Environmental Modelling & Software 78 (2016) 40–53

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

Irrigation control based on model predictive control (MPC): Formulation of theory and validation using weather forecast data and AQUACROP model

Dilini Delgoda [a,*], Hector Malano [a], Syed K. Saleem [b], Malka N. Halgamuge [b]

[a] Department of Infrastructure Engineering, The University of Melbourne, Parkville, Victoria, Australia
[b] Department of Electrical and Electronics Engineering, The University of Melbourne, Parkville, Victoria, Australia

ARTICLE INFO

Article history:
Received 11 September 2015
Received in revised form
8 December 2015
Accepted 11 December 2015
Available online xxx

Keywords:
Model predictive control (MPC)
Automation
Weather forecasts
Irrigation
Uncertainty
Simple model

ABSTRACT

This research proposes A THEORETICAL FRAMEWORK based on model predictive control (MPC) for irrigation control to minimize both root zone soil moisture deficit (RZSMD) and irrigation amount under a limited water supply. We (i) investigate means to incorporate direct measurements to MPC (ii) introduce two Robust MPC techniques – Certainty Equivalence control (CE) and Disturbance Affine Feedback Control (DA) – to mitigate the uncertainty of weather forecasts, and (iii) provide conditions to obtain two important theoretical aspects of MPC – feasibility and stability – in the context of irrigation control. Our results show that system identification enables automation while incorporating direct measurements. Both DA and CE minimize RZSMD and irrigation amount under uncertain weather forecasts and always maintain soil moisture above wilting point subject to water availability. The theoretical results are compared against the model AQUACROP, weather data and forecasts from Shepparton, Australia. We also discuss the performance of Robust MPC under different water availability, soil, crop conditions. In general, MPC shows to be a promising tool for irrigation control.

1. Introduction

From the perspective of a typical farmer, an ideal irrigation control system is one that looks ahead at the water availability and weather forecasts, and adjusts the present irrigation amount to reduce the irrigation demand. As root zone soil moisture level is strongly coupled with irrigation demand, this aim can be interpreted as maintaining a reference soil moisture level through the use of irrigation.

The term root zone soil moisture deficit (RZSMD) is defined as the difference between a given reference level and current root zone soil moisture level. As such, the ideal irrigation control method would be one that maintains the RZSMD close to zero, while minimizing irrigation amount subject to water availability and weather forecasts. Automation is required to achieve this goal as manual control is inadequate.

Automated irrigation control has been given considerable attention during the past decade. State-of-the-art technologies have been developed and tested (Allam (2002); Hibbs et al., (1992); Hornbuckle et al., (2009)). Some irrigation control methods depend on complex physical models, which closely resemble the actual physical system, based on principles of crop phenology, soil physics and hydrology (Steduto et al., (2009); Raes et al., (2009); Jones et al., (2003); Rossi et al., (2004)). Another important avenue is data assimilation. Data associated with proxy variables such as sap flow, stomatal conductance and trunk diameter are used to infer the soil water requirements (Lu et al., (2004); Kanemasu et al., (1969); Goldhamer and Fereres, (2003)). Irrigation decisions are based on these inferences or estimates which are almost always precise. Nevertheless, the underlying irrigation control logic is limited to only few categories. One method is to replenish the soil moisture when RZSMD or water demand exceeds a certain level. They are called rule-based or 'ON–OFF' category. Some methods follow a predefined irrigation schedule and belong to open-loop control methods. Former is reactive to current soil moisture conditions (closed-loop) however in both cases, the control method cannot utilize future weather information. In contrast, Giusti and Marsili-Libelli (2015) use weather forecasts and fuzzy rules for irrigation control, based on approximate fuzzy models of the complex physical model. Kia et al. (2009); Bahat et al. (2000); Zhang et al.

* Corresponding author.
E-mail address: d.delgoda@pgrad.unimelb.edu.au (D. Delgoda).

http://dx.doi.org/10.1016/j.envsoft.2015.12.012

List of symbols and abbreviations

Abbreviation

MPC	model predictive control
RMPC	robust model predictive control
CE	Certainty Equivalence Control
DA	Disturbance Affine Feedback Control
RZSMD	root zone soil moisture deficit[1]
FC	field capacity [1]
RP	refill point [1]
WP	wilting point [1]
ISS	input to state stability

Symbol

D	current RZSMD
D^+	RZSMD at next time step
E	current crop evapotranspiration
P/P^e	current rainfall/effective rainfall
I/I^e	current irrigation amount/effective irrigation amount
x	system state
u	control input
w	disturbance
N	control horizon
H	water holding capacity
S,Q,R	weights on MPC objectives
$\langle c \rangle_{max}$	upper bound on variable $\langle c \rangle$
$\langle c \rangle_{min}$	lower bound on variable $\langle c \rangle$
$\langle \tilde{c} \rangle$	estimate of variable $\langle c \rangle$
$\mathbb{R}$	real number set
X_f	target set

(1996) use fuzzy rules on simple evapotranspiration models. However, considering the objectives and constraints mentioned previously, defining fuzzy rules is a difficult task which demands perfect knowledge on the system and most of the time the decision making becomes ad-hoc. In all the above cases, no attention is given to optimizing the irrigation amount and in most occasions, the methods assume an unlimited supply of water to the field.

On the contrary, model predictive control (MPC) based irrigation control systems are proactive in that they aim to achieve a desired soil moisture level by adjusting the present irrigation amount. Examples include Park et al. (2009); McCarthy et al. (2014); Romero Vicente et al. (2011); Romero et al. (2008) where receding horizon control based on complex physical models are used to optimize irrigation. All except McCarthy et al. (2014) used nonlinear optimization which utilized trial and error method. All methods need a high level of calibration due to use of the complex physical model. If not properly analyzed, constrained nonlinear optimization can be infeasible or suboptimal, making the optimization process redundant and irrigation control unreliable. This could be further complicated by uncertainty in rainfall which none of the methods have considered and actual weather data are used instead of forecasts to test the method.

Some works use dynamic programming to optimize inter-seasonal and intra-seasonal water allocations subject to seasonal water limitations (Bras and Cordova (1981); Dudley et al. (1971); Yaron and Dinar (1982); Rao et al. (1992); Protopapas and Georgakakos (1990); Sunantara and Ramirez (1997)). Nonetheless, getting no feedback on crop soil conditions during the calculation stages, could lead to large propagation errors. Among these, the work in Bras and Cordova (1981); Protopapas and Georgakakos (1990); Sunantara and Ramirez (1997) and references therein consider rainfall forecasts and their uncertainty. However, due to the incorporation of a closed form expression for the rainfall forecast, the optimization becomes nonlinear and no guarantee can be given on the reliability of irrigation control. Uncertainty only in crop evapotranspiration is considered in Aboitiz and Labadie (1986).

In Saleem et al. (2013), we propose to use MPC, based on a system model which is a simplified water balance model, that captures main dynamics of the actual physical system. The irrigation control problem is solved by minimizing both the irrigation amount and RZSMD. It also considers maximum allowed irrigation amount and maximum and minimum soil moisture deficits. In the current paper, we extend our previous work presented in Saleem et al. (2013) and propose a theoretical framework based on MPC for irrigation control.

The MPC approach and that in Giusti and Marsili-Libelli (2015) are equivalent in that both use simplified system models adequately representative of the actual physical system instead of complex physical models and both control methodologies are based on these system models. Using these approximate models reduce the calibration requirement significantly. However, authors of Giusti and Marsili-Libelli (2015) do not focus on the control action and their approach does not optimize RZSMD. This can be attributed to the ad-hoc manner of defining the rules. Further, the method assumes an unlimited amount of water supply to the field. In other words, the control method in Giusti and Marsili-Libelli (2015) minimizes the total irrigation amount subject to a given soil moisture threshold. The MPC method described herein (1) minimizes RZSMD and daily irrigation amount (and reduces total amount subsequently) (2) subject to daily irrigation water availability and RZSMD thresholds.

Saleem et al. (2013) introduced a few assumptions when developing the MPC approach which are removed in this paper. It was assumed in Saleem et al. (2013), that the effective values of all variables in water balance model are known, when in reality they are not. In this study, we propose to use system identification so that direct measurements can be incorporated into MPC to accommodate online calculations.

Second, Saleem et al. (2013) used actual rainfall data as weather forecasts which removes the uncertainty in weather forecasts. We now relax this assumption to match the real field application by designing MPC to accommodate uncertainty in weather forecasts. In this regard, we consider and compare two MPC formulations that are well studied in the area of MPC under uncertainty in disturbance also known as 'robust MPC' (RMPC): Certainty Equivalence Control (CE) and Disturbance Affine Feedback Control (DA).

Third, it was assumed in Saleem et al. (2013) that the MPC is feasible and (possibly) stable at all times. In this paper, we first explain how these aspects are important in irrigation control then discuss how they can be guaranteed.

A case study is selected to verify the theory developed in this research. The weather data required are obtained from The Bureau of Meteorology (BoM), Australia for Shepparton, Victoria, Australia. The model AQUACROP (FAO (2011); Steduto et al. (2009); Raes et al. (2009)) by United Nations Food and Agriculture Organization was used to simulate the actual physical system.

Section 2 describes the formulation of irrigation control using MPC.

[1] *volume/volume%* converted to *mm*.