Design and Optimization of IoT Based Smart Irrigation System in Sri Lanka

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***Abstract*—In the field of agriculture, development of efficient IoT based smart irrigation system is similarly a valuable requirement for farmers. In this research, a low cost IoT and weather based smart irrigation system is developed. First, an efficient drip irrigation system which can automatically control the water supply to plants based on soil moisture conditions is developed. Next, this water efficient irrigation system is given IoT based communication capabilities to remotely monitor soil moisture conditions and to manually control water supply by a remote user. Further, temperature, humidity and rain drop sensors are integrated to the system and is upgraded to provide monitoring of these parameters by the remote user via internet. These weather parameters of the field are saved in real time in a remote database. Finally, a weather prediction algorithm is implemented to control the water supply according to the existing weather condition. The proposed smart irrigation system will provide an effective method to irrigate farmer's cultivation.**

***Index Terms*—IoT (Internet of Things), smart irrigation, drip irrigation, soil moisture condition**

I. Introduction

The innovative IoT applications can address many issues in agriculture and increase the quality, quantity, sustainability and cost effectiveness of agricultural production [1]. IoT based smart irrigation systems can further monitor soil moisture content, temperature, humidity, rainfall and other parameters in the field [2]. These data can be stored in a remote server and can be used for further processing such as in weather prediction, soil condition analysis, disease analysis etc[1]. There are some major environmental factors such as temperature, light, water, nutrient, atmosphere etc., affecting productivity of plants. One major advantage is to automate watering crops to optimize water consumption and increase productivity. Lack of water as well as over supply of water could lead to water stress of plants and also reduce the growth rate of plants. Identifying the level of water evaporation and supplying water to maintain the soil moisture level at a proper level would enhance the productivity of plants [3]. Nagarajapandian et al. [4] reported that drip irrigation allows increased efficiency of water usage by providing precise amounts of water directly to the root zone of individual plants while minimizing the evaporation. Drip irrigation roughly requires only half of the water requirement that of the sprinkler or surface irrigation. In addition, lower operating water pressures and flow rates also reduce the energy costs [4]. Therefore, a proper automated watering system is very useful in optimizing plant growth and reducing water expenses. By detecting soil moisture levels before activating the water pump the water supplied to plants can be optimized further [5]. Therefore, with the help of a soil moisture sensor based controller system with drip irrigation system could be selected as the finest water optimizing irrigation model compared to using other irrigation systems [5,6]. Therefore, at the development stage of the prototype of this research, a drip irrigation system is considered with soil moisture based controller system. Weather prediction can be used in further optimization of water resource usage in irrigation systems. Moreover, weather predictions can help to control the amount of water need to be supplied for the crops based on future weather forecasts. i.e. if the weather in near future is rainy, the amount of water supplied at the present could be reduced. In large scale agriculture, this is immensely helpful in saving water [7]. Kapoor et al. [9] and Rao et al. [8] stated that the weather prediction techniques using artificial neural networks (ANN) suffered from anomalies like local minima, noise, over fitting, computational cost and so on. A Hidden Markov Model (HMM) has been used to predict daily rainfall occurrences over Northeast Brazil and they suggested that a non-homogeneous HMM provides a useful tool for to understand the statistics of daily rainfall occurrence of large-scale atmospheric patterns [10]. With the HMM, it is possible to calculate probability of not only the weather one day ahead, but beyond that. [11]. In [12], they used HMM to forecast metrological drought. According to their results HMM provides a considerable likelihood between observed and forecasted values [12]. In [13], a HMM is used to forecast snowfall at Indian Himalaya. According to their model, it is possible to predict snowfall for two days in advance [13]. Therefore, in general weather prediction models can be learnt from collected weather data, as for our case, using the smart irrigation system. With more data, more reliable weather prediction models can be developed.

This research proposes a solution to above problems by efficiently optimizing and managing the water consumption of the plant. The main goal of this research is to implement a prototype low cost IoT and weather based smart irrigation system with capabilities of controlling and automating water supply based upon soil moisture conditions. In addition, weather parameters from the field is collected and stored in a remotely located database. Using collected weather data, such as temperature, humidity and rainfall, an investigation on local weather prediction is carried out.

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This paper is organized as follows: section II describes the methodology used. Results and discussion is explained in section III and furthermore, section IV describes the conclusion and future works.

II. Methodology

Proposed smart irrigation system has three main objectives.The overall smart irrigation system is shown in Fig 1.

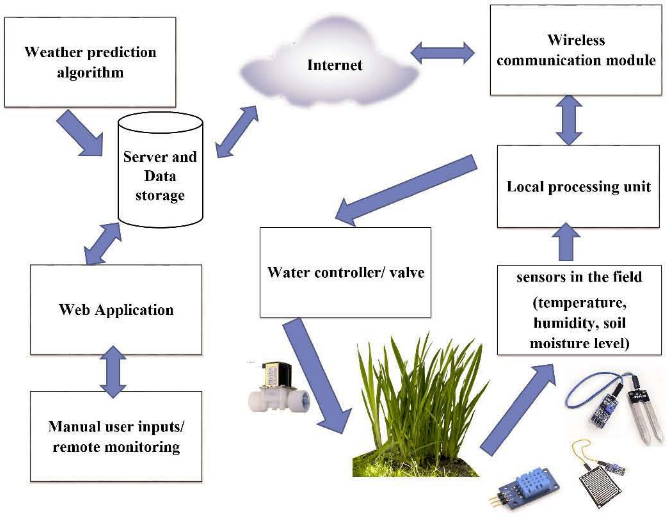


Fig. 1. Components of the proposed IoT based smart irrigation system

A. Implementing IoT based prototype irrigation system

Prototype irrigation system is implemented with equipment's of the water supply control unit, soil moisture sensing unit, Wi-Fi communication unit and local processing unit. IoT is enabled with Wi-Fi communication unit (Node Mcu).

B. Implementing a database to store agricultural/ weather parameters

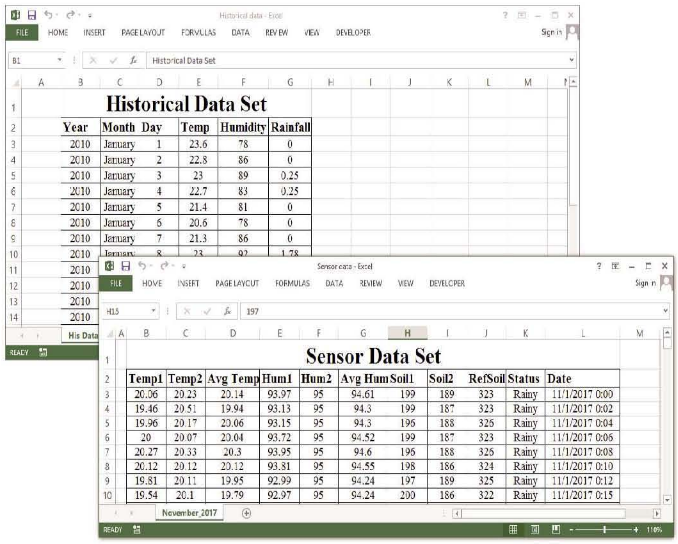
A web application using HTML and PHP is developed to access and control the IoT based smart irrigation system. A remote database is setup to store local agricultural/ weather parameters such as soil moisture level, temperature and humidity which are received from the field in every two minutes. With the user interface of the web application, user can,

- Control the water valve by simply changing the Mode selection
- Monitor real time weather conditions in the field
- Monitor current status of the water valve
- Download historical data of the field into an excel file
- Access this web interface with a personal computer or a smart mobile phone

C. Investigating weather forecasting model

Historical weather data set and sensor weather data set (collected by implemented IoT based irrigation system) were used to evaluate weather forecasting. The sample of historical data set and sensor data set is shown in Fig 2. In this research, three types of algorithm are tested. The flow of the tested algorithms is shown in Fig 3. Here weather forecasting is separated into two sections.

i Rainfall prediction (daily basis).
ii Temperature, humidity and soil moisture prediction (hourly basis)



Historical Data Set

Year	Month	Day	Temp	Humidity	Rainfall
2010	January	1	23.6	78	0
2010	January	2	22.8	86	0
2010	January	3	23	89	0.25
2010	January	4	22.7	83	0.25
2010	January	5	21.4	81	0
2010	January	6	20.6	78	0
2010	January	7	21.3	86	0
2010	January	8	23	92	1.78
2010					
2010					
2010					
2010					

Sensor Data Set

Temp1	Temp2	Avg Temp	Hum1	Hum2	Avg Hum	Soil1	Soil2	RefSoil	Status	Date
20.06	20.23	20.14	93.97	95	94.61	199	189	323	Rainy	11/1/2017 0:00
19.46	20.51	19.94	93.13	95	94.3	199	187	323	Rainy	11/1/2017 0:02
19.96	20.17	20.06	93.15	95	94.3	196	188	326	Rainy	11/1/2017 0:04
20	20.07	20.04	93.72	95	94.52	199	187	323	Rainy	11/1/2017 0:06
20.27	20.33	20.3	93.95	95	94.6	196	188	326	Rainy	11/1/2017 0:08
20.12	20.12	20.12	93.81	95	94.55	198	186	324	Rainy	11/1/2017 0:10
19.81	20.11	19.95	92.99	95	94.24	197	189	325	Rainy	11/1/2017 0:12
19.54	20.1	19.79	92.97	95	94.24	200	186	322	Rainy	11/1/2017 0:15

Fig. 2. Historical data set and Sensor data set

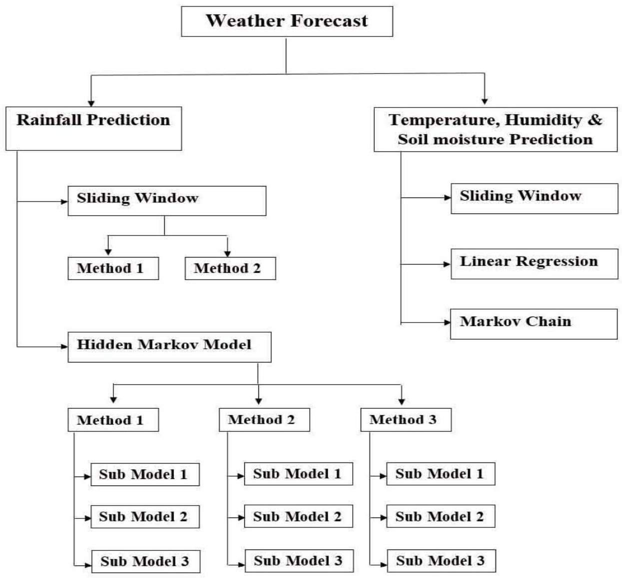


Fig. 3. Flow chart of tested weather prediction algorithms

1) Rainfall prediction with Sliding Window:

Proposed Sliding Window algorithm is evaluated for different window sizes from one to fifteen.

$$R_s = NextVal\left[{}^{Min}_{NPW_x} \left|\left|NCW_s - NPW_x\right|\right|\right] \tag{1}$$

Method 1:

$$R_{forecast} = R_s + PV \tag{2}$$

Method 2:

$$R_{forecast} = R_s \tag{3}$$

NCW: Normalized current year window
NPW: Normalized past data window
NextVal: a function output next day rainfall value of PW_x (non-normalized past data window) corresponding to Min(NPW_x) is given a rainfall value (R_s) of CW (non normalized current year window)
PV: Predicted variation

R_s: Predicted rainfall value by the algorithm

2) Rainfall prediction with Hidden Markov Model(HMM): Three types of HMM are evaluated and three sub models are evaluated under each type of HMM.
Three types of HMM models are,

- HMM type 1 (Method 1): Two states 1st order model
  - Two states are rainy day and dry day
- HMM type 2 (Method 2): Four states 1st order model
  - Four states are No Rain (Dry day), Low Rain, Medium Rain and Heavy Rain
- HMM type 3 (Method 3): Two states 2nd order model
  - Two states are rainy day and dry day

Three types of sub-models are,

- Sub-Model 1
  - State transition matrix is fixed for every day (use historical data sets from year 2010 to 2016)
  - Emission probability parameters are fixed for every day (μ,σ)
- Sub-Model 2
  - State transition matrix is fixed for every month(use historical data sets from year 2010 to 2016)
  - Emission probability parameters are fixed for every month(μ,σ)
- Sub-Model 3
  - State transition matrix is changed dynamically for every day (use N number of past data of the current year to calculate state transition matrix)
  - Emission probability parameters are fixed for every month (same as sub model 2)

Simplified version of HMM is given by,

$$(S_n|S_{n-1},T_{n-1},H_{n-1}) = \left(\frac{(T_{n-1}|S_n)}{P(T_{n-1})} * (S_n|S_{n-1})\right) * \left(\frac{(H_{n-1}|S_n)}{P(H_{n-1})} * (S_n|S_{n-1})\right) \quad (4)$$

S_n: State of today
S_{n-1}: State of yesterday
T_{n-1}, H_{n-1}: Observations of yesterday

3) Temperature, Humidity and Soil Moisture Prediction: The greenhouse cultivation can be increased by properly maintaining the temperature, humidity because they play a critical role in the greenhouse [14]. Therefore, next hour temperature, humidity and soil moisture level are predicted for further analysis of greenhouse model. In this research, three algorithms are tested to predict temperature, humidity and soil moisture levels. These algorithms are Sliding Window algorithm, Linear Regression and Markov chain (Gaussian). Three models described below are used to predict next hour temperature(t_s). Models are evaluated for different window sizes from one to twenty-one.

1) Sliding Window

$$t_s = NextVal\Big[^{Min}_{T_x} ||T_s - T_x||\Big] \quad (5)$$

Here,
t_s:Next hour temperature
T_s:Current temperature window
T_x:Past temperature data window
NextVal:A function output next time interval given a temperature window T_s

2) Linear Regression

$$t_s = \beta_1 t_{s-1} + \beta_2 t_{s-2} + ... + \beta_L t_{s-L} = \sum_{i=1}^{L} \beta_i t_{s-i} \quad (6)$$

Here,
t_s:Next hour temperature
L:Number of dependent variables
β_i:Weights

3) Markov Chain(Gaussian)

$$t_s = \mathcal{N}\Big(\sum_{i=1}^{L} \beta_i t_{s-i}, \sigma^2\Big) \quad (7)$$

Here,
t_s:Next hour temperature
L:Number of dependent variables
β_i:Weights
σ^2:Variance of training data set

III. Results and Discussion

The implemented web interface of IoT based smart irrigation system is shown in Fig. 4 and it is hosted in a '000Webhost' free web domain.

Fig. 4. Web interface of IoT based smart irrigation system

Fig.5 illustrates the True Positive Rate (TPR) and False Positive Rate (FPR) of 'Method 1' employed in weather prediction stage of which, the window size (WS) 10 shows an accuracy of 85% in predicting rainy day as a rainy day. Moreover, 'Method 2' has reached its maximum prediction accuracy of 71% at window size 3 in predicting dry day as a dry day. Fig.6 shows the accuracy of predictions for different window sizes for 'Method 2'(maximum, minimum and intermediate WS). Run-time result of Sliding Window algorithm (WS 10) for January 2017 is shown in Fig.7.

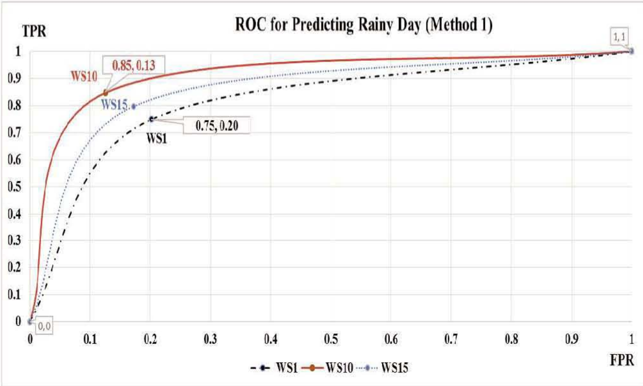


Fig. 5. TPR vs FPR of Sliding Window Method 1

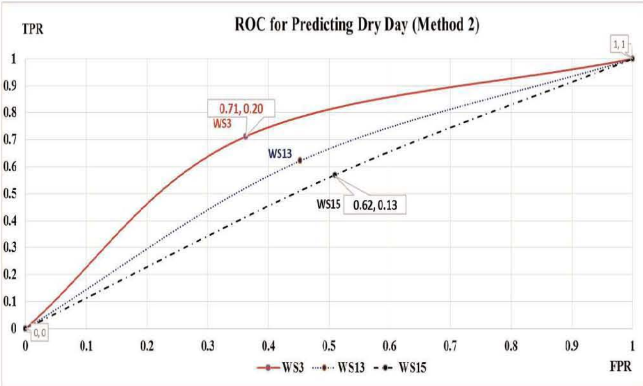


Fig. 6. TPR vs FPR of Sliding Window Method 2

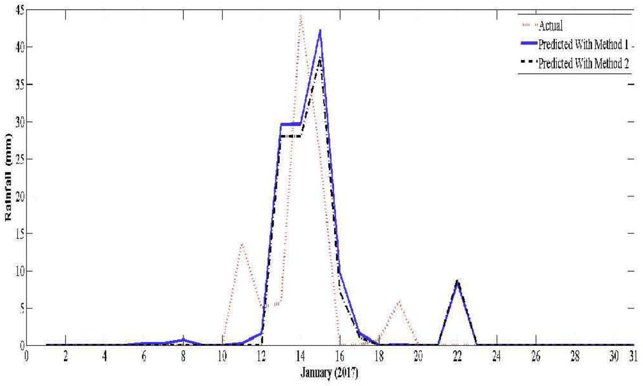


Fig. 7. Run-time Sliding Window algorithm for WS 10

Fig.8 illustrates the performance of 'HMM Type 1' (Method 1) for different sub models in weather prediction for rainy day. 'Sub model 2' projects the best performance value as 75.5% for predicting a rainy day as a rainy day. Fig.9 illustrates prediction accuracy of the sub models for predicted day being a dry day. According to the results, 'Sub model 1' exhibits the maximum accuracy of 89.5% in predicting a dry day as a dry day.

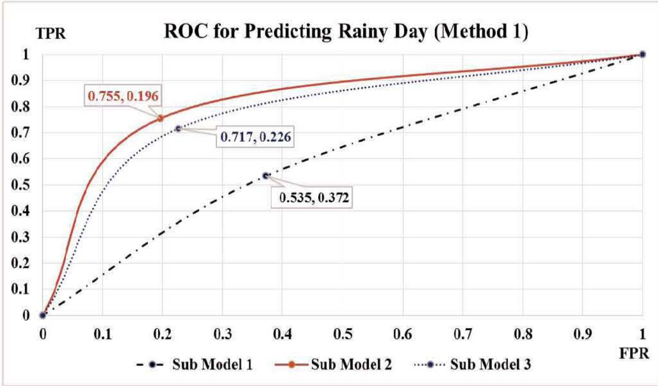


Fig. 8. TPR vs FPR of HMM Method 1 for predicting rainy day

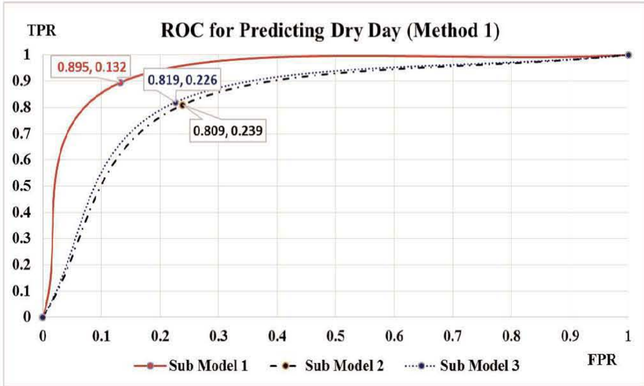


Fig. 9. TPR vs FPR of HMM Method 1 for predicting dry day

Fig.10 illustrates accuracy of weather prediction with sensor data collected by implemented IoT based irrigation system. The 'Sub Model 2' of HMM 'Method 1' is used to predict weather condition for November 2017 with sensor data. According to the results, the prediction accuracy of predicted day being rainy day or dry day is 76% (22 days are correctly predicted out of 29 days)

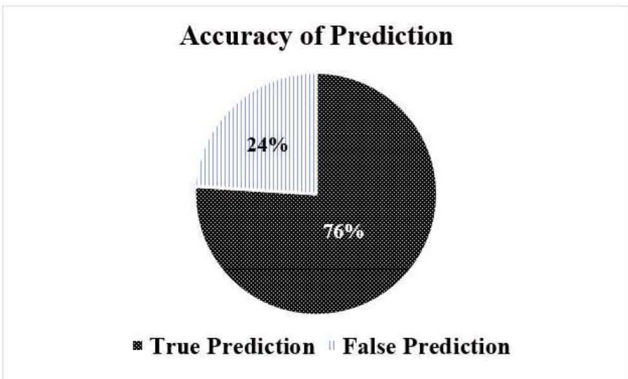


Fig. 10. Accuracy of weather prediction with sensor data

According to the tabulated results in Table 1, Linear Regression model is the best model for predicting next hour temperature and humidity. Sliding window model is the best model for predicting next hour soil moisture level.

TABLE I
BEST ACCURACY OF THE PREDICTION MODELS

	Best Window Size	Lowest Prediction Error	Best Algorithm
Temperature Prediction C°	1	0.5	Linear Regression
Humidity Prediction %	4	1.5	Linear Regression
Soil Moisture Prediction %	2	0.9	Sliding Window

IV. CONCLUSION

The proposed IoT based smart irrigation system has the capability of regulating soil moisture level as per requirement and user can remotely monitor, control, and collect data through the online website. When considering all weather prediction models tested in this research, the both Sliding Window algorithm and HMM cannot provide an the acceptable level of prediction accuracy for rainfall (in ml). However, by adding more weather parameters other than temperature and humidity, this accuracy could be improved. The maximum TPR for rainy day is given by Sliding Window algorithm (85%) with window size 10 of Method 1 and the maximum TPR for dry day is given by HMM (89.5%) with Sub Model 1 of Method 1. Linear Regression model is the best model to predict temperature and humidity for next hour and Sliding Window model is the best model to predict soil moisture level for next hour. The proposed smart irrigation system is significantly useful for Sri Lankan agriculture as it helps to optimize the water consumption. Despite the accuracy of weather prediction, valve is controlled to provide only the required amount of water to each plant there by, eliminating the wastage of water. Moreover, it will reduce the overall electricity consumption as well.

There are some modification left to do in future for this research such as, enhancing Sliding Window algorithm to predict the rainfall amount by adding extra features like density of clouds by taking cloud images, satellite images etc. Enhance HMM to predict hourly states (rainy hour or dry hour) instead of predicting one state for whole day. Enhance LPU system to work with low power and also to power the system via solar power to be implemented the system in areas with difficulty accessing grid power.

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