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Dynamic modelling of lettuce transpiration for water status monitoring

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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.

Keywords: Plant water status; Transpiration; Modelling; System Identification; Irrigation

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 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 behaviour 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 ($T_p(gm^{-2}min^{-1})$) is dependent on the incoming solar radiation ($R_{sw}(Wm^{-2})$) and the vapour pressure deficit of the ambient air ($\Delta(kPa)$). This is expressed as

$$T_p = R_{sw}C_A + \Delta C_B \quad (1)$$

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 behaviour.

In this study, the identification process was conducted based on prior knowledge of the plant transpiration process as shown in equation 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

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

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

In equation 2,

$$A(L) = 1 + a_1 L + \cdots + a_n L^n \quad (3)$$

$$B(L) = b_0 + b_1 L + \cdots + b_m L^m$$

$A(L)$ and $B(L)$ are polynomials of the order n and m respectively. The backshift operator L is such that $L^j y_t = y_{t-j}$. $a_i(i = 1,2, \dots\dots, n)$ and $b_j(j = 1,2, \dots\dots, m)$ 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.

2.3 Plant water status monitoring framework

The plant water status monitoring algorithm proposed in this paper is data-driven. The algorithm is founded on an estimated dynamic model of the plant transpiration. The model is identified as a time domain model and the parameters of the model are identified online from the real-time measurements of input-output data. The water status monitoring principle is based on a premise that the transpiration dynamics of a plant will vary as a function of the prevailing climatic conditions and its water status. A model of the plant is built at a known water status state and predictions from this model is then compared to real-time output data obtained from the plant. A schematic illustration of the algorithm is presented in Figure 1.

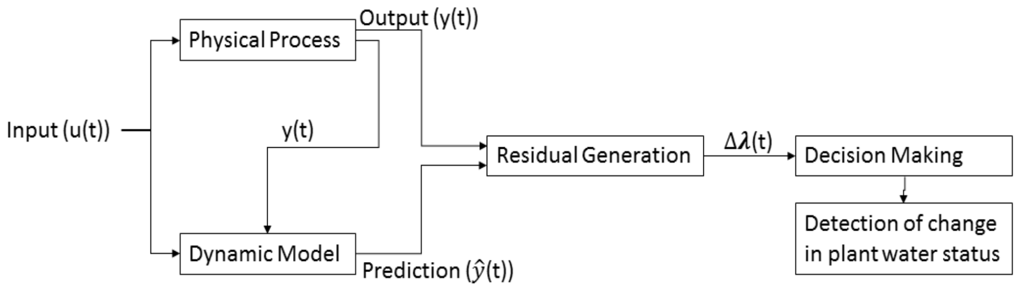

Figure 1: Schematic illustration of the proposed water status monitoring framework

The decision-making module assumes that the residuals (measured transpiration – model predicted transpiration) generated from a healthy mode of the process i.e. non-significant deviation in water status state will conform to an established statistical distribution. A change in this distribution will indicate a significant deviation in the water status state of the plant.

When there is a significant change in plant water status, the model obtained during a particular water status state is unable to predict the observed plant response. This causes the difference between the measured and predicted transpiration rate i.e. the magnitude of the residuals to increase. The decision-making algorithm is further explained in section 2.3.1

2.3.1 Decision-making algorithm

During system identification, the residuals obtained between the measured and modelled output is assumed to be a normally distributed Gaussian sequence (Taylor et al., 2007). For a properly defined model identified during a known process state, the residuals obtained between the measured and predicted output will also conform to this distribution. However, when there is a significant change in the process state, the distribution of the residuals obtained as a function of the predicted output will deviate from the distribution obtained during the modelling phase.

A Gaussian Mixture Model (GMM) can be applied in modelling the distribution of the residuals obtained during the identification process. The GMM assumes we have k normal distributions to describe the data $\{N(\mu_1,\sigma_1) \dots \dots N(\mu_k,\sigma_k)\}$ and estimates the parameters for those individual distributions that when combined best describes the data (Reynolds, 2015). The probability of observing a value X_n^j for a specific data point is expressed as (Reynolds, 2015)

$$p\left(X_n^j\right) = \sum_{k=1}^{k} \pi_k \aleph(X_n^j | \mu_k, \sigma_k) \qquad (4)$$

With

$\sum_{k=1}^{k} \pi_k = 1$

$\forall_k : 0 \leq \pi_k \leq 1$

Where μ_k and σ_k are the mean and standard deviations of each k distribution and π_k expresses the weight of each distribution.

An expectation maximization algorithm is applied in deriving the parameters that maximize the likelihood of the GMM given the training data, here, the residuals obtained during identification. These parameters are then applied in computing the probability of each observation. The best number of distributions to fit the data is also determined by minimizing the Akaike information criterion (AIC) (Xiao et al., 2016).

Once the GMM is fitted on the training data, a normal or anomalous process state can be identified by computing the probability of observing the residuals computed for that state using the GMM fitted on the residuals obtained during identification. The probabilities of observing the residuals during the anomalous state will be much lower compared to the probability of observing the residuals obtained during the normal process state and also during identification. This methodology has been shown to achieve state of the art performance when detecting faults in rotary machinery and high-voltage electronic equipment (Yan et al., 2017).

3 Materials and Methods

3.1 Greenhouse and experimental setup

Two six week studies were conducted in a climate controlled greenhouse. The heating and ventilation set points were approximately 17 and 23°C respectively. Lettuce plants were planted in individual 2.5 L containers containing a sandy loam soil (FC= 0.186 m^3m^{-3} , PWP= 0.071 m^3m^{-3}). To prevent evaporation, the soil surface of the pots were covered with a 5 cm layer of plastic beads.

During the initial study, the plants were irrigated every two hours. However, four hours prior to the initiation of measurements, four lettuce plants were selected and irrigated to replace 100% of the water lost by transpiration, four plants were irrigated to replace 90% of the water lost by transpiration, and four other plants were irrigated to replace 75% of water lost by transpiration. These irrigation treatments are hereafter referred to as 100ET, 90ET and 75ET respectively. Irrigation volumes corresponding to the treatments was applied every two hours. This approach was used in other to ensure the uniform development of the plant population's leaf area index.

During a follow-up study, after four hours into a diurnal measurement period, irrigation was withheld from four lettuce plants which have been receiving the 100ET irrigation treatment. Four other lettuce plants also received the 100ET irrigation treatment all through the diurnal measurement period. Irrigation was applied every two hours to these set of plants.

3.2 Microclimate measurements

Environmental variables measured at plant canopy level included ambient air temperature and relative humidity using a temperature and humidity probe (Model EE08, E+E Elektronik, Engerwitzdorf, Austria), and incoming radiation using a pyranometer sensor (Model SP-110, Apogee Instruments, Logan, Utah, USA). Wind speed was measured using a hot wire anemometer (Model AM – 4202, Lutron Electronics, London, UK) installed 10cm above the crop canopy. The VPD was calculated using temperature and relative humidity data following the equations outlined in Allen et al. (1998). Sensor readings were obtained at a 5 s interval and averaged online over 1 min periods with a CR1000 data acquisition system (Campbell Scientific, Logan, Utah, USA). All sensors were factory calibrated by their respective manufacturers.

3.3 Transpiration measurements

Crop transpiration of the lettuce plants was measured using three load balance systems (Model ALC, Acculab, Englewood, USA) with a $16\ kg$ capacity and $\pm 0.1\ g$ resolution. Each load balance recorded the mass of the four plants in each treatment group.

The total transpiration for a time period was calculated as the mass difference, ΔM between two consecutive time instants as recorded by the mass balance system. This was then converted to the units of volume by multiplying ΔM by the density of water $(1000\ kgm^{-3})$. In the various irrigation treatments, a computer controlled irrigation system applied irrigation to replace the predefined percentage of water loss based on the calculated water loss volume. The total irrigation volume calculated for a treatment group was divided equally among the plants assigned to that group.

The transpiration rate was calculated as

$$T_p = \frac{M(t_{i+1}) - M(t_i)}{A.(t_{i+1} - t_i)} \frac{j}{n} \tag{5}$$

Where $M(t_i)$ is the mass (g) given by the balance at time t_i (min), A (m^2) is the area of the shelve on which the plants are placed, n is the number of pots on the balance tray and j is the number of plants on the shelve. During irrigation, the transpiration rate was assumed to be constant. Data from the balance system was directly stored every minute.

3.4 Leaf area index measurements

The leaf area index (LAI) values for the plants placed on the balance were assessed using digital images captured with a mobile phone camera. The LAI values were then extracted from the digital images using the Easy leaf area software (Department of Plant Sciences, University of California).

3.5 Ancillary measurements

The soil moisture status of the plants placed on the balance was measured at hourly intervals using a model GS1 soil moisture sensor (Decagon Devices, Pullman, Washington, USA). The stomatal conductance of the plants was also measured using a diffusion leaf porometer (Model AP4, Delta-T Devices, Cambridge, UK) between 13:00 and 15:00 hrs local standard time.

4 Results and discussion

The nighttime transpiration of the plants was negligible all through the study period, with a maximum cumulative transpiration of 3 g being recorded. As such, the daytime transpiration recorded between 8:00 am and 4:00 pm was further explored.

4.1 Dynamics of crop transpiration

The measured typical daily dynamics of the crop transpiration along with prevailing environmental conditions for a sunny and cloudy day are presented in Figure 2 and Figure 3 respectively. It is seen that the 100ET and 90ET plants maintain a higher transpiration rate when compared to the 75ET plants. The transpiration dynamics also seem to follow the dynamics of the incoming radiation. However, there isn't a significant difference in the transpiration rates of the 100ET and 90ET plants $(p > 0.1)$. Stomatal conductance measurements conducted on the plants also didn't indicate a significant difference in their water status $(p > 0.1)$. The reverse was the case for comparisons of stomatal conductance measurements of both the 100ET and 90ET plants with the 75ET plants. In Figure 2 and Figure 3 , the datapoints indicating a higher transpiration rate for the 75ET plants are attributed to measurement errors. This anomaly is addressed in section 4.2.

Overall, the difference in transpiration rate between both the 100ET and 90ET plants, and the 75ET plants indicated a significant difference in their plant water status. This is in agreement with the results presented by Agam et al. (2013). They reported a significant difference in the transpiration rates of well-watered and water-stressed olive trees. During the course of the study, a maximum transpiration rate of 1.8 $gm^{-2}min^{-1}$ was recorded for the 75ET plants while a value of 3.2 $gm^{-2}min^{-1}$ was recorded for the 90ET and 100ET plants.

Due to the non-significant difference in the transpiration and water status of the 100ET and 90ET plants, the 100ET and 75ET plants were considered in the subsequent analysis.

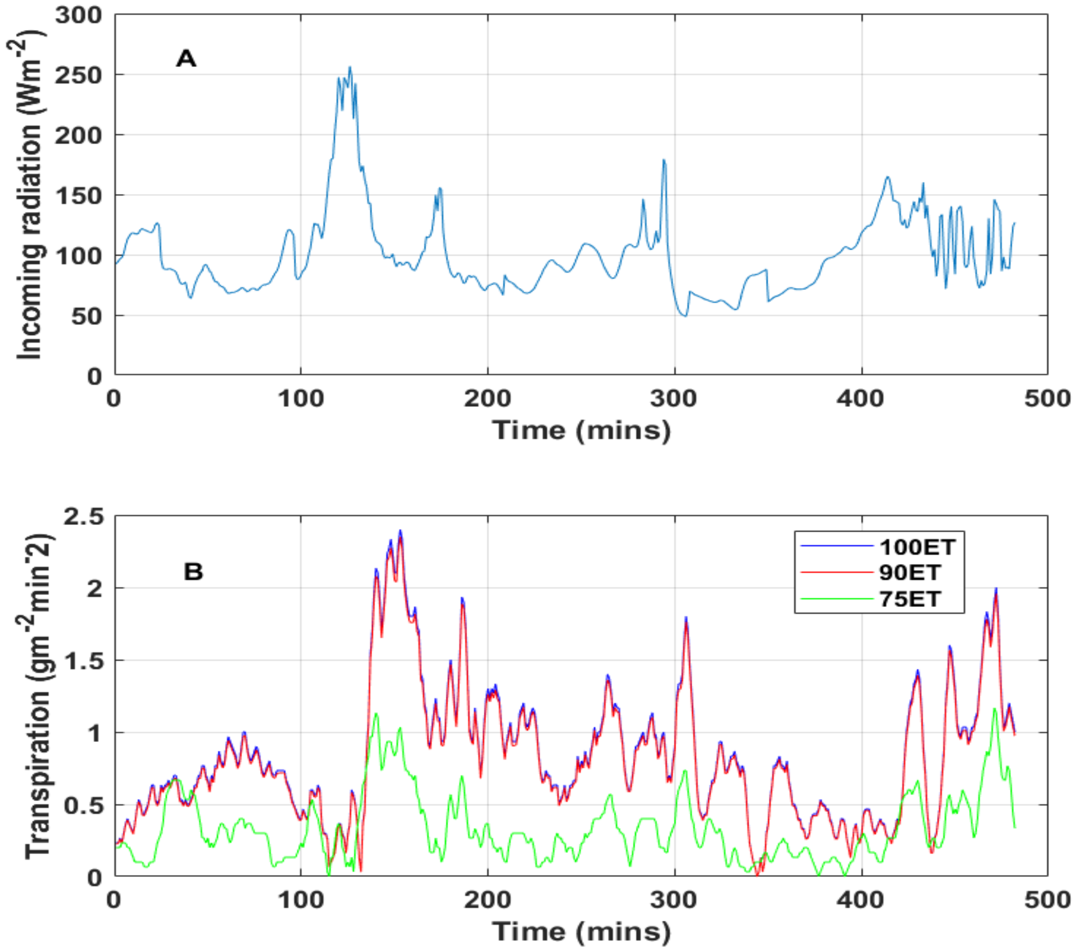

Figure 2: Measured incoming radiation and transpiration dynamics of the lettuce crops during a sunny day (a) incoming radiation (b) transpiration

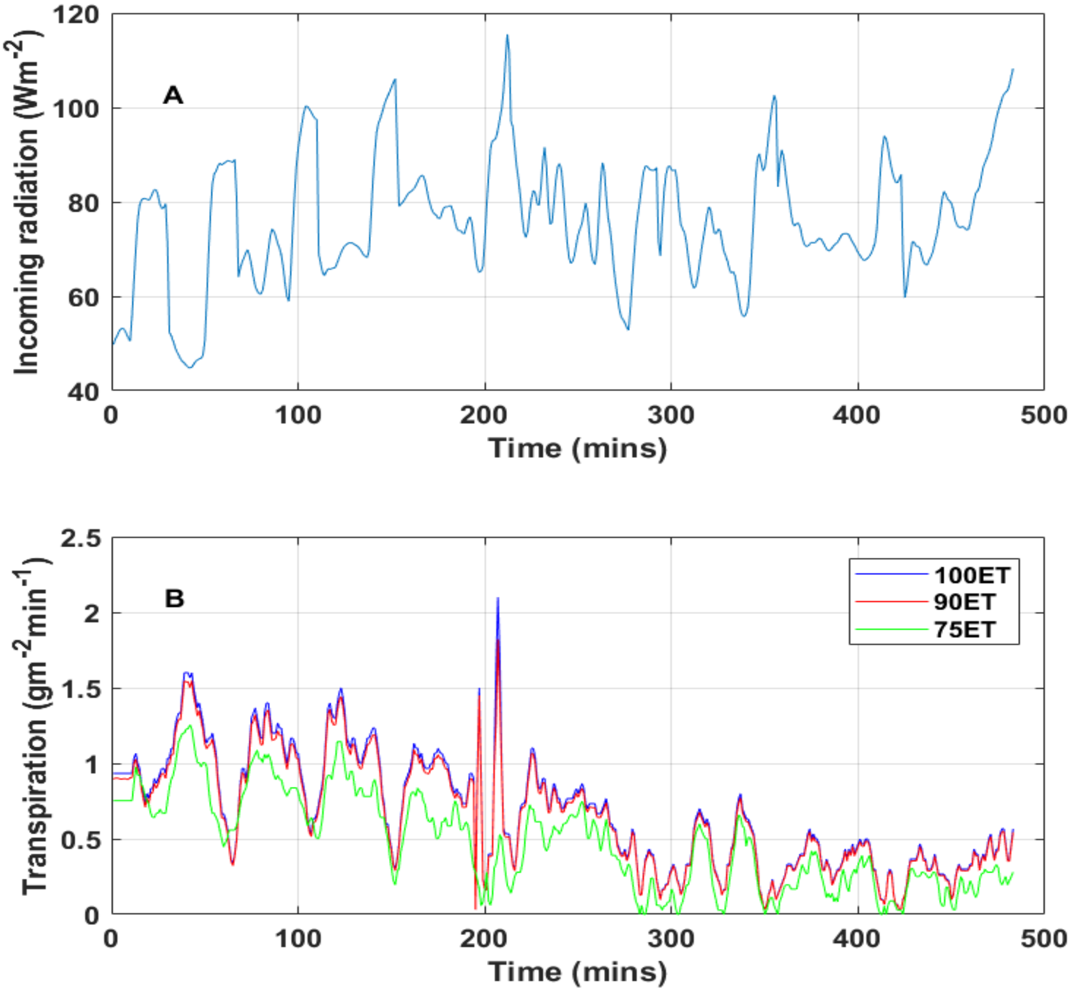

Figure 3: Measured incoming radiation and transpiration dynamics of the lettuce plants during a cloudy day (a) incoming radiation (b) transpiration

4.2 Decoupling and filtering of the transpiration signals

The measured transpiration signals contained different components, some of which were of low amplitude and others characterized by higher amplitudes. The higher amplitude components were determined to be a result of measurement noise and short-term variability in the environment. Such components were decoupled and analysed by calculating the power spectrum of the measured signals using fast Fourier transformation algorithm (FFT) (Welch, 1967). Figure 4 shows an example of the power spectrum results obtained from the measured transpiration signals. The results showed that the signals are a combination of different components that have statistical characteristics but which cannot be observed directly (Taylor et al., 2007).

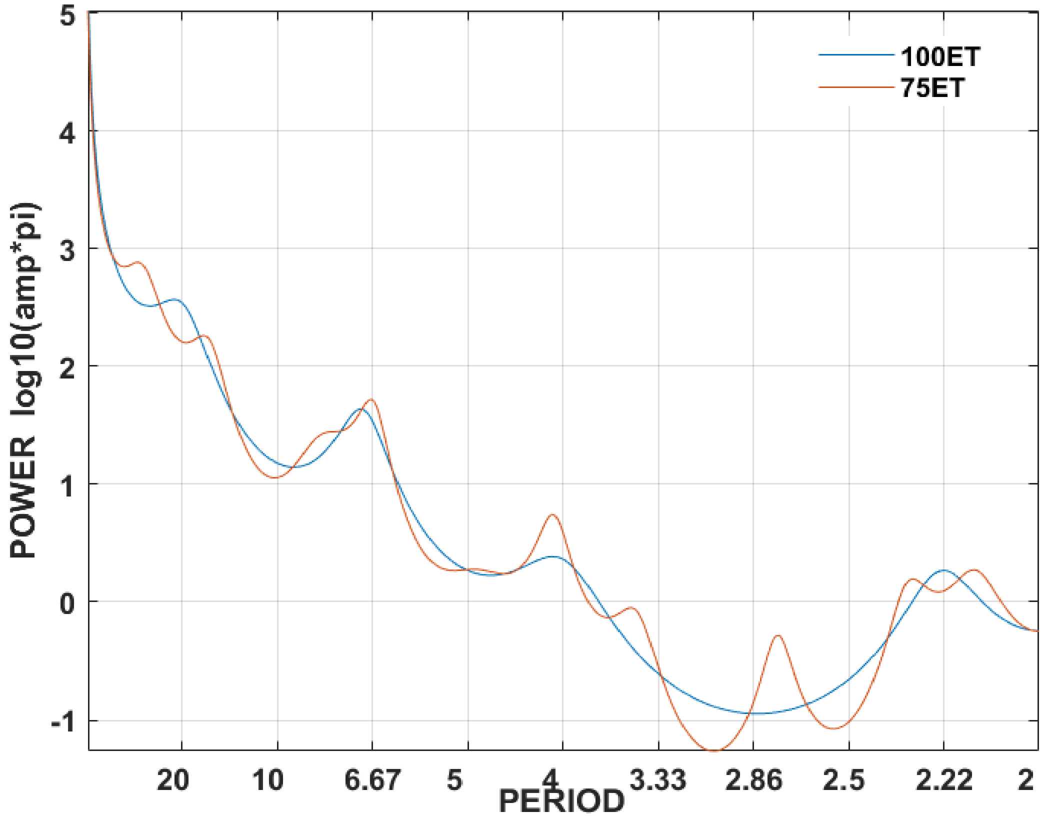

Figure 4: Power spectrum of the measured transpiration signals

The overall transpiration signal $T_p(t)$ as a function of the different components can be represented by the following discrete time equation

$$T_p(t) = T_k + C_k + f_{(uk)} + e_k \tag{5}$$

Where T_k is the trend or low frequency component, C_k is the cyclical or higher frequency component, $f_{(uk)}$ captures the influence of the input variables and e_k is the noise component.

To reduce model complexity, only the T_k and $f_{(uk)}$ components of the transpiration signal were considered. The components are decoupled from the measured transpiration signals and represented as

$$y(k) = T_k + f_{(uk)} \tag{6}$$

Where $y(k)$ is the decoupled transpiration signal. As an example, the decoupled transpiration signals of the 100ET and 75ET plants shown in Figure 3 are presented in Figure 5. It can be seen that their transpiration dynamics is clearly separated and the measurement noise is sufficiently filtered.

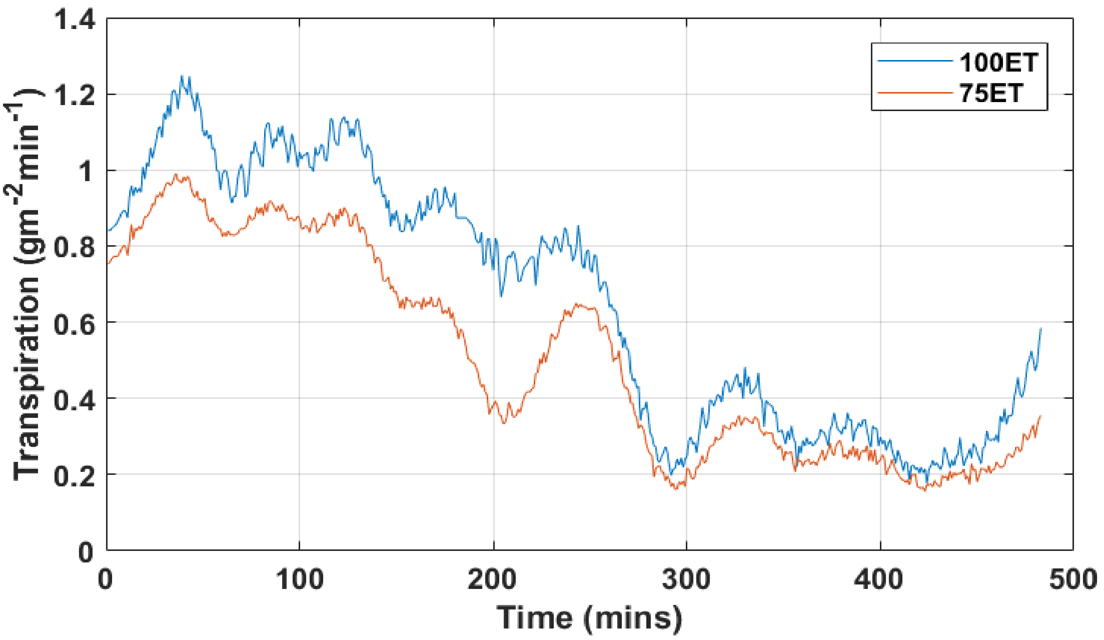

Figure 5: Decoupled transpiration signals

4.3 System Identification and dynamic modelling of the plant transpiration

The dynamic model of the plant transpiration was identified online by applying system identification on the incoming time-series data of the measured transpiration rate and environmental variables.

A second-order discrete-time transfer function model was sufficient to describe the transpiration dynamics with an average coefficient of determination $R_T^2 = 0.93 \pm 0.04$ and average Young identification criterion $YIC = -8.00 \pm 3.00$ (Young and Jakeman, 1980).

An example of the measured and modelled transpiration rate for the 100ET and 75ET plants is presented in Figure 6. It is seen that the modelled values closely match that measured values while capturing the dominant dynamics.

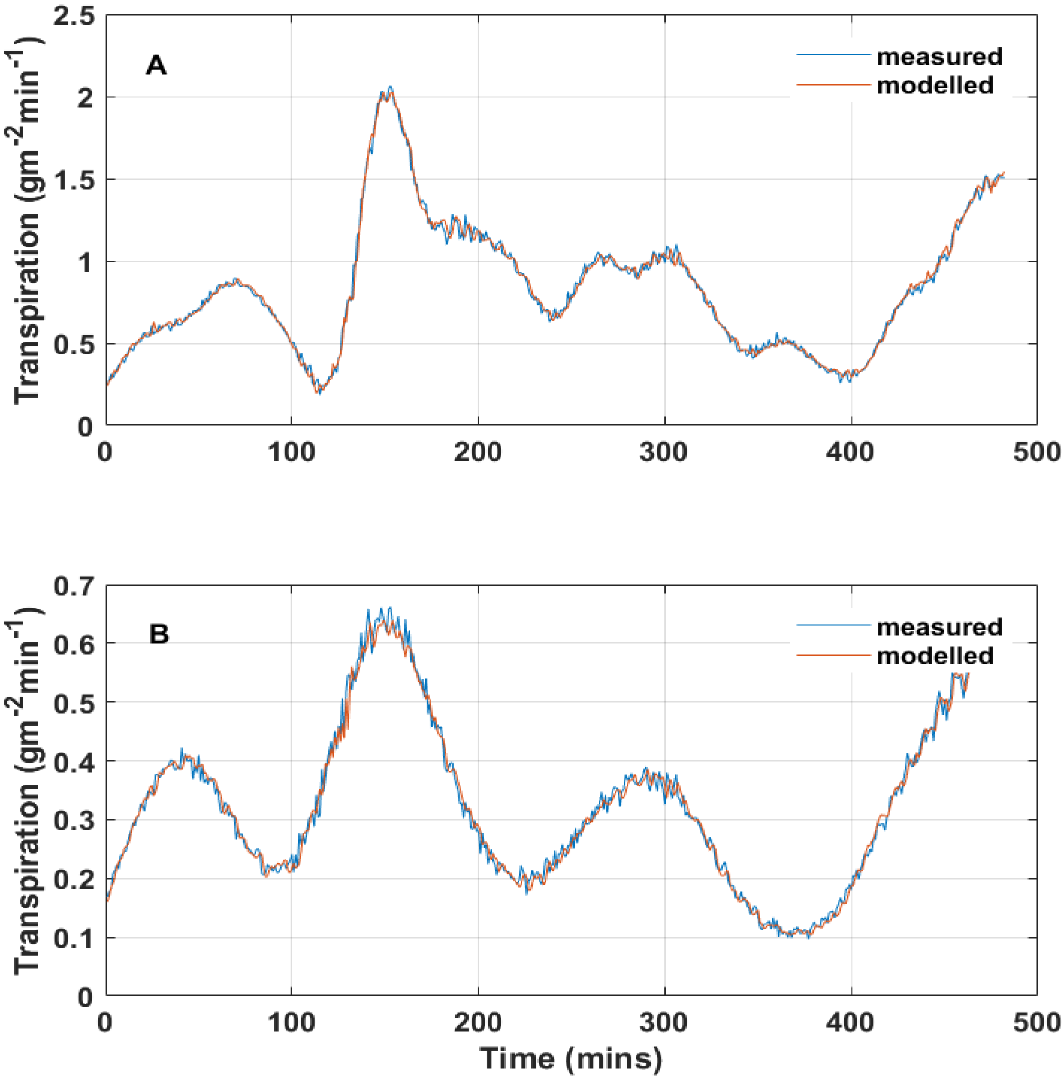

Figure 6: Measured and modelled transpiration dynamics of the lettuce plants (a) 100ET (b) 75ET

The time delay associated with the input parameters was however found to vary as a function of plant growth. As such, the LAI was used to divide the model into different intervals as summarized in Table 1. For the division, it is easy to change the LAI into other time units such as days after planting.

Table 1 – Results of the model identification as a function of the LAI interval. n is the equation's order, m_{SR} is the number of parameters associated with the radiation input, m_{VPD} is the number of parameters associated with the VPD input. δ_{SR} and δ_{VPD} are the time delay associated with the radiation and VPD inputs respectively.

LAI interval	n	m_{SR}	m_{VPD}	δ_{SR}	δ_{VPD}
0.8 or lower	2	2	2	0	0
0.8 to 1.6	2	2	2	2	0
1.6 or higher	2	2	2	4	0

Sánchez et al. (2012) reported that a dynamic model of the transpiration is able to overcome the limitations encountered by steady-state models of crop transpiration. These include the overestimation of transpiration rates at low values of LAI and underestimation at higher values. The steady-state models are also unable to sufficiently capture the dominant dynamics which results in an advancement of the real dynamics over the modelled values.

4.4 Online update of model parameters and prediction of the plant transpiration rate

The biosystem, such as the lettuce plant, is a complex assemblage of interacting physical, chemical and biological processes. As such, its transpiration dynamics will vary from day to day due to changes in the stomatal response, biological adaptation, and the prevailing environment. Accordingly, during the follow-up study, the parameters of the identified models were updated at the start of each diurnal measurement period.

It was found that the incoming time-series measurements of input/output data obtained during the first 120 mins of active transpiration were sufficient to model the transpiration dynamics of the plants in a defined water status state. The parameterized model was then applied in predicting the transpiration dynamics for the subsequent time period and updated after 240 mins. Explained further, at the start of active transpiration at time $t-120$, the data points recorded during the time period $t-120$ to t were used for parameter identification and prediction was made during time t to $t+240$. At time $t+240$, the model parameters were then updated recursively using data points recorded during t to $t+240$ which were flagged as conforming to the defined water status state. Predictions are then made for the subsequent time period.

The average prediction performance of the model is summarized in Table 2. Table 2 shows that the models are able to achieve a satisfactory level of performance at all crop growth stages

Table 2 – Average prediction performance of the identified models. Standard deviations are included in the brackets

LAI interval	Mean absolute error($gm^{-2}min^{-1}$)	Root mean square error ($gm^{-2}min^{-1}$)
0.8 or lower	0.05 (± 0.0035)	0.06 (± 0.0044)
0.8 to 1.6	0.13 (± 0.0106)	0.15 (± 0.0128)
1.6 or higher	0.09 (± 0.0046)	0.11 (± 0.0059)

Pollet et al. (2000) reported results for a PM type model for estimating the transpiration of greenhouse grown lettuce plants. They reported a 6% overestimation of transpiration by the model. It should also be noted that the parameters of PM type models are fitted for a particular water status state. The dynamic modelling approach presented in the paper can easily be applied to a plant at any water status state. This is because the parametrization of the model can be achieved using routinely measured environmental variables and transpiration measurements. The need to explicitly model the stomatal response is eliminated as this is implicitly accounted for in the online estimated model parameters and time delay. This is in agreement with the conclusions of Sánchez et al. (2012).

4.5 Monitoring of plant water status

The transpiration rate of lettuce plants is dependent on their water status as demonstrated in section 4.1. This suggests that the difference in the transpiration dynamics as a function of water status can be exploited as a means of monitoring the water status of the plants.

As an example, in Figure 7, the model predicted transpiration dynamics of lettuce plants for which irrigation was not withheld along with the measured values during a measurement period is shown. It should be noted that data points applied in parameter identification are not included in the prediction phase. The measured and modelled values closely match each other during this period as irrigation was not withheld from the plants; this period of normal irrigation is defined as state 1. Succinctly, parameter identification was conducted in state 1 and prediction was made at a later period when the plants remained in state 1. The average stomatal conductance recorded for the plants during this period was 139.22(±1.14) $mmolm^{-2}s^{1}$ and the average soil moisture content was 0.18(±0.002) m^3m^{-3}, a value close to the field capacity of the growing media.

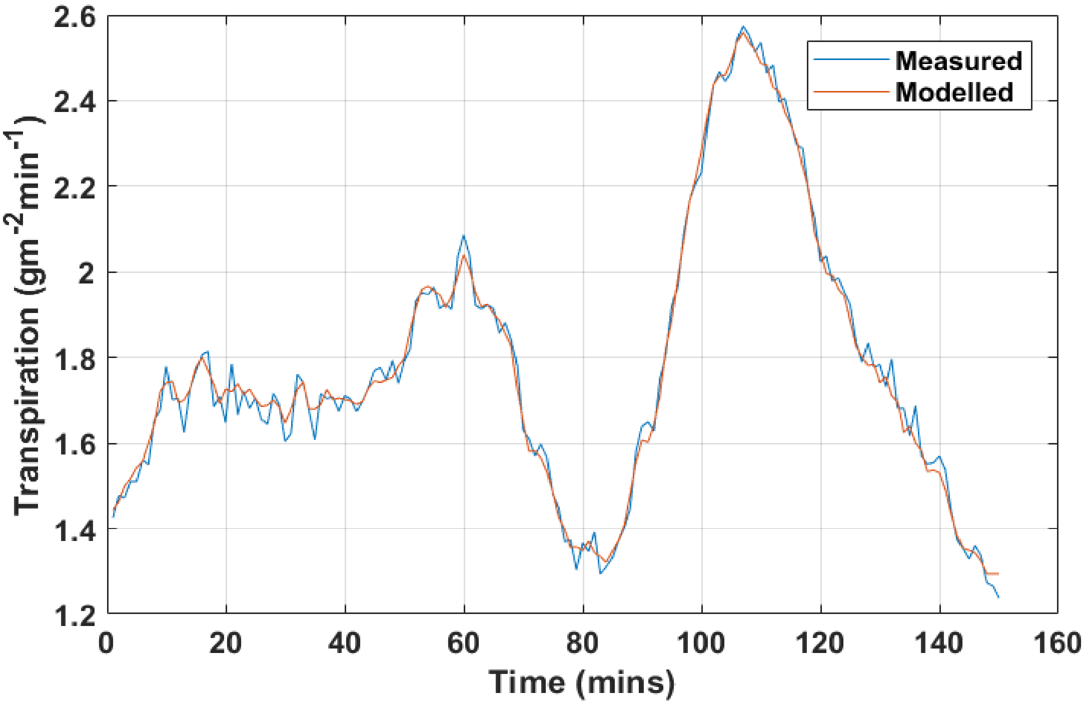

Figure 7: Measured and model predicted transpiration dynamics during a period of normal irrigation

Figure 8 shows the measured and model predicted transpiration dynamics of the set of plants for which irrigation was withheld after a period of normal irrigation, defined as state 2. It is seen that there is a wide deviation between the measured and model predicted values. This is because the model was parameterized for a water status state of the plant during which irrigation was constantly applied to replace transpiration water loss (state 1). The average stomatal conductance recorded during this period was 116.94(±0.92) $mmolm^{-2}s^{1}$ while the average soil moisture content was 0.16(±0.001) m^3m^{-3}. The stomatal conductance values show a clear significant difference ($p < 0.05$) in water status of the plants in state 1 and state 2. It is interesting to note that this difference in plant water status is also indicated in the measured transpiration rate even though the soil moisture status was above the maximum allowable depletion level of 35% (lower soil moisture target = 0.15 m^3m^{-3}) defined for the lettuce crop.

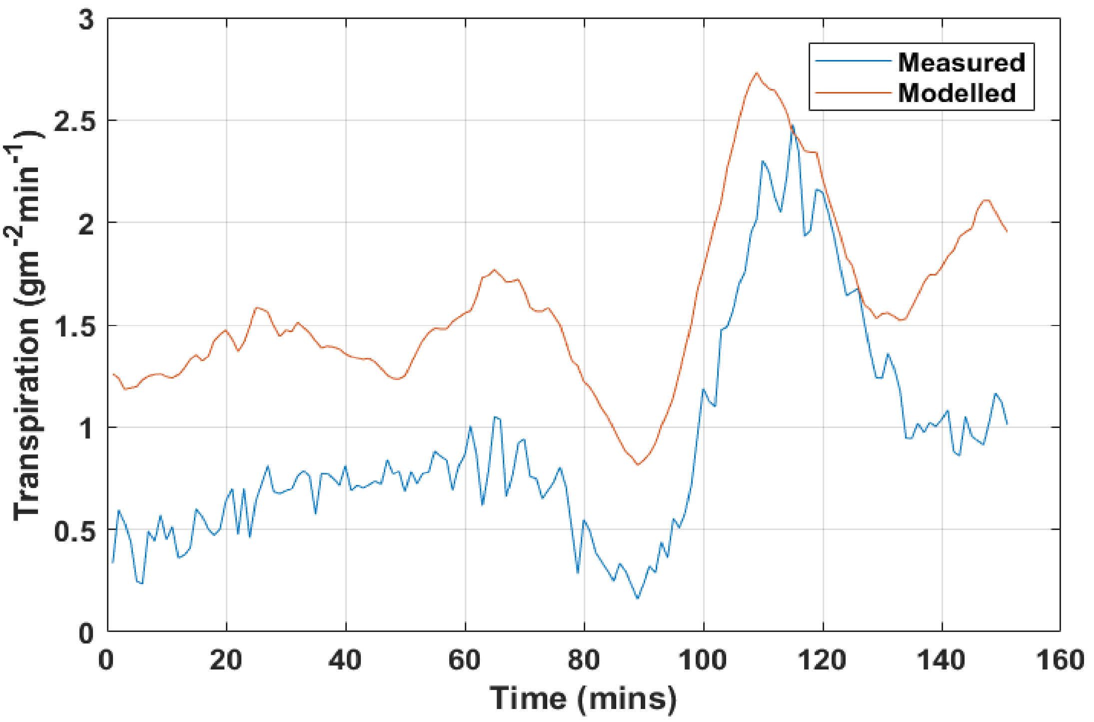

Figure 8: Measured and model predicted transpiration dynamics during a period after which irrigation had been withheld

These results give evidence that the transpiration dynamics can indeed be applied as a tool for monitoring the water status of the lettuce crop. This was consistently shown in the data obtained all through the follow-up study. The results also show that the proposed water status monitoring framework is able to exploit the deviation in transpiration dynamics to provide information on a change plant water status with a sensitivity similar to stomatal conductance measurements.

Figure 9 shows the distribution of the residuals during the identification phase in state 1 (normal irrigation). The residuals conform to a Gaussian distribution suggesting a well-defined model for the state.

Figure 10 shows the range of the predicted probabilities of observing the data points of the residuals in the identification phase in state 1, during prediction in state 1 and during prediction in state 2.

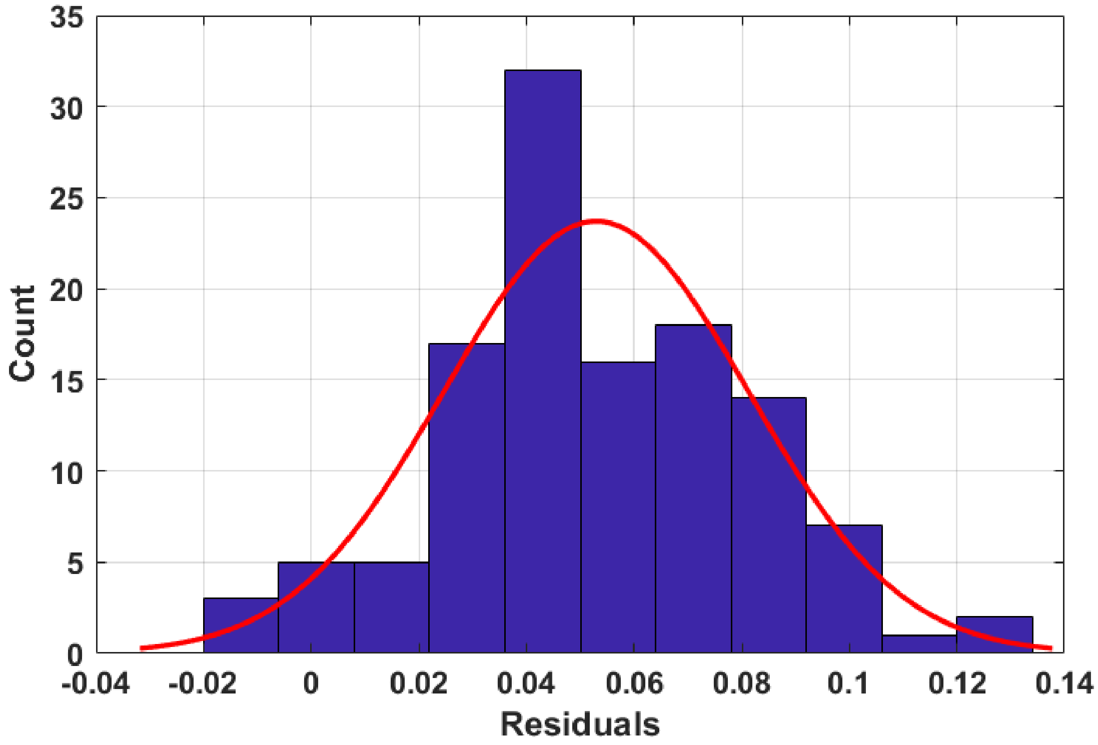

Figure 9: The distribution of the residuals obtained during the system identification phase

These predictions were made using the Gaussian mixture model fitted on the residuals obtained during system identification. Figure 10 shows that there is a high probability of observing the data points during the identification phase and also during prediction in the state for which the model was identified. The lowest probability of observing the data point of the residuals during the prediction in state 1 was 0.8. The reverse was the case during predictions in state 2. Low probabilities were predicted for observing the data points of the residuals in this state, with the highest probability predicted being 0.53. In Figure 10, the notches of the identification and state 1 boxes overlap which indicates that the median of their predicted probabilities is not significantly different at 5% significance level. It can also be seen that notches of the state 2 box do not overlap with the two other boxes indicating a significant difference in its median value when compared with the other predicted probabilities. The information contained in the predicted probabilities of observing the data points of the residuals provides an adequate indication of the water status state of the plants i.e. high probabilities will be predicted when the plant is in the state for which the model was identified and low probabilities will be predicted when there is a significant change in the water status state.

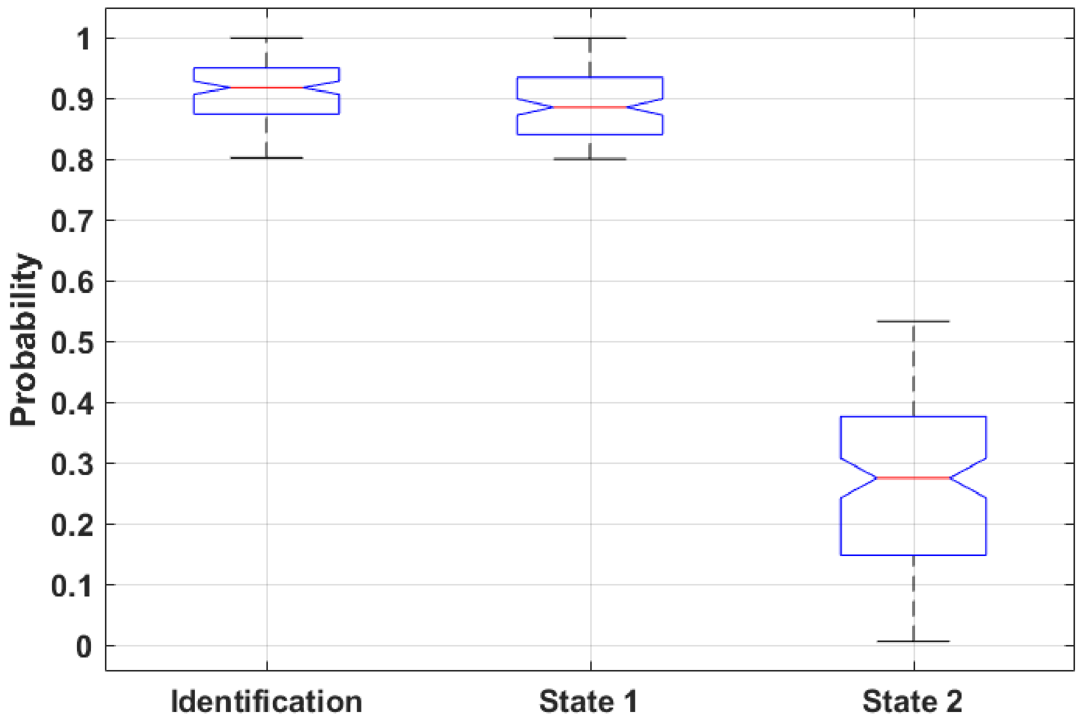

Figure 10: Boxplot of the probabilities predicted by the Gaussian Mixture Model fitted on the residuals obtained during the system identification phase for the identification residuals, state 1 residuals and state 2 residuals

Previous studies e.g. Earl (2003), Prehn et al. (2010), Beeson (2011) have also attempted to use the measured transpiration rate as a tool for monitoring the onset of drought/water stress. They attempt to achieve this by comparing the measured transpiration rate at a particular instance to the initial transpiration rate of the same plant when in a well-watered state. They, however, neglect the influence of the prevailing environment on the transpiration dynamics. The model presented in this paper addresses this drawback by predicting the ‘healthy state’ transpiration rate as a function of the known water status and real-time measurements of the environmental variables.

The water status monitoring tool proposed in this paper can be applied in regulating the water deficit of greenhouse crops. This can be achieved by applying system identification to identify a model for the plant transpiration at a known water status state and then comparing the real-time measurements to the model prediction. This approach is used extensively for performing fault detection in the process industry (Das et al., 2012; Sharma et al., 2010).

The intensity of water deficit can be easily quantified by computing the transpiration ratio proposed by Fernández et al. (2008). This is defined as the ratio between the actual transpiration measured on a plant and the transpiration rate expected for a well-watered plant. A value of 1 will indicate the absence of a deficit and a value of zero will indicate a severe deficit. This can be adapted to compute a deficit intensity for any desired reference water status state.

It should be noted that the system identification modelling technique constitutes a data-driven approach in which the dynamic response of the plant transpiration is parametrized for the specific ranges of environmental and crop conditions encountered during model development, and therefore the models are only applicable to the specific crop and environment for which they are developed.

5 Conclusions

A model for predicting the transpiration dynamics of greenhouse cultivated lettuce plants is presented in this paper. The data-driven model has the incoming radiation, vapour pressure deficit as input variables, and its structure varies as a function of plant growth in form of the LAI evolution.

Experimental results indicated that the transpiration dynamics of lettuce plants varied as a function of their water status. This phenomenon was therefore exploited as a tool for monitoring the water status of the plants. A model of the plant transpiration is identified online at a period during which the plant is in a desirable and known water status state. This model is then applied in predicting the crop transpiration. When there is a significant change in the water status state, the identified model is unable to explain the measured transpiration, resulting in a change in the statistical properties of the calculated residuals.

This approach has an advantage over similar approaches which use the plant transpiration as an indicator of its water status because it takes the time-varying nature of the plant system into account through the online adaptation of the model parameters. The difficult to model variation in stomatal response is also implicitly accounted during the online parameter estimation. This makes it a suitable plant water status monitoring tool in commercial greenhouses where the application of mechanistic models have received limited attention, due to their complexity and large input requirements. The implementation of this model in a commercial greenhouse and model development for other high-value crops will be the focus of future research.

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