

Hourly Real-Time Rainfall Estimation for Improved Smart Irrigation System Using Nearby Automated Weather Station

ABSTRACT —Smart irrigation is done by extracting climatic data such as historical data, off-site data, weather station, moisture sensor, wireless sensor network and web-based forecast. In existing sensor-based smart irrigation schedule, the decision-making of current irrigation depends on the current climatic data. Irrigation control decision making systems can be improved by using neighborhood real-time rainfall for approximate local rainfall estimation. This method can result in better water saving techniques. This paper shows the development of low-cost smart irrigation system which consists of Automatic Weather Station (AWS), Central Irrigation Control Server, wireless modules, soil moisture sensors and solenoid valves. For improved decision making an artificial neural network with back-propagation algorithm is implemented to estimate real-time hourly rainfall by using nearby AWS. Depending on the estimated rainfall input, the irrigation decision can be immediate irrigation if no rainfall or reschedule of irrigation for next cycle if expecting sufficient amount of rainfall or may be partial irrigation for insufficient rainfall. This method can utilize rainfall for fields and saves ground water resources. This method also avoids flooding and damage to crop due to significant rainfall just after scheduled irrigation. Avoiding of flooding is very curial especially in germination period of any crop. In study area of NCMRWF, National Captial Region (NCR) on particular day of 22nd and 23rd Jan 2015 continuous rainfall of 152mm of record, shows that for irrigation area of 1000m² we can save up to 1,52,000 litre of fresh water by using real-time rainfall estimation technique. This technique can save ground/reservoir water resources in arid and semi-arid regions like India.

Keywords-Smart Irrigation; Automatic Weather Station; Soil Moisture Sensors; Real-time Estimation; Back-propagation Algorithm; Precision Irrigation, Water Preservation

1. INTRODUCTION

Our Indian agricultural land is mainly arid and semi-arid area. 80% of water is used for irrigation purpose. Due to Indian population growth and climatic changes there is a severe water shortage on the ground level [1]. How population rise increases will increase water scarcity in India is projected in [2]. Whereas [3] discuss the climate change and its impact on ground water.

Agriculture is one of the major sectors where fresh water is used in large amount. Therefore we have to come up with an efficient way of using irrigational water resources by using some good techniques. Smart irrigation is the only way to give the right amount of water at right time which will increase crop productivity. This paper explores yet another way to save irrigation water in smart irrigation by taking real-time neighbor rainfall data into consideration before starting the scheduled irrigation.

Smart controllers for irrigation systems are systems which automatically update the watering schedule depending on the changes in environmental conditions. Prior to smart irrigation, automated irrigation systems are developed which automatically control the irrigation schedule. These automated systems are designed with embedded system components like microcontroller with timer, sensors and electrical valves for water flow control. Some examples of automated irrigation systems described by [4] are timer-based systems, volume-based systems, open loop system and closed loop system.

The time-based automatic irrigation system has a timer an integral part of design. This timer is set for a particular duration, during which irrigation valves are opened automatically. This kind of irrigation can lead to under or over irrigation if they are not correctly programmed because of incorrect irrigation demand calculation. Also, time-based irrigation system has to be re-programmed for any changes in soil, climate or growth stages of the crop.

In volume-based irrigation system, the pre-set amount of water will be dispatched by using automatic volume controlled metering valves. This kind of irrigation is more suitable for paddy fields. Again this kind of irrigation has similar disadvantages as that of time-based irrigation of under- or over- irrigation.

In open loop system, the operator makes the decision on volume of water and duration of irrigation to be done. Water saving solely depends on the operator decision. If operator's estimation fails, this may result in over or under irrigation. In closed loop systems[5], the general control strategy is defined by classic PID controller to make a decision on when to irrigate and how much to irrigate by taking continues feedback from one or more sensors attached to the system for measuring rainfall, controller windup, under-watering and plant stress conditions.

Advanced automatic irrigation is basically smart irrigation in which decision making depends on the use of historical data, historical data with sensor or by real-time data acquisition of environmental parameters such as soil moisture, temperature, radiation, wind speed, humidity, rain sensor and so on. Example for such irrigation systems is real-time feedback system, soil-moisture based system, weather station based system, remote weather access based system and wireless sensor networks. Detail work on automated irrigation has been reported in "Weather- and Soil Moisture- Based Landscape Irrigation Scheduling Devices" in [6].

In real-time feedback systems, as explained by [7] irrigation depends on the actual dynamic demand of the plant itself by taking the condition of the plant root zone and these feedbacks can also be used for site-specific variable rate irrigation. Various sensors like tensiometers, relative humidity sensor, rain sensor, temperature sensors etc are used to make a decision on irrigation schedule.

In soil moisture sensors based irrigation systems, one used by [8], where soil moisture sensor measures volumetric water content in the soil. These measurements are used by decision making of irrigation control systems to schedule the irrigation depending on the moisture threshold value defined for particular crop and soil texture. Soil moisture sensors come in variety which includes capacitance, neutron moisture, resistive, time domain transmission and time domain reflectometry, heat dissipation and tensiometers. Before using any of these soil moisture sensors, they have to be calibrated for particular soil types and a thus process is difficult and time-consuming. One of the limitations of using soil moisture sensor for irrigation is that if irrigation is scheduled at T time and rainfall occurs immediately after T there is no check for this situation.

Automatic Weather Station (AWS) based systems are very accurate irrigation systems, where one can have their own weather station or use nearby weather stations which are installed by the government agency. These systems use real-time data from sensors like rain gauge, wind speed and direction, temperature, relative humidity and solar radiation. These data are used for calculation of evapotranspiration (ET_o) [9] which is further used for irrigation demand calculation. Costs involved in having your own AWS are very high as much as Rs. 2,25,000/-(this values are quoted by some Indian company). For small farming land (less than 2 hectares) it is costly and hence difficult for farmers to accommodate this kind of water saving technology in their irrigation systems.

Wireless Sensor Network (WSN) for irrigation control [11-12] is used for variable rate and site-specific irrigation. Some of the agricultural lands have the spatial variability of soil. In such cases most suitable monitoring systems are wireless sensor networks. Similar to that of AWS this system also uses real-time data from sensors like rain gauge, wind speed and direction, temperature, relative humidity and solar radiation for irrigation calculation. For the site-specific irrigation use of WSN are very accurate. Again these systems use current climatic data for irrigation calculation. Any rainfall within few hours of irrigation is not taken care of and also installation cost of WSN is high.

Recent internet –weather based smart irrigation systems uses forecasted or estimated climatic data from the internet for their irrigation schedule. [12] has forecasted data using radar map whereas [13] forecasted data using the rain gauge and radar map. These forecasted data includes temperature, wind speed, wind direction and precipitation details are taken into consideration for decision-making systems. Related to these systems some of the products like Cyber-Rain Controllers, Skydrop Controllers, Irrigation Caddy Web Based Timer and Weathermatic Internet Based Controllers are available from Sprinkler Ware House. These products use the smart-phone and internet to control their irrigation schedule. The cost of these products varies from 500 to 1000 dollars. One of the major problems with good forecasted climatic data is limited to specific location and some of them are not accurate. In “AccuWeather.com” site provides the hourly estimation of weather forecasts such as temperature, wind direction, humidity, dew point, rain and other details. Again, the problem is that data is available for the specific location of India and there is a

significant error associated with forecasted data. On the particular day of 25th June 2015 the forecasted rainfall data for the complete day is 16mm from “AccuWeather.com” where as the actual rainfall is 59mm as per Indian Meteorological Data (IMD). This kind of variation can fail total smart irrigation system.

This paper discusses cost effective smart irrigation solution by taking advantage of some of the above system as follows:

- AWS is used to extract the nearby climatic parameter conditions.
- Local soil moisture sensor is used to calibrate local condition.
- Irrigation schedule decision making like an experienced farmer. Farmer intuitions about rainfall by seeing nearby climatic condition are used for irrigation control. This farmer intuition is implemented using back-propagation neural network.

Detailed work of improved smart irrigation is organized as follows: Section 2 describes the case study area considered for experimentation. Section 3 discusses material and method used for implementation of low-cost smart irrigation system. Section 3.1 discusses how irrigation demand is calculated by using remote Automatic Weather Station (AWS). Section 3.2 discusses possible error associated with irrigation demand calculation using remote AWS and reason behind them. Section 3.3 discusses how soil moisture sensors are used to calculate irrigation demand. Section 3.4 discusses the relation between soil moisture data and remotely accessed temperature using AWS. Section 4 discusses how rainfall in neighbor influences the decision making of local irrigation. Section 5 discusses how rainfall estimation is done using Neural Network with back-propagation algorithm. Section 6 discusses implementation and results. Section 7 concludes the paper how this technique is helpful in saving ground water and utilizing oncoming rainfall just before the scheduled irrigation.

2. STUDY AREA

To demonstrate the influence of rainfall in NCMWF with respective to its neighborhood location NCR, Delhi locations is considered. Where AWS are installed by IMD, Government of India. Location namely Akshardham, Ayanagar, Delhi University, Jafarpur, Najafgarh, Narela, NCMRWF(National Centre for Medium Range Weather Forecast), Pitampura and Pusa are the areas under consideration were these locations come under National Capital Region (NCR) of Delhi as shown in Fig. 6. Latitude and longitude of these places are as shown in the below Table 2 and they are located within 25 km of radius.

3. MATERIALS AND METHODS

The proposed system is cost effective solution for the smart irrigation in which local irrigation is done using nearby AWS, local sparse soil moisture sensor network and an intelligent decision-making system based on the local estimation as shown in Fig. 1.



Fig. 6. NCR, Delhi Map showing AWS location 1→New Delhi, 2→Sports Complex Delhi 3→Pitampura 4→Pusa, 5→Narela, 6→ Najafgarh, 7→ NCMRWF, 8→Mungeshpur,9→ Jafarpur,10→Delhi University, 11→ DPS Indirapuram, 12→ Ayanagar 13→ Akshardham

TABLE 2: LATITUDE AND LONGITUDE OF NCR, DELHI

Sr. No	Location of NCR	Latitude	Longitude
1	Akshardham	28.617	77.279
2	Ayanagar	28.47	77.12
3	Delhi University	28.58	77.16
4	Jafarpur	28.57	76.90
5	Najafgarh	28.606	76.99
6	Narela	28.84	77.09
7	NCMRWF	28.62	77.36
8	Pitampura	28.69	77.13
9	Pusa	28.63	77.157

The main modules used for improved smart irrigation systems are AWS (installed by the government agency), Central Irrigation Controller server, wireless communication module, electrical solenoid valves, and microcontroller. Total cost this system is less than Rs. 20,000/-(\$294).

AWS are installed by Indian Meteorological Department, Government of India across the India. AWS data is available on their website www.imd.gov.in for every one-hour interval for the complete day (24 hours) up to 1 week of time.

Central Irrigation Controller server has various software's like crawler for extracting AWS data, Wamp server to store data, Visual C++ application to calculate ETo, back-propagation neural network implementation for estimating rainfall and X_CTU software for sending and receiving wireless data.

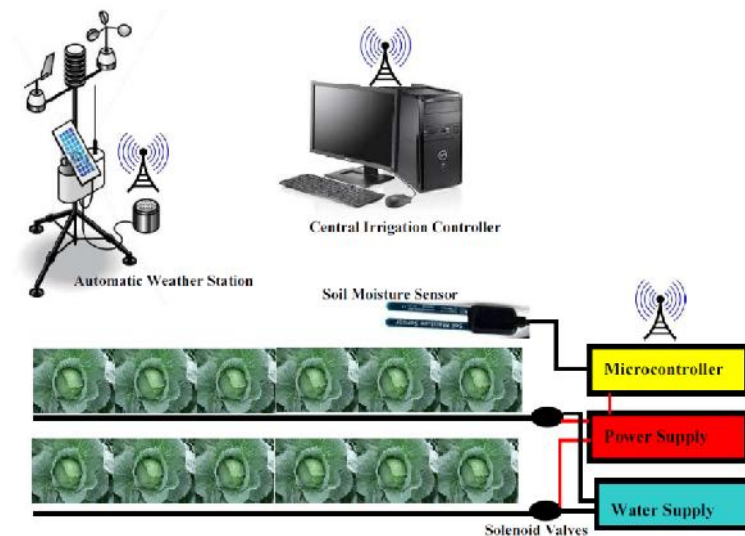


Fig. 1. Block Diagram of Automated Irrigation using ASW, Soil Moisture Sensor, and Decision Making system

For wireless communication, Digi Key XBee S2 is used which is having coverage up to 100 meters and it operates at 2.4GHz radio band frequency. XBee S2 wireless module is reliable and uses the standard baud rate of 9600 bps.

Soil moisture is conductive and has 10-bit digital output. Digital output for zero percentage moisture is around 1023 and 100 percentage moisture gives reading less than 180. The microcontroller used is an 8-bit ATmega168 microcontroller.

The detail discussion on the architecture and components used can be referred in [15]. This system is not only cost-effective but they are also very accurate system as it estimates accurate rainfall by taking real-time nearby climatic data into consideration. The system uses the intuition like the farmer, whether to irrigate the field or to reschedule for some other time based on current temperature, cloud, and wind direction and also nearby neighbor climate.

3.1 IRRIGATION CALCULATION USING INDIAN AWS

Automatic Weather Stations has various weather measuring sensors, data loggers, and data communication. Weather measuring sensors are air temperature, relative humidity, atmospheric pressure,

wind speed, wind direction, rain, solar radiation, soil temperature and soil moisture. These sensors are with highest accuracy and reliability even in extreme weather conditions, which are used to make an accurate prediction of weather. Data loggers are used to store the sensor data and data communication is done via satellite communication.

To acquire AWS data, the Indian Meteorological Data website is used where hourly calibrated sensors data are displayed on the website “<http://www.imdaws.com/viewawsdata.aspx>.”

Below Fig. 2 shows the snap shot of data displayed on IMD site. Data which are available is Station Name, Date, Time (UTC), Latitude[N], Longitude[E],Sea Level Pressure –SLP [hPa],Mean Sea Level Pressure-MSLP, Rainfall(mm), Temperature(Deg C), Dew Point(Deg C), Wind Speed [kt], Wind Direction(Deg),Maximum Temperature(Deg C),Minimum Temperature(Deg C), Pressure Tendency- PTEND[hPa], Sun Shine In Hour and Minute- SSHM.



SLP [hPa]	MSLP [hPa]	Rainfall [mm]	Temperature [Deg C]	Dew Point [Deg C]	Wind Speed [kt]	Wind Direction [Deg]	Maximum Temperature [Deg C]	Minimum Temperature [Deg C]	Pressure Tendency [hPa]	Sun Shine In Hour and Minute [SSHM]
1013.0	1013.0	0	24.4	19.4	1	340	25.1	18.8	-0.1	11
1013.0	1013.0	0	24.4	19.4	1	340	25.1	18.8	-0.1	11
1013.0	1013.0	0	24.4	19.4	1	340	25.1	18.8	-0.1	11
1013.0	1013.0	0	24.4	19.4	1	340	25.1	18.8	-0.1	11

Fig. 2. Indian Meteorological Data website view

To extract the data we have designed real-time crawler which accesses the displayed data and stores it on the local server using WampServer. WampServer automatically installs the Apache Server, configures MySQL database and installs Php support application for easy configuration and maintenance. Php script has been written to extract the required data and stores the data in text files as shown in Fig. 4. Further, this file is accessed by VC++ tool to calculate the irrigation demand calculation using Penman-Monteith method [16] for the referential crop. The working of the climatic data extraction is as show in the below Fig. 3.

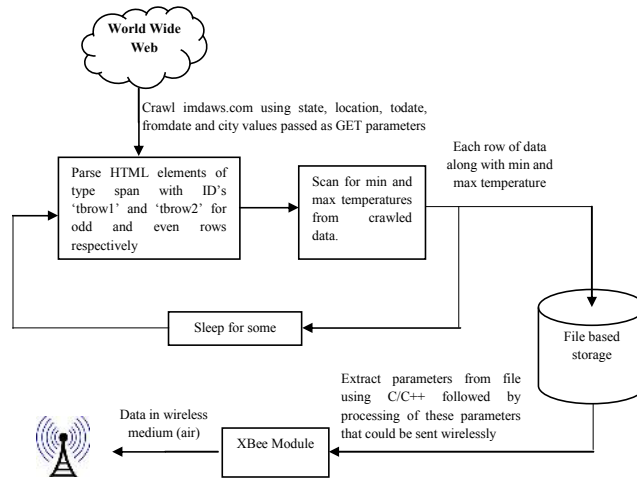


Fig. 3. Extraction of data from IMD website for Precipitation Calculation

3.2 ERROR ASSOCIATED WITH IRRIGATION DEMAND CALCULATION USING REMOTE AWS

AWS may have incorrect meteorological data due to non-working of the sensor because of over currents, damages in electronic components, incorrect data manipulation, bad maintenance, non-calibrated sensor and incorrect placement of sensors and stations [17]. These error sources can provide empty, clearly incorrect or suspicious data. Therefore certain standard validations are defined before this could load sensor data into their respective website. In one such standard validation [18] is UNE 500540 which follows seven validation levels such as validation in record structure data, range test, step test, internal consistency test, persistence test, spatial consistency test and visual inspection test by expert.

In addition to these, small spatial variations can also lead to temporal changes in evapotranspiration [19-21]. Some of the main causes for change in evapotranspiration are rainfall, vegetation index, change in attitude (hill stations) and river basin. Therefore remote AWS data for irrigations calculation are not always accurate especially if the distance of AWS located beyond the 25KM radius from the local irrigation field. Estimation of local climatic parameter provides solution for these variations.

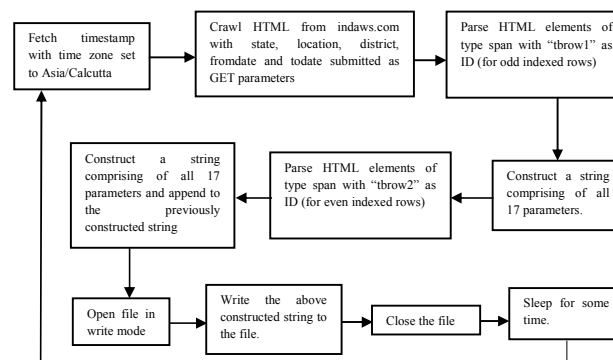


Fig. 4. Php script flow for extraction of data into text file

3.3 SOIL MOISTURE SENSORS FOR CALCULATE OF IRRIGATION DEMAND

Soil moisture sensors are used to measure the available water that plants can use. Available soil moisture is the difference between the field capacity moisture and permanent wilting point. This measurement varies with the different texture of soils. Soil moisture sensors can be used to determine the appropriate interval between the irrigation schedule, the volume of irrigation and duration of irrigation by using Net Irrigation equation (1) given by FAO, Irrigation Module-4. In equation 1, the components of G_e, W_b is taken as soil moisture reading. To increase the accuracy of irrigation calculation the numbers of soil moisture sensors can be used at different depth of soil level for a different growing stage of roots of the plant.

$$IR_n = ET_c - (P_e + G_e + W_b) + LR_{mm} \text{ ----(1)}$$

Where, IR_n = Net irrigation requirement (mm)

ET_c = Crop evapotranspiration (mm)

P_e = Effective dependable rainfall (mm)

G_e = Groundwater contribution from water table (mm)

W_b = Water stored in the soil at the beginning of each period (mm)

LR_{mm} = Leaching requirement (mm)

Soil moisture sensors can be of different types like capacitance sensors, neutron moisture sensors, electrical resistance sensor, time domain transmission and time domain reflectometry, heat dissipation sensor and tensiometer [22]. While each sensor has advantages and disadvantages, proper installation and calibration for different soil texture can make them effective tools for better irrigation schedule.

3.4 RELATION BETWEEN LOCAL SOIL MOISTURE DATA AND REMOTELY ACCESSED TEMPERATURE USING AWS

Soil moisture preservation mainly depends on the soil texture, land slope, vegetation and air temperature. Soil texture and land slope changes over a long period of time and this does not have any influence on day to day reading of soil moisture sensor. Due to change in air temperature, there will be a major change in the sensor reading and this influence the calculation of irrigation demand.

To conduct the experiment, conductive soil moisture sensors are used which acts as local data loggers. In this experiment, it was required to collect humidity profile for which sensors were placed at a different depth of soil. All the sensory information along with timestamp was required to be stored in an EEPROM based memory cell block for analysis.

To implement this data logger, it is required to have 32 bits for timestamp and three 10-bit sensors information. For space efficiency, the entire data is bit stuffed into 64 bits (8 bytes) with first 32 bits being information related to time stamp, next 30 bits for sensor information and 2 bits for CRC checksum to ensure data integrity.

To compute the checksum, it was done using XORING in pairs of 2 bits and appended this information after the 62 bits to complete the octet.

During the data retrieving, the reverse process was applied to download the data on a PC. The mode of operation was toggled using one of the digital pin named as *download/logging*.

Table 1 shows the reading of the local soil moisture sensor taken on 13th May 2014 from 13:00 hr till 23:00 hr verses remote NCMRWF AWS temperature for the location nearby. Readings are taken on a cloudy day with 1-3 mm rainfall in nearby locations and are converted into percentage level as shown in Table 1. Fig.5 shows that decrease in air temperature causes very low-level soil moisture depletion i.e. about 3% for a total of 10 hours reading. The temperature at night gets cooler, dew point increases and few mm of rainfall in nearby places influence the increase of moisture level in the soil. This increase was recorded around 3% elevation. This shows that changing soil moisture reading has reflections with nearby AWS air temperature. Any variation in interpolating climatic value can be rectified and synchronized by local soil moisture reading.

TABLE 1: VARIATION OF SOIL MOISTURE SENSOR WITH AIR TEMPERATURE FROM REMOTE NCMRWF AWS

Time	Soil Moisture	Air Temperature from AWS
13:00	76	28.1
14:00	76	27.1
15:00	75	26.6
16:00	75	26
17:00	74	25.4
18:00	74	25
19:00	74	24.2
20:00	74	23.3
21:00	74	23.2
22:00	73	22.9
23:00	73	20.5

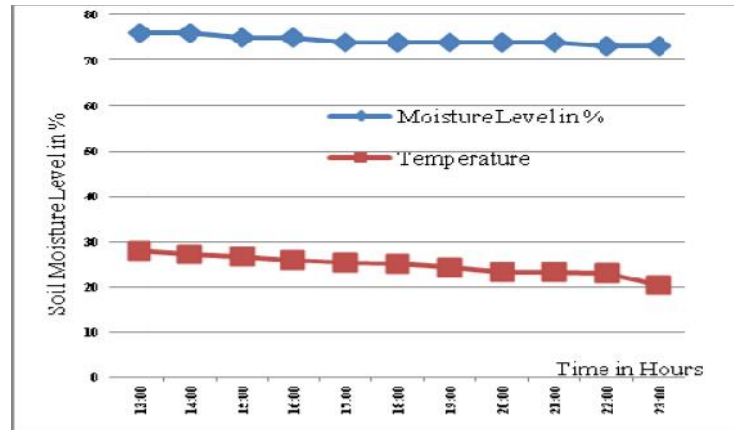


Fig. 5. Local soil moisture reading verses remotely accessed AWS temperature data

4. INFLUENCES OF NEIGHBOR RAINFALL IN DECISION MAKING OF LOCAL IRRIGATION.

Neighbour rainfall has some influence on its local irrigation schedule. Just before irrigation, if we consider its neighbour precipitation occurrence then irrigation should be delayed or check influence factor of P_e . For the area under consideration, about 806 hours of AWS data is acquired during the rainfall of that particular week, in which 226 hours of random hour rainfall has been recorded. For the illustrative purpose the day of 29th and 30th March of 2015 has been considered for analysis, where continuous rainfall is recorded for around 10hrs as shown in Table 3. Places like Jafarpur and Nerala has been recorded more than 18hrs of continuous rainfall.

Smart irrigation is about irrigation schedule at right time for right amount using soil moisture or AWS or Web based or WSN. Suppose by using any of these techniques, if the irrigation is scheduled on 29th March 15 at 18:00 hours for some volume of water dispensed depending on the vegetation at location like Akshardham, Delhi University, NCMRWF, Pitampura or Pusa, where no rainfall has been recorded at that duration. From the remaining neighbor station data we can observe that rainfall has started at the same time on 29th March 15 at 18:00 hour. Within next hour, most of the location considered in case study observes some rainfall.

If decision making system can foresee the rainfall before irrigation scheduling by using neighbor data, a significant amount of ground water can be saved. This technique can improve the water saving technology.

In Table 3 shows the temperatures before and after along with total rainfall in mm in each of above mentioned area.

TABLE 3: TEMPERATURES BEFORE AND AFTER ALONG WITH TOTAL RAINFALL ON 29TH AND 30TH MARCH 2015.

Sr. No	Location of NCR	Total rainfall in mm	Temp before 1 or 2Hr of	Temp after rainfall in Deg C
1	Akshardham	69	24.4	20.4
2	Ayanagar	60	23.9	20.7
3	Delhi University	71	26.8	25.2
4	Jafarpur	40	22.7	19.5
5	Najafgarh	10	22.9	21.6
6	Narela	16	22.5	21.2
7	NCMRWF	136	24	21.1
8	Pitampura	19	23.2	20.8
9	Pusa	108	13.4	9.9

5. RAINFALL ESTIMATION USING ARTIFICIAL NEURAL NETWORK (ANN) WITH BACK-PROPAGATION ALGORITHM.

Artificial Neural Networks (ANN) are systems of interconnected “neurons” which read set of input and trains networks on these inputs and classify/estimate for new a set of data. Fig.7 shows the simple neural network with 6 input nodes, 2 hidden layers with 7 nodes and one output nodes. Neural networks are similar to that of biological neural networks in performing collectively and in parallel by the unit to perform the single task. Each neuron is interconnected with some initialized weights and they are updated in training processes.

The Advantage of using neural networks for rainfall estimation is because of their adaptive learning, self-organization, real-time operation and fault tolerance characteristics. Various types of neural network structures are available like multilayer perceptrons (MLP) of back-propagation, radial basis function (RBF) networks, wavelet neural networks and self-organizing maps (SOM).

In MLP structures the neurons are grouped into different layers called input nodes, output nodes, and hidden nodes layers. First and last layers are always input and output nodes; whereas hidden layers can vary from $(2n+1)$ to $(2\sqrt{n+m})$, where n is the number of input nodes and m is the number of output nodes.

Artificial neural networks are popularly used in weather forecasting because of complex mapping between input and desired output. Also, training of neural network can be done by using large amount of historical data. [23] Estimates six hour rainfall over the south east coast of Tasmania. [24] shows that rainfall estimation can be computed around 10 times faster than conventional techniques. ANN is also used by

[25] to estimate rainfall intensity from radar observation. [26] uses ANN to forecast daily flows at multiple gauging stations in Eucha Watershed.

In our study, we have taken 10 neighbour AWS precipitation data as input from Jan 2015 to Jan 2016 and estimated unknown AWS precipitation. Ten such experiment are conducted to estimate unknown location with respect to their neighbor AWS. Table 4 shows estimated results RMSE in mm for each AWS precipitation data. The overall RMSE of estimated data is 0.44

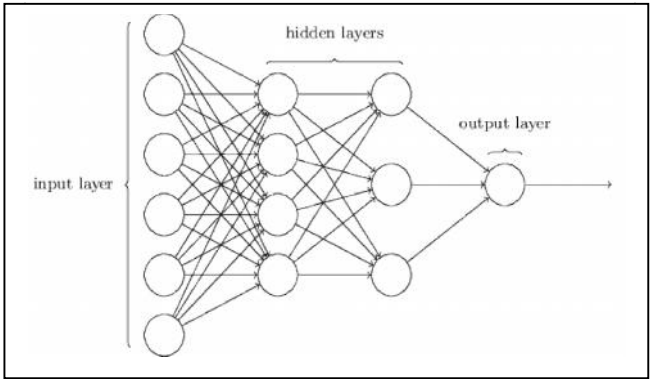


Fig. 7. Neural Network Structure

Back-propagation neural network is used for backward propagation of errors. Back-propagation network is trained in such a way that it requires to known desired output for each input value using gradient descent optimization method. This is achieved in two phases called propagation and weight update.

Phase- I of Propagation involves following steps:

- a) Feed forwarded training data into neural network to generate propagation’s output activation.
- b) Backward propagation of output to neural network to generate the δ of all output and hidden neuron to minimize the targeted error.

Phase –II of Weight update involves following steps:

- a) Multiply its output δ and input activation to get the gradient of the weights.
- b) Minus a ratio of the gradients from weight.

Table 4: Estimation RMSE for each AWS

Stations	RMSE of Estimation
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Akshardham	0.67
Ayanagar	0.37
Delhi University	0.49
Jafarpur	0.76
Najafgarh	0.36
Narela	0.18
NCMRWF	0.50
New Delhi	0.42
Pitampura	0.37
Pusa	0.62
Sports complex Delhi	0.11
Total	0.44

6. RESULT AND DISCUSSION

To estimation rainfall using nearby AWS data, a back-propagation neural network is used with sigmoid activation function which is defined as follows in (1):

$$S_c(x) = 1/(1+e^{-cx}) \quad (1)$$

where, c can be having any values like 1, 2, 3.....

The shape of sigmoid curve changes as per the value is chosen for c.

In the case study of NCR (Delhi), Automatic Weather Station climatic data are considered for rainfall estimation for unknown location NCMRWF in NCR. The distance between NCMRWF and other station is as shown in the following Table 5.

For the experimentation purpose, we have considered the dates 15th, 22nd, 23rd, 25th, 26th and 27th Jan 2015, where some rainfall for locations mentioned in Table 5 has been recorded by AWS of IMD. Out of 144 hrs we have considered only 89 hours of data for training and testing of neural networks where actual rainfall has occurred within its entire neighborhood. The Maximum temperature, minimum temperature, and total rainfall during these days is as shown in the below Table 6.

TABLE 5: DISTANCE OF NEIGHBOR LOCATION FROM NCMRWF

Sr. No	Station Name	Distance from NCMRWF
1	Akshardham Delhi	28
2	Ayanagar	29
3	Delhi University	20
4	Jafarpur	45
5	Najafgarh	36
6	Narela	36

7	NCMRWF	0
8	New Delhi	16
9	Pitampura	24
10	Pusa	20
11	Sports Complex	7

Out of 89 hours of data, 64 hours of data are used for training neural network, where as rest of data are used for testing. Estimation gets better with more number of hours of data and when estimation value is larger. Around 38 hours of rainfall data is correctly predicted and 2 hours of data is incorrectly predicted. The snap short of neural network used to train the data is given in below Fig.8 and was able to predict correct data about 95% and incorrect prediction around 5% with training error 0.001.

TABLE 6: MAX TEMP, MIN TEMP AND TOTAL RAINFALL ON THE DATE 15TH, 22ND, 23RD, 25TH, 26TH AND 27TH JAN 2015

Sr. No	AWS Location	Rainfall in mm	Tmax	Tmin
1	Akshardham_Delhi	62	18.8	6.5
2	Ayanagar	48	18.6	5.1
3	Delhi University	132	18.6	6.5
4	Jafarpur	73	18.5	4.5
5	Najafgarh	74	19.3	4.7
6	Narela	47	19.1	4.8
7	NCMRWF	224	19.7	7.2
8	New_Delhi	148	18.9	6.4
9	Pitampura	99	16.4	7.3
10	Pusa	110	17.8	6.3
11	Sports Complex	44	19.7	7.5

This hourly estimate can be used to postpone irrigation\ if irrigation is scheduled in next coming hour. The decision making of postponing of irrigation schedule is as shown in the below flow chart in the Fig. 9.

At NCMRWF rainfalls is recorded for two days on 22nd Jan 2015 from 3:00 Hrs to 23rd Jan 2015 till 3:00 Hrs. The continuous rainfall has been recorded up to 152mm. If irrigation is scheduled at this place just before 22nd Jan 2015 3:00 Hrs, by using neural network rainfall estimation, if rainfall occurs for next hour then irrigation can be postponed for next cycle. The amount of that harvested rainfall is the total saving of reserve water /ground water resource in the irrigation system. If the irrigation area is about 1000m² in NCMRWF then around 152000 litres of rainfall water can be directly used for the irrigation.

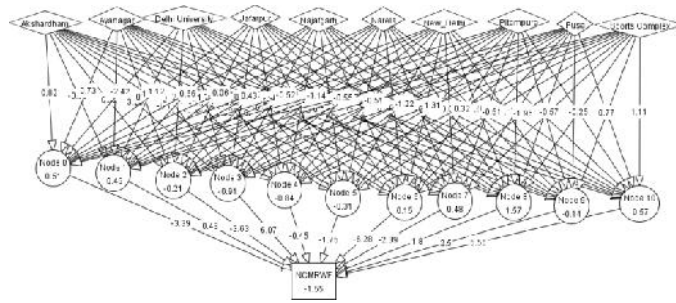


Fig. 8: Input are nearby AWS precipitation of NCMRWF, output is NCMRWF estimation

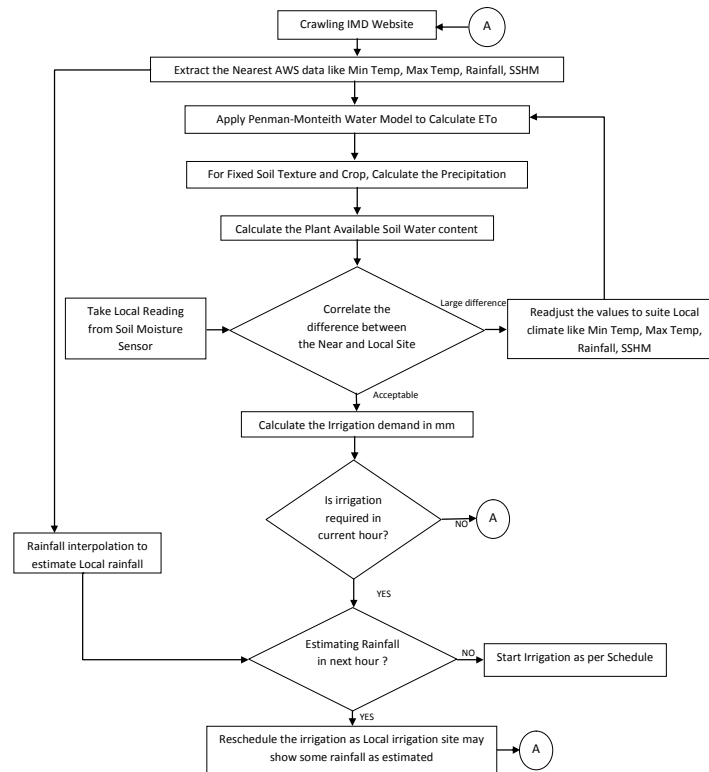


Fig.:9 Decision Making of Postponing the Irrigation Schedule

7. CONCLUSIONS

The proposed solution is not only going to save the ground/reservoir water resources by estimating real-time rainfall before irrigating the field, but it is also a cost effective system. Irrigation scheduling system is taking the advantage of nearby Automatic Weather Station and also improving its accuracy by using local soil moisture sensor. Real-time rainfall estimation is done using neural network's back-propagation algorithm, where as any missing climatic parameters are also accommodated for training and testing. Just

before irrigating the fields if you know the climatic condition before hand, it will help to make better decision on irrigation schedule especially the real-time rainfall estimation. In one such scenario for location NCMRWF, NCR has continuous rainfall of 152mm in two consecutive days, can save ground water of 152000 litre of water for 1000m² irrigation area.

List of abbreviations

AWS	Automatic Weather Station
NCMRWF	National Centre for Medium Range Weather Forecast
NCR	National Capital Region
WSN	Wireless Sensor Network
IMD	Indian Meteorological Data
ETo	Evapotranspiration
MLP	Multilayer perceptrons
RBF	Radial basis function
SOM	Self-organizing maps
ANN	Artificial Neural Networks
RMSE	Root Mean Square Error
FAO	Food Agriculture Organization

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