Real-Time Energy Optimization of Irrigation Scheduling by Parallel Multi-Objective Genetic Algorithms

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Abstract

The present work is motivated by the need to reduce the energy costs arising from the pressure demands of drip and sprinkling irrigation, compounded by the increase in the energy price in recent years. Researchers have demonstrated that proper operation of the irrigation network reduces associated pumping costs. The main challenge was to obtain the optimal operation parameters on near real-time due to the fact that the high complexity of the optimization problem requires a great computational effort. The classic approach to the problem imposes a strict fulfilment of minimum pressures as a restriction. This study, however, presents a new methodology for the reordering of irrigation scheduling, incorporating the constraint of daily volume requests for each hydrant. The methodology is capable of minimizing the cost of energy while maximizing pressures at the critical hydrants. Cost reductions of about 6–7% were reached for scenarios without pressure deficit for the case study. Greater computational efficiency was achieved by posing the problem from a multi-objective approach, on the one hand, and by establishing the parallel evaluation of the objective function, on the other. The speed-up obtained by combining a reduction in the number of function evaluations thanks to the faster convergence of the multi-objective approach and the reduction of the computational time due to the parallelization of the algorithm achieved results about 10 times faster. This improvement allowed the tool to be implemented for the daily optimization of irrigation requests.

Keywords

Cost minimization, pressure maximization, computational efficiency, online optimization.

1 Introduction

The introduction of drip or sprinkler irrigation systems has increased the operation costs of irrigation networks due to the extra energy consumption needed to raise the pressure at the required level (Rodríguez Díaz et al., 2011). Furthermore, the growing price of electricity in recent years and the change in tariff structures have increased pumping costs (Langarita et al., 2017).

One of the research lines aimed at the energy optimization of irrigation networks has focused on enhancing their operation. Particularly, actions in the scope of demands have been demonstrated to permit the generation of more efficient consumption scenarios. Rodríguez Díaz et al. (2009) demonstrated that network sectoring, where demands are grouped by topographic criteria, could produce energy savings of up to 30% compared to on-demand managed irrigation systems, particularly when the pressure of the pumping station is set to the lowest value that guarantees the minimum working pressure at hydrants. However, the topographic criteria do not generate optimum scenarios, since they do not consider key factors such as friction losses at pipes. Metaheuristic algorithms are the most suitable means for solving this type of problem, due to their non-linear and multimodal nature. Jiménez-Bello et al. (2010) approached the optimization problem to define the best network sectoring that minimizes the global energy consumption, while guaranteeing a minimum working pressure at all hydrants, by using a Genetic Algorithm.

Fernández García et al. (2013) considered irrigation networks with multiple water sources and used a multi-objective genetic algorithm. The two objectives were to obtain the normalized sum of pumping cost plus the deficit in the supplied volume, and the normalized sum of the proportion of hydrants with a pressure deficit plus the magnitude of the deficit. Nevertheless, this methodology still established network sectoring by topologic criteria.

With regard to network sectoring, there is room for improvement in the methodologies outlined above. On the one hand, as different plots may be growing different crops, or the phenological stages might be distinct, a single irrigation time should not be forced for all the plots of a sector. The option to set a particular irrigation time for each plot, defined in order to meet the water needs of the crop, raises the degrees of freedom in the optimization problem and, therefore, can lead to higher energy savings. This was demonstrated by Jiménez-Bello et al. (2015). Moreover, the water needs of crops vary throughout the year, sometimes requiring daily watering, depending on the weather conditions. For that reason, an optimal operation of the network requires solving the optimization problem in real time, thus fitting the irrigation schedule to the actual daily water needs of the various crops.

Following this research line, García et al. (2015) developed a methodology to optimize the irrigation scheduling on a daily or weekly basis. The methodology is based on a metaheuristic algorithm of the ACO family (Ant Colony Optimization) (Dorigo et al., 2006). Metaheuristics have proven to perform well with this kind of problem, given their versatility and ease of implementation. However, these algorithms have lower computational efficiency than mathematical programming (linear, non-linear programming, etc.)—i.e., they require a high number of function evaluations in order to achieve a near-optimal solution. The need for long computational time reduces the applicability of an on-line irrigation scheduling optimizer based on a daily estimation of the water needs of the crops.

With the aim of enhancing the computational efficiency of metaheuristic-based optimizers, Alonso et al. (2015) presented an alternative approach for a particular case of the irrigation scheduling problem which reduced the computational time, while maintaining the quality of the initial solutions. The main challenge tackled in the present paper was to achieve a better computational efficiency to solve the irrigation scheduling optimization problem in general terms.

The present work introduces and demonstrates two improvements to the algorithm proposed by Jiménez-Bello et al. (2015). The previous work solved the irrigation scheduling optimization problem by a single objective – single thread genetic algorithm where the objective was to minimize the energy consumption by proper irrigation scheduling of the irrigation intakes. The problem tackled here is the same, but a new goal function that minimizes the pressure deficit at hydrant has been added. Moreover, the improvements have reduced the convergence time span. Unlike the previous work, first, the problem was approached and solved with a multi-objective perspective, and second, the algorithm was parallelized. The parallelization has been successfully applied in other research fields (Liu et al., 2018). Thanks to these novelties, a daily scheduling optimizer could be implemented and applied to a pilot project in the Water User Association (WUA) of “Pantano Estrecho” in Peñarroya (Spain).

Several techniques to speed up evolutionary algorithms have been reported. There are techniques based on the optimization of mutation and crossover functions (Nia and Alipouri, 2009), other based on the use of surrogate models (Rasheed et al., 2005), other based on enhancing the diversity of the population (Jassadapakorn and Chongstitvatana, 2011) and that based on taking advantage of multithread computation (Sinha et al., 2015). In this work a combination between enhancement of the population diversity and multithread computation have been exploited, because the mutation and crossover functions were optimized in previous works and the use of surrogate models reduces the precision of the simulations.

2 Materials and Methods

2.1 Problem description

The present work tackled the problem of obtaining the optimal irrigation schedule for a generic network fed from a pumping station including variable speed pumps (VSP). The control system maintains a certain pressure downstream of the station. Although energy savings could be higher if the set pressure were adjustable online, or even better if the system allowed remote control of the pumps switching and their rotational speed, current control system is local and do not permit this. Hence, the variables of the present problem did not include the operation of the pumping station. Instead, the approach fixed the same downstream pressure as the real setting of the controller. Then, the global efficiency was obtained as a function of just the global flow, by means of the knowledge of the individual curves of each pump and the switching configuration of the controller, which responds to conditions to achieve the highest possible efficiency for all flow rates. Fig. *1* shows the calculated efficiency curve for the pumping station of the case study.

Actions in the scope of water demands could lead to greater energy savings. Estimating the actual crop water requirements by scientific methods, for example that proposed by the Food and Agriculture Organization (Allen et al., 1998), would guarantee the supplied water would meet the strict minimum. So far, this action has been regarded with suspicion by the owners, and thus, the process has not yet been incorporated into the optimizer. Accordingly, the optimizer receives water requests from the users based on their own irrigation criteria, the irrigation time for each plot being fixed by means of the hydrant base flow, which is supposed to be known and constant.

The remaining degree of freedom for the optimization problem is to establish the most convenient starting time of each hydrant. Once the hydrant starts the irrigation, it remains active until the predefined time finishes. Therefore, the problem variables indicate the start time of each irrigation, including the option of requesting several irrigation events per plot.

The temporal horizon for the optimization is, at most, 24 hours. Initially, the total span of the irrigation day matches the duration of the proposed solution. Only when there is no solution without pressure deficit is the span of the irrigation day increased.

Finally, each of the scenarios is simulated by means of the Epanet Toolkit (Rossman, 2000; Vegas Niño et al., 2017) in order to obtain the flows and pressures at each time step of the irrigation journey. Epanet is a hydraulic simulator developed by US EPA, and today is the main reference in this field (Iglesias-Rey et al., 2017). Software election will not affect in problem solution. It could affect time computation but Epanet has been shown to be the very efficient in computation time (Alvarruiz et al., 2015).

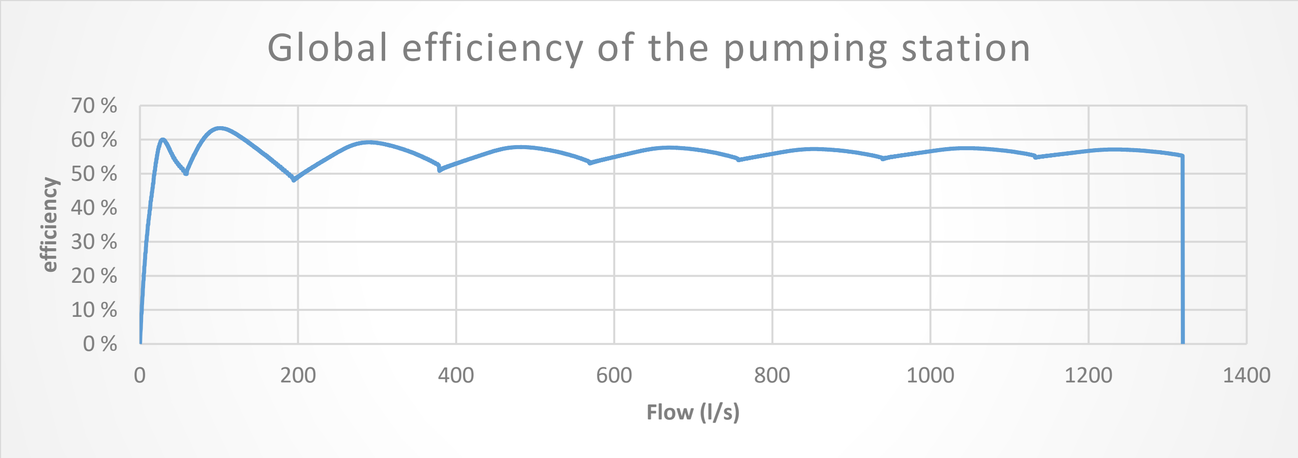

Fig. 1. Global efficiency of the pumping station of Peñarroya WUA, sector III (case study), calculated to obtain the best performance from the individual curves of each pump, for a pressure setting of 38 m.

2.2 Algorithm description

As mentioned above, metaheuristic algorithms are suitable for the type of problem presented here. From the variety of proposed algorithms, this methodology uses the Multi-objective Genetic Algorithm known as NSGA-II (Non-dominated Sorting Genetic Algorithm), mainly due to its faster convergence in comparison to similar algorithms (Deb et al., 2002). It is also easy to adapt to multi-objective problems. The selection of other genetic algorithms would affect in time processing, but the goal of this paper was not to compare parallel algorithms between them. It was to compare parallel optimization versus single-thread optimization. The implementation of the base algorithm was taken from the JMetal Package, available under GNU (from the recursive acronym "GNU is Not Unix") Lesser General Public License (Durillo and Nebro, 2011).

The chromosomes were encoded as integer numbers (genes). Each gene corresponds to an irrigation request and indicates its start time. Time discretization is another key factor in the problem complexity and, therefore, in the computational efficiency. Hence, with regard to the time discretization, the coarser the better, provided that it gives a suitable frame for all the requests. The time discretization was defined as the greatest common factor of the set of durations, provided that it is at least 5 minutes. This method allows the systematization of the problem through a more general approach, which includes the particular case of network sectoring represented by a set of requests of equal duration.

Regarding chromosome evaluation, the proposed multi-objective approach focuses on the minimization of the global pumping cost on the one hand, and on the minimization of the service pressure deficit, on the other. Previously, the pressure deficit has been handled through cost penalties in a single-objective approach. In multi-objective optimization, the fact that *a priori* solutions are not discarded—which would be discarded in a single-objective approach—promotes diversity within the population. The improvement is based on the hypothesis that a greater diversity will enhance the convergence rate and will avoid a local optimum trap.

The total cost (TC) of the irrigation day comprises the global efficiency of the pumping station, the hourly cost of energy, and penalties due to power excess, as shown in Eq. (1), adapted to the charging policy of the local electricity dealer:

$$TC = \sum_{t=1}^{Nt}\left(\frac{\gamma Q(t)H}{\eta(Q(t))}\cdot\Delta t\cdot Ce(t)\right) + \sum_{i=1}^{i=6}\left[K_i\cdot 1{,}4064\cdot\sqrt{\sum_{j=1}^{j=n}\left(Pd_j - Pc_i\right)^2}\right] \quad (1)$$

where:

Nt is the number of time steps of the irrigation day discretization.

γ is the specific weight of the water (N/m^3).

$Q(t)$ is the total pumped flow at time step t (m^3/s).

H is the head supplied by pumps, which is assumed to be constant thanks to the local controller (m).

$\eta(Q(t))$ is the global efficiency of the pumping station, which depends on the flow, as shown in Fig 1.

Δt is the length of the time step, along which the flow is assumed to be constant (h).

$Ce(t)$ is the energy cost depending on the time of the day and the time of the year (€/Wh).

K_i is a penalty factor for power excess that depends on the tariff period and has the values shown in Table 1.

Pc_i is the hired power for period i (kW).

Pd_j is the maximum demanded power in each fourth hour j within the period i when Pd_j is greater than Pc_i (kW). Note that j and n depend on the period distribution of the tariff throughout the day.

Table 1. Value of the coefficient for the power excess penalty in six tariff periods.

Period	**1**	**2**	**3**	**4**	**5**	**6**
K_i (€/kW)	1	0.5	0.37	0.37	0.37	0.17

The second objective APD (Average Pressure Deficit) takes the minimum required pressure $P_{min,req}^{h}$ at each hydrant individually. This parameter accounts for the difference of elevation between the pumping station and the hydrant, as well as the head loss in the path between it and the source. For each solution, the minimum pressure at active hydrants is calculated and compared to the minimum required. The value for the objective function is the average of the differences between the required pressure and the calculated one, provided that the difference is positive—i.e., there is a pressure deficit.

$$APD = \frac{1}{Nh}\cdot\sum_{h=1}^{Nh} max\{(P_{min,req}^{h} - P_{min,calc}^{h}), 0\} \quad (2)$$

where:

Nh is the number of hydrants with irrigation requests.

$P_{min,req}^{h}$ is the minimum desired working pressure at hydrant h.

$P^{h}_{min,calc}$ is the minimum computed pressure at hydrant h throughout the optimization period, but only regarding the time steps in which the hydrant flow is greater than zero.

Taking into account that the total delivered volume to each hydrant D_h expressed in m^3 must equal the users' requests, the optimization problem can be stated as follows: $\min\{TC, APD\}$ (3)

$$s.t. \qquad \sum_{h=1}^{Nh} q_h(t)\Delta t = D_h$$

Where q_h (m^3/h) are the delivered flow to each hydrant h at time t.

For all studied cases, the parameters of the Genetic Algorithm remained invariable. The population size was fixed at 500 chromosomes, the crossover rate at 0.9 and the mutation rate at 1/number of variables.

In order to check the effectiveness of the new approaches, this paper presents several analyses. On the one hand, these analyses aim to demonstrate that the multi-objective approach reaches a better solution than a single-objective one in the same number of function evaluations. On the other hand, they also propose to illustrate that parallelizing the algorithm by using multi-core processors, commonly used nowadays in any computer, effectively reduces the computation time span. The program was tested on an Intel© i7 8-core processor. In the single-objective approach, the pressure deficit was managed by means of cost penalties; nevertheless, this did not constitute a problem for the results comparison because all cases finally achieved a scenario without pressure deficit. The stochastic nature of Genetic Algorithms forces a convergence analysis to be performed based on statistical criteria. Specifically, repeating each scenario 50 times was considered sufficient to conclude whether the changes in average values were statistically meaningful.

When a multi-objective approach is applied, it does not provide a unique solution, instead there is a set of non-dominated solutions known as Pareto Front—i.e. among the elements within the set, no one element is better than any other in all of the objectives. Thus, choosing a solution from among the Pareto Front can rely on multiple criteria. In the present case, the quality of service prevailed over economic savings and, therefore, the least pressure deficit solution among the Pareto Front was chosen as the best. The proposed scenarios permitted the algorithm to reach solutions without pressure deficit in few iterations, the chosen solution being, in any case, that with the least pressure deficit, which is indicated with a circle in Fig. *2*. However, the Pareto Front keeps the solutions with pressure deficit and this enhances population diversity. Fig. *3* shows the value of the two mentioned objectives for the best solutions (the circled ones) at the end of the evaluation after different generations in one of the analysed scenarios.

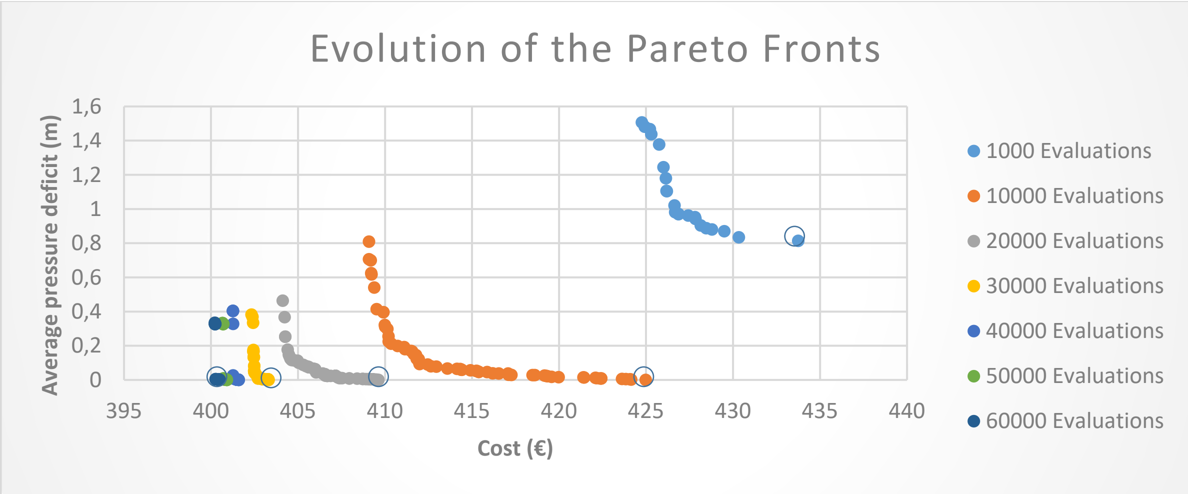

Fig. 2. Representation of the non-dominated solutions within the population set at the end of different generations. The selected chromosome is indicated with a circle.

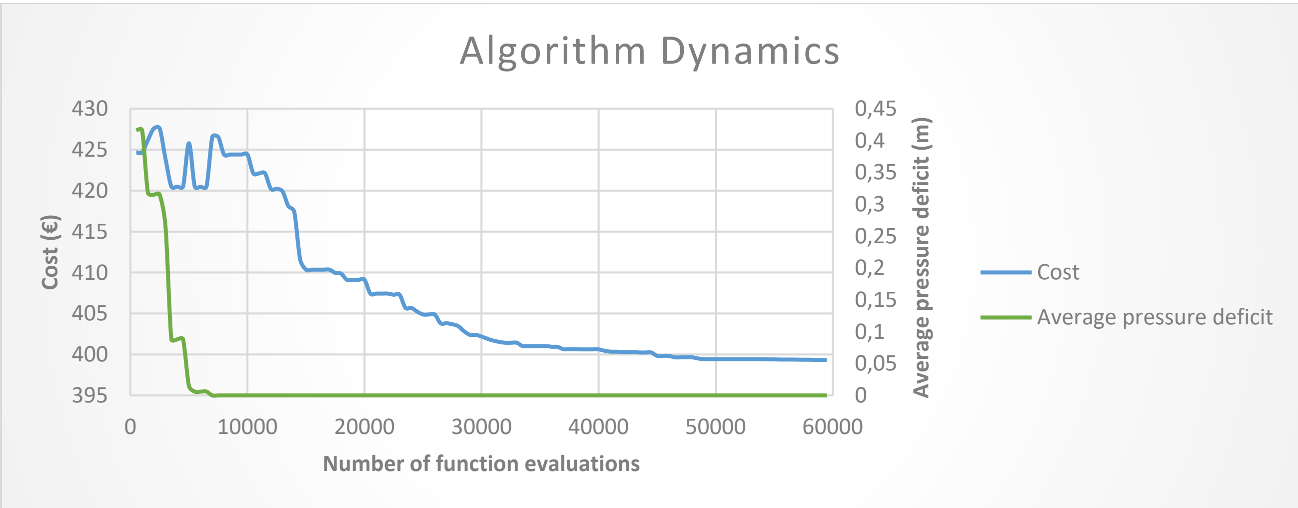

Fig. 3. Value of both objectives of the selected chromosome (circled in Fig. 2) among the Pareto Front at the end of the evaluation of each generation.

With regard to the algorithm dynamics, performing the analyses appears to be suitable within the frame of the first 60,000 function evaluations (120 generations). The analysed scenarios are the following:

- Scenario A: multi-objective optimization with parallel evaluation of 20,000 chromosomes.
- Scenario B: single-objective optimization with parallel evaluation of 30,000 chromosomes.
- Scenario C: multi-objective optimization with parallel evaluation of 30,000 chromosomes.
- Scenario D: single-objective optimization with parallel evaluation of 60,000 chromosomes.
- Scenario E: multi-objective optimization with parallel evaluation of 60,000 chromosomes.
- Scenario F: multi-objective optimization with single-thread evaluation of 30,000 chromosomes.

The scenarios have been chosen with the aim of having enough diversity of options in order to effectively assess the differences between the performances of the different approaches. The results showed that the studied scenarios were enough to effectively observe those differences.

Finally, the assessment of the parallelization effectiveness in the computation time reduction was performed with regard to the theoretical maximum speed-up, which is the relation between the execution time of the sequential algorithm and the execution time of the parallelized algorithm. The maximum theoretical speed-up $S(N)$ was stated by Amdahl's Law (Amdahl, 1967), defined by Eq. (3), which depends on the relation f between the computation time of the unavoidable sequential part of the program and the total computation time, and on the number of available processors *N.*

$$S(N) = \frac{1}{f + \frac{1-f}{N}} \tag{3}$$

2.3 Case study

The methodologies proposed here were applied to a real irrigation network located in Ciudad Real (Spain). An optimizer was implemented as a set of web services programmed in the .NET environment using API-REST technology and it was integrated in CORENET-COREGEST, which is the management platform of the case study network.

Specifically, the network under study is sector III of the Water User Association (WUA) of Peñarroya (39°08'03.3"N 3°06'17.6"W), with an irrigated area of 1,022 ha and 380 hydrants (

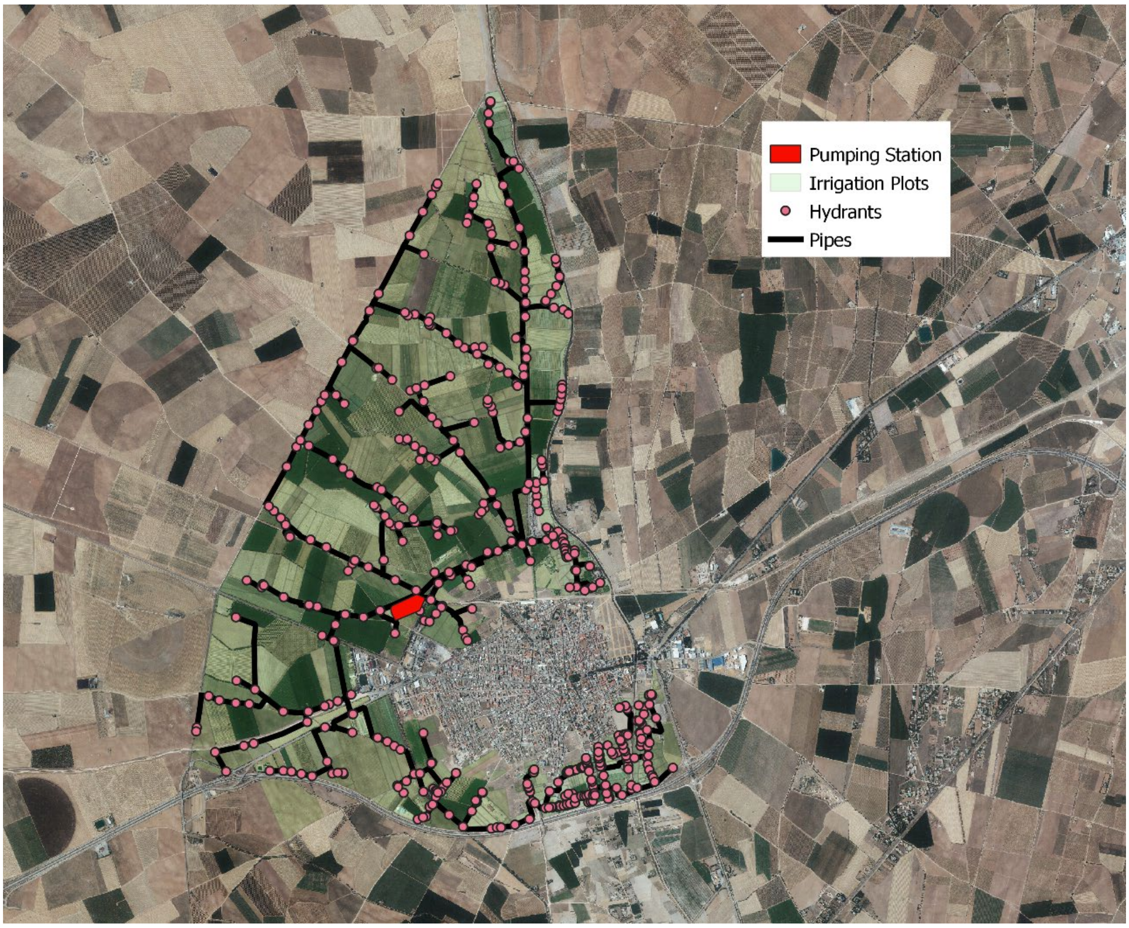

Fig. 4). The pumping station has 8 pumps, 7 of them are identical with a nominal power of 189 kW, and the other 55 kW. The latter is a variable speed pump (VSP) and is only active when the demanded flow is very low. Among the big pumps, one is also a VSP. The pumping station is controlled by an automatism that follows a certain setting for the outlet pressure and it has been programmed according to maximum efficiency criteria—i.e., the combination of active pumps and the speed of VSPs is chosen to deliver any flow at the set pressure with the best possible efficiency.

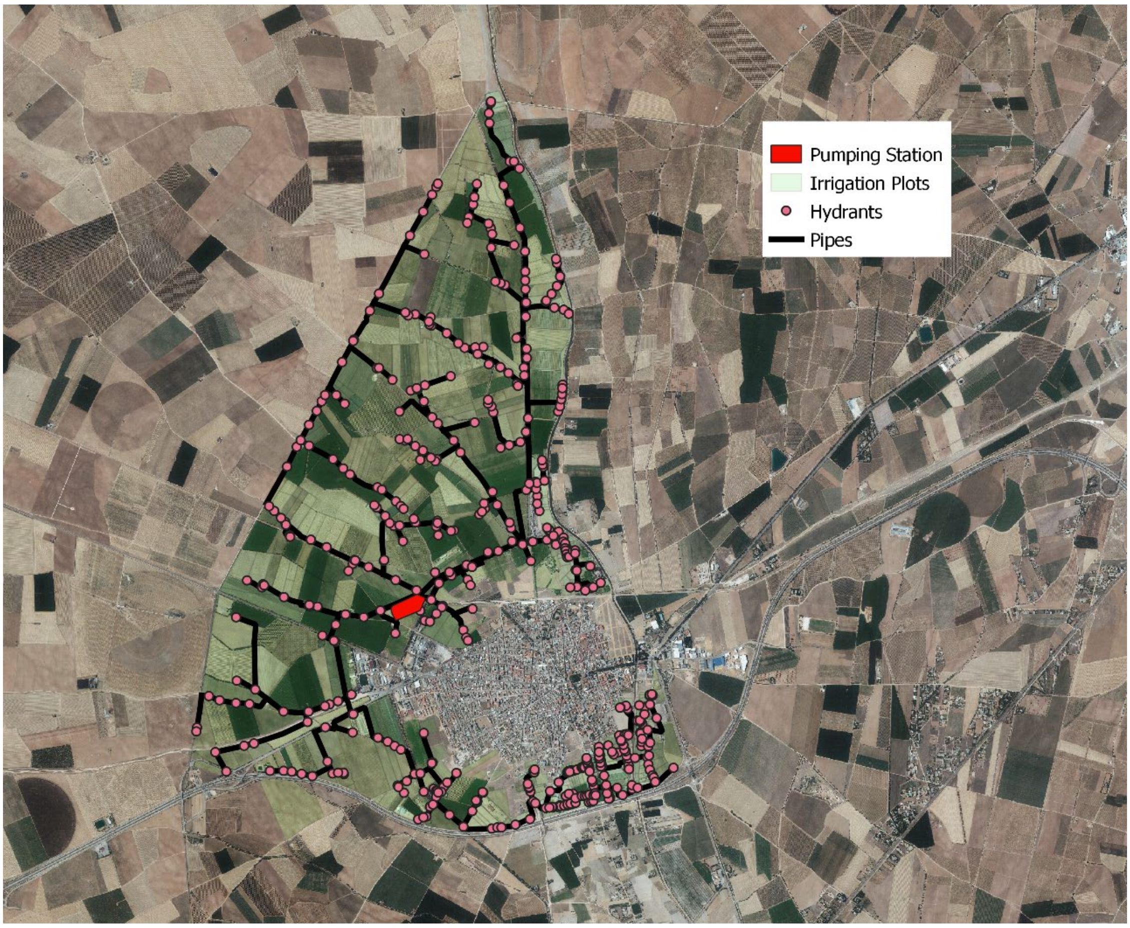

Fig. 4. Irrigation network of Peñarroya WUA, sector III.

Due to mechanical limitations of the network (age and material of pipes), the set pressure of the pumping station cannot exceed 4 bar; otherwise, the risk of pipe bursts is too high. This limitation highlights the advantages of the multi-objective approach, as in some high-demand scenarios a certain pressure deficit may be unavoidable.

The electric tariff is 6.1A, which is an electricity tariff with hourly discrimination of 6 periods, where P6 is the cheapest and P1 the most expensive. Table *2* shows the distribution of the 6 hourly periods throughout the year. The WUA has contracted power of 50 kW for periods P1 and P2, 850 kW for P3 to P5 and 900 kW for P6. The analysed irrigation day has 78 requests with a fixed irrigation time each one, which entails a total volume of 33,823 m^3 to be delivered over a maximum period of 24 hours.

Table 2. Yearly distribution of the hourly periods for the 6.1A tariff.

Hour	JAN	FEB	MAR	APR	MAY	JUN1	JUN2	JUL	AUG	SEP	OCT	NOV	DIC
00:00	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6
01:00	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6
02:00	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6
03:00	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6
04:00	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6
05:00	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6
06:00	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6
07:00	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6	P6

08:00	P2	P2	P4	P5	P5	P4	P2	P2	P6	P4	P5	P4	P2
09:00	P2	P2	P4	P5	P5	P3	P2	P2	P6	P3	P5	P4	P2
10:00	P1	P1	P4	P5	P5	P3	P2	P2	P6	P3	P5	P4	P1
11:00	P1	P1	P4	P5	P5	P3	P1	P1	P6	P3	P5	P4	P1
12:00	P1	P1	P4	P5	P5	P3	P1	P1	P6	P3	P5	P4	P1
13:00	P2	P2	P4	P5	P5	P3	P1	P1	P6	P3	P5	P4	P2
14:00	P2	P2	P4	P5	P5	P3	P1	P1	P6	P3	P5	P4	P2
15:00	P2	P2	P4	P5	P5	P4	P1	P1	P6	P4	P5	P4	P2
16:00	P2	P2	P3	P5	P5	P4	P1	P1	P6	P4	P5	P3	P2
17:00	P2	P2	P3	P5	P5	P4	P1	P1	P6	P4	P5	P3	P2
18:00	P1	P1	P3	P5	P5	P4	P1	P1	P6	P4	P5	P3	P1
19:00	P1	P1	P3	P5	P5	P4	P2	P2	P6	P4	P5	P3	P1
20:00	P1	P1	P3	P5	P5	P4	P2	P2	P6	P4	P5	P3	P1
21:00	P2	P2	P3	P5	P5	P4	P2	P2	P6	P4	P5	P3	P2
22:00	P2	P2	P4	P5	P5	P4	P2	P2	P6	P4	P5	P4	P2
23:00	P2	P2	P4	P5	P5	P4	P2	P2	P6	P4	P5	P4	P2

3 Results

3.1 Comparison between scenarios

For each scenario, as described above, 50 independent tests were performed. The results are summarized in Table 3 and shown in Fig. *5*. The box and whisker chart suggest that the differences between the scenarios regarding the minimum cost reached were significant, except for scenarios C and F, which is unsurprising as in both cases the optimization was multi-objective and of 30,000 evaluations, the only difference being the parallelized or single-threaded calculations, that is, the parallel evaluation of the objective function does not affect the convergence rate of the algorithm. It only speeds up the process by increasing the computation capacity, so on equal number of function evaluations, the expected cost results are the same.

Scenarios A and B also appear to be similar.

Table 3. Summary of the main statistical indicators for the set of analysed scenarios.

Scenario	Number of tests	Average objective	Cost Standard deviation	Average computational time	Time Standard deviation
		(€)	(€)	(s)	(s)
A	50	409.25	3.36	62.54	1.45
B	50	408.96	2.98	95.10	2.79
C	50	403.82	2.25	89.60	3.55
D	50	406.21	2.83	193.06	5.55
E	50	400.66	1.94	179.28	4.71
F	50	404.67	1.99	418.21	14.03

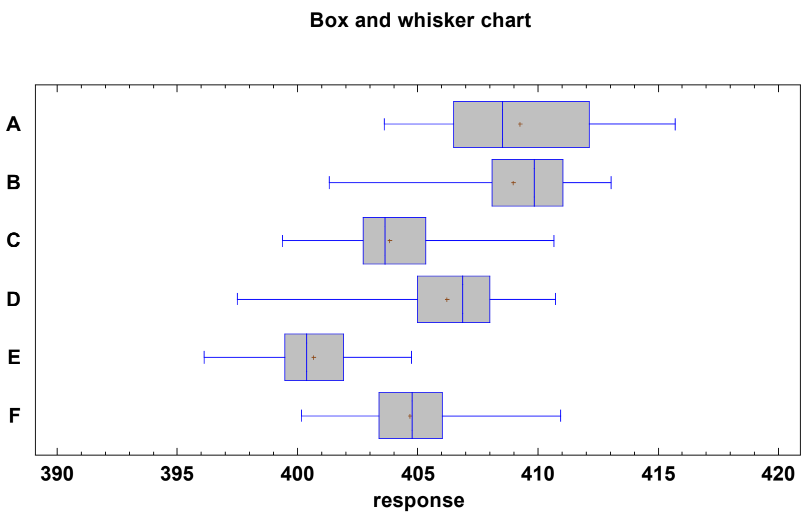

Fig. 5. Representation of the values for the cost objective of each scenario by means of the box and whisker

chart.

The subjective appreciation mentioned above was confirmed by the t-test (Student, 1908) for comparing two means, as it is the most extended and accepted test for comparing independent samples in when the statistic follows a normal distribution. In case the data were noticeably non-normal, the t-test would give inaccurate results. However, the dataset handled in this work has fulfilled the normality conditions.

As suggested before, the P-value for the comparisons A with B and C with F proved to be greater than 0.05, hence the null hypothesis was accepted, so there is a probability of 95% that the means are equal. The remaining comparisons resulted in a P-value lower than 0.05; therefore, the differences in the mean values were statistically significant.

These results allow us to affirm that the multi-objective approach for the optimization problem achieves better results in fewer iterations. As particular examples, the comparison between A and B shows that the multi-objective approach reached the same value in 33% less function evaluations. Comparing scenario B with C, and D with E, it can be concluded that, with the same number of evaluations, the multi-objective approach achieved a better result. Finally, perhaps the best example to demonstrate the better performance of the multi-objective approach is the comparison between C and D, since the solution is slightly better in the multi-objective case with only half of the evaluations.

3.2 Assessment of the parallelization

Regarding the computation time, although the results show that the multi-objective approach was slightly faster than the single-objective one with the same number of evaluations, this improvement was negligible compared to that achieved by the parallelization of the algorithm, as well as the potential reduction that can be achieved due to the fewer iterations needed by the algorithm to converge.

In order to obtain the relation f between the computation time of the unavoidable sequential part of the program explained here and the total computation time, the unavoidable sequential part of the code had to first be distinguished. One of the advantages of population based optimization algorithms is that the evaluation of each chromosome within a generation is independent of the rest. Hence, the evaluation of each generation is suitable for parallelization. The time measurement for the parallelizable code is about 95% of the total timespan. This means that the maximum ideal speed-up with unlimited resources would be:

$$\lim_{N \to \infty} S(N) = \frac{1}{0.05} = 20$$

However, the dependency between generations limits the number of parallel processes to the population size. As this paper proposes a population size of 500 chromosomes, the maximum theoretical speed-up would be:

$$S(500) = \frac{1}{0.05 + {}^{0.95}/_{500}} = 19.27$$

The analysis was performed in a personal computer with eight processors and, therefore, the expected ideal speed-up to be reached was:

$$S(8) = \frac{1}{0.05 + {}^{0.95}/_{8}} = 5.93$$

In reality, this ideal speed-up is limited due to task scheduling, load balancing or communication costs (Grama et al., 2003). The comparison between scenarios C and F show that the actual speed-up achieved by the parallelization of the objective function evaluation was:

$$S = \frac{T(F)}{T(C)} = \frac{418.21}{89.60} = 4.67$$

This means that the real efficiency of the parallelization was around 80%, with regard to the theoretical speed-up. It should be remarked that, theoretically, there is room for improvement by simply increasing the number of processors, although it is also expected that the real efficiency would worsen.

A further conclusion with respect to the algorithm parallelization concerns the effect of upscaling the problem. As predicted by Gustafson's observation to Amdahl's Law (Gustafson, 1988), the ratio between the unavoidable serial part of the program and the parallelizable part could reduce as the problem scales. In the present case study, the ratio f was measured for various numbers of function evaluations. The results shown in Fig. *6* confirm that prediction. It can be concluded that the potential benefits of parallelizing the program are greater as the problem scales.

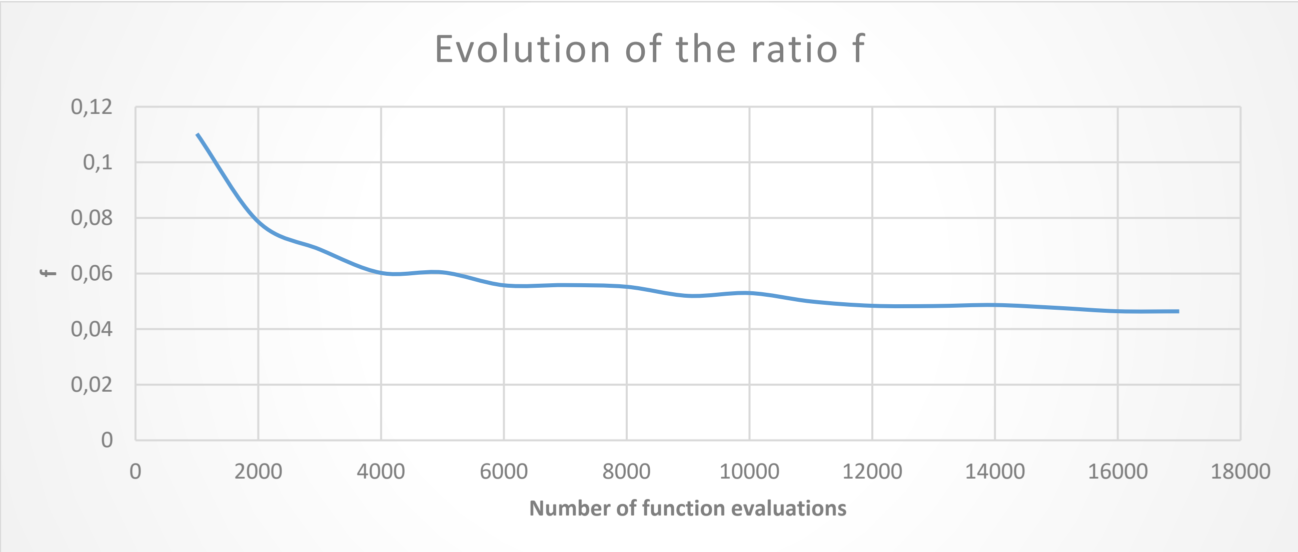

Fig. 6. Value of the ratio between the unavoidable serial part of the algorithm and the total computational time depending on the total number of function evaluations.

3.3 Achieved savings compared to actual scenario

With regard to the improvement achieved by the algorithm in the value of the objectives compared to the initial schedule carried out by the WUA, **¡Error! No se encuentra el origen de la referencia.** summarizes the main indicators obtained by one of the solutions from the scenario C.

Table 4. Comparison between the main indicators of the real irrigation schedule and the optimized solution.

	Initial scenario	**Proposed solution**
Number of hydrants	78	78
Delivered volume (m3)	33823.28	33823.28
Energy consumption (kWh)	6302.22	6072.3
Total cost (€)	428.44	402.69
Power penalty (€)	0	0
Average pressure deficit (m)	0.87	0

Pressure at critical hydrant (m)	16.43	25.38
Number of hydrants with pressure < 25 m	4	0

4 Conclusions

The present paper proposes a new approach for the energy optimization of irrigation networks by reordering the irrigation schedule based on pre-established volume (or time) requests for each hydrant, regarding both the energy term and the excess power penalty for the different tariff periods. Furthermore, an improved optimization algorithm was proposed to solve the problem of obtaining optimal irrigation scheduling from both energy and service quality points of view. One of the main objectives was to reduce the computational effort required by the algorithm for the real-time application. By means of the analysis of several cases, the multi-objective approach was shown to achieve convergence in a smaller number of evaluations, up to 50% less evaluations for the same result, and that the parallelization of the algorithm, taking advantage of today's multi-core processors common in any Personal Computer (PC), can reduce the computation time by almost 80%. In the case study a cost reductions of about 6–7 % was achieved without pressure deficit in any hydrant.

In summary, an algorithm was developed that is capable of delivering an optimal solution in a few minutes, representing a viable tool to optimize daily water demands. The optimizer was implemented as a series of web services programmed in the .NET environment using API-REST (Application Program Interface - REpresentational State Transfer) technology, which allows it to be easily integrated in any WUA management platform.

With regard to the size of the problem, the hydraulic complexity of WUA irrigation networks can vary, although the chosen case study could be representative. The proposed methodology is suitable for networks of equal or smaller size. Further improvements and new approaches would be necessary in order to tackle the real-time irrigation scheduling optimization in more complex networks.

Moreover, due to the benefits of combining the use of conventional electric energy with renewable sources, such as photovoltaic or wind energy, the development of more sophisticated algorithms would be of great research interest for the irrigation management in the near future.

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