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An algorithm to schedule water delivery in pressurized irrigation networks

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A R T I C L E I N F O

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A B S T R A C T

This study presents a deterministic constrained optimisation algorithm developed for using in a pressurized irrigation network. In irrigation networks —or water networks supplied by a head tank— utility managers can fully adapt the delivery times to suit their needs. The program provides a strategy for scheduling water delivery at a constant flow rate (opening and closing of hydrants, units, and subunits) to minimise energy consumption. This technique improves on earlier approaches by employing a deterministic method with little computing time. This method has been tested in the University of Alicante pressurized irrigation network, where decision-makers have identified the need to diminish the energy expenditure for watering University's gardens.

1. Introduction

The relationship between water and energy became one of the trendiest issues in the water business, as managing water is an energy-hungry process; 4% of overall electricity consumption (IEA, 2019) and they expect this expenditure to be doubled in 2040. Crop irrigation consumes 70% of total water consumption worldwide (Boretti and Rosa, 2019), while the Spanish still increase these large values (79% of the water in agriculture and 21% for urban consumption) (Olcina Cantos et al., 2018). Pressure irrigation networks increased energy expenditure because of drip irrigation (Llamas and Martínez-Santos, 2005) and this energy consumption varies between 0.28 and 0.34 kWh/m^3 (Hardy et al., 2010).

Many methods to diminish energy expenditure have been analysed when designing or operating pressurized irrigation networks (PIN) (Belaud et al., 2020). This question has been discussed from different viewpoints, such as improving the energy efficiency of pumping devices (López-Morales et al., 2021), and also considering the performance of the distribution network (Abadía et al., 2018). Many research focused on using variable speed drives (Buono da Silva Baptista et al., 2019), dealing with electricity costs (Langarita et al., 2017) or scheduling water delivery to meet energy production in photovoltaic arrays (Dursun and Özden, 2014). Many approaches dealt with sensors measuring soil moisture and humidity (among others) to select the percentage valve opening (Jaiswal and Ballal, 2020) to cut down crop water stress.

Dividing the irrigation network into segments (groups of hydrants or units) and organising irrigation in rigid rotation scheduled (Jiménez-Bello et al., 2015) showed up as a core policy, etc. As a consequence of network segmentation, the flow rate injected into the water irrigation network is constant and energy consumption diminished by 15–30% (García et al., 2016)influencing. This strategy demands the PIN scheduled as rigid rotation delivery (the service manager selects the irrigation schedule). Utility managers can satisfy water demands for every consumption node, but they can change irrigation time in pressurized irrigation networks. As a result, changing the irrigation time for every node (He et al., 2020; Sabzzadeh and Shourian, 2020) can cause significant energy savings in pumping devices (Lima et al., 2019) which reduces also the carbon footprint (Siyal et al., 2021). So, the practitioner requires an algorithm (or an application) that minimises fluctuations between the target and the real injected flow rate.

Researchers and practitioners developed algorithms to optimise this or any alternative issue in the agriculture (Osroosh et al., 2016), being stochastic or deterministic among the most accepted algorithms. A deterministic algorithm gives the same outcome given the same input, while a non-deterministic algorithm may return to different outcomes, being the stochastic algorithm less efficient (Saha et al., 2021). The typical complication in stochastic algorithms is not using the gradient of the objective function. Consequently, the evolutionary algorithms allow changing a result to change until receiving the optimal solution by seeking a process that simulates living beings in nature, such as genetic algorithms (Villacampa et al., 2019) or insect colonies (Nguyen et al., 2017), etc. In earlier work, researchers have employed genetic

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algorithms (GAs) to schedule irrigation in PINs (Alonso Campos et al., 2020), to consider soil moisture requirements (Gu et al., 2021) and seasonal variations (Casadesús et al., 2012). Moreover, GA has also been used to create water decision-making models (Chen et al., 2019), to find the smallest amount of water needed by each crop (Polinova et al., 2019) or to schedule irrigation considering precipitation data for many years (Shen et al., 2021). However, the non-deterministic algorithm simulation was very time-consuming and, although it sets up the question, the great computing times performed make this a non-practical solution for the problem in the long term.

Gradient algorithms serve as the most significant group of deterministic algorithms. The algorithm follows the direction (with the derivative of the objective function) to be established on the optimisation variables. The optimisation variables change to minimise the discrepancy between the predicted and targeted values. Once the objective function has been selected, the issue is comparable to getting the scheduling that minimises a variance, a problem present in a variety of fields (Paridar et al., 2018). So, the algorithm will be called minimum variance scheduling (MVS) and it minimises the variation between the injected flow rate and the target flow rate. The MVS algorithm makes these evaluations (their mean advantage) and water expenditure at every hydrant (unit or subunit) can vary for every slice. One limitation of our earlier approach (Pardo et al., 2020) was that irrigation time must be proportional to the pattern time step in the PIN hydraulic model. So, if this value is 5 min, water can be delivered to crops for 5, 10, 15 min, etc. (but not for 7 or 13 min).

This method is tested on a real PIN, where water demands of every consumption unit as is the input data. The algorithm changes the scheduling irrigation plan and results as output data the schedule, which minimises the objective function. The computation time is low related to other stochastic methods already employed (reduced from 3 to 4 days using a GA approach (Pardo et al., 2020) up to 0.02 s in the current approach).

The energy expenditure is analysed later using UAEnergy, an interactive MATLAB® application to quantify energy expenditure in PINs https://bit.ly/2FbNqdr This is a slope for saving energy. But this handling may find the best solution to meet other targets.

The work is organised as follows. Section 2 describes the material and methods, basic concepts, the algorithm, the objective function, and the research limitations. Section 3 describes the software requirements, input data, output data, the pseudocode and a flowchart describing the processes are commented here. The real case study is proposed in Section 4 and section 5 shows the results and discussion. Section 6 states the key conclusions.

Notation

e_i is a state, called basic that corresponds with the case where only the i-th valve is connected.

Ef (kWh) Friction energy for the simulation period
En (kWh) Energy supplied by the reservoirs for the simulation period
Ep (kWh) Energy supplied by pumping stations for the simulation period
Eu (kWh) Energy supplied to users for the simulation period
m_i(-) multiplicity (number of slides when it is connected) of each irrigation node in a working plan
M (-) total number of connected slides in a working plan
MSE (-) mean squared error
N (-) number of valves
P (-) number of slices
$\left(\frac{P}{\gamma}\right)_{treshold}$ (m.w.c.) minimum threshold pressure
Q (l/s) constant injected flow rate into the pressurised network
Q^{obj}_{p,t_j} (l/s) target flow rate at pipe l
Q^{sim}_{p,t_j} (l/s) simulated flow rate at pipe l achieved at the time t_j
R (Real numbers set)
RMSE (-) root mean squared error
s_i Boolean variable to consider the state of a valve D_i. $\{0,1\}$ for switched off/switched off.

(continued on next column)

(continued)

e_i is a state, called basic that corresponds with the case where only the i-th valve is connected.

$s = S(D) = (s_1, s_2, .., s_N)$ Corresponds to the set of states, including all the devices. The set of admissible values for s is represented by Ω.
$s^{(k)}$ represents the variable s in the k-th slice
T (hours) simulation time
t_0(min) the instant of the start time for slice 0
t_1(min) the instant of the start time for slice 1
t_{P-1}(min) the instant of the start time for slice P-1
$V(2002)$ is a function that depends on the state of the system. The present application corresponds to the flow rate in the network for a configuration (state) s.
$V(s^{(k)})$(l/s) flow rate injected into the network according to the k combination predicted by the model
Δt(hours) time interval of every slice
δ_{ij} is the Kronecker delta defined as 1 if $i = j$, and 0 if $i \neq j$.
ε a change in the value function corresponding to an arbitrary state change.
ε_m the value assigned in the last scheduling assignment step
$\pi_i(s)$ is an operator that returns the i-th component of a set of states s.
σ Working plan for the irrigation network defined by P states $\{s^{(1)}, s^{(2)}, .., s^{(P)}\}$. From the definition of s, each admissible working plan is an element of Ω^P.
Φ_P the objective function of the optimisation problem.

2. Materials and methods

This section defines the minimum variance scheduling (MVS) algorithm. This algorithm optimises a constrained vector in which each part of this vector describes a period (or "slice"; 5, 10 or 15 min) in which the injected flow rate is as similar as possible to an objective value (constant). This algorithm finds the discrete demand values (which are a consequence of opening or closing hydrants or units dealing with the Kronecker delta values) that minimise the resulting variance when comparing injected and the target flow rates. This is an optimisation problem with a deterministic algorithm incorporated in programming software, like Phyton.

2.1. Basic concepts

Let us address the challenge of scheduling irrigation in a pressurised network D composed of N devices $D = D_1 \oplus .. \oplus D_N$. Each device can be in two distinct configurations (switched on and switched off), that can be represented by an application defined over each device $S(D_i) = s_i \in \{0,1\}$.

Then, the configuration of the network can be easily got by extending the definition of S as:

$$s = S(D) = (s_1, s_2, .., s_N) \in \Omega = \{0, 1, ..2^N - 1\} \quad (1)$$

Now, the i-th projection function π_i is defined as:

$$\pi_i(s) = s_i \quad (2)$$

Also, it is possible to introduce the basic states e_i as those of Ω with $\pi_i(e_j) = \delta_{ij}$, where δ_{ij} is the Kronecker delta defined as 1 if $i = j$, and 0 if $i \neq j$.

Let us introduce now a real function called the value function defined on Ω:

$$\begin{aligned} V &: \Omega \rightarrow R \\ s &\mapsto V(s) \end{aligned} \quad (3)$$

The simplest case is when the value function is linear, for every index i and every state,

$$V(s + e_i) = V(s) + V(e_i) \quad (4)$$

The management problem is defined over a temporal interval (day, week, month, etc…) denoted by T. The corresponding time interval can be divided into P elemental temporal slices of size $\Delta t = T/P$ with start times $\{t_0, t_1, .., t_{P-1}\}$, where $t_k = t_0 + k \bullet \Delta t$. A working plan for the irrigation network is a set of P states $\sigma = \{s^{(1)}, s^{(2)}, .., s^{(P)}\} \in \Omega^P$.

Given a working plan, the multiplicity of each irrigation node can be defined as:

$$m_i = \sum_{k=1}^{P} \pi_i\left(s^{(k)}\right) \tag{5}$$

Then, the total number of connected slides in a working plan will be $M = \sum_{i=1}^{N} m_i$.

2.2. Objective function

The objective of the scheduling problem is to get as good as possible agreement between the simulated (i.e., model predicted; $V(s^{(k)})$) and constant values (Q) over the entire simulation period. . The simplest way to account for these differences is to consider the sum of their squares. An objective function parametrised with a factor Q can be defined:

$$\Phi_P : R \times \Omega^P \rightarrow R$$
$$(Q,\sigma) \mapsto \Phi_P(Q,\sigma) = \frac{1}{P} \sum_{P}^{k=1} \left(Q - V\left(s^{(k)}\right)\right)^2 \tag{6}$$

where the constraint associated with the equality of the volume of water, given by the following formula, must also be met:

$$P \bullet Q = \sum_{k=1}^{P} V\left(s^{(k)}\right) \tag{7}$$

Eq. (6) refers to the mean squared error (MSE). The very name of the minimum variance scheduling algorithm describes the key concept of the algorithm itself, as the algorithm finds a schedule to minimise the variance between the simulated injected flow rates and the target injected flows. This algorithm also minimizes the root-mean-square error (RMSE) for the states $s^{(r)}$(Eq. (8)):

$$RMSE = \sqrt{\frac{1}{P} \bullet \sum_{k=1}^{P} \left(Q_{l,t_j}^{obj} - V\left(s^{(k)}\right)\right)^2} \tag{8}$$

Being P the number of flow rates observations at the injection pipe l, $Q = Q_{p,t_j}^{obj}$ and $V\left(s^{(k)}\right) = Q_{p,t_j}^{sim}$ are the target (constant value) and simulated flow rate at link l and referred at the time t_j. Here, the time of observation t_j always coincides with the simulated time, but in other cases Q_{p,t_j}^{sim} may be interpolated from the computed data at link j (just before and after time t_j).

2.3. MVS optimisation algorithm

Taking Equation (6) squared, we get the expression:

$$\Phi_P(Q,\sigma) = \mathrm{Q}^2 + \frac{\sum_{j=1}^{n} V\left(s^{(j)}\right)^2}{P} - 2 \bullet \mathrm{Q} \bullet \frac{\sum_{j=1}^{n} V\left(s^{(j)}\right)}{P} \tag{9}$$

Applying here the constraint given by equation (7), we get an equivalent expression for the objective function:

$$\Phi_P(Q,\sigma) = Var\left(V\left(s^{(j)}\right)\right) \tag{10}$$

The objective function is a quadratic function with a single global minimum, so the existence and uniqueness of the solution sought is established.

Thus, the problem becomes to distribute the elements $V\left(s^{(j)}\right)$ subject to the condition (7) in a way that minimises their variance

To determine the algorithm that gets the solution, let us consider the variation induced in the objective function when any of the states $s^{(r)}$ is changed adding an arbitrary basic state e_i.

$$\Phi_P(Q,\sigma') = \frac{1}{P} \bullet \sum_{k=1}^{P} \left(Q - V\left(s^{(k)} + \delta_r^k \bullet e_i\right)\right)^2 \tag{11}$$

where $\sigma' = \left(s^{(1)}, .., s^{(r)} + e_i, .., s^{(P)}\right)$.

Developing the squared term in the linear case:

$$\Phi_P(Q,\sigma') = \Phi_P(Q,\sigma) + \frac{V(e_i)^2}{P} - \frac{2 \bullet V(e_i)}{P} \bullet \left(Q - V\left(s^{(r)}\right)\right) \tag{12}$$

Given e_i, to reduce the objective function as much as possible, the following condition must accomplish:

$$\min_r \Phi_P(Q,\sigma') \equiv \max_r Q - V\left(s^{(r)}\right) \tag{13}$$

So, the best choice is to change the r-th time slide that has the greatest difference between the current state and the parameter Q.

Given a value for the index r, the maximum reduction is given by the condition:

$$\min_i \Phi_P(Q,\sigma') \equiv \max_i V(e_i) \tag{14}$$

That the result accomplished by the algorithm corresponds to a minimum can be checked assuming that the planning has been completed following the proposed algorithm, so that the states $\sigma = \left(s^{(1)}, .., s^{(P)}\right)$ are achieved. Under these conditions, the effect of a change between two states $s^{(j)}$ and $s^{(k)}$ can be considered, where we assume that $V\left(s^{(j)}\right)$ corresponds to the smallest of the values $\left\{V\left(s^{(1)}\right), .., V\left(s^{(P)}\right)\right\}$. Then:

$$\begin{aligned} V\left(s'^{(j)}\right) &= V\left(s^{(j)}\right) - \varepsilon \\ V\left(s'^{(k)}\right) &= V\left(s^{(k)}\right) + \varepsilon \end{aligned} \tag{15}$$

The variation in the objective function caused by this change is:

$$\Phi_P(Q,\sigma') = \Phi_P(Q,\sigma) + 2 \bullet \varepsilon \bullet \left[\varepsilon + V\left(s^{(k)}\right) - V\left(s^{(j)}\right)\right] \tag{16}$$

In order to result in an improvement of the initial planning, it should be fulfilled that $\varepsilon + V\left(s^{(k)}\right) - V\left(s^{(j)}\right) \langle 0$. Since we have assumed that $V\left(s^{(j)}\right)$ is the smallest of all the possible ones, the term in square brackets has a positive sign, which implies that no better combination can be got by decreasing the value of $V\left(s^{(j)}\right)$.

In the same way, combinations can be considered where the value of the function associated with the $s^{(j)}$ the state is increased.

$$\begin{aligned} V\left(s'^{(j)}\right) &= V\left(s^{(j)}\right) + \varepsilon_m \\ V\left(s'^{(k)}\right) &= V\left(s^{(k)}\right) - \varepsilon_m \end{aligned} \tag{17}$$

where ε_m has been taken as the value assigned in the last scheduling assignment step. Now, the improvement condition in the objective function is given by: $\varepsilon_m + V\left(s^{(j)}\right) - V\left(s^{(k)}\right) \langle 0$. But this is equivalent to $\varepsilon_m < V\left(s^{(k)}\right) - V\left(s^{(j)}\right)$. Therefore, in the step where ε_m was assigned, it should have been done to state $s^{(j)}$ and not to $s^{(k)}$.

From the above, there can be no change that improves the smallest of the values on the state functions. By removing that state from the set, the previous study can be redone with the smallest of the remaining ones, thus proving that the solution achieved by the algorithm is optimal.

2.4. Optimising a real PIN

The limitation presented here are parameters that affect the algorithm introduced. They study the physical limitations of the current research to be employed in real pressurized irrigation networks.

2.4.1. Pressure requirements

Our procedure involves a pressure condition, as pressure must be higher than the minimum threshold pressure called for by the service standards. The utility manager must make sure pressure at the consumption nodes is closer than possible (always above) to the threshold pressure for diminishing the energy expenditure. The lower network flow rate threshold (smallest injected flow rate, which does not satisfy the pressure requirements; $Q_{low,th}$) is calculated (Pardo et al., 2019). As not workable to open every hydrant together, this optimisation problem must range between these two amounts. An opposite phenomenon occurs, as higher flow rates cause more energy to be dissipated in friction through the pipes, but this results in lower energy costs as the pumps run for fewer hours. Since pressurised irrigation systems are oversized, the energy savings (pumps run fewer hours) are greater than the increase in energy dissipated by friction (Pardo et al., 2013).

3. Software description

3.1. Input data

The hydraulic input data are the volume delivered m^3 and the daily time every hydrant is opened. If the PIN manager demands to determine the energy expenditure calculation, further data are needed:

- A calibrated water PIN model. This file must comprise the hydraulic components. The program most employed is EPAnet (Rossman, 2000). The user must confirm this software runs successfully.
- $\left(\frac{p}{\gamma}\right)_{treshold}$, in (m.w.c.). This restriction allows for calculating the lower and upper network flow rate threshold.

3.2. Pseudocode

The algorithm receives as input parameters those that determine the hydraulic model that represents the hydraulics in the PIN. With these limits, the number of slides can be calculated. The next step reading the network parameters (id of devices and their flow rates). At this moment, the optimising algorithm starts, selecting in each step the most suitable device and assigning it to the optimum available slide following Eqs. (7) and (8). This process continues until all the devices have been distributed to one slide. The pseudocode is depicted in Fig. 1:

The procedure described in Eqs. (11) and (13) corresponds to the instructions $s^{(k)} \leftarrow s^{(k)} + d_i$ and $V^{(k)} \leftarrow V^{(k)} + \Phi_i$ that appear inside the while loop (Fig. 1).

3.3. General procedure

The general flow-chart of the procedure that visualizes this approach is shown in Fig. 2.

Step 1: The user has built the calibrated pressurised irrigation network model. This process involves gathering every information related to base demands, elevation at consumption nodes; diameters, materials in pipelines, etc. This step is only compulsory if the utility manger wants to compare current and future scenarios (Steps 1, 5 and 6 for comparing cases).

Step 2: The hydraulic input data needed to run the MVS algorithm are the consumption per node, the minimum service pressure required by the user and the target flow rate (l/s). The consumption data can be recovered from the hydraulic model itself (Case 0) while the other values are selected by the user.

Step 3: With the date provided by stage 2, the algorithm can work.

Step 4: The algorithm returns the new programmed irrigation scheduling. Steps 2, 3 and 4 can work performing the MVS algorithm. The other steps are used to compare current and future cases. These are not compulsory but highly recommended.

Step 5: The user will need Case 0 (to get all the network data in a hydraulic simulation model) and the new programme proposed by the algorithm. The user will have to merge them into the hydraulic model simulating future potential scenarios.

Step 6: The user will perform an energy audit on Case 0 and Case 1 to get energy results and compare them.

4. Case study

To describe this method, we analyse the pressurized programmed irrigation network employed for irrigating the garden of the University of Alicante, SE Spain (38°23′4.06″N, 0°30′44.06″W; Fig. 3). The technicians realised irrigation is an energy-hungry process. Consequently, the Vice-Rectorate for Infrastructures is calling for a study to be carried out to reduce the energy expenditure required to irrigate the University's gardens. The irrigation area of this garden has grown through time, and the gardeners have introduced different species to the grass

Algorithm 1 PIN Water delivery scheduling

Input:
  V_t: Total volume,
  Q: Average flow,
  Δt: Time slide (minutes)
Output:
  $s^{(1)}, .., s^{(P)}$: Vector of scheduling slides,
  $V^{(1)}, .., V^{(P)}$: Injected volume by slide
  procedure OptimizeScheduling
    $P \leftarrow ceil(1000 * V_t/(Q * 60 * \Delta t))$
    /*Read network data*/
    Read devices: $(d_1, .., d_{N_d})$
    Read device flows: $(\Phi_1, .., \Phi_{N_d})$
    $i \leftarrow 1$
    while i $< N_d$ **do**
      $device \leftarrow d_i$
      $k \leftarrow max(Q - V^j, j = 1..P)$
      $s^{(k)} \leftarrow s^{(k)} + d_i$
      $V^{(k)} \leftarrow V^{(k)} + \Phi_i$
      $i \leftarrow i + 1$
    return $s^{(1)}, .., s^{(P)}, V^{(1)}, .., V^{(P)}$

Fig. 1. Pseudocode VSM algorithm.

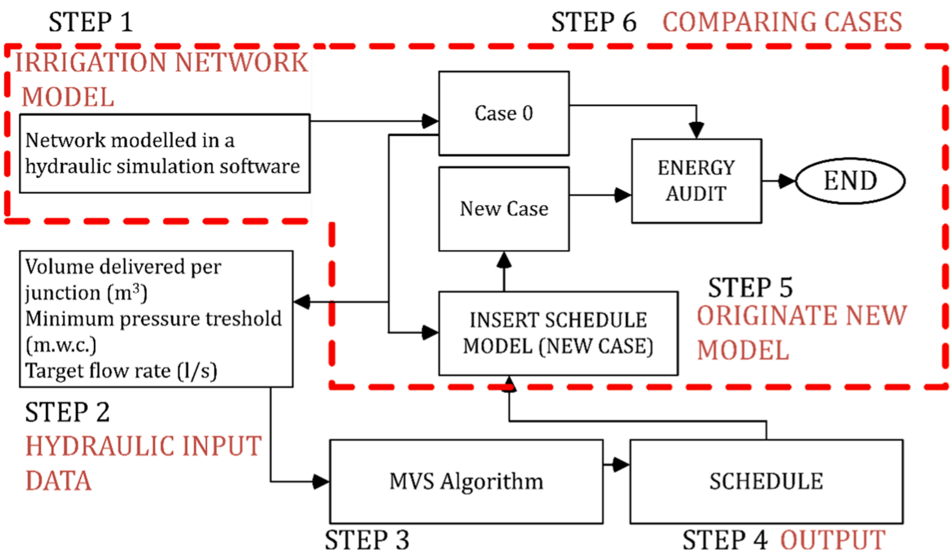

Fig. 2. Workflow of the system.

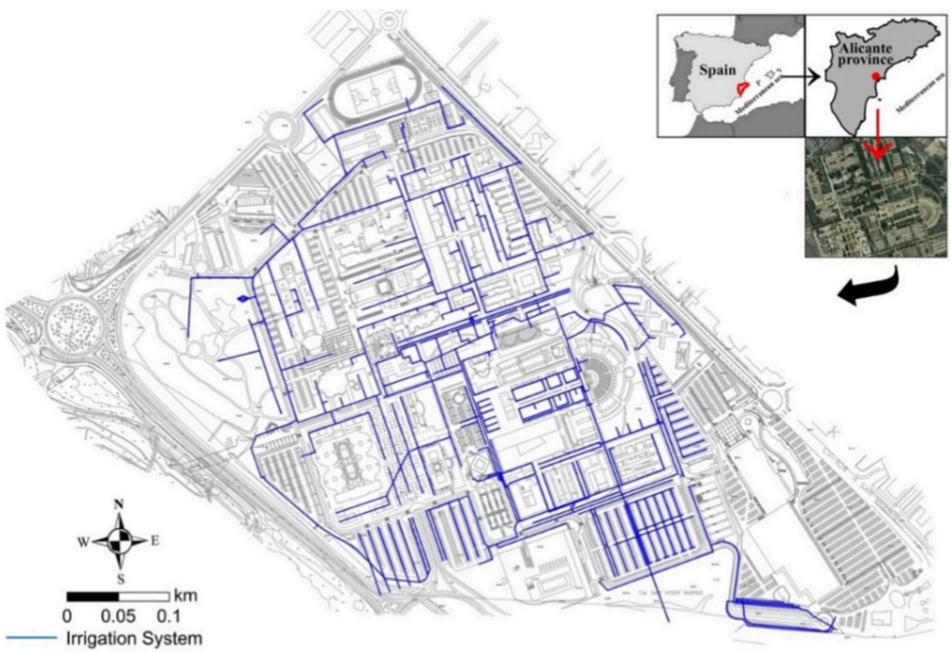

Fig. 3. The University of Alicante-Irrigation System.

meadow (i.e. Festuca arundinacea and Poa annua). Water is taken from a lake near the University (reservoir) and the pumping station comprising 4 pumps (“EVM 32 2-0F5/4.0”; (Ebara, 2019)) which may run in parallel. The pump curve is $H = -0.2163Q^2 + 0.3509Q + 44.713$ as provided by the manufacturer’s catalogue. The area of the garden is 0.67 Km^2, and the PIN comprises 891 pips (made of PVC”a”d fibre cement) with a diameter ranging between 1”-8”. The minimum service pressure adopted for this work is $\left(\frac{P}{\gamma}\right)_{threshold} = 25$m.w.c. The Hazen-Williams roughness coefficients are 100. 160 consumption nodes are incorporating a valve that is opened or closed when water is delivered (or not) to each plot. The optimisation criterion in our approach is the scheduling time of each subunit.

4.1. Lower network flow rate threshold

This network has been analysed in deep and after over 15,000 simulations in earlier research, we identified the combination ($s^{(k)}$) which contained the lower injected flow rate with at least one consumption node with pressure below the required standards (Pardo et al., 2020). This flow rate was called “l““er network flow rate” ””8.57 l/s) and this value involves that lower flow rates always produce that the pressure at the valves (consumption nodes) was higher than the service standards. Analysing the simulations performed, we identified the upper network flow rate threshold is (51.37 l/s) as the greatest flow rate in which a combination ($s^{(k)}$) can retrieve successful simulations (with pressures above the standards). In short, the decision-maker knows that if a flow rate lower than 25.57 l/s is injected, the standard values about pressure are always met, and on the contrary, higher values than 51.37 l/s the pressure standard are never met. If every consumption node (n = 160) is opened, the largest water demanded would be 861.94 l/s (an ideal value, as the greatest flow meeting standards is far from this value). The irrigation duration per node varies from 1 to 16 slices (which means 15 min and 16*15 = 4 h). The injected volume is$V_{inj}(t) = 1539.85$ m^3 (the current schedule involves watering twice per week), and considering a constant flow$Q_{low,th} = 28.57$ l/s (a value that complies with the pressure conditions) the intervals of time (k_i) demanded to supply this volume can be calculated,

$$V_{inj}(t) = 28.57{*}60{*}15/1000{*}k_i. = 1539.85\text{m3} \quad (18)$$

Finally, k_i=59.88 ~ 60 and the new simulation time results$t_p^* = k_i\cdot\Delta t_k = 900$ min = 15 h.

4.2. Potential cases

The present set-up is repeated twice per week (3077.74 m^3). Gardeners organised irrigation remote-controlling electro valves to deliver water on rotation scheduled. The duration of simulation in case 0 is 72 h, being the pumping hours for each pump 24, 22.5, 11.5 and 7 h.

The volumes delivered to the crops are kept constant (to allow for comparison) and four future scenarios are proposed in which the potential energy savings are to be quantified. Each of these scenarios has a different constant injected flow rate (Table 1), and, as a result, a different probability of not being able to meet the pressure restrictions. These percentages were got after performing 15,000 simulations and establishing a relationship between flow rates injected and the probability of not meeting the pressure standards (Pardo et al., 2020). Thus, the greater flow rate injected the higher probability of not meeting pressure standards. The Cases selected are:

- Case I represent the first scenario irrigating with a constant flow rate equal to the lower network flow rate (28.5 l/s). With equation (18), the simulation time was identified as 15 h.
- Case II and III were selected as the percentage was very close to 100% for values of flow rates below 34 l/s (Pardo et al., 2020). Case II was selected for irrigating in 14 h and Case III for irrigating in 13 h.
- Case IV was selected as the flow rate 34.2 l/s, a value for irrigating in 12 h. This scenario involves the higher injected flow rate and, the lower percentage of successful simulations.

Without doubts, higher injected flow means fewer pumping hours and a higher risk of not meeting pressure standards. Therefore, a compromise solution must be found between the different alternatives.

With the knowledge of the network, the targeted flow rates with the probability of meeting pressure restrictions areare incorporated (Table 1).

5. Results and discussion

5.1. Results from the MVS algorithm

The outputs of the MVS algorithm are the working plan for every hydrant (Fig. 4) and a graph, including the flow, injected for the entire simulation time (Fig. 5). , The columns of this matrix represent each slice (10, 15 min, a value selected for the PIN manager) comprising the total duration while each row is a consumption node(Fig. 4). As each column is correlated with a instant of time ($t_0, t_1, \cdots, t_m$). In short, it means that the i-th consumption node is opened at the j-th slice if this square is marked in blue but closed if not. Summing the row, it is calculated the consumption per node.

Table 1
Presentation of the cases.

	Case 0	Case I	Case II	Case III	Case IV
Total duration (h)	72	15	14	13	12
Objective Injected flow (l/s)	–	28.50	29.48	31.66	34.20
Percentage (%)	–	99.91%	99.91%	99.91%	98.29%

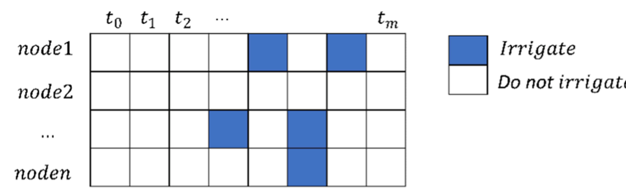

Fig. 4. Schedule which minimises the objective function.

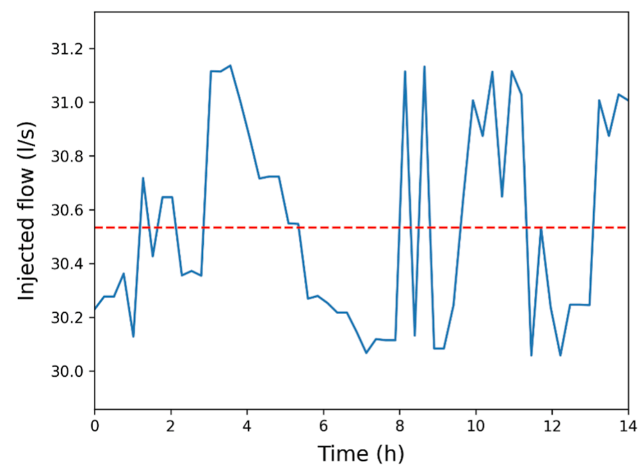

Fig. 5. Injected flow into the PIN.

Fig. 4 represents the discrepancy between the values got with the new water delivery scheduling and the targeted injected flow. The red line shows the constant flow value used in the run. The blue line is the flow injected into the network at each instant for the optimal planning of the problem. As seen, the average flow is an average value regarding the optimal flow.

The MVS method reports a document register called “Name– report.txt” and is deposited in the network path (Fig. 6).

5.2. New schedule for the cases.

The algorithm produces a schedule in irrigation to get constant flow. The values got by the simulations are depicted in Table 2.

When the schedule is introduced into the PIN model, the injected flow for the cases is shown by the algorithm in Fig. 7.

5.3. Energy audit

The MVS algorithm generates a new irrigation schedule. This schedule is fed into a calibrated hydraulic simulation of the irrigation network (in this case, we used Epanet). Subsequently, this irrigation network is input as data to the calculate the energy audit in pressurized networks (Pardo et al., 2013). We compute the energy audit using a graphical user interface called (UAEnergy) and the results are shown in (Table 3). n. The values depicted in Table 3 are means the natural energy provided by the reservoir (En), the energy consumed by pumps(Ep), the useful energy (Eu; which means the energy delivered to crops) and the energy dissipated in friction through pipelines (Ef).

5.4. Discussion

The new schedule strategy allows the utility manager to check the alternative model is meeting the key objectives (maintaining the volume of water delivered and keeping the pressure at the consumption nodes above the minimum service pressure). This method has been performed from a conservative standpoint for adopting the target injected flow

```
*********************************************************************
            MVS Water dellivery scheduling report file
            Hidraulic modelling:                  mpardo@ua.es
            Algorithm design:                     villacampa@ua.es
                                                  francisco.navarro@ua.es
            Coding & testing:                     francisco.navarro@ua.es
*********************************************************************
Authors are not responsible for any potential harm that may arise
from the use and/or the interpretation of the results obtained
when running the MVS software
Date:                   08 March 2022
Time:                   14:14:39
Input file:             ../UA/caudales.csv

PIN network data
------------------------
Number of watering nodes:               160

Model parameters
--------------------------
Average flow (Q):                       30.533050140023214 l/s
Total working time:             14 h
Number of slides:                       56
Size of slide:                          15 min

Model results
-------------------
Total injected volume:          1538865.72705717 m3
Minimum injected flow:          30.0579638182 l/s
Maximum injected flow:          31.1360720296 l/s
RSME:                           0.368022351491041
Computation time:               0.014621257781982422 s
```

Fig. 6. Text file exported when running VSM algorithm.

Table 2
Results achieved by the cases studied.

	Case I	Case II	Case III	Case IV
Target Injected flow (l/s)	28.50	29.48	31.66	34.20
Minimum flow (l/s)	27.95	29.68	31.79	34.32
Maximum flow (l/s)	28.83	30.54	32.51	35.37
Objective function	0.20	0.31	0.16	0.42
Time (s)	0.02	0.05	0.01	0.01

(28.5–34.2 l/s with a 99.91–98.29% percentage of success (Table 1). According to these hypotheses, all the cases meet pressure requirements (Table 3) and overpressure in the hydrants has been diminished.

This algorithm makes it possible manage consumption demands as water delivery in pressurized irrigation networks. The key idea of keeping the injected flow rate as constant as possible is to reduce energy consumption satisfying water delivery to crops. Considering that water consumption is equal to 3077.74 m^3/week for all cases, the entire volume delivered is 156964.74 m^3/year.

The energy per unit of volume reduces by getting a higher flow rate with a few pumping hours. The number reduces from (0.093 to 0.053 kWh/m^3) which means 0.040 kWh saved per cubic meter supplied. These values are lower than other approaches at farm level 0.19 kWh/m^3 (Soto-García et al., 2013) or 0.23 kWh/m^3 (Pardo et al., 2013) or even higher values 0.75–1.55 kWh/m^3 (regarding the energy needed to extract groundwater from the aquifers; (Soto-García et al., 2013)).

With these numbers, we get the whole energy consumption in pumps (Table 3) and the energy reduction achieved is (1–77.38/93.35) = 17.10% (Case I), 22.74% (Case II), 31.95 (Case III) and 43.01% (Case IV). The reductiong in energy consumption is of the same order of magnitude as that found in other research 15–30% (García et al., 2016); 36.3% (Jiménez-Bello et al., 2015), 23.9% (Karasekreter et al., 2013). Finally, the energy consumed by pumps is reduced by 143.66–81.87 = 61.79 kWh (43.01%) accounting for 6302.58 kWh/year.

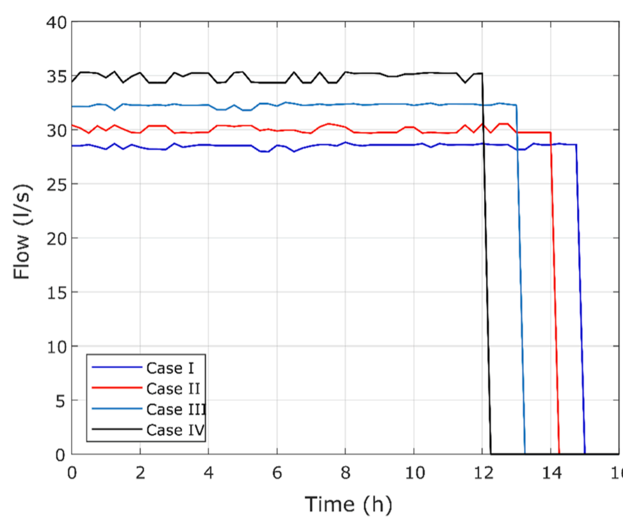

Fig. 7. The injected flow rate into the system for the cases.

The PIN layout is remarkably flat and 80–88% of the input energy

Table 3
Results from the energy audit for the cases proposed.

	Case 0	Case I	Case II	Case III	Case IV
Total duration (h)	72	15	14	13	12
En (kWh)	590.47	589.44	590.76	589.76	590.28
Ep (kWh)	143.66	119.08	110.98	97.76	81.87
Eu (kWh)	701.94	674.33	665.70	643.76	631.00
Ef (kWh)	31.88	34.14	36.04	43.76	41.16
Pmin (m.w.c.)	43.63	53.09	54.09	35.58	35.58
Ep/Volume (Wh/m^3)	93.35	77.38	72.12	63.53	53.20
Eu (MWh per year)	14653.3	12146.2	11320.0	9971.5	8350.7

comes from natural potential energy (while 20–12% comes from pumping devices). In this approach, we do not consider energy used extracting water from the aquifer. Table 3 shows that the friction losses are increase from (31.88 kWh in Case 0 up to 41.16 kWh in Case IV). This is an expected result as fewer hours of pumping involves higher flow rates and subsequently, greater headlosses. In Case 0 and IV, the PIR wastes 0.021 and 0.026 kWh/m^3 in friction. The energy dissipated into friction for Case 0 and IV represent 4.34 and 6.12% of the provided energy, similar values as 4.10% achieved by Pérez-Sánchez et al. (2017). sroThe overpressure is observed from the useful energy (Eu; energy supplied to the crops). Consequently, greater pressures at the consumption nodes are indicating excess energy expenditure. From Case 0 (701.94 kWh/m^3) up to Case IV (631 kWh/m^3). This term reveals the most substantial part of the energy savings.

5.5. *Comparison between the GA and the deterministic approach*

The results calculated and published in earlier article (Pardo et al., 2020) were attained using the ‘ga’ solver of the Matlab function ‘optimoptions’. The genetic algorithm gets an approximate solution to the problem with an exponential evolution regarding the error. It is therefore a good method for finding approximate solutions to a problem, although the rate of convergence decreases as the need for exactitude in the solution increases.

Next, we wish to compare results achieved by the GA approach and the deterministic approach developed here. For this purpose, the target flow 28.57 l/s with irrigation for 15 h is selected. While the GA approach got an RSME = 1.8643 in 3–4 days, the deterministic approach got the results in 0.2 s and the RSME = 0.20 (Table 2). The results are presented in Fig. 8.

6. Conclusions

This manuscript presents a deterministic constrained optimisation algorithm. This MVS algorithm has been programmed in Python and authors encourage professional civil and hydraulic engineers to use this algorithm and to confirm the results achieved. An executable file of the interactive program can be freely uploaded by email. In our analysis, this algorithm retrieves better results than any others found in literature about calculation speed and fitting to the targeted values. The presented method solves an optimisation problem, by reducing substantially the calculation speed and finding the best result in comparison with stochastic approaches such as genetic algorithms. The computing time has been reduced from days to tenths of seconds. Together with this faster behaviour, the achieved result has a better fit to the constant target flow.

The research line opened by this paper will be enhanced by considering other scenarios as non-constant flow constraints or more complex cases as non-linear value functions. Also, the presented solution can apply to other related problems with small modifications. This algorithm was tested in several PINs, but the University of Alicante PIN is the network presented here. This MVS algortithm achieved better (RSME = 0.20–0.42) than those obtained with the GA algorithm (RSME = 1.8643) and much shorter computational times (t = 0.20 s versus 3–4 days with the GA). Finally, an energy reduction has been found therefore to get a steady injected flow rate. This tool helps to quantify potential energy management reduction so, these savings can be fully exploited.

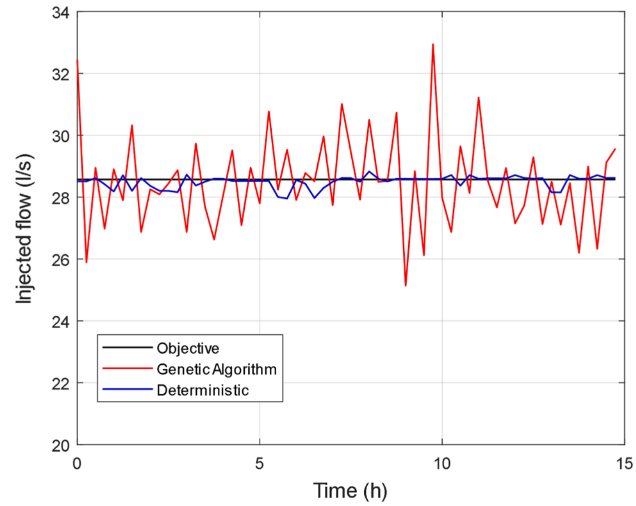

Fig. 8. Comparison between the solution found by GA (Pardo et al., 2020) and the Deterministic approach presented here.

This work highlights that new scheduling delivery adjusting injected flow rates to a constant value involved energy consumption reduction with values oscillating among 17.1–43.01% for Cases I and IV. The less irrigation hours needed (less hours of operation of the pumping equipment); the less energy consumed. The only limitation is because of hydraulic hydrants and/or sub-units must make sure a minimum service pressure (25 m.w.c.).

CRediT authorship contribution statement

M.A. Pardo: Conceptualization, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Resources, Data curation, Funding acquisition. **F.J. Navarro-González:** Conceptualization, Methodology, Software, Formal analysis, Validation, Writing – original draft, Writing – review & editing. **Y. Villacampa:** Resources, Data curation, Validation, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2022.107290.

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