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Model based predictive control strategy for water saving drip irrigation

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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

Traditional irrigation control systems is characterized with inefficient management of water and often results in low water productivity index and reduced cultivation yield. In addition, insufficient water supply and high rate of water loss due to evapotranspiration increases plant stress which often affects its growth and development. Therefore, to address this issues, this paper is aimed at developing a model predictive control (MPC) strategy for water saving drip irrigation experiment that will regulate the soil moisture content within the desired field capacity and above the wilting point, while scheduling irrigation to replace the loss of water from soil and plant due to evapotranspiration in the greenhouse environment. The controller design involves a data driven predictive model identified and integrated with the MPC designer in MATLAB and thereafter exported in Simulink for simulation. The generate controller code was modified and deployed on a Raspberry Pi 4 controller to generate a pulse width modulated signal to drive the pump for the control water mixed with fertilizer. To achieve enhancement of controller an Internet of Things (IoT) integration was used for easy soil, weather, and plant monitoring which are used to update the MPC model for the irrigation control. The performance of the proposed MPC controller deployed drip irrigated Greenhouse(GH1) is benchmarked against an existing automatic evapotranspiration (ETo) model based controller in Greenhouse(GH2), with each greenhouse containing 80 poly bags of Cantaloupe plant with similar growth stage. The results obtained shows that, the proposed MPC-based irrigation system has higher water productivity index of 36.8 g/liters, good quality of fruit with average sweetness level of 13.5 Brix compared to automatic ETo-based irrigation system with 25.6 g/liters and 10.5 Brix, respectively. However, the total mass of harvested fruit for ETo-based irrigation system is higher than MPC-based irrigation system by 21.7%. The performance of the proposed MPC controller was achieved through the integration of event based scheduling with IoT monitoring as well as inclusion of evapotranspiration effect in the plant dynamics.

1. Introduction

Water is one of the most precious resources on the earth, it is therefore imperative to measure, control and preserve for sustainable agricultural production and healthy living. The severe global competition for food and water is due to the effect of increase in world's population and climate change. This has increased the interest on how to achieve optimal use of scarce resources such as water using precision irrigation aimed at increasing food production and water saving [1]. The rate of water loss known as reference evapotranspiration (ETo) from plant and soil is dependant on the nonlinear dynamic change of soil, plant, and weather interaction. The regular change in evapotranspiration has effect in the available water in the soil for plant use, as a very high rate of ETo could lead to plant wilting. This remains a significant issue affecting the control strategies for crop irrigation, as there is a need for irrigation controller to adaptively adjust to the dynamic variations of soil, plant and weather parameters to ensure effective irrigation management [2]. Commonly, most farmers do not consider these dynamic varying factors when making irrigation scheduling decisions, which may lead to many draw backs such as low water use efficiency, reduced yield

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Table 1
Summary of previous work compared with the proposed data driven controller for irrigation management.

References	Monitored/Analysed Parameters				Monitoring Method	Predictive modelling	Control Algorithm	Performance Evaluation				Nature of Implementation	
	Soil (Soil moisture)	Plant (Kc, LAI, Plant Height)	Weather(ETo, Temp, Hum, Sol. Rad, Wind	Irrigation Volume				Water Use Efficiency	Yield	Constraint & Disturbance Management	Image processing of plant for Kc estimation	Simulation	Hardware (Real-time)
[64]	✓		✓		✓	✓	**SVR+KNN**					✓	
[65]	✓		✓		✓	✓	**KNN**					✓	
[46]	✓		✓			✓	**ANN**					✓	
[59]							**MPC**					✓	
[24]	✓	✓					**LQR**			✓		✓	
[20]				✓			**Fuzzy PID**	✓				✓	✓
[66]	✓		✓			✓	**MPC**			✓		✓	
[67]	✓		✓		**WSN**	✓	**MPC**			✓		✓	✓
[68]	✓		✓				**GPC**	✓					
[69]	✓		✓			✓	**LSTM**	✓				✓	
Proposed Method	✓	✓	✓	✓	**IoT**	✓	**Data driven MPC**	✓	✓	✓	✓	✓	✓

and more energy usage in driving pumps to supply of water for irrigation [3]. Consequently, the real time monitoring of weather, soil, and plant parameters within a cultivation environment using Internet of things (IoT) as well as wireless sensor networks (WSN) can enable the realization of smart management of different methods irrigation systems [4–10].

There are various control strategies that can be used for irrigation management. The irrigation control strategies are basically categorized in open loop and close loop control methods. Irrigation decisions using open-loop control approach are managed based on the farmer intuition and using either on or off irrigation timers to control opening and closing of valves. The irrigation timing and volume is often specified and applied based on the farmers experience without considering sensors feedback on the changing parameters that has effect on plant such as soil moisture contents, and other weather parameters [11–13] The issues affecting with open-loop control of irrigation system affected by various environmental disturbances such as evapotranspiration, effect of different growth stage requirement of plants (Kc), and requires regular adjustment to ensure better performance [14]. The close loop control approach has been reported to be able to address the issue associated with open loop through the use of sensor based signal as feedback to keep the measured output condition close to the desired trajectory while deciding the duration of water supply to plants [14,15]. Research work on close loop control of irrigation have been implemented through simulation using the linear control approach such as proportional integral differential (PID) [16–20] and also linear quadratic regulator (LQR) [21–26]. The works reported a good control performance through simulation, but their real time deployment on hardware was not thoroughly explored. Similarly, several works on intelligent control such as fuzzy logic and expert system approach where rules and formulated based on expert knowledge of the dynamics of the system was used to decide the timing and volume irrigation were carried out [27–36]. This method has proven to be effective, but the drawback of this method is that no matter how well formulated the rules are, there will always be situations that don't exist in the rules. In most cases fuzzy based irrigation controllers are not often adaptive to the varying dynamics of plant, weather, and soil parameters. Also, reported in literatures is the use of artificial neural networks for soil moisture prediction [37–48] as well as metaheuristic algorithm for irrigation optimization [49–55]. The works were carried out as a good proof of concept through simulation, but the need for training of the ANN models on embedded hardware makes their real time implementation for irrigation of plant cultivation challenging, hence difficult to access their performance and suitability for farmers use. Also, the use of predictive models for irrigation scheduling has been reported in Refs. [56–59]. The predictive models were used to predict the future trajectory of the control variable, while optimizing the cost function according to the reference trajectory. However, the work was only conducted through simulation only without experimental validation. In addition, the use of generalized predictive control (GPC) method for scheduling irrigation for tomato plant was reported to have achieved 20% water saving. However, the controller was not designed to handle constraint management on the control variables as well as the changing dynamics of the crop coefficient effect on ETo [60,61].

MPC is a model based algorithm that utilizes the model of a process to predict the future trajectory of the system controlled, by solving an online optimization at every time stamp to compute the future control action [62]. One of the issue reported in literature is on the applicability of MPC for process control application will provide a burden on producing high computational complexity associated with solving online optimization repeatedly on hardware [63]. Since the application of the MPC controller is in the area of precision irrigation agriculture has a slow process response, the integration of the concept of hourly event based triggering has been considered in this paper to decide the sampling instant at which the controller will solve online optimization to compute the optimal control action needed to minimize the error

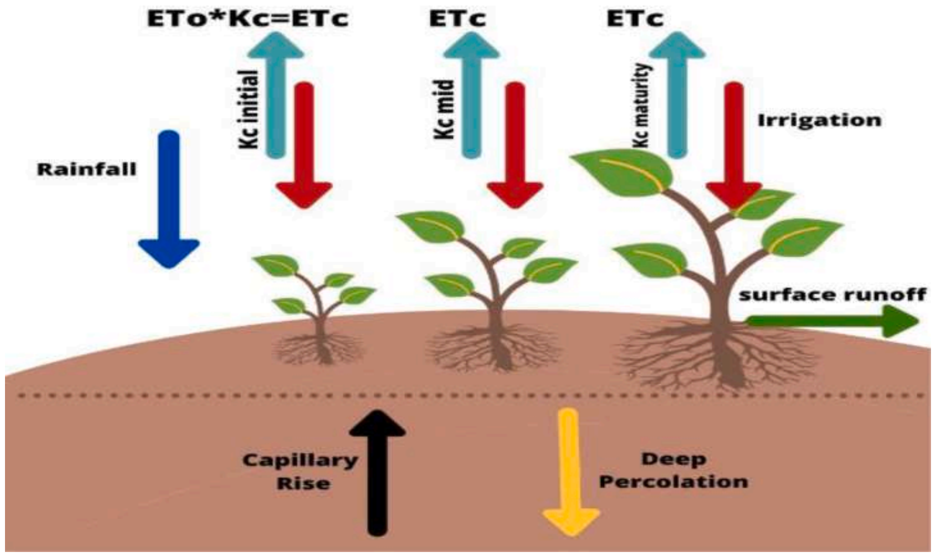

Fig. 1. Hydrological balance model for plant dynamics.

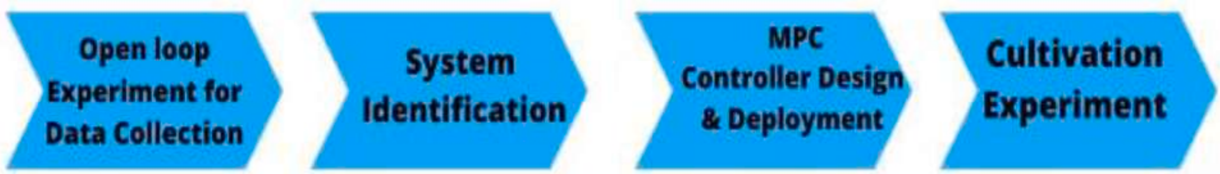

Fig. 2. The block diagram of the main stages of the methodology.

between the predicted moisture content of the soil and the set point trajectory can be used to address this issue. The summary of the comparison of the various related literatures to the proposed technique is illustrated in Table 1, where the proposed technique has more features considered in terms of monitored parameters, performance evaluation as well as implementation in both simulation and hardware.

This paper is aimed at the design and experimental implementation of a data driven MPC controller on Raspberry Pi that will regulate the volumetric water content of the soil within a desirable limit known as field capacity and wilting point towards water saving drip irrigation. These is achieved through the scheduling irrigation to replace the water loss due to high ETo in the greenhouse environment. The performance on the proposed MPC controller deployed in greenhouse 1 (GH1) was benchmarked with an existing automatic ETo based controller deployed in greenhouse 2 (GH2). The significant contribution of this paper as illustrated in Table 1 which includes the consideration of soil, plant and weather dynamic change using a predictive model and image processing to estimate the value of Kc in a greenhouse. The simulation and real time experimental implementation of the predictive control algorithm for greenhouse cultivation experiment leveraging on the developed IoT frame work towards effective monitoring of the various sensed variables to update the model of the controller.

2. Methodology

MPC requires a good model that captures the dynamics of a process, to formulate an optimal control action that can drive the process through it reference trajectories. The process of model formulation for a drip irrigation system is based on the hydrological balance model as illustrated in Fig. 1, which has established that the change in soil moisture content during a period of time is as result of water inflow actions such as rainfall, irrigation as well as water outflows such as evapotranspiration, capillary rise, deep percolation and surface run off effect. The reference evapotranspiration also known as water loss from the process, is an important parameter of the model that depend on the weather variable, namely speed of wind, solar radiation, air temperature, air humidity, and the plant characteristic such as crop coefficient (Kc). Some measurable and estimated parameters of the hydrological process dynamics can be formulated into input and output data and use to fit an existing model structure through data driven modelling. The model that best fit to the data was further use for the MPC controller design needed for optimal water saving in a drip irrigation system.

The sequence of methodology that was adopted in the research is illustrated using Fig. 2. The setting of IoT framework for open loop experimental cultivation of Cantaloupe and Mustard leaf cultivation is designed to assist the data collection needed for the data driven modelling [70]. Thereafter, a data driven system identification was carried out based on the data collected in the open loop experiment. The developed model was used to design the proposed model predictive controller, and subsequent deployment of the proposed controller on Raspberry Pi 4 as a target hardware for cultivation experiment.

Fig. 3 illustrate an IoT based framework setup in an experimental greenhouse environment situated within Universiti Teknologi Malaysia (1^0 33.554′N, 103^0 37.507′ E), which was initially described in Ref. [70]. In this setup, an on and off decision based scheduling algorithm was embedded in Raspberry Pi and was it is used for to collect experimental data soil, plant, and weather between 30th July, 2019 to 24th August, 2019 as well as 15th September 2019 to 30th November, 2019 for Mustard leaf cultivated in GH2 and Cantaloupe plant cultivated in GH1 respectively. The experimental dataset were analysed, while the development of data driven models that captures the changing dynamics of the system was implemented through system identification [70].

However, an improvement has been made as shown in Fig. 3 where an integration of model predictive controller has been designed in Raspberry Pi to control the pulse width modulated signal to drive the pump for supply of water through the drip irrigation network. Through

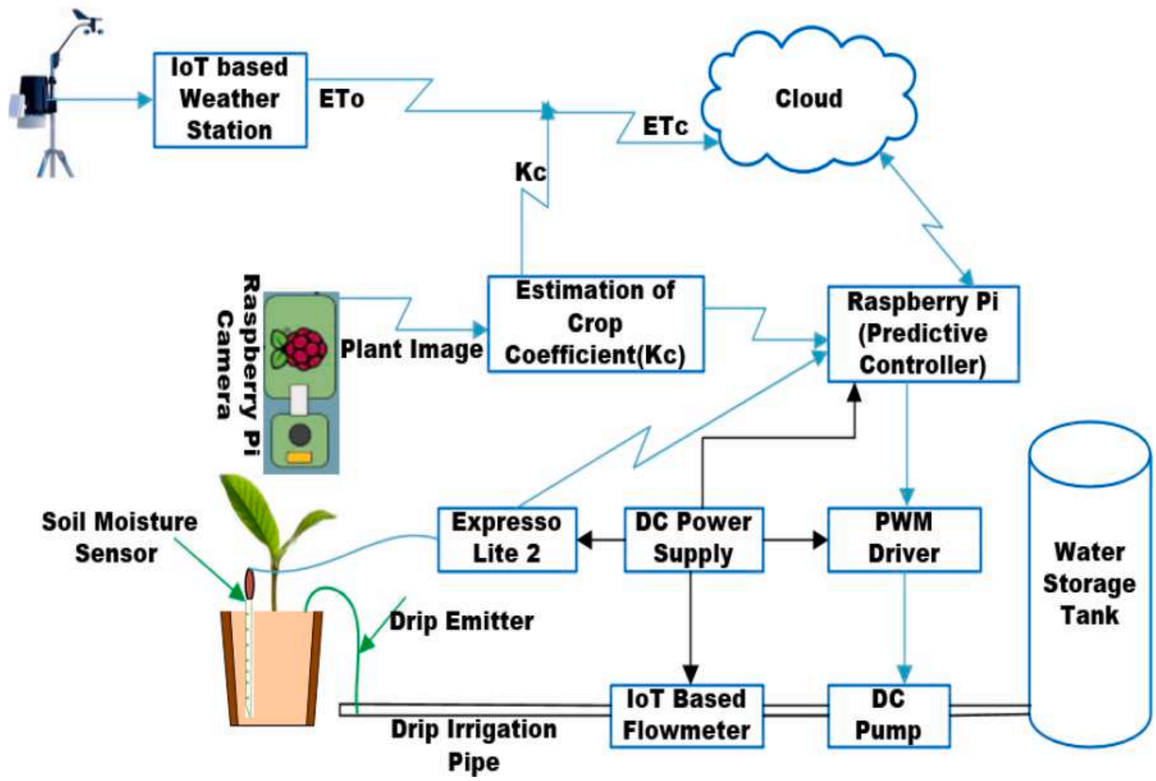

Fig. 3. An IoT based model predictive control framework.

the aid of a real-time IoT based weather station that senses weather parameters, an hourly computation of reference evapotranspiration (ETo) inferring the loss of water from soil surface and plant leafs is estimated based on Modified FAO-56 Penman–Monteith equation as shown in Eq. (1). The equation was developed in a customized IoT controller interfaced with the Davis weather station.

Similarly, the real time computation of the crop coefficient (Kc) using image processing method which has effect on the rate of reference evapotranspiration (ETo) shown in Eq. (2) is also known as water loss which acts as disturbance to the process.

$$ET_{O=}\frac{0.408\Delta(R_n) + \gamma\frac{900}{T+273}U_2\ (e_2\ )}{\Delta + \gamma(1 + 0.34U_2\ )} \tag{1}$$

where, ET_O denotes the reference evapotranspiration (mm/hour); Rn represents the reference crop canopy net radiation (W/m^2); Δ represents the slope of saturation vapour pressure (kPa °C-1); λ represent the latent heat of vaporization (kPa °C $^{-1}$); T represents the mean air temperature in Celsius; U_2 is the Mean daily or hourly wind speed at 2 m height (ms^{-1}) and e_2 represent the stream pressure of saturation vapour (kPa) [71]. The estimated ETo is used to derive the actual evapotranspiration (ET_C), which is the loss of water from a specific crop, from where the estimated amount of water to replace the water loss is computed for further application to the plant, based on the crop coefficient (K_C) which is of different value from one crop to another.

$$ET_C = ET_O * K_C \tag{2}$$

Based on the framework shown in Fig. 3, the real time sensing of soil moisture in terms of volumetric water content (*vwc*) was carried out using a VH400 sensor connected to the IoT Expresso board. The VH400 sensor probe is a resistance based soil moisture content sensor which measures the dielectric constant of the soil when inserted vertically into the ground close to the root area of the plant [72]. The VH400 soil moisture sensor was calibrated using the piecewise linear equations as described in Eqs. (3)–(5).

$$y = mx + c \tag{3}$$

$$vwc = mV + c \tag{4}$$

$$m = \frac{vwc_2 - vwc_1}{V_2 - V_1},\ c = mv - vwc \tag{5}$$

where, m is the slope of the line. The VH400's voltage (v) to the *vwc* curve can be approximated with 4 segments of the form in Eq. (3) and Eq. (4), respectively [73]. Similarly, V_1 and V_2 are the voltages recorded at the respective *vwc* levels of vwc_1 and vwc_2. The sensor has an inbuilt voltage regulator that operates with a DC input voltage of 3.5 to 20 Volts, which requires an input current of less than 7 mA. It produces a DC output voltage in the range of 0 to 3V which infers different level of the soil water content [74].

Similarly, the irrigation volume and reference evapotranspiration $ET_o$was computed using an IoT based flow metre and weather station. Similarly, the irrigation volume of the IoT based flowmeter produces an output digital pulse and then further counted by the IoT Expresso board to calculate the amount of water flow per each irrigation event. The water flowrate R is calibrated using Eqs. (6) and (7).

$$R = \frac{N *\ 60(Pulse\ per\ minute)}{M(Pulse\ per\ litre)} \tag{6}$$

where, the number of pulses M generated per litre of water flowing through the sensor can be found in the water flow sensors specification datasheet, while N is the number of pulse count generated by the flow sensor. The water flow volume can be calculated by summing up the product of flowrate and the time interval.

$$Water\ flow\ volume = \sum_{k=0}^{N} Flowrate * Time\ Interval \tag{7}$$

Water loss also known as disturbance of the process plant which requires an estimation of real time crop coefficient (K_C) to guide an efficient water management [75]. To accurately estimate the water loss

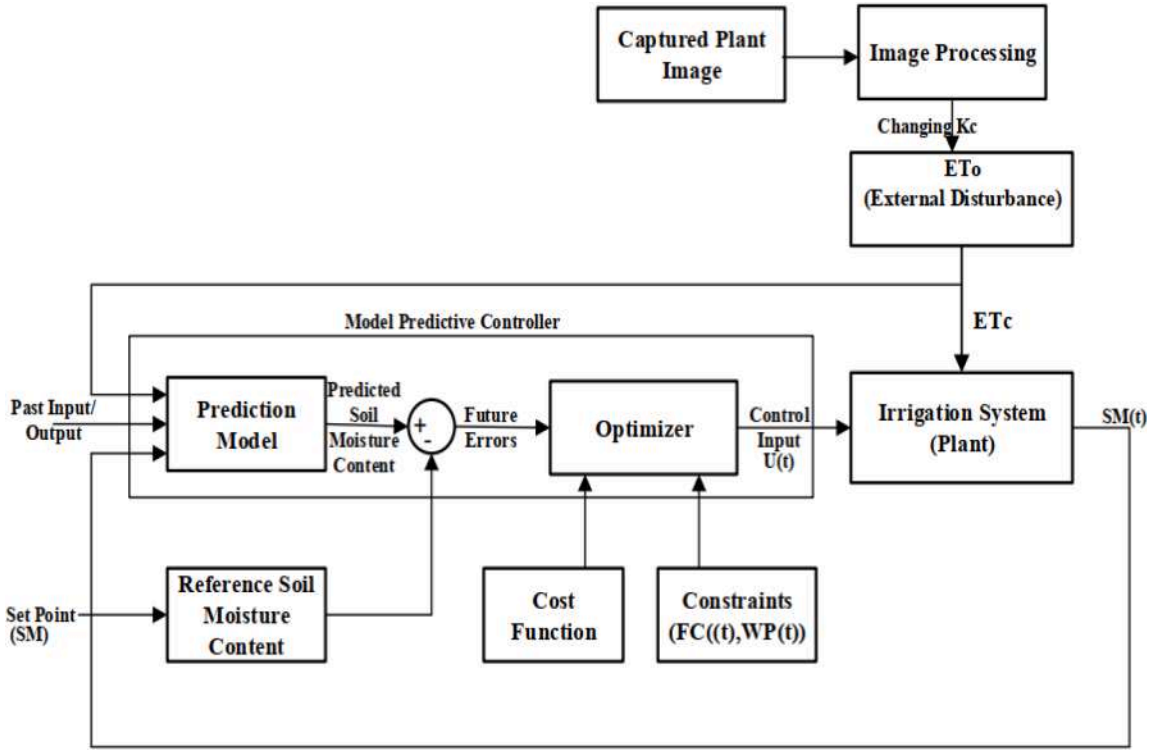

Fig. 4. Model predictive control for drip irrigation system.

actual evapotranspiration (ETc) termed water loss requires real time monitoring of Kc at different growth stage as well as measurement of real time of reference evapotranspiration (ETo). Determining the height of the plant as well as the leaf area index (LAI) using image processing to compute the K_C can guide the accurate determination for the actual water loss and enable the model predictive controller to be able to compensate for the loss [75]. The computation of the K_C was carried out using the ratio of LAI and plant height estimated based on Eq. (8) using and computed on Raspberry pi with camera.

$$K_C = \frac{LAI}{Plant\ Height} \tag{8}$$

2.1. Data driven system identification of the system

The data driven system identification of the process was carried out offline in MATLAB using the input and output data collected from a previous open loop experiment on similar plant. The experimental data collected was pre-processed and split into two, one for estimation and the other for validation. The data driven model is obtained using a system identification method, in which 3700 data point of input and output experimental dataset with sampling time of 10 min was used for the identification.

Different time series model structures were selected to get a good model of the best fit, but the discrete-time state space model was chosen due to it suitability for controller design. The identified state space model is represented by Eqs. (9) and (10) with, B, C, and D matrices was used to represent the dynamics of the real system. Also, $x(k)$ is the state variable at time instant k, $u(k)$ is the manipulated variable (irrigation flow), $y(k)$ is the measured output (volumetric water content of the soil).

$$x(k+1) = Ax(k) + Bu(k) \tag{9}$$

$$y(k) = Cx(k) + Du(k) \tag{10}$$

where,

$$A = \begin{bmatrix} 0.9996 & 0 \\ 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} -9.062\times10^{-9} \\ -7.245\times10^{-6} \end{bmatrix}$$

$$C = [-5530\ 0] \quad D = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

2.2. Model predictive control for drip irrigation system

Model predictive control (MPC) is a process control algorithm that uses a model of a system to predict the future evolution of the system to optimize the control signal according to the cost function, while bringing the predictive output of the system to track the desired reference trajectory [76]. MPC requires a model that fully capture the varying dynamics of the plant to allow a good estimation of the future process while the controller takes decision based on the forecasting of the system's behaviour through optimization. The prediction horizon $N_p$is the future number of samples to which the controller can predict the output of the plant, while the control horizon is the number of samples within the prediction horizon to which the controller have effect on the control signal.

The MPC irrigation controller block diagram illustrated by Fig. 4 shows the irrigation system (plant) which is the cultivation environment with crop whose major monitoring and control parameter is the soil moisture, and often disturbed by high ETc, hence that requires the control action in terms of irrigation volume $u(k)$ to compensate for the water loss in order to maintain the desired reference trajectory of the soil moisture content implied as the control variable. The MPC controller needs to predict the volume of irrigation in order to optimize some desired characteristics of the plant required at each sampling instance.

2.3. Model predictive control formulation

Assuming that the soil moisture that is denoted as the state variable SM(t) is $x(k)$, i.e. $x(k+1)$, $x(k+2)$,…, $x(k+N)$, where $x(k+N)$, is the state variable predicted at the sampling instant $k+N$. The prediction

Table 2
Parameters of the proposed MPC controllers.

Parameters	Description	Value	Unit
T_S	Sampling Time	10	0.4
N_c	Control Horizon	5	–
N_p	Prediction Horizon	10	–
SM_{min}	Wilting Point	0.1	m^3/m^3
SM_{max}	Field Capacity	0.4	m^3/m^3

Table 3
Model predictive control algorithm.

Algorithm 1: MPC optimal control signal for the current interval
Get measurements of the plant Input $Ir[k_i-1]$, $ETc[k_i-1]$, Output $\theta[k_i-1]$
Use the previous input and output data to identify a predictive model
While simulation is ongoing **do**
Use the process model, predict the process output $\theta_p[k_i]$ over a horizon
Estimate the error $e[k_i]$ ie $\theta_p[k_i]-\theta[k_i]$ and Minimize J
If $\theta_p[k_i]-\theta[k_i]>0$ *or* $ETc \geq ETc_{max}$
Solve an optimal control problem to compute $u(k),\ k=1,\ldots\ldots,m$, considering the constraints and future ones in a prediction horizon (N) steps to minimize the error $e[k_i]$
Apply the first decision to implement the first event computed move $u(k)$
end
Move to the event and repeat the procedure from the beginning $k=k+1$

horizon N_p, denotes the number of future predicted samples. The objective of the MPC is to optimize the future control effort trajectory $\Delta U(k) = [u(k)\ u(k+1)\ldots\ldots..u(k+N_c-1)]^T$ where $u(k)$ is the control input or applied irrigation, N_c is the control horizon that denotes the number of parameters that determines the future control trajectory. Note that $N_c \leq N_p$, while $E(k)$ denote the reference evapotranspiration which act as disturbance on the plant state variable. According to Ref. [77], in order to calculate the set of predicted state and output variables as a function of the future control variable using a state space model ($A,\ B,\ C\ and\ D$) over a prediction horizon of N_p as follows:

$$x(k+1) = \text{axe}(k) + Bu(k)$$

$$x(k+2) = \text{A}x(k+1) + Bu(k+1) \tag{11}$$

$$x(k+2) = A(Ax(k) + Bu(k)) + Bu(k+1)$$

$$x(k+2) = A^2x(k) + \text{A}Bu(k) + Bu(k+1) \tag{12}$$

$$x(k+N_p) = A^{Np}x(k) + A^{Np-1}Bu(k) + A^{Np-2}Bu(k+1)$$

$$+\ldots + A^{Np-Nc}Bu(k+N_c-1) \tag{13}$$

Similarly, the predicted output variables can be derived using the set of future control variables as follows

$$y(k+1) = \text{CA}x(k) + Du(k) \tag{14}$$

$$y(k+2) = \text{CA}x(k+1) + Du(k+1)$$

$$y(k+2) = CA(\text{axe}(k) + Bu(k)) + Du(k)$$

$$y(k+2) = CA^2x(k) + \text{CA}Bu(k) + Du(k+1) \tag{15}$$

$$y(k+N_p) = CA^{Np}x(k) + A^{Np-1}Bu(k) + A^{Np-2}Bu(k+1) +$$

$$\ldots + A^{Np-Nc}Bu(k+N_c-1) \tag{16}$$

Therefore the future control moves and the future state variable are calculated from the augmented matrix and based on this the predicted output variable derived from Eqs. (9) to (16) and is given by Eq. (17).

$$Y_{PR} = \varphi x(k) + \varnothing\ \Delta U(k) + \gamma E(k) \tag{17}$$

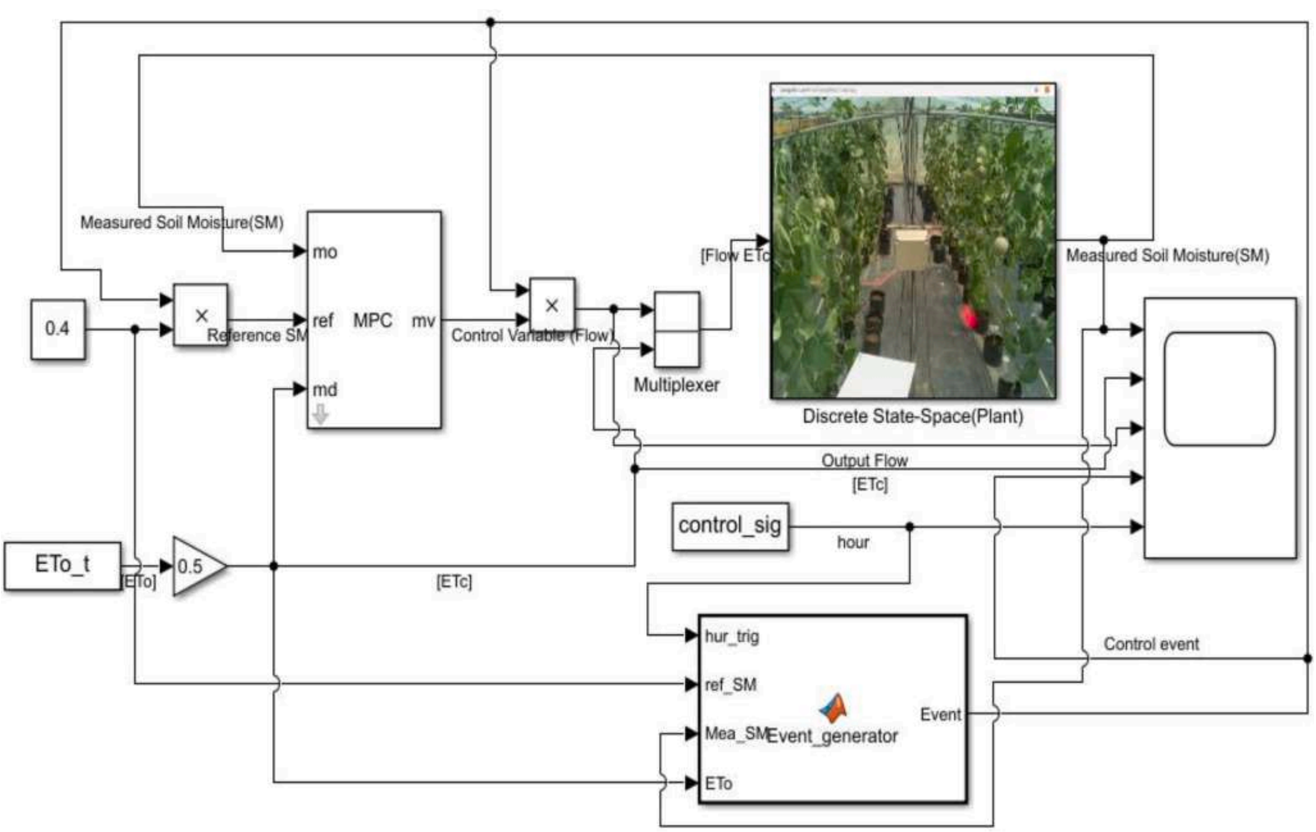

Fig. 5. Implementation diagram of MPC irrigation controller in Simulink.

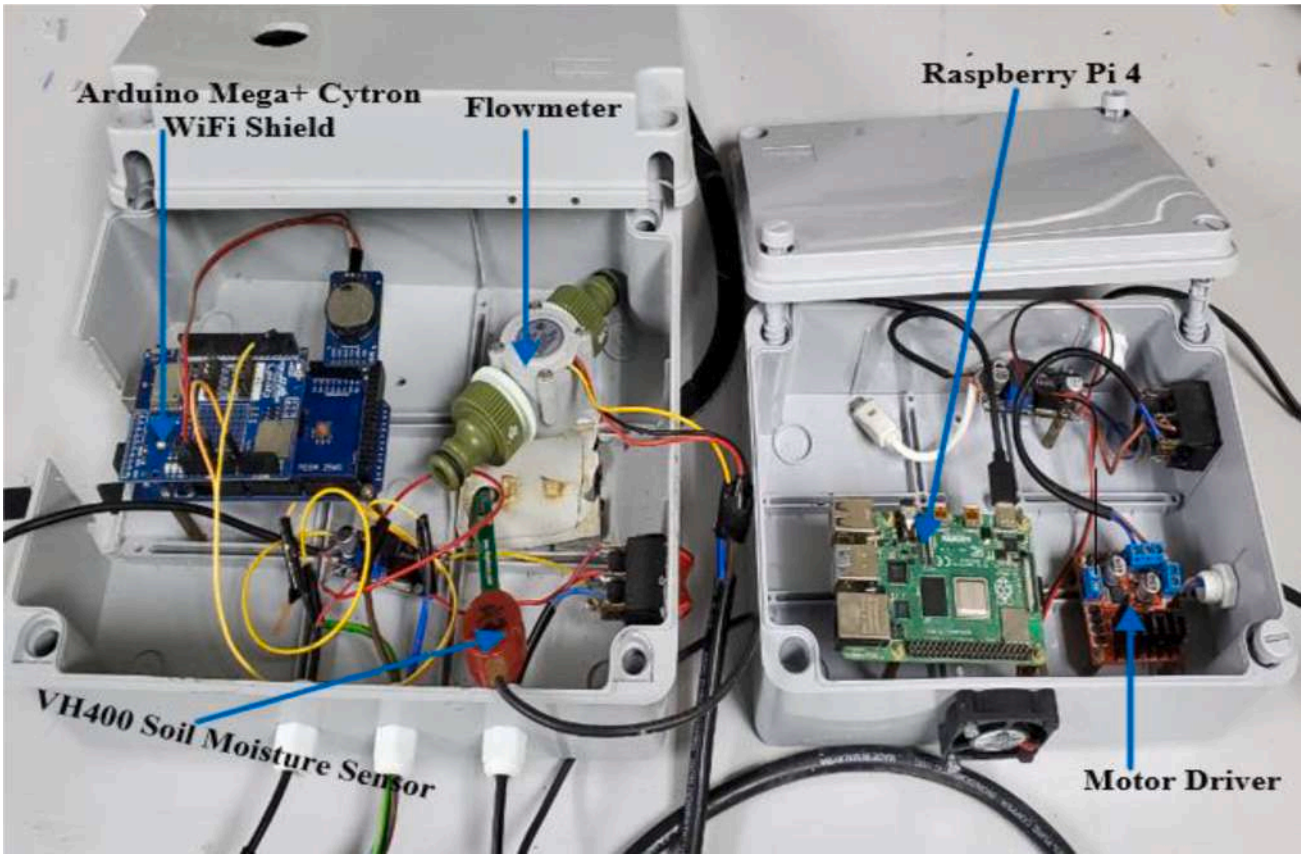

Fig. 6. Hardware implementation of the data driven MPC on Raspberry Pi with IoT integration.

Where $$E(k) = \begin{bmatrix} e(k) \\ e(k+1) \\ \vdots \\ e(k+Nc-1) \end{bmatrix} \tag{18}$$

$$Y_{PR} = \begin{bmatrix} y(k+1) \\ y(k+2) \\ \vdots \\ y(k+N) \end{bmatrix} \tag{19}$$

$$\Delta U = \begin{bmatrix} u(k) \\ u(k+1) \\ \vdots \\ u(k+Nc-1) \end{bmatrix} \tag{20}$$

$$\varphi = \begin{bmatrix} CA \\ CA^2 \\ \vdots \\ CA^{Np-1} \end{bmatrix} \tag{21}$$

and

$$\varnothing = \begin{bmatrix} CB & 0 & \cdots & 0 \\ CAB & CB & \cdots & 0 \\ CA^{Np} & CAB & \cdots & 0 \\ & \vdots & & \\ CA^{Np-1}B & CA^{Np-2}B & \cdots & CA^{Np-Nc}B \end{bmatrix} \tag{22}$$

$$\gamma = \begin{bmatrix} CBd & 0 & \cdots & 0 \\ CABd & CB & \cdots & 0 \\ CA^{Np}Bd & CAB & \cdots & 0 \\ & \vdots & & \\ CA^{Np-1}Bd & CA^{Np-2}Bd & \cdots & CA^{Np-Nc}Bd \end{bmatrix} \tag{23}$$

The cost function (J) of the optimization is formulated in Eq. (24) as follows:

$$J = \left(R_f - Y_{Pr}\right)^T Q_\delta \left(R_f - Y_{Pr}\right) + \Delta u^T Q_\lambda \Delta U \tag{24}$$

$R_f$is the reference trajectory of the target soil moisture value, Y_{Pr} is the future value of the soil moisture content, Q is the function of the state $x(k)$ and input $u(k)$ variable. Where $R^T = [1,\ 1,\ 1, \ldots\ldots, 1]SM(k)$ the vector of the references over is N_p, $SM(k)$is the current reference. Q_δ is the weighting matrix of the tracking error while Q_λ is the weighting matrix of the control increase. The tuning of Q_δ and Q_λ can enhance the error and control tracking performance of the MPC irrigation controller. The goal of the controller cost function to satisfy the dynamics of the system. That is to make the future output as close to the set point or reduce the error $e(k)$ between the future output and the set point R_f, ie reduce $e(k) = Y_{Pr} - R_f$ by generating the sequence of the appropriate control input action u(k) in steady state where the change in control signal is eliminated. The formulation optimization problem for the MPC irrigation system design is to find the n sequence of input that will minimize the cost function in Eq. (25).

$$\min_{\Delta u} J = \left(R_f - Y_{Pr}\right)^T Q_\delta \left(R_f - Y_{Pr}\right) + \Delta u^T Q_\lambda \Delta U \tag{25}$$

Subject to the constraints that the initial state are measured at any time is known and measured and maintained between the field capacity

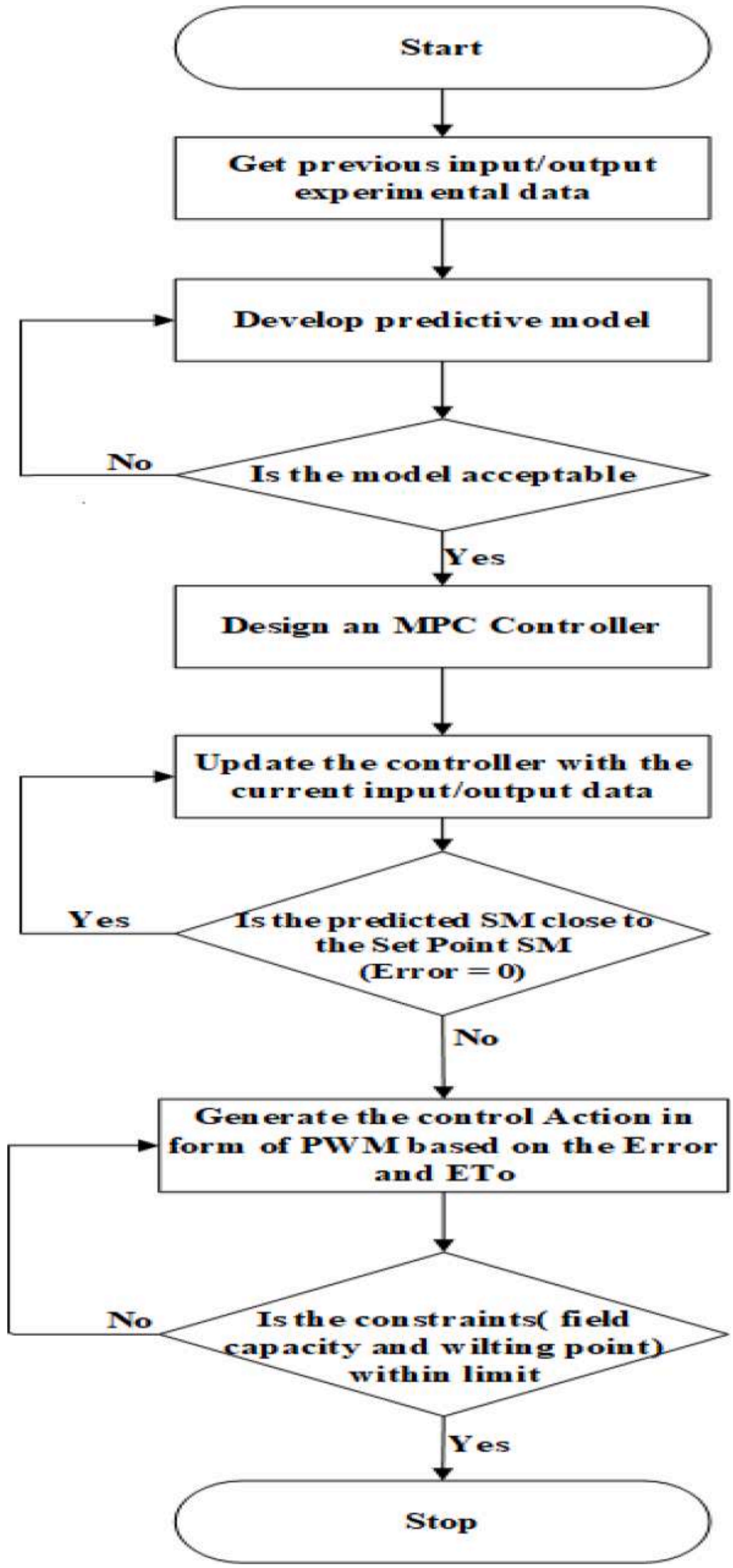

Fig. 7. Flowchart for the MPC based irrigation control system.

of the soil (SM_{max}) and wilting point (SM_{min}). The minimization also need to satisfy the system dynamics as well as the irrigation volume so as not to over irrigate the greenhouse to prevent over flooding with water and also maintain the soil moisture between the field capacity and wilting point.

$0 \leq u(k) \leq EI_{max}$

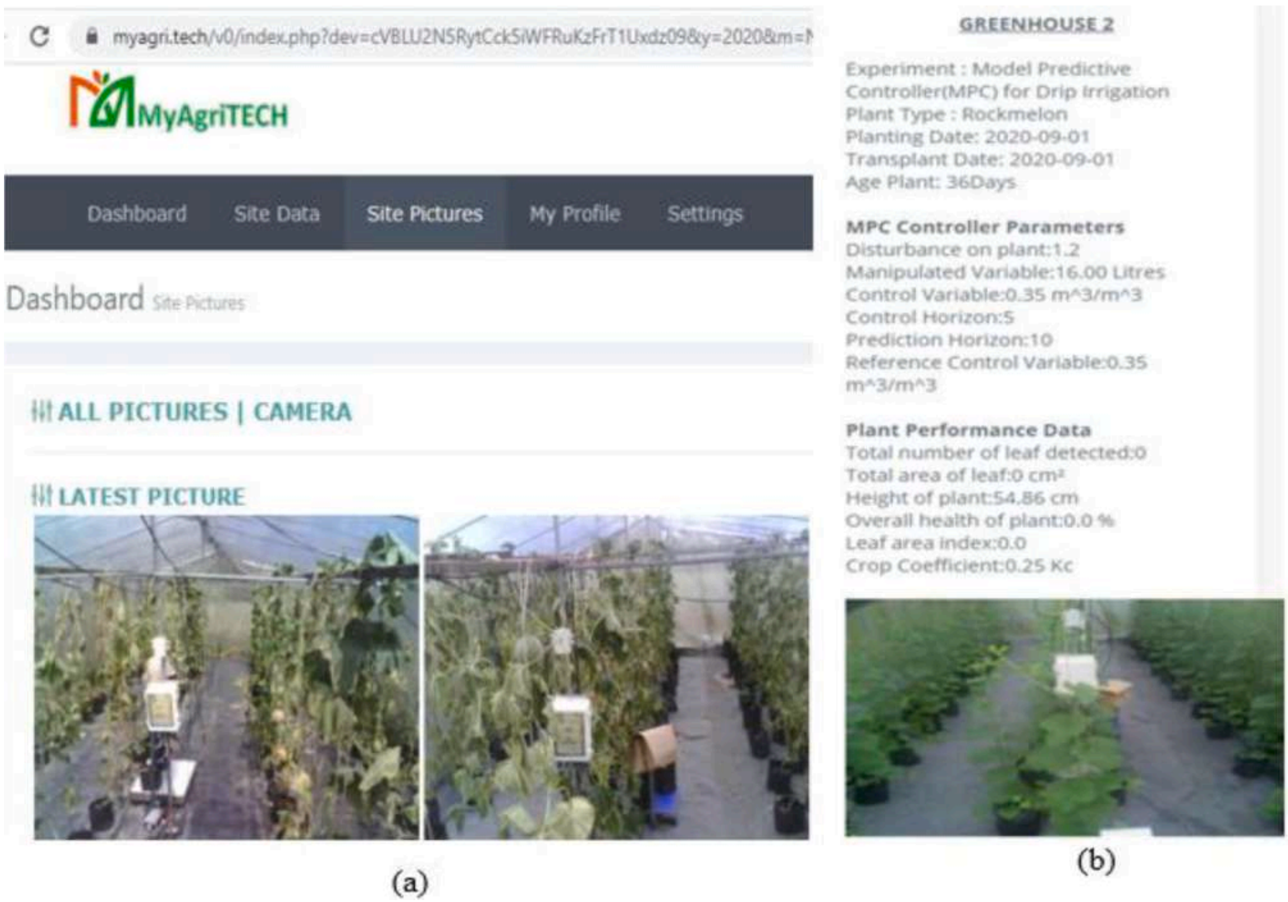

Fig. 8. (a) IoT based monitoring dashboard for GH 1 and GH2 with cultivated plant at maturity (b) Deployed model predictive controller in a GH1 cultivation experiment.

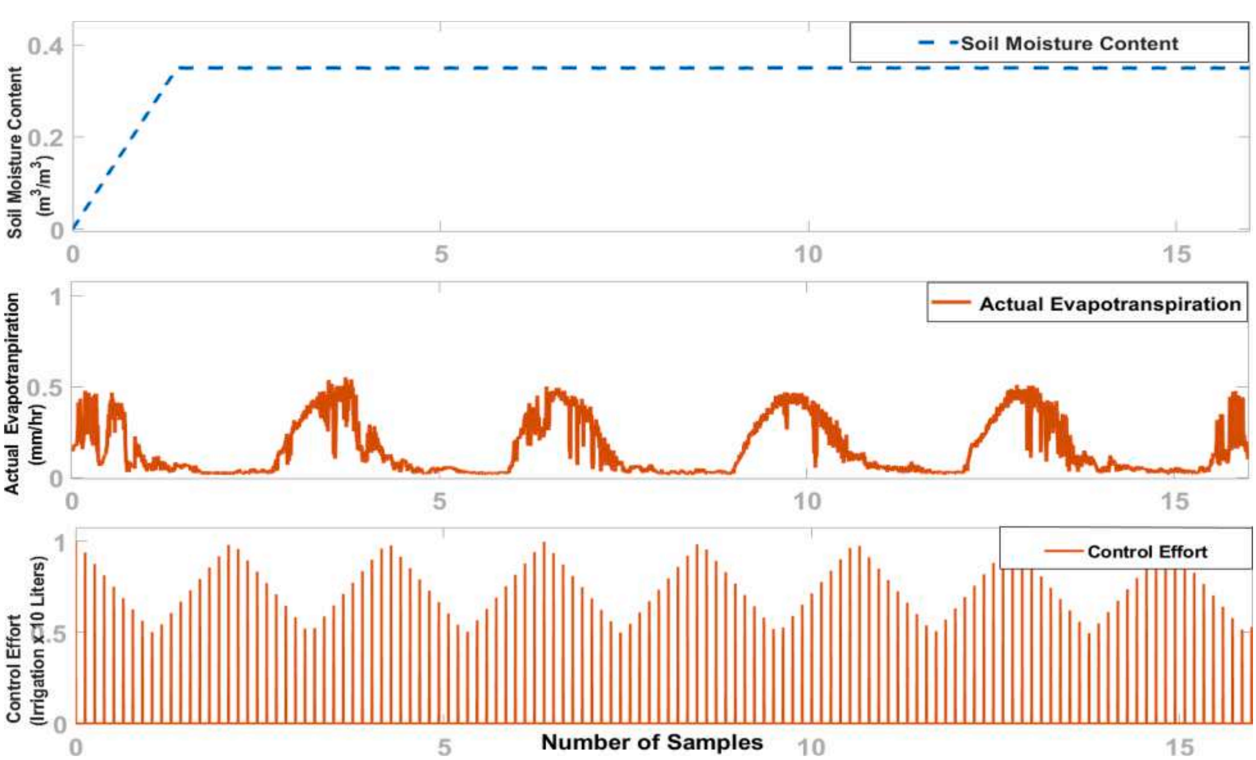

Fig. 9. Simulation of the MPC controller in Simulink.

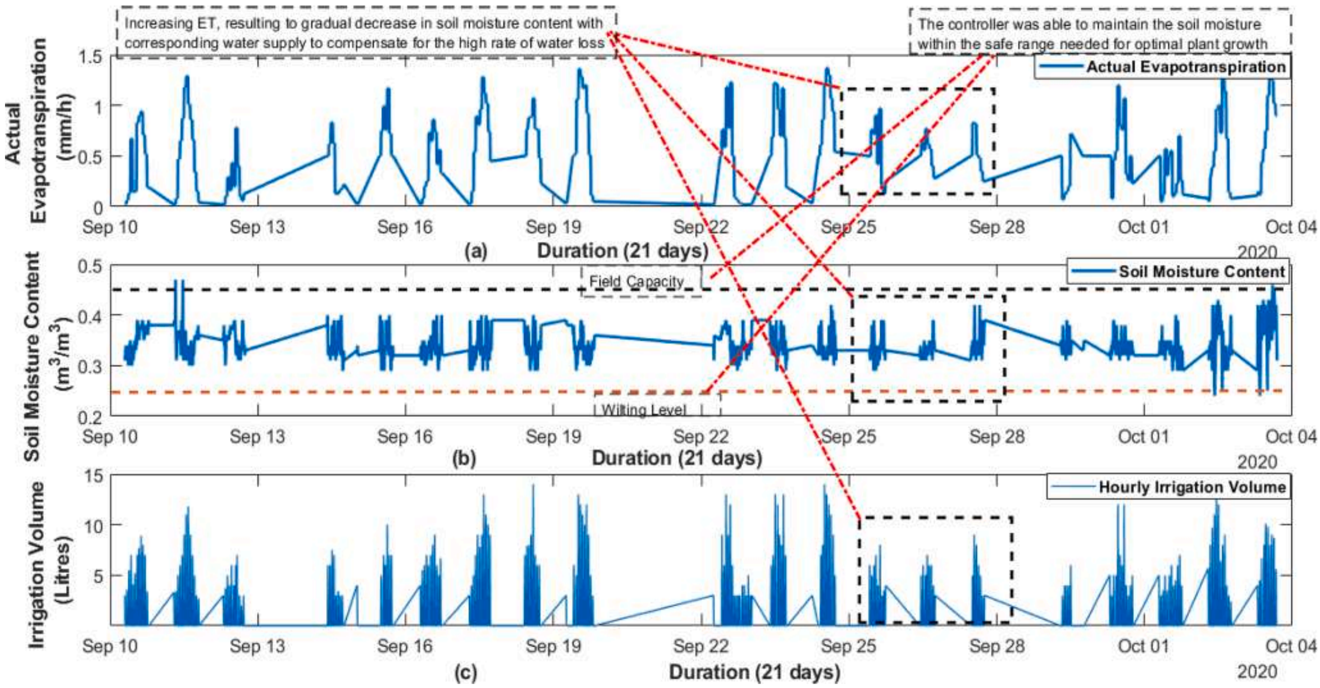

Fig. 10. Experimental Results (a) Daily Reference Evapotranspiration (mm/day) (b) Volumetric water content of the soil (m^3/m^3) (c) Daily Hourly irrigation volume (Liters).

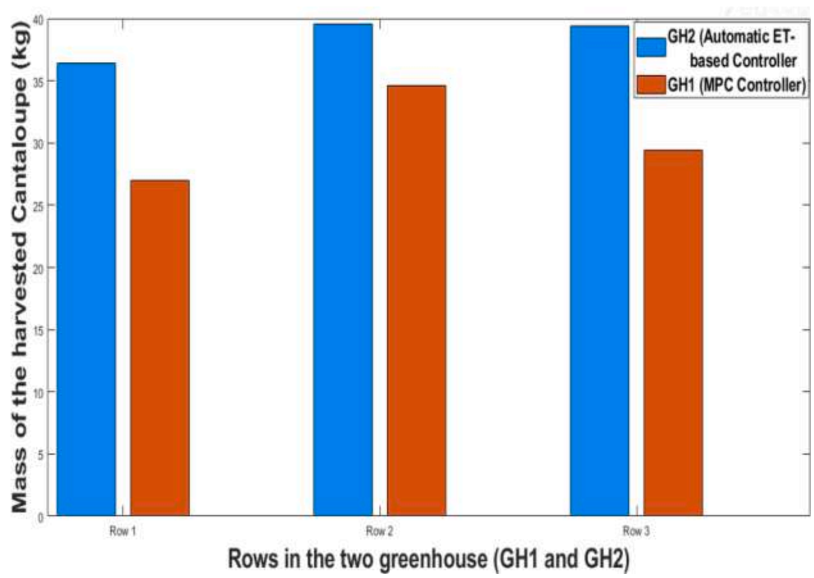

Fig. 11. Comparison of both controllers in GH1 and GH2 in terms of the total mass of the harvested Cantaloupe yield.

$SM_{min} \leq Z \leq SM_{max}$

where, EI_{max} is the allowable optimal effective irrigation effort, SM_{min} andSM_{max} are the wilting point and field capacity of the plant root zone deficit which serves as constraints to the irrigation system. The optimal control signal is obtained as follows in Eq. (26).

$$\frac{\partial J}{\partial \Delta U} = 0$$
$$\Delta U = \left(\varnothing^T \varnothing + \overline{R}\right)^{-1} \varnothing^T \left(R_f - \varphi \mathrm{x}(k)\right) \tag{26}$$

2.4. Real time implementation of data driven MPC design in Simulink

This section describe the application of MPC for designing a real time irrigation controller simulation *via* Simulink. The MPC controller block was designed with the state space model identified using the data driven modelling through system identification, and imported into the MPC designer app for configuration and tuning as described by algorithm 1 in Table 3, while flowchart guiding the controller is also illustrated using Fig. 8. The performance of the MPC also depends on the choice of the control and prediction horizon, and constraints on the control variable. The parameters used to design the predictive controller are, the prediction horizon of 5 and control horizon of 10 was chosen as seen in Table 2. One of the main strength is the ability to handle constraint on

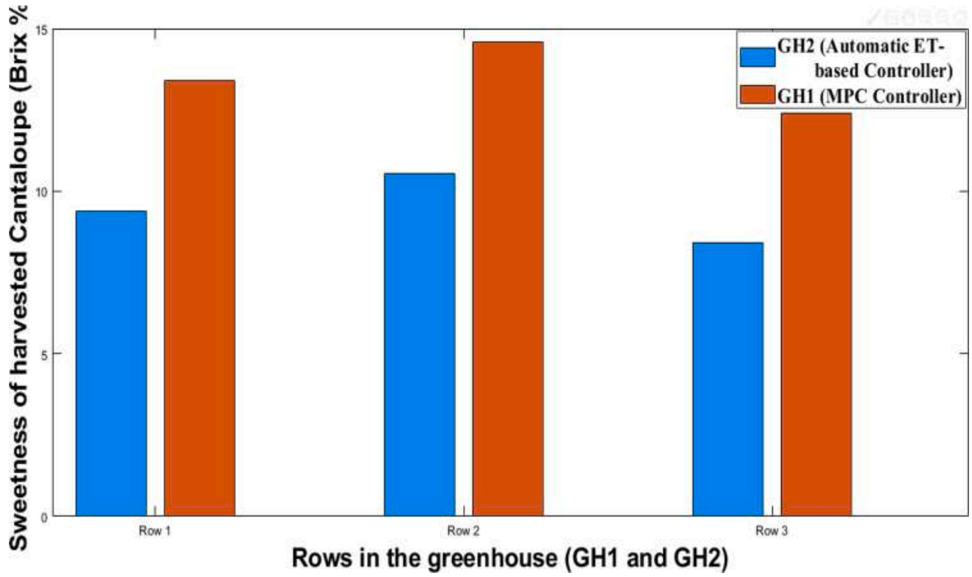

Fig. 12. Comparison of both controllers in GH1 and GH2 in terms of the sweetness of the harvested Cantaloupe yield.

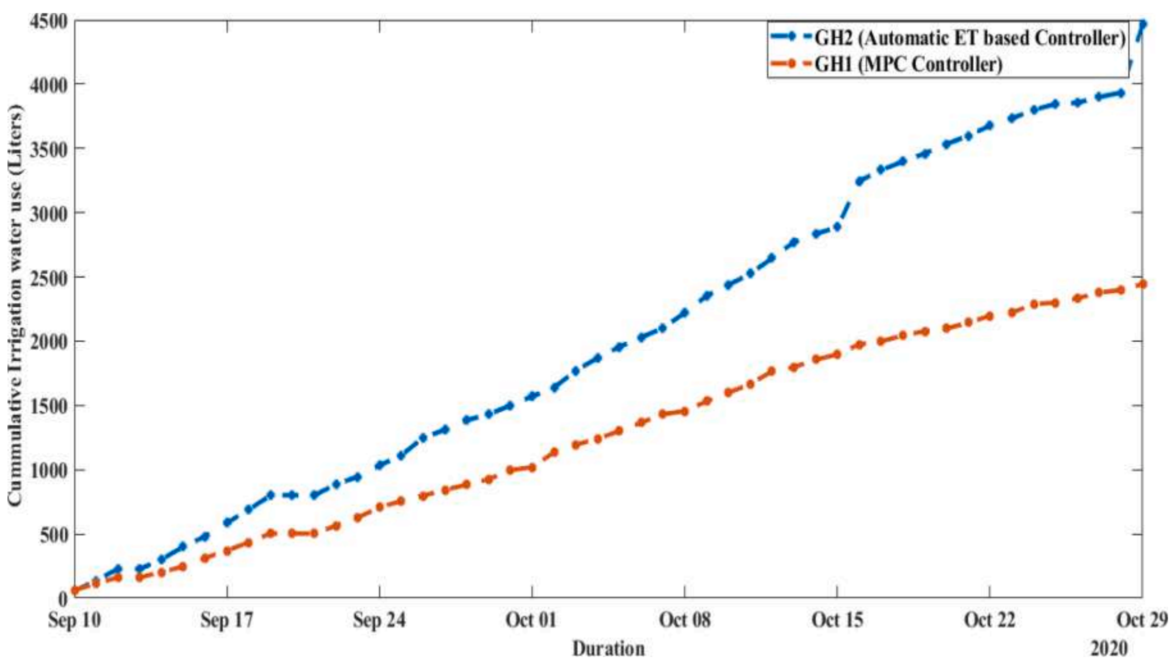

Fig. 13. Cumulative Irrigation water use (Liters).

the plant. The constraint on the control variable (soil moisture) y is set within the lower limit ($0.2m^3/m^3$) and upper limit ($0.45\ m^3/m^3$) called wilting point and field capacity respectively.

Similarly, the weights on the control and manipulated variable (MV) was use to adjust the controller performance. The weight on the MV was used to penalise the control action, meaning that because the system is strongly nonlinear, with rapid variations of some variable with time, if the sampling interval is set too long, the process will be out of control for a long time simulation [59,78]. The input weights were chosen as close to zero (0.01), to provide more good control response. After the design, the controller is exported to the MATLAB workspace and saved as mat file. The MPC controller was exported and integrated with the event generator function in Simulink as shown in Fig. 5. In order to ensure optimal computational and controller performance and event based generator was integrated to update the controller based on a triggering event at one hour interval and when ETo is more than 1 mm/day for up to 10 min.

3.5. *The hardware implementation for experimental cultivation validation*

The close loop simulation of the MPC controller design implemented in Simulink was deployed through of it support package for Raspberry Pi the hardware implementation realization as illustrated in Fig. 6. The model predictive irrigation algorithm generates the control action in form of pulse width modulated (PWM) signal a with a varying duty cycle to drive the manipulated variable while compensating for the loss and disturbance on the plant. The motor driver receives PWM control action signal from the GPIO pin 12 and 13 of the Raspberry Pi and provides the necessary driving current to the direct current (DC) water pump from the power supply. Raspberry-Pi 4 micro-computer was used to

Fig. 14. IoT based monitoring devices in GH1 and GH2.

implement the model-based irrigation control system in real-time. The Raspberry pi uses a 1.5 GHz quad-core Broadcom processor, 64 bit SoC with 4 GB DDR4 of RAM, GPU 500 MHz video core vi. With this SoC specification, the model predictive control algorithm was able to run efficiently. The deployed MPC controller illustrated using the flowchart in Fig. 7 was used to adaptively control irrigation volume based on the rate of water loss for Cantaloupe plant cultivation in greenhouse 1 (GH1) from 10th September, 2020 and 29th October, 2020. Similarly, the automatic ET-based controller deployed in greenhouse 2 (GH2) was used to bench mark the performance of the proposed MPC controller.

3. Results

The results comprises of both the controller simulation outcome as well as the deployment of the controller in a greenhouse for the experimental cultivation of Cantaloupe. The dashboard in Fig. 8 shows the greenhouse monitoring for both GH1 and GH2. The model predictive controller as deployed in GH1 for experiment, while the controller deployed in GH2 is an automatic ETo based irrigation controller. The controller in GH2 work based on feed forward control strategy, where estimation of irrigation is based on rate of water loss due to evaporations, and used for benchmarking purpose. The dashboard enhances the real-time monitoring of the process in the greenhouse, with data of soil, weather and plant that have been uploaded on the server to be viewed remotely. Also the mini dashboard in Fig. 9(a) contains details of the experiment and controller performance.

The simulation result of the proposed MPC controller in Simulink is shown in Fig. 9. The graphs show the interaction plot of the soil moisture content, actual evapotranspiration, and irrigation flow against several sampling instant. The simulation results shows that the control variable, also the volumetric water content of the soil was brought to the set point of 0.35 m^3/m^3 even when the disturbance (water loss) in terms of actual evapotranspiration ETc is high, there is also corresponding control action to replace the water loss from the soil. The simulation result of the proposed MPC controller in Fig. 8 has similar trend with the bench marked works of [66,79], in terms of the control action denoted as irrigation volume, used to compensated for the water loss while regulating the soil moisture content within field capacity and wilting point.

Similarly, the Fig. 10(a)–(c) further shows the relationship between the measured daily ETo, daily soil moisture content, and the daily hourly irrigation volume in (Liters) measured in MPC controlled GH1 respectively. The proposed controller was able to regulate the soil moisture content within the field capacity and wilting point, even when the rate of water loss in terms of ETo is high, while the pumped irrigation water was able to adaptively compensate the water loss (ETo).

The result of the performance evaluation is presented in Figs. 11–13. Different indices were used to determine the performance comparison of the two irrigation methods on the cultivated Cantaloupe plants, which are cumulative water consumption (litre), water use efficiency, weight of fruit (kg), and sweetness of fruit (brix). From the bar chart in Figs. 11 and 12 illustrates the performance comparison of the both controllers deployed in both greenhouse in terms of the mass of the harvested Cantaloupe fruit and the quality of the fruit.

4. Discussion

Based on the comparison of the yield performance from the two greenhouses controlled by the MPC controller (GH1) and ETo based controller (GH2), the total mass of the harvested fruit in GH2 is higher than that of the GH1 as seen in Fig. 11. This could be as a result of the fact that a lot of water was consumed during the irrigation process in GH2, when compared to that of GH1. However the quality of fruits harvested in terms of sweetness was recorded in GH1 is observed to be better that the harvested fruits in GH2 as illustrated in Fig. 12. Therefore, the GH1 irrigated using the MPC has better fruit quality in terms of sweetness and improved water use efficiency. This could be due to the gradual increase of water supply to the plant root area based on the plant, soil and weather demand.

Furthermore, the computation of the daily cumulative water use was carried out to be able to track the water saving capability of both controllers. From the graph of cumulative irrigation water use (Liters) shown in Fig. 13, it can be seen that irrigation water consumed by the automatic ETo controller is higher than that of the MPC controller. Similarly, about 2022 liters of water was saved in GH1 controlled by MPC. It can also be deduced from Fig. 13, the MPC controller in GH1 was able to achieve a 30.4% water saving when compared to automatic ETo based controller in GH2. This is due to the fact that MPC in GH1 was able to adaptive to the changing dynamics of the process as compared with the GH2 controller.

$$\text{Water productivity index} = \frac{\text{Total mass of the harvested Cantaloupe (kg)}}{\text{Total cummulative irrigation volume (Liters)}} \tag{27}$$

In addition, the performance of both controllers in GH2 and GH1, in terms of the water productivity index which relates the total mass on Cantaloupe produced with the total irrigation water use was further estimated using Eq. (27). According to Fig. 13, the total cumulative irrigation volume for GH2 and GH1 is 4467 and 2445 liters respectively, while total mass of equal samples of yield in GH2 and GH1 is 115.3 kg and 90 kg. Therefore, the water productivity index of GH1 is 36.8 kg/litres as against 25.6 kg/litres in GH2. It can be further deduced that the MPC controller in GH1 gives water productivity of 30.4% higher than the automatic ETo based controller in GH2, hence, highly suitable for water saving agriculture. The Fig. 14 illustrates the IoT based monitoring devices in GH1 and GH2 used to enable the deployment of both controllers for the experimental cultivation of the Cantaloupe plant.

5. Conclusion

This paper presents the design and experimental implementation of data driven MPC for precision irrigation. The MPC controller was designed using a data driven identified state space model that captures the changing dynamics of the process, with the ability to adaptive control the irrigation volume required to compensate for the water loss within the greenhouse environment and also minimise the error between the measured soil moisture and the reference trajectory of the volumetric water content of the soil. The performance of the MPC controller deployed on Raspberry Pi 4 was put to test on the experimental cultivation of Cantaloupe plant using drip irrigation in GH1. The MPC irrigated greenhouse (GH1) recorded a good quality of fruit with average sweetness level of 13.5 Brix and higher water productivity index of 36.8 g/liters compared to automatic ETo based controller irrigated greenhouse (GH2) with 10.5 Brix and 25.6 g/liters respectively. However, the total mass of harvested fruit in GH2 is higher than that of GH1. From the performance comparison, both irrigation methods have their strength and weakness on Cantaloupe plant cultivation. Therefore, it is expected that this research effort will guide farmers to adopt an effective irrigation controller which comply with their cultivation objectives such as water saving, improve yield, and quality.

Data availability

Data will be made available on request.

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