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An IoT based smart irrigation management system using Machine learning and open source technologies

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A R T I C L E I N F O

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A B S T R A C T

The scarcity of clean water resources around the globe has generated a need for their optimum utilization. Internet of Things (IoT) solutions, based on the application specific sensors' data acquisition and intelligent processing, are bridging the gaps between the cyber and physical worlds. IoT based smart irrigation management systems can help in achieving optimum water-resource utilization in the precision farming landscape. This paper presents an open-source technology based smart system to predict the irrigation requirements of a field using the sensing of ground parameter like soil moisture, soil temperature, and environmental conditions along with the weather forecast data from the Internet. The sensing nodes, involved in the ground and environmental sensing, consider soil moisture, soil temperature, air temperature, Ultraviolet (UV) light radiation, and relative humidity of the crop field. The intelligence of the proposed system is based on a smart algorithm, which considers sensed data along with the weather forecast parameters like precipitation, air temperature, humidity, and UV for the near future. The complete system has been developed and deployed on a pilot scale, where the sensor node data is wirelessly collected over the cloud using web-services and a web-based information visualization and decision support system provides the real-time information insights based on the analysis of sensors data and weather forecast data. The system has a provision for a closed-loop control of the water supply to realize a fully autonomous irrigation scheme. The paper describes the system and discusses in detail the information processing results of three weeks data based on the proposed algorithm. The system is fully functional and the prediction results are very encouraging.

1. Introduction

Water scarcity is already affecting a part of the world and the situation is getting worse over time due to the increasing world population and fresh water demands. The current world population is around 7.2 billion and it is expected to be more than 9 billion by 2050 (United Nations, 2013). The agriculture sector, particularly irrigation, consumes a major portion of the freshwater. Due to lack of cost-effective intelligent irrigation systems, developing countries are consuming more water in contrast to the developed countries for achieving the same yield. For example, India has approximately 4% of world's freshwater resources to serve 17% of the world population; however, it takes 2–4 times more water for some of its major agri-produce in comparison to the other countries like China, USA (G. o. I. NITI Aayog, 2015). Therefore, there is a dire need to come up with advanced technologies based smart strategies and systems for effective utilization of fresh water.

Gubbi et al. (2013) discussed an IoT framework with cloud centric storage, processing and analysis of the data received from ubiquitous sensors along with a decision support interface. Cruz et al. (2018) suggested a reference model for an IoT middleware platform that would support intelligent IoT applications. IoT based solutions are proving very helpful in many dimensions of the agricultural landscape (Sharma et al., 2016), and these intelligent solutions could also be fruitful in smart irrigation with optimum utilization of water. Soil moisture, precipitation, and evaporation are the essential parameters for designing a smart irrigation system.

The precipitation and evaporation are important key factors, which influence the soil moisture. In geography and climatology, the wetness of soil is estimated by the proportion of annual (or monthly) precipitation and evaporation (Shang et al., 2007). Daily soil moisture can also be evaluated by the ratio of daily precipitation and evaporation in the above perspective. Precipitation is directly accessible in the routine weather reports; nonetheless, evaporation can be calculated using other

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metrological essentials. For evaporation, we use an empirical model given by Penman (Chen and Chen, 1993)

$$E_T \propto (E_h + E_m) \tag{1}$$

The entire evaporation (E_T) depends on the thermodynamic evaporation (E_h) and the dynamic evaporation (E_m), where E_m depends upon the velocity of the land storm, air temperature, relative humidity of the air and UV radiation.

To achieve water saving, irrigation system frameworks have been proposed based on various techniques, e.g., thermal imaging, Crop Water Stress Index (CWSI), direct soil water measurements, etc. Thermal imaging is a prominent technique for irrigation management and it is based on the shade temperature distribution of the plant. In this framework, the status of the water in the plant is checked over continuous intervals and irrigation is planned in view of the shade temperature distribution of the plant (Wang et al., 2010). In addition, CWSI based framework has been proposed for irrigation scheduling of the crops for efficient use of water. The observation of CWSI was first characterized more than 30 years ago (Idso et al., 1981). O'Shaughnessy and Evett (2010) proposed an automatic irrigation scheduling based on direct soil water measurement that utilizes water proficiently over manual irrigation system. Allen et al. (1998) suggested evapotranspiration (ET) based approach, which is an important parameter to decide crop irrigation needs influenced by climate parameters, e.g., solar radiation, relative humidity, temperature, wind velocity, and crop features such as phase of the crop growth, assortment and plant density, properties of soil, nuisance, and disease control. ET-based frameworks can save water up to 42% over time-based water irrigation scheduling (Davis and Dukes, 2010). Davis et al. (2009) conducted the investigations in Florida and verified that ET-based watering scheduling controllers are more beneficial in term of cost, size and labor requirement for irrigation. ET-based irrigation system uses much less water as compared to scheduled practices. Viani et al. (2017) proposed a fuzzy logic-based decision support system based on farmer's experience with the understanding of crop condition. This system provides more water saving over single-threshold and multi-threshold based irrigation scheduling. Gutiérrez et al. (2014) proposed an automated irrigation system using a wireless sensor network and GPRS module to save water in irrigation. In this system, a network of soil moisture sensors with controller has been installed in a crop field for real-time monitoring and irrigation control. Gill et al. (2006) suggested a method for soil moisture prediction using support vector machines based on air temperature, relative air humidity and soil temperature.

Jaguey et al. (2015) developed irrigation sensor based on smart phone. For sensing soil moisture, the digital camera of smart phone is used to process RGB to gray for estimation of ratio between wet and dry area of soil. The ratio of wetness and dryness is transmitted via gateway to water motor controller. A Mobile Application (APP) is developed to control sensor activity (like wakeup) and to set sensor in sleep mode. Goldstein et al. (2017) proposed irrigation recommendations based on machine learning algorithm with support of agronomist's encysted knowledge. It was found that the best regression model was Gradient Boosted Regression Trees (GBRT) with 93% accuracy in prediction of irrigation plan/recommendation. The developed model is helpful to the agronomist's irrigation management. Roopaei et al. (2017) proposed an intelligent irrigation monitoring system based on thermal imaging. The proposed technique uses thermal imaging camera mounted on Drone. An algorithm is developed using images processing techniques for identification of water requirement, Leaf water potential, and non-uniform irrigation, which are used for irrigation monitoring.

Majority of the earlier irrigation systems do not consider the weather forecasting information (e.g., precipitation) while making irrigation decisions. It leads to a wastage of fresh water, energy and loss of crop growth (due to excess water) when a rain is followed immediately by the watering of the crop. To handle such cases, IoT based solutions can provide a better decision support for irrigation by utilizing weather forecasting information (e.g., precipitation) from the Internet. Further, the accuracy of weather forecasting is improving due to the advancement of satellite imagery technology.

For effective and optimum utilization of fresh water in irrigation, it becomes essential to develop the smart irrigation systems based on dynamic prediction of soil moisture pattern of the field and precipitation information of upcoming days. This paper presents an intelligent system that predicts soil moisture based on the information collected from the sensors deployed at the field and the weather forecast information available on the Internet. The field data has been collected through a self-designed sensor node. The server-side software has been developed with node side connectivity along with information visualization and decision support features. A novel algorithm has been developed for soil-moisture prediction, which is based on Machine Learning techniques applied on the sensor node data and the weather forecast data. The algorithm shows improved accuracy and less error. The proposed approach could help in making effective irrigation decisions with optimum water usage.

2. Methods/Techniques used

Prediction of soil moisture is vital for effective irrigation management system. The estimation of soil moisture depends upon evapotranspiration Hargreaves and Samani (1985) developed a method based on temperature and extra-terrestrial radiation to estimate ET_0. It is expressed as

$$ET_0 = 0.0023R_a\left(\frac{T_{max}+T_{min}}{2}+17.8\right)\sqrt{T_{max}-T_{min}} \tag{2}$$

where ET_0 = reference evapotranspiration (mm/day); T_{max} and T_{min} = maximum temperature and minimum temperature (°C) and R_a = extra-terrestrial radiation (MJ m^{-2} day^{-1}).

Ritchie developed another method for estimation of ET_0 (Jones and Ritchie, 1990) based on temperature and solar radiation. It is expressed as

$$ET_0 = \alpha_1 \bullet [3.87\times10^{-3} \bullet R_s \bullet (0.6T_{max} + 0.4T_{min} + 29)] \tag{3}$$

where ET_0 = reference evapotranspiration (mm/day); T_{max} and T_{min} = maximum and minimum temperature (°C) and R_s = solar radiation (MJ m^{-2} day^{-1}). When

$$\left.\begin{array}{ll} 5 < T_{max} \le 35\ ^\circ C & \alpha_1 = 1.1 \\ T_{max} > 35\ ^\circ C & \alpha_1 = 1.1 + 0.05(T_{max}-35) \\ T_{max} < 5\ ^\circ C & \alpha_1 = 0.01\exp[0.18(T_{max}+20)] \end{array}\right\} \tag{4}$$

Cobaner (2011) developed evapotranspiration estimation method based on Neuro-Fuzzy (NF) inference and found that the NF model (based on solar radiation, air temperature, and relative humidity) exhibits better accuracy than the combination of solar radiation, air temperature and wind speed.

From state of art, it has been analyzed that prediction of soil moisture is possible using sensors placement at the field and weather forecasted data. So, we have considered evaporation of soil moisture based on air temperature, air relative humidity, soil temperature, and radiation. The parameters are considered for analyzing the soil moisture drain (change/difference) pattern based on the recorded data of soil moisture.

An IoT based architecture (Fig. 1) has been proposed to collect, transmit and process the physical parameters (soil moisture, air temperature, air relative humidity, soil temperature, and radiation) of farming land along with the weather forecast information to manage the irrigation efficiently.

An algorithm based on a combination of supervised and unsupervised machine learning techniques (block diagram shown in Fig. 3 and pseudocode is discussed in Section 3.2.1) has been developed using Support Vector Regression (SVR) and k-means clustering for estimation of difference/change in soil moisture due to weather conditions. It gives good accuracy and less Mean Squared Error (MSE) (Theobald, 1974; "Mean Squared Error, 2018") in the prediction of the soil moisture of

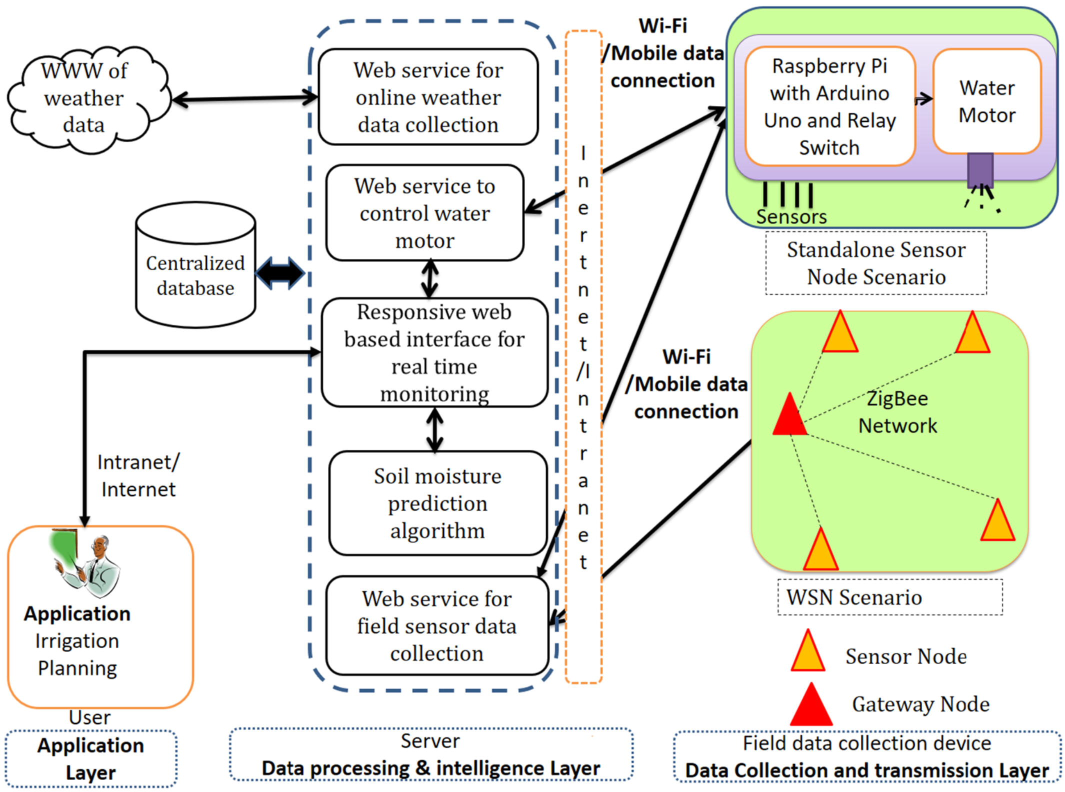

Fig. 1. Architecture of proposed system.

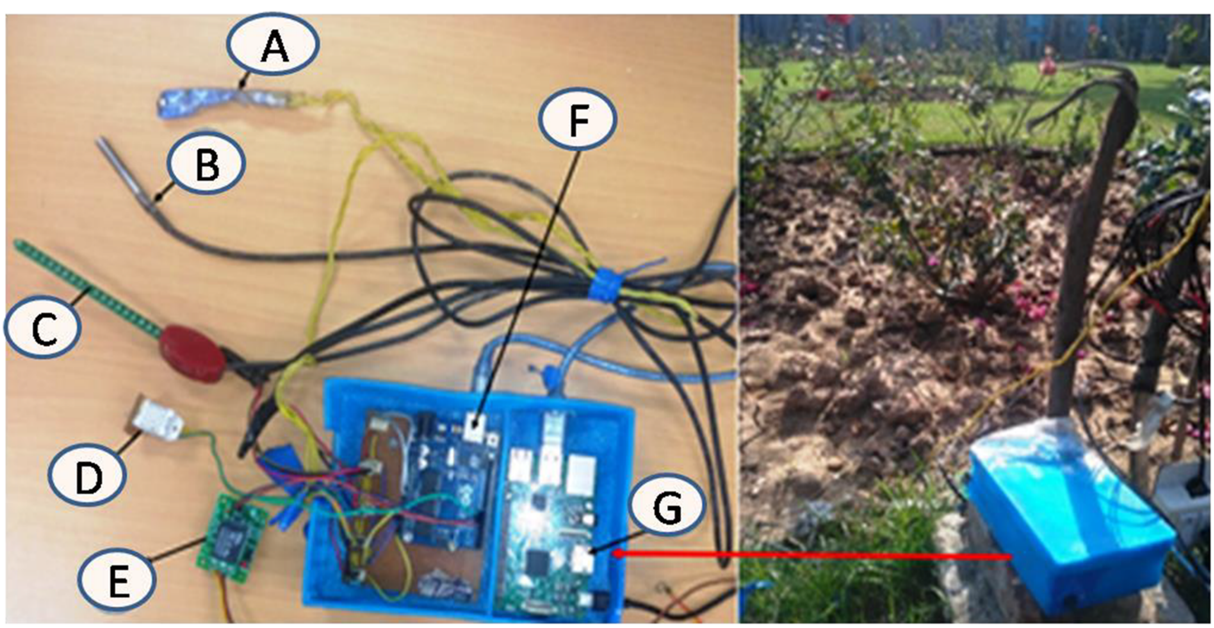

Fig. 2. Field data collection device. [Legends A: UV Sensor, B: Soil Temperature Sensor, C: Soil Moisture Sensor, D: Air Temperature & Humidity Sensor, E: Relay Switch, F: Arduino Board, G: Raspberry Pi]

upcoming days with the help of sensors data and the weather forecasting data. SVR model has been trained using data (air temperature, air relative humidity, soil temperature, radiation, and soil moisture difference) collected from field device shown in Fig. 2. The Soil Moisture Differences (SMD) of upcoming days have been predicted using trained SVR model and the predicted value of SMD is given as input for *k*-means clustering for improving the accuracy of soil moisture difference (centroid value of *k*-means), which is more accurate (Table 2) with less MSE (Table 3). The final predicted soil moisture (Table 4) has been used in the development of smart irrigation scheduling algorithm (Section 3.2.2) to efficiently utilize the natural rain (precipitation) information for effective irrigation. To visualize the predicted soil moisture of upcoming days along with precipitation information and to control (start and stop) the irrigation, a responsive web portal has also been developed (Figs. 4 and 5).

Support Vector Regression (SVR) (Drucker et al., 1997) is the modified version of Support Vector Machine (SVM) (Hearst et al., 1998), where the dependent variable is numerical in lieu of categorical.

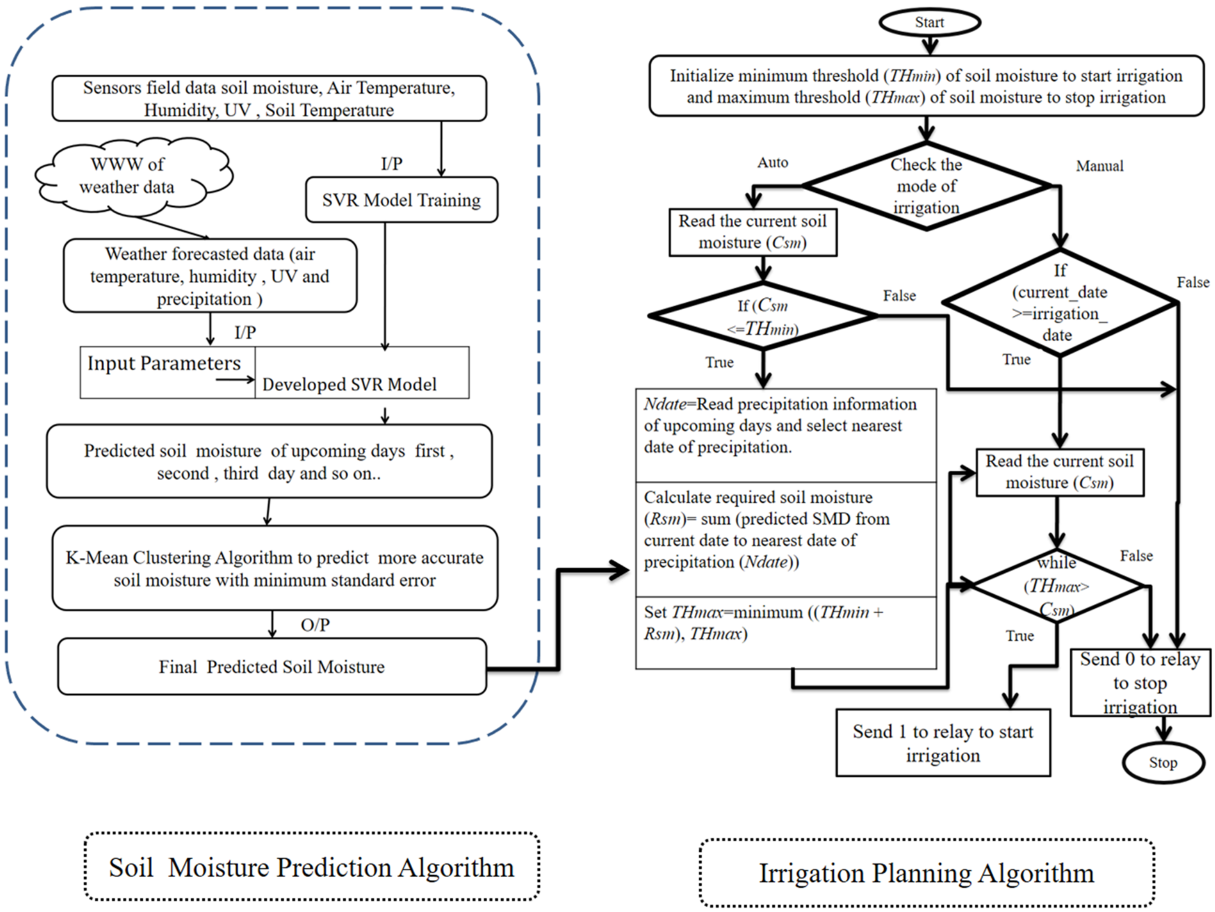

Fig. 3. Schematic diagram of prediction algorithm with irrigation planning.

Table 1
The variables used in the algorithm for soil moisture prediction.

Variable name	Input/output type	Variable details
SMD	Input	Soil Moisture Difference (SMD) is defined as minimum recorded soil moisture of the previous day (*x-1*) minus minimum soil moisture for the current day (*x*) (As the soil moisture is affected by air temperature, relative air humidity and UV changes)
H	Input	Average air relative humidity of the day
Temp	Input	Average air temperature of the day
MSD	Input	Maximum SMD value during all days of data used in training set of regression model
UV	Input	Average Ultraviolet radiation of the day
W_D	Input	Array of forecasted weather data {$Temp_i$, H_i, UV_i} that will be used in soil moisture prediction
ST_i	Input	Average soil temperature
PSMD	Output at intermediate level	Predicted SMD using regression model of upcoming days with the help of forecasted weather data
NoC	Input	Number of cluster (⌈MSD⌉)
SVR	Input	Support vector regression
S_D	Input	Array of field sensor data {$Temp_j$, H_j, UV_j, ST_i, SMD_j}
SVR_Model	Output	Generated training model to predict SMD
NPSMD	Output	New predicted SMD using centroid value of *k*-means clustering
STD	Input	Soil temperature difference is average soil temperature for the previous day (*x-1*) minus average soil temperature for the current day (*x*)
PST	Output	Predicted soil temperature based on predicted soil temperature difference and weather data

SVR is a non-parametric technique and allows the creation of nonlinear models. The SVR method utilizes kernel functions to generate the model. Some of the frequently used kernel functions are Polynomial, Linear, Radial Basis and Sigmodal.

k-means clustering (Kanungo et al., 2002) takes a straightforward and simple methodology to group a given information set into a definite number of clusters. The objective is to find *k* centroids, one for each bunch. First, it divides *n* number of the objects into *k* non-empty sub-groups/cluster, and then finds the cluster centroids (mean point) of every subgroup/cluster. Then it calculates the distances from every point to the centroids and allocate each object to a specific cluster where the distance is minimum from the centroid. The process iterates to re-assign the points and identify the centroid of the new clusters.

3. The proposed system

3.1. System architecture

The architecture of proposed IoT based smart irrigation system is shown in Fig. 1. It has seven main components, viz., Field data

Table 2
SMD based on sensor data and prediction algorithm.

Date	SMD based on sensor data	Predicted SMD using SVR	Predicted SMD using proposed algorithm (SVR + *k*-means)
15-11-2017	1.236227211	0.807615	0.9741
16-11-2017	0.928945011	0.845376	0.8265
17-11-2017	0.681400791	0.673736	0.9026
18-11-2017	0.433856571	1.037236	0.9632
19-11-2017	1.034538866	1.186209	1.0965
20-11-2017	1.735615593	1.111515	1.0995

Table 3
Comparison of Correlation, and MSE between SMDs based on sensor data and prediction algorithm.

Parameter	Predicted SMD using SVR	Predicted SMD using proposed algorithm (SVR + *k*-means)
R (Correlation coefficient)	0.313454	0.559295
MSE (Mean squared error)	0.160337	0.135599

Table 4
Soil moisture based on the sensor data and the proposed algorithm.

Date	Soil Moisture recorded by sensor	Predicted soil moisture using SMD by SVR	Predicted soil moisture using SMD by proposed algorithm (SVR + *k*-means)
15-11-2017	25.66197279	26.09058	25.9241
16-11-2017	24.73302778	25.24521	25.0976
17-11-2017	24.05162699	24.57147	24.195
18-11-2017	23.61777042	23.53424	23.2318
19-11-2017	22.58323155	22.34803	22.1353
20-11-2017	20.84761596	21.23651	21.0358

collection device with relay switch (Standalone and WSN Scenario); Web service for collecting field sensor data; Web service for collecting weather information available online (Internet); Web service to control water motor; Soil moisture prediction algorithm; Responsive web based interface for real-time monitoring; IoT enabled motor pump. These components are grouped into three different layers, i.e. Data collection and transmission layer, Data processing & intelligence layer and application layer of IoT (Fig. 1). These components are discussed in the following sections.

3.1.1. Field data collection device

Depending on the field requirements, a standalone sensor node or a wireless sensor network of the sensor nodes may be deployed. In standalone scenario field data collection device consists of four sensors, viz., VH-400 Soil Moisture sensor, Soil temperature sensor, DHT22 temperature and humidity sensor, and Ultraviolet (UV) Light Radiation sensor based on GUVA-S12SD and SGM8521 Op Amp. The output of these sensors is read by an Arduino-Uno, which is connected to Raspberry Pi (R-Pi). In R-Pi a program is written in Python language to hourly fetch the data from sensors and to store the data in SQLite database, which is synched with the server database using developed web service.

For large farming area, a Wireless Sensor Network (WSN) (Ojha et al., 2015) scenario with ZigBee (Pandey et al., 2017; Gutiérrez et al., 2014) technology can be implemented in which multiple sensor nodes can be planted in the specified area. Each sensor node will consist of the sensors similar to the standalone device. The output of these sensors is read by an Arduino-Uno connected to ZigBee for sending data to Gateway Node (similar to the standalone device with ZigBee connectivity) that will aggregate the received data and store it locally in SQLite and also send the data to the server using web service. The current analysis (statistical analysis of predicted soil moisture and its accuracy is exhibited in Fig. 6, Tables 3 and 5) has been done with the standalone device. The standalone device is shown in Fig. 2.

3.1.2. Web service for field sensor data collection

The Web service is written in PHP with a light weighted REST API to communicate the data between the field device and the server. The service is hosted on Apache (Web server) at server machine. The R-Pi sends the field data to the server using this web service. This web service can handle the network fluctuation/outage during synchronizing the data from the filed device to the server with the help of flag settings at the database level.

3.1.3. Web service for online weather data collection

A web service has been developed in Python to collect the weather forecasting data. This web service also aggregates the weather forecasting data like temperature, humidity, cloudiness, UV Index and precipitation of different web forecasting portal like OpenWeather and AccuWeather using API of these portal (Weather API, 2012; API Reference, 2017). These portals provide the forecasted information in JSON, XML, or HTML format. The developed web service read the forecasted data (JSON format) of the specified location using API and store it in MySQL database at the server, which is considered in the prediction algorithm.

3.1.4. Soil moisture prediction algorithm

An algorithm has been developed (Fig. 3) to predict the soil moisture based on field sensors data and weather forecasting data using support vector regression model and *k*-means clustering algorithm. The algorithm shows information regarding soil moisture of the upcoming days. It also provides irrigation suggestions, based on the defined level of soil moisture and predicted precipitation, to save water and energy. The generated information by algorithm and device is stored in MySQL Database at the server. The algorithm is discussed in detail in Section 3.2.

3.1.5. Responsive web based interface for real-time monitoring

A responsive web based user interface is developed using PHP, MySQL and Bootstrap API for real-time monitoring and scheduling of irrigation activities (Figs. 4 and 5). The interface visualizes real-time sensors data, predicted soil moisture of upcoming days, and precipitation information. Further, it also provides a facility for irrigation scheduling. The user can schedule the irrigation at a specified threshold value of soil moisture. The system guides to maintain the threshold value based on the predicted pattern of soil moisture and precipitation information. The system can automatically start the irrigation, which stops after achieving the specified threshold value of soil moisture.

3.1.6. Web service to control water motor

A web service has been developed on top of HTTP protocol to start and stop the water motor. This web service has been accessed by Python code in R-Pi to start and stop the water motor. The Python code (running on R-Pi) send signal to Arduino-Uno that controls the relay switch to start/stop the water motor.

3.1.7. IoT enabled water pump

In this module, a water pump is connected to a relay switch that is controlled by a Wi-Fi enabled node. The node is controlled by the web service through a trigger from the responsive web based interface for real-time monitoring. Using this web based interface the water pump can be managed remotely in manual and auto modes.

3.1.8. Communication technologies used in proposed architecture

In the proposed architecture, the WiFi module/Mobile data communication module can be used as communication media between the

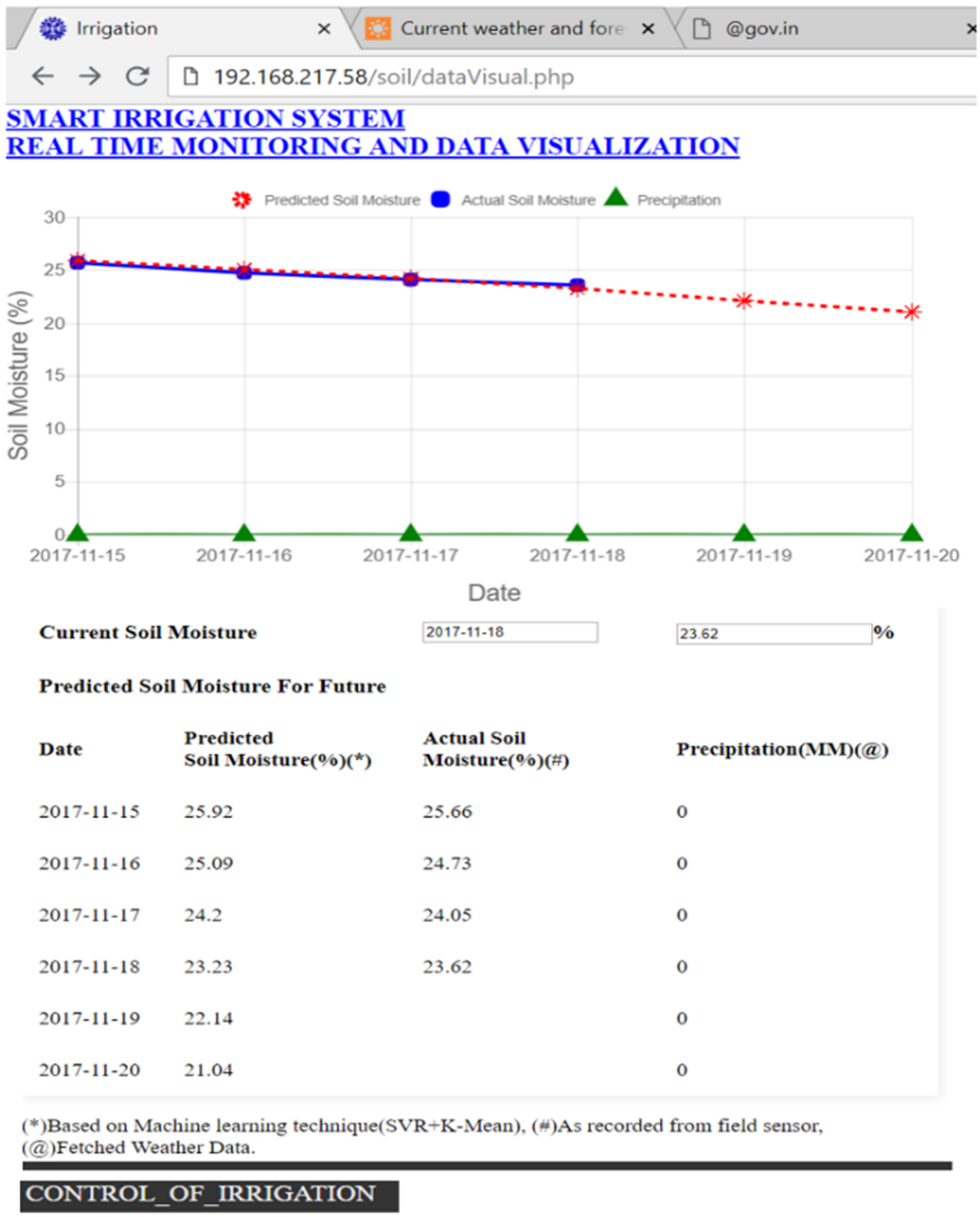

Fig. 4. GUI of real-time monitoring and decision support system.

field device and the server. In this experiment (Standalone device scenario), a WiFi module has been used to send the data to the server. In WSN scenario, ZigBee network can be used between sensor node to Gateway Node and then a WiFi module or Mobile data communication module can be used to send the data from the gateway node to the server.

3.2. Prediction algorithm and data visualization

Flow diagram of the proposed soil moisture prediction algorithm and the irrigation planning algorithm for data visualization and decision support is shown in Fig. 3.

3.2.1. Algorithm for soil moisture prediction

Algorithm Steps (Variables as in Table 1.)

- Initialize weather data (W_D = {$Temp_i$, H_i, UV_i}) from weather forecasting web portals
- Initialize sensor data (S_D = {$Temp_j$, H_j, UV_j, ST_j, SMD_j})collected from the field
- Train SVR model for prediction of soil temperature using $Temp_j$, H_j, UV_j, STD_j
- Predict *PST* using weather data W_D
- Train SVR model for prediction of soil moisture using $Temp_j$, H_j, UV_j, ST_j, SMD_j
- Predict soil moisture difference (PSMD) using weather data W_D and PST
- *PSMD* [where P_0, P_1, P_2, ……P_n are predicted SMDs of day 1, 2, 3…n]
- For i = 0 to n (n = total number of days of PSMD)

  {

  k-means clustering on *(SMD of S_D, P_i, NoC) //calling k-means clustering function* $NPSMD_i$ = Centroid value of cluster to which P_i belongs *// Final predicted value of SMD of day 1, 2 …n*

  }
- Output ($NPSMD_0$, $NPSMD_1$, $NPSMD_2$, …., $NPSMD_n$)

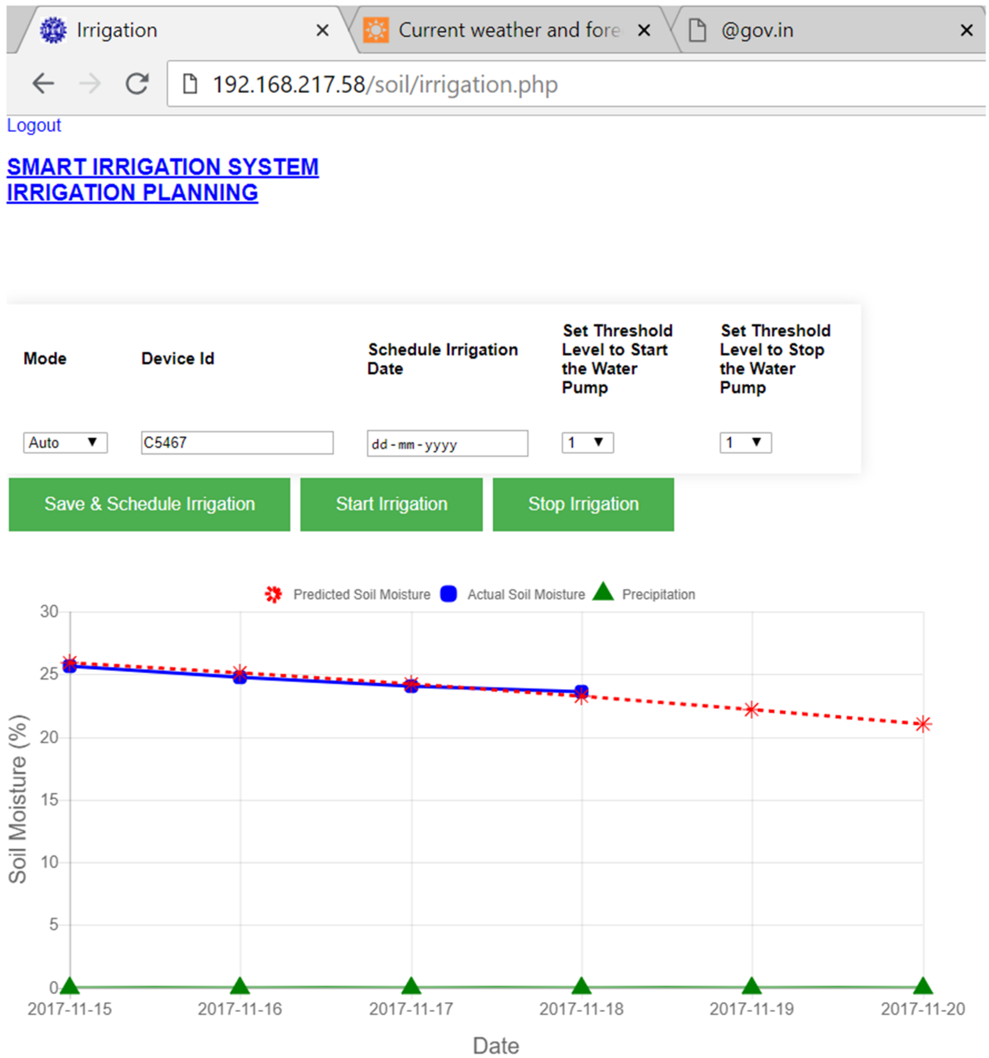

Fig. 5. The GUI of Irrigation Planning Module.

Table 5
Comparison of correlation, R squared and MSE between soil moisture values based on the sensor data and the proposed algorithm.

Parameter	Predicted Soil Moisture using SVR	Predicted Soil Moisture using proposed algorithm (SVR + *k*-means)
R (Correlation coefficient)	0.98	0.98
Accuracy (R squared)	0.96	0.96
MSE	0.15	0.10

3.2.2. *Algorithm of irrigation scheduling*

Algorithm Steps

Step 1. Initialize minimum threshold (TH_{min}) of soil moisture to start irrigation and maximum threshold (TH_{max}) of soil moisture to stop irrigation

Step2. Set mode (manual/auto) for irrigation

Step 3. If (mode = auto)

{

Read and check current soil moisture (C_{sm})

If (C_{sm} < = *THmin*) *// condition check of current soil moisture from its set threshold value by user*

{

Ndate = Read precipitation information of upcoming days and select nearest date of precipitation.

Calculate required soil moisture (R_{sm}) = sum (predicted SMD from current date to nearest date of precipitation *(Ndate)*) *//Total change in soil moisture till nearest precipitation date*

Set TH_{max} = *minimum ((THmin +* R_{sm}*),* TH_{max}*) // selection of minimum soil- moisture required to maintain crop growth*

while (TH_{max} > C_{sm}) *// condition for watering till soil moisture reaches its minimum required value.*

{

Send 1 to relay to start irrigation *//Signal to Start Water motor*

}

Send 0 to relay to stop irrigation *//Signal to stop the water motor*

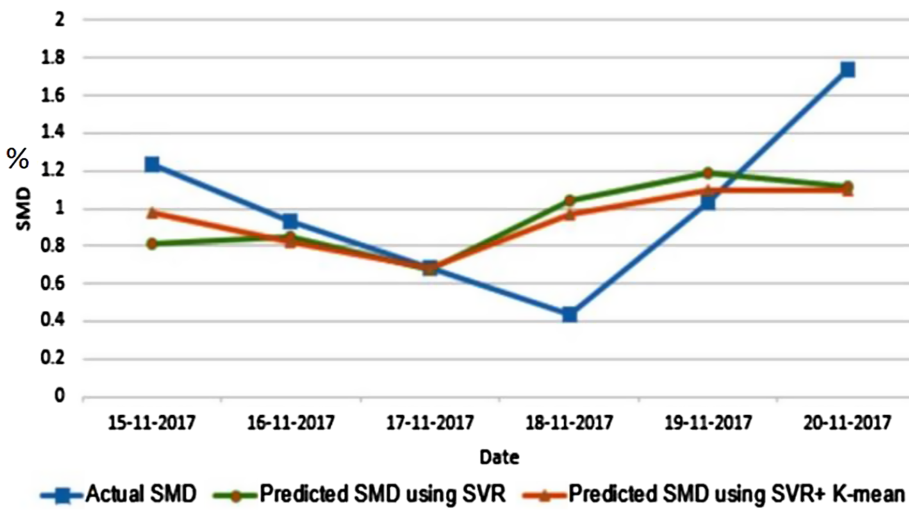

Fig. 6. Graphical representation of the results shown in Table 2.

```
    }
  Else
      {
        Send 0 to relay to stop irrigation //Signal to stop the water motor
      }
    }
  Else
    {
      Enter/Set date to start irrigation
        If (current_date > = irrigation_date) // condition to start the
    irrigation at specify date
        {
          while (TH_max > C_sm)
          {
            Send 1 to relay to start irrigation //Signal to start the water
    motor
          }
        }
        Else
        {
          Send 0 to stop irrigation //Signal to stop the water motor
        }
    }
```

3.2.3. Experimental setup

The main objective of this experiment is to collect the physical parameters of a farming land using sensors and to utilize these sensors' data along with weather forecast information for developing an algorithm for prediction of soil moisture of the upcoming days. The algorithm uses a hybrid machine learning approach, as discussed in Section 3.2, to achieve higher accuracy in soil moisture prediction. It provides a probable estimate of soil moisture to plan and provision the optimum irrigation. Statistical measures, R squared (Table 5) and Mean Squared Error (Tables 3 and 5), are used for estimation of accuracy and error rate of the proposed algorithm. The experiment shows that a good estimation (close to the actual value) of the soil moisture (Table 4), with the help of field data and forecasted information, can be utilized for optimum irrigation with an effective utilization of natural rain.

As described in Section 3.1, one field data collection device (node) has been deployed in the garden of our organization to collect the field data (Fig. 2). The data is collected at the server using the web services. Then, the data is analyzed using the proposed machine learning approach (Section 3.2.1). Further, a responsive web based interface has been developed for real-time monitoring, data visualization and decision support system, and for the scheduling of irrigation. Fig. 4 shows the GUI of responsive web based interface for real-time monitoring and decision support system, which shows the current soil moisture recorded by the sensor, and the predicted soil moisture generated by the algorithm. This information, predicted soil moisture and precipitation information, will help user/farmer in planning/scheduling of optimum irrigation.

Fig. 5 shows the GUI of irrigation planning module to schedule the irrigation by setting Irrigation Date, and Threshold Levels for Soil Moisture. It works in two modes, viz., auto, and manual, as discussed in Section 3.2.2. In manual mode, the user takes the scheduling decision based on predicted soil moisture and precipitation information. In auto mode, user sets the Soil Moisture Threshold levels, and the system automatically schedules the irrigation date based on the predicted soil moisture and weather forecast (precipitation) information. For example, if rain is expected on the scheduled irrigation date or near to scheduled date, then the system will wait for the rain and it will suspend the artificial/manual irrigation or it will start watering (if needed, based on the algorithm) the field to maintain minimum soil moisture till the arrival of rain. Further, the system can handle the changes in forecasted precipitation values.

4. Results and discussion

The smartness of the proposed system is dependent on the accuracy of the predicted soil moisture (Tables 4 and 5). To verify the accuracy of soil moisture prediction algorithm, the hourly field data for air temperature, air humidity, soil moisture, soil temperature, and UV is collected for three weeks. The three weeks' hourly data has been averaged out on per day basis and the 21 days' data is divided into a training set (70% of the data) and testing set (30% of the data) for applying the proposed algorithm. Initially, we have predicted SMD of upcoming days using the proposed algorithm (Fig. 3) and the predicted values of SMD has been used in prediction of soil moisture of upcoming days. The results are summarized in Tables 2–5.

The SVR + *k*-means approach has higher accuracy with lower mean squared error over SVR approach while calculating SMD (Table 2 and Table 3).

The graph (Fig. 6) shows that predicted SMD using proposed algorithm (SVR + k-means) is nearer to actual SMD as compared to predicted SMD using SVR only.

The SVR + *k*-means approach has the same accuracy with the lower mean squared error over SVR approach in soil moisture prediction (Tables 4 and 5). The predicted soil moisture shown in Table 4 has been calculated based on soil moisture and SMD of previous day, e.g. soil moisture on 14-11-2017 is 26.8982 then the soil moisture of the next day (15-11-2017) will be equal to the difference of soil moisture on the previous day (i.e., 14–11-2017) and SMD difference predicted for 15-11-2017 (Table 2).

From the Tables 2 and 3, we have observed that the prediction of SMD using SVR + *k*-means approach gives higher accuracy with less MSE as compared to SVR approach, and we have also observed the same accuracy (R squared = 96%) with lesser MSE in prediction of soil moisture using combined approach (SVR + *k*-means) (Table 5). It shows that the proposed algorithm (based on SVR + *k*-means) is better as compared to SVR based approach. Due to higher accuracy and minimum MSE, SVR + *k*-means based hybrid machine learning algorithm has been used in irrigation planning module.

5. Conclusion

The soil moisture is a critical parameter for developing a smart irrigation system. The soil moisture is affected by a number of environmental variables, e.g., air temperature, air humidity, UV, soil temperature, etc. With advancement in technologies, the weather forecasting accuracy has improved significantly and the weather forecasted data can be used for prediction of changes in the soil moisture. This paper proposes an IoT based smart irrigation architecture along with a hybrid machine learning based approach to predict the soil moisture. The proposed algorithm uses sensors' data of recent past and the weather forecasted data for prediction of soil moisture of upcoming days. The predicted value of the soil moisture is better in terms of their accuracy and error rate. Further, the prediction approach is integrated into a standalone system prototype. The system prototype is cost effective, as it is based on the open standard technologies. The auto mode makes it a smart system and it can be further customized for application specific scenarios. In future, we are planning to conduct a water saving analysis based on proposed algorithm with multiple nodes along with minimizing the system cost.

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