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Design and Development of an IoT Based Intelligent Controller for Smart Irrigation

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Abstract Internet of Things (IoT) is a rapidly developing area in the world because users can enormously benefit from real-time monitoring and controlling of remotely located devices over the internet, without being physically present at the location of the device. In the field of agriculture, development of efficient IoT based smart irrigation systems are similarly a valuable requirement for farmers, because they can remotely monitor crops and remotely control parameters in the field such as water supply to plants and collect data for further research purposes. In this research, a low cost IoT and weather based intelligent controller 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. This system brings greater benefits in terms of saving water, compared to traditional pre-scheduled watering systems. 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 with different features. 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 IoT based intelligent controller system will provide an effective method to irrigate farmer's cultivation.

Keywords: *IoT (Internet of Things), smart irrigation, drip irrigation, soil moisture condition, weather prediction*

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1. Introduction

Internet of Things (IoT) allows networked devices to sense and collect data from the world around us, and share that data across the internet, where it can be processed and utilized for various interesting purposes. IoT in agriculture industry and horticulture can greatly benefit farmers and gardeners by providing remote monitoring, controlling and data collection capabilities. 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 level 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]. In our research, therefore, in development of the prototype, a drip irrigation system is considered with soil moisture based controller system.

IoT has recently become an important technology which allows number of networked devices to communicate through the Internet and understand each other [7]. In agriculture, IoT helps to increase crop productivity by managing and controlling the water supplies in an efficient way. In areas of drought condition, IoT can prove that limited water supply can be smartly managed with least wastage of water resources [1]. Soil moisture sensors, temperature & humidity sensors, digital camera, etc. are commonly used to get environmental information in the field and send them to the webserver with the helps of IoT [8,1,2]. In most research in the literature, wireless sensor networks (WSN) have been used to accumulate environmental information in different locations. Most commonly used WSNs are Wi-Fi and ZigBee [8,9]. The power consumption of the ZigBee network is comparatively very low [8,9]. Therefore, even using AA type alkaline batteries, WSN can be energized for a long period [8]. Therefore, ZigBee network is suitable for a land where it is difficult to access main grid power and need to operate with minimum power, using a solar cell or a battery bank [8]. Raspberry Pi or Arduino Mega or Arduino Uno microcontrollers are commonly used to activate the water pumps through the relays. Furthermore, a GSM module or a Wi-Fi module can be used to access the Internet for fulfilling IoT purposes [1,2,7,8,9]. MySQL database is used in most of the recent research to store data, received from WSN [7,8,9] and some of them use 'ThingSpeak' free website as IoT interface [2]. In this research, NodeMCU Wi-Fi modules are used for IoT purposes and MySQL database is used for sensor data storing. Web interface has been designed using PHP scripting language. Major advantage of proposed IoT application is, user has several options to activate the water pumps according to their choices.

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 [10]. Kapoor et al. [12] and Rao et al. [11] 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 [13]. With the HMM, it is possible to calculate probability of not only the weather one day ahead, but beyond that. [14]. In [15], they used HMM to forecast metrological drought. According to their results HMM provides a considerable likelihood between observed and forecasted values [15]. In [16], 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 [16]. 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 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.

2. Implementation of Prototype Irrigation System

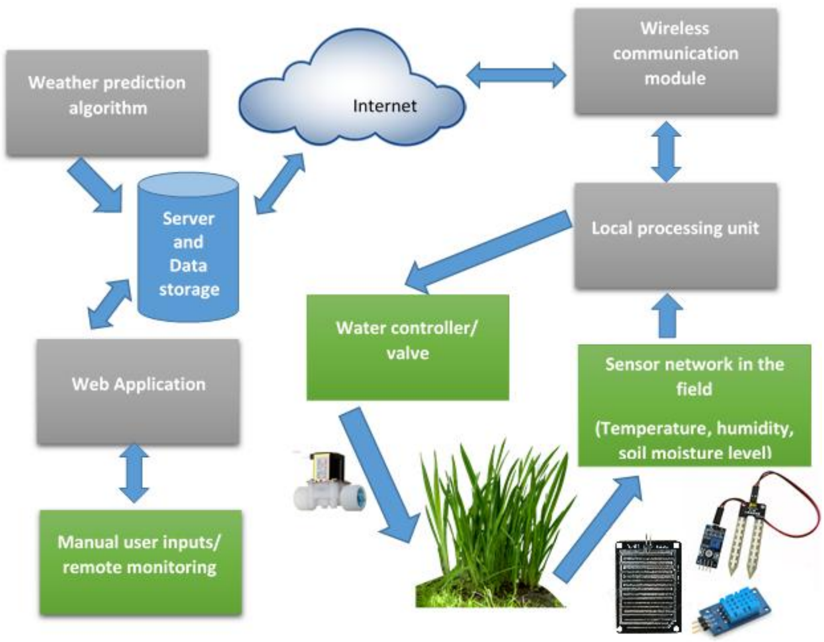


Figure 1. Components of the proposed IoT based smart irrigation system

A block diagram of overall proposed irrigation system is shown in Figure 1. As illustrated in Figure 1, temperature sensors, humidity sensors, soil moisture sensors and rain drop sensor deployed in the field will send information to the Local Processing Unit (LPU). These sensor data collected by LPU are transmitted via a wireless communication module to a local wireless internet router / internet gateway and communicate to a remote webserver through internet.

Technically overall irrigation system can be divided into two sections because of one part of the system is functioning on the server side and other part of the system is functioning on the field with the help of LPU. So the overall system can be denoted as the combination of the 'server based subsystem' and 'controller based subsystem'.

The structure of controller based system is further illustrated in Figure 2. LPU is connected to the sensors, communication modules and water valve controlling unit through the sensors/modules plugging board. Sensors/ modules plugging board makes it easier to extend the system by plugging more sensors/modules as required in future and/or to replace damaged sensors/modules. The LPU is working with 5V DC supply, provided using step down transformer and a rectifier unit having an output voltage level of 5V DC. Sensors and communication modules get power from the LPU and the water valve controlling unit gets power from 12V DC power supply.

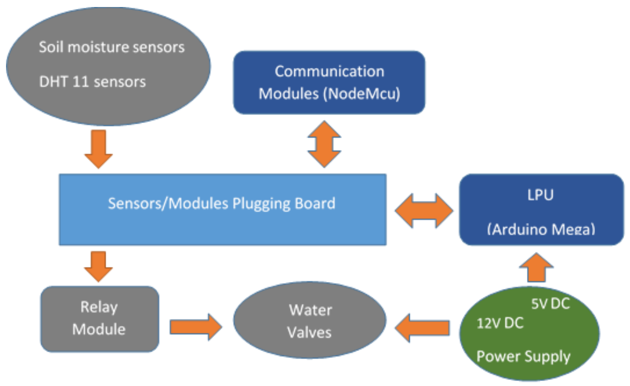


Figure 2. Structure of the Controller based subsystem

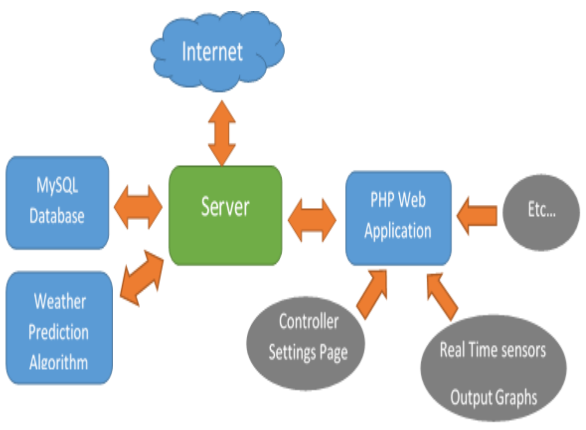


Figure 3. Structure of the server based subsystem

Structure of server based subsystem of the IoT based irrigation system is shown on Figure 3. Communication to the outside world is done through the communication modules (NodeMcu which shows on Figure 3) which connect to the local internet gateway/internet router and share data through the internet. A website is developed using PHP script language with the MySQL database connection. For the hosting purposes, here 000webhost server is used. 000webhost server is freely available on the internet and one major disadvantage of this free webserver is, the connection between webserver and the user may be disconnected due to a heavy network traffic in some occasions.

3. Web Interface and Valve Control Program

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 is received from the field every two minutes. The implemented web interface is shown in Figure 4.

With this 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 (On or Off)
- Download historical data of the field into an excel file
- Access this web interface with a personal computer or a smart mobile phone

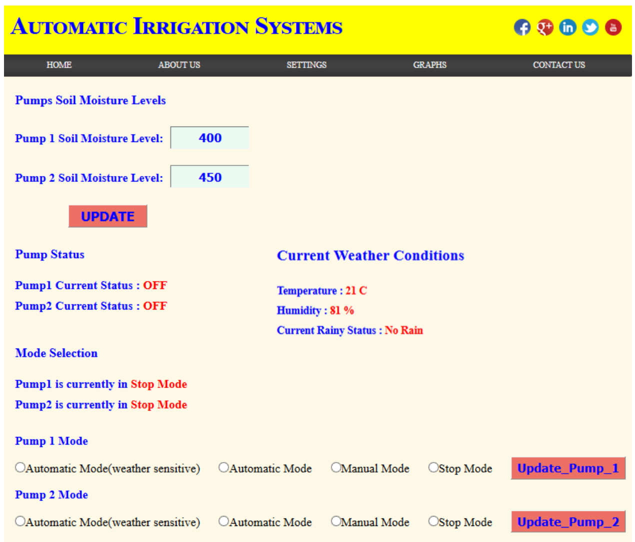


Figure 4. Web interface of IoT based smart irrigation system

The main program of LPU predominantly contains the water valve control algorithm. Four options are available for the user to control the water valve. User can select the option via the web application shown in in Figure 4. LPU will receive the selected option on the web page and control the water valve according to the relevant option.

3.1. Automatic Mode 1 (Weather Sensitive Mode)

In this mode LPU is checking the current soil moisture levels before activating water valve. User can set the minimum soil moisture level. If a weather prediction algorithm can provide the probability of rain, then this information can also be integrated to the program. As an example, if raining probability (P) is greater than 75%, then automatically turn on the water valve and supply water to plants until soil moisture level is 25% of required soil moisture level (M) i.e. 0.25*M. In this way, until rain will start, the plant will be without water stress but also saves water during rain. The program of this automatic mode 1 is shown in Figure 5.

M is required soil moisture level (define by user according to crop type)

X is current soil moisture level (measured using soil moisture sensor)

Z is mode identification number (0 for the automatic mode 1).

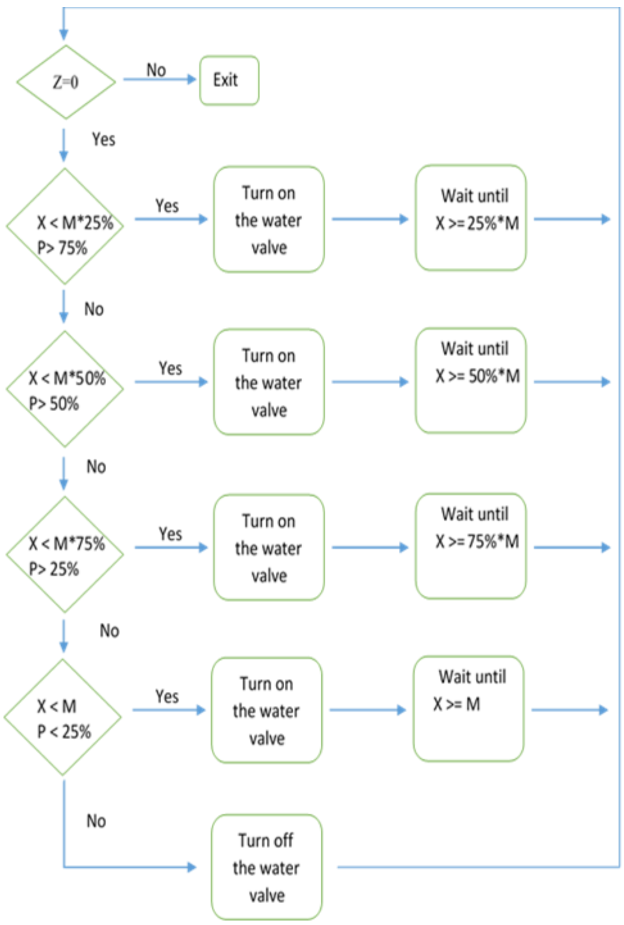


Figure 5. Flow chart of the program of the automatic mode 1

3.2. Automatic Mode 2

In this mode LPU is checking the soil moisture levels and if it is less than half of the required level then LPU will send the signal to the relay to turn on the water valve. The program of this automatic mode 2 is shown in Figure 6. In this mode, LPU is checking soil moisture level of the plants and once they reach to the M/2 value, then LPU automatically turn on the valve and wait until soil moisture level become M and also again wait until soil moisture level become M/2 for watering. This process continuously will happen until change of the operating mode.

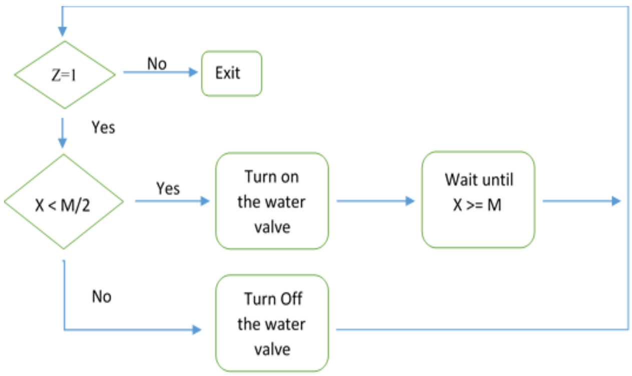


Figure 6. Flow chart of the program of the automatic mode 2

3.3. Manual Mode

In this mode LPU directly turn on the water valve without considering the soil conditions and weather condition. The user can turn on/off the water valve manually over the internet as desired. The program of this manual mode is shown in Figure 7.

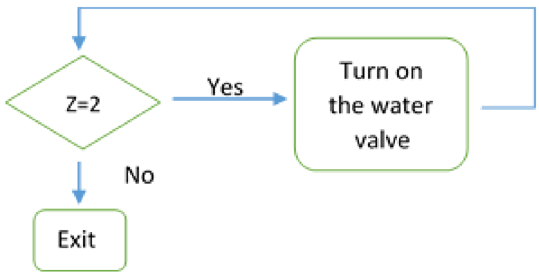


Figure 7. Flow chart of the program of the manual mode

3.4. Stop Mode

In this mode LPU directly turn off the water valve and waits until this mode is changed to another mode. The program of this stop mode is shown in Figure 8.

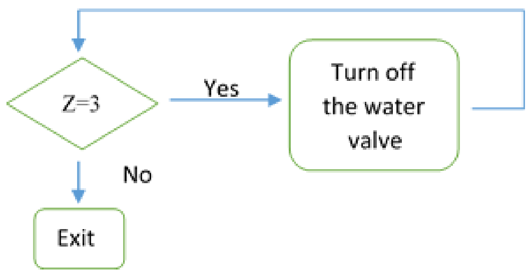
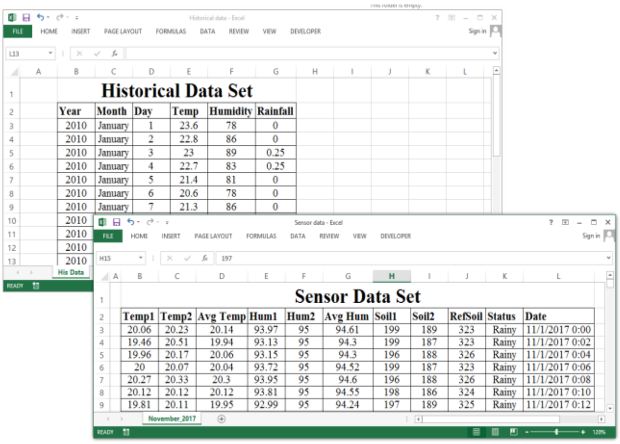


Figure 8. Flow chart of the program of the stop mode

4. Investigating Weather Forecasting Models

Historical weather data set and sensor weather data set (collected by implemented IoT based irrigation system) were used to evaluate weather forecasting. Historical data set and sensor data set is shown in Figure 9.



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					
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

Figure 9. Historical data set and Sensor data set

In this research, three types of algorithm are tested. The flow of the tested algorithms is shown in Figure 10. Here weather forecasting is separated into two sections.

1. Rainfall prediction (daily basis).
2. Temperature, humidity soil moisture prediction (hourly basis)

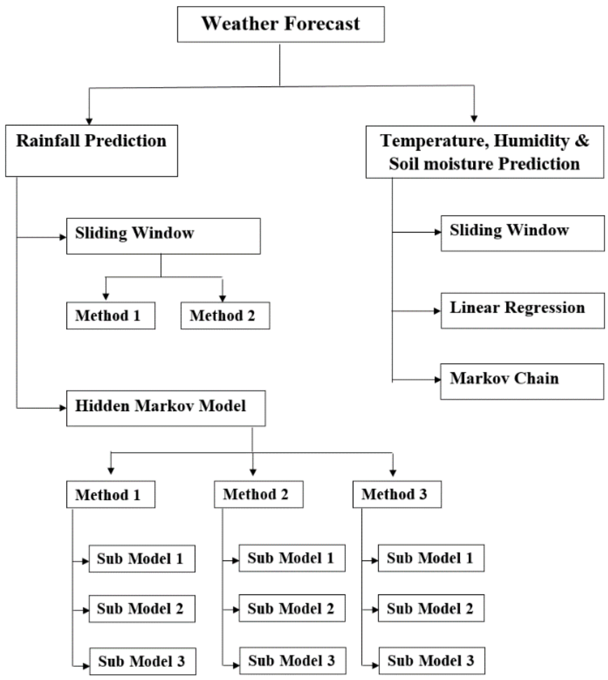


Figure 10. Flow chart of tested weather prediction algorithms

4.1. Rainfall Prediction with Sliding Window Algorithm

In this research for weather prediction, firstly Sliding Window algorithm is adjusted according to the current problem. The historical data set is separated into training set (2010-2016 weather data) and test set (2017 weather data). After that, proposed Sliding Window algorithm is evaluated for different window sizes from one to fifteen.

$$R_s = NextVal\left[\min_{NPW_x} NCW_s - NPW_x\right]. \tag{1}$$

Where, R_s – Rainfall value of s^{th} day

$$NCW_s = \begin{bmatrix} T_{s-1} & H_{s-1} & R_{s-1} \\ T_{s-2} & H_{s-2} & R_{s-2} \\ \vdots & \vdots & \vdots \\ T_{s-N} & H_{s-N} & R_{s-N} \end{bmatrix} \tag{2}$$

$$NPW_x = \begin{bmatrix} T_{x-1} & H_{x-1} & R_{x-1} \\ T_{x-2} & H_{x-2} & R_{x-2} \\ \vdots & \vdots & \vdots \\ T_{x-N} & H_{x-N} & R_{x-N} \end{bmatrix}. \tag{3}$$

Method 1:

$$R_{forecast} = R_s + P_V \tag{4}$$

Method 2:

$$R_{forecast} = R_s \tag{5}$$

N: Window size
T: Normalized Temperature
H: Normalized Humidity
R: Normalized Rainfall Value
NCW: Normalized Current year window
NPW: Normalized Past data window
PV: Predicted variation
Rs: Predicted rainfall value by the algorithm.

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).

4.2. Rainfall Prediction with 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 model are,

- Sub Model 1
  - State transition matrix is fixed for every day (use historical data sets 2010 – 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 2010 – 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,

$$P(S_n \mid S_{n-1},T_{n-1},H_{n-1}) = \left(\frac{P(T_{n-1} \mid S_n)}{P(T_{n-1})} \times P(S_n \mid S_{n-1})\right) \times \left(\frac{P(S_n \mid H_{n-1})}{P(H_{n-1})} \times P(S_n \mid S_{n-1})\right). \quad (6)$$

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

The emission probabilities can be calculated using the below equation (7) when the standard deviation (σ) and mean (μ) of the distribution are known. Here, O_{n-1} is yesterday observation. Standard deviation and mean can be calculated for every month using historical data.

$$P\left(\frac{O_{n-1}}{S_n}\right) = \frac{1}{\sigma\sqrt{2\pi}} * e^{\frac{-[x-\mu]^{\wedge}2}{\sigma^{\wedge}2}}. \quad (7)$$

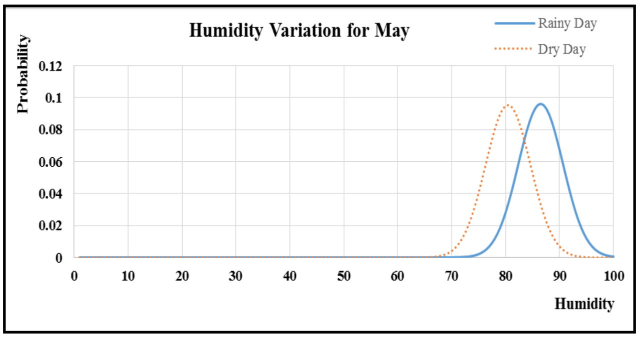


Figure 11. Humidity variation with rainy day and dry day P(Hn-1|Sn)

Figure 11 shows the variation of humidity with rainfall for May. Blue color curve shows how the rainy days vary with previous day average humidity value and brown color curve shows how the dry days vary with the previous day average humidity value.

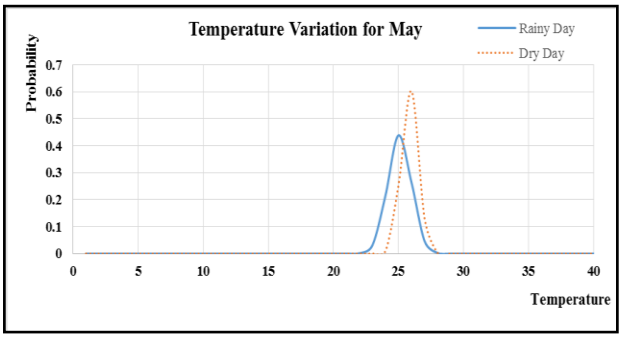


Figure 12. Temperature variation with rainy day and dry day P(Tn-1|Sn)

Figure 12 shows the variation of temperature with rainfall for May. Blue color curve shows how the rainy days vary with the previous day average temperature value and brown color curve shows how the dry days vary with previous day average temperature values.

4.3. 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 [17]. 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 (SW), Linear Regression (LR) and Markov chain (MC). 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

$$t_s = Next\ Val\left[\min_{T_x} \|T_s - T_x\|\right] \quad (8)$$

Where t_s – temperature of s^{th} time interval

$$T_s = \begin{bmatrix} t_{s-1} \\ t_{s-2} \\ t_{s-3} \\ \vdots \\ t_{s-L} \end{bmatrix}; T_x = \begin{bmatrix} t_{x-1} \\ t_{x-2} \\ t_{x-3} \\ \vdots \\ t_{x-L} \end{bmatrix}. \quad (9)$$

L: Window size
T_s: Test data window
T_x: Training data window
Next Val: a function output next time interval given a temperature window T_s

2) Linear Regression

$$t_s = \beta_1 t_{s-1} + \beta_2 t_{s-2} + \ldots + \beta_L t_{s-L} = \sum_{i=1}^{L} \beta_i t_{s-i} \quad (10)$$

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

3) Markov Chain (Gaussian)

$$t_s = N\left(\sum_{i=1}^{L} \beta_i t_{s-i}, \sigma^2\right). \quad (11)$$

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

5. Performance Evaluation of Weather Prediction Algorithms

Figure 13 illustrates the True Positive Rate (TPR) and False Positive Rate (FPR) of the 'Method 1' employed in weather prediction stage with Sliding Window algorithm, the window size (WS) 10 shows an accuracy of 85% in predicting rainy day as a rainy day. Figure 14 shows the accuracy of predictions for dry day with 'Method 1' and maximum accuracy is given by WS 1 (69%). Run-time result of Sliding Window algorithm (WS 10) for January 2017 is shown in Figure 15. Moreover, 'Method 2' has reached its maximum prediction accuracy of 71% at window size 3 in predicting dry day as a dry day and Figure 17 shows the result of predictions. Figure 16 shows the accuracy of predictions for rainy day being rainy day and maximum accuracy is given by WS 4 (75%).

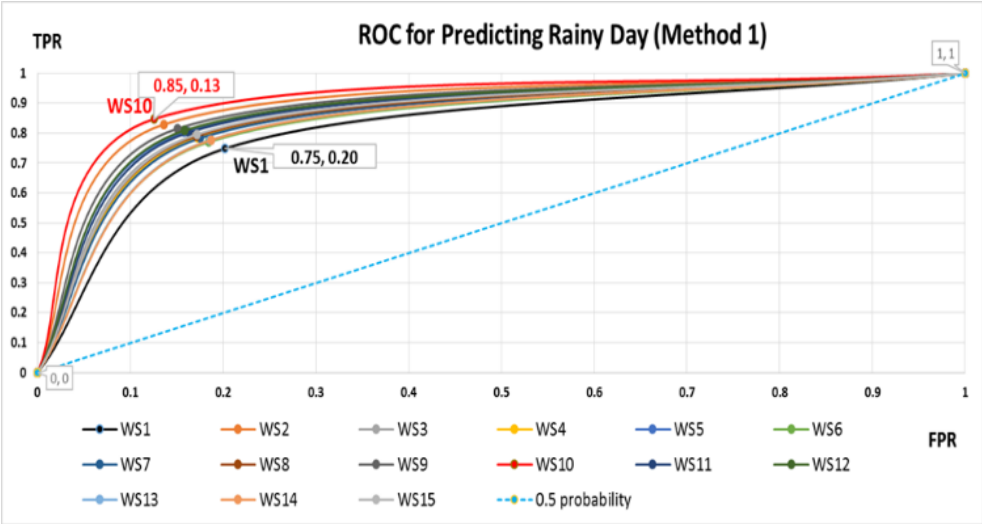


Figure 13. TPR vs FPR of SW Method 1 for rainy day

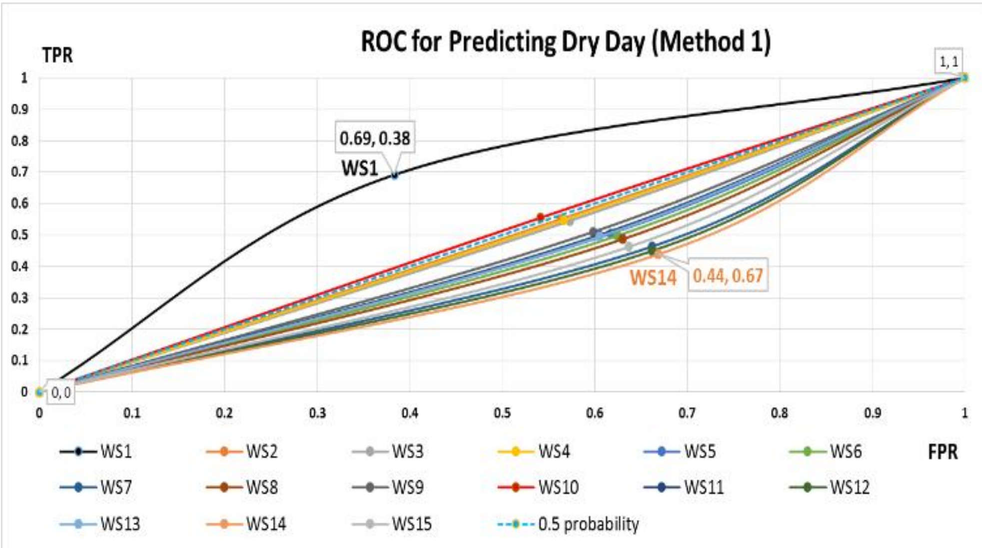


Figure 14. TPR vs FPR of SW Method 2 for dry day

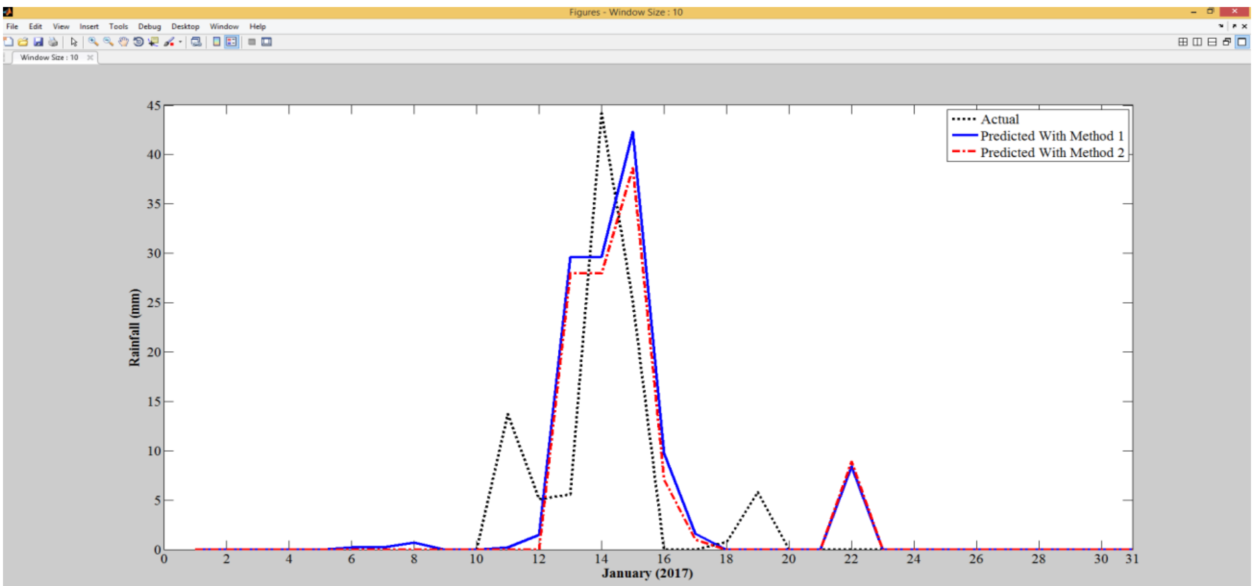


Figure 15. Run-time Sliding Window algorithm for WS 10

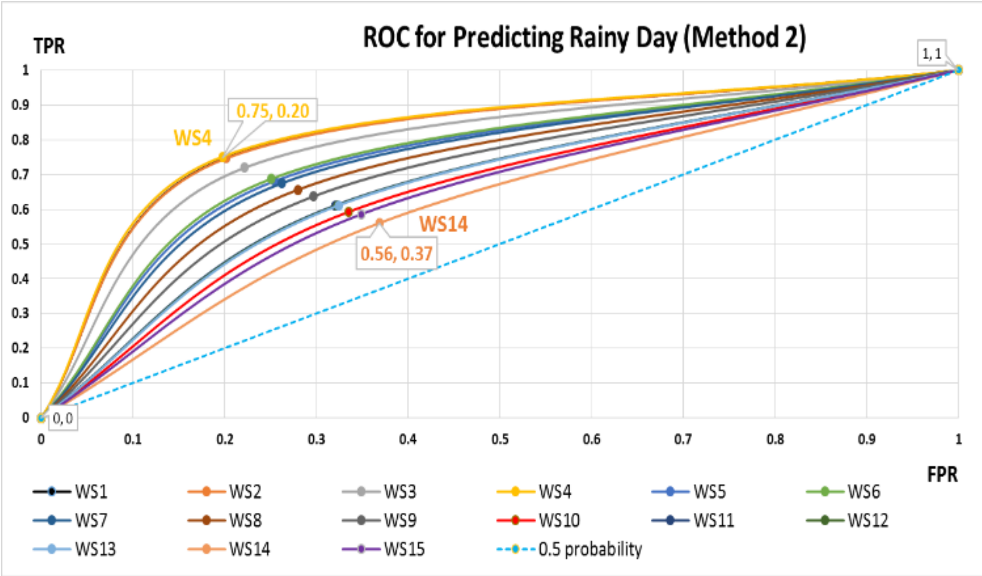


Figure 16. TPR vs FPR of SW Method 2 for rainy day

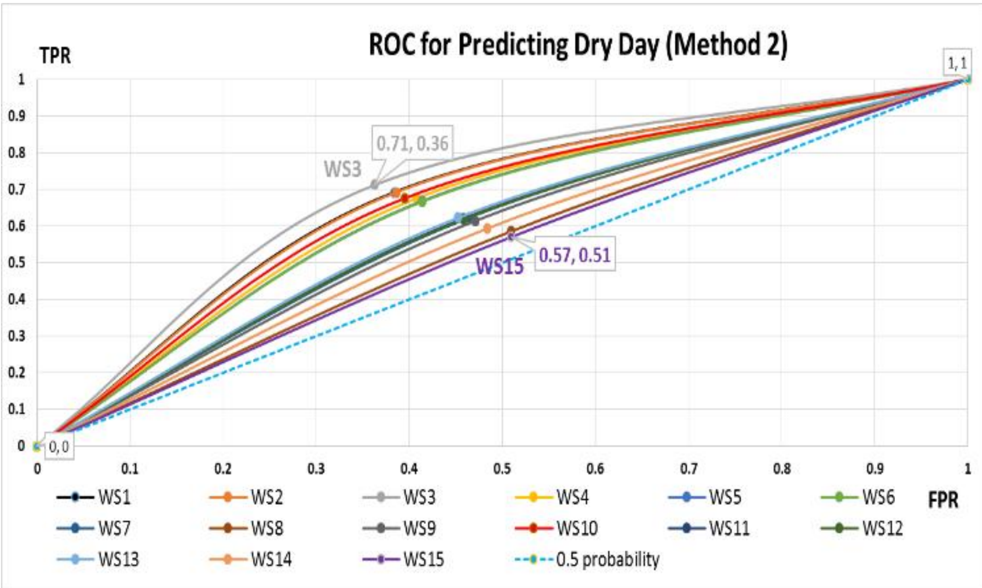


Figure 17. TPR vs FPR of SW Method 2 for dry day

Table 1 shows overall weather prediction accuracy of HMM. According to the results, 'Method 1' has the highest weather predicting accuracy and 'Method 3' has the second highest weather predicting accuracy. In 'Method 1', the proposed HMM evaluates the predicted day being rainy day or dry day since 'Method 1' is two states 1st order HMM. According to the results in Table 1, 'Sub Model 2' of 'Method 1' has the highest predicting accuracy (78.5%).

Table 1. Weather prediction accuracy of HMM

	Method 1 Accuracy	Method 2 Accuracy	Method 3 Accuracy
Sub Model 1	73.50%	72.30%	76.80%
Sub Model 2	78.50%	67.00%	76.50%
Sub Model 3	77.40%	67.60%	74.30%

Figure 18 illustrates the performance of ROC curve 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.

Figure 19 illustrates prediction accuracy of the sub models for predicted day being a dry day together with 'Method 1'. According to the results, 'Sub model 1' exhibits the maximum accuracy of 89.5% in predicting a dry day as a dry day.

Figure 20 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).

Figure 21 shows the temperature prediction errors for SW, LR & MC models. According to the results, LR model has a lowest temperature prediction errors than other two models. In LR model, window size 1 has a lowest temperature prediction error (0.5±0.8℃). Therefore, LR model with window size 1 is capable to be predicted temperature in next hour more accurately.

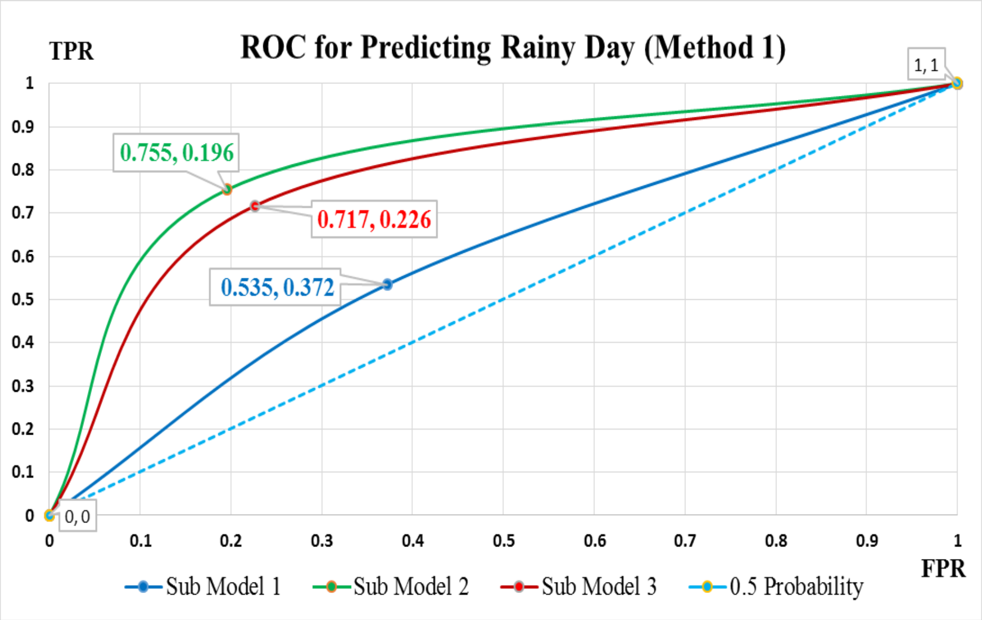


Figure 18. ROC curve for HMM Method 1 predicting rainy day

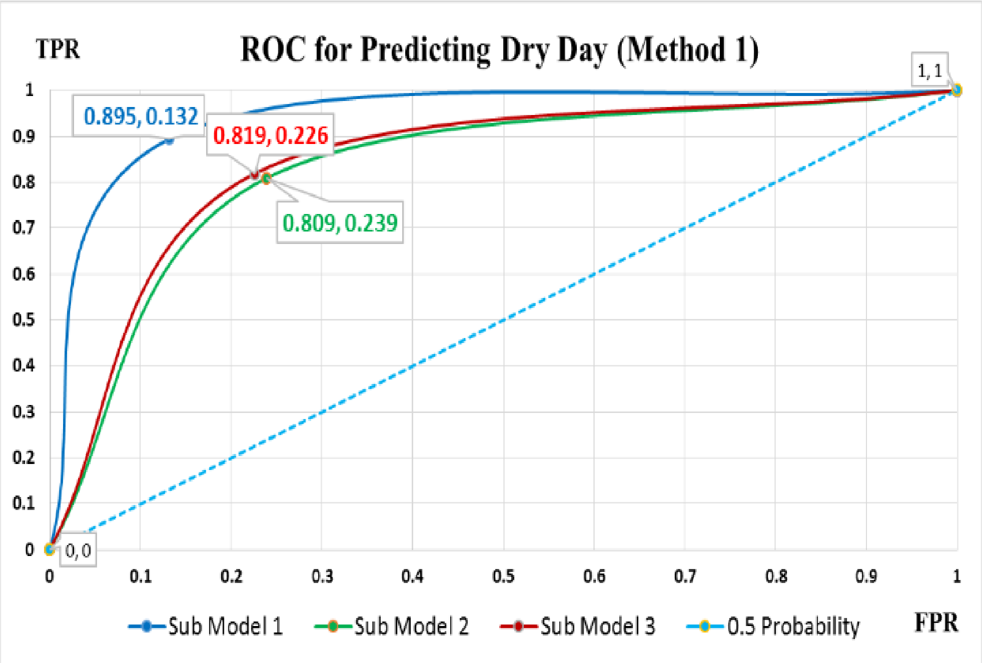


Figure 19. ROC curve for HMM Method 1 predicting dry day

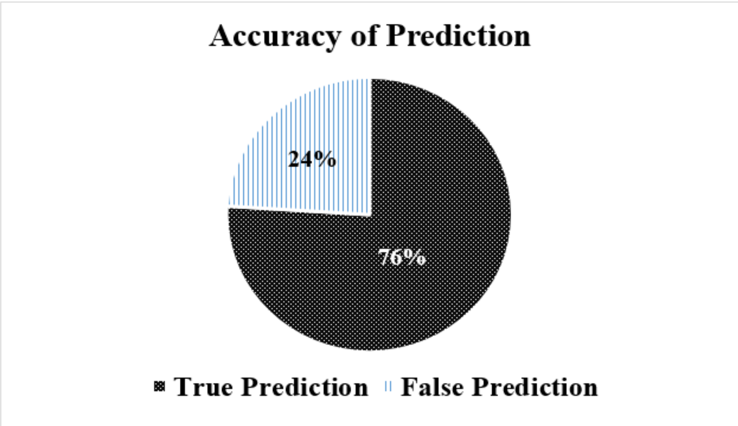


Figure 20. Accuracy of weather prediction with sensor data

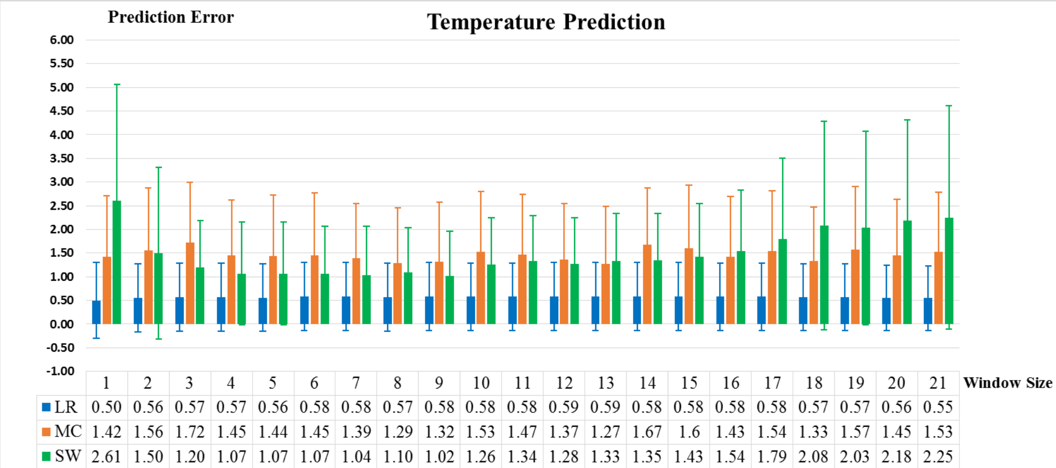


Figure 21. Temperature prediction errors

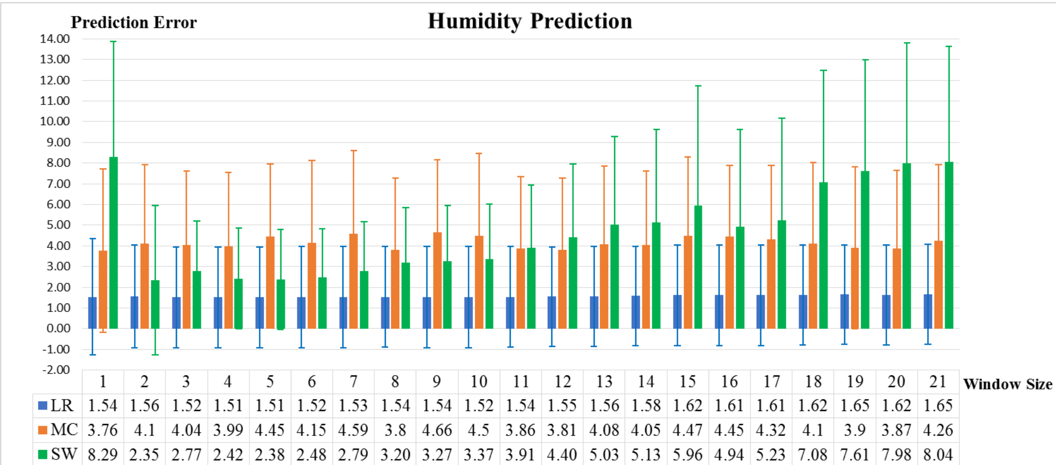


Figure 22. Humidity prediction errors

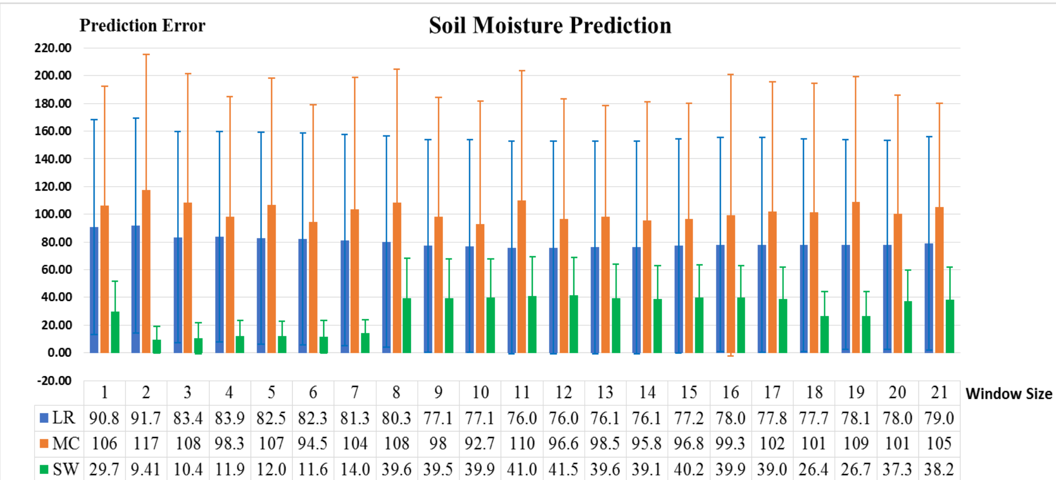


Figure 23. Soil moisture level prediction errors

Figure 22 shows the humidity prediction errors for SW, LR & MC models. According to the results, LR model has a lowest humidity prediction errors than other two models. In LR model, window size 4 & 5 have a lowest humidity prediction error (1.51±2.43 %). Therefore, LR model with window size 4 or 5, is capable to be predicted humidity in next hour more accurately.

Figure 23 shows the soil moisture prediction errors for SW, LR & MC models. According to the results, SW model has a lowest soil moisture prediction errors than other two models. In SW model, window size 2 has a lowest soil moisture prediction error (9.41±9.54). Prediction error is calculated between 0 to 1023 analog input values of soil moisture sensor. Therefore, SW model with window size 2 is capable to be predicted soil moisture level in next hour more accurately.

The summarize results for best algorithm, best window size and lowest prediction error for next hour temperature, humidity and soil moisture prediction are shown in Table 2.

Table 2. Best accuracy of the prediction models

	Best Window Size	Lowest Prediction Error	Best Algorithm
Temperature Prediction ℃	1	0.5	Linear Regression
Humidity Prediction %	4,5	1.5	Linear Regression
Soil Moisture Prediction %	2	0.9	Sliding Window

6. Conclusion and Future Works

The proposed IoT based intelligent controller has the capability of regulating soil moisture level as per requirement and user can remotely monitor, control, and collect data through the online website. The IoT part of the proposed system provides four options to user. If there is a fault in weather prediction then the pump may be automatically activated, but user can always override that faulty condition by just changing the operating mode to manual mode or stop mode. When considering all weather prediction models tested in this research, the both Sliding Window algorithm and HMM cannot provide an 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. Enhance the soil moisture sensors for durability and reduce the corrosion of the probes by supplying an A/C voltage. Enhance the rain drop sensor to measure rainfall amount at particular locations.

References

[1] Priyadharsnee, K.S. and Rathi, S., 2017. Iot based smart irrigation system. Int J Sci Eng Res, 8(5), pp.44-51.

[2] Rawal, S., 2017. IOT based smart irrigation system. International Journal of Computer Applications, 159(8), pp.7-11.

[3] Marshall, R.H., 1988, February. Environmental factors affecting plant productivity in. In Fort Keogh research symposium (Vol. 1, pp. 27-32).

[4] Nagarajapandian, M., Ram Prasanth, U., Selva Kumar, G. and Tamil Selvan, S., 2015. Automatic irrigation system on sensing soil moisture content. International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering, 3(1), pp.96-98.

[5] Parmar, B., Chokhalia, J. and Desarda, S., 2019. Terrace Garden Monitoring System Using Wireless Sensor Networks. Research Journal of Engineering Technology and Management (ISSN), 2(01).

[6] Devkar, P., Kumari, A., Choudhari, S. and Dhanawate, H., 2017. Automated Irrigation System using IoT. System, 159(8).

[7] Saraf, S.B. and Gawali, D.H., 2017, May. IoT based smart irrigation monitoring and controlling system. In *2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)* (pp. 815-819). IEEE.

[8] Zografos, A., 2014. Wireless Sensor-based Agricultural Monitoring System.

[9] Thaker, T., 2016, March. ESP8266 based implementation of wireless sensor network with Linux based web-server. In *2016 Symposium on Colossal Data Analysis and Networking (CDAN)* (pp. 1-5). IEEE.

[10] Susmitha, A., Alakananda, T., Apoorva, M.L. and Ramesh, T.K., 2017, August. Automated Irrigation System using Weather Prediction for Efficient Usage of Water Resources. In IOP Conference Series: Materials Science and Engineering (Vol. 225, No. 1, p. 012232). IOP Publishing.

[11] Rao, D.V.N.K., Anusha, M., Babu, P.N., Sri, M.D., Rajesh, N. and Kumar, K.S., 2015. Prognostication of Climate Using Sliding Window Algorithm. International Journal of u-and e-Service, Science and Technology, 8(4), pp. 225-232.

[12] Kapoor, P. and Bedi, S.S., 2013. Weather forecasting using sliding window algorithm. ISRN Signal Processing, 2013.

[13] Robertson, A.W., Kirshner, S. and Smyth, P., 2004. Downscaling of daily rainfall occurrence over northeast Brazil using a hidden Markov model. Journal of climate, 17(22), pp.4407-4424.

[14] Khiatani, D. and Ghose, U., 2017, October. Weather forecasting using hidden Markov model. In 2017 International Conference on Computing and Communication Technologies for Smart Nation (IC3TSN) (pp. 220- 225). IEEE.

[15] Khadr, M., 2016. Forecasting of meteorological drought using Hidden Markov Model (case study: The upper Blue Nile river basin, Ethiopia). Ain Shams Engineering Journal, 7(1), pp.47-56.

[16] Joshi, J.C., Tankeshwar, K. and Srivastava, S., 2017. Hidden Markov Model for quantitative prediction of snowfall and analysis of hazardous snowfall events over Indian Himalaya. Journal of Earth System Science, 126(3), p.33.

[17] Zou, W., Yao, F., Zhang, B., He, C. and Guan, Z., 2017. Verification and predicting temperature and humidity in a solar greenhouse based on convex bidirectional extreme learning machine algorithm. Neurocomputing, 249, pp.72-85.