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IoT-based monitoring and data-driven modelling of drip irrigation system for mustard leaf cultivation experiment

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The changing dynamics, non-linearity of soil moisture content, as well as other weather and plant variables requires real-time monitoring and accurate predictive model for effective irrigation and crop management. In this paper, an improved monitoring and data-driven modelling of the dynamics of parameters affecting the irrigation of mustard leaf plant is presented. An IoT-based monitoring framework is implemented using ESPresso Lite V2.0 module interfaced with different soil moisture sensors (VH-400), flowmeter (YF-S201) as well as Davis vantage pro 2 weather station to measure soil moisture content, irrigation volume, and computation of the reference evapotranspiration (ETo). The data collected including plant images were transmitted to the Raspberry Pi 3 controller for onward online storage and the data are displayed on the IoT dashboard. The combination of both soil moisture and ETo values was used for scheduling a drip irrigated plant grown in a greenhouse for 35 days. A total number of 20, 703 experimental data samples are collected from the IoT-based platform was further used for data driven modelling through system identification in MATLAB. The result shows the development of different predictive models for soil moisture content prediction. The ARX prediction model is found to perform better than the ARMX, BJ and State space model in terms of estimated fit of 91.31%, 91.09%, 91.08%, and 90.75% respectively. Therefore, a robust monitoring framework for irrigation system has been developed, while the performance of the identified ARX model is promising to predict the volumetric soil water content.

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1. Introduction

The effect of global warming and increasing drought are creating an unprecedented strain on the continued availability of water resources. There is also a threat to food security and water crisis because of the expected increase in population to 9.8 billion by 2050 [1]. Since irrigation is a significant consumer of freshwater, wastage of resources in this sector could have substantial consequences on food security [2,3]. Consequently, to improve the efficiency of water use through precision irrigation, the integration of cutting-edge technology such as the Internet of Things (IoT), for irrigation management, identification, and control strategies for prediction and optimization is used by taking account of the variabilities in the environment and also to enhance precision irrigation system [4,5].

Precision irrigation system plays a significant role in providing significant contributions to food production and to reduce the stress experienced by farmers. Therefore, there is need to precisely design an irrigation system that can predict, adapt and deliver the appropriate amount of water to the crops where and when it is needed in response to the changing dynamics of the soil, weather and the plant [6,7].

The term internet has been associated with things and is now being identified as IoT, which implies the interconnection of electronic devices through internet via Wi-Fi, radio frequency identification device (RFID), LoraWan, Zigbee, Bluetooth, Long term evolution (LTE), and other wireless communication technologies [8,9]. In the current decade, IoT has provided an efficient means in the monitoring system as the user can monitor and control the system anywhere and at any time [10]. In agriculture, the application of IoT has the main aim to connect physical objects (things) such as sensors, cameras, flow meters, actuators, and robots to the internet using wireless network connectivity to measure variables such as soil moisture, temperature, humidity, images of plant and other weather conditions [10-18]. Therefore, it would be advantageous to leverage on IoT system platform towards enhancing the monitoring and control process of irrigation operation and to observe plant response in terms of growth and water stress [7].

The application of IoT and WSN for monitoring has been successfully implemented on several agricultural operations such as water quality management [19–21], smart irrigation system [22–31] data analytics and machine learning [14,23,32–34], disease monitoring [35], remote sensing and NDVI imagery [36–42], and greenhouse monitoring [43–47]. Other related underground monitoring domain on sensing and communication was demonstrated by [29,48], where a novel internet of underground things was used for soil moisture monitoring and relative permittivity estimation through the help of propagation path loss and velocity of the propagated wave from an antenna radiating at 433 MHz buried in different depths of the soil. It was reported that both parameters were measure with high accuracy with minimal error when compared with other methods. Similarly, real time sensor measurement of weather parameters, soil moisture and nutrient content data using wireless technologies towards efficient irrigation measurement was reported by [46-48], where reasonable amount of water usage for irrigation was optimised through the adoption of IoT-based monitoring.

The data generated by different sensors in modern agricultural operations via IoT platform can enable a better understanding in the interaction of dynamic changes of the crop, soil, and weather conditions of the greenhouse environment, which can be further used for data-driven modelling predictions for more accurate and faster decision making in real-time towards achieving water-saving agriculture [49–51].

Predictive modelling involves using dynamic models and algorithms that combine data from various sources such as operational, physical, physiological processes and chemical, in order to predict specific trends or outcomes for decision making about the process [52]. It helps to improve irrigation efficiency and productivity of crops as well as mitigating the effect of the changing dynamics of weather conditions in order to optimise the use of agricultural inputs [53,54].

Previous work on dynamic modelling in precision agriculture using grey-box system identification was carried out on baseline temperature in a greenhouse cultivated lettuce crop and cucumber [55,56], transpiration of lettuce plant [57–59], tomato plant transpiration dynamics[60,61], volumetric water content of the soil [62,63], as well as reference evapotranspiration(ETo) [64–66]. Similarly, the identification of underwater sea cucumber using convolution and residual deep learning networks was implemented. The results obtained shows that the accuracy of both models reached 89.53% using stochastic gradient descent algorithm which signifies good identification of sea cucumber [66].

Before a model-based control system for precision irrigation is designed and implemented, a good predictive model that can help represent the dynamic behaviour of the soil, plant and weather condition is needed [61]. Therefore, in designing the predictive control system, a system identification approach can be used to construct the predictive models of dynamic systems to mimic the interaction of the observed data for a process [67-69]. The identification of the system parameters is needed through the use of adjustable modelling method, which consists of using an existing fixed model structure to fit the data collected from the system. The parameters of that model need to be modified to make its dynamic behaviour more close to that of the system [70]. This model can be obtained through two approaches: grey-box or black-box modelling approach. The model obtained must be able to replicate the process behaviour of the system actions under all the conditions necessary for the system to function. In this work, the black-box modelling approach using the volumetric water content of the soil, reference evapotranspiration estimated from weather variables, and irrigation volume as input and output data collected using the IoT-based experimental framework to construct a predictive model that mimic the dynamic behaviour of the system.

This paper proposes a data-driven modelling approach to develop an accurate predictive model for the system using the data obtained from the IoT-based irrigation monitoring system during the cultivation of mustard leaf plant. The model which represents the changing behaviour of the system is needed for simulation of the process, predicting of the future behaviour of the control variable and designing adaptive controller for irrigation control.

2. Materials and methods

2.1. *Experimental design*

The cultivation experiment on mustard leaf vegetable plant was conducted in a greenhouse environment located at Universiti Teknologi Malaysia, Johor Bahru, Malaysia (1° 33.554′N, 103° 37.507′E) [71]. A transparent plastic nylon and tick net material is used as the roof top while treated net is used to surround and cover up the greenhouse, this is to provide natural ventilation and prevent attack from pests.

An IoT based drip irrigation system with emitters placed closed to the roots zone of the plants was installed to supply water to the coco peat inside the poly bags, which is the growing medium to minimise soil erosion, runoff, and save water. The coco peat is a good plant growing medium with high water holding capacity as well as moderate electrical conductivity and PH which is suitable for greenhouse cultivation [72,73].

The cultivation process of the Mustard vegetable leaf started with planting of the seedling as nursery on the 18th of July 2019, after which it germinated after 4 days and ready for transplanting on the 30th of July 2019. About 65 units were transplanted on the 1st of August 2019 into the poly bag within that greenhouse that is naturally ventilated. Immediately after transplant an, electrical conductivity (EC) value of 1 dS/m, was maintain with A and B fertigation used to aid the growth for two weeks after transplant.

2.2. *Developed IoT-based monitoring framework of the cultivation experiment*

Effective monitoring which is crucial for the management of mustard leaf plant is needed to capture the changing dynamics of the soil, weather and plant parameters in the cultivation environment. In order to realise this, an IoT-based monitoring framework comprising of Davis Vantage Pro 2 weather station and a Raspberry Pi as controller was interfaced with the various EXPresso Lite2 with a sensor (flowmeter, VH400 soil moisture sensors) to setup an IoT-based automatic irrigation monitoring system as shown in Fig. 1. The weather station was integrated with an IoT-based Arduino prototyping board where the ETo was computed to estimate the amount of water loss from the plant. Evapotranspiration is a process that relates to the loss of water from the plant as well as soil surface into the environment, which is being affected by weather parameters, plant management, and environmental characteristics [74].

The hourly computation and estimation were computed using an FAO-56 Modified Penman-Montieth equation that calculated ETo value based on weather data measured by the Davis Vantage Pro 2 shown in Eq. (1).

$$ET_{O=}\frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \quad (1)$$

where:

R_n is the soil surface solar radiation,

U_2 is the speed of the wind measured at 2 m height,

T is the daily mean temperature of the air,

G is soil heat flux density,

$e_s - e_a$ is the saturation vapour pressure deficit,

Δ are the gradient of the pressure curve and γ the psychometric constant as inputs [75,76].

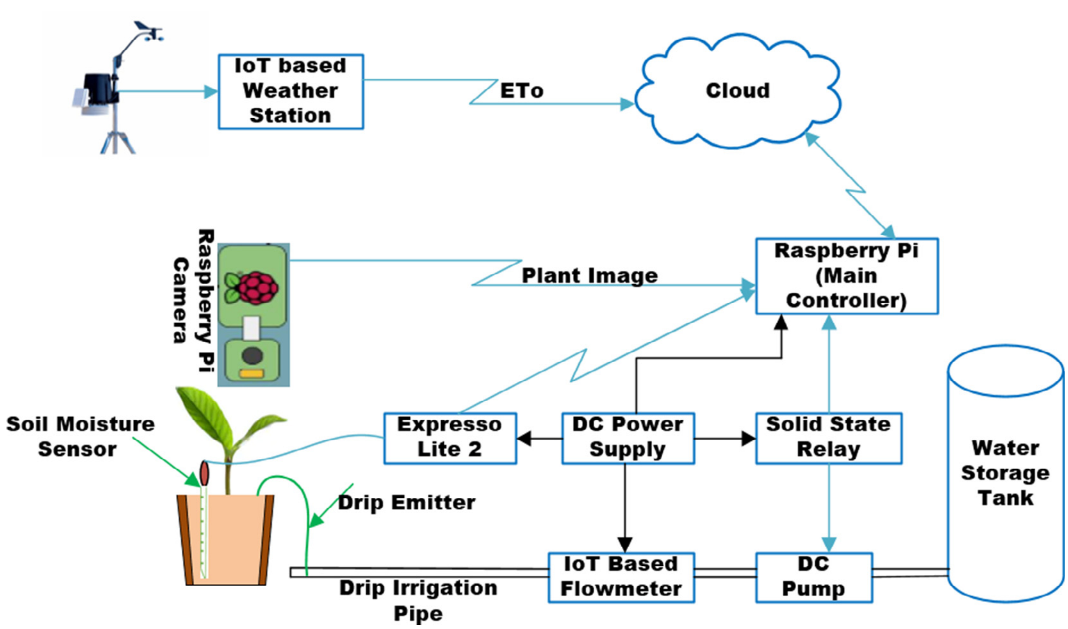

Fig. 1 – Developed IoT-based Drip Irrigation System Monitoring Framework.

The ETo and other weather variables of the greenhouse were logged into the cloud database and are available on the greenhouse IoT website.

The IoT Irrigation monitoring system is shown in Fig. 1 has been developed using ESPresso Lite V2 and Raspberry Pi 3 as the controller and processing unit. The VH400 moisture sensor senses the volumetric water content of the soil, while an IoT based weather station deployed in the greenhouse computed the ETo value to estimate the crop water use. The YF-S201 flow meter sensor measures volume of water used for irrigation at every irrigation time step has been interfaced with Raspberry Pi via an ESPresso Lite V2.0, where all the sensed data is collected for decision making and action base on the scheduling algorithm embedded on the Raspberry Pi. In addition to these sensors, the actuator (water pump) also connected via a solid-state relay to the Raspberry Pi to supply water, while a camera connected to the Raspberry Pi was used to monitor the growth rate and health status of the plant, from which image is uploaded on the IoTwebpage platform on hourly basis.

Fig. 2 shows the stored data which is being displayed on the dashboard of the agro-IoT website. The data were stored in a database and displayed on the webpage for farmers to access and monitor trends as well as performance. The irrigation decision algorithm embedded on the Raspberry Pi is based on the combination of the real time volumetric water content (VWC) and ETo value which are used to decide the irrigation instance of the system. When the ETo is increasing, more water is released to compensate for the water loss, while the volumetric water content of the soil is being checked to avoid exceeding the coco pit field capacity.

3. Data analysis and modelling

The experimental data collected were stored in a comma separated value (CSV) file on the database of the webpage in Fig. 2 and analysed offline, while the data driven modelling via system identification was carried out using MATLAB computational software.

3.1. *System identification of drip irrigation system variables*

System identification is an important method of modelling which can be applied to develop the representation of a dynamic system using different model structures [78]. System identification is used to simultaneously linearize and reduce model complexity, to expose its 'dominant modes' of dynamic behaviour [79]. The formulation of the multiple-input single-output (MISO) model illustrated in Fig. 3, is based on hydrological balance model showing their interaction between the irrigation amount, reference evapotranspiration and volumetric water content of the soil.

This approach is applied in developing predictive models of dynamic systems based on the collected time series data of output-input variables during the cultivation of mustard leaf from the IoT platform. The basic steps involved in modelling via system identification are; setting up the experiment, data collection, selection of model structure, estimation of the model, and finally, validation of the estimated model, as illustrated in Fig. 4

The Fig. 4 shows the framework for the data-driven modelling approach, where the first two blocks illustrate the cultivation of the Mustard Leaf plant and IoT monitoring for data collection. The pre-processing blocks help in preparing the data such as remover of trends and means, to get a good model. Other blocks illustrate the usage of the model structure to fit the prepared data and also acceptance of the model based on how good is the performance metrics are such as the mean square error (MSE), final prediction error (FPE) and estimated fit of the model [80].

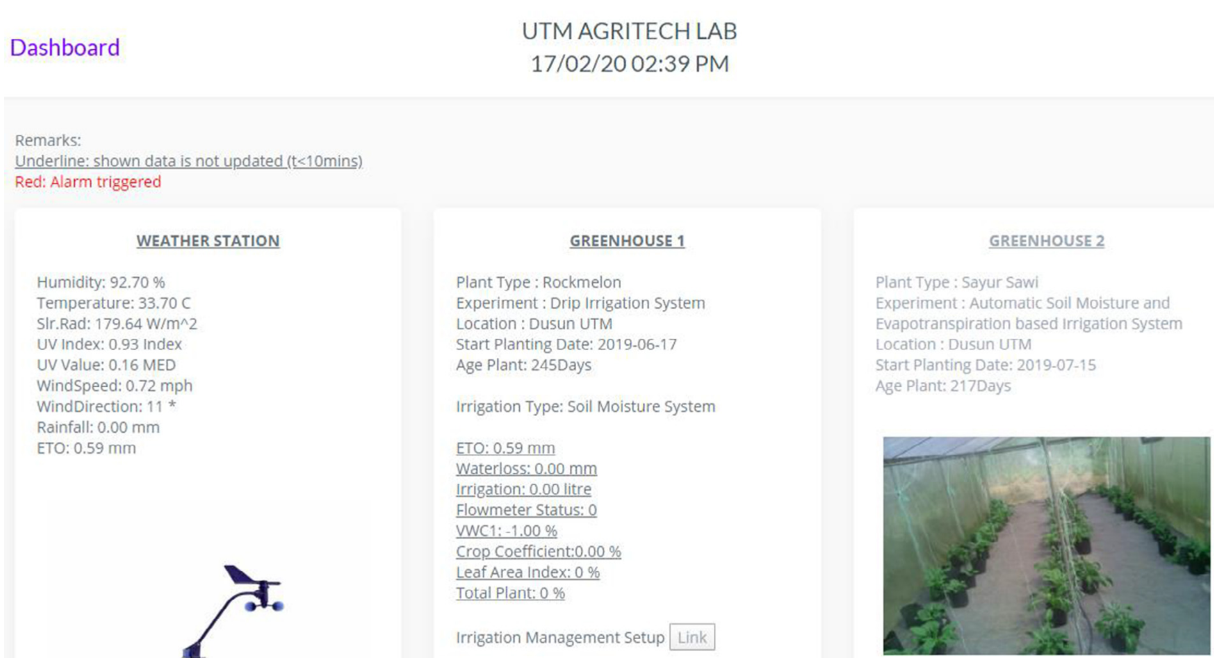

Fig. 2 – UTM AgroIoT Dashboard for Monitoring [77].

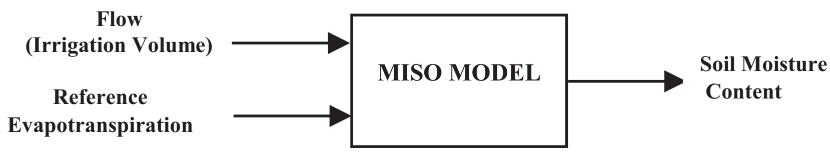

Fig. 3 – Multiple Input Single Output (MISO) model based on the hydrological balance.

3.2. *Parametric model structures and estimation methods*

Since the experimental process was multivariable (MISO) with m manipulated variables (or inputs) which are reference transpiration, canopy temperature, effective irrigation (water amount) and the controlled variables (or outputs) is the volumetric water content of the soil, the sequence of data collected from an identification test is shown in Eq. (2):

$$m(z) = (u(a), u(b), u(c), \cdots\cdots..u(z), y(a), y(b), y(c), \cdots\cdots .y(z) \quad (2)$$

where $u(a), u(b) \cdots\cdots. \in u(t)$, and $u(t)$ is the manipulated variables which is an m-dimensional input vector, $y(t)$ is the control variable with p-dimensional output vector, and n is the number of data points. It is assumed that the linear process derived in Eq. (3) is used to generate the data:

$$y(t) = G(x^{-1})u(t) + H(x^{-1})e(t) \quad (3)$$

where x^{-1} is the unit delay operator, $G(x^{-1})$ is the process transfer function and $H(x^{-1})$ is the noise model and $e(t)$ is a p dimensional white noise vector [81]. The model to be identified is the same structure as in Eq. (3) while the general model structure is shown in Eq. (4)[82].

$$A(x^{-1})y(t) = \frac{B(x^{-1})}{F(x^{-1})}u(t) + \frac{C(x^{-1})}{D(x^{-1})}e(t) \quad (4)$$

where $y(t)$ is the volumetric water content of the soil at instant t, $u(t)$ is the input variables while $e(t)$ is the estimation error. The polynomials that define the output (soil moisture), inputs to the model(irrigation amount and ETo), and the error estimation are represented by $A(x), B(x), C(x), D(x)$, and $F(x)$ [83]. The parametric model structures that was used to model and identify the experimental time series data are autoregressive with external input model, output error model, autoregressive moving average with external input model, and box jenkins model.

3.2.1. *The autoregressive with external input model*

The autoregressive with external input model (ARX) model structure is derived from Eqs. (3) and (4) [67].

$$\text{where } G(x^{-1}) = x^{-d}\frac{B(x^{-1})}{A(x^{-1})} \text{ and } H(x^{-1}) = \frac{1}{A(x^{-1})} \quad (5)$$

Also, $A(x^{-1}) = 1 + \sum_{k=1}^{n_a} a_k x^{-k}$ and$B(x^{-1}) = \sum_{k=0}^{n_b} b_k x^{-k}$are polynomial matrices, $\boldsymbol{d}$ is the delay of the system.

Therefore, the ARX model can be expressed, as shown in Eq. (6) [82].

$$A(x^{-1})y(t) = x^{-d}B(x^{-1})u(t) + e(t) \quad (6)$$

3.2.2. *The autoregressive moving average with external input model*

This autoregressive moving average with external input model (ARMAX) has a broader structure than the ARX shown as follows:

$$G(x^{-1}) = x^{-d}\frac{B(x^{-1})}{A(x^{-1})} and H(x^{-1}) = \frac{C(x^{-1})}{A(x^{-1})} \quad (7)$$

where $C(x^{-1}) = 1 + \sum_{k=1}^{n_c} c_k x^{-k}$

which is a polynomial, the presence of which means that noise term is explicitly modelled and expressed as Eq. (8) [67].

$$A(x^{-1})y(t) = x^{-d}B(x^{-1})u(t) + C(x^{-1})e(t) \quad (8)$$

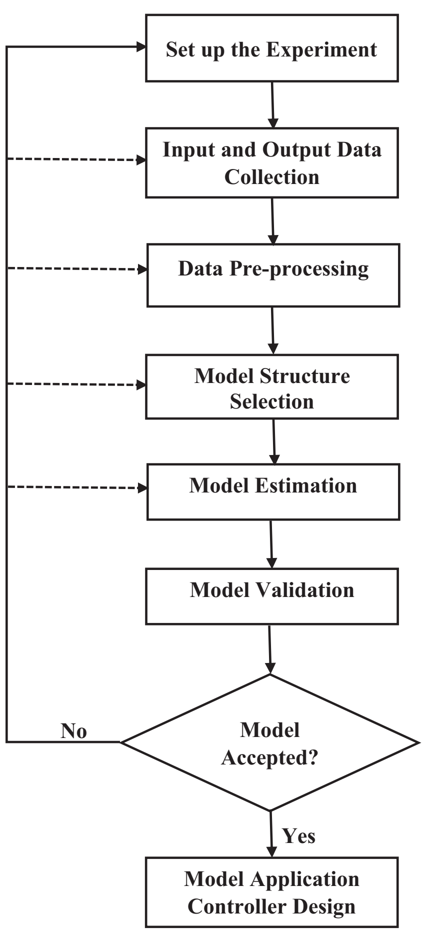

Fig. 4 – The Data-Based modelling approach.

3.2.3. *The box Jenkins model*

The Box Jenkins (BJ) model provides completely independent parameterisation for the dynamics and the noise using a rational polynomial function. The box Jenkins model structure is represented by Eq. (9) [80].

$$y(t) = x^{-d}\frac{B(x^{-1})}{F(x^{-1})}u(t) + \frac{C(x^{-1})}{D(x^{-1})}e(t) \tag{9}$$

$$D(x^{-1}) = 1 + \sum\nolimits_{k=1}^{n_a} Dx^{-k} \tag{10}$$

3.2.4. *The output error model*

The Output Error (OE) model structure is used in the case when the process output is disturbed by only white measurement noise as represented by Eq. (11) [80].

$$G(x^{-1}) = x^{-d}\frac{B(x^{-1})}{F(x^{-1})} \text{ and } H(x^{-1}) = 1 \tag{11}$$

This model can be expressed as

$$y(t) = x^{-d}\frac{B(x^{-1})}{F(x^{-1})}u(t) + e(t) \tag{12}$$

where,

$$F(x^{-1}) = 1 + \sum\nolimits_{k=1}^{n_f} F_k x^{-k} \tag{13}$$

3.2.5. *The state space model*

The following set of equations describes the state-space (SS) model of a multivariable process.

$$x(t+1) = Ax(t) + Bx(t) + Pe(t) \tag{14}$$

$$y(t) = Cx(t) + Dx(t) + e(t) \tag{15}$$

In Eqs. (14) and (15), the A, B, C, D and P matrices are estimated by using the subspace state-space identification method. The vector $x(t)$ is the state vector of the process at a discrete-time *(t)*, $y(t)$ denotes the output at the time *(t)*, $u(t)$ represents the input at a time *(t)*, while $e(t)$ is called the process noise disturbance.

3.3. *Model identification implementation in MATLAB*

This subsection describes the data-driven modelling using the experimental dataset. A MATLAB Toolbox called system identification can be used for the dynamic modelling of the process, starting with the lower order, increasing and decreasing the order of the polynomial (n_a,n_b, n_c, n_d, and n_f) and also the variable delay n_k[85]. Fig. 5, shows the user interface of the system identification toolbox, where the processing and model estimation was carried out which resulted in the different model generation of ARX 125, state space, ARX 2221, and box Jenkins.

The total number of 20,703 experimental data samples was used for the modelling, which was split into two halves, which is 10,351 and the number was used for the model estimation, and

the other half was used for validation of the model, while a sampling period of 600 s was chosen. In addition, the experimental data pre-processing was carried out to remove the trends, filtering, outliers, and means.

3.4. *Model evaluation criteria*

The developed models using the MATLAB system identification toolbox are evaluated by the lowest order of their dynamics to predict the system's output behaviour and shows the interaction between the input and output variables of the sys-

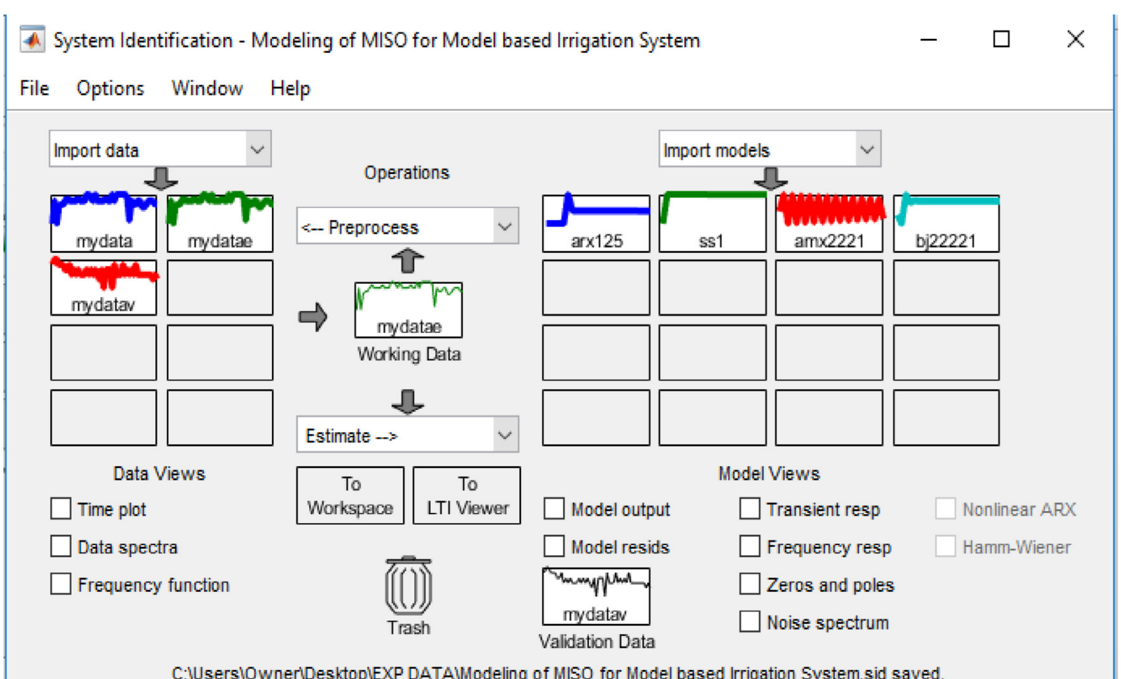

Fig. 5 – The MATLAB system identification user interface.

tem using mathematical model. The statistical performances of the developed models can be evaluated in terms of the final prediction error (FPE), best fit, and the mean square error (MSE) [84,86].

3.4.1. *Final prediction error*

The final prediction error (FPE) describes the measure of the model quality of the situation when the model is tested on a different data set. The accuracy of a developed predictive model depends on how small is the FPE, according to Akaike's theory [35]. It is defined as FPE and shown in Eq. (16):

$$\mathrm{FPE} = \det\left(\frac{1}{N}\sum_{1}^{N} e\left(t,\widehat{\theta}_N\right)\left(e\left(t,\widehat{\theta}_N\right)\right)^N\right)\left(\frac{1+\frac{d}{N}}{1-\frac{d}{N}}\right) \tag{16}$$

where: N is the number of values in the estimation data set, $e(t)$ is an n-by-1 vector of the prediction errors and,θ_N represents the estimated parameters, and d is the number of estimated parameters.

3.4.2. *Mean square error*

The mean square error (MSE), is a statistical parameter that assesses the quality of prediction in the same unit of the variable. The MSE value close to zero shows that the model prediction is accurate. The Eq. (17) defines the MSE:

$$E = \frac{1}{n}\sum_{i=1}^{n}\left(y_{i-}\widehat{y}_i\right)^2 \tag{17}$$

where y_i and $\widehat{y}_i$ are observed and predicted the value at the time i (i = 1, 2.……..,n), and n is the data point.

3.4.3. *Estimated fit*

The Estimated fit (%) is a measure of the correlation between the measured output (y) and the predicted output ($\widehat{y}$) as shown is Eq. (18). For a N number of input–output pairs, given the measurement output (y) and the simulated or predicted output ($\widehat{y}$), the estimated fit can be computed as:

$$EstimatedFit = \left(1 - \frac{\sqrt{\sum_{i=1}^{n}\left(y_i - \widehat{y}_i\right)^2}}{\sqrt{\sum_{i=1}^{n}\left(y_i - \frac{1}{N}\sum_{i=1}^{n} y_i\right)^2}}\right) \times 100 \tag{18}$$

where y_i and $\widehat{y}_i$ are observed and predicted value at the time i (i = 1, 2.……..,n), and n is the data point.

4. Results and discussion

This section describes the results of the changing dynamics of soil, plant and weather during the period of the experiment. Fig. 6 shows the graph of the daily estimation of reference ETo and solar radiation. From the figure, there exists a close relationship between the data of the ETo and solar radiation, with ETo directly proportional to the solar radiation. The ETo value is shown to reach its peak by mid-day which also depends on the changes in daily weather. The maximum Value of ETo and solar radiation recorded during the period of experiment is 0.85 mm and 800 W/m^2 respectively.

A similar trend of curves between temperature and humidity measured immediately after transplant, between July 1st to 22nd 2019 as shown in Fig. 7. The daily data were sampled every 10 min and stored on the IoT cloud database. The average maximum temperature and minimum temperature measured was 36.5 ℃ in the afternoon and around 22 ℃ at night, respectively while the humidity decrease in the afternoon as temperature increases, with maximum and minimum value at 98% and 25% respectively. The irrigation volume in litres measured by the flow meter was compared with the reference evapotranspiration and shown in

Fig. 8, the irrigation volume applied is able to compensate for the water loss at every estimated instant while maintaining the volumetric water content of the soil.

The graph of the volumetric water content of the soil against the time which is maintained within wilting point (0.1) and field capacity (0.45) of the coco pit after transplant

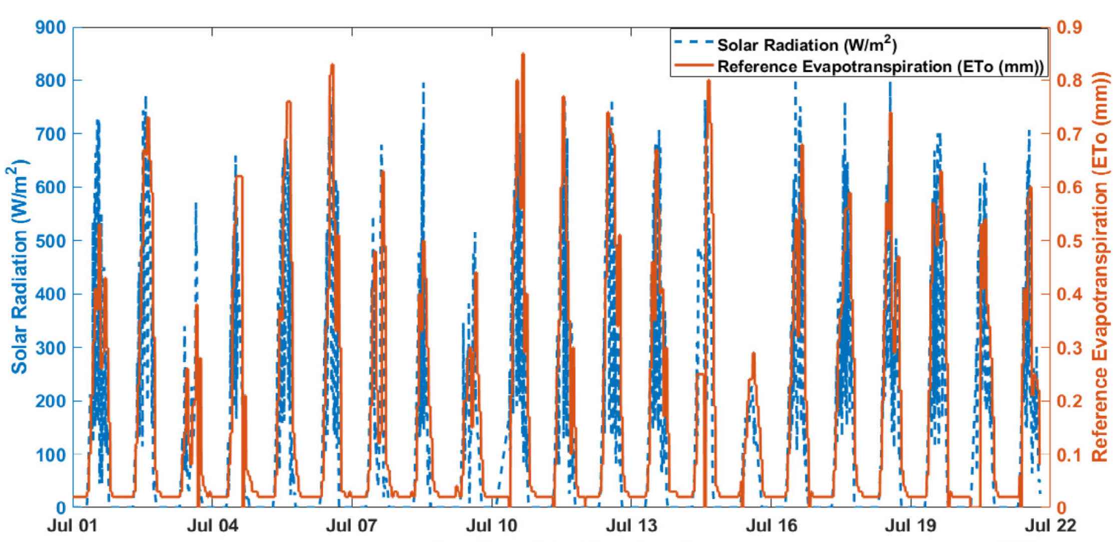

Fig. 6 – Daily estimation of ETo (mm) and Solar Radiation (W/m^2).

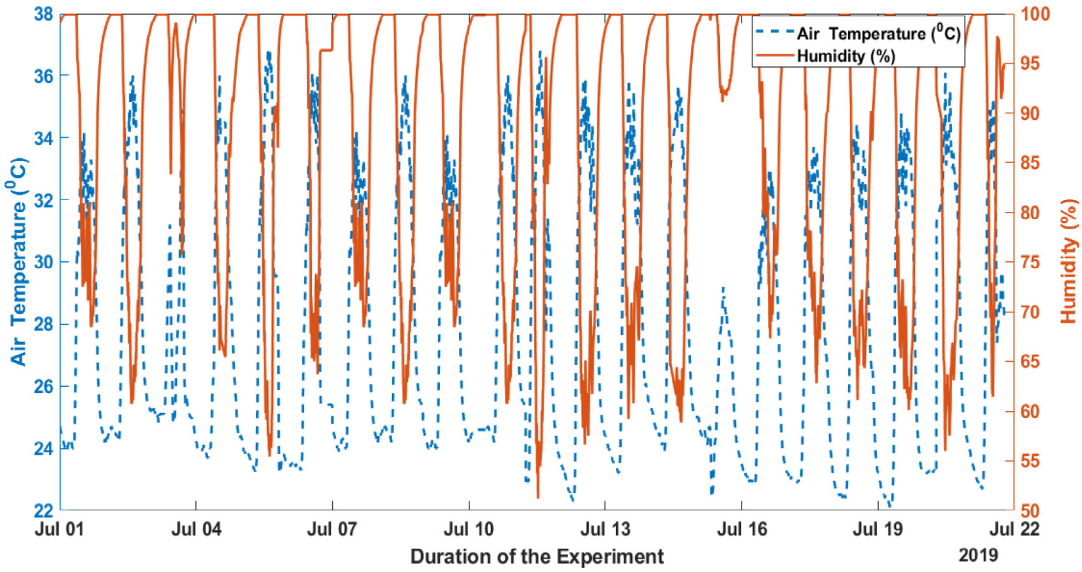

Fig. 7 – Air Temperature (C) and Humidity (%).

between 1st and 22nd July 2019 is shown in Fig. 9. It can be seen that the dynamics is changing, due to the effect of the plant uptake of water and environmental (weather) effect. As the water loss due to evapotranspiration increases or decreases, there is also a corresponding effect on the volumetric water content of the soil, showing that more or less water is needed to be supplied for irrigation. Therefore, both variables have a direct impact on the amount of water to be applied to the plant.

With the help of the Crontab scheduling programming of the Raspberry Pi and its camera, real-time images of the plant are always captured at intervals during the day and uploaded to the IoT webpage where the growth and performance of the plant in three greenhouses are monitored remotely as shown in Fig. 10.

The data driven modelling results in terms of model evaluation as well as statistical and prediction performance at different step ahead predictions of the developed models is shown in Tables 1 and 2. The statistical performance of different models that was used to fit the experimental dataset as shown in Table 1. The developed ARX model with the estimated fit of 91.31% with the least MSE and FPE of 0.753 and 0.764 respectively, was chosen from among all other models that has low performance. The model can predict the measured output variable effectively as well as another dataset that was not used for estimation but was collected for the same cultivation experiment. Table 2 shows the performance in terms of the best fit of each model at different prediction step ahead. It can be seen that the 1 step prediction has the best-estimated fit, with the ARX model having the highest estimated fit.

The chosen model estimated parameters are shown in Eqs. (19)–(22):

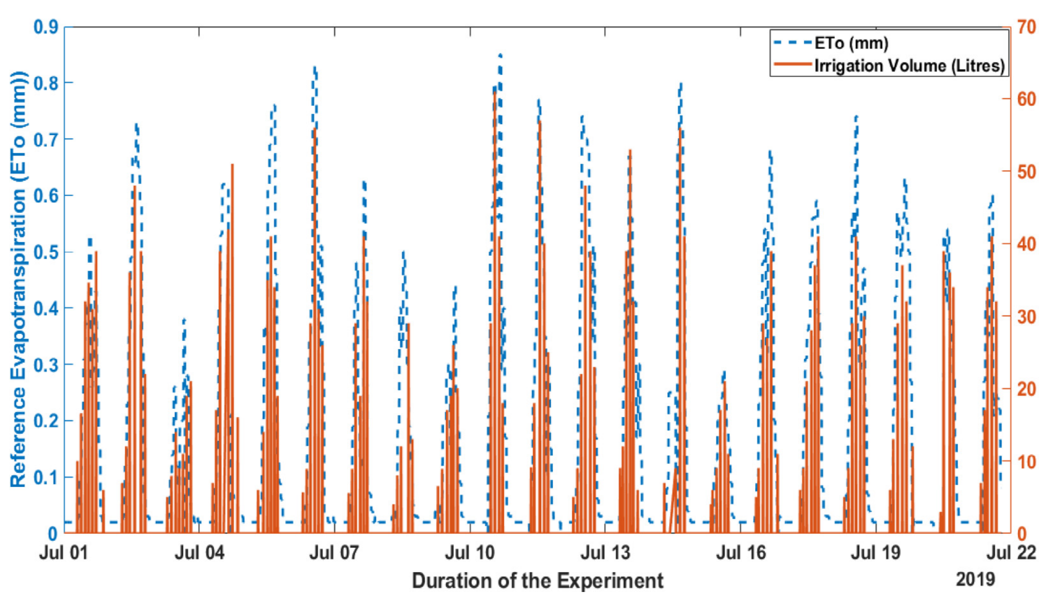

Fig. 8 – Reference Evapotranspiration-(ETo (mm)) against Irrigation volume (Litres).

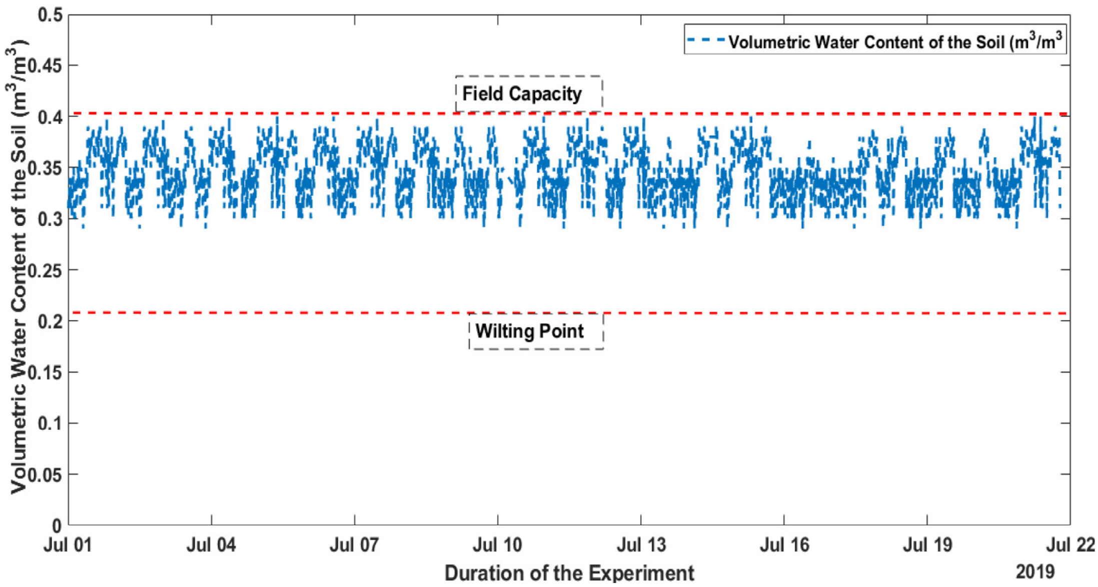

Fig. 9 – Volumetric water content (VWC) of the soil (m^3/m^3).

Fig. 10 – Experimental setup of smart drip irrigation system for Mustard Leaf cultivation in a greenhouse monitored via IoT based Raspberry Pi camera.

Table 1 – Statistical Performance of the Models.

Model	FPE	MSE	Estimated Fit
ARX	0.764	0.753	91.31
BJ	2.815	2.812	91.08
ARMX	2.814	2.813	91.09
State space (SS)	2.806	2.829	90.75

Table 2 – Prediction performance of the different models by Estimated Fit.

Model	5 Step ahead prediction	3 step ahead Prediction	1 Step ahead prediction
ARX	81.47	85.57	91.31
BJ	81.42	85.3	91.08
ARMX	81.35	85.41	91.09
State Space (SS)	81.28	85.21	90.75

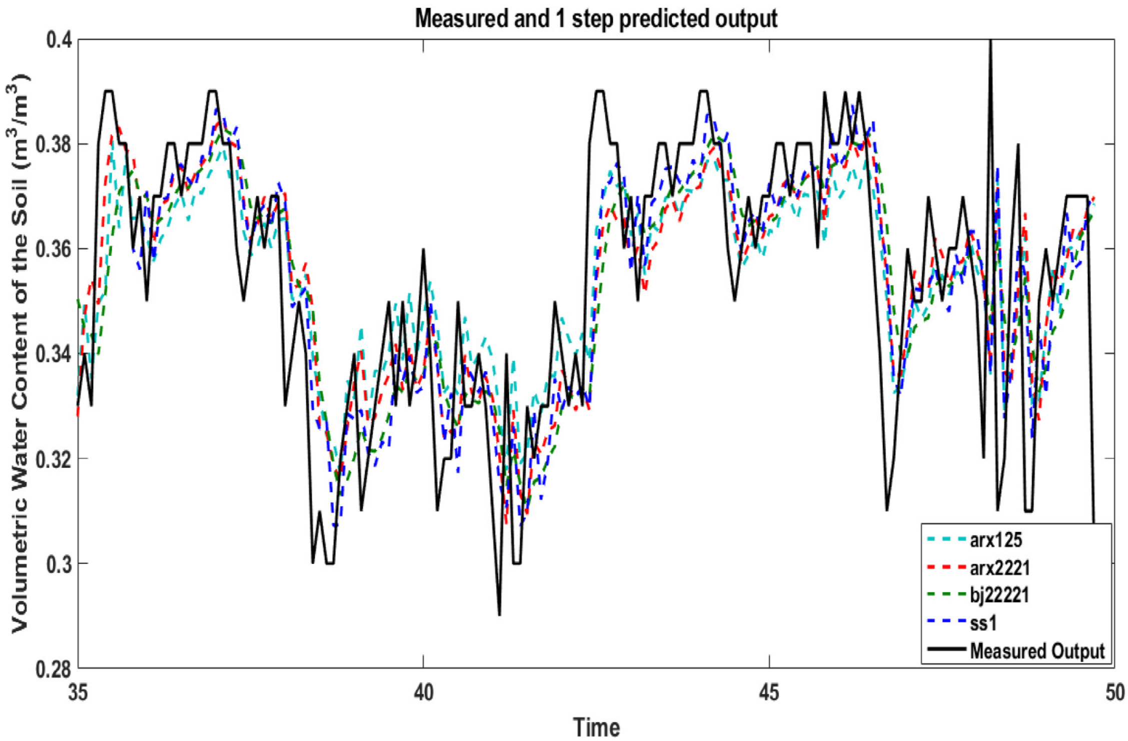

Fig. 11 – The measured and predicted output.

Discrete-time ARX model:

$$A(z)y(t) = B(z)u(t) + e(t) \quad (19)$$

$$A(z) = 1 - 0.9991z^{-1} \quad (20)$$

$$B1(z) = 0.0006301z^{-5} - 0.00035z^{-6} \quad (21)$$

$$B2(z) = 1.035z^{-5} - 0.9762z^{-6} \quad (22)$$

Polynomial orders: $na = 1, nb = [66], nk = [55]$, indicates a first-order model with a dead time of 5 samples.

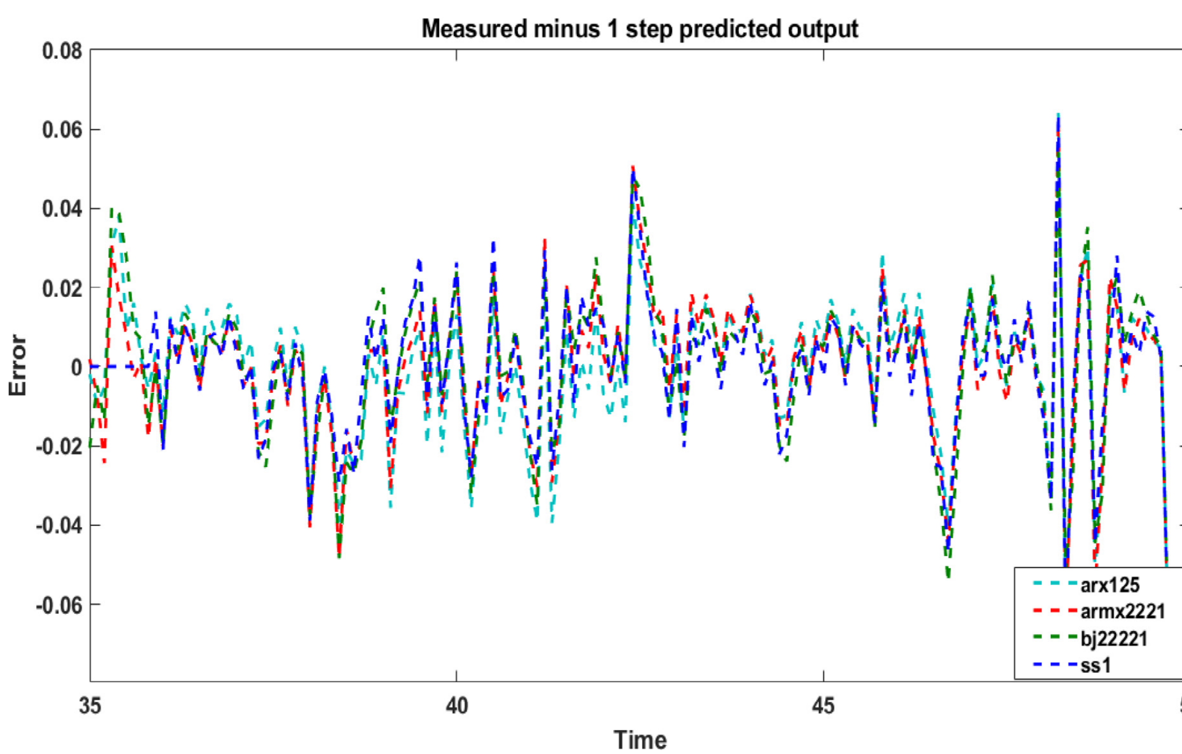

Fig. 12 – The error between the real and the estimated models' interpretation.

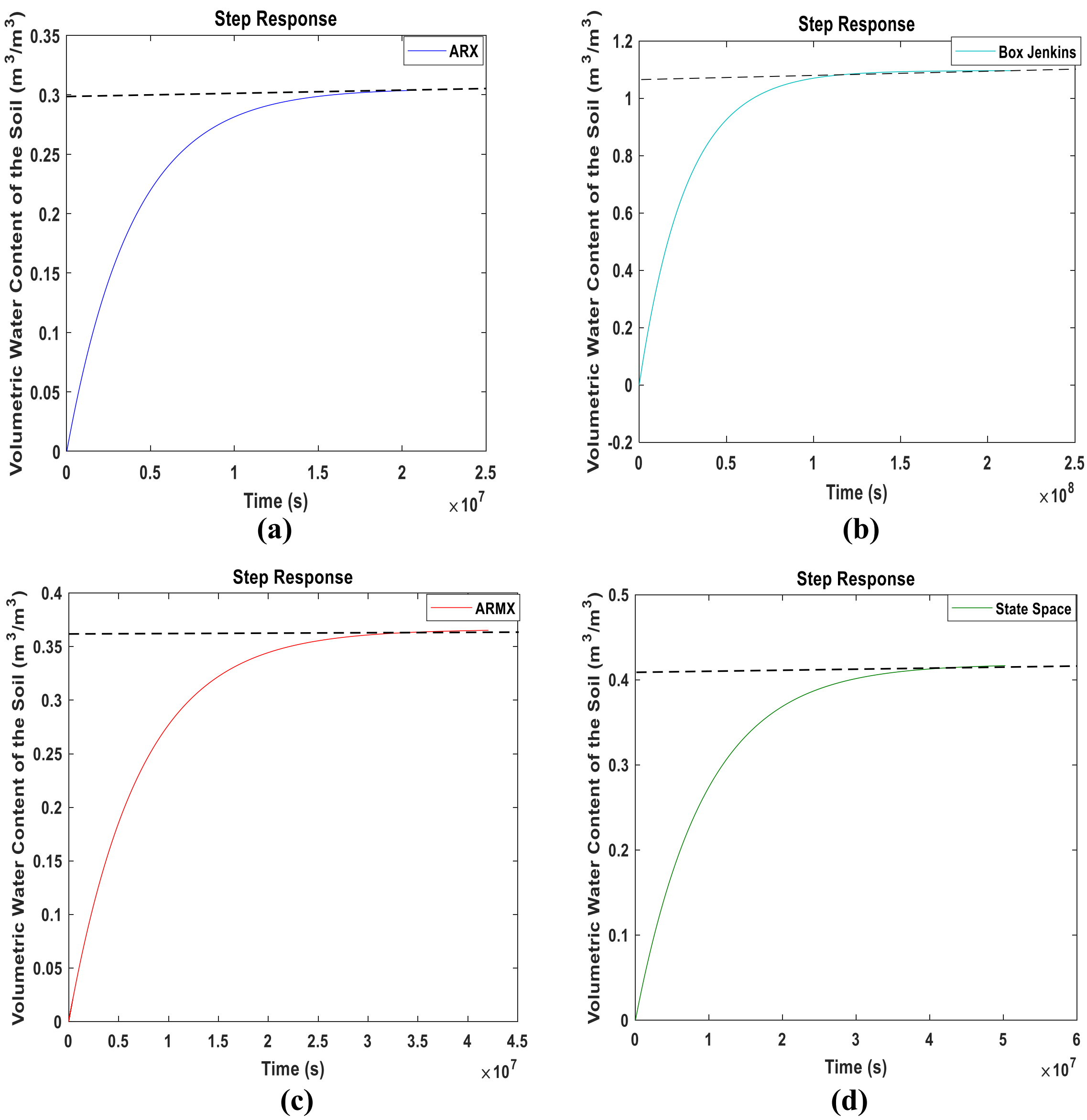

Fig. 13 – The step response of system: (a) ARX model (b) SS Model (c) ARMAX model (d) BJ model.

The Fig. 11 shows the output models obtained using the system identification toolbox while the measured minus the predicted output ARX model involved is shown Fig. 12. This error is about 8.69% (100–91.31%), which is acceptable in the field of agriculture, where the work with empirical relationships is most prevalent [61].

The developed models are evaluated by the lowest order of their dynamic response of these models as shown in Fig. 13 (a)–(d) are the first-order models and are suitable as there were no overshoot or undershoot, but with slow response. Also, there no time delay and lesser rise time except that of the BJ model with offset.

The frequency response curve is shown in Fig. 14, which measures the magnitude and phase of the output as a function of frequency in comparison to the input and shows all the model structure dynamics are similar. This data-driven modelling has been done to obtain predictive models that is needed for the design of model-based controller for the real system

The results show that there is an overall stable output based on nonlinear inputs. Concordance between the real and estimated models is reached at the output (soil moisture), which is the aim sought by the farmer and the control specialist. The predictive model developed in this research is subject to some margin of uncertainty despite experimental validation.

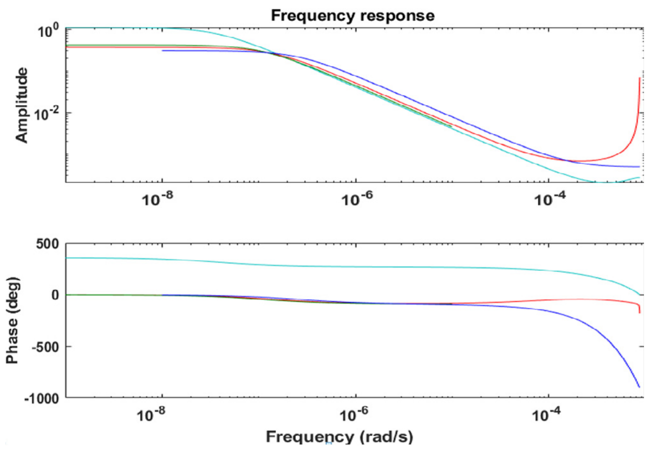

Fig. 14 – Frequency Response curve.

5. Conclusion

This experimental framework has demonstrated enhanced precision irrigation leveraging on the IoT platform, which was used for monitoring through the use of different sensors and IoT based weather station. An innovative IoT based irrigation monitoring for the cultivation of Mustard Leaf together with data driven modelling of experimental dataset has been carried out. The cultivated plant was harvested after four weeks of cultivation period with a total of 1920 Litres of water for a total number of seventy-five (65) poly bags. The mathematical predictive model describing the relationship of water flow (irrigation amount), water loss (ETo) and soil moisture were developed using system identification toolbox in MATLAB. The ARX model was chosen over the other model such as ARMAX, BJ, and state-space because it performed better when tested for MSE of 0.753, FPE of 0.764, the best fit of 91.31%, and good response time. The choice was based on the smallest order, the linearity, and adequate response for prediction of volumetric water content of the soil. Future work; could focus on integrating the constructed model to develop a model predictive irrigation controller for deployment in a greenhouse. When implemented, the controller will help achieve optimal control action for better high water saving, reduced energy use and increased yields.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

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