RESEARCH ARTICLE

Calibrating a flow model in an irrigation network: Case study in Alicante, Spain

Modesto Pérez-Sánchez[1], Francisco J. Sánchez-Romero[2], Helena M. Ramos[3] and P. Amparo López-Jiménez[1]

[1]Universitat Politècnica de València. Dept. Hydraulic and Environmental Engineering. Valencia 46022. Spain. [2]Universitat Politècnica de València. Dept. Rural and Agrifood Engineering, 46022 Valencia. Spain. [3]Universidade de Lisboa, Instituto Superior Técnico. CERIS. Dept. Civil Engineering, Architecture and Georesources. Lisboa 1049-001 Portugal.

Abstract

The usefulness of models depends on their validation in a calibration process, ensuring that simulated flows and pressure values in any line are really occurring and, therefore, becoming a powerful decision tool for many aspects in the network management (*i.e.,* selection of hydraulic machines in pumped systems, reduction of the installed power in operation, analysis of theoretical energy recovery). A new proposed method to assign consumptions patterns and to determine flows over time in irrigation networks is calibrated in the present research. As novelty, the present paper proposes a robust calibration strategy for flow assignment in lines, based on some key performance indicators (KPIF) coming from traditional hydrological models: Nash-Sutcliffe coefficient (non-dimensional index), root relative square error (error index) and percent bias (tendency index). The proposed strategy for calibration was applied to a real case in Alicante (Spain), with a goodness of fit considered as "very good" in many indicators. KPIF parameters observed present a satisfactory goodness of fit of the series, considering their repeatability. Average Nash-Sutcliffe coefficient value oscillated between 0.30 and 0.63, average percent bias values were below 10% in all the range, and average root relative square error values varied between 0.65 and 0.80.

Additional key words: water management; calibration model; Key Performance Indicators.

Abbreviations used: E (Nash-Sutcliffe coefficient); KPIF (key performance indicators for goodness of fit); O (observed values); P (simulated values); PBIAS (percent bias); RMSE (root mean square error); RN (random number); RRSE (root relative square error); SCADA (supervisory control and data acquisition); WDN (water distribution network).

Introduction

Currently, the management of water distribution networks (WDNs) is increasingly based on use of models as decision support tools, particularly in performance and energy efficiency implications (Rodriguez-Diaz *et al*., 2010; Arbat *et al*., 2013; Cabrera *et al*., 2014). When different database and mathematical algorithms are combined, these hydraulic models are an useful tool to analyze WDNs, if these models are properly calibrated.

Water management becomes more efficient when a deep knowledge of the network is done by modelling (Carravetta *et al*., 2012; Pardo *et al*., 2013; Cabrera *et al*., 2014; Butera & Balestra, 2015; Emec *et al*., 2015; Delgoda *et al*., 2016), increasing the sustainability of the whole system and decreasing the water footprint (Corominas, 2010; Ramos *et al*., 2010a,b). This knowledge of the network (mainly flows and pressure) allows the design of strategies to transform the WDNs in multipurpose systems (Choulot, 2010). For instance, the replacement of pressure reducing valves by hydraulic machines is an efficient solution, considering the feasibility in the investment (Ramos

& Borga, 1999; Ramos *et al*., 2010a; Carravetta *et al*., 2012, 2013, 2014). The installation of hydraulic machines in existing networks is cheaper than the development of small similar hydropower stations. When already installed machines are used, the facilities (*e.g.* reservoir, pipes, and excavation) are already done for satisfying the demand to users (Ramos & Borga, 1999).

Particularly, models become necessary to analyze the flow distribution over time at each pipe of the irrigation network. If discretized flows and pressures are known, energy balance can be obtained in any WDN. Throughout the 20th century, different authors have proposed and revised different methodologies to determine the maximum flows in on-demand irrigation networks and to design the pipe sizes (Clément, 1955; Boissezon & Haït, 1965; Granados, 1986; Lamaddalena & Sagardoy, 2000). Clèment (1955) developed the so called expression Clément's first formula, one of the most used to design on-demand irrigation networks. Boissezon & Haït (1965) introduced new terms in the Clément's first formula, in which the irrigation probability depends on crop rotation over year, with a mathematical method similar to Clément. Later, Clément (1966) developed the Clément´s second formula. This new method considers the time as variable. Both methods (Boissezons' methods and Clément´s second formula) do not provide great accuracy in the calculation, being the Clement´s second formula more complex than the first one (Clément, 1955; Granados, 2013). Afterwards, new methodologies have been developed by different authors, requiring a high database treatment. These methods are based on increasing computers capacity. For instance, Moreno *et al*. (2007) propose random generation of scenarios with different hydrants opened in the network. In other cases, flows are determined by computational neural networks or genetic algorithms (Pulido *et al*., 2003; Martínez-Solano *et al*., 2008).

The need for determining flows and pressure over time at any line or joint has contributed to the use of models, which are increasingly getting common (Ritter *et al*., 2009). Nevertheless, the reliable use of these models must be exposed to a correct and systematic calibration process, generally related with the study of pressures and roughness (Braun *et al*., 2010; Tabesh *et al*., 2011). Some models for determining flows can be found in the references consulted (*e.g.,* the method presented by Preis *et al*. (2009)). This method uses a statistical data-driven algorithm to estimate the circulating flow, being necessary that an SCADA (supervisory control and data acquisition) is installed in the irrigation network. Other similar studies have been developed by different researchers (Datta & Sridharan, 1994; Clark & Wu,

2006; Davidson & Bouchart, 2006; Ghiassi *et al*., 2008; Sanz & Perez, 2014, 2015).

Generally, these systems have pressure and flow sensors installed, which is located in different points of the network. These sensors transmit to SCADA the registered data. Existence of these measurement devices allows the application of computational methods, which determine the flows using the database of SCADA to correct the predicted values by the analytical methods. Unfortunately, most of irrigation networks do not generally have these control elements installed as consequence as idiosyncrasy of the agricultural sector. This fact hinders the flow control along the water management process.

When the water managers do not have information about the flows in the network, other strategies for calibrating the model must be developed. A calibration is defined as a process of changing values for certain input parameters in an attempt to match some reference conditions within acceptable criteria (Mulligan & Brown, 1998). This is a difficult task, as a model is an idealization of the reality, in which the real behavior is hoped to be simulated by mathematical modelling. Thus, calibration is of utmost importance in determining the reliability of any method to ensure its future use as a decision tool.

A strategical method for calibration is therefore needed to avoid trial and error procedures. To determine the goodness fit of model, some indicators must be used to estimate errors between observed estimated values. The evaluation of the ability prediction in a particular a model should contain an error index, a non-dimensional index and a graphic method between the observed values (O) and simulated values (P) (Legates & McCabe, 1999).

In this research, a new methodology to determine distribution flows over time in any line by a numerical model is presented. This method which is based on farmers' habits, allows the knowledge of flows over time, when no sufficient measurement devices are installed in the network. Unfortunately, the lack of flow measurement devices is a very common situation in irrigation networks, especially in systems older than 20 years as consequence as technology was more expensive two decades ago and water managers were not aware of the need to increase hydraulic efficiency in the WDN. As novelty in this manuscript, the calibration process of this method is described, dealing with time series of values. To do so, the implementation of calibration indexes adopted from traditional hydrological studies is proposed. Different authors (Nash & Sutcliffe, 1970; Willmott, 1981; Gupta *et al*., 1999; Legates & McCabe, 1999; Singh *et al*., 2005; McCuen *et al*., 2006) proposed different statistical indexes of "goodness of fit", which

were applied in this strategy. This calibration method, as far as the consulted references depict, is initially applied to calibrate flows in irrigation water distribution networks. This calibration was based on flow time series registered, contrasting estimated with measured data set. The results were very promising for calibrating of this model, transforming the model in a reliable decision making tool for water managers.

The proposed strategy was used to determine the assignment of flow in a particular case study focused on an irrigation network allocated in the township of Callosa d'en Sarrià, in Alicante (Spain).

Material and methods

Methodology for flow assignation

In this section, the assignation flows method was described as well as calibration strategy was also proposed. Flows variability in the irrigation network was high as the consumption, which depended on many factors along the year (*e.g.* weather conditions, type of crops, habits of farmers, among others).

The method determined the irrigation probability (P_I) at each irrigation point of the network and simulated the operation of any network, which was based on the generation of demand in consumption points (Pérez-Sánchez *et al.*, 2016). The method considered the irrigation needs of the crops and the farmers' habits to generate the P_I (*e.g.,* weekly trend of irrigation, watering duration, maximum days between irrigations and hour of time start irrigation). Farmers' habits were obtained from: interviews to farmers, records of water meter, and records of flowmeters installed in the network. The information asked in interviews (*e.g.*, irrigation crop, maximum days between irrigation, irrigation weekly trend) was described

in Pérez-Sánchez *et al*. (2016). The aim of the method was to generate the consumption patterns for all irrigation points over year by following the next steps (Fig. 1).

A. Estimation of the cumulative volume consumed in the irrigation point

The cumulative volume consumed was estimated by the comparing the previous irrigated volume and the irrigation needs. This volume was individually assigned to all the irrigation points (Data Set I). If the balance (V_{Na}) at each irrigation point was positive, the method established that this was not an irrigation day. If the balance was negative, the method goes to step *B*, and the P_I was calculated in this consumption point. The calculus of irrigation needs was developed according to Allen *et al*. (2006). In this case, the climatic data (*i.e.,* temperature, wind, humidity, and rainfall) have been obtained from their own weather station, installed within the irrigated surface.

B. Calculation of the irrigation probability (P_I)

The P_I was based on two functions: irrigation weekly pattern (w_{dj}, 'Data Set II'), and patterns of maximum days between irrigations (d_d, 'Data Set III'). Both functions were obtained from interviews. Furthermore, the method generated a random number (RN) between zero and one. The generation of this RN is uniform, but the opened law was established by the function irrigation weekly trend ('Data Set II') and maximum days between irrigation ('Data Set III'). The irrigation was only carried out if RN $\leq P_I$ (Pérez-Sánchez *et al*., 2016). The P_I is defined by Eq. [1].

$$P_I = \frac{w_{dj}}{\sum_{n=1}^{n=d-j+1} w_{dn}} \qquad [1]$$

where *d* is the numbers of days inside of irrigation interval, and *j* is the day of decision making. On the
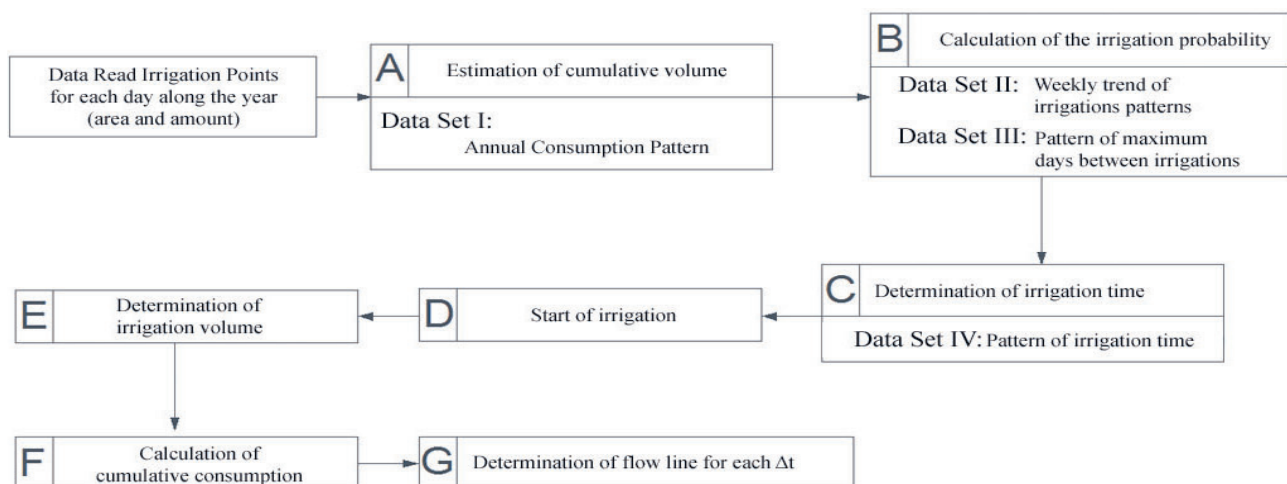

Figure 1. Schematic description of the method for flow estimation at each irrigation point.

one side, w_{dj} is the pattern to irrigate one particular day inside the interval. This pattern is an integer number which shows the irrigation trend of that day related to the rest of days of the week. This trend was defined according to farmer's habits (Data II). On the other side, $\sum_{n=1}^{n=d-j+1} w_{dn}$ is the total addition of patterns of the days included in the irrigation interval, according to Data Set III.

C. Determination of the irrigation time

The interviews allowed to establish the irrigation time. This value depends on irrigation needs ('Data Set I') and irrigation amount (i_i). This irrigation amount is considered as the average flow rate unit of consumption in each irrigation plot of the irrigated surface.

The method considered the number of on-farm irrigation sectors. On the one hand, the number of sectors has been considered to develop the trends of irrigation. On the other hand, the number of sectors was implicit in the irrigation time, because the irrigation needs of the crops and the average unit consumption flow had units of volume per surface.

The irrigation unit discharge (i_i) depends on the planting layout (area defined by the space between rows of the plantation), determining the number of plants per hectare (n_p), the number of drippers per plant (n_d) and the dripper discharge (d_d) in L/h. This parameter was defined by Eq. [2]:

$$i_i(L/(s \cdot ha)) = n_p \cdot n_d \cdot d_d \cdot \frac{1}{3600} \qquad [2]$$

The irrigation time (t_r) depends on daily irrigation needs of crops (V_c) and the irrigation unit discharge (i_i). Both parameters define the irrigation time in each hydrant by Eq. [3]:

$$t_r(s) = \frac{V_c}{i_i} \qquad [3]$$

D. Start of irrigation

The method determined the start time of irrigation for each irrigation point. The cumulative probability pattern was used in this step. These patterns were defined by twenty-four intervals (one per hour) and they were also defined from interviews performed to farmers. A new RN was generated between zero and one, and it was compared with cumulative probability patterns. This RN established the start irrigation period, considering the irrigation time within the selected day and the maximum days between irrigations ('Data Set III'). The irrigation time depended on daily irrigation needs of crops (V_c) and the irrigation unit discharge (i_i), as was described in Step C. After this step, the day and hour for the irrigation to start is known for each consumption point.

E. Determination of irrigation volume

In this step, the irrigation volume was determined from the irrigation supply and the irrigation time (step C).

F. Calculation of cumulative consumption
The volume of cumulative consumption was calculated.

G. Determination of flow line

When all consumption patterns have been determined during the year, the flow was calculated by Epanet toolkit (Rossman, 2000). This tool calculated the circulating flow in each line considering the demanded flow of the opened irrigation points downstream in each instant. The demanded flow at each irrigation point depends on irrigation unit discharge (i_i) and surface of the opened tap, being the addition of these flows in each hydrant equal to the circulating flow by the same in each interval time.

Evaluation of goodness of fit

The method used to evaluate the goodness of fit, is focused on:
1. Graphic representation of the observed values (O) *vs* simulated values (P).
2. Determination of the Nash-Sutcliffe coefficient (E). This non-dimensional index is a fit indicator, which is recommended in the calibration of hydrologic models and simulations of temporal series. The value of E can oscillate within the interval $-\infty \leq E \leq 1$. The goodness of fit is optimal if E = 1. If the index was inside of a range between zero and one, E was accepted as good indicator. Negative values of E are considered poor. The Nash-Sutcliffe index is defined by Eq. [4]:

$$E = 1 - \frac{\sum_{i=1}^{N}[O_i - P_i]^2}{\sum_{i=1}^{N}[O_i - \bar{o}_i]^2} \qquad [4]$$

where O_i is the observed value in each interval; $\bar{O}_i$ is the average of the observed values; and P_i is the simulated value in each interval. These values were obtained from the model.
3. Determination of the root relative squared error (RRSE). This non-dimensional index quantifies the

Table 1. Classification of goodness of fit, according to Moriasi *et al.* (2007) and Cabrera (2009)

Goodness of fit	E	RRSE	PBIAS
Very good	E>0.6	0.00≤RRSE≤0.50	PBIAS<±10
Good	0.40<E≤0.60	0.50<RRSE≤0.60	±10≤PBIAS<±15
Satisfactory	0.20<E≤0.40	0.60<RRSE≤0.70	±15≤PBIAS<±25
Unsatisfactory	E<0.20	RRSE>0.70	PBIAS>±25

E: Nash-Sutcliffe coefficient. RRSE: root relative squared error. PBIAS: bias percentage

prediction error of the model with the normalized variable. If RRSE is zero, this value indicates a perfect fit. Low values of RRSE indicate that the root mean square error (RMSE) is minor, meaning the performance of the model simulation is better. RRSE is defined by Eq. [5]:

$$RRSE = \sqrt{\frac{\sum_{i=1}^{N}[O_i - P_i]^2}{\sum_{i=1}^{N}[O_i - \bar{O}_i]^2}} \qquad [5]$$

4. Determination of bias percentage (PBIAS). This parameter measures the tendency of the simulation and determines if the simulated values are smaller or larger than observed values. Negative values indicate that the model overestimates the variable analyzed; positive values indicate that the variable is underestimated, and a PBIAS equal to zero is optimal. This index is defined by Eq. [6]:

$$PBIAS \, (\%) = \frac{\sum_{i=1}^{N}[O_i - P_i]*100}{\sum_{i=1}^{N}[O_i]} \qquad [6]$$

The goodness analysis of the temporal simulated series is established in Table 1, according to developed analyses by Moriasi *et al.* (2007) and Cabrera (2009). These authors classified the goodness of fit in four categories: very good, good, satisfactory, and unsatisfactory. These categories depend on the value of previously enumerated parameters (*i.e.,* E, RRSE, and PBIAS). Furthermore, the estimations of E, RRSE, and PBIAS will be nominated as key performance indicators for goodness of fit (KPIF) in this calibration strategy.

The goodness of fit in the calibration was based on the peak flows value for different time intervals. This time interval was the step in which the developed model were discretized, and it can oscillate between 1 h and 336 h. Simulated values reached then the maximum observed values.

Finally, variability of the goodness of fit indexes was analyzed in the calibration proposed. This analysis was of paramount importance, as the proposed method was based on randomness in the opening at each irrigation point. To analyze this variability, the model was run 200 times for the same irrigation scenario (*i.e.,* annual consumption pattern, weekly trend of irrigation patterns, maximum days between irrigations, and pattern of irrigation time). The repetition allowed the analysis of average and standard deviation of the sample.

Case study

A drip irrigation network located in Callosa d'en Sarrià (Alicante, Spain) was proposed to illustrate the calibration procedure method for the flow assignment model. The network supplies 120 hectares, with water coming from a well (Fig. 2).

The most extended crop is loquat (*Eryobotrya japonica* [Lindl.]), although there is a small area with citrus and avocado pear trees. The water is accumulated in a reservoir with a capacity of 4000 m³. The topography varies between 273 and 102 m above sea level. The tank is located sufficiently high (278 m above the sea level) to ensure the minimum pressure head of 30 m in every irrigation point.

The pipelines of the network are built on asbestos cement pipes, with diameters ranging between 200 and 250 mm. The installation has 34 multiuser hydrants, supplying to 143 irrigation points, connected to steel collector in the hydrant by polyethylene pipes. Counters were placed to register the consumption volume in all hydrants. On the one hand, the data of a flowmeter installed in the main line of the network were registered for every 5 minutes in year 2015, summing up a total of 105120 values. On the other hand, the water manager has data enabling the definition of the inputs, previously described in the method (Fig. 1):

• Data Set I - Quarterly consumption in each irrigation point. This pattern were obtained from records of the water metered at each irrigation point. In each plot, registers were taken quarterly corresponding to the months of March, June, September and December of year 2015. Irrigation area, number of irrigation sector, and type of crop was also known for each plot of crop the irrigation area.

• Data Set II - Weekly trend of irrigation patterns. The weekly trend of irrigation has been defined from flowmeters records. Ratio among daily consumed volume and weekly consumed volume were obtained for each day, defining 52 weekly trend of irrigations patterns (one per week of year).

• Data Set III - Pattern of maximum days between irrigations. These patterns have been developed from the farmers´ habits. These habits (based on patterns described in Pérez-Sánchez *et al.*, 2016, after a survey campaign) were established by agronomic engineer,
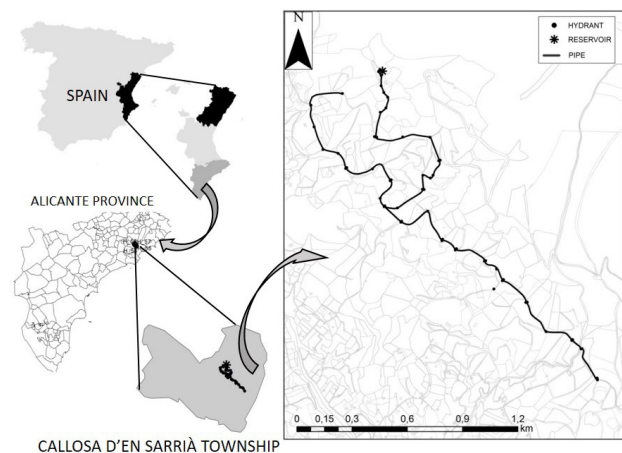

Figure 2. Location of the irrigation network

Table 2. Irrigation unit discharge (i) depending on planting layouts

Planting layout (m × m)	n_p (tree/ha)	n_d (dripper/tree)	d_d (L/h)	i_i (L/(s·ha))
6.0 × 6.0	312.11	5	4	1.73
4.5 × 6.0	410.26	5	4	2.28
4.5 × 5.0	487.67	5	4	2.71
4.0 × 4.5	603.78	5	4	3.35
3.0 × 5.0	721.00	5	4	4.01

according to meteorological station data located at Experimental plot of Cooperative of Callosa d'en Sarrià.
• Data Set IV - Pattern of irrigation time. This time was determined by Eq. [3]. The irrigation needs of crops were obtained throughout irrigation schedules which were provided by technical service of the irrigation community. These irrigation needs were adapted over year, considering climatic parameters as well as an application efficiency (defined as the ratio between accumulated volume in root bulb and applied volume in the plot) of 0.754. This datum has been obtained from river Jucar's basin management plan (BOE, 2016).

Results

Calibration parameters

Flow variability in irrigation networks is due to many factors which have been previously enumerated (*i.e.,* weekly trend of irrigation, watering duration, maximum days between irrigations, and hour of time to start irrigation). Among them, the i was determinant, as can be observed in Fig. 3a. This figure shows the obtained result of maximum estimated flows when the factors (maximum days between irrigations and i) were changed in the case study.

The importance of i in the maximum flow values was obvious when simulated values were compared with observed data. Other factors (*e.g.,* maximum days between irrigations) were not so sensitive to changes in maximum flow rates.

These variations can be seen in Fig. 3b, where the variation of the i modified the estimated flow significantly, when these flows were compared to observed ones.

Calibration results

Once the flow was calculated at each line, the goodness of fit was evaluated using the observed data. Irrigation

characteristics were considered (*i.e.,* maximum days between irrigation, weekly trend of irrigation, and patterns of start irrigation) for 2015, with different values for i as a calibration parameter. Irrigation supply value was established from different planting layouts, number and characteristics of drippers used in the area. Table 2 shows the i values that depend on the different parameters defined by Eq. [2]. These parameters were selected according to the common agricultural design in different plots of crop, considering irrigated surface.

The exposed procedure in section 'Evaluation of goodness of fit' was used in the analyses. Fig. 4a shows the values of E depending on irrigation units discharge (defined in Table 2) and different hourly intervals calculations (from 1 h to 336 h). This analysis allowed determining i that best simulates the maximum flows compared to the maximum observed flows for the studied interval. E values oscillated between -0.1 and 0.65 (Fig. 4a) depending on i and time interval. E values obtained were positive in all range when i was 2.28, 2.71, or 3.35 L/(s·ha). According to Table 1, if E > 0.2, the goodness of fit is satisfactory.

Fig. 4b shows PBIAS values obtained; i=1.73 L/(s·ha) had PBIAS values between 5 and 20%. If irrigation supply was 2.28 L/(s·ha), the index oscillated within 3% and 15%. PBIAS obtained was near to zero when i was 2.71 L/(s·ha), and the majority of times, PBIAS was below to 5% (except the interval of 12 and 24 h). PBIAS were negative with i values of 3.35 and 4.01 L/(s·ha), in which PBIAS oscillated between 0 and -10% (except for the time interval of 12 and 24 h, with irrigation supply of 3.35 L/(s·ha), in which PBIAS value was 3.01% and 4.25%, respectively).

Fig. 4c shows RRSE values for calibration evaluation. These RRSE values oscillated between 0.60 and 1.05, depending on i and time interval. Results obtained for i=2.71 L/(s·ha) presented values between 0.6 and 0.80 in all range of time interval (Fig. 4c).

Fig. 5 depicts observed flow data and simulated values, considering i=2.71 L/(s·ha). This figure represents averaged hourly flow (observed *vs* simulated), and they present a $R^2 = 0.503$. This figure complete the necessary parameters to evaluate the goodness of fit of a temporal series according to the method described in section 'Evaluation of goodness of fit' (graphic representation, non-dimensional index, error index and tendency index).

Finally, Fig. 6 shows the range of oscillation obtained in all KPIF parameters when the case study was simulated 200 times, considering i=2.71 L/(s·ha). The randomness in the opening of the irrigation points was only factor that varied along different simulations. KPIF parameters oscillation can be observed within very constrained intervals in Fig. 6. This variability did not affect the results of goodness of fit of the series.
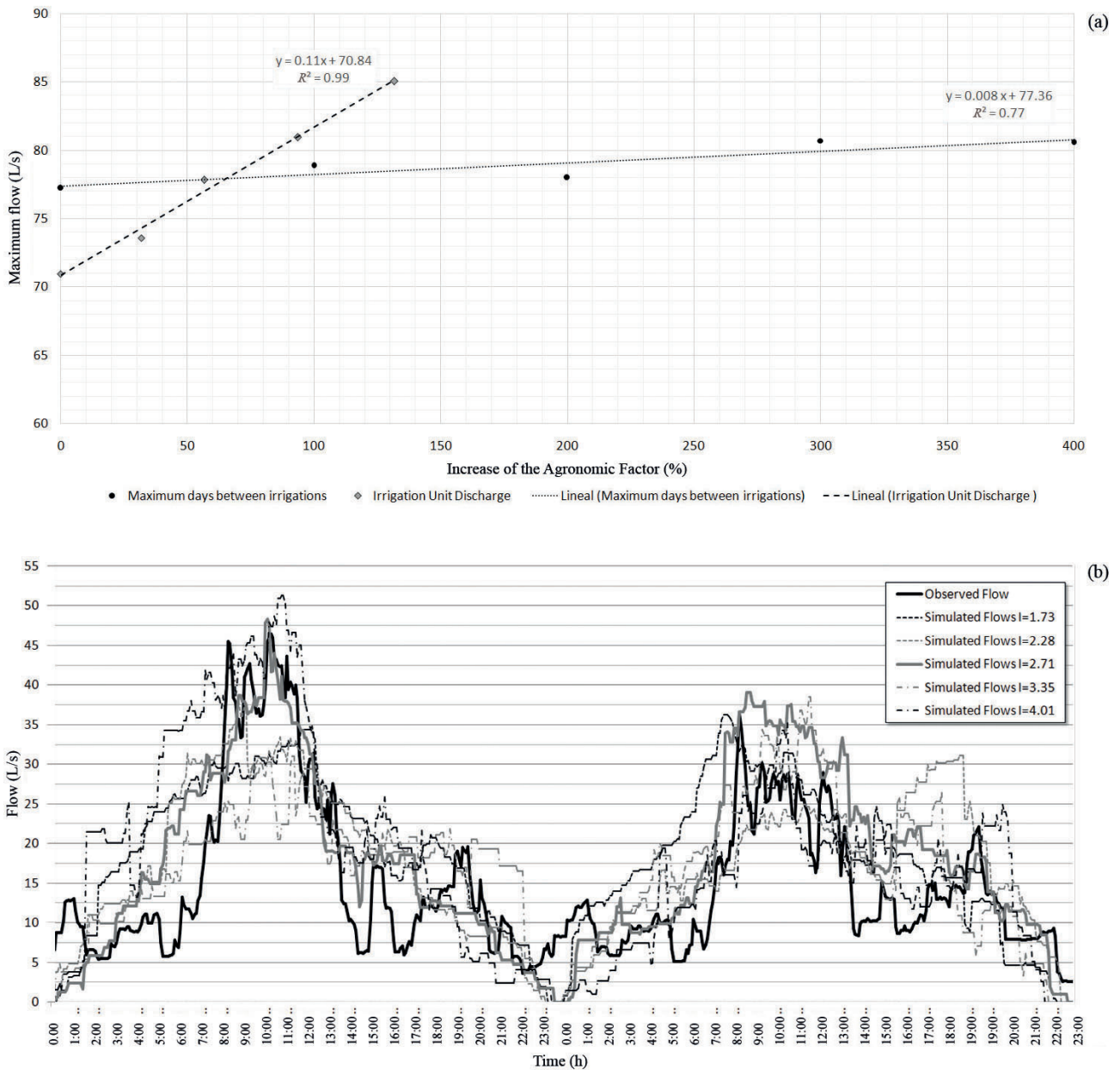
Figure 3. Maximum flow *vs* increment (a) and observed and simulated flows (b) of different irrigation unit discharges (i) and maximum days between irrigations in Callosa d'en Sarrià
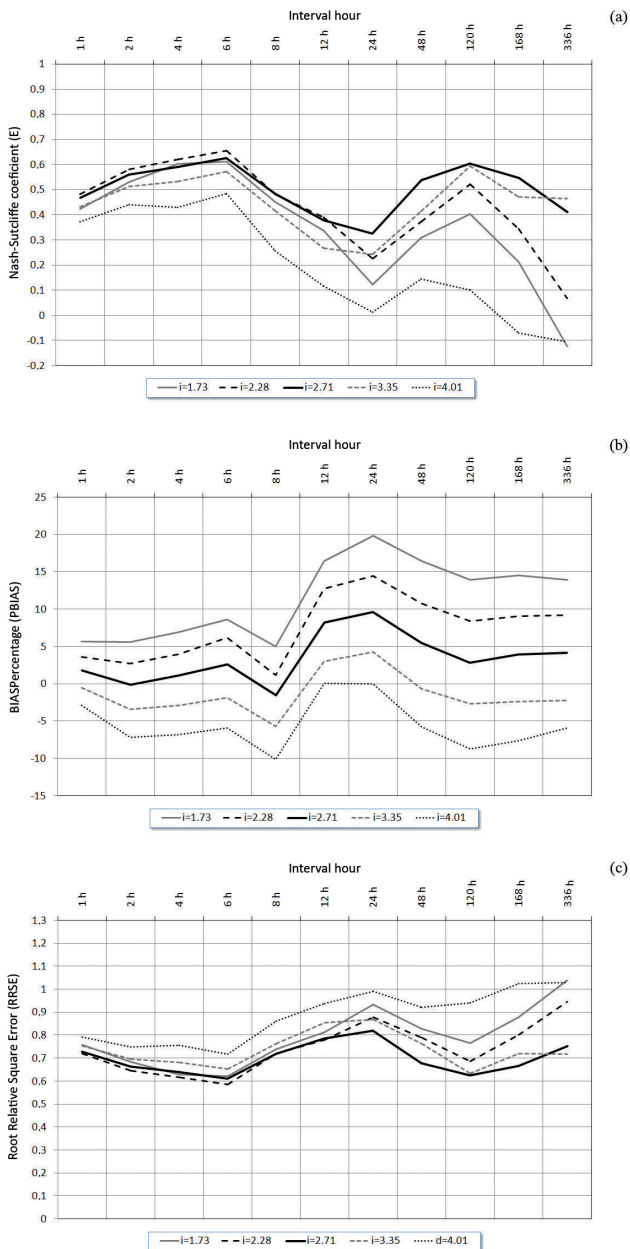
Average E value oscillated between 0.30 and 0.63. Average PBIAS value was below 10% (very good, Table 1) in all the range. RRSE (root relative square error) presented average values between 0.65 and 0.80.

Discussion

In this research, a method to determine irrigation circulating flow along the time in the network has been implemented (Pérez-Sánchez *et al*., 2016). This method allows water managers to know the flows in any pipe of a pressurized system discretized in the time, considering from irrigation needs and farmer's habit (*i.e.,* weekly trend of irrigation, maximum days between irrigation, irrigation time and pattern of start irrigation) when flow measurements are not available. *RN* generation (defined in Step B-Calculation of the P_I. Fig. 1) is uniform, varying between zero and one, when the PI was determined by Eq. [1]. This equation considers weekly trend irrigation and maximum days between irrigation and, therefore, indirectly, the distribution of climatic variables was also considered. This fact can be observed if the relative frequency histogram of flow is drawn when this method is applied (Pérez-Sánchez *et al*., 2016).
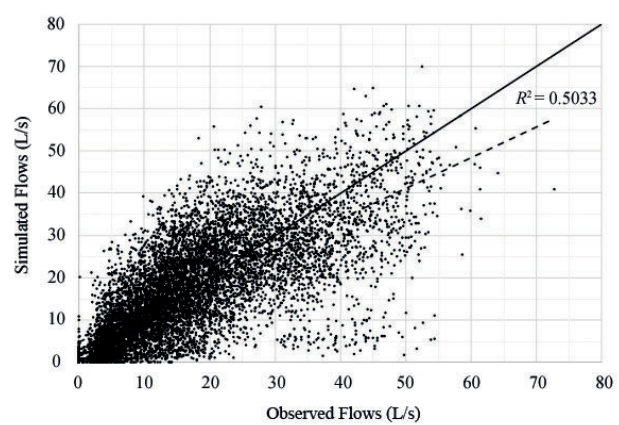
Proposed method randomly determined the opening time at each irrigation point, based on farmer's habits
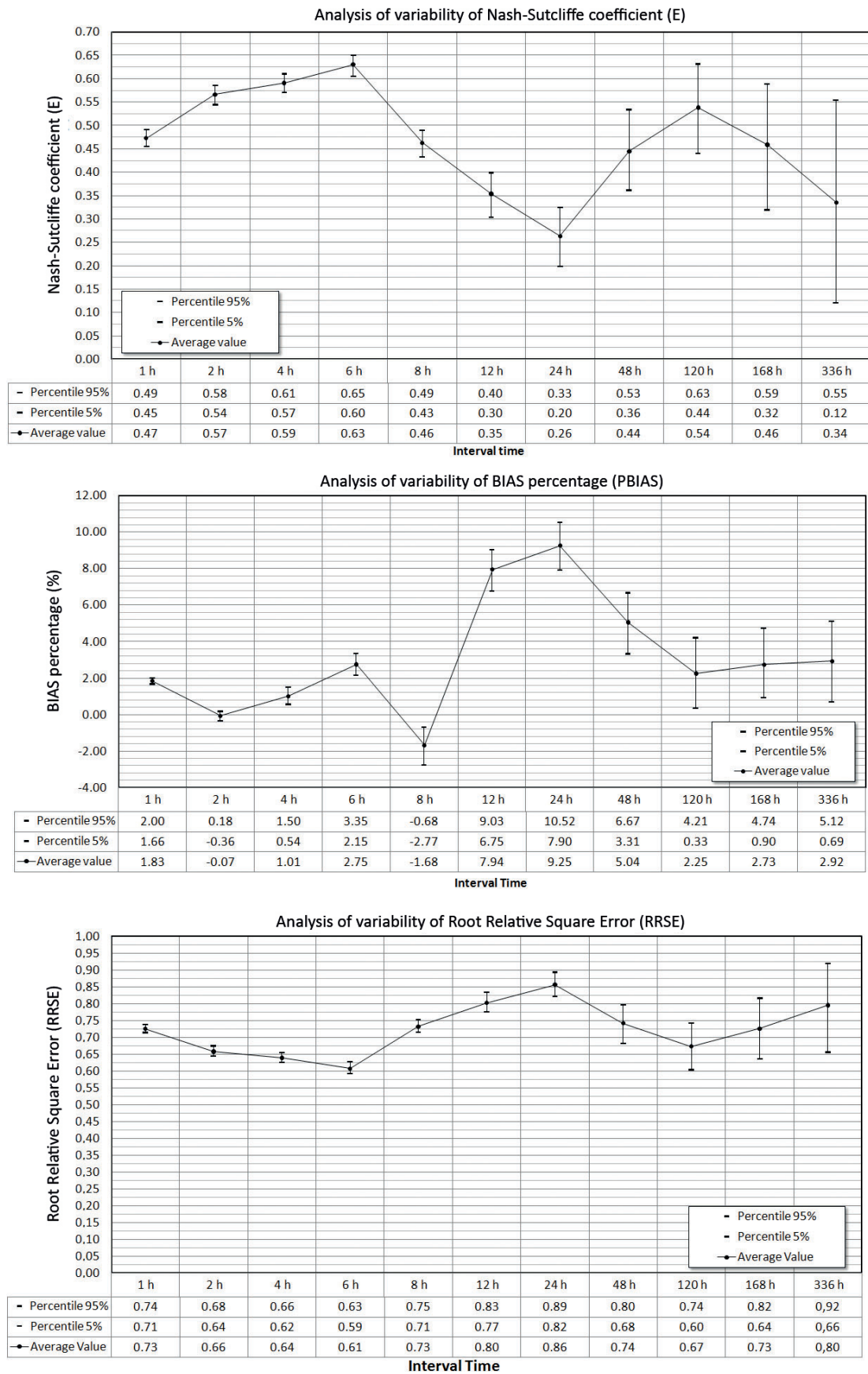
Figure 5. Visual comparative between average observed flows and average simulated flow with irrigation amount equal to 2.71 L/(s·ha).

of crops, planting layout, installed irrigation system, and other agricultural factors (Granados, 2013), being essential to determine the maximum circulating flow in different design methods used in irrigation networks (Granados *et al*., 2015). Demand flow at each irrigation point depended on i when Clément first formula was applied (Clément, 1966). Fig. 3a shows this sensitivity analysis of maximum flows when i and maximum days between irrigation were varied. As can be seen, on the one hand when Δi=100%, the variation of maximum flow was 11 L/s (15.49% of main flow). This hypothesis was confirmed when the maximum flow was calculated by the generalized Clément first formula, in which probabilities values are directly proportional to i (Lamaddalena & Sagardoy, 2000). In contrast, when the increment of maximum days between irrigations was 100%, the variation of maximum flow was 1.6 L/s (2.15% of main flow). The analysis of flows variation depending on maximum days between irrigations were described in Pérez-Sánchez *et al*. (2016). The obtained results in the sensitivity analysis showed that variation of flows was minimum, when maximum days between irrigation were modified. This variation was negligible when compared to the measurement errors of the flowmeter and water meters.

According to the foregoing, Fig. 3b shows the variability of the simulated flows when they were compared with the observed values (13-14 Oct, 2015). A first visual comparison shows that some irrigation values for unit discharge underestimated the results of flow (*e.g.,* 1.73 L/(s ha)), while other i values (*e.g.,* 4 L/(s ha)) overestimated main flow when compared to observed data. Fig. 3b also shows the importance of the irrigation supply in the maximum flows, meaning that goodness of fit evaluation must consider maximum flows along time, whilst minimum flows were trivial (null or close to zero). Therefore, maximum flows were almost insensitive to big

Figure 4. Nash-Sutcliffe coefficient, E (a), bias percentage, PBIAS (b) and root relative squared error, RRSE (c) depending on irrigation unit discharge (i) predicting maximum flows

(Data Sets II and III). Unlike traditional methods (Clément, 1965; Boissezon & Haït, 1965; Soler *et al.*, 2016), operating probabilities were constant at each tap for the analyzed time interval (Soler *et al.*, 2016). Described method also determines the instantaneous flow, whilst other traditional methods only obtain the maximum flow (*e.g.,* if the applied method is Clément, the obtained flow is the value corresponding with the percentile of 95%).

A sensitivity analysis was performed, determining that unit discharge was the most important parameter in the flow assignment in lines, over other considered aspects for calibration. This parameter depends on type

Analysis of variability of Nash-Sutcliffe coefficient (E)

	1 h	2 h	4 h	6 h	8 h	12 h	24 h	48 h	120 h	168 h	336 h
– Percentile 95%	0.49	0.58	0.61	0.65	0.49	0.40	0.33	0.53	0.63	0.59	0.55
– Percentile 5%	0.45	0.54	0.57	0.60	0.43	0.30	0.20	0.36	0.44	0.32	0.12
Average value	0.47	0.57	0.59	0.63	0.46	0.35	0.26	0.44	0.54	0.46	0.34

Interval time

Analysis of variability of BIAS percentage (PBIAS)

	1 h	2 h	4 h	6 h	8 h	12 h	24 h	48 h	120 h	168 h	336 h
– Percentile 95%	2.00	0.18	1.50	3.35	-0.68	9.03	10.52	6.67	4.21	4.74	5.12
– Percentile 5%	1.66	-0.36	0.54	2.15	-2.77	6.75	7.90	3.31	0.33	0.90	0.69
Average value	1.83	-0.07	1.01	2.75	-1.68	7.94	9.25	5.04	2.25	2.73	2.92

Interval Time

Analysis of variability of Root Relative Square Error (RRSE)

	1 h	2 h	4 h	6 h	8 h	12 h	24 h	48 h	120 h	168 h	336 h
– Percentile 95%	0.74	0.68	0.66	0.63	0.75	0.83	0.89	0.80	0.74	0.82	0,92
– Percentile 5%	0.71	0.64	0.62	0.59	0.71	0.77	0.82	0.68	0.60	0.64	0,66
Average Value	0.73	0.66	0.64	0.61	0.73	0.80	0.86	0.74	0.67	0.73	0,80

Interval Time

Figure 6. Analysis of key performance indicators for goodness of fit (KPIFs) variation with an irrigation amount equal to 2.71 L/(s·ha) and predicting maximum flows with two-hundred randomness simulations
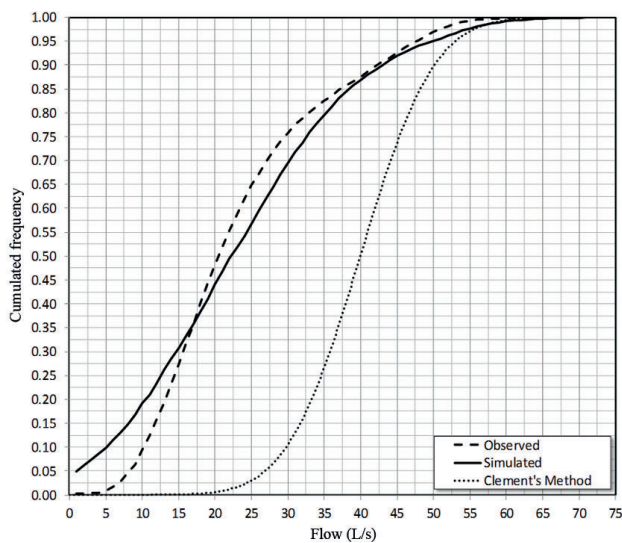
Figure 7. Comparison of cumulated frequency between observed, simulated and Clément's method to maximum irrigation needs

variations of maximum days between irrigation. On the contrary, these flows substantially changed when i was slightly modified. As a consequence, here, the parameter to be adjusted in this calibration strategy was i, in order to fit the predictions to the observed values.

As a novelty, in this calibration process for irrigation WDNs modeling, some parameters have been proposed for estimating the goodness of fit. These have been called 'key performance indicators for goodness of fit (KPIF) (*i.e.,* E, RRSE and PBIAS). These parameters have usually been used in hydrological analysis with good results (Legates & McCabe, 1999; McCuen *et al.*, 2006). As previously justified, the calibration of the proposed method has only been established depending on i. This agronomic parameter is the most important one in the pipe's sizing in networks (Granados *et al.*, 2015), considering that others factor as irrigation time and irrigated volume depend on it (Clément, 1966). In addition, i is a crucial factor in the analysis of flows over year (Fig. 3b).

According to Fig. 4 the model simulation had an optimal fit when i was 2.71 L/(s·ha). For this value, KPIF parameters were the best in the calculated series. If i <2.71 L/(s·ha), PBIAS values were higher than 5%. These positive PBIAS values indicate that the proposed method slightly undervalued the maximum flows (Moriasi *et al.*, 2007). When irrigation supply reached values greater than 2.71 L/(s·ha), the simulation overestimated maximum flows values (Fig. 3b). When PBIAS values were compared with the obtained index by these researchers (Moriasi *et al.*, 2007), the first ones were nearer to zero and, therefore, the proposed calibration made better estimations. When E was analyzed, the optimal values were obtained for

i=2.71 L/(s·ha). Values obtained were positive (higher than 0.45 for maximum flows) for all studied interval time, being more precise when they were compared to values obtained in the hydrologic model proposed by Ritter *et al.* (2008), as well as the obtained indexes in the hydrologic and hydroclimate model developed by Legates & McCabe (1999). Obtained parameters were lower and even negative when other i values were considered. Negative values indicated that the goodness of fit was unsatisfactory, as stated in Cabrera (2009).

Finally, the lowest values of RRSE corresponded to i = 2.71 L/(s ha) (Fig. 4c), which is the optimal fit. RRSE values were greater if these were compared to values obtained in the hydrologic calibration developed by Singh *et al.* (2005).

In this case, the necessary number of data included in the different Data Sets was high because the objective was an exhaustive calibration process. However, if Data Sets I, II or III are not exactly defined, then, KPIF's results are satisfactory for predicting average flows, but non-satisfactory for predicting maximum flows, which are the most important.

As instance, in the first place, when Data Set I was varied (considering double irrigation needs), KPIF results were 0.63, 0.61, and -0.01 (E, RRSE and PBIAS respectively) for average flows. These values were considered satisfactory according to Table 1. With these values for irrigation needs, KPIF values to maximum flows were: 0.47, 1.21, and 12.42 (E, RRSE and PBIAS respectively). These values were considered satisfactory according to Table 1.

In the second place, when Data Set II was simplified (uniform irrigation trend), obtained KPIF values were 0.93, 0.23, and 0.14 (E, RRSE and PBIAS respectively) for average flows. These values were considered satisfactory according to Table 1. Same Data Set II were used to obtain KPIF values for maximum flows. In this assumption, E, RRSE, and PBIAS were -0.02, 1.01, and 11.78 respectively. These values were considered non-satisfactory according to Table 1.

In the third place, when Data Set III was simplified (with uniform interval of 1 day between irrigations), KPIF values related to average flows were 1.00, 0.01, and -0.01 for E, RRSE, and PBIAS, respectively. These values were considered satisfactory according to Table 1. If KPIF values to maximum flows were determined, obtained results were 0.38, 0.78, and 5.64 for E, RSR, and PBIAS, respectively. These values were considered non-satisfactory according to Table 1.

When KPIF parameters were estimated for this WDN by means of reiterations (simulated 200 times), the goodness of fit was considered satisfactory for time intervals lower than 2 and 4 h. The intervals of 1 h and 8

h had satisfactory indexes of E and PBIAS, but RRSE> 0.70 (the range of values was 0.71-0.75 in Fig. 6). If greater time intervals were considered (>8 h), E and PBIAS values continued positive (E > 0.2 and PBIAS < ± 15%). These values established a satisfactory goodness of fit according to Moriasi *et al*. (2007) and Cabrera (2009), but the values of RRSE were higher than 0.70 (oscillating between 0.72 and 0.87).

If the average simulated flows were analyzed with i=2.71 L/(s ha), E oscillated between 0.37 and 0.41 for interval of one hour (these values were extracted of the variability analysis). PBIAS for this interval was -0.008% and RRSE varied between 0.76 and 0.78 (Fig. 4). These values have a good goodness of fit, except the RRSE value. If time interval greater than one hour was considered, E was higher than 0.47, PBIAS = 0.008%, and RRSE < 0.69 (these values were for time interval of 2 h; if the interval time increased, the statistical parameters improved the goodness of fit). Goodness of fit was considered good and very good for average flow and interval of 1 and 2 h, according to criteria presented in Table 1. E obtained by Moriasi *et al*. (2007) for average flows were lower than obtained values in this calibration. The obtained results with average flows were more precise than statistical indexes obtained with maximum flows, considering in both cases i = 2.71 L/(s ha).

The statistical analysis finalized with the verification of the visual goodness of fit, which was confirmed in Fig. 5, in which the determinant coefficient of maximum flows observed versus maximum flows estimated was $R^2 = 0.503$. This value was similar to the obtained value in the hydrological calibration of temporal series in synthetic models (Abbasi *et al*., 2004). R^2 was used to carry out the first visual comparison between observed and simulated values.

The reiteration of the performed analysis (Fig. 6) showed method proposed was robust. If flow values obtained were compared to those obtained by Clément's Method (Clément, 1966), results were similar. The results used to compare both methods were the flow values obtained on June (month in which irrigation needs were maximum). On the one hand, the Clément's flow was 52.87 L/s (Clément, 1966), according to individual probability at each tap (Fig. 7). The opening probabilities oscillate between 0.08 and 0.32 in this network, according to characteristics in each one of 143 taps. On the other hand, the maximum obtained flow with proposed method to estimate flows over time varied between 47.67 and 54.09 L/s, depending on habit's farmers. These probabilities were different and independent to Clément's method. When 200 repetitions were considered, the average obtained flow was 50.17 L/s. The cumulated frequency of flow

depicted in Fig. 7 showed a better fit (when compared to observed values) than cumulated frequency obtained by Clément's method.

KPIF variations obtained were lower (in percentage) than those obtained by Mulligan & Brown (1998). This fact confirms proposed method is able to simulate the circulating flows over time in any pipeline of a pressurized irrigation network.

This method can be used in pressurized networks when water managers are developing the design stage or when the network is operating, and they want to improve the hydraulic and energy efficiency. In addition, the method can be used to optimize pumped systems according to histogram of circulating flow frequency. The knowledge of flows range allows the selection of optimal pump as well as operation rules, considering not only maximum obtained flow but the more frequent ones. In the case of design of pressure networks distributed by gravity, it could be applied with the same criteria.

This method can also be used by water managers, when pumped systems are oversized. In these cases, a new design is needed to reduce the electrical operating costs. In the case of gravity networks, the predicted flows can be used to select the operation range of the pressure reduction valves, or to analyze the possibility to recover energy in the locations where the pressure is greater than minimum pressure for irrigation. In the last case, the method allows the determination of the range and frequency flows used to calculate the theoretical recovered energy (Pérez-Sánchez *et al*., 2016). This permits multipurpose system in these infrastructures, increasing the energy efficiency and reducing the exploitation costs and consumed water.

In conclusion, a new method to calibrate flows rate over time in hydrological process has been presented in this contribution. This method has been successfully applied to calibrate the circulating flows in a particular WDN. The obtained values in this calibration verify a satisfactory, good or very good goodness of fit according to time intervals considered. This calibration method may have great utility in determining circulating flows inside networks when no measurement devices exist in the main lines.

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