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# SIMULATING SPRINKLER DISTRIBUTION PATTERN IN WINDY CONDITION USING ARTIFICIAL NEURAL NETWORK

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**ABSTRACT**

Sprinkler distribution pattern is key factor for efficient use of irrigation system. Ballistic method for simulation has been accepted by many researchers. This method demands deep knowledge about droplet dynamics. The purpose of this work is to present ANN model which simulate sprinkler distribution pattern at various wind speeds and operating conditions. Main input parameters for ANN are Wind Speed, CV% of Wind Speed, Operating Pressure, Radial Distance of Grid Point and Effective Angle of catch can. Using five input parameters ANN structure is trained and compared with observed data of sprinkler distribution pattern. Out of 31311 data 80% was used for training the model and 20% data was applied for testing of trained models. The results revealed that the ANN structure (5-24-4-1) performed better than the other ANN structures.

***Key words***: Artificial Neural Network, Feed Forward Back Propagation, Sprinkler Distribution Pattern, Simulation, Windy Condition.

## Introduction

The water distribution pattern and spacing of sprinklers are two important factors that can affect the application uniformity of sprinkler irrigation systems. For a particular sprinkler with a given nozzle size that works under an optimal operating pressure in field conditions, the resulting water distribution depends on wind speed. Wind causes the distortion of the distribution pattern, and this increases with increasing wind speed (Keller & Bliesner, 1990).

To avoid laborious field tests and to improve the design of irrigation systems, several studies have been conducted over the last 30 years to develop irrigation simulation models which can be used for the estimation of water distribution patterns of irrigation systems under real or controlled conditions. These models have been categorized to ballistic, semi-empirical and statistical (Granier *et al*., 2003).

The most common approach of sprinkler irrigation modeling is the ballistic method that is based on simulating trajectory of individual drops. A sprinkler is considered as a device emitting water drops in different diameters from a nozzle, which travel separately until landing on the soil surface (or crop canopy, or experimental catch-can). For a given sprinkler configuration in a no-wind condition, droplet diameter is a major factor that affects the travel distances of droplets (*i.e*. the horizontal distance between droplet landing point and the sprinkler nozzle). The Flight path of each droplet is subjected to an initial velocity vector and a wind vector (parallel to the ground surface) which can be determined using ballistic theory. Gravity and drag are two other forces that act on each water droplet in vertical and opposite of drop trajectory directions, respectively. Regarding the ground, the droplet velocity is equal to the velocity of the drop in the air plus the wind vector (Playan *et al*., 2006). The major advance of ballistic models has occurred in the last few decades and several irrigation simulations models have been developed (Fukui *et al*., 1980, Vories *et al*., 1987, Seginer *et al*., 1991a, Carrion *et al*., 2001, Montero *et al*., 2001, Dechmi *et al*., 2004, Lorenzini, 2004, De Wrachien &

Lorenzini, 2006, Playan *et al.*, 2006, Yan *et al.*, 2010).

Simulating the modified shape of distribution patterns in accordance with initial shape of wetted area and wind conditions (speed and direction) is the basis for semi-empirical methods. It is assumed that the distribution pattern of water applied from a single sprinkler has a ûexible shape on the soil surface. The shape of distribution pattern in no-wind condition depends only on sprinkler configuration and operating pressure and could be derived from radial distributions of water measured with laboratory tests. Wind distorts this shape and the objective of semi-empirical models is to find a relationship between observed distortion and wind conditions. Calibration of such models is typically carried out using spatial distribution patterns measured in field conditions (Granier *et al.*, 2003).

The statistical approach could be applied to a set of sprinklers: line or complete solid set cover (Karmeli, 1978), center pivot (Heerman *et al.*, 1992), or to a single sprinkler (Solomon & Bezdek, 1980). By defning a limited number of parameters, observed water distribution curves or maps under an isolated sprinkler in various operating conditions have been adjusted to laws of probabilistic distribution (Solomon & Bezdek, 1980). The adjustment could be performed using several simultaneous measurement series according to statistical criterion (Le Gat & Molle, 2000). The radial distribution curve from the sprinkler is identified and then the spatial distribution pattern in the wetted area can be estimated by generalizing it.

Artifcial Neural Networks (ANNs) are an emerging, computational or mathematical tool that has been implemented for modelling a wide range of complex and multivariate real-world systems. These networks that mimic characteristics of the biological neural systems have some remarkable advantages such as nonlinearity, high parallelism, robustness, fault and failure tolerance, learning ability, handling imprecise and fuzzy information, and generalization capability. Without any assumption and knowledge about the underlying principles, ANNs are able to precisely extract the generalized relationship between input and output data and their accuracy increases with increasing of available data (Basheer &Hajmeer, 2000; Jain *et al.*, 2004).

**Fig. 1:** Mini sprinkler assembly.

An important aspect of ANNs is multi-layer feed forward networks. In general, this class of network consists of multiple interconnected layers which are: an input layer that contains a set of sensory units (source nodes), one or more hidden layers of computation nodes, and an output layer. The input signal propagates layer-by-layer through the network only in a forward direction. These neural networks are commonly referred to as a Multi-Layer Perceptron (MLP).

## Material and Methods

The study was conducted at the Instructional Farm, Department of Soil and Water Engineering, College of Agricultural Engineering and Technology, Junagadh Agricultural University, Junagadh, Gujarat.

### Experimental Details

Mini sprinklers were used in which the water jet strikes a bearing that possess one or two channels causing the mini sprinklers to rotate quickly and distribute water. It is manufactured from plastic material and is used in solid sets in orchards and gardens mostly. It runs at an operating pressure of about 1.0 to 2.0 kg/cm$^2$

In the present study, "Double Nozzle-full Circle" mini sprinkler (Make; Nimbuss Irrigation Company) were used. These mini sprinklers are mounted on an installation stake 1.2 m long, 8 mm x. The mini sprinkler were connected to the lateral using a PVC tube of 1.2 m, 12 mm x. The mini sprinkler consists of two nozzles. (Fig. 1).

### Experimental Design of Sprinkler Set

Two rows of mini sprinklers with two sprinklers on each row was arranged at 20 m row to row and 18 m sprinkler to sprinkler spacing. The system was operated at different pressures in the range of 1 kg/cm$^2$ to 2 kg/cm$^2$ in an increment of 0.1 kg/cm$^2$ for generating training data of ANN. The layout of the experimental setup is shown in Fig. 2.

A network of 20 × 20 catch-cans was placed at the testing stand at a spacing of 1 m ×1 m. The sprinkler was placed in the center of the network at a height of 1 m using a metal frame, and the point under the sprinkler

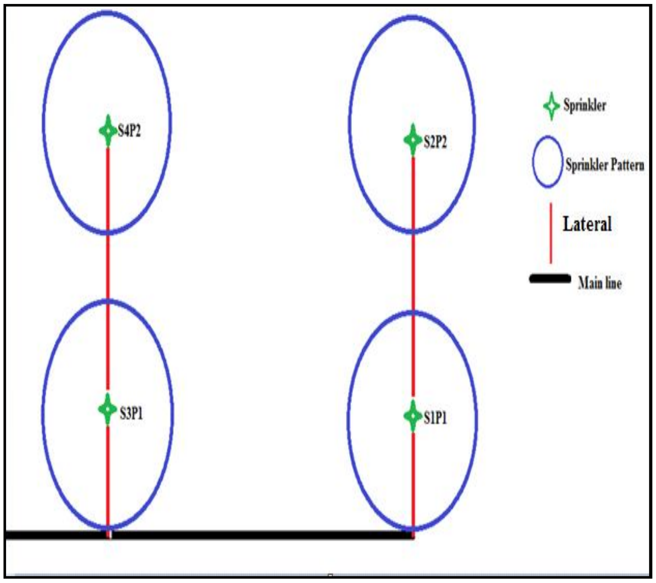


**Fig. 2:** Sprinkler set design for experiment.

position was without a catch-can, therefore in total 400 catch-cans were used in the network. Water volumes collected in the catch-cans were measured after each experiment. Fig. 3 shows schematic of the single sprinkler testing network. Climate data and weather conditions (*e.g.* temperature, air humidity, and speed and direction of wind at the height of 2-m from ground level) were recorded on a 1-min frequency.

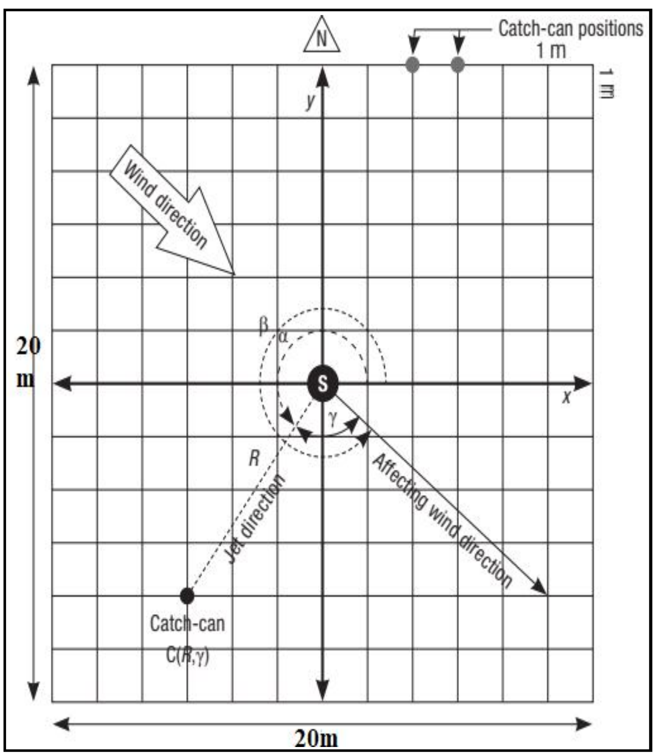


**Fig. 3:** Schematic of testing stand and defned parameters of problem (S: sprinkler position; R: radial distance to catch-can [C(R,γ)]; α: angle of jet trajectory vector; β: angle of affecting wind vector; γ: difference between β and α)

## Problem Definition and Formulation

Appropriate definition and formulation of the problem is an important step in the development of successful ANN-based projects. In this study, it is assumed that there are some spatial distribution patterns which are measured under real field conditions for various wind speeds, and simulating distribution patterns in none measured wind speeds is the objective of ANNs-based model. In fact, ANNs would be used here as an interpolation tool for developing a model to simulate the wind distorted distribution pattern of a sample single sprinkler. A dataset of water volumes collected in catch-cans (*i.e.* precipitation rate; PR) for each experiment were used as the targets of the neural network.

The radial distance (R) of catch-cans to the sprinkler indicates the horizontal travel distance of emitted droplets and the two alternative parameters of wind vector (*i.e.* speed, V, and its direction) were considered as the two most important parameters. A trigonometric circle has been employed to present the direction of wind and therefore an angle of zero is related to wind direction from West to East. As illustrated in Fig. 3, the incidence angle of the jet trajectory vector and wind vector is named γ that is a representative for drag forces acting on a jet element.

Each catch-can at the test network is related to a function of C (R,γ), in which R is a constant for any given catch-can but ã varies in relation to wind direction for each individual test. Thus, volume of collected water in each catch-can for any wind speed (PRC(R,γ),V) composed the output neuron of the ANN with the neurons of the input layer consisting of R, γ and V.

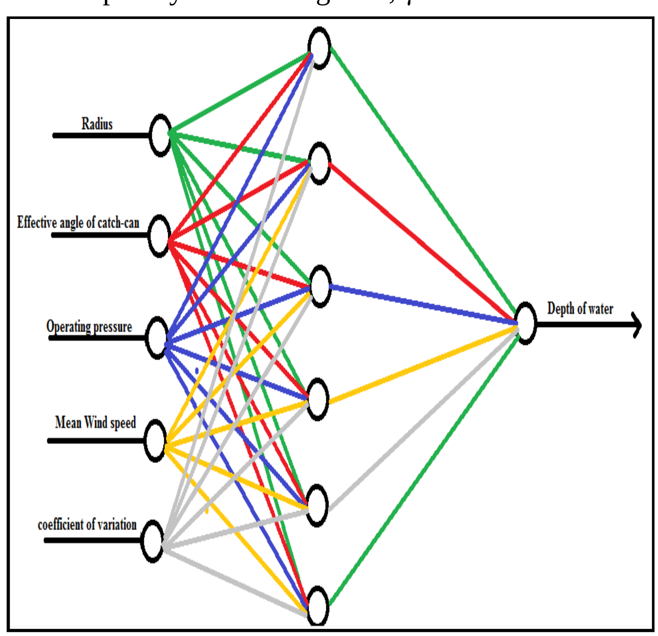


**Fig. 4:** Scheme of multi-layer perceptron (MLP) neural network.

**Table 1:** Performance evaluation of one hidden layer ANN models.

| Sr. No. | Network structure | Training epochs | $R^2$ | | | | MSE | RMSE |
|---|---|---|---|---|---|---|---|---|
| | | | Training | Validation | Testing | Over ALL | | |
| 1 | 5—2—1 | 220 | 0.8395 | 0.8359 | 0.8046 | 0.8330 | 0.0004 | 0.0200 |
| 2 | 5—3—1 | 15 | 0.8488 | 0.8252 | 0.8034 | 0.8375 | 0.0005 | 0.0219 |
| 3 | 5—4—1 | 17 | 0.8739 | 0.8395 | 0.8237 | 0.8610 | 0.0004 | 0.0211 |
| 4 | 5—5—1 | 37 | 0.8681 | 0.8804 | 0.8756 | 0.8709 | 0.0003 | 0.0178 |
| 5 | 5—6—1 | 27 | 0.8676 | 0.8676 | 0.8774 | 0.8689 | 0.0003 | 0.0183 |
| 6 | 5—7—1 | 90 | 0.8880 | 0.8815 | 0.9022 | 0.8890 | 0.0004 | 0.0191 |
| 7 | 5—8—1 | 19 | 0.8875 | 0.8820 | 0.8697 | 0.8838 | 0.0003 | 0.0173 |
| 8 | 5—9—1 | 39 | 0.9097 | 0.9114 | 0.8763 | 0.9040 | 0.0002 | 0.0152 |
| 9 | 5—10—1 | 46 | 0.9081 | 0.9035 | 0.9049 | 0.9069 | 0.0003 | 0.0169 |
| 10 | 5—11—1 | 41 | 0.9067 | 0.9032 | 0.9047 | 0.9060 | 0.0003 | 0.0159 |
| 11 | 5—12—1 | 36 | 0.9027 | 0.9105 | 0.8960 | 0.9027 | 0.0003 | 0.0168 |
| 12 | 5—13—1 | 70 | 0.9129 | 0.9090 | 0.8441 | 0.9001 | 0.0002 | 0.0148 |
| 13 | 5—14—1 | 142 | 0.9152 | 0.9012 | 0.9127 | 0.9128 | 0.0003 | 0.0164 |
| 14 | 5—15—1 | 81 | 0.9105 | 0.9145 | 0.8983 | 0.9089 | 0.0002 | 0.0148 |
| 15 | 5—16—1 | 96 | 0.9148 | 0.9111 | 0.9150 | 0.9143 | 0.0002 | 0.0156 |
| 16 | 5—17—1 | 45 | 0.9174 | 0.9109 | 0.9153 | 0.9162 | 0.0002 | 0.0155 |
| 17 | 5—18—1 | 17 | 0.9055 | 0.8985 | 0.8892 | 0.9016 | 0.0003 | 0.0165 |
| 18 | 5—19—1 | 19 | 0.9177 | 0.8534 | 0.9014 | 0.9030 | 0.0005 | 0.0228 |
| **19** | **5—20—1** | **93** | **0.9227** | **0.9203** | **0.9112** | **0.9207** | **0.0002** | **0.0139** |
| 20 | 5—21—1 | 59 | 0.9148 | 0.9113 | 0.9101 | 0.9135 | 0.0003 | 0.0160 |

### Observations

Five observations were recorded as follows

(1) Mean wind speed (km/h)

(2) Radius of catch-can to sprinkler (m)

(3) Operating pressure of sprinkler ($kg/cm^2$)

(4) Effective angle of catch-can ($^o$)

(5) Depth of water collected in individual catch – can (mm)

### Design and training of networks

Fig. 4 represents a schematic of the MLP neural networks. The number of neurons in the input and output layers was set with respect to the formulation of the problem, so there were 5 and 1 neuron (s) in the input and output layers, respectively. However, determining the most appropriate number of neurons in the hidden layers is more flexible. In the present study to attain an optimal network structure, the number of neurons in the hidden layer (s) was determined by several trials.

A variety of learning algorithms could be implemented for training MLP neural networks and the most common algorithm is error backpropagation. Basically, an error backpropagation algorithm consists of a forward pass and a backward pass through the different layers of the network. In the forward pass, a set of data, as input vector are applied to the sensory nodes of the network, and therefore a set of outputs is produced as the actual response of the network. All the weights of the network are fixed during the forward pass. Then, the error signal is produced by subtracting the network responses from target values and propagated backward through the network to adjust all weights in accordance with an error-correction rule (Haykin, 1999).

### Performance evaluation criteria

(1) Root mean square error (RMSE)

(2) Nash-Sutcliffe efficiency (EF)

(3) Coefficient of determination ($R^2$).

(4) Coefficient of residual mass (CRM)

(5) Absolute error (AE)

(6) Akaike information criteria (AIC)

(7) Bayesian information criteria (BIC)

(8) Mean square error (MSE)

## Results and Discussion

Artificial neural network (ANN) sprinkler pattern distribution models have been developed using five main input combination for different wind speed and operating pressure. (1) Mean wind speed, (2) CV% of wind speed, (3) Radius of catch-can to sprinkler, (4) Operating pressure of sprinkler, (5) Effective angle of catch-can, and in the output, there was only one type of data (1) Depth of water collected in individual catch –can as input

**Table 2:** Performance evaluation of two hidden layers ANN model.

| Sr. No. | Network structure | Training epochs | $R^2$ | | | | MSE | RMSE |
|---|---|---|---|---|---|---|---|---|
| | | | Training | Validation | Testing | Over ALL | | |
| 1 | 5—4—2—1 | 25 | 0.8758 | 0.8785 | 0.8759 | 0.8762 | 0.0003 | 0.0176 |
| 2 | 5—5—2—1 | 82 | 0.8898 | 0.9029 | 0.8608 | 0.8871 | 0.0003 | 0.0163 |
| 3 | 5—6—2—1 | 33 | 0.8793 | 0.9018 | 0.8986 | 0.8853 | 0.0002 | 0.0156 |
| 4 | 5—7—2—1 | 21 | 0.877 | 0.9076 | 0.903 | 0.8848 | 0.0002 | 0.0152 |
| 5 | 5—8—2—1 | 0 | 0.0717 | 0.096 | 0.0916 | 0.0961 | 0.0018 | 0.0427 |
| 6 | 5—9—2—1 | 44 | 0.9092 | 0.891 | 0.8904 | 0.9028 | 0.0003 | 0.0185 |
| 7 | 5—10—2—1 | 64 | 0.9074 | 0.8983 | 0.895 | 0.9044 | 0.0003 | 0.0164 |
| 8 | 5—11—2—1 | 137 | 0.9216 | 0.8902 | 0.8819 | 0.9104 | 0.0003 | 0.0177 |
| 9 | 5—12—2—1 | 61 | 0.9184 | 0.8345 | 0.922 | 0.9035 | 0.0006 | 0.0237 |
| 10 | 5—13—2—1 | 51 | 0.9075 | 0.9146 | 0.8759 | 0.9037 | 0.0002 | 0.0151 |
| 11 | 5—14—2—1 | 26 | 0.9027 | 0.9131 | 0.9073 | 0.9047 | 0.0002 | 0.0147 |
| 12 | 5—15—2—1 | 28 | 0.896 | 0.91 | 0.9076 | 0.8996 | 0.0002 | 0.0149 |
| 13 | 5—16—2—1 | 38 | 0.9136 | 0.9002 | 0.9046 | 0.9101 | 0.0003 | 0.0172 |
| 14 | 5—17—2—1 | 78 | 0.9224 | 0.9155 | 0.9007 | 0.9181 | 0.0002 | 0.0155 |
| 15 | 5—18—2—1 | 66 | 0.919 | 0.9121 | 0.9163 | 0.9176 | 0.0002 | 0.0151 |
| 16 | 5—19—2—1 | 18 | 0.8879 | 0.9054 | 0.8973 | 0.8915 | 0.0003 | 0.0158 |
| 17 | 5—20—2—1 | 30 | 0.9094 | 0.9182 | 0.8804 | 0.9062 | 0.0002 | 0.0154 |
| 18 | 5—21—2—1 | 27 | 0.9233 | 0.8693 | 0.9122 | 0.9126 | 0.0004 | 0.0202 |
| 19 | 5—22—2—1 | 45 | 0.92 | 0.9193 | 0.9037 | 0.9175 | 0.0002 | 0.0145 |
| 20 | 5—23—2—1 | 41 | 0.9019 | 0.9081 | 0.9104 | 0.9039 | 0.0002 | 0.0153 |
| 21 | 5—24—2—1 | 18 | 0.9085 | 0.8652 | 0.9071 | 0.9012 | 0.0004 | 0.0202 |
| 22 | 5—25—2—1 | 28 | 0.9223 | 0.9223 | 0.8937 | 0.9174 | 0.0002 | 0.0143 |
| **23** | **5—26—2—1** | **47** | **0.9266** | **0.9258** | **0.9112** | **0.9244** | **0.0002** | **0.0142** |
| 24 | 5—27—2—1 | 30 | 0.9178 | 0.8866 | 0.911 | 0.9111 | 0.0004 | 0.0193 |
| 25 | 5—28—2—1 | 22 | 0.9287 | 0.9135 | 0.8712 | 0.9177 | 0.0002 | 0.0151 |
| 26 | 5—3—3—1 | 32 | 0.8502 | 0.873 | 0.8576 | 0.8576 | 0.0003 | 0.018 |
| 27 | 5—4—3—1 | 167 | 0.897 | 0.9064 | 0.8924 | 0.8924 | 0.0003 | 0.0165 |
| 28 | 5—5—3—1 | 63 | 0.8817 | 0.8982 | 0.8805 | 0.8805 | 0.0003 | 0.0159 |
| 29 | 5—6—3—1 | 106 | 0.9007 | 0.8714 | 0.8941 | 0.8941 | 0.0004 | 0.0199 |
| 30 | 5—7—3—1 | 41 | 0.904 | 0.8938 | 0.8956 | 0.8956 | 0.0003 | 0.0166 |
| 31 | 5—8—3—1 | 69 | 0.9174 | 0.9085 | 0.9079 | 0.9079 | 0.0002 | 0.0158 |
| 32 | 5—9—3—1 | 19 | 0.8898 | 0.8833 | 0.8921 | 0.8921 | 0.0003 | 0.0185 |
| 33 | 5—10—3—1 | 26 | 0.9108 | 0.8707 | 0.9035 | 0.9035 | 0.0004 | 0.0199 |
| 34 | 5—11—3—1 | 28 | 0.8924 | 0.8989 | 0.896 | 0.896 | 0.0003 | 0.0165 |
| 35 | 5—12—3—1 | 17 | 0.886 | 0.912 | 0.8922 | 0.8922 | 0.0002 | 0.0153 |
| 36 | 5—13—3—1 | 30 | 0.906 | 0.8704 | 0.9007 | 0.9007 | 0.0004 | 0.0204 |

variables. As per trial-and-error total 134 ANN structure was trained and tested. As per ANN structure, the numbers of input nodes are considered equal to number of inputs.

## Training of ANN Model

In this study total 71 sprinkler distribution pattern ware used to train ANN model. Each pattern has 21×21 data point of depth of water collected in catch-can, therefore total amount of data for training were 21×21×71=31311. Input data was divided in to two part, one for training and another for checking model efficiency. In this study 80% data was used to train ANN model and remaining 20% data was used for model efficiency check. This 20% data was selected in such a way that it represents the entire population.

## Architect of ANN Model

A multi-layer perceptron with backpropagation training algorithm was used for simulation of single sprinkler distribution pattern. A tangent-sigmoid transfer function was selected between the input and hidden layers, and a linear transfer function selected between the hidden and output layer; due to sufficient neurons in the hidden layer this structure for a neural network is reported to have the ability to approximate any function (Mathworks,

**Table 3:** Rank of trained ANN structures based on overall $R^2$ value.

| Sr. No. | Network structure | Training epochs | $R^2$ Training | Validation | Testing | Over ALL | MSE | RMSE |
|---|---|---|---|---|---|---|---|---|
| 1 | 5—24—6—1 | 53 | 0.9402 | 0.9197 | 0.9056 | 0.9323 | 0.0002 | 0.0148 |
| 2 | 5—24—4—1 | 26 | 0.9294 | 0.9194 | 0.9154 | 0.9261 | 0.0002 | 0.0149 |
| 3 | 5—26—2—1 | 47 | 0.9266 | 0.9258 | 0.9112 | 0.9244 | 0.0002 | 0.0142 |
| 4 | 5—21—4—1 | 53 | 0.9296 | 0.9234 | 0.9024 | 0.9242 | 0.0002 | 0.0152 |
| 5 | 5—23—6—1 | 35 | 0.9332 | 0.8895 | 0.9155 | 0.9235 | 0.0003 | 0.0184 |
| 6 | 5—18—4—1 | 38 | 0.9233 | 0.9227 | 0.9231 | 0.9232 | 0.0002 | 0.0146 |
| 7 | 5—13—5—1 | 82 | 0.9245 | 0.9170 | 0.9231 | 0.9232 | 0.0002 | 0.0150 |
| 8 | 5—19—4—1 | 60 | 0.9306 | 0.9271 | 0.8879 | 0.9230 | 0.0002 | 0.0143 |
| 9 | 5—17—6—1 | 39 | 0.9295 | 0.9166 | 0.8992 | 0.9230 | 0.0002 | 0.0151 |
| 10 | 5—12—7—1 | 64 | 0.9275 | 0.9190 | 0.9003 | 0.9222 | 0.0002 | 0.0146 |

2007). Feed forward back propagation neural network with Levenberg–Marquardt algorithm was used to train the network. Start with one and then two hidden layer were applied for maximum iterations of 1000. ANN models were solved using MATLAB 7.9.0 version.

For each distinct network, after post-processing, the MSE and $R^2$ values for the training, validation and testing subsets were calculated. Observed water depth at different cache-can was used as an output for supervised learning of ANN. Developed models were compared with observed data for checking their accuracy of prediction. The best ANN architecture during training period for various hidden layer neuron combination is presented in Table 3.1 for predicting sprinkler distribution pattern. Various statistical criteria for each combination of input variables were estimated during the testing period are presented in Table 3.2.

The results showed that the neural network containing one hidden layer was not increasing the R2 value after (5- 20 -1) structures it goes down with increased neurons in hidden layer. Then go for two hidden layers.

Training results shows in Table 4.3 and 4.4 indicates that, ANN architecture with two hidden layers having (5-24-6-1) structure gave comparatively better result than the one hidden layer. If the ANN training is over fitted then it may be possible that the best trained network might not give the proper results. To ensure that the trained network is not over fitted, validation has been simulated with 10 ranked ANN structures (shown in Table 4.5).

Table 4.6 shows that ANN with 5-21-4-1 structure gave better result in compare to the best structure from the training which was 5-26-6-1.

All performance criteria were calculated as 10 rank model which was better in all training structure. On the basis of all performers' criteria except AIC ANN structure (5-21-4-1) gave batter result. Table 3.4 shows that ANN with 5-21-4-1 structure gave better result in compare to the best structure from the training which was 5-26-2-1.

## Conclusion

On the basis of training and performance criteria of the all structure, ANN network should be used which has 21 neurons in first layer, 4 neurons in second layer, back propagation algorithm, TRANLM training function, TANSIG transfer function was used for simulating sprinkler distribution pattern at various wind speed and operating pressure.

## Acknowledgement

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**Table 4:** Performance evaluation of various ANN model.

| Sr. No. | Network structure | CRM | AE | MSE | RMSE | AIC | BIC | EF | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 5—21—4—1 | 0.008 | -0.004 | 0.094 | 0.306 | -0.785 | 1.282 | 0.839 | 0.839 |
| 2 | 5—26—2—1 | -0.060 | 0.030 | 5.577 | 2.362 | 1.259 | 3.326 | 0.801 | 0.804 |
| 3 | 5—24—4—1 | -0.011 | 0.006 | 0.192 | 0.438 | -0.425 | 1.643 | 0.795 | 0.801 |
| 4 | 5—17—6—1 | -0.051 | 0.025 | 4.044 | 2.011 | 1.098 | 3.166 | 0.793 | 0.802 |
| 5 | 5—13—5—1 | -0.021 | 0.011 | 0.691 | 0.831 | 0.215 | 2.282 | 0.793 | 0.798 |
| 6 | 5—19—4—1 | -0.017 | 0.008 | 0.446 | 0.668 | -0.004 | 2.063 | 0.792 | 0.799 |
| 7 | 5—12—7—1 | -0.019 | 0.009 | 0.554 | 0.744 | 0.104 | 2.172 | 0.789 | 0.795 |
| 8 | 5—24—6—1 | -0.017 | 0.008 | 0.421 | 0.649 | -0.033 | 2.035 | 0.787 | 0.796 |
| 9 | 5—18—4—1 | -0.021 | 0.011 | 0.691 | 0.831 | 0.215 | 2.282 | 0.786 | 0.794 |
| 10 | 5—23—6—1 | -0.022 | 0.011 | 0.752 | 0.867 | 0.257 | 2.324 | 0.781 | 0.791 |

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