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Soft computing applied to stem water potential estimation: A fuzzy rule based approach

Mercedes Valdés-Vela [a,*], Isabel Abrisqueta [b], Wenceslao Conejero [b], Juan Vera [b], M. Carmen Ruiz-Sánchez [b]

[a] Departamento de Ingeniería de la Información y las Comunicaciones, Facultad de Informática, Universidad de Murcia, Campus de Espinardo, 30100 Murcia, Spain
[b] Departamento de Riego, Centro de Edafología y Biología Aplicada del Segura (CEBAS-CSIC), P.O. Box 164, 30100, Espinardo, Murcia, Spain

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ABSTRACT

Measuring the stem water potential (Ψ_{st}), which is an essential parameter for assessing plant water status, is a tedious and labor-consuming task. In this work, hybrid soft computing techniques were applied to design a model able to estimate Ψ_{st} based on agro-meteorological and soil water content data. A Takagi–Sugeno–Kang fuzzy inference system (TSK-FIS) was obtained. This kind of model approximates non-linear systems by combining a set of functions local to fuzzy regions described by fuzzy rules. Such models have approximative power and are sufficiently descriptive. Starting from a set of input–output data, inputs relevant to Ψ_{st} were automatically selected and fuzzy rules were identified based on the fuzzy clusters found in the data. The rule parameters were optimized by means of a neuro-fuzzy approach. The result was an accurate (86% variance explained) and simple model with five rules that considered soil water content at 0.3 m depth, the day of the year and mean daily air temperature as input variables, confirming the suitability of such approach. In addition, a rule simplification method allowed a consistent agro-linguistic interpretation of the fuzzy sets of the rules: DRY, MOIST and WET for the soil water content, BLOOM, FRUIT GROWTH, EARLY POSTHARVEST and LATE POSTHARVEST for the day of the year, and COLD, MILD and WARM for mean daily air temperature.

1. Introduction

Irrigation management strategies that reduce crop water use without affecting final production are increasingly considered a necessity in semi-arid areas where uncertainty in irrigation water supply requires a more efficient use of the available resources. In peach trees, water deficits during the second fruit rapid growth phase are more harmful than in other phenological stages (Besset et al., 2001; Naor et al., 2005), and the postharvest phase is the most suitable period for applying irrigation deficits (Ruiz-Sánchez et al., 2010; Mounzer et al., 2008). For the implementation of regulated deficit irrigation strategies, crop critical periods, the overlapping stages of vegetative and fruit growth and the exact plant response to water deficits under local conditions must be understood (Abrisqueta et al., 2010; Girona et al., 2003; Girona et al., 2005). Identification of the level of water stress suffered by the plant is therefore essential when using deficit irrigation strategies (Hsiao, 1990; Naor, 2006). Several indicators of water status have been used to quantify peach tree water stress levels (Conejero et al., 2011; Goldhamer et al., 1999), among them stem water potential (Ψ_{st}), which is accepted as one of the most accurate plant water status indicator (Shackel et al., 1997). However, measuring Ψ_{st} is a labou-intensive and destructive method.

In this work, we propose a model able to estimate Ψ_{st} of adult peach trees under different drip irrigation conditions by the application of soft computing techniques to agro-meteorological and soil water content data. Soft computing is a field of artificial intelligence whose main objective is the design of intelligent systems to manage uncertain and imprecise information (Zadeh, 1993). Evolutionary computing, fuzzy logic and artificial neural networks (ANN) are some of the main components of soft computing, along with hybrid mechanisms such as neuro-fuzzy approaches which combine the approximative and adaptive capabilities of ANNs with the expressiveness of fuzzy logic-based models such as fuzzy inference systems (FISs). This expressiveness, also called *interpretability*, is the main incentive for using FISs as an alternative to other models such as ANNs. While ANNs are considered black-box models, FISs express the behavior of the system in terms of fuzzy rules

* Corresponding author.
E-mail addresses: mdvaldes@um.es (M. Valdés-Vela), iavillena@cebas.csic.es (I. Abrisqueta), wenceslao@cebas.csic.es (W. Conejero), jvera@cebas.csic.es (J. Vera), mcruiz@cebas.csic.es (M.C. Ruiz-Sánchez).

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which are understandable for an expert and whose parameters are easily adjustable if needed.

FISs in particular and soft computing techniques in general have been successfully applied to different problems in the agro-meteorological context. Valdés et al. (2005) proposed a neuro-fuzzy approach to estimate reference evapotranspiration (ET_0). Kumar et al. (2011) also applied an ANN to obtain ET_0, while Valdés et al. (2003) used another FIS for the interpolation of solar radiation, as this is one of the inputs needed to the Penman–Monteith ET_0 equation (Allen et al., 1998). Pulido-Calvo and Gutiérrez-Estrada (2009) proposed an FIS tuned by a genetic algorithm for irrigation water demand forecasting. Capraro et al. (2008) applied a neural approach to infer the water demand and time needed to take the soil moisture level to a desired value. Martí et al. (2013) proposed an ANN for the estimation of Ψ_{st} of citrus trees under a single irrigation treatment and a limited dataset.

In this work, we propose a FIS to estimate Ψ_{st}. This model is based on fuzzy rules and, therefore, is quite interpretable while being sufficiently accurate. The FIS was generated using data of different irrigation treatments with the aim of making it as general as possible.

The paper describes the process by means of which the model for Ψ_{st} estimation is generated. FISs can be designed based on expert knowledge or data, in general, the latter being more accurate. On the other hand, those based on expert knowledge are more interpretable than those based on data (Guillaume, 2001). Given that the main goal in this work is accuracy, an FIS is generated from input–output data using the so-called *fuzzy modeling* process. The process is composed of three main phases. The first task is the selection of the input variables that are relevant to Ψ_{st}. Then, the structure of the fuzzy rules is generated and their parameters are optimized in order to improve the accuracy.

In addition, a rule simplification method that reduces the complexity of the model can be applied. The simpler the model, the more understandable it is, the easier to manually modify its parameters if be necessary and the less memory and computation time needed.

2. Materials and methods

2.1. Plant material and irrigation treatments

The experiments were performed over five growing seasons (2009–2013) in an orchard of adult early-maturing peach trees (*Prunus persica* (L.) Batsch, cv. Flordastar, on GF-677 rootstock), located in an experimental 0.8 ha plot in Santomera–Murcia (S.E. Spain): 38°06N, 1°02W. The soil is highly calcareous, stony and 0.9 m deep, with a clay-loam texture. Trees were spaced 5 m × 5 m and irrigated by a drip irrigation system consisting of a single lateral line per tree row, with eight emitters per tree, placed 0.5 m from the trunk, providing 2 L/h. Irrigation was initiated in mid-February at flowering and suspended in early November. More details on the experimental plot, plant material and cultural practices have been described elsewhere (Mounzer et al., 2008; Vera et al., 2013). Five irrigation treatments, distributed in a completely randomized design with four replications (each consisting of one row of 13 trees), were set up: control (T_{100}) irrigated to fulfil crop evapotranspiration (100% ET_c), which was estimated from the crop reference evapotranspiration (ET_0) values, calculated with the Penman–Monteith equation (Allen et al., 1998), and local crop coefficients (Abrisqueta et al., 2013); continuous deficit irrigation (T_{50}) irrigated at 50% of ET_c all season; regulated deficit irrigation (T_{RDI}) irrigated to fully cover 100% ET_c during the fruit growth period, with the irrigation water reduced to 70 and 25% ET_c during the postharvest period; automatic control of irrigation (T_{Soil}) based on soil water content threshold values measured with FDR-type capacitance probes (Vera et al., 2013), and a non-irrigated treatment (T_0), which received no water except during the fruit growth period (irrigated 100% ET_c). The irrigation water volumes were obtained from inline flow meters.

2.2. Measurements

Agro-meteorological data were recorded every 15 min by an automatic weather station located within the peach orchard with real-time access via the web. From these data the following variables were calculated: mean daily air temperature T_m (°C), relative humidity RH_m (%), vapor pressure deficit VPD_m (kPa) and solar radiation R_m (Wm^{-2}); also daily crop reference evapotranspiration ET_0 (mm) was calculated using the Penman–Monteith equation (Allen et al., 1998). The volumetric soil water content was measured weekly in the morning with a neutron probe (TROXLER, mod. 4300; Troxler Electronic Laboratories Inc., Research Triangle Park, NC, USA) from 0.2 to 0.8 m in 0.1 m increments (S_2 to S_8) in access tubes installed in the wetted area (0.1 m from the second emitter) of one tree of each replication and treatment. The soil water content in the top 0.1 m of the soil (S_1) was measured by time domain reflectometry (TDR) (TEKTRONIX, mod. 1502B; Tektronix Inc., Beaverton, OR, USA). Midday (12 h GMT) stem water potential Ψ_{st} (MPa) was measured weekly with a pressure chamber (Soil Moisture Equip., model 3000) in one leaf per tree of four randomly selected trees per treatment (one per replicate). The leaves were selected from within the canopy and close to the trunk, wrapped in small bags of aluminum foil for at least 2 h prior to measurement (Shackel et al., 1997) and placed in the chamber within seconds of excision and following the precautions recommended by Hsiao (1990).

In addition to the previously mentioned variables, the day of the year (*DOY*) was also taken into account, since it can be considered as an indicator of the phenological state of the plant.

The available data $Z = \{z^1, z^2, \ldots, z^n\}$ are distributed for the different year and treatments as shown in Table 1, with $n = 391$ and $z^i = (doy^i, t^i_m, hr^i_m, r^i, et^i_0, vpd^i_m, s^i_1, s^i_2, s^i_3, s^i_4, s^i_5, s^i_6, s^i_7, s^i_8, \Psi^i_{st})$, for $i = 1, \ldots, n$. The third and fourth years have the same percentages for data of the different treatments. In contrast, for the first year, no T_{100} data are available and the second year lacks T_0 data while having a number of T_{100} data that doubles the normal number of data of the remaining treatments. Nevertheless, the data are almost equally distributed across treatments. Having the same number of data for every treatment avoids a biased training.

2.3. Fuzzy sets

A fuzzy set A, on a domain, $\mathbb{X}$, is defined by the membership function $\mu_A(x) : \mathbb{X} \to [0, 1]$. Given an element $x \in \mathbb{X}$, if the value $\mu_A(x)$ equals one, then x is said to completely belong to the fuzzy set A. If it equals zero, x does not belong to A. If $\mu_A(x)$ is between 0 and 1, x is a partial member of the fuzzy set A.

Table 1
Distribution of data for each year and treatment.

Year	T_{100}	T_{50}	T_{RDI}	T_{Soil}	T_0	Total
1	0 (0 %)	24 (25%)	24 (25%)	24 (25%)	24 (25%)	96
2	44 (40%)	22 (20%)	22 (20%)	22 (20%)	0 (0%)	110
3	23 (20%)	23 (20%)	23 (20%)	23 (20%)	23 (20%)	115
4	14 (20%)	14 (20%)	14 (20%)	14 (20%)	14 (20%)	70
Total	81 (21%)	83 (21%)	83 (21%)	83 (21%)	61 (16%)	391