



Research Article

Genetic algorithm based smart irrigation system for agricultural fields using linear regression and IOT to ensure proper utilization and saving of natural water resources

Abhijit Dnyaneshwar JADHAV^{1,*}, Archana A. CHAUGULE², Harish U. TIWARI²,
Prashant G. AHIRE³

¹School of CSIT, Symbiosis Skills and Professional University, Pune, 412101, India

²Pimpri Chinchwad College of Engineering and Research, Ravet, Pune, M.H., 412101, India

³Nutan Maharashtra Institute of Engineering and Technology, Talegaon Dabhade, M.H., 410507, India

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ABSTRACT

Irrigation is crucial to agriculture. For available smart irrigations, accuracy is still a concern. Also, many of these systems are not affordable with practical usability, especially in rural areas of Maharashtra state. The proposed approach performs smart irrigation using Internet of Things (IoT) sensors, which collect the data about the water level in the agricultural field and provide the details of weather conditions, also uses Genetic Algorithm to optimize the input data, and Linear Regression model is used to predict the necessary water demands for the agricultural field. Here, the combination of Genetic Algorithm and linear regression is the useful and novel combination which helps to generate efficient results. By considering the level of soil moisture available in the crop field, the linear regression based model predicts the water needs and accordingly drives the motor pump for watering. The accuracy is found to be better as compared to existing approaches with 98.33% and the Mean Squared Error (MSE) is observed as 0.017, which is very less. The water demand predictions are given for various value ranges of soil moisture and temperature. For 278.93wfv soil moisture and 36°C temperature, the predicted water demand by model is 6.11mm against the actual water demand of 6.28mm. The finding justifies the usability of the system in real-time agricultural fields as given in Results section.

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INTRODUCTION

The expansion of the agricultural sector is one of the best methods for guaranteeing social stability and

economic development. In India a priority is given to the growth in this field in response to the significant economic, social, and geographical concerns that are highlighted by this industry [1]. The irrigation of agricultural fields is

*Corresponding author.

*E-mail address: abhijit.jadhav29@gmail.com

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the most significant source for development. An efficient and suitable irrigation water supply considerably boosts agricultural productivity as water shortage has become a major worldwide problem [2]. There are two primary water sources for agriculture: irrigation and rainfall. But the precipitation isn't enough to supply the plant with the water it needs. On the other hand, excessive wetness hinders plants' capacity to absorb nutrients and increases their susceptibility to disease [3]. Open loop and closed-loop control are two sorts of irrigation control technologies [4, 5].

A farmer who uses an open-loop control system must manually choose when to irrigate. Based on his knowledge of the crop's perceived response, the operator chooses the quantity of irrigation, the amount of water used, and the rate of irrigation. This technique is widely used since it is simple to implement and doesn't need the use of sensors [6]. The consequence might be adverse water stress as some places receive excessive irrigation while others receive insufficient irrigation [7]. Significant water and energy losses are also experienced, which is in opposition to the worldwide goal of rationalizing and conserving water resources. Farmers who want to irrigate crops on fields that are stocked with vegetables must get up in the middle of the night due to the absence of power in rural areas. Furthermore, they were unable to go to the farms during COVID-19 to irrigate the plants, because of which many farmers have faced the heavy losses and also resulted in a food shortage across the nations [8].

Hence, automated irrigation systems powered by the Internet of Things (IoT) should replace manual irrigation. Lack of full end-to-end standards is one of the deployment-limiting concerns that currently affect the extent of IoT adoption [9]. As already said, contemporary situations have their limitations [10], we are exploiting the IoT and data science link to generate smart irrigation without the need for manual involvement. Therefore, the development of intelligent irrigation systems (closed-loop control) presents a useful alternative to traditional irrigation approaches. The intelligent system provides required amount of water to the agricultural field for plant growth and development by monitoring a variety of elements that have an impact on irrigation performance. The judgments are frequently made using the sensor data, which is then compared to the anticipated set points [11].

The disadvantages of the existing smart irrigation systems as well as the inconveniences of the manual irrigation systems are to be eliminated as a result of this research. Two components makeup the suggested smart irrigation system. First is a hardware sensor for gathering the input values of various parameters such as soil moisture, temperature etc. and second is processing of input data by using Genetic Algorithm (GA) and Linear Regression to predict the water demands. An effective adaptive method for resolving exploration and optimization problems is the IoT-based genetic algorithm [12]. In the second portion, a Linear Regression is used to estimate the probable water requirements of the agricultural field utilizing the optimum attribute values that

have been gathered. As a result, this research project blends IoT with genetic algorithm optimization and machine learning. Here, the system's cost, timeliness, and accuracy are the main points of attention.

The next sections of this research paper discuss the literature review of existing methodologies, the recommended architecture of the research effort related to smart irrigation, the type of data to be used, the results and comparison with existing approaches and the conclusions of the study.

RELATED WORK

The thorough analysis of existing irrigation systems is done, which is as follows.

In an irrigation system review [13] has studied the combination of discrete forecasting and soil-, weather, and plant-based monitoring approaches in open fields. There are uncertainties in open-area agricultural-irrigation systems that need to be explored, unlike in environmentally controlled agriculture research. Also, in an smart irrigation using IoT presented by [14], it is concluded that two most important parameters for the creation of an intelligent irrigation system are the water level in the soil and the weather. It is also studied that, a variety of factors, including air temperature, soil temperature, air humidity, UV radiation, and many others, influence soil moisture.

An irrigation systems presented in [7] by Benzaouia Mohammed et al., in order to create an effective and long-lasting irrigation plan that intends to conserve water in the eastern part of Morocco. Closed-loop feedback control and a fuzzy logic-based irrigation strategy were proposed in this work. The length of irrigation for a particular plant type is determined by Mamdani's Fuzzification, Trapezoidal, and Triangular Membership functions. The risk of under-irrigation is eliminated by using the fuzzy control to keep soil moisture above the user-defined value. The findings demonstrate the system's effectiveness and dependability in both the summer and autumn. The work does not explain about automation of the system, also accuracy of the system can be enhanced with optimization approach for sensory value analysis. The system's timeliness is not stated by the researchers and comparison with existing systems is missing to prove the effectiveness of the system.

An irrigation system presented in [15] by Maona Li et al., to make irrigation scheduling easier, a fuzzy inference-based irrigation decision support system that incorporates a lucerne growth model, a soil water model, and pertinent software was created. The technique uses weather forecasting to anticipate the lucerne growth stage and variations in soil water. The fuzzy inference algorithm within the irrigation decision support system determines irrigation timing and amount of water taking the soil water and difference in lucerne height into account. The irrigation decision assistance system's effectiveness has been evaluated. The findings demonstrated NRMSE of 8.28% and 6.29%, respectively, the predictive models performed well in forecasting the development stage

of lucerne and soil water. The SW-based irrigation approach was contrasted with the irrigation decision support system's advantages and disadvantages. The disadvantage of the system is that, advancements should put an emphasis on crop yield, water conservation, and geographical variability as system doesn't provide this support.

Dr. Geetha S. et al. proposed the autonomous irrigation system in [16], which is designed to continuously monitor the moisture level of the soil. The system reacts appropriately by watering the soil precisely with proper amount of water and then cutting off the water supply once the required level of soil moisture is attained. There are two beneficial components. These are a moisture sensor and a motor or pump. Arduino boards are programmed using the Arduino IDE software. A soil moisture sensor is used to assess the moisture level of the soil. Water is supplied to plants via a motor or pump. Regardless of moisture level, the timer module distributes the water at specified intervals of time that are programmed in Arduino. The circuit's total current draw ranges from 200 to 220 mA. The main advantage of the system is that it promptly turns off the water pump when there is enough water and only activates it when it is required. This prevents water waste and ensures the most effective use of water. The method is limited in that just one feature is used to estimate a plant's water demands, and other significant parameters are not taken into account. This makes the system less accurate and increases the risk of false positives and drowning of plants.

An irrigation system proposed by V. Vinoth Kumar et al. presented in [17], is utilising the internet of things. In this system, data is collected at the user end regarding the status of the soil moisture, and if there is any deviation from the reference value, the user can send a command through the internet of things server to maintain the desired value of the field parameter for proper irrigation. The suggested IoT-based irrigation system is capable of measuring the field's temperature and moisture content and sending real-time data to the user using Wi-Fi and an IoT server. The system's drawback is that since the irrigation system is not automatically operated and technical field data are not provided to users who may not comprehend them, it cannot be used to all types of farms and gardens.

An irrigation system presented in [18] methodology, M. S. Goodchild et al. demonstrate the effective implementation of a PID (PI) controller for 32 strawberry plants cultivated in coir over a 94-day period and a potted poinsettia plant, utilizing a straightforward change to the integral function. The limited integral PI controller has been demonstrated to respond to the diurnal cycle in the potted poinsettia plant while keeping soil moisture to better than 1.5% with a 2-hour watering interval. Regardless of the input inaccuracy, the integral function is limited to only output values that are comparable to positive water supply volumes and to a maximum of half the daily water need. After "rain-fall" and water supply disruption incidents, the PI controller was able to reestablish irrigation control. Additionally,

none of the literature-described controller windup symptoms were triggered by these events. The improved PID controller described here has been demonstrated to give reliable and accurate irrigation management throughout a wide-range of solar radiation levels while responding promptly to changes in environmental conditions and the diurnal cycle. The strawberry growth experiment on coir substrate demonstrates how the limited integral PID controller can adapt water delivery to the demands of the plant from germination to harvest while responding to changing solar radiation levels. The limitations of the system are its cost, unfriendliness for the farmers, lack of timeliness and also the accuracy of the system is not justified.

An irrigation system presented in [19], Gilberto Souza et. al, in order to limit the quantity of water irrigated, have offered an irrigation management based on a fuzzy inference system that employs the soil moisture level, as determined by capacitive soil moisture sensors, and the rain forecast from a PWS. Given the first findings, it is feasible to confirm the model's successful operation in this reduction, maintaining the soil moist at the plant's root zone. It is also possible to confirm that the system takes the soil moisture level into account when determining the irrigation prescription, and that when this level is high—for example, as a result of recent rains—it reduces the irrigation prescription to a low number. When compared to the FAO irrigation method, the results also show a 20% reduction in the amount of irrigated water, which allows us to predict that this reduction will remain the same or be similar after the crop cycle is over. Given the modest size on which the experiment was conducted, it would be important to assess the outcomes in a pilot under more realistic circumstances and with bigger dimensions. However, the initial outcomes in this direction are encouraging. The indirect automation of the soil moisture measuring process (using a capacitive sensor) enables the farmer to make an irrigation choice more quickly, increasing agricultural productivity and crop output. Still, full automation is required, also timeliness, accuracy and cost of the system is still the unsolved and non targeted issues in the irrigation system.

Using LabVIEW, Ravi Kumar et al. provided a contemporary design strategy for controlling and monitoring soil moisture in [20], which offers all the capabilities required to build any measurement or control irrigation in a noticeably shorter amount of time. A rain sensor is also part of the design, which is essential to limit unnecessary power use. According to the authors, farmers are not only able to produce crops with less water overall, but they are also able to increase crop yields and quality by regulating soil moisture more efficiently throughout crucial plant growth phases. The system's drawback is that it uses a small number of parameters and completely automates the watering system. Additionally, the quality attributes attained through the research work are not specifically mentioned in the results.

An irrigation system presented in [21] by Farid Touati et al. is a, wireless monitoring and feedback fuzzy control were

proposed as a way to create an irrigation system that promotes water conservation and improved irrigation management in extremely dry regions like Qatar. The created fuzzy controller effectively determined the timing and duration of irrigation for a particular crop by utilizing trapezoidal and triangular membership functions based on Mamdani fuzzification. With smooth oscillations, fuzzy control helped measure soil moisture above a preset value, preventing frequent system run-off and conserving water and energy. With a notable over-irrigation in winter, the system compensated for the quantity of water lost by evaporation as anticipated by the Penman-Monteith model in summer and winter. As a result, the technique makes it possible to estimate future watering demands. A wide-range ZigBee-GPRS based wireless system was also built in order to track system performance in real-time and build a database. Important environmental and climatic conditions, the timing and length of irrigation, as well as the quantity of water used, were all noted. This is much assisting with data analysis and system enhancement. The system is simple to use. An early cost-benefit study demonstrated that the system is financially viable. The system still should predict and automate the irrigation system with more accuracy and also time value of prediction and managing irrigation is also unsolved issue. Farmers in rural areas may not have sufficient technical knowledge to operate such complex irrigation design.

IoT Boards for Irrigation

As per the study done by GEORGE-CĂLIN SERIȚAN et al. [24], regarding various IoT boards, following comparison is done to ensure proper selection of IoT board for our proposed model (Table 1).

From the given Table 1, it is observed that An Arduino Nano is frequently chosen over a Raspberry Pi or ESP8266 for a basic irrigation system because it is easier to program, uses less power, and is made specifically for direct interaction with sensors and actuators. This makes it more effective for simple tasks like controlling water valves and reading soil moisture levels, especially when battery life is

an issue. In contrast, a Raspberry Pi is better suited for complex applications with a full operating system and higher processing power, which may be excessive for a basic irrigation system. Also, the cost of the model is low when using the arduino board as compared to others with less maintenance.

From the discussion in survey and after studying the systems in [13-18] as well as few more studies provided by [19-22], the following problems are identified, which are commonly faced in smart irrigation systems.

- The input readings received from the sensors are passed to the irrigation controller without preprocessing and hence noisy readings are also used, which leads to erroneous watering requirements determination
- The accuracy is low and should be enhanced with more sophisticated irrigation model [23].
- The time constraints are missing, which leads to poor performance of the irrigation system. It would be incorrect to claim that a system's processing power rises in direct proportion to the quantity of resources used [24]. The amount of time and amount of water should be calculated while watering the crop fields.
- The complete automation is missing and manual intervention is still needed while setting the calculation of watering needs, which should have to be calculated automatically by the irrigation systems.
- The systems are not fault tolerant, Rollback and check pointing approaches provide intriguing ways to provide fault tolerance without a significant increase in cost and complexity. It includes practical features that reduce the amount of human programming work and increase availability [25].

One significant component influencing networked components performance is the distribution of workload among processing units (Fig. 2) [26]. To solve these problems, this research uses more optimized model elements to be added in designing the innovative irrigation system to overcome the mentioned challenges.

Table 1. Comparison of IoT boards

Sr. No.	Arduino nano	Raspberry Pi	ESP8266
1.	Microcontroller for simple control duties, sensor reading, and basic input/output.	More processing power and capabilities than Arduino are provided by this mini-computer like board with a complete operating system.	An inexpensive, Wi-Fi-capable microcontroller that is perfect for Internet of Things (IoT) applications.
2.	Large number of projects and tutorials, Easy to operate and better community support.	Ability to handle sophisticated programs, is adaptable, and comes with Ethernet and WiFi built in.	It is inexpensive, compact, and simple to integrate into Internet of Things applications.
3.	Less memory and computing power than the Raspberry Pi.	More costly and power-hungry than the ESP8266 or Arduino.	Less memory and computing power than the Raspberry Pi.
4.	· Applications: Basic automation, Small scale robotics, sensor projects	· Applications: IoT devices, Web servers, High level robotics and media centers	· Applications: Wireless sensors, Smart home devices and remote control

Objectives

Here, in this research, the researchers have identified the prioritized limitations and the objectives are defined as follows:

- To design and develop the smart irrigation system using machine learning and optimization technique
- To improve an accuracy of smart irrigation system using Genetic Algorithm
- To implement the smart irrigation system which will calculate the actual water needs to efficiently use the available water resources.

MATERIALS AND METHODS

The proposed model for smart irrigation comprises of important steps as shown in Figure 1, architecture of the system. In the first step the hardware circuitry of IoT using arduino collects the input values, which will be passed in the second step for optimization of the genetic algorithm and in the third phase the linear regression model uses these optimized input values to generate the watering requirements and driving the pump mechanism. The IoT plays very important role in connecting the various components

of the smart irrigation system and driving the communication mechanism to pass information from one component to other component (Fig. 3) [27-29].

It takes care of collecting the input data as well as handling the output information generated by the module to drive the watering pump on and off mechanism in the proposed smart irrigation system. The mentioned three steps of the architecture are explained in the following sub sections.

Designing of Optimization Based Smart Irrigation Model Using IoT

The researchers encourage the use of Arduino based IoT circuit, which is user friendly and performance efficient hardware for irrigation system. The Figure 2 shows arduino board [30, 31] parts important for hardware connections to build smart irrigation system. Arduino boards may be used to transform analogue or digital input data from several sensors into an output, such as a motor, an LED, a link to the cloud, or a number of other tasks. By using the Arduino IDE to upload software to the board's CPU, we may configure the board to function in a certain manner; here we are configuring it for the settings to read

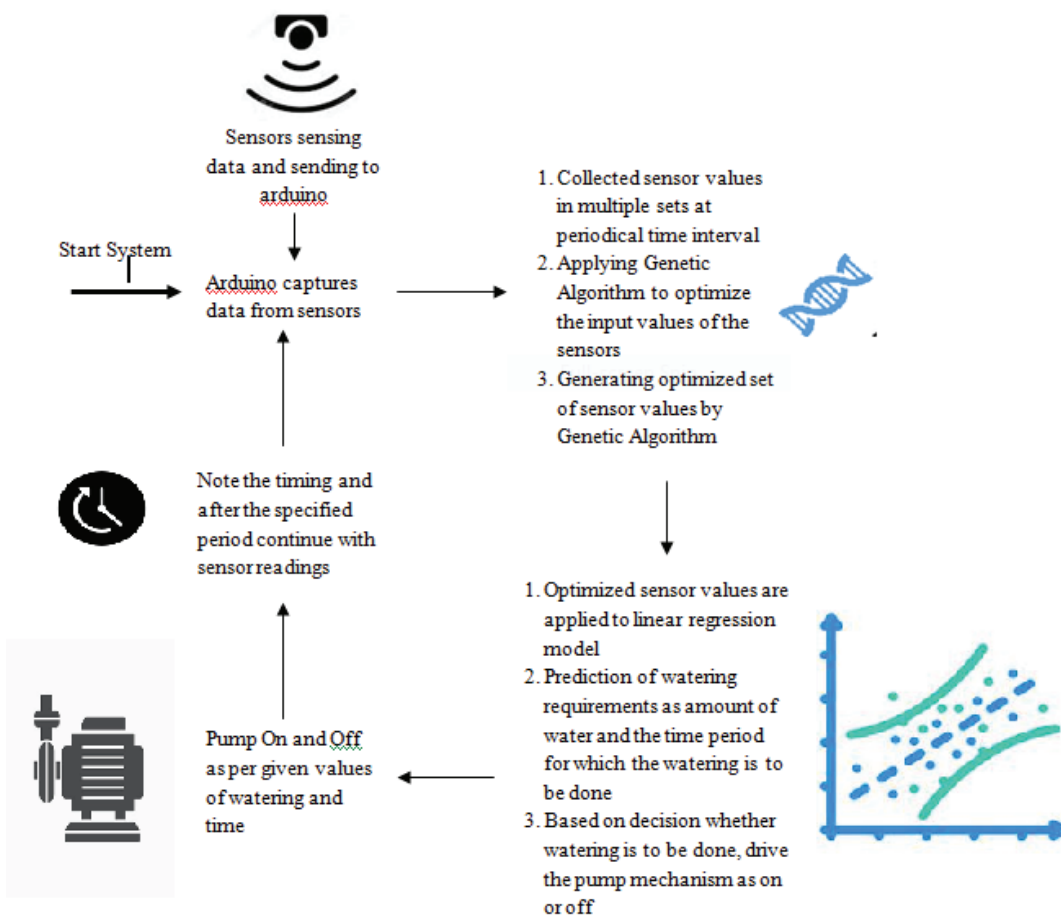


Figure 1. Proposed architecture of genetic algorithm based smart irrigation system.


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1:  $t \leftarrow 1$ 
2: initialize  $\mathcal{P}(t)$ 
3: evaluate  $\mathcal{P}(t)$ 
4: while  $t \leq T$  do
5:   mutate  $\mathcal{P}(t)$  and generate  $\mathcal{C}_m(t)$ 
6:   cross  $\mathcal{P}(t)$  and generate  $\mathcal{C}_c(t)$ 
7:    $\mathcal{C}(t) \leftarrow \mathcal{C}_m(t) \cup \mathcal{C}_c(t)$ 
8:   evaluate  $\mathcal{C}(t)$ 
9:    $\mathcal{E}(t) \leftarrow \mathcal{P}(t) \cup \mathcal{C}(t)$ 
10:  select  $\mathcal{P}(t+1)$  from  $\mathcal{E}(t)$ 
11:   $t \leftarrow t + 1$ 
12: end while

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Figure 3. The reasoning behind using GA.

irrigation system. Following section discusses the application and working of GA in smart irrigation system.

Figure 3 illustrates the reasoning behind this genetic algorithm implementation. It includes the following variables: t , the generation counter; T , the maximum number of generations; $\mathcal{P}(t)$, the population at that generation; $\mathcal{C}_m(t)$ and $\mathcal{C}_c(t)$, the children populations obtained by the mutation and crossover operators, respectively; $\mathcal{C}(t)$, the children population; and $\mathcal{E}(t)$, the expanded population formed by the current population and their offspring.

The GA is implemented with following steps:

- **Initial Population**

The chromosome in proposed model is made up of non-repeated integer-valued genes with lengths equal to the number of sensor readings such as soil moisture and temperature values at given specified time. The input sensor readings of pair of soil moisture and temperature in a specified time interval represents gene. Since permutations are thought of as a natural representation for optimized readings, the population is made up of randomly produced permutations of set of paired values of soil moisture and temperature sensor readings.

- **Selection**

For the current models, the finest individual selection is employed. [36,37] refers to the best individual selection as “elitism,” in which the elite member is not only chosen but also preserved and passes onto the following generation unaffected by crossover or mutation operators. The best individuals are chosen from a larger population in this instance’s best individual selection. Both individuals from the existing population and children resulting from parental crossing and mutation makeup the larger population [38,39]. The Selection probability is $P_c=0.6$ to 0.8 .

Hence, in our example the soil moisture and temperature sensor readings are selected based on their closeness with previous values and in relation with temperature readings the soil moisture readings are considered, as we know, the value of temperature drives the value of soil moisture. Appropriate and best values are selected for further iterations of GA.

- **Crossover**

Linear crossover is utilized for this proposed smart irrigation system iterations. In linear crossover the parents are selected for generating the offspring. After identifying parents the genes are selected at randomly among the parents. Now, as required in linear regression, we need to set the values for the α and β parameters.

Now to generate the offspring, the k th gene of the parents is modified using the following formula of equation (1):

$$O_{ik}: \alpha_i * P_{1k} + \beta_i * P_{2k} \quad (1)$$

Where,

i represent the number of offspring

P_1, P_2 represents the parents selected for the crossover.

After crossover the offspring are generated by the linear crossover as per formula given in equation (1).

- **Mutation**

The mutation operator utilized for all contiguous models is inversion mutation [40]. In inversion mutation, a randomly selected permutation section’s order is reversed. For example, if the sequence is 1-2-3-4-5-6 and the randomly selected section is 3-4-5, then the mutated permutation is 1-2-5-4-3-6. Preserving both practicality and variety is the goal. With a 0.2 mutation rate, which was found satisfactory during preliminary experimentation, is used in the current models. The mutation rate is regarded as the likelihood of mutation of a particular genotype.

- **Termination**

For the current model, the number of generations or number of readings in a set has served as the termination criterion. The disadvantage, despite its simplicity and ease of implementation, is that evolution cycles continue needlessly until the very end if the optimal solution is discovered in the early generations. If the maximum number of generations is selected properly, this might be avoided. Termination criteria include either obtaining a certain value for the cost function that is desirable, hitting saturation, or after a specific number of iterations by choosing the generation number; this choice is based on experience and is often made big enough to guarantee convergence. It may be deemed adequate to double or triple the population size.

As given above the genetic algorithm at the end provides the optimized values of the soil moisture and temperature sensor readings. Now, these values are passed as input to the linear regression model to generate the watering needs. Now, we will discuss the third step of our implementation model.

Linear Regression and Smart Watering Mechanism of Irrigation System

By assuming a linear relationship between the independent and dependent variables, linear regression forecasts the relationship between two variables. In order to minimize the sum of squared differences between the anticipated and actual values, it searches for the ideal line. The

Table 2. Input attributes for linear regression model of smart irrigation system

Independent Variable	X1	X2	X3	X4	X5	X6	X7
Attributes/ Features	Soil Moisture (wfv)	Average temperature °C	Average wind speed (m/s)	Relative humidity (%)	Sunshine hours (h)	Pressure X5 (Pa)	solar radiation (W/m ²)

linear regression may have one dependent and one independent variable for developing a model, which is called as a simple linear regression. Other type is multi linear regression, which we are utilizing in this irrigation model, where, there are several independent variables and one dependent variable in this situation [41-45]. Following equation (2) is the multiple linear regression equation.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n \quad (2)$$

where:

Y is the dependent variable

X₁, X₂, ..., X_n are the independent variables

β₀ is the intercept

β₁, β₂, ..., β_n are the slopes

Y is the water demand in (mm), to be provided to the applicable crop field, which is a continuous value prediction by the linear regression module.

Linear regression calculates the amount of watering required by the crop field or agricultural field. When the amount of watering required is more than or equal to 1mm, then the linear regression model drives the watering pump mechanism to ON state and the watering is done till the calculated amount of water flows out of the watering pump. This is how the smart irrigation system using genetic algorithm and linear regression works.

RESULTS AND DISCUSSION

Dataset

The Del-Coco and et. al. [46] have found out that a lot of work has been done to combine ICT and IoT technologies to create smart architectures, or to focus on the physical layer. However, it takes a lot more work to reach maturity at the

processing level and associated datasets. The key to utilizing recent machine learning techniques is the availability of trustworthy and carefully selected datasets. This could be the tipping point for a fully automated smart irrigation system, which should eventually incorporate application models into the training process. This will result in fully data-driven machine learning tactics from start to finish [46].

In order to ensure a representative sample by capturing variations in water application across the field, we have gathered data points from various locations across the irrigated area while taking into account factors like the type of irrigation system, the water source, and the topography of the field. We have also considered measurements such as soil moisture, temperature, and water flow rate parameters at each sampling point. For accurate analysis, it is important to conduct the survey of data values for these parameters at various locations in the irrigation field as well as conducting survey at various environmental conditions. Considering the place of irrigation, we have collected data by using random sampling method which leads to the selection of random locations in the irrigation field to collect data values of various irrigation parameters. Also, as data is collected season wise, during collection in each season the periodic sampling is executed to collect data samples at various time intervals in a day. As the samples are collected by us only, so we have taken care that, noisy samples should not be a part of the dataset, and also optimization of the input values to increase the model accuracy is done by using the Genetic Algorithm as a part of data preprocessing.

We started using IoT devices including sensors and arduino boards in different environments with several domestic plants in the mass collection process for the absolute need of information. This collection process was lasting for six months including winter, summer and rainy

Table 2. Sample data set with relevant attributes and Water demand

Soil Moisture (wfv)	Average temperature (°C)	Average wind speed (m/s)	Relative humidity (%)	Water demand (Y in mm)
278.93	36	2.32	19.62	6.28
318	34.5	2.41	16.56	6.02
.
.
777.85	15.3	3.35	18.52	4.68
865.29	14	1.78	19.33	4.46

season samples to ensure data samples with mostly all seasons for making system be useful throughout the year. Accompanying this growth are the following findings for few of the important attributes:

Attribute 1 - Soil Moisture: The data is generated by an analog sensor within a data interval of 0 to 1023. The smallest value is 278.93, and the maximum value is 865.29.

Attribute 2 – Temperature: These data were gathered with the help of a temperature sensor that displays the current temperature in Celsius. We can see that, during the collection months, the average temperature was 24.5°C, whereas the lowest value was 14°C, and the highest value was 36 °C.

Attribute 3 – Air Humidity: We collected humidity data using the same sensor that guaranteed the collection of temperature values. The results of our analysis pass show that the lowest value is 29.7%, and the greatest value is 84.1%.

Dependent Variable – Water demand: Based on the observations and communication with the expertise, the data for the water demands is collected in various environmental conditions and various possible combinations of the above mentioned input parameters. The maximum water needs identified are 6.65mm and minimum water demands is 2.94mm in different conditions. The model is trained and tested using the mentioned dataset only. The sample dataset with important attributes is as shown in Table 2.

Results for Smart Irrigation Using Linear Regression with GA and without GA

We have collected total 350 samples with depicting varying environmental conditions. The dataset is divided into 80% for training with 280 samples and 20% for testing with 70 samples. The results are explained as follows.

The Figure 4a to 4d shows the results for smart irrigation using linear regression without GA and with GA. All

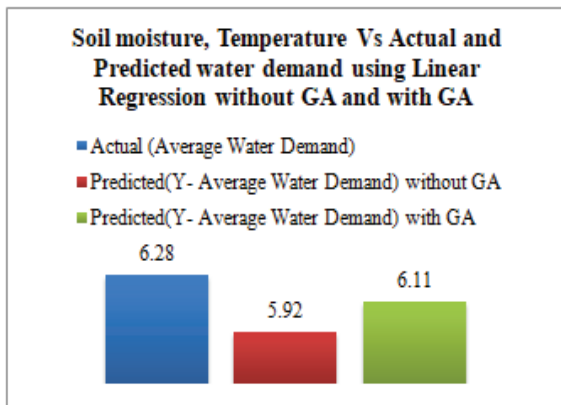


Figure 4a. Actual Vs Predicted water demand for given average soil moisture using Linear Regression without GA and with GA for Range of:
Soil moisture from 278.93 to 414.16 and Temperature from 30.5°C to 36°C

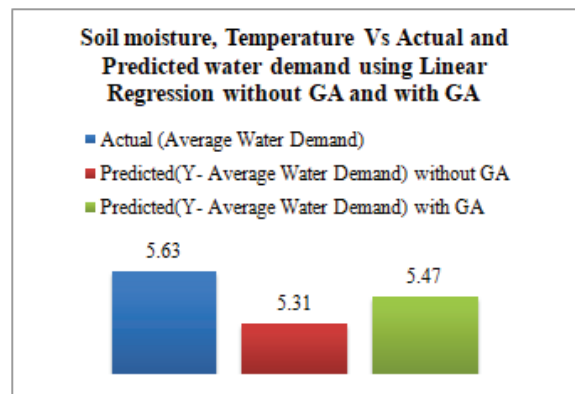


Figure 4b. Actual Vs Predicted water demand for given average soil moisture using Linear Regression without GA and with GA for Range of:
Soil moisture from 415.92 to 568.81 and Temperature from 25.6°C to 30.4°C

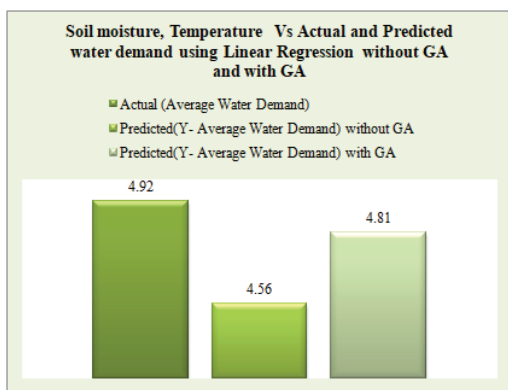


Figure 4c. Actual Vs Predicted water demand for given average soil moisture using Linear Regression without GA and with GA for Range of:
Soil moisture from 569.22 to 736.51 and Temperature from 20.5°C to 25.5°C

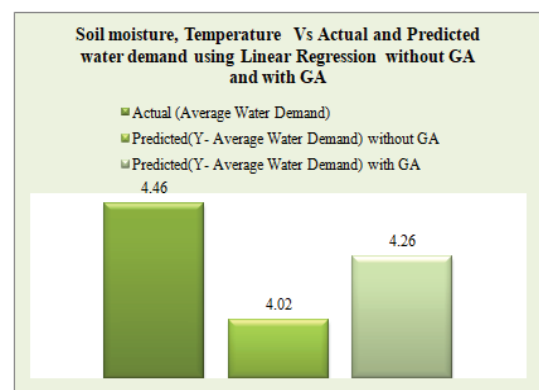


Figure 4d. Actual Vs Predicted water demand for given average soil moisture using Linear Regression without GA and with GA For Range of:
Soil moisture from 736.65 to 865.29 and Temperature from 14°C to 20.4°C

Figure 4. Graphs showing the actual water demands Vs predicted water demands without GA and with GA.

the graphs show the actual Vs predicted water demands using GA and without using GA for various soil moisture ranges and various temperature ranges.

As we can see, for low soil moisture range and high temperature range as shown in Figure 4a, the average water demand is 6.11mm as generated by our model using GA against the actual demand of 6.28mm. Also, for high soil moisture range and low temperature range as shown in Figure 4d, the average water demand is 4.26mm as generated by our model using GA against the actual demand of 4.46mm. The Figure 4b and Figure 4c shows the predicted water demands for medium soil moisture and temperature ranges as specified.

Internet of things along with optimization is found useful and effective to bring automation in agriculture [12], especially for irrigation system as stated in graphs.

The Figure 5 shows the comparison for MSE of our model with the other machine learning techniques. It is observed that MSE is very less as compared to the existing models of smart irrigation. The MSE of our model is only 0.017533.

This graph in Figure 5 shows the results for linear regression with genetic algorithm for smart irrigation are superior to other machine learning techniques used for smart irrigation without optimization technique. Here the GA helps to optimize the sensor reading values and generate nearly closer water demands to cope up with the accuracy issue of the smart irrigation system.

Figure 6 shows the accuracy comparison of our model with existing systems. We found that, our model of smart irrigation performs better as compared to existing systems in literature. The comparative study is as follows.

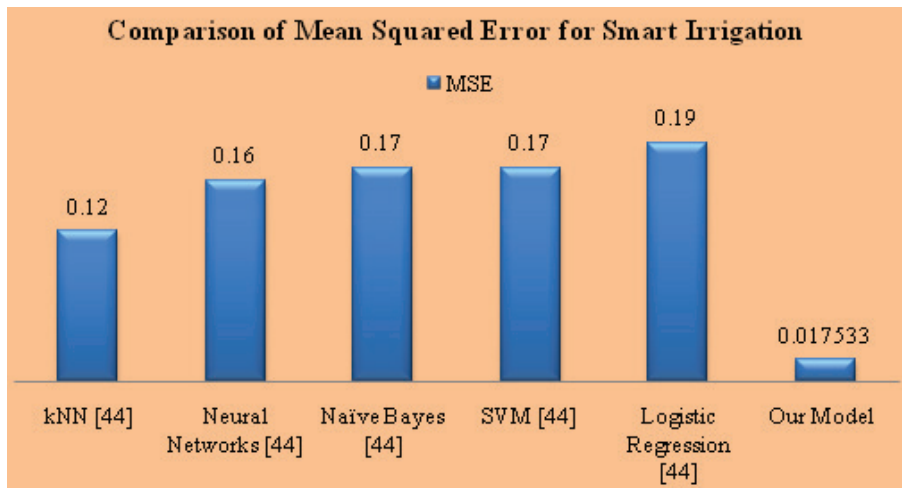


Figure 5. Comparison of our model with existing machine learning techniques for smart irrigation.

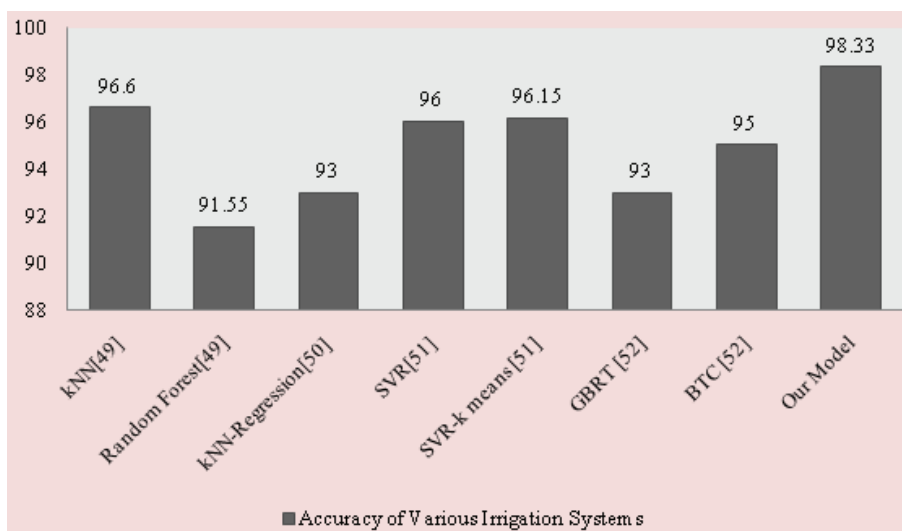


Figure 6. Accuracy Comparison of Our model with existing machine learning techniques for smart irrigation.

As per the Bavilla et al. [47], the accuracy of irrigation model using kNN is 96.60% and for Random forest it is 91.10%, with limited size dataset for training and same dataset is used for testing also. On the other hand, Akshay & Ramesh [48] have used kNN-Regression and observed the accuracy of 93%. In irrigation model by [49], the Goap, Amrendra et al. have used SVM for which the accuracy is 96%, also they have tested the system using combination of SVM-k-means, of which accuracy is found to be slightly increasing to 96.15%, which is better than SVM, kNN and Random Forest as studied above. In another research article, Goldstein, Anat et al. [50] have implemented the irrigation using Gradient Boosted Regression Trees (GBRT), for which the accuracy is observed as 93% and they have compared it with classifier model BRT i.e. Boosted Tree Classifier, which was found the best classifier with the accuracy of 95%.

After comparison, it is observed that accuracy of Smart Irrigation with linear regression model using genetic optimization is more than any of the standalone machine learning based irrigation systems. It is 98.33% and better than any of the other mentioned irrigation systems. This accuracy will help the real-time utilization of our irrigation system in rural areas of Maharashtra for watering to agricultural fields.

CONCLUSION

Herewith the researchers have implemented the smart irrigation system to calculate the watering needs for agricultural fields for various environmental conditions by using genetic algorithm optimization and linear regression. The soil moisture and other parameter values and readings generated by the IoT circuit which is developed using various sensors and the arduino board. The genetic algorithm optimizes the values of the input for linear regression and then linear regression is applied to generate the nearly accurate water demands. We have analyzed the results of smart irrigation using linear regression with and without genetic algorithm and found that the better accuracy is achieved with genetic algorithm optimization. The average MSE depicted in the results is 0.017 and accuracy is found to be 98.33 percent, which is better as compared to any of the existing smart irrigation systems without optimization algorithm. The future scope of the work considers the iterations for optimization in genetic algorithm with number of samples generated, which may lead to unnecessary processing of the input samples. With optimum number of iterations using more feasible approach, it can be avoided.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw

data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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