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Data-driven model predictive control for precision irrigation management

Erion Bwambale[a,b,c,*], Felix K. Abagale[a,b], Geophrey K. Anornu[d]

[a] West African Center for Water, Irrigation and Sustainable Agriculture (WACWISA), University for Development Studies, P. O. Box TL 1882, Tamale, Ghana
[b] Department of Agricultural Engineering, University for Development Studies, P. O. Box TL 1882, Tamale, Ghana
[c] Department of Agricultural and Biosystems Engineering, Makerere University, P. O. Box 7062, Kampala, Uganda
[d] Department of Civil Engineering, Regional Water and Environmental Sanitation Center Kumasi (RWESCK), Kwame Nkrumah University of Sciences and Technology, Kumasi, Ghana

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ABSTRACT

The future of agriculture faces a threat from a changing climate and a rapidly growing population. This has put enormous pressure on water and land resources as more food is expected from less inputs. Advancement in smart agriculture through the use of the Internet of Things and improvement in computational power has enabled extensive data collection from agricultural ecosystems. This review introduces model predictive control and describes its application in precision irrigation. An overview of the application of data-driven modelling and model predictive control for precision irrigation management is presented. Model predictive control has been applied in irrigation canal control, irrigation scheduling, stem water potential regulation, soil moisture regulation and prediction of plant disturbances. Finally, the benefits, challenges, and future perspectives of data-driven model predictive control in the context of irrigation scheduling are presented. This review provides useful information to researchers and agriculturalists to appreciate and use data collected in real-time to learn the dynamics of agricultural systems.

1. Introduction

The current and future generations face significant challenges in ensuring that nutritious food is sustainably produced from limited land and water resources. The FAO's food and agriculture report of 2020 posits that 40% of the world population are inhabitants of water-scarce agricultural areas; of these, 37% inhabit agricultural zones with severe water scarcity [27,51]. Coupled with the rising population indices, meeting the food demand by 2050 will need a 70% increase in food production [28]. In addition to developing quick maturing and high-yielding plant varieties, scientists need to ensure that less water is used to produce more food. It is estimated that about 70% of the water abstracted for irrigation is lost through conveyance losses and poor water allocation methods [76]. This means that a lot of water is presently used to produce a unit of food. Improving water use efficiency in irrigation systems requires intelligent irrigation monitoring and control systems to ensure that no water is wasted and precise water application is achieved [15]. Sustainable precision irrigation presents a timely solution to water wastage in irrigated agriculture by ensuring that intended irrigation amounts are applied at the right time and place. Precision irrigation scheduling is striving to achieve efficient water use per plant, in space and time, in the right quantities to compensate for losses. This is possible through effective monitoring and optimal control strategies, reducing pumping costs.

Over the years, there has been a paradigm shift from traditional irrigation methods to smart irrigation systems. This has somewhat improved the water use efficiency by reducing conveyance losses. However, irrigation control is still a challenge due to the complex nature of agricultural systems. For example, most irrigation systems are designed based on historical climatic data, and irrigation schedules are developed based on this data. Precision agriculture has been facilitated by the tremendous advancement in the agricultural Internet of Things (IoT) and Wireless Sensor Networks (WSN) through remote sensing [32, 69]. The controlled monitoring of agricultural systems has enhanced the sapience of the changing dynamics of the water, plant and soil environment throughout the cropping season [5]. With advances in Big data analytics, more agricultural systems are becoming data-driven for decision-making purposes rather than relying on heuristic physics-based models [68].

Sustainable irrigation necessitates the adoption of irrigation control strategies that precisely direct irrigation water to the plant's root zone. Boman et *al.* [11] observed improved water, energy, and fertilizer use

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[*] Correspondence author.
E-mail address: erionbw209@uds.edu.gh (E. Bwambale).

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efficiency when precision irrigation control strategies are implemented. Precision irrigation control strategies are divided into two, namely, closed-loop systems and open-loop systems. Whereas open-loop systems apply a preset action like in simple irrigation timers, closed-loop systems receive feedback from sensors, make decisions and implement the resulting findings in the irrigation system [15]. Several authors have reviewed and classified closed-loop irrigation control strategies into three, namely, linear control, intelligent control and optimal control [4, 15,23]. Model predictive control has evolved over the past four decades with advances in real-time data measurements and an increase in computational power.

Model Predictive Control (MPC) refers to a category of advanced computer-controlled algorithms that use an explicit process model to predict a plant's future response [23]. Developed in the 1960s, Model Predictive Control emanates from optimal control. The basic principle of MPC is to use a dynamic model to predict system behavior and optimize the prediction to decide the control move at the current time [71]. In addition to its flexibility, Model predictive control repeatedly solves constrained optimal control problems online ([57]b). The ability to handle multivariate processes and address state and input constraints has made MPC indispensable in modern manufacturing industries [23, 56,55,70]. In a control problem, the model predictive controller's goal is to compute the plant input to follow the desired reference [60]. MPC uses a plant model to predict future plant output behavior and an optimizer that ensures that the predicted plant output tracks the desired reference [15,60]

MPC has been widely studied and applied in processing industries ([4,23,33]; F. [38,52]; L. [78]). However, in the agricultural sector, not much has been reported on the application of model predictive control in modelling dynamic agricultural systems. The most recent review by Ding *et al.* [23] focused on model predictive control applications in agriculture in general. [23] assert that the application of MPC to agriculture can yield significant productivity and efficiency benefits despite its limited use in the past years. However, no review of data-driven model predictive control in precision irrigation applications has been reported. MPC has been applied to agriculture, but it has not been applied in all respects. This work builds upon existing reviews in the field of agriculture with a particular focus on precision irrigation. This review presents an overview of model predictive control in section 2; data-driven MPC can be done through system identification, machine learning, and iterative learning control, as discussed in section 3. Section 4 presents the specific application domains of data-driven MPC in irrigation systems. The challenges and future perspectives of data-driven MPC are discussed in section 5. Finally, the conclusion and future research are presented.

2. Overview of model predictive control

2.1. Historical perspective of model predictive control

The concept of model predictive control dates way back in the 1960s to 1970s [66]. However, MPC found its way into process industries until the 1980s [23]. Since then, model predictive control has undergone several stages of development. The first stage involves classical model predictive control between 1980 and 1990 and mainly solves multivariable constraint control problems [52]. As a result of the failure to handle nonlinear systems in process industries, improved MPCs evolved towards the end of the 20th century giving more computational power with an extraordinary ability to handle constraints. This phase saw the continued penetration of the commercial MPC algorithms into various industries and a sound theoretical foundation for it. In the 1st decade of the 21st century, latest MPC evolved as many industries adopted model predictive control [52]. The latest MPC methods reduced computation time by decentralizing large-scale problems, reducing computation time directly, or simplifying computational processes [23]. The fourth phase has seen the evolution of data-driven model predictive control techniques aided by machine learning and data science advancements. Table 1 summarizes the different types of MPC since 1980. Fig. 1 presents the evolution of model predictive control.

There has been a progression from the past decades in the category of systems where model predictive control is applied. Literature has reported a significant rise in MPC application in mechanical and electrical systems [52]. Some of the application domains include suspension [34], vehicle traction control [12], direct injection stratified charge engines [35], Grain drying processes [82], traffic management [48], automatic boats for aquaculture [81], modelling temperatures in buildings [25], amongst others. This is facilitated by the precedent developments, which enable MPC implementation on hardware, making it faster than traditional processes.

2.2. Main components of model predictive control

The key to effective implementation of a control strategy is understanding how model predictive control works. Model predictive control has seven essential components (Fig. 2): prediction, receding horizon, modelling, performance index, degrees of freedom, constraint handling, and multivariable [73].

Prediction: Model predictive control considers the future implication of current control actions by computing the predicted behavior over a horizon. Predictions must capture all the system's transient and steady-state behavior [73]. Therefore, the prediction horizon dictates how far the future state will be predicted.

Receding horizon: This is the horizon over which system dynamics are predicted. After defining the optimal trajectory of the future state, the actual control input to the plant only takes the first sample of the control signal, neglecting the rest of the trajectory [78].

Modelling: Prediction of a system's future state requires a plant model. A good dynamic model will give a consistent and accurate prediction of the future. A mode of the system shows the dependence of the output on the current measured variable and the present/future inputs.

Performance index: Performance index measures the numerical definition of the best input trajectory. Performance indices of a model change with time as the system's internal model gets better over time. Performance indices must therefore be realistic and matched with model accuracy.

Degree of freedom: Degrees of freedom describe the complexity of input trajectories. Brownlee [13] defined degree of freedom as the sum of parameters in the model that are determined from data. This is inclusive of the coefficients of the model and the data used to calculate the error of the model.

Constraint handling: Model predictive control embeds constraints into the strategy development. The proposed input trajectory is optimal while satisfying constraints. The systematic embedding of constraint information is critical to effective and robust closed-loop behavior.

Multivariable: Almost all dynamic systems have numerous inputs and outputs. Model predictive control can handle multi-input-multi-output systems (MIMO) systematically. In traditional control like Proportional Integral Derivative (PID), it is complex to design MIMO systems because limited data about the plant is used in the model design, and interaction becomes cumbersome. On the other hand, model predictive control algorithms require a model and thus utilize more data, making it easier to handle MIMO systems.

2.3. Theoretical formulation of model predictive control

A model predictive controller is designed based on the state space equation of the process dynamics model as described by Rawlings *et al.* [71]. A state-space model is a probabilistic graphical model that describes probabilistic dependence between the latent state variable and the observed measurement [16,20]. Model predictive control solves an optimal control problem over a receding horizon, subject to system constraints, to determine the next control action ([43], 2018). The

Table 1
Historical perspective of model predictive control.

MPC	Examples	Characteristics	Reference				
Classical MPC	Dynamic matrix control	Model algorithm control	Generalized predictive control	The first-generation model predictive control strategy aimed to solve industrial multivariable control challenges.	Its major setback was inability to handle nonlinear systems.	[66] [71]	[23]
Improved MPC	Adaptive MPC	Robust MPC	Nonlinear MPC	Improved model predictive control solve the problem of robustness associated with classical MPC. It was able to handle nonlinear systems.		[18,23,36,39,78]	
Latest MPC	Hybrid MPC, Tube-based MPC, Stochastic MPC	Distributed MPC	Explicit MPC	Customized optimization of algorithms because of improved computing power.		([47,52,83,85])	
Data-Driven MPC	Robust data-driven MPC	Model of the system derived from experimental data	Requires real-time data collection	High computational power required	Enabled by advancement in IoT and WSN technologies.	([9,10,14,42,47,52,72,77,83,85])	

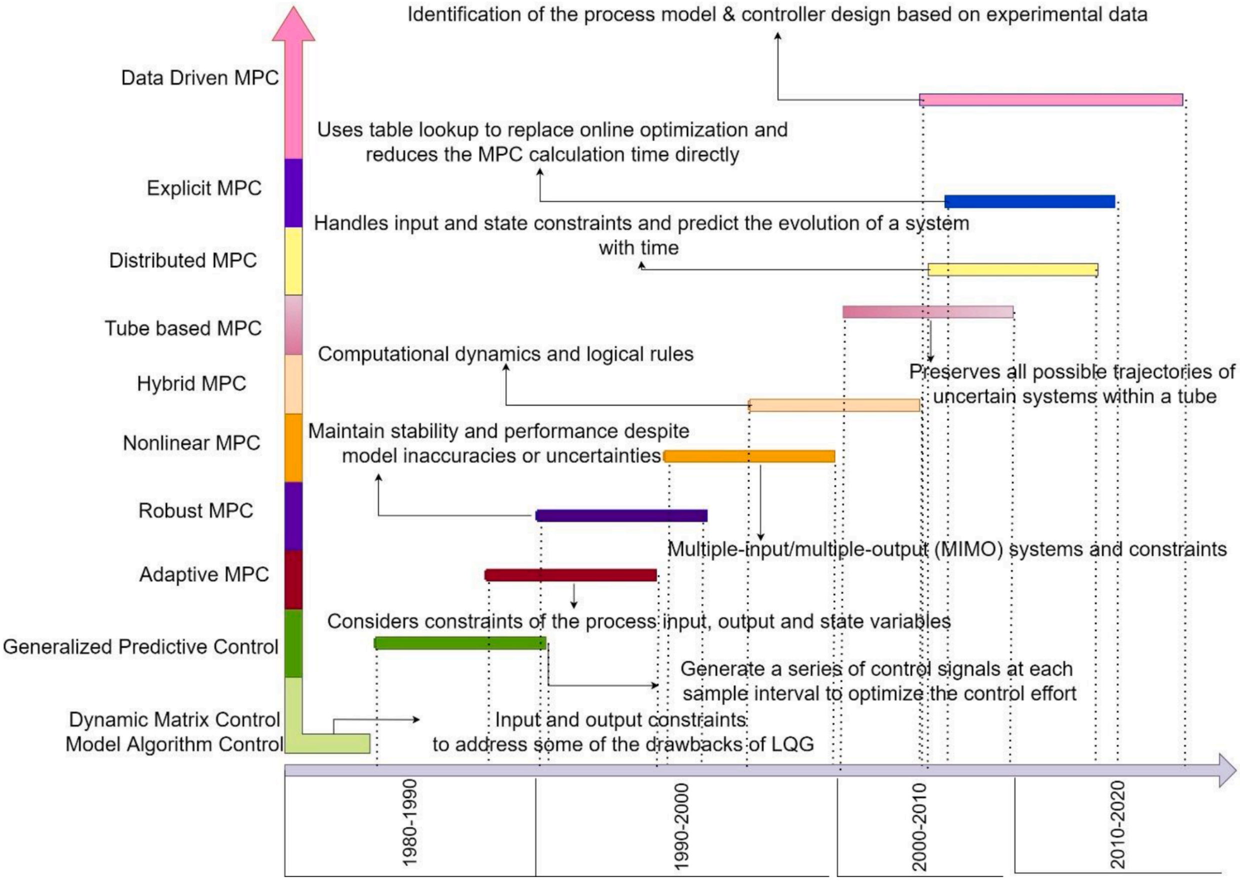


Fig. 1. Evolution of model predictive control.

optimization is iterated at each time step, and the control law is updated Fig. 3a .

Kaiser *et al.* [44] formulates a receding horizon control problem as an open-loop optimization for every time step with an optimal sequence of control inputs u (Fig. 3b)

$$u(\cdot|x_j) := \{u_{j+1}, \ldots, u_{j+k}, \ldots, u_{j+m_c} \tag{1}$$

Over the control horizon $T_c = m_c \Delta t$ given the current measurement x_j that minimizes a cost J over the prediction horizon $T_p = m_p \Delta t$, where Δt is the timestep of the model. The control horizon is less than or equal to the prediction horizon such that $T_c \le T_p$; *if* $T_c > T_p$ then the input u is assumed constant after that. The first control value u_{j+1} is then applied and the optimization is reinitialized and repeated at each subsequent timestep to solve for the unknown sequence $u(\cdot|x_j)$. This results in an implicit feedback control law.

$$K(x_j) = u(j+1|x_j) = u_{j+1} \tag{2}$$

The cost optimization at each timestep is described as minimizing a performance index with up to three terms; an output penalty, an input penalty, and an input rate penalty;

$$J = \left[\| \widehat{x}_{j+m_p} \|^2_{Q_{m_p}} + \sum_{k=0}^{m_p-1} \| \widehat{x}_{j+m_p} \|^2_{Q} + \sum_{k=1}^{m_c-1} \left(\| \overset{\frown}{u}_{j+k} \|^2_{R_u} + \| \Delta \overset{\frown}{u}_{j+k} \|^2_{R_{\Delta u}} \right) \right] \tag{3}$$

The minimized cost function J is subject to constraints on the inputs and outputs;

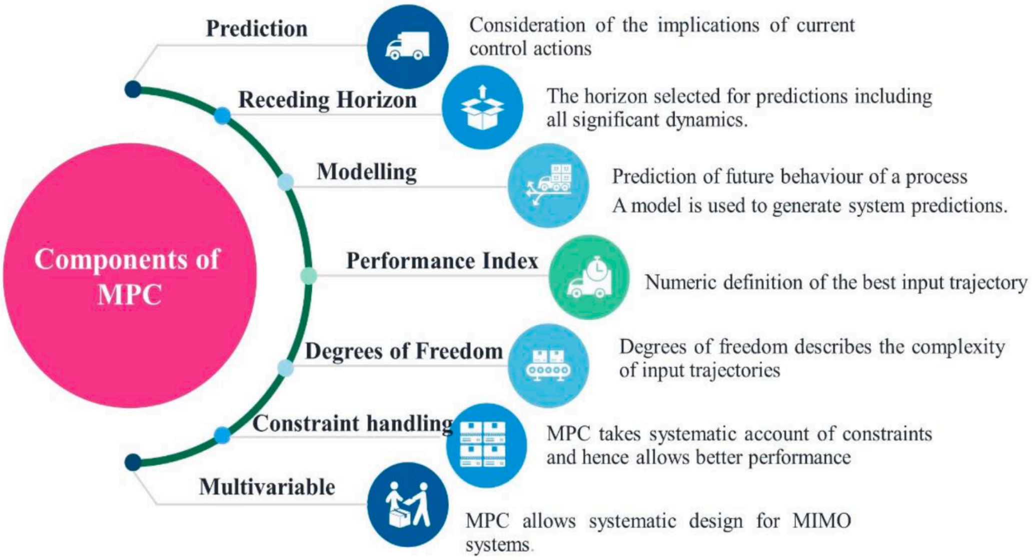
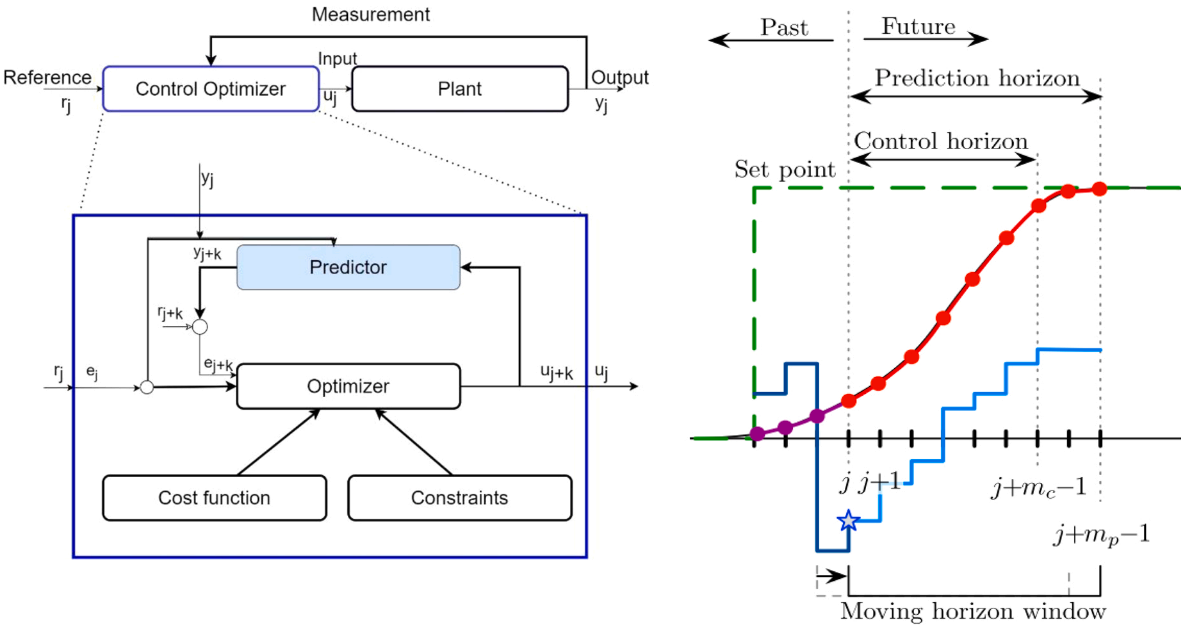


Fig. 2. Components of Model Predictive Control.



(a) (b)

Fig. 3. Schematic of model predictive control with a moving horizon window. Adapted from [14].

$$u^m = \left(u_0^T, u_1^T, \ldots u_{m-1}^T\right)^T \quad \underline{u} \le u_k \le \overline{u}$$

$$x_{k+1} = f(x_k, u_k) \quad \underline{\Delta u} \le \Delta u_k \le \Delta \overline{u}$$

$$y_{k+1} = g(x_{k+1}) + b_{k+1} \quad \underline{y} \le y_k \le \overline{y} \tag{4}$$

2.4. Data-driven model predictive control

Data-driven control systems are broadly classified under control systems. The identification of the process model and the design of the controller are based entirely on experimental data collected from the plant [9]. Learning dynamical systems models from data is a vital challenge in mathematical physics, with a rich history dating back as far as the time of Kepler and Newton and the discovery of the laws of planetary motion. Initially, modelling of dynamic systems relied on a combination of high-quality measurements and expert intuition. With vast data and increasing computational power, the automated discovery of governing equations and dynamical systems is a new and exciting scientific paradigm. Data-driven models require automatic data collection, as they can react in real-time to changes in the input variables [31]. The data-driven models' response can create a feedback loop into a larger online system. However, automatic data collection is associated with some challenges, and thus, characteristics of big data, namely, volume, velocity, variety, value and veracity (5Vs), need to be considered (Fig. 4).

3. System identification

System identification is a form of machine learning, where an input-

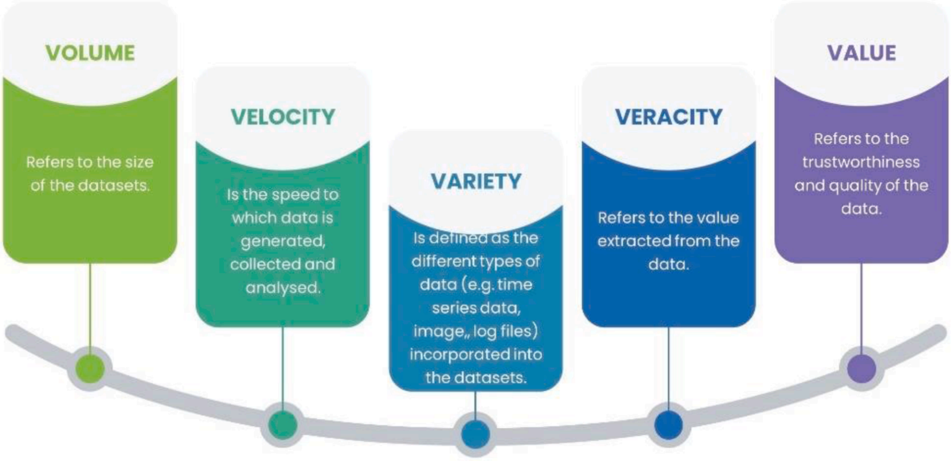


Fig. 4. The 5Vs of data-driven modelling.

output map of a system is learned from training data in a representation that generalizes the data that was not in the training set [14]. Ljung [53] defined it as the art and science of building mathematical models of dynamic systems from observed input-output data. System identification is essential where first principles or physics-based modelling of the system is not possible. Here, nothing is known about the system dynamics, also known as the black-box approach. Data is used to learn a mathematic model that mimics the input-output relationship using a model structure that represents the system behavior and parameter selection for fitting the data. A better understanding of the model is achieved with system identification, and future prediction becomes easy. Fig. 5 represents a flowchart for a system identification process

System identification can be done for linear systems, nonlinear systems and online and recursive systems.

3.1. Nonlinear system identification for control

Powerful model-based control techniques like linear optimal control and model predictive control are aided by data-driven techniques that characterize the input-output dynamics from observed measurements without relying on first principles modelling. Nonlinear systems identification is made possible due to high computing power and powerful data-driven techniques.

Once a low order model of the input-output dynamics from actuation u to measurements y and a full state x of the system is measured, then identification of dynamics f is made possible that satisfy

$$\frac{d}{dt}x = f(x, u) \tag{5}$$

This then is discretized since data is collected in time steps and control laws are digitally implemented. This state dynamics then becomes.

$$x_{k+1} = F(x_k, u_k) \tag{6}$$

3.2. Online and recursive system identification

Online systems identification means that the algorithm is running during the operation of the physical system. Online system identification algorithms estimate the parameters and states of a system model as data is obtained in real-time or near real-time from measuring devices [24]. Referring to the agro-hydrologic balance equation, the process dynamics of the system can be described as one with three inputs, rainfall, irrigation, and crop evapotranspiration and one output, soil moisture, as shown in Fig. 6. The process dynamics model assumes that deep percolation in an irrigated agricultural system is proportional to soil moisture.

The soil moisture dynamics of the system can be denoted as

$$\dot{x}(t) = P(t) + I(t) - b_0 x(t) - ET_C(t) \tag{7}$$

Where;

b_0 = Constant the denotes relationship between soil moisture and deep percolation

Euler approximation theory is used on the soil moisture variations to create a discrete model for the soil moisture.

$$\dot{x}(t) = \frac{\theta(k+1) - \theta(k)}{T_s} \tag{8}$$

Where T_s is the sampling interval

The discrete-time dynamics then can be written as,

$$\frac{x(k+1) - x(k)}{T_s} = P(k) + I(k) - b_0\theta(k) - ET_C(k)$$

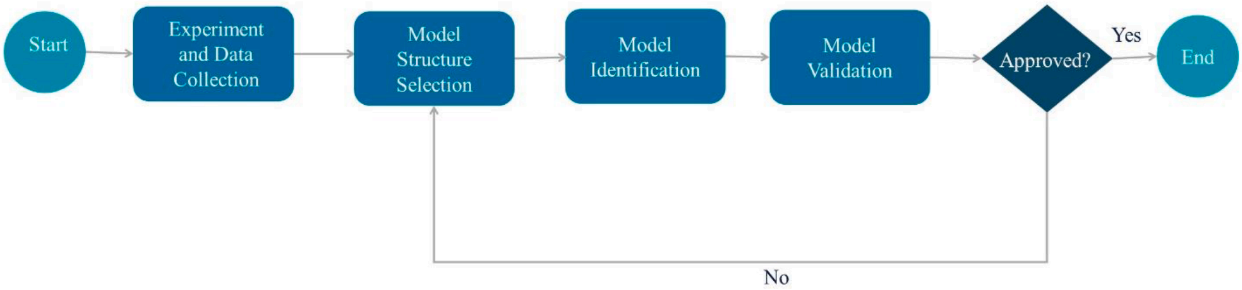


Fig. 5. System identification process.

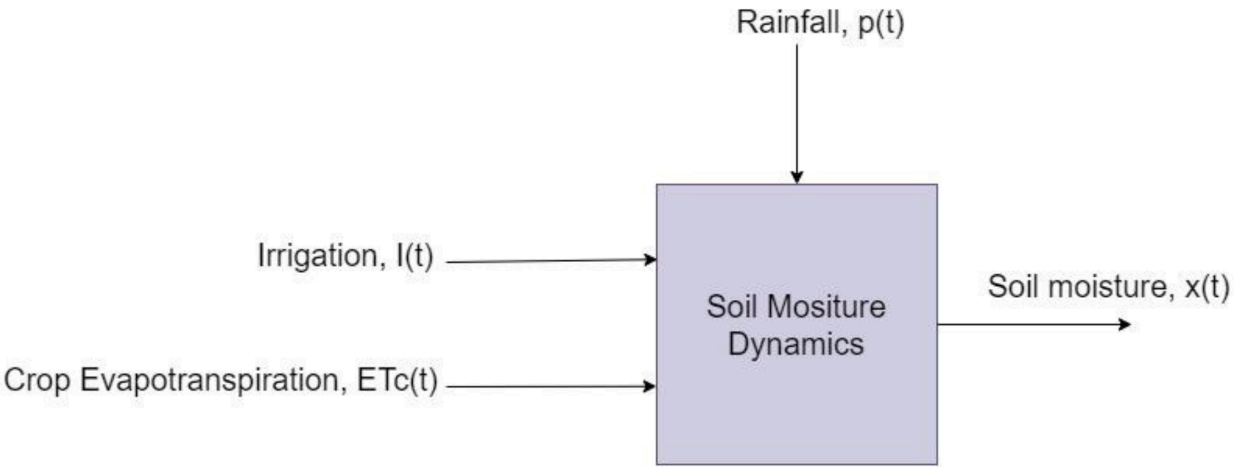


Fig. 6. Inputs and outputs of the process dynamics model.

$$x(k+1) = b_1P(k) + b_2I(k) + b_3x(k) - b_4K_cET_0(k) \tag{9}$$

Where;

b_1, b_2, b_3, b_4 *are discrete coefficents*

K_c is the crop coefficient and varies according to the crop growth stage.

A soil model can be developed over time by updating the model parameters each time step. For example, the algorithm could measure irrigation and compare it with the predicted irrigation amount to produce a prediction error. An online algorithm adjusts the model parameters to reduce the error. In the next step, a new set of measurements is recorded and compared with the model prediction. An error is again obtained and added to the old measurements and the process repeats itself. Online system identification is crucial where the model parameters are time-variant, especially as is the case for the weather parameters in the crop evapotranspiration model.

4. Machine learning control

Machine learning is a rapidly developing field transforming our ability to learn and characterize dynamic systems [14]. Machine learning makes the control of complex, nonlinear systems possible because of its high dimensional, nonlinear and optimization techniques [26]. For example, given a schematic in Fig. 7 with high dimensional dynamics with external disturbances to achieve a high-level objective function.

The objective is to design a controller based on sensor measurements of the system that can then drive the system through actuation. Examples of machine learning methods include genetic algorithms, genetic programming, reinforcement learning and adaptive neural networks (Fig. 8). These machine learning algorithms use biological principles like neural networks, evolutional algorithms, and reinforcement learning. Detailed information on machine learning control can be found in ([8, 14,26] and [64])

5. Iterative learning control

Iterative learning control (ILC) is an efficient technique used to improve the performance of transient systems that operate repetitively [79]. The aim of ILC is to improve the transient response through input adjustment based on observed errors. A standard iterative learning control scheme assumes stable dynamics, and the system returns to the same initial conditions at the start of each trial of the same length. A schematic of data-driven iterative learning control is presented in Fig. 9 [65].

An Iterative Learning Control takes the form

$$u_{k+1}(t) = u_k(t) + \gamma^{e_k(t+1)} \tag{10}$$

Where;

u_k = input to the system during the kth repetition,
e_k = tracking error during the kth repetition and
γ = design parameter representing operations on e_k.

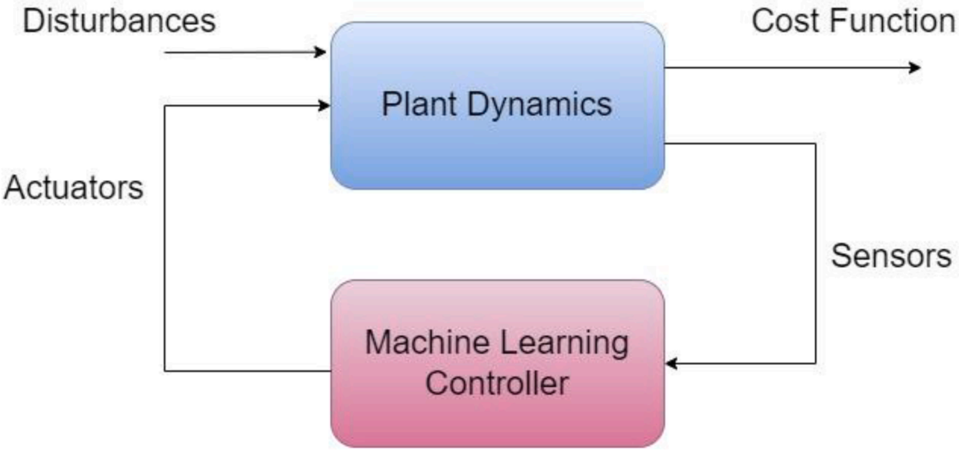


Fig. 7. Schematic of machine learning control.

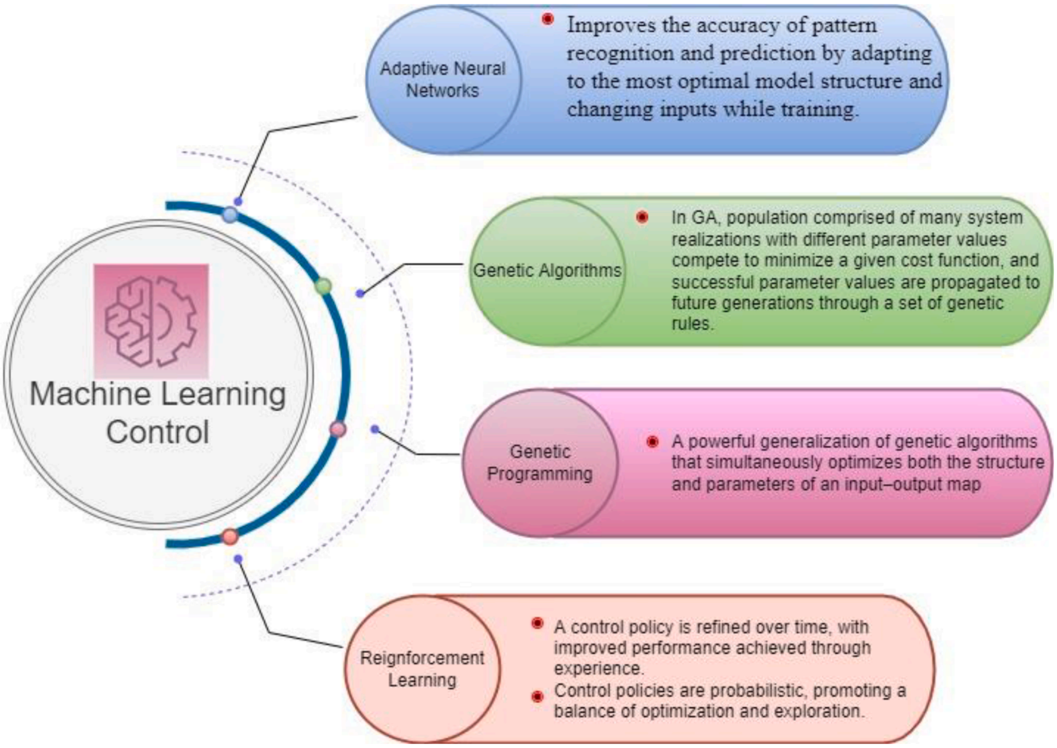


Fig. 8. Sub-divisions of machine learning control.

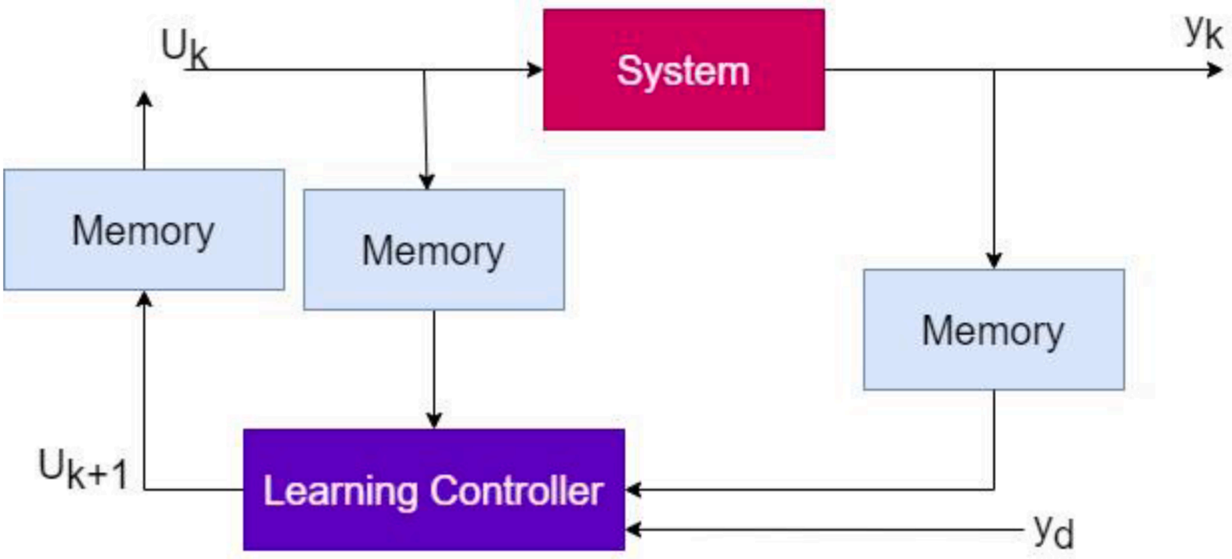


Fig. 9. Iterative learning control process.

There has to be a convergence of the input signals as k becomes large. This will ensure perfect tracking through the iteration process. The rate of convergence represents the desirable need for a rapid iterative learning process. Despite the uncertainty about the process dynamics, good algorithm performance is desirable. The operation γ ranges from simple scalar gains to sophisticated optimization computations and is necessary to achieve design objectives.

5.1. Applications of data-driven model predictive control in precision irrigation management

Owing to the similarity of agricultural processes to industrial processes, model predictive control has been applied in product processing, agricultural production, greenhouses and irrigation systems [23]. For example, model predictive control has been applied in canal flow control and regulation, irrigation scheduling, stem water potential regulation, soil moisture regulation and precipitation and evapotranspiration prediction.

5.2. Irrigation canal flow control and regulation

Model predictive control has found applicability to canal flow control and gate operation. The management objective of MPC for irrigation canals is to keep the water levels as close to the setpoints as possible

[45]. Therefore, a suitable model representing the canal water level dynamic is needed. Furthermore, the models need to be set up in such a way that they contain the appropriate dynamics of the water system for water level regulation. In this regard, MPC has been applied to model the behavior of the water movement in the open channel, maintaining certain water levels at various locations and the water flows that influence these water levels [29,30,63,79,80,84].

Control structures are used to manipulate the water flows, through which the controller can achieve the management objective [45]. However, achieving this objective is not straightforward, as some varying inflows and outflows disturb the water system. To predict the future water levels and flows as a result of disturbances and control actions, the water system (canal reaches, structures, disturbances, controller) needs to be modelled. Fig. 10 depicts a typical irrigation canal with water flowing by gravity and different offtakes along the canal reach.

De Saint Venant partial differential equations Eqs. (11) and (12) accurately describe the water flow dynamics in the irrigation canal.

$$\frac{\partial y}{\partial t}+\frac{1}{T}\frac{\partial Q}{\partial x}+\frac{q}{r}=0 \tag{11}$$

$$\frac{\partial Q}{\partial t}-\frac{Q^2}{A^2}\frac{\partial A}{\partial x}+\frac{2Q}{A}\frac{\partial Q}{\partial x}+gA\left\{\frac{\partial y}{\partial x}-s_0+s_f\right\}+qv=0 \tag{12}$$

Where; y is the depth of water in m,

T the top width of the canal at the water surface in m,

Q is the water flow rate in the canal m^3/s, x is the longitudinal distance on the flow direction in m, q the lateral outflow per unit length of the channel in m^2/s, v the velocity in m/s,

A is the wetted cross-sectional area, g the acceleration due to gravity (9.81 m/s^2), s_o the channel bottom slope and s_f is the friction slip of the irrigation canal.

Several scholars have used model predictive control in controlling irrigation canal flows. Puig *et al.* [70] used model predictive control to generate flow control strategies from the water source to the consumer and irrigation areas in the Guadiana River. The results showed effectiveness in the use of model predictive control. Zhang *et al.* [83] designed a non-cooperative distributed model predictive control algorithm based on Nash optimality for water level regulation in irrigation canals. The system simulation results showed the effectiveness of the proposed algorithm. To effectively deliver canal flow without fluctuations, Han & Qiao [39]; Hashemy *et al.* [41,40]combined model predictive control with online water storage to compensate for an existing time delay and avoid wave disturbances. The results showed significant improvement for canal operations employing automation. Recently, Kong *et al.* [50] used model predictive control toolbox to control gate interval and water level. The authors tested it on a simulation model of an irrigation canal in Beijing consisting of 13 cascaded canal pools. The authors affirmed that model predictive control is a useful control strategy for gate opening at different intervals [49].

6. Irrigation scheduling

Irrigation scheduling is the process of determining the frequency, duration and quantity of irrigation water to apply to meet the crop water requirements [59]. In conventional irrigation systems, irrigation scheduling is determined through experience, observation, and heuristic methods. On the other hand, precision irrigation systems rely on feedback from sensing devices. Irrigation scheduling can be achieved through weather-based, soil-based, or plant-based approaches. Precision irrigation systems aim at spatio-temporal irrigation scheduling depending on weather, soil, and plant physiological characteristics [3].

Model predictive control is used to perform irrigation scheduling using real-time field data to calibrate a crop and soil model and then using the calibrated model to determine optimum irrigation schedules [61]. Plant and soil real-time measurements are crucial to calibrate the model during the growing stages of the crop as irrigation advances. Considering the soil moisture balance model, the plant input is the irrigation amount, whereas the plant output is the soil moisture deficit. The crop evapotranspiration and precipitation values are considered disturbances as they cannot be controlled.

Delgoda *et al.* [22], Lozoya *et al.* [56], and Saleem *et al.* [74] used model predictive control to predict the frequency, duration and quantity of irrigation water using a soil moisture dynamics model. The authors used a combined mechanistic and data-driven modelling approach to describe the dynamics of the soil-plant-atmosphere system using sensing devices for real-time feedback to the control algorithm. However, the authors neglected the effect of precipitation and crop water use on the system dynamics. Delgoda et al. [21] addressed the drawbacks noted in the above model predictive control framework. The authors employed a disturbance affine feedback control approach and uncertainty modelling techniques to account for the dynamic nature of rainfall and crop water use. Moreover, the study reported optimal system performance in a humid region where considerable uncertainties in climate variables existed. Recently, Abioye, Abidin, Aman, *et al.* [2] and Abioye, Abidin, Mahmud, *et al.* [2] used a data-driven model predictive control to schedule irrigation in a greenhouse irrigation experiment. The authors used Laguerre functions in order to reduce the computation complexity brought about by input constraints.

6.1. Stem water potential regulation

Another important aspect in precision irrigation management is the soil water potential. It determines the ease with which plants can extract water from the soil. Soil water potential is a measure of the energy status of the soil water relative to that of water at a standard reference [59]. On the other hand, stem water potential (SWP) is the direct measure of water tension within the plant [75]. Suter *et al.* suggested that plant

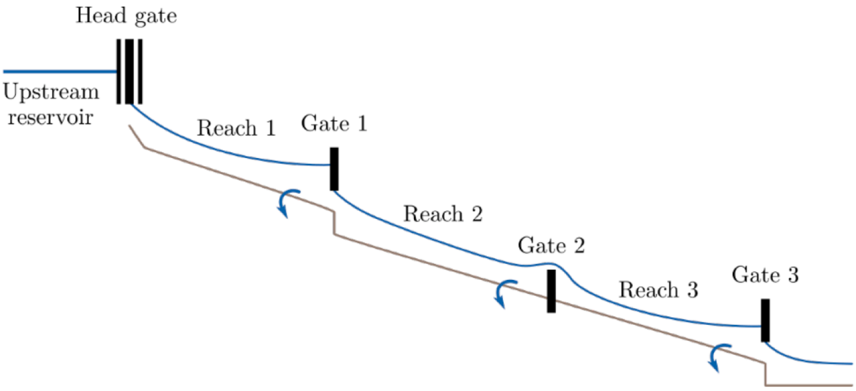


Fig. 10. Irrigation canal with control gates. Adapted from [45].

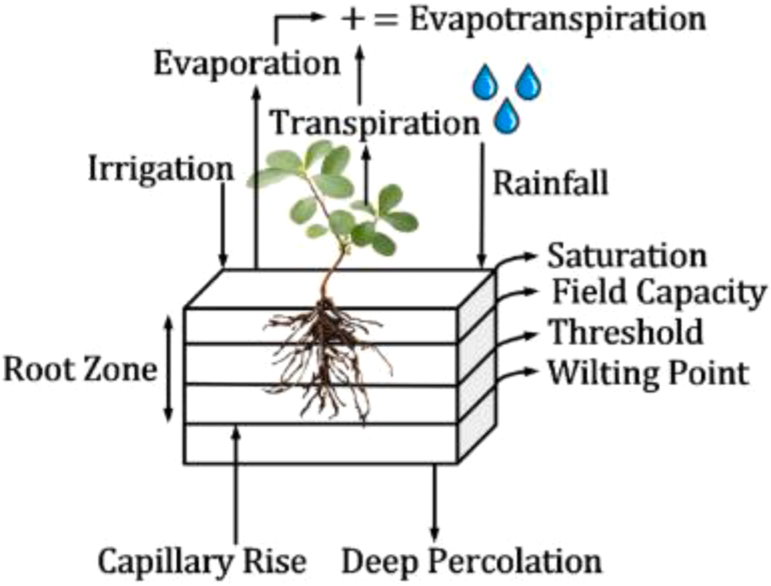


Fig. 11. Schematic of an agro-hydrological system. Adapted from [7].

moisture status needs to be determined through SWP measurements rather than the soil moisture content. Chen *et al.* [18] developed a stem water potential model using data-driven model predictive control to help reduce uncertainty in weather forecast errors. The authors formulated a state-space model that captures water dynamics in a plant-root-soil system. The water status of the system was modelled by monitoring water flow in the soil, root and plant system. Precipitation in the system was the water inflow, and evapotranspiration was the driving force in the system. The state-space model was linearized to reduce the computation burden caused by robust nonlinear optimization. The authors used the formulation of a robust optimal control problem that maintained stem water potential within certain limits. The authors reported a 7.9% reduction in the water consumption in almond trees using data-driven robust model predictive control.

6.2. *Soil moisture regulation*

Irrigation aims to maintain the root zone soil moisture between field capacity and the permanent wilting point (Fig. 10). When the soil moisture goes above the field capacity, the soil becomes saturated, and below the wilting point, the plant experiences water stress and eventually dies. Management allowable depletion of 50% is adopted for most irrigation designs to ensure that the available moisture does not get depleted before irrigation occurs. This available moisture in the root zone depends on the plant's effective root zone. Model predictive control has been used to minimize root zone soil moisture and irrigation amounts within a specific threshold or at specific set points [22,55,62]. However, recent studies argue that a zone needs to be considered rather than a reference set point to ensure maximum water extraction from the root zone. The aim should be to regulate the soil moisture within the readily available moisture zone.

Mao *et al.* [57c] proposed a methodical approach to system identification and root zone model predictive control design for soil moisture control of agro-hydrological systems. First, the authors simulated the soil water dynamics of the field from a mechanistic soil-water balance model. The model consisted of a nonlinear partial differential equation with source and sink terms characterizing the root water extraction, evaporation and transpiration, precipitation, and irrigation. A linear parameter varying model was identified based on the input and output data of the soil-water balance model, which was then used for zone model predictive control design. The authors report a satisfactory approximation of the soil moisture dynamics and the designed zone model predictive control suitability.

6.3. *Precipitation and evapotranspiration prediction*

One of the challenges in precision irrigation management is the scarcity of climate data. Precision irrigation requires real-time data to aid in irrigation decisions. In developed countries, prediction systems are used to predict future weather events, and this data is availed to farmers for irrigation management decisions. In the absence of such, there is a need to bridge the gap using model predictive control to quantity the sources of uncertainty in the soil moisture dynamics model. To address this, Guo and You [37] used a novel data-driven local precipitation and evapotranspiration prediction by implementing an artificial neuro-network (ANN). It was embedded in the model predictive control toolbox and updated in real-time to formulate the dynamic uncertainty set to account for weather prediction errors in the irrigation control system. The authors reported effective control of the root zone soil moisture. A summary of studies conducted in the different application domains is presented in Table 2.

6.4. *Challenges and future perspectives of data-driven modelling in smart irrigation*

Data collection that is representative of the real dynamic system is challenging. When more data is provided, machine learning can be used in data-driven modelling to fit data and make predictions when more data is required. Some of the challenges encountered in data collection are discussed in this section.

One of the major challenges affecting precision irrigation is the high

Table 2
Summary of applications of MPC in irrigation.

Application Domain	Author
Irrigation Canal control	([6,17,30,54,80]; R. [83,84, 86])
Irrigation scheduling	[1,2,16,37,46,55,67]
Soil moisture regulation	([7,57]c, [57,58]
Soil water potential regulation	([19], 2021; [75])
Prediction of Precipitation and Evapotranspiration	[37]

cost of obtaining data in irrigation systems. To develop a data-driven model for smart irrigation, data about the soil, plant, and environment need to be monitored. Plant sensors need to monitor the physiological processes in plant-like crop water use. The different growth stages and their effect on the crop factors need to be established. The climatic factors that affect the rate of evapotranspiration need to be monitored in real-time, otherwise relying on historical data that is not representative of the real system. The data collection strategies and control methods are discussed in [4,15]. The challenges relating to data availability range from sampling frequency, incomplete data, sensor malfunction, working conditions, communication exceptions or database shutdown. This can affect the integrity of the experimental dataset collected, thereby resulting in poor model development.

In addition, developing models from data requires capturing a large volume of data to represent the real systems and capture any variations. For example, in irrigation, the components of the agro-hydrological model vary from time to time. This variation must be captured, which makes the data collection process time-consuming. This may involve monitoring the dynamics for the entire season or year to get a representative model for the dynamics.

Predictions are a key feature of data-driven models for irrigation optimization and intelligent decision-making. System boundaries define the capability of data-driven models. If the data is only a subsection of the field, the model may fail to make accurate predictions for an entire irrigation field. Therefore, it is pertinent to define the system boundaries and ensure model data development extends to the boundaries ensuring that only predictions made from the model boundaries are acted upon.

The application of model predictive control in irrigation is still limited compared to processing industries. Large water and irrigation systems must reduce computation times and now incorporate data-driven model predictive control. In the future, there's a need to model soil moisture dynamics in open field agricultural systems as past studies stopped at simulation or implemented in a controlled environment agricultural system where disturbances to the model are minimized. Model predictive control can be applied to diverse aspects of precision agriculture to enhance agricultural productivity in the future. These application domains include aquaponics, hydroponics, viticulture, controlled environment agriculture, aquaculture, disease and pest control, and mechanization systems.

7. Conclusion

Data-driven modelling in agriculture is on the rise due to the advancement of Internet of Things technologies and improved computational power. This article presents an overview of model predictive control over the past four decades, and data-driven model predictive control is discussed. From the review, model predictive control has been used in precision irrigation management, ranging from irrigation canal control, irrigation scheduling, stem water potential regulation, soil moisture regulation, and precipitation prediction and evapotranspiration. It is noted that for data-driven MPC to solve complex dynamic systems in irrigation, the availability of data, variability, boundary conditions and model evaluation must be harmonized for one to come up with a good representative model of the system. There is more research opportunity to explore on the application of data-driven modelling and controller development for predictive irrigation management.

8. Author contributions

Conceptualization, EB; methodology, EB; formal analysis, EB; investigation, EB; writing original draft preparation, EB; writing—review and editing, FKA, GKA YK; visualization, FKA; supervision, FKA, GKA YK; project administration, FKA; funding acquisition, FKA, GKA YK. All authors have read and agreed to publish the manuscript.

Declaration of Competing Interest

The authors declare no conflict of interest

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