter's values are recorded in an observatory in the daily basis as per the standard norms.

Table 1. Observatory weather Dataset

Observatory weather parameters	Units	Data type	Data range
Maximum temperature (Max)	Celsius	Float	27 - 398
Minimum temperature (Min)	Celsius	Float	2 - 335
Relative humidity 1 (Rh1)	Percentage	Float	5 - 100
Relative humidity 2 (Rh2)	Percentage	Float	1- 99
Wind speed (Ws)	Km/hrs	Float	01 - 227
Solar radiation (Sr)	KCalories	Float	24-688
Sunshine (Ss)	Hrs	Float	01-98
Evapotranspiration (Evp)	mm	Float	01-75
Precipitation prediction (Pp)	mm	Categorical	Yes/no

5. AGRONOMIC DISASTER MANAGEMENT MODEL

The sequentially hybridized artificial intelligence centered precipitation prediction model consists of input assessment, model training and testing phase. The model output enable the framing decisions such harvesting, sowing seeds, spraying pesticides or fertilizers to crops in the cultivated regions and other decisions such as storage, sale etc. Henceforth this model is referred as an agronomic disaster management model. A farmer is assisted to make a strategic decision on the farming activities such as harvesting early before damage if there is heavy precipitation in the next one or two days. Similarly farmers can plan for spraying the fertilizers ahead or in later time based on the environmental factor owing to precipitation.

This decision support system modelled for agronomic disaster management is mainly designed based on data-driven modeling concept using rough sets based evolutionary computing and the three layered multi-layered back-propagation system. The learner is subject to learn the environment during the training process from the target input and evaluated with set of test data. The training algorithm uses sigmoid transfer function which is a well-known suitable neural network activation function. The input data can be one of the factors that may influence the output of the architecture. Subsequently, a multi-layered back-propagation multi-layered algorithm [22] is employed to train the ADM model in more effective way.

The pseudocode of the multi-layered back-propagation algorithm is as below:

Begin
Initialize with randomly chosen weights and biases in *network*;
while error is above the threshold, do
for each training tuple ***X*** in W
{
for each input layer unit *k*
{
for each hidden or output layer unit *k*
{
//compute the net input of unit *k through* previous layer, *i*
for each unit k in the output layer
$Errj = Ok(1 - Ok)\,(Tk - Ok)$
$Errj = Ok(1 - Ok)\, \Sigma j\, Errj\, Wkj$
for each weight in *network* "n"
$\vartriangle Wik = (l)ErrkOi)$
// weight increment
// weight update
for each bias in *network* "n"
// bias increment
} // bias update
} }

The proposed system is developed and implemented using Microsoft NET framework and its process flow is shown in Fig. 2. It consists of feature reduction stage, training and testing phase. The target data in the input for selection stage then the proposed system has been trained by reducts dataset generated using the proposed technique. The complexity of training the network for given |D| tuples and w weights, each epoch requires O (|D| x w) time [22].

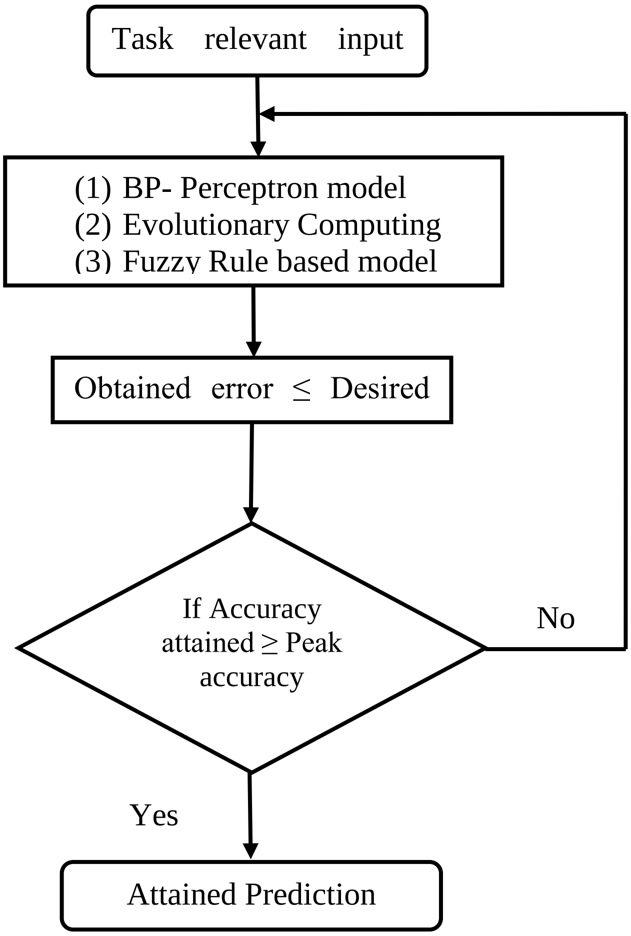

Figure 1. Flow design of Agronomic Disaster Management model

5. RESULTS

The learning rate and momentum are set for approximately suitable random value and adjusted according to attain the desired output. From this methodical evaluation, the learning rate and momentum is fixed as 0.7 and 0.5 as in Table 2. The comparative evaluation of the various models under this investigation as projected in Table 3 and Figure 2 evidently reports that the prediction techniques have substantial improved when trained after feature reduction and the proposed model acquired high accuracy. The classification models used for training have shown better results when trained using the selected list of observatory parameters. The proposed model outperformed the existing approaches by reporting a nominal error rate of 2.71 % when compared to other existing classification algorithms. Random-forest classifier has reported low accuracy of 81.07 % with an error rate of 19.93 % and revealed the limitation of adopting this classifier in modeling real-time forecasting. Also, some hidden inferences such has any classification model utilizing artificial intelligence exhibits better optimization potential when compared to other learning methods. The learning potential of a neural network and the benefit of error propagation strategy of the multi-layered back-propagation learning algorithm have enabled to attain the desired accuracy. The predictive models were judged statistically using the percent error of prediction and prediction yields. The experimental assessment revealed the potential of AI centered precipitation prediction model for harvesting, sowing seeds, spraying pesticides or fertilizers to crops over other existing prediction models.

Table 2. Performance evaluation of proposed system for adaptable learning rate

Learning Rate	Momentum	Accuracy rate	Error rate
0.1	0.5	93.67%	6.32 %
0.5	0.5	94.17%	5.82%
0.7	0.5	97.21%	2.79%

Table 3. Performance evaluation of Data-driven AMD vs existing models

Parameter Selection	Prediction Models	Software	Accuracy
Exhaustive-forward selection search	Random-forest classifier	Weka-tool	81.07 %
Information gain	Fuzzy-unordered-rule-induction	Weka-tool	84.97 %
PSO	Bayesian-network classifier	Weka-tool	89.75 %
Attribute weighting	Fuzzy-neural classifier	Weka-tool	91.79 %
Relative fitness function	Proposed -ADM	RSES2.0 .NET	97.21

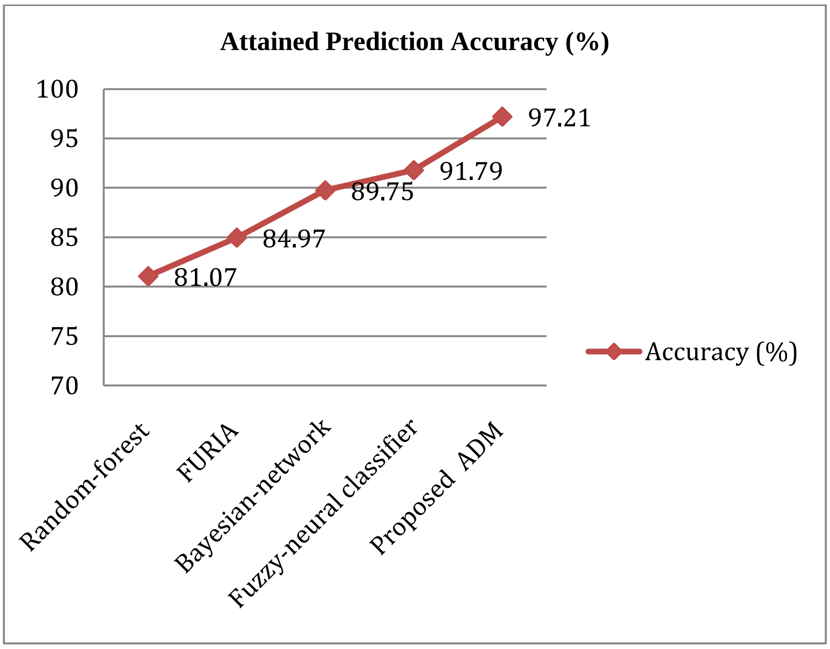

Figure 2. Precipitation prediction accuracy optimization report

6. CONCLUSIONS

Modeling user interactive agronomic disaster management model to support farming activities such as harvesting, sowing seeds, spraying patricides or fertilizer's to crops utilizing real-time weather data is the primary concern of this research. Many intelligent techniques are employed in modeling precipitation forecast scenario. However, most of the techniques are not dealing with qualitative data. Therefore, this research has evolved input selection methods that could remove the superfluous parameter. Besides this, an efficient data-driven intelligent system is designed assimilating rough set based evolutionary computing and neural network to attain optimal prediction accuracy. Also, the limitations of the existing data mining models and the benefits of intelligent techniques in modeling weather forecast scenario has been reported based on the experimental outcomes. The proposed ADM achieved an optimal prediction accuracy of 97.21 % with the nominal error rate of 02.79%. The research attained the intent of developing an ADM with interactive user interface to enable operators to make regional prediction to support farming decisions.

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This paper may be cited as:

Sudha, M. 2017. Agronomic Disaster Management using Artificial Intelligence - A Case Study. *International Journal of Computer Science and Business Informatics, Vol. 17, No. 2, pp. 12-22.*