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Prediction of applied irrigation depths at farm level using artificial intelligence techniques

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ABSTRACT

Irrigation water demand is highly variable and depends on farmer behaviour, which affects the performance of irrigation networks. The irrigation depth applied to each farm also depends on farmer behaviour and is affected by precise and imprecise variables. In this work, a hybrid methodology combining artificial neural networks, fuzzy logic and genetic algorithms was developed to model farmer behaviour and forecast the daily irrigation depth used by each farmer. The models were tested in a real irrigation district located in southwest Spain. Three optimal models for the main crops in the irrigation district were obtained. The representability (R^2) and accuracy of the predictions (standard error prediction, SEP) were 0.72, 0.87 and 0.72; and 22.20%, 9.80% and 23.42%, for rice, maize and tomato crop models, respectively.

1. Introduction

Climate change and the growing demand for water in some economic sectors such as industry and agriculture are reducing the availability of freshwater. Irrigated agriculture is the main water user, accounting for nearly 70% of total water consumption in the world (Conforti, 2011). The sustainability of irrigated agriculture is strongly linked to the improvement of water use efficiency. Water demand forecasting could be one of the main tools to accurately design new irrigation systems and improve the management of older pressurized irrigation networks. Irrigation water demand is highly variable and depends on the behaviour of each farmer, which is affected by both measurable variables (e.g. agroclimatic variables or the size of the irrigated area) and non-measurable variables (e.g. local traditional practices or holidays during the irrigation season).

Fuzzy logic (FL) is an artificial intelligence (AI) technique initially developed by (Zadeh, 1965) to explain human intelligence and decision-making behaviour. FL can be applied as a fuzzy inference system (FIS) designed to transform linguistic concepts into mathematical and computational structures for daily water demand forecasting. FIS is a rule-based system that consists of a rule base, a database with membership functions (MFs) which determine the membership grades of each input variable to each fuzzy set and where the combination of fuzzy rules produces the system results (inference system).

However, FIS has two major limitations. The first restriction is to set the type of membership functions and their optimal number. In most works, these variables are determined by trial and error, so finding an optimal solution is not guaranteed. Thus, one of the most popular approaches to overcome this constraint is the use of genetic fuzzy systems (GFSs), a hybrid combination of FL and genetic algorithms (GAs).

In the field of water management, AI has been used in probabilistic hydrology prediction (Zhang et al., 2011), groundwater level forecasting (Shirmohammadi et al., 2013), for the prediction of furrow irrigation infiltration (Mattar et al., 2015) or even for the prediction of filtered volume in micro-irrigation and sand filter systems (Puig-Bargués et al., 2012). Adaptive neuro-fuzzy inference system (ANFIS) and FL techniques have also been applied for the prediction and simulation of groundwater level fluctuations (Zare and Koch, 2018) and for irrigation scheduling optimization using a flexible decision support system (Yang et al., 2017). However, there are very few useful tools for irrigation district managers and farmers to forecast irrigation depth at farm level in pressurized irrigation networks.

GFSs have already been used for water demand forecasting at the irrigation district level (Pulido-Calvo and Gutiérrez-Estrada, 2009), but no previous work has used these systems to predict farmer behaviour. The second restriction is the inability of FIS to automatically select the MF parameters and design the fuzzy rules. However, ANFIS, which is a combination of artificial neural networks (ANNs) and FL, overcomes this drawback. Thus, an ANFIS uses the learning ability of an ANN to define fuzzy rules. ANFIS has been used for several applications such as the intelligent allocation of water resources (Chang et al., 2016) and the optimization of reservoir operations (Safavi et al., 2013), but has not yet been applied to characterize farmer behaviour. Therefore, in this work a hybrid methodology that combines GFSs and ANFIS has been

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developed to forecast the daily amount of water applied by each farmer. The non-sorting genetic algorithm, NSGA-II (Deb et al., 2002), is the multi-objective GA included in the GFS developed in this work. The methodology has been applied to a real irrigation district in Spain to predict farmer behaviour during the 2015 irrigation season.

2. Methodology

2.1. Study area and data source

The data recorded in the Canal del Zujar Irrigation District (CZID) of southwest Spain was used to develop and test the predictive model built in this work. CZID is made up of ten independent hydraulic sectors and covers a total irrigated area of 21,141 ha. Sector II of the CZID was selected for this study. The sector covers an irrigated area of 2,691 ha where the main crops are tomato, maize, grapevine and rice.

Sector II of the CZID has a telemetry system with flowmeters that record hourly flow rates at hydrant level. For the 2015 irrigation season, hourly records were aggregated at daily level. In addition, information was also available about crop types and sizes of the farms irrigated by each hydrant. Daily climate data were obtained from a weather station located in the irrigation sector.

2.2. Problem approach

The irrigation scheduling process consists of two main steps: the occurrence of the irrigation event and the amount of water applied. In this work, a model of farmer behaviour that forecasts the daily irrigation depth applied by each farmer is developed using GFS and ANFIS. The first phase of the model building process is to identify the main input variables. A FIS is then designed using an ANFIS model optimized by the NSGA-II GA.

2.3. Model input identification

Although the construction of forecasting methods requires a huge amount of data, the first step in this process is to reduce the dimension of the input space in order to identify the relevant input variables in the whole dataset. There are several techniques to do this, such as principal components analysis or partial least square cardinal components. However, when the selected variables are used in nonlinear models, model predictions are usually quite poor (Lin et al., 1996). Therefore, in this work, fuzzy curves and fuzzy surfaces have been used to easily and automatically select the independent significant inputs for the hybrid model following the methodology developed by Lin et al. (1996). For each potential input variable, a plot is initially created that relates each potential input variable to the target variable to be predicted (DaW, daily amount of water applied by each farmer). Then, for each point represented in each plot a fuzzy membership function is created according to the following expression:

$$\mu_{v,k}(PI_v) = \exp(-(\frac{PI_{v,k}-PI_v}{b})^2) \tag{1}$$

where $\mu_{v,k}$ represents the fuzzy membership function of point k in the plot which relates the potential input variable v and the daily amount of water applied by each farmer; PI_v is the potential input variable v; $PI_{v,k}$ is the value of PI_v at point k and b takes a value close to two (Lin et al., 1996).

Hereafter, each fuzzy membership function is defuzzied producing a fuzzy curve c_v for each potential input PI_v using:

$$c_v(PI_v) = \frac{\sum_{k=1}^{M} \mathrm{DaW}_k \bullet \mu_{v,k}(PI_v)}{\sum_{k=1}^{M} \mu_{v,k}(PI_v)} \tag{2}$$

where M is the total number of points in the space PI_v - DaW and DaW_k is the daily amount of water applied by each farmer in point k of the space PI_v - DaW.

Then, the mean square error (MSE) is computed for each space $PI_v - c_v$:

$$MSE_{c_v} = \frac{1}{M}\sum_{k=1}^{M}(c_v \bullet (PI_{v,k}) - \mathrm{DaW}_k)^2 \tag{3}$$

where MSE_{c_v} is the mean square error for the fuzzy curve c_v.

The MSE values of each c_v are sorted in ascending order. If there is a completely random relationship between the PI and the daily amount of water applied by each farmer, the fuzzy curve is flat and the MSE_c is large. Conversely, if the MSE_c value is small, the relationship between PI and the daily amount of water applied by each farmer is more significant.

A fuzzy surface is a space with a two-dimensional fuzzy curve. According to Lin et al. (1996), a fuzzy surface ($fs_{v,j}$) is defined as Eq. 4.

$$fs_{v,j}(PI_v, PI_j) = \frac{\sum_{k=1}^{M} \mathrm{DaW}_k \bullet \mu_{v,k}(PI_v) \bullet \mu_{j,k}(PI_j)}{\sum_{k=1}^{M} \mu_{v,k}(PI_v) \bullet \mu_{j,k}(PI_j)} \tag{4}$$

where PI_v and PIj are two potential input variables.

Then, similarly to Eq. 3, the MSE is computed for the fuzzy surfaces:

$$MSE_{fs_{v,j}} = \frac{1}{M}\sum_{k=1}^{M}(fs_{v,j}(PI_v, PI_j) - \mathrm{DaW}_k)^2 \tag{5}$$

Fuzzy curves are initially used to rank all the potential input variables in ascending order. The potential input variable with the smallest MSE_c is the most important input variable. According to Lin et al. (1996), 20% of the potential input variables with the largest MSE_c are eliminated. Fuzzy surfaces are then used to find the independent input variables and to eliminate the related input in each step. Thus, in each step new fuzzy surfaces are computed and 20% of the potential input variables with the largest MSE_{fs} is eliminated.

2.4. Fuzzy inference system (FIS)

Due to its unique features in forecasting complex phenomena, the FIS is one of the best tools for modelling human thinking (e.g. farmers' decisions). A fuzzy system is a nonlinear relationship between inputs and outputs based on a set of "IF-THEN" rules. While the antecedent of a rule defines a fuzzy region in the input space (e.g. crop, maximum daily temperature, weekday, etc.), the consequent specifies the output in a fuzzy region. Fig. 1 shows a flow chart of a typical three-step FIS. The aim of the first step (fuzzification) is to transfer the input vector into fuzzy If-Then rules through the MFs and linguistic variables. That is, a vector with input variables (crisp values) is turned into linguistic variables (e.g. the value of the variable temperature is 25 °C, the crisp value, becomes the linguistic variable 'the temperature is HIGH'). The rule base and the MFs form the knowledge base (Fig. 1). Then, the optimal design of the knowledge base is established by an ANN (Section 2.5).

There are two types of FISs: the Sugeno-Takagi (TS) (Takagi and Sugeno, 1985) FIS and the Mamdani FIS (Mamdani and Assilian, 1975). The main differences between the two are the way that the outputs (Fig. 1) are determined. Due to its more compact and computationally

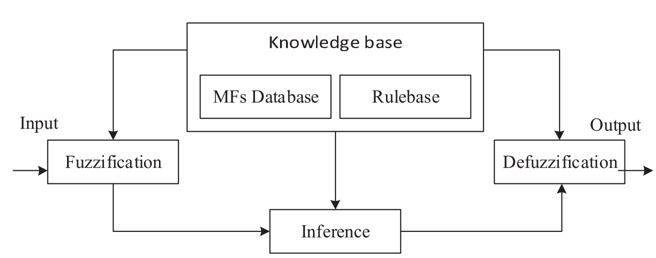

Fig. 1. Structure of a fuzzy inference system (FIS).