Computers and Electronics in Agriculture 155 (2018) 50–57

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

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

Original papers

Dynamic modelling of lettuce transpiration for water status monitoring

Olutobi Adeyemi[a], Ivan Grove[a], Sven Peets[a], Yuvraj Domun[a], Tomas Norton[b,*]

[a] Engineering Department, Harper Adams University, Newport, Shropshire TF10 8NB, United Kingdom
[b] M3-BIORES Research Group, Division of Animal and Human Health Engineering, Department of Biosystems, Katholieke Universiteit Leuven, Belgium

ARTICLE INFO

Keywords:
Plant water status
Transpiration
Modelling
System identification
Irrigation

ABSTRACT

Real-time information on the plant water status is an important prerequisite for the precision irrigation management of crops. The plant transpiration has been shown to provide a good indication of its water status. In this paper, a novel plant water status monitoring framework based on the transpiration dynamics of greenhouse grown lettuce plants is presented. Experimental results indicated that lettuce plants experiencing adequate water supply transpired at a higher rate compared to plants experiencing a shortage in water supply. A data-driven model for predicting the transpiration dynamics of the plants was developed using a system identification approach. Results indicated that a second order discrete-time transfer function model with incoming radiation, vapour pressure deficit, and leaf area index as inputs sufficiently explained the dynamics with an average coefficient of determination of $R_T^2 = 0.93 \pm 0.04$. The parameters of the model were updated online and then applied in predicting the transpiration dynamics of the plants in real-time. The model predicted dynamics closely matched the measured values when the plants were in a predefined water status state. The reverse was the case when there was a significant change in the water status state. The information contained in the model residuals (measured transpiration – model predicted transpiration) was then exploited as a means of inferring the plant water status. This framework provides a simple and intuitive means of monitoring the plant water status in real-time while achieving a sensitivity similar to that of stomatal conductance measurements. It can be applied in regulating the water deficit of greenhouse grown crops, with specific advantages over other available techniques.

1. Introduction

The precise determination of irrigation water requirement and timing is a precursor to the successful precision irrigation management of crops (Kochler et al., 2007). This requires a knowledge of the plant water status in real-time which can then guide in arriving at optimal irrigation scheduling decisions.

Contact monitoring methods such as measurements of stomatal conductance, sap-flow, and leaf turgor pressure have been shown to provide an adequate indication of plant water status. However, these methods are plant-based, requiring large replication to provide an indication of water status at crop level. They also require technical expertise for implementation, laborious and difficult to deploy as a real-time monitoring tool (Jones, 2004). Non-contact measurement of plant canopy temperature (T_c) which is normalized using a crop water stress index (CWSI) also provides a good indication of plant water status (Ben-Gal et al., 2009). Its application as a monitoring tool in commercial crop production is however limited because of the need to know the baseline temperatures which are required for its computation under the same environmental conditions as T_c (Maes and Steppe, 2012). Non-contact monitoring tools which can provide a real-time indication of the plant water status at crop level, with non-laborious implementation, and minimal instrumentation and computation requirements will therefore be beneficial in implementing precision irrigation management in commercial crop production (Adeyemi et al., 2017).

The plant transpiration is perhaps the best indication of plant water status (Jones, 2008; Maes and Steppe, 2012). Plants experiencing unrestricted water supply (well-watered plants) have been shown to transpire at a higher rate when compared to plants experiencing a shortage in water supply (Ben-Gal et al., 2010; Villarreal-Guerrero et al., 2012). This is due to the regulation of water loss by the plant's stomates with the stomates of well-watered plants opening up more in response to atmospheric demand. The stomates of plants experiencing water shortage open up less in response to atmospheric demand in order to limit water loss (Blonquist et al., 2009). Therefore, the water status of a plant can be inferred from measurements of its transpiration rate.

Traditionally, the knowledge of crop transpiration over time has been applied in the dynamic control of water supply to greenhouse crops (Daniel et al., 2013). This is usually in form of an off/off control

* Corresponding author.
E-mail address: tomas.norton@kuleuven.be (T. Norton).

https://doi.org/10.1016/j.compag.2018.10.008
Received 10 June 2018; Received in revised form 30 September 2018; Accepted 6 October 2018

strategy in which irrigation is applied after the accumulation of a set point cumulative transpiration amount (Davis and Dukes, 2010). These computer-controlled irrigation systems make use of mechanistic or empirical models to estimate crop transpiration based on environmental and physiological factors (Barnard and Bauerle, 2015).

Several models have been developed for the estimation of transpiration from greenhouse cultivated ornamental and vegetable crops (Baptista et al., 2005; Fatnassi et al., 2004; Jolliet and Bailey, 1992; Montero et al., 2001). Most of these models are based on the thermal energy balance equation of the plant canopy and are similar to the Penman-Monteith (PM) equation (Howell and Evett, 2004). These models are able to account for the effect of actual water supply on transpiration through the incorporation of a stomatal resistance component. The stomatal resistance is expressed as a function of several factors including solar radiation, leaf vapour pressure deficit, leaf temperature, CO_2 concentration, photosynthetically active radiation, leaf water potential etc. (Kochler et al., 2007). The development of these models requires the calibration of several hard-to-measure parameters which limit their practical application as an irrigation monitoring tool (Villarreal-Guerrero et al., 2012). Furthermore, these models are unable to account for the time varying nature of the plant system, as their parameters are assumed to remain constant once identified. The response of a plant will vary as a result of growth, biotic and abiotic factors, and adaptation processes (Boonen et al., 2000).

Data-driven modelling approaches based on measured input-output data of a process have been shown to provide robust approximations of various biological processes and often require fewer input parameters when compared to mechanistic models (Navarro-Hellín et al., 2016). The later is difficult to implement as a perfect knowledge of the physical process under consideration is often required (Bennis et al., 2008). Sánchez et al. (2012) applied a system identification approach in predicting the transpiration rate of a greenhouse grown tomato crop. Their approach showed promise in accounting to the time-varying plant response through an online update of the model parameters. Speetjens et al. (2009) also applied an extended Kalman filtering algorithm for the online estimation of model parameters for predicting the transpiration of a greenhouse grown crop. Both studies reported improved prediction of plant transpiration rates when compared to values predicted by mechanistic models. The modelling approach presented in both studies are data-driven making their practical application as an irrigation monitoring tool viable. They also do not require the stomatal behavior to be modelled explicitly as it is accounted for in the online parameter estimation process.

System identification is a data-driven modelling approach which is applied in modelling dynamic systems (Chen and Chang, 2008). It has been successfully applied in simplifying and modelling complex environmental and biological processes(Taylor et al., 2007; Young, 2006), predicting time-varying biological responses (Kirchsteiger et al., 2011; Quanten et al., 2006) and in many other irrigation decision support applications (Delgoda et al., 2016; Lozoya et al., 2016). It is extensively applied as part of the fault detection methodologies in the advanced process control industry (Young, 2006). During fault detection, a system identification approach is used to build a dynamic model of a process in a known healthy state. The output predicted by the model can then be compared to the actual real-time measurements from the process. The parameters of the model can also be updated as new data is acquired from the process (Gil et al., 2015). This methodology, which has proven to be successful in the process control industry, can be adapted and applied as part of an adaptive decision support system for irrigation monitoring (Adeyemi et al., 2017).

The objectives of this study are to investigate if the transpiration rates of greenhouse grown lettuce plants (*Lactuca sativa*) maintained at different water deficit levels will differ. This will provide a justification for the application of this measurement as a plant water status monitoring tool. A system identification approach is thereafter applied in developing a model of the transpiration dynamics and predicting the transpiration rate of these plants. Finally, the predicted transpiration rate is used as a tool for monitoring the water status of the lettuce plants and real-time detection of deviations from a defined water status state.

2. Background

2.1. Plant transpiration

Plant transpiration can be described by the Penman-Monteith equation (Monteith, 1973). This equation and other transpiration models derived from it specify that the transpiration ($T_p(\mathrm{gm^{-2}\ min^{-1}})$) is dependent on the incoming solar radiation ($R_{sw}(\mathrm{W\ m^{-2}})$) and the vapour pressure deficit of the ambient air ($\Delta(\mathrm{kPa})$). This is expressed as

$$T_p = R_{sw}C_A + \Delta C_B \tag{1}$$

where the coefficients C_A and $C_B$are crop dependent parameters.

Baille et al. (1994) noted that the coefficient C_B is a function of the plant leaf area index (LAI), and it adopts different values during the day due to oscillations in stomatal resistance.

2.2. System identification

System identification is applied in constructing mathematical models of dynamic systems based on the incoming time-series of input ($u(t)$) and output ($y(t)$) data. The goal is to infer the relationship between the sampled input/output data. During system identification, the model structure is first identified using objective methods of time series analysis based on a given general class of time-series models (here, linear discrete time transfer functions). The resulting model must be able to explain the structure of the observed data. System identification is used to simultaneously linearize and reduce model complexity, so exposing its 'dominant modes' of dynamic behavior.

In this study, the identification process was conducted based on prior knowledge of the plant transpiration process as shown in Eq. (1). The vapour pressure deficit and incoming radiation were selected as climatic input, and the LAI was selected as crop growth input. The identification of the model structure is considered the first step of the identification problem in the present study. An online estimation algorithm is thereafter implemented to update the model parameters based on the real-time data obtained from the process.

In this way, it is possible to detect the changes in the dynamics of the system thus accounting for the time-varying nature of the plant system.

The linear discrete-time transfer function is written as

$$y(t) = \frac{B_1(L)}{A(L)}U_1(t-\delta_1) + \cdots + \frac{B_k(L)}{A(L)}U_k(t-\delta_k) + e(t);\ e\ \ WN(0,\ \sigma_e^2) \tag{2}$$

where $y(t)$ is the output (transpiration rate), $U_i(t)(i = 1,\ 2,\ \cdots,\ K)$ are a set of K inputs that affect the output (incoming radiation, vapour pressure deficit), $\delta_i(i = 1,\ 2,\ \cdots,\ K)$ are the delays associated with each input.

In Eq. (2),

$$A(L) = 1 + a_1L + \cdots + a_nL^n \tag{3}$$

$$B(L) = b_0 + b_1L + \cdots + b_mL^m$$

$A(L)$ and $B(L)$ are polynomials of the order n and m respectively. The backshift operator L is such that $L^jy_t = y_{t-j}$. $a_i(i = 1, 2, \cdots, n)$ and $b_j(j = 1, 2, \cdots, m)$ are coefficients of the polynomials $A(L)$ and $B(L)$. They represent the unknown parameters that are to be identified. The identified model is defined by the triad $[n, m_i, \delta_i]$, where n is the number of denominator parameters; indicating the model order, and m_i is the number of numerator parameters associated with each input. δ_i is defined earlier.

The identification process was conducted using the refined instrumental variable algorithm (Taylor et al., 2007) implemented in the Captain toolbox (Young et al., 2007) on the MATLAB® software.