Intelligent Irrigation System Using Machine Learning Technologies and Internet of Things (IoT)

Sarika Patil(✉) and Radhakrishana Naik

Dr. BAM University, Aurangabad, India
sarikapatil181@gmail.com, naikradhakrishna@gmail.com

Abstract. Scare water resources necessitates technological involvement in irrigation scheduling, that can help to manage water according to the weather condition of different seasons, crop growth stage and landscape information. The proposed method calculates actual water required using machine learning model and Evapotranspiration. The model is trained using real time weather data to predict actual water requirement. Reference Evapotranspiration is calculated with the help of Penman-Monteith Method. Before starting with this real time system proposed model is implemented with the help of past 10 years web scraped weather data. Proposed algorithms of water requirement and Irrigation scheduling is executed on scrapped data. After successful results system is implemented for real time use.

Furthermore, system consists of eight Arduino nodes that acting as a slave to read weather, soil landscape and rain data. In addition, three Raspberry-pi equipped with the Wi-Fi module, acting as server to send collected data to a remote web server. These databases are used as input for machine learning algorithm. As per the observations of proposed system water usage is getting reduced in large quantity as compared to the traditional irrigation system used for irrigation.

Keywords: Weather data · Irrigation · Machine learning · Temperature · Agriculture · Water · Soil · Algorithm · Crop growth · Scheduling · Sensors · Communication · Evapotranspiration · Automation · Crop

1 Introduction

Agricultural productions consume more than 85% of freshwater over the planet than any other water uses. Freshwater consumption for agricultural uses will continue to increase because of increasing population and food demand [1]. Day by day freshwater resources getting reduced so it is mandatory to optimize water use in agriculture.

In India, most of agricultural part is irrigated through the manual system. The manual system gives irrigation only based on observation. The microcontroller and sensor-based automated system that will provide irrigation based on sensor data has many advantages [2]. Proposed system has been considering all aspects of water requirement and irrigation system like water requirement based on crop growth stage, canopy of crop, crop age, landscape information like slope of farm, sea-level elevation, soil type, total sunshine

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hours, dew point temperature, relative humidity, actual and saturation vapor pressure etc. Some static information is fed at the time of installation, and remaining information updated periodically to execute the algorithm and estimate water requirement, if any, also adjust any aperiodic task with water requirement calculations.

This paper focus on the different methodology used previously for automated irrigation system followed by the proposed methodology. A proposed system is fully automatic, as compared to other method that send alerts to farmer for further processing. The system uses Machine learning approach to fulfill irrigation requirements in modern days by making full automation and smart water utilization. Once configured this system calculates irrigation needs and provides an irrigation schedule that includes time, duration and interval of irrigation that is handled automatically by sending signal to the solenoid valve. Solenoid valve opens automatically as per irrigation schedule and also taking extra care of maintaining the water level in the tank using ultrasonic sensors.

The water requirement is different in every stage of the crop. Proposed system considering three crop stages i.e. Initial, Mid, Harvesting stage. Based on that crop coefficient gets changed in the machine learning algorithm.

This paper discusses related work followed by the proposed framework research methodology, assumptions, mathematical work, algorithm, evaluation, optimization, and a conclusion.

2 Related Work

Evapotranspiration is an important parameter for most of the agricultural evaluation process and water resource management studies. Water evaporated through crop is estimated with the help of evapotranspiration and crop coefficient, which depends on many things like crop growth stage, canopy and age of crop [5]. Different methods exist to estimate reference evapotranspiration, among them Ravazzanietal method [8] is used when only temperature data is available. In this method, the Hargreaves coefficient is adjusted based on local elevation.

$$\mathrm{ET0} = (0.817 + 0.00022\mathrm{z})0.0023\mathrm{Ra}(\mathrm{Tmean} + 17.8)(\mathrm{Tmax} - \mathrm{Tmin})^{0.5} \tag{1}$$

Another method is Hargreaves and Samani (1985) method [4] that is radiation based method used when some weather data is missing [8]. It is expressed as:

$$\mathrm{ET0} = 0.0023\mathrm{Ra}(\mathrm{Tmean} + 17.8)(\mathrm{Tmax} - \mathrm{Tmin})^{0.5} \tag{2}$$

Here Ra is extraterrestrial radiation, daily Temperature is represented by Tmin, daily minimum Temperature is represented by T_(min) and daily max Temperature by T_(max). Another method is solar radiation-based method (Irmak, 2003). It is expressed as

$$\mathrm{ET0} = 0.489 + 0.289R_s + 0.023T_{mean} \tag{3}$$

Here R_s is solar shortwave Radiation and Teman is average of Min and max temperature [10].

Net Radiation based method (Irmak, 2003). It is expressed as,

$$ET0 = 0.489 + 0.289R_n + 0.023T_{mean} \tag{4}$$

Here R_n is Net radiation and Tmean is average of Tmax and Tmin [10].

By using the FAO Penman-Monteith equation, crop coefficients can be calculated by using this equation.

Crop Coefficient = Crop Evapotranspiration/Reference.

Evapotranspiration Penman method giving best results to calculate water requirements.

Artificial neural network and Fuzzy logic are used to optimize green roof irrigation [11]. The model is trained using Artificial neural network and Fuzzy logic to calculate soil moisture for irrigation scheduling. Aperiodic conditions are not considered in this system. This system uses weather data from nearby weather station.

CommonKADS expert system [12] provided solution to optimize water usage for crops. The main objective of the CommonKADS expert system is to determine optimal water quantity and time. Parameters considered are the crop, climate, water, soil, and farm data. Fababean crop is taken for case study. Knowledge base of Fababean crop is extracted from the existing knowledge base of fababean crop built based on the Common-KADS methodology. The system is considering all required parameters. While considering any crop for case studies, its knowledge base should be exist to use commonKADS methodology. Not any a-periodic tasks are not considered in the system.

Gene Expression Programming (GEP) [13] is used to develop predictive model for furrow irrigation infiltration. Genetic Programming is the successor of Genetic Algorithm. GEP encodes information in linear chromosomes, which then expressed in expression trees. GEP model is developed using ready dataset of available literature. Z under furrow irrigation is estimated using this model. In this method data set is randomly distributed as training, testing and validation set. In training stage model is trained to get the best performance. Testing phase measures statistical fit of the model. Furrow irrigation is a complex phenomenon. The model is giving good results for furrow irrigation.

IRRINET is developed using Artificial Intelligence Expert – Decision support system (DSS) based on daily water balance methodology [14] of soil-plant-atmosphere. It determines daily irrigation schedule including water quantity and duration of watering. Web based interface is used to gather all data on Central sever for further analysis. Parameter used are climate and soil data. Real time data are used for irrigation scheduling. Web based server is used to collect data on a central server. Aperiodic conditions are not considered in this system.

A feed forward neural network and fuzzy logic-based hybrid smart decision support system (DSS) [15] is implemented to determine soil moisture for irrigation. The model is trained using real time data to predict soil moisture contents and Evapotranspiration is calculated by Blaney-Criddle methodology. Advantages of this system are real time monitoring of data and quick SMS alerts provided to farmer. Soil moisture is measured with the help of training data.

To summarize, Most of the methods are based on Artificial Intelligence and fuzzy logic. The actual soil data collection is challenging task, to overcome that most of researcher train their models to predict soil moisture [11, 15]. Some methods use ready dataset from previous literature instead of real time data. Proposed method using real time weather data and trying to optimize the use of water and making irrigation fully automatic task for farmers. In proposing method Modern Machine Learning algorithm with multiple regression analysis is used to predict water requirement using real time data. IOT architecture is designed and implemented to read real time weather data. This method tries to reduce the error deviation of actual and predicted water requirement with a small error value among all available methods in literature.

3 Details of Proposed Framework

3.1 Mathematical Model

Over the last 50 years, several methods developed by various scientists all over the world with various climatic parameters. However, accuracy testing of the method is time-consuming and costly and not possible to calculate it in short duration, Evapotranspiration data are repeatedly required at a short interval to schedule the irrigation. Among the method given in the paper [6], the modified Penman-Monteith method was offered better results with a tiniest possible error about a living grass reference crop.

$$ETo = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_{2)} (e_s - e_{a)}}{\Delta + \gamma(1 + 0.34u_{2)}} \tag{5}$$

Where ET0 is reference Evapotranspiration [mm day-1],
Rn is net radiation at the crop surface [MJ m-2 day-1],
G is soil heat flux density [MJ m-2 day-1],
T is mean daily air temperature at 2 m height [°C],
u_2 is Wind speed at 2 m height [m s − 1],
e_s is Saturation vapor pressure [kPa],
e_a is Actual vapor pressure [kPa],
$e_s - e_a$ is Saturation vapor pressure deficit [kPa],
Δ is Slope vapor pressure curve [kPa °C − 1],
Γ is psychrometric constant [kPa °C − 1].
Rn is net radiation expressed as the difference of Net shortwave (solar) radiation (Rns) and Net Longwave radiation (Rnl).

The Soil Heat flux is presented here follows the idea of soil temperature follows air temperature.

$$\mathrm{G} = C_s \frac{T_i + T_{i-1}}{\Delta t} \Delta z \tag{6}$$

Where G soil heat flux [MJ m-2 day-1], Cs soil heat capacity [MJ m-3 °C − 1], Ti air temperature at the time i [°C], Ti − 1 air temperature at the time i − 1 [°C], Δt length of time interval [day], Δ effective soil depth. For one day to ten days, period soil heat flux considered approximate to zero.

Wind speed instrument placed at the site may be at a different height, so wind speed data is adjusted at 2-m height using following logarithmic wind speed profile calculations.

$$u_2 = u_z \frac{4.87}{ln(67.8z - 5.42)} \tag{7}$$

Where u_2 wind speed at 2 m above ground surface [m s − 1], u_z measured wind speed at z m above ground surface [m s − 1], z height of measurement above ground surface [m]. Saturation vapor pressure is related to air temperature

$$e^0(T) = 0.0618 exp\left[\frac{17.27T}{T + 237.3}\right] \tag{8}$$

Where e° (T) saturation vapor pressure at the air temperature T [kPa], T air temperature [°C].

Because of non-linearity of Eq. 8, the mean saturation vapor pressure for any period must be computed as the mean between the saturation vapor pressure at the mean daily maximum and minimum air temperatures for that period:

$$e_s = \frac{e^0(T_{max}) + e^0(T_{min)}}{2} \tag{9}$$

Slope vapor pressure can be calculated using the following formula,

$$\Delta = \frac{4098 e^0(T)}{(T + 237.3)^2} \tag{10}$$

Where: Δ slope vapor pressure curve [kPa°C − 1] T air temperature [°C] e°(T) saturation vapor pressure at temperature T [kPa].

Figure 1 shows a scatter plot of ET0 (Dependent variable) and Max Temperature (Independent variable). As per plot Temp_max data appearing closely with a regression line. It shows strong linear relationship with ET0.

$$Y = 0.3296x - 5.1516 \tag{11}$$

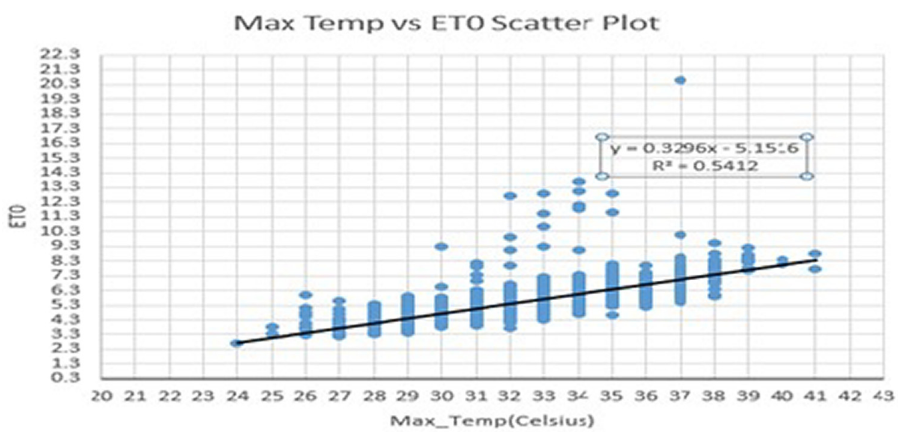

Fig. 1. Scatter plot of ET0/Max_Temp

Regression summery shown in Fig. 2. Having multiple r value is 0.7 and p value is 0. As per p and r value. So both of them showing significant relationship with ET0. Above summery giving double validation of high linearity between Max Temp and ET0.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.735657832
R Square	0.541192446
Adjusted R Square	0.541006091
Standard Error	0.740233326
Observations	2464

ANOVA

	df	SS	MS	F	Significance F
Regression	1	1591.279552	1591.2796	2904.0843	0
Residual	2462	1349.041517	0.5479454		
Total	2463	2940.321068			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-5.151613156	0.19927531	-25.851738	1.41E-130	-5.542377693	-4.76084862	-5.54237769	-4.76084862
Max_Temp	0.329553404	0.006115348	53.889556	0	0.317561647	0.34154516	0.31756165	0.34154516

Fig. 2. Regression output

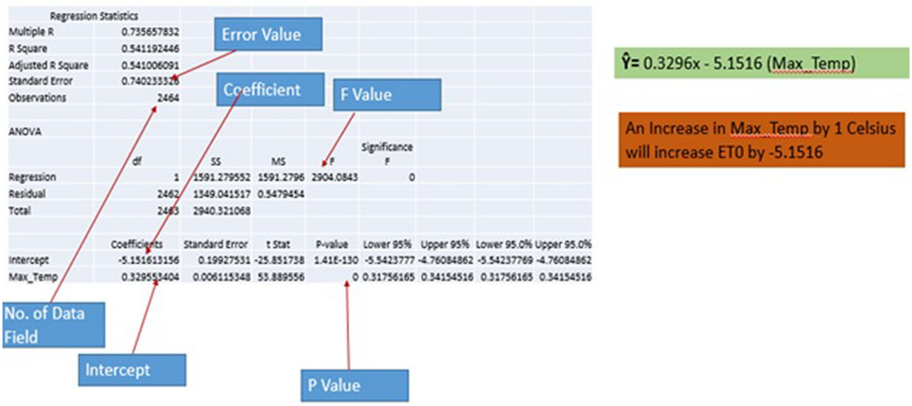

Fig. 3. Regression details

3.2 Algorithm

Configuration of the proposed system with static parameters required for machine learning algorithm.
Configuration of system with crop plantation date, harvesting date and growth status data.
Calculation of the crop coefficient that is mandatory information while executing machine learning algorithms.
Calculation of Reference Evapotranspiration.
Calculation of crop Evapotranspiration using reference Evapotranspiration and crop coefficient.

Calculation of Adjusted crop Evapotranspiration for different stages of crop.
Calculation of total water requirement by considering all the above information.
Calculate Irrigation interval and duration.
Irrigation scheduling.
Fine-tuning of aperiodic activity.

4 Experimentation

For a case study Vineyard is considered. 8 Arduino nodes are used to measure weather, soil and landscape data by applying different orientation. Raspberry-pi is used and equipped with WIFI module acting as gateway to send data over the internet. Soil, Temperature, Rain, Humidity and ultrasonic sensor are placed using different orientation. Vineyard main season started from mid - October and ends at March. October to November is the initial stage, December–January is mid stage and February- March is the end stage of vineyard. Type of soil in selected region is loam/clay. The Site is located in Nashik district at 19.9975° N, 73.7898° E. Elevation level of Nashik is 980m. Hardware and site design details are as given in below.

As shown in Fig. 3 the system uses 8 Arduino Uno R3 controller that acting as slaves. Each Arduino is connected to Bluetooth HC-05, Temperature and Humidity sensor (DHT11) and soil moisture sensor. Raspberry – Pi 4 model is connected to Wi-Fi (ESP8266) model to send data to a central server. Ultrasonic sensors are used to maintain adequate water levels in a water tank. The test bed of 20 feet * 20 feet is used for plantation of 40 crops. 2 emitters of speed ½ gph for each plant are considered, thus for 40 plant 80 emitters of speed ½ gph are required. The total water requirement is calculated with the help of proposed irrigation water requirement algorithm. As per calculations 40 plants we require 40 gallons water per hour per plant (Fig. 4).

$$\text{Calculate total no of hour of irrigation per month} = \frac{\text{Total water required}}{\text{Irrigation Rate per hour}} = \frac{240\text{ gallon per month}}{40\text{ gallon per hour per plant}} = 6\text{ hours per month}$$

Irrigation schedule Method 1: Suppose we decided to give irrigation after every 6th day means 5 times in a month.

360/5 = 71 min = watering cycle time.
240/5 = 48 gallons water is required for each cycle.

Irrigation Schedule method 2: Suppose we decided to give irrigation after every 4th day (30/4 = 7) means 7 times in a month.

360/7 = 51 min watering time.
240/7 = 34 gallons water is required for each cycle.

The time complexity of the system is O (N). Three loops are used in the implementation, but only one of them is executed based on crop stage. If the day is between 1st

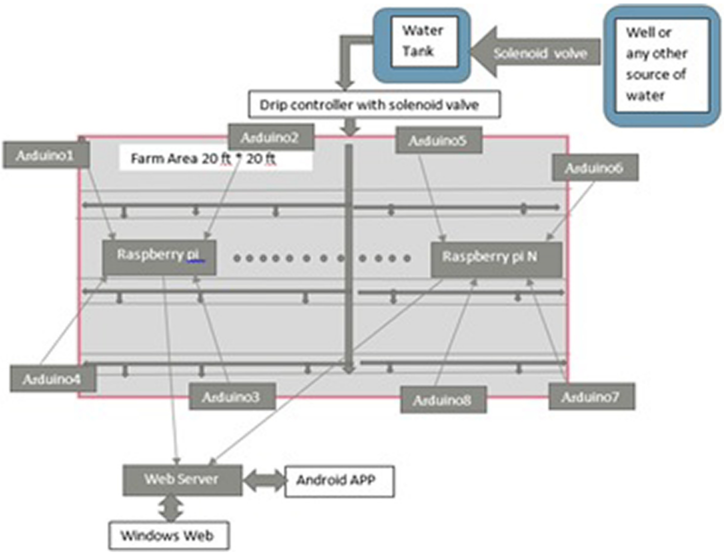

Fig. 4. Test bed design with IOT framework

of October and 30th November then 1st for loop get executed because this period is the initial stage of crop. So N is the number of days and each statement in the loop is executed in O (1) time.

5 Conclusion

Irrigation methods used in literature are based on fuzzy logic, Knowledge base expert system, Genetic programming. Fuzzy logic based methods train the model to predict soil moisture values and trying to overcome soil moisture reading challenge. Knowledge base methods require a ready knowledge base of required crop. IRRINET system using web based server to store tank scheduling. Main objective of proposed method is not only irrigation but also optimization of water used in irrigation. Modern Machine Learning approach used in the proposed system to make it more intelligent and perform all task in irrigation automatically based on real time data and proposed algorithms. As compared to other method proposed system does not require any manual interruption once installed on the farm. The proposed system is totally automatic collecting real time data, executing algorithms, generating irrigation schedule and executing irrigation schedule by automatically opening solenoid valve.

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