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Comparison of Neuro-Fuzzy and Regression Models for Prediction of Outflow of on-farm Reservoir

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Abstract

Neuro-fuzzy and regression models predicting of outflow of an on farm reservoir of 300 m^3 capacity, located at Indian Agricultural Research Institute (IARI), New Delhi site of India, were developed and validated using crop water requirement, evaporation losses and farm pond inflow data. The outflow predicted by these two models was compared with each other. It is raveled that Neuro-Fuzzy model predicted the outflow with high coefficient of determination (R^2) of 0.98, model efficiency (E) of 0.97 and absolute average deviation (AAD) of 0.002. The regression model was found to be inferior with R^2 = 0.940.78, E = 0.72 and AAD = 0.031. MATLAB software was used for development of Neuro-Fuzzy and regression model.

Highlights

- On farm reservoir (OFR) is very vital component of water resource network which stores the excess runoff and which can be used to ground water recharge or for supplementary irrigation
- Neuro-Fuzzy and regression models were to predict the outflow of the OFR of 3000 m^3 capacity, located at IARI, New Delhi.
- Both the models were compared with each other and it was found that Neuro-Fuzzy model has better performance than that of regression model.
- Values of model evaluation parameters like coefficient of determination (R^2), model efficiency (E) and absolute average deviation (AAD) showed that Neuro-Fuzzy model was superior to the regression model.

Keywords: neuro-fuzzy, regression model, outflow, model efficiency

Water is one of the most vital and important natural resources found on planet earth. Census, carried out recently, raveled that the population of India is in tune of 1.21 billion and it is expected to reach at 1.5 to 1.8 billion by 2050 AD. To fulfill the demand of ever increasing population, the food grain production also has to grow at the rate of growing population. This would lead to increase in irrigation water demands to support the agricultural production.

On farm reservoirs (OFRs) or Farm pond plays important role in water resource network at village or farm level. The two main important uses of OFR are storage of surface runoff generated in field and ground water recharge. The water harvested in OFR can be effectively used for irrigation for growing crops as and when needed. Management of OFRs is a matter of great concern. Faulty operating policies of leads to poor distribution of water in space and time.

Judicious use of water at field level can be achieved by effective operation of the OFR. For large and multipurpose reservoirs operational management strategies have been standardized being implemented successfully. There seems to have no study which is undertaken to develop management strategies for OFR (Sonawane, 2011).

Soft computing techniques like fuzzy logic, ANN, GA, etc. and their combinations have been used extensively for modeling the complex water resource system network problems. These technique handle uncertainty and ambiguity in effective manner by imitating human way of reasoning and decision making. These techniques can be successfully employed to handle such problems when conditions of the systems are uncertain (Mehta and Jain, 2009). As OFRs are more susceptible to poor distribution of water due to highly uncertain demand, supply and storage, soft computing techniques can be are very well adapted to develop farm pond management strategy.

Therefore the study was conducted to develop Neuro-fuzzy and regression models for prediction of outflow of the farm pond of 300 m^3 capacity, located at Indian Agricultural Research Institute (IARI), New Delhi site of India. Crop water requirement, evaporation losses and farm pond inflow data were used to develop and validate the model which determines the outflow of the reservoir. The developed models were compared for their possible acceptance.

Study Area

The experimental area was at center for protected cultivation technology (CPCT), Indian Agricultural Research Institute, (IARI), New Delhi, located between latitudes of 28^o 37'22'' N and 28^o 38'39'' N and longitudes of 77^o 08'45'' E and 77^o 10'24'' E at an average elevation of 230 m above mean sea level (MSL). Farm pond of 3000 m^3 was the source of water for irrigation and other uses in the experimental farm of 10 ha area, which consists of greenhouses, shed nets, nurseries, orchards, open fields, packaging house etc.

Materials and methods

Soft Computing Techniques

The term soft computing was first given by Lotfi Zadeh in 1965 (Sonawane, 2011). The soft computing is inspired by human neural system and can be exploited to achieve tractability, robustness and low solution cost. It can handle the uncertainty and partial truth effectively. The Components of soft computing are as follows,

1. Fuzzy Logic (FL)
2. Artificial Neural Network (ANN)
3. Probabilistic Reasoning (PR)
4. Belief Networks, Genetic Algorithm, Chaos Theory, etc.

Fuzzy Logic (FL)

Fuzzy logic refers to a logical system which generalizes classical two-valued logic for reasoning under uncertainty (Yen and Langari 2003). Fuzzy logic works on fuzzy set theory and is a powerful tool which effectively handles uncertainties and partial truth by mathematical methods. Fuzzy set theory deals with using ambiguous meaning of the natural linguistic terms in valuation and reasoning (Hong and Lee, 1996). It was introduced by Zadeh in 1965 and first used in system control application by Mamdani in 1974.

Fuzzy set is defend as, if 'S' is a collection of objects denoted generally by '*s*' then a fuzzy set *A* in S is a set of ordered pairs as shown in Eq. 1:

$$A = \{(s, \mu_A (s)) \mid \varepsilon^{a} S\} \quad (1)$$

Where $\mu_A (s)$ is called as membership function (degree of truth) of '*s*' in *A*. It indicates the interval or membership space of real numbers from 1 to 0. If the membership space contains two points 0 and 1 only, *A* is non fuzzy (crisp) and $\mu_A (s)$ is identical to characteristics function of crisp set (Zimmermann, 1996). The functional elements of FL is shown in figure 1.

Fuzzy logic system describes process in terms of linguistic variables and If-Then rules. Each linguistic variable is represented by different terms ($_i^j$) where i indicates the linguistic variable, i= 1, 2. ….., n; and j indicates the term of i-th linguistic variable, j= 1, 2 ,....., m_i, and m_i is the number of terms of i^{th} linguistic variable. Each term $_i^j$ is described by its membership function (μ_i^j)and each crisp value of linguistic variable will have a degree of membership $_i^j$.

Fuzzy decision making involves following three processes,

- Fuzzification
- Fuzzy inference
- Defuzzification

The Fuzzification process translates all of the crisp input

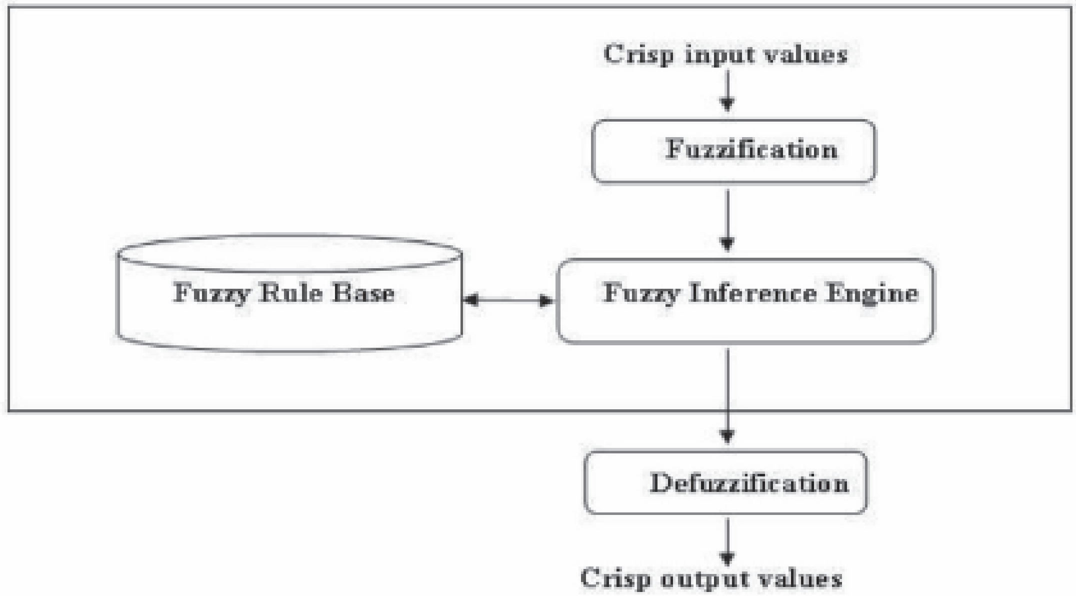

Figure 1: Functional Elements of Fuzzy Logic

values into linguistic terms. Membership functions are of different shapes like triangular, trapezoidal, Gaussian shapes and they describe each of the linguistic terms. The degree of membership is represented by 'V'

Fuzzy inference is the computation of fuzzy rule consequences. In fuzzy system the relationship between input and output in linguistic terms are represented using fuzzy rules. The rules consist of precondition (If-part) and consequences (Then-part). Defuzzification is the process where the fuzzy output is converted in to crisp values using membership functions. Most common method of Defuzzification are Center of Area (CoA) and Center of Maximum (CoM).

In this study Center of maximum is selected for defuzzification. It computes the crisp output as a weighted average of the center of membership function ($c_i^{\,j}$), weighted by the inference results (μResults ^j_i) as shown in Eq 2.

$$\text{Crisp output} = \sum_j(\text{m Result}^{\,j}_{\,i} \times c_i^{\,j}) / \sum_j \text{m Result}^{\,j}_{\,i} \quad (2)$$

Artificial Neural Network (ANN)

ANN is considered as replicated model of brain system. It functions as parallel distributed network which is composed of neurons, which imitate the brain nerve cells. ANN must be trained using training algorithms. It has the capability to learn new associations, new patterns and new dependencies. ANN represents the new generation of information processing networks (Fuller, 2000).

The basic structure of ANN is shown in Figure 2, it consists of three layers viz. input, hidden and output layer. Each neuron processes each incoming inputs into an output. The output is then again connected to other neurons which form net of neurons. The information enters the net at the input layer. All layers of the net, process these signals through the net until and unless they reach to the output layer.

Let the inputs of certain neuron are (X_1, X_2........ X_n, w_1, w_2....... w_n) where X_i denotes an i^{th} input, w_i, represents the i^{th} connection weight, and n represents the number of the neuron s input connections. Each node produces an output value O.

The process of transformation of input value is described by two functions (Eq. 3 and Eq. 4).

$$Int = \sum w_i X_i, \ (i = 1 \text{ to } n) \quad (3)$$

$$Act = 1/(1+ e^{-Int}) \quad (4)$$

Where, Int is the standard form of the integration or propagation function that performs a weighted sum for

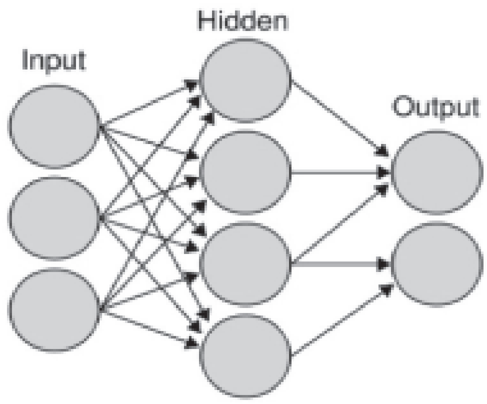

Figure 2: Generalized Structure of Neural Network

inputs and Act is standard form of activation function that computes the neuron's output. There are two major phases in designing neural networks.

- *Learning phase*
- It consist of the process of teaching the net a desired behavior by using training sets and training algorithm.
- *Working phase*:
- After the training the ANN can be ready to use. The network gives the output values similar to those in sample data set, when the input matches one of the training samples.

Neuro-Fuzzy System

Neuro-Fuzzy System is integration of FL and ANN, which combines advantages of both in one system and simultaneously reduces their weakness. (Hasan, 2007) ANN is good in acquiring knowledge automatically but fails to explain how it performs and reaches outputs as it is a "Black box" model. On the other hand FL is effective tool in handling imprecise and uncertain situations in as understandable and transparent logical structure (If-Then), but it cannot acquire or learn knowledge.Integration approach of ANN and FL was classified into three groups by Kruse and Nauck (1995). It is very popular because it can learn governing relations from given data and the fuzzy rules obtained can provide the linguistic description for the working of the model (Tutmez *et al*., 2006).

- *Concurrent Neuro-Fuzzy Model*
- It is considered to be weakest form of integration of both systems. ANN and FL are used concurrently on the same task. ANN could be used as pre and post processor to the fuzzy system, but it does not change any parameters of the fuzzy system. pre and post processor to the fuzzy system, but it does not change any parameters of the fuzzy system.
- *Cooperative Neuro Fuzzy Models*
- In this group, the ANN learning algorithm is used to learn certain components (membership function, fuzzy rules, rules weight) of FL. Once the learning process has been performed, only fuzzy system is used.
- *Hybrid Neuro Fuzzy Models*
- It is considered to be the strongest form of integration of both systems in which a new architecture is created and both system are linked together. It is the most modern form of Neuro-Fuzzy models. ANFIS is the examples of this type.

Common structure of the hybrid Neuro fuzzy model is of following pattern.

- The input layer performs the Fuzzification process
- The Hidden layer functions as fuzzy rules
- Output layer performs Defuzzification

Development of Neuro-Fuzzy model consists of three steps viz. Training, Testing and Validation. The entire data are divided into three parts to complete modeling procedure. For the sake of pattern recognition between input and output, various combinations of data are provided into training step to Nero-Fuzzy network. In Testing phase modification of internal representation takes place while in validation phase the third set of data is used and predictability of model is tested statistically.

Data Preparation and standardization

Sensitivity analysis was done to select only relevant parameters and to remove non relevant parameters. The parameters which affect the output are only selected for model development. The parameters which remains constant throughout or which did not change significantly should not be taken into consideration for model development. Daily data for crop water requirement, evaporation losses, inflow and outflow of farm pond were collected for the years 2001 to 2010. Out of the data used for model development 60% of the data were used for training, 20% for testing and remaining 20% were used for validation of the model.

Development of Neuro-Fuzzy and regression models

For developing Neuro-Fuzzy model the computer programme was written in MATLAB 7.5 compatible language for predicting outflow. Sugeno type Fuzzy Inference System (FIS) was used which improves the efficiency of defuzzification process. All relevant inputs (cropwater requirement, pan evaporation, farm pond inflow) and output (outflow) were used to develop the model. Model was trained with a set of known input and output data. The training was repeated with sets of shuffled data. The RMSE was noted down for each analysis and cross validation was done to determine the R^2 values. When an optimum prediction statistic was obtained in relation to epoch size and cross-validation results, the learning process was terminated. Three dimensional views of input and output were developed.

The regression model was developed using MS-Excel using the same set of data as that of used in the development of Neuro-fuzzy model.

Model evaluation

For evaluation of models the model efficiency factor (E), coefficient of determination (R^2) and absolute average deviation (AAD) between the observed and the predicted values were estimated for different predictions on validation data sets. The models were compared on the basis of highest R^2 and E values and AAD (Sonawane, 2011).

Results and discussion

The models developed based upon Neuro-Fuzzy and regression approaches were tested for predictability by validating them against unseen datasets. The validation statistics for Neuro-Fuzzy yielded R^2 of 0.98, model efficiency factor of 0.97 and average absolute deviation (AAD) of 0.002. While that of for regression model were 0.76, 0.71 and 0.031 respectively. The resulted statistics are summarized in Table 1. The coefficient of determination (R^2) and model efficiency factor (E) should be close to one and AAD should be near to zero value for the model to be highly predictable and reliable. It was found that Neuro-Fuzzy model was superior to the regression model. Figs 3 and 4 shows the deviation in observed and predicted outflows for both the models.

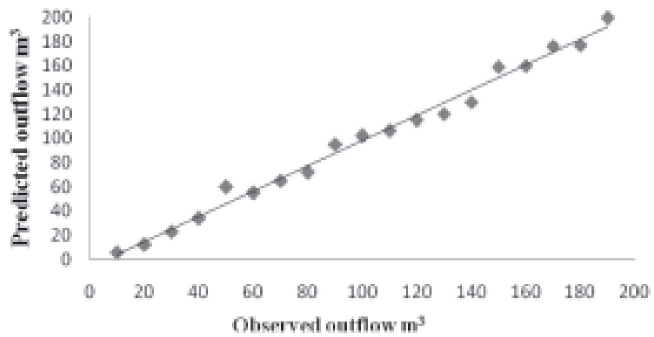

Figure 3: Observed and predicted outflow Neuro-Fuzzy model

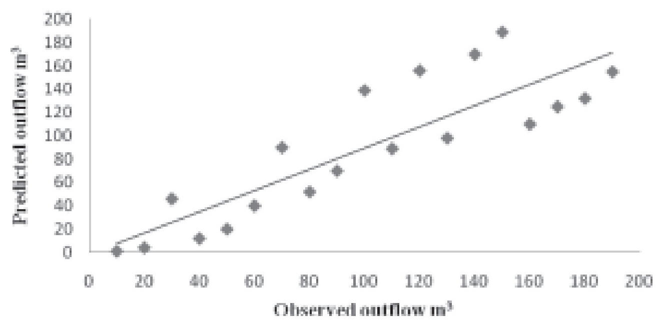

Figure 4: Observed and predicted outflow using regression model

Conclusion

Soft computing techniques are efficient in handling the uncertainty and partial truth and therefore are widely adopted in the field of water resource management. These

Table 1: The validation statistics of different models for randomized data sets

Model	Maximum R^2	Minimaum R^2	Maximum E	Minimaum E	AAD
Neuro-Fuzzy	0.98	0.92	0.97	0.88	0.002
Regression	0.76	0.69	0.71	0.59	0.031

techniques are extensively used for determining operating policies of reservoirs and dams. In the present study two models, predicting outflow of OFR, using Neuro-Fuzzy and regression approaches, were developed. The models were tested and compared statistically for their superiority. Neuro-Fuzzy model was found to have better predictability than that of regression model. This model can be adopted for efficient water management at the site so that sustainable water management can be achieved.

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