Water Research X 27 (2025) 100300

Contents lists available at ScienceDirect

Water Research X

journal homepage: www.sciencedirect.com/journal/water-research-x

A new Digital Harmony Search algorithm for optimizing Pump Scheduling in Water Distribution Networks

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ARTICLE INFO

Keywords:
Pump Scheduling
Meta-heuristic algorithm
Harmony Search
Number of switches
Cost optimization

ABSTRACT

Pumps in Water Distribution Networks (WDNs) adequately provide effective pressure where low elevation or high head losses are detected within the system. One of the most effective strategies to ensure economic sustainability is Pump Scheduling (PS), assuring the optimization of pump management and enabling significant energy cost saving. Meta-heuristic algorithms can be applied to Pump Scheduling, given their ability to provide reliable global solutions, further complemented by limited computational efforts. Nevertheless, they do not assure the achievement of the optimal global solution.

In this paper, the Pump Scheduling optimization was solved by applying a modified Harmony Search (HS) algorithm, aimed at optimizing the energy consumption and the maintenance costs of pumps, by limiting the number of daily switches. The EPANET 2.0 solver was employed for hydraulic simulations and novel setting equations and penalties were included to limit the number of feasible solutions. The model was tested on two benchmark water networks, showing its capability to return near-optimal solutions within a short computational time.

1. Introduction

Pump Scheduling (PS) within Water Distribution Networks (WDNs) is a relevant topic in the field of the Best Management Practices (BMPs) of water systems, given its technical and economic edges. Indeed, the energy costs of pumps represent a significant rate of WDN management, leading to the design of an effective optimization procedure to ensure the required network service, at the expense of limited costs. The optimal pump operations also limit the maintenance costs for their repair or replacement. The PS issue thus aims to minimize the pumping costs, while satisfying the supplied water to users at allowable pressure and assuring the restoration of tank levels. Nevertheless, given the complexity of WDN, the dynamic water demand and the variable electric tariff, the PS optimization still results in a complex and unsolved issue that needs to be addressed.

In the literature, over the last decades, several approaches for optimizing the PS were proposed, showing high uncertainties when applied to complex systems (Brion and Mays 1989; Jowitt and Germanopoulos 1992; Vieira and Ramos 2008). Indeed, the higher the number of variables and functions, the greater the computational effort.

In this context, meta-heuristic approaches allow for gaining effective results, as well as improving computational effectiveness (Creaco and Pezzinga 2015). Several authors applied meta-heuristic models to solve the PS. Beckwith and Wong (1995) and Mackle et al. (1995) first tested the reliability of the Genetic Algorithm (GA) to solve the PS in a multi-storage tank water supply system. Savic et al. (1997) implemented an improved GA by considering a multi-objective optimization to reduce both the energy costs and the number of switches in complex systems, observing the ability of the procedure to detect near-optimum solutions in affordable computational times. Shamir and Salomons (2008) developed a reduced GA, aimed at significantly limiting the computational efforts, however, assuring a satisfying accuracy in achieving a near-optimal solution. López-Ibáñez et al. (2008) applied the Ant-Colony Optimization (ACO) to minimize the electricity cost of pumps while assuring the allowable pressure at each node and the equilibrium of water within tanks. They observed the ACO reliability to return better results than a GA in both the results of the objective function and computational efforts. Then, López-Ibáñez (2009) proposed a single-objective evolutionary algorithm named Simple Evolutionary Algorithm (SEA) to solve the PS task, showing challenging outcomes when applied to different benchmark WDNs.

De Paola et al. (2017) implemented a modified Harmony Search (HS) algorithm for the optimal PS in WDNs. To improve the computational

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https://doi.org/10.1016/j.wroa.2024.100300
Received 7 October 2024; Received in revised form 18 December 2024; Accepted 28 December 2024
Available online 31 December 2024

List of Acronyms

ACO	Ant-Colony Optimization
AT(M)	AnyTown Modified
B&B	Branch-&-Bound
BMP	Best Management Practices
BO	Bayesian Optimization
DHS	Digital Harmony Search
GA	Genetic Algorithm
GS	Gaussian Process
HM	Harmony Matrix
HMCR	Harmony Memory Considering Rate
HMS	Harmony Memory Size
HS	Harmony Search
MC	Memory Considerations
NSGA	Non-dominated Sorting Genetic Algorithm
P	Pump
PAR	Pitch Adjusting Rate
PS	Pump Scheduling
R	Randomization
RF	Random Forest
RTTC	Real Time Trigger Control
SEA	Simple Evolutionary Algorithm
SMBO	Sequential Model Based Optimization
SS	Stepping Setting
T	Tank
WDN	Water Distribution Network

List of symbols

η	Pump efficiency (-)
N_p	Number of pumps (-)
C^T	Total daily energy cost ($/day or £/day)
H_m	Pump head (m)
NS	Total number of switches within the network (-)
N_{SW}	Number of pump switches (-)
OF	Objective function
P	Pressure (m)
Q	Flow Rate (m^3/s or l/s)
S	Water level (m)
T	Time period (h)
TN_{SW}	Total number of pump switches (-)
x	Decision variable (-)
c_E	Unit energy rate ($/kWh or £/kWh)
c_t	Hourly demand factor (-)

List of subscripts/superscripts

k	k-th pump
i	i-th decision variable
j	j-th tank
t	t-th time step
max	Maximum
min	Minimum

performance, a Relative Time Trigger Control (RTTC) was employed, along with the a priori exclusion of unfeasible solutions. The model was tested on two benchmark WDNs, showing good results in short computational times and the number of iterations.

Makaremi et al. (2017) applied the metaheuristic Non-dominated Sorting Genetic Algorithm NSGA-II to the PS optimization, focusing the attention on the improvements of the Pareto-optimal solutions achievable by admitting a small tolerance in satisfying the tank water levels at both the beginning and the end of the simulation. Cimorelli et al. (2020) proved the GA reliability in solving the PS by introducing a new decision-variable representation.

Conversely, Costa et al. (2016) applied an enumerative Branch-and-Bound (B&B) algorithm to get the exact solution for minimizing both the energy cost and the number of switches of three pumps installed within the benchmark AnyTown Modified (AT(M)) network. The algorithm, although enumerating all the feasible solutions and neglecting the unfeasible ones, by setting proper constraints (i.e. limitation on the maximum number of pump actions), showed effective performances, with computational times not longer than meta-heuristic approaches. Whereas Candelieri et al. (2018) applied two Sequential Model Based Optimization (SMBO) models, based on Bayesian Optimization (BO), namely the Gaussian Process (GS) and the Random Forest (RF) to both the benchmark network of AnyTown and the real-life large-scale WDN of Milan (IT). They observed comparable results with both approaches for the small benchmark network, whereas the RF model proved to be more effective for the real-life network.

In this work, following the algorithm by De Paola et al. (2017), a novel digital approach (Digital Harmony Search, DHS) for optimizing pump scheduling in WDNs is presented. By mimicking the improvisation process of musicians, the algorithm adjusts pump operations to minimize energy consumption and operational costs while ensuring efficient water distribution. In its digital form, HS can integrate real-time data and digital simulations, improving the algorithm's accuracy and responsiveness. This approach considers various constraints, such as pump capacities and demand fluctuations, enabling smarter scheduling decisions. The result is a more reliable and sustainable water distribution system, with improved energy efficiency and reduced operational costs. The algorithm proposed, aimed to limit both the evolutive stalling and the computational efforts, however, achieves near-optimum results with allowable computational efforts.

Hereinafter, Section 2 outlines the algorithm features; Section 3 introduces the two case studies investigated, Section 4 discusses the results, whereas Section 5 gives the concluding remarks.

2. Material and methods

The PS optimization of a water network with N_p pumps is aimed at defining the best combination of the pumps operating, able to minimize the energy costs. Considering the potential daily working of pumps, the feasible problem solutions are 2^{24N_p} corresponding to the set of feasible on/off combinations of all the pumps during the day. Thus, to increase the complexity of the system and the number of pumps, enumerating approaches entails relevant computational efforts. Meta-heuristic models allow limiting the number of feasible solutions and, consequently, the computational time, instead. Eq. (1) defines the objective function (OF), aimed to minimize the daily energy cost of the entire pumping system C_T:

$$\min C_T = \sum_{k=1}^{N_p} \sum_{t=1}^{N} (C_{k,t} \cdot E_{k,t}) \tag{1}$$

where t is the time step, N is the number of time steps, whereas $C_{k,t}$ and $E_{k,t}$ are the energy cost and consumption of the k-th pump at the t-th time step, respectively. The maintenance cost depends on the number of switches of each pump TN_{SW}, included within the total cost. Indeed, to safeguard the pump from exceeding wear, the number of switches should be limited. The Eq. (2) thus estimates the minimum number of daily switches of each pump:

$$\min TN_{SWk} = \sum_{t=1}^{N} N_{SWk,t} \tag{2}$$

where $TN_{SW\,k}$ is the total number of daily switches of the k-th pump and $N_{SW\,k,t}$ is the number of pump switches at the t-th time step.

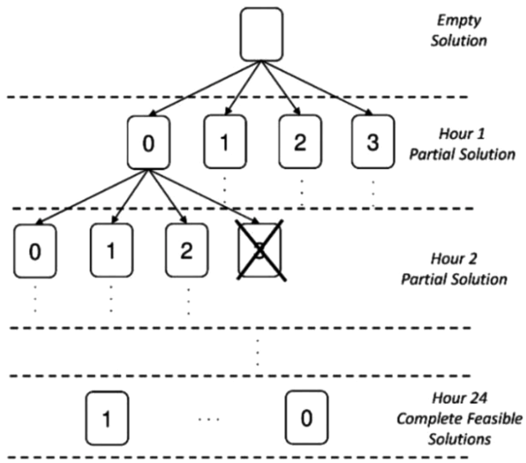


Fig. 1. Enumeration tree of a generic B&B algorithm.

The PS can thus be considered as a multi-objective optimization, aimed at minimizing both the Eq. (1) and the Eq. (2). Solving the PS optimization via enumerating algorithm, such as the B&B (Hendy and Penny 1982) gains the optimal solutions by neglecting those not satisfying the hydraulic constraints. The enumerating tree is built (Fig. 1), structured to detect a partial solution at each time step when increasing the number of pumps switched on.

In the present work, to significantly limit the space of feasible solutions, the HS meta-heuristic algorithm (Geem et al. 2001) was employed. According to its classic framework, the algorithm is composed of the following five steps:

- STEP 1: it initializes the optimization and set the HS parameters, namely the Harmony Memory Considering Rate (HMCR), the Pitch Adjusting Rate (PAR), the Harmony Memory Size (HMS) and the stopping criterion. The former two parameters allow improving the solution vectors through the operators of Step 3. When a multi-objective algorithm is solved, the Pareto Front is generated, composed of solutions not dominated by any others. The not dominated solutions are recorded in the Harmony Matrix (HM).
- STEP 2: HM is filled up with the ordinated values of the objective function ($f(x^1) \leq f(x^2) \leq f(x^{HMS})$). In the frame of this work, the schedules of each pump represented the solution vectors:

$$\mathrm{HM} = \begin{bmatrix} \mathbf{x}_1^1 & \dots & \mathbf{x}_N^1 \\ \vdots & \vdots & \vdots \\ \mathbf{x}_1^{\mathbf{HMS}} & \dots & \mathbf{x}_N^{\mathbf{HMS}} \end{bmatrix} \begin{matrix} \to f(x^1) \\ \vdots \quad \vdots \\ \to f(x^{HMS}) \end{matrix} \tag{3}$$

- STEP 3: new HM improvisation, by generating a new solution vector x' = (x'$_1$, x'$_2$, …, x'$_N$) through three operators: Memory Considerations (MC), Stepping Setting (SS) and Randomization (R), aimed at improving the solutions stored into the HM. The first decision variable x'$_1$ can be either drawn by the HMCR or randomly generated (Eq. (4)):

$$x_i' = \begin{cases} x_i' \in \{x_i^1, x_i^2, \dots, x_i^{HMS}\} \text{withprobabilityHMCR} \\ x_i' \in X_i \text{withprobability}(1 - \text{HMCR}) \end{cases} \tag{4}$$

where X_i is the set of all feasible solutions for x'$_i$, HMCR is the probability from 0 to 1 to extract a historical value from the HM, whereas 1-HMCR is the probability to select a random value among the feasible ones.

Thus, in the PS optimization the new solution vector is defined as:

$$x_i' = \begin{cases} x_i' = x_i^1 \text{if} r_1 < \text{HMCR} \\ R = Z(P_r) \text{else} \end{cases} \tag{5}$$

where r_1 is a real number between 0 and 1, R is the integer rate (Z) of P_r. The latter represents the operator randomly generating values uniformly distributed from 0 to 24, namely the hourly time-step of a daily simulation. The PAR parameter is set to calibrate the velocity at each step.

- STEP 4: it updates the HM replacing the worst solution vector of the HM with the new one, when the latter is better than the former.
- STEP 5: the stopping criterion is applied (i.e. the achievement of the set maximum number of iterations). Differently, Steps 3 and 4 are performed again.

In the frame of the PS optimization, the daily functioning of a pump can be set using a binary string scheme (Fig. 2), composed of 24 cells (equal to the number of hours in a day), set equal to 1 when the pump is turned on, or else equal to 0.

De Paola et al. (2017) improved the HS for PS purposes, by adjusting the pump string scheme and introducing the relative-time intervals. The latter represents couples of decision variables (t_i, t_i'), stating the time duration of a pump status, namely the number of hours passing from being turned off (with duration t_i) to turned on (with duration t_i'), respectively. For the sake of clarity, Fig. 3 reports the example of a pump relative-time intervals scheme for $TN_{SW} = 6$.

The set hydraulic constraints of the PS optimization are:

$$P_{min,i} \leq P_{i,t} \leq P_{max,i} \forall i, \forall t \tag{6}$$

$$S_{min,j} \leq S_{j,t} \leq S_{max,j} \forall j, \forall t \tag{7}$$

$$S_{j,t=24} \geq S_{j,t=0} \forall j \tag{8}$$

$$TN_{SW\,k} \leq N_{SWmax} \quad \forall k \tag{9}$$

$$0 \leq Q_{k,t} \leq Q_{kmax,t} \forall k, \forall t \tag{10}$$

where $P_{i,t}$ is the pressure of the i th node at the t-th time step, $S_{j,t}$ is the water level of the j-th tank at the t-th time step, $TN_{SW\,k}$ is the number of switches of the k-th pump and NS_{max} is the daily maximum number of switches of each pump. Subscripts min and max refer to the minimum and maximum allowable values, instead.

The Eq. (6) sets the allowable pressure range of each node, the Eq. (7) stresses the water level of each tank within a specific range, the Eq. (8)

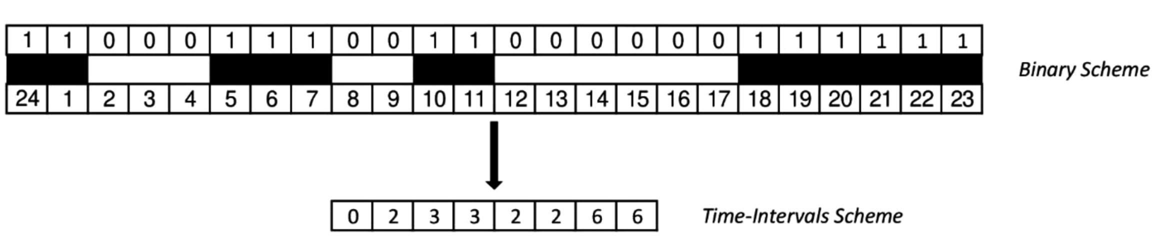


Fig. 2. Daily pump scheduling through relative-time intervals, for $TN_{SW} = 6$.

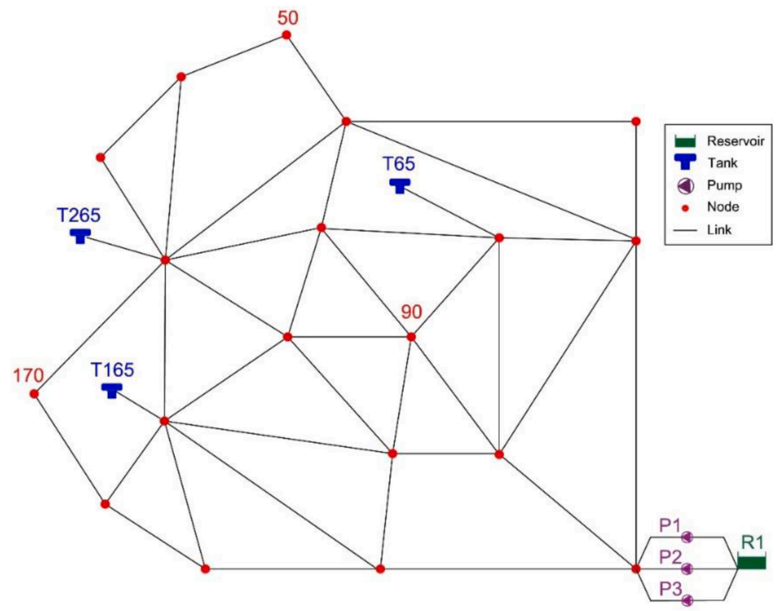


Fig. 3. Sketch of AT(M) network.

sets the water level of each tank at the end of the day not lower than the initial value, the Eq. (9) limits the daily number of switches of each pump not higher than the set maximum allowable number, whereas the Eq. (10) forces the flow rate across each pump in the allowable range set by its performance characteristic curve.

In the frame of this work, the sum of all time steps of each pump was first set equal to the optimization period T (24 h). Then, this constraint was relaxed as follows:

$$\sum_{i=1}^{TN_{swk}} \left(t_i + t_i^{'}\right) \leq 24 \tag{11}$$

Moreover, to easily identify the unfeasible solutions, notably those not satisfying one or more constraints of Eqs. (6-10), a penalty equal to 9′999 \$ (or £) was added to the total cost C_T of these solutions, resulting in such an order of magnitude to make the corresponding solution not suitable for optimization and preliminary discarded by the potentially allowable solutions within the HM. This criterion allowed the algorithm to evolve faster, thus, increasing its effectiveness in detecting near-optimum solutions.

The novelty of this work entails a new criterion to set the HMCR parameter. The sinusoidal function of Eq. (12) was indeed set, useful to avoid the algorithm stalling and reduce the computational effort:

$$HMCR = HMCR_{min} + (HMCR_{max} - HMCR_{min}) \cdot \left(\frac{\sin(2 \cdot iter) + 1}{2}\right) \tag{12}$$

where $HMCR_{min}$ and $HMCR_{max}$ are the minimum and maximum set HMCR values, respectively, and iter is the number of iterations.

This approach deals with a mono-objective function, namely the minimization of the daily energy cost C_T was only addressed. Nevertheless, the costs related to the management and maintenance activities were implicitly regulated by adequately limiting the total number of switches of all the pumps within the system NS. The optimization algorithm was coupled with the EPANET 2.0 (Rossman 2000) solver for the hydraulic simulations, ensuring the technical feasibility of the solutions.

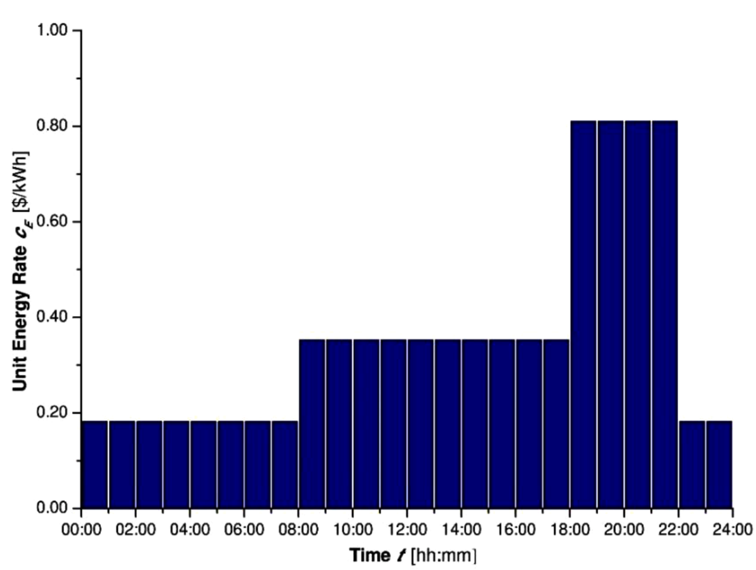


Fig. 4. Daily pattern of the c_E - AT(M) network.

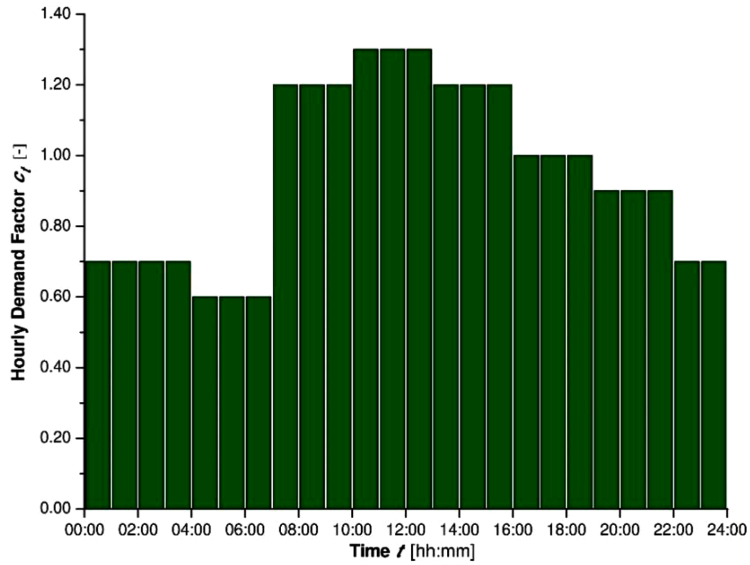


Fig. 5. Daily pattern of the hourly demand factor c_i - AT(M) network.

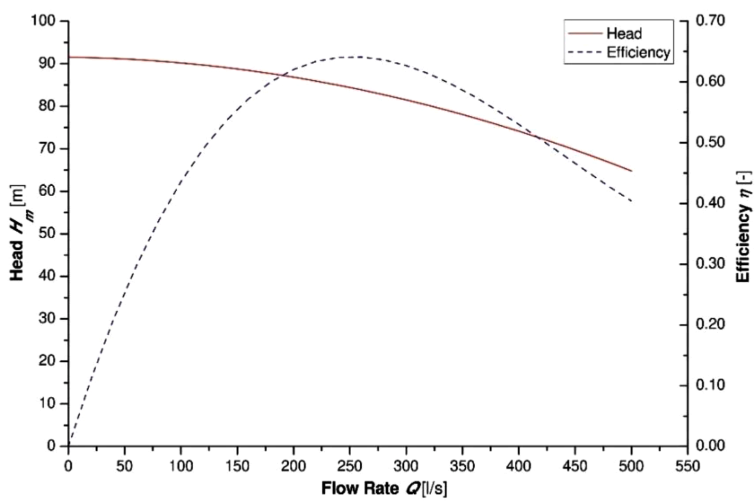


Fig. 6. H(Q) and η(Q) characteristic curves of P1, P2, and P3 - AT(M) network.

3. Case studies: a) Any Town Modified AT(M) network and b) van Zyl network

The modified HS algorithm was tested on the two benchmark networks: a) the AT(M) network and b) the van Zyl (van Zyl et al. 2004) one.

a) Any Town Modified AT(M) network

The AT(M) network was first tested by Rao and Salomons (2007), as an upgraded scheme of Any Town network by Walski et al. (1987). It is made up a reservoir (R1), three identical pumps (P1, P2, P3), three tanks (T65, T165, T265), 41 links and 19 nodes, as shown in Fig. 3. Consistently with Costa et al. (2016), the upper and lower water levels $S_{max,j}$ and $S_{min,j}$ in the tanks were set equal to 71.53 m and 66.53 m, respectively whereas the initial water level $S_{j,t=0}$ was 66.93 m. The minimum pressure at three control nodes (50, 90, 170) was set of 42 m, 51 m and 30 m, respectively. As of Costa et al. (2016), the constraint of Eq. (10) was not included in this study.

Moreover, as in Costa et al. (2016), the simultaneous activation of the three pumps was neglected at the highest energy rate (hours 18÷21). Fig. 4 shows the energy rates reported by Rao and Salomons (2007).

The daily energy cost of the k-th pump $C_{E,k}$ was thus estimated as:

$$C_{E,k} = \sum_{t=1}^{N} \frac{9.81 \cdot Q_{k,t} \cdot H_{mk,t}}{\eta_{k,t}} \cdot c_{E,t} \tag{13}$$

where 9.81 is the specific weight of water (kN/m^3), $Q_{k,t}$ (m^3/s), $H_{m\ k,t}$ (m) and $\eta_{k,t}$ (-) are the flow rate, the head and the efficiency of the k-th pump at the t-th time step, respectively, whereas $c_{E,t}$ ($/kWh) is the unit energy rate at the t-th time step.

The mean flow rate across the identical P1, P2 and P3, when working for $N = 24$ h/day, was 169.16 l/s, thus, resulting in the overall mean flow rate of 507.48 l/s within the whole network. Fig. 5 shows the daily water demand pattern of the network, where the hourly demand factor c_i is the rate $Q_t/\overline{Q}$between the hourly demand Q_t and the daily average demand $\overline{Q}$. Fig. 6 plots the head and efficiency characteristic curves of the three identical P1, P2, and P3 pumps, instead.

$HMCR_{min}$ and $HMCR_{max}$ were set equal to 0.10 and 0.90, respectively and the Eq. (12) was employed during simulations. The stopping criterion of the HS was fixed as the maximum number of iterations set equal to 20′000.

To compare the results with Costa et al. (2016), three sets of

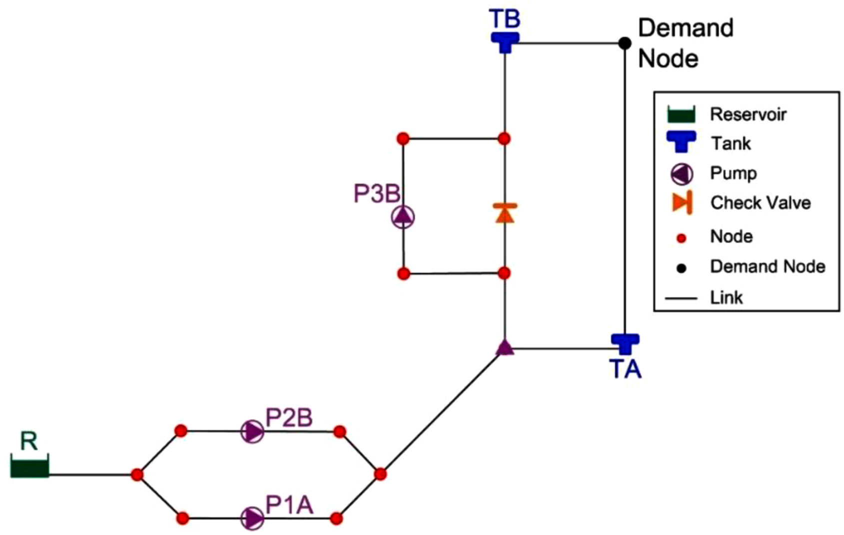


Fig. 7. Sketch of van Zyl network.

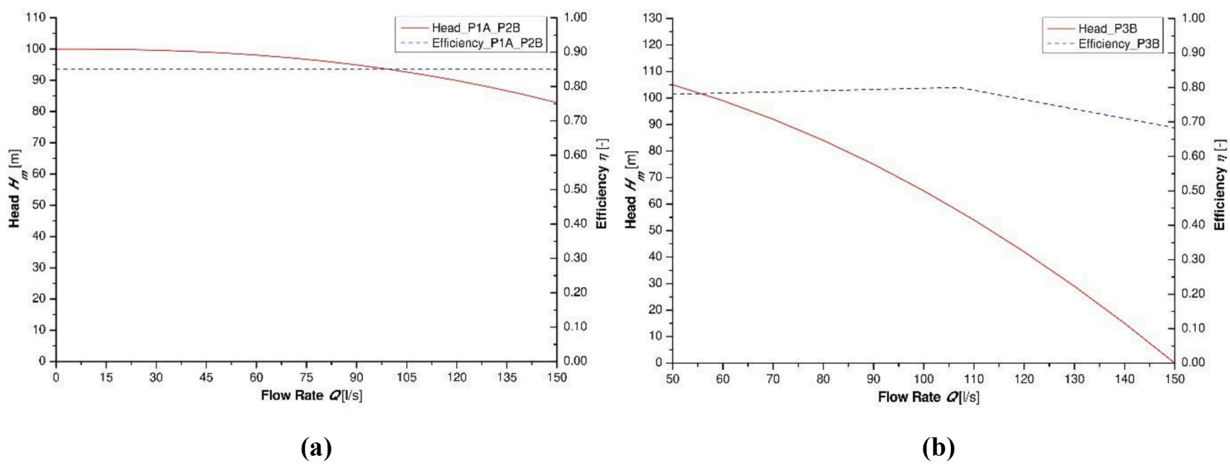


Fig. 8. (a) H(Q) and (b) η(Q) characteristic curves of P1A, P2B and P3B - van Zyl network.

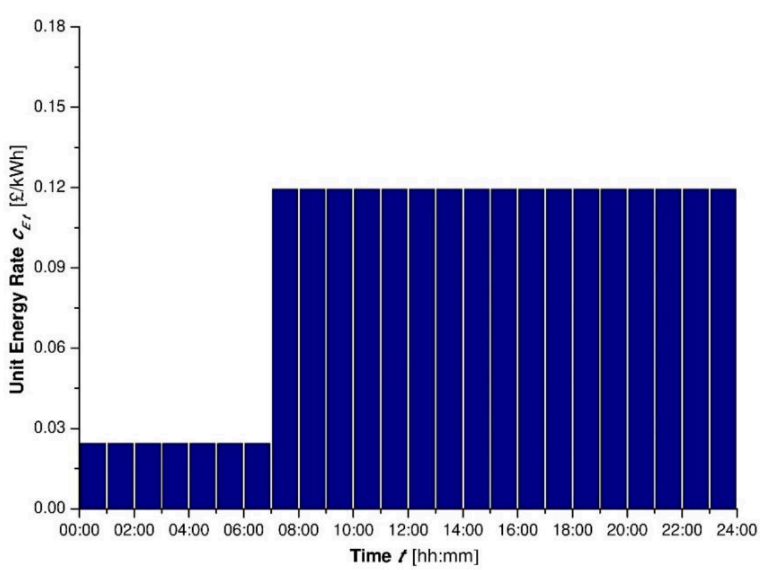


Fig. 9. Daily pattern of $c_{E\ t}$ of van Zyl network.

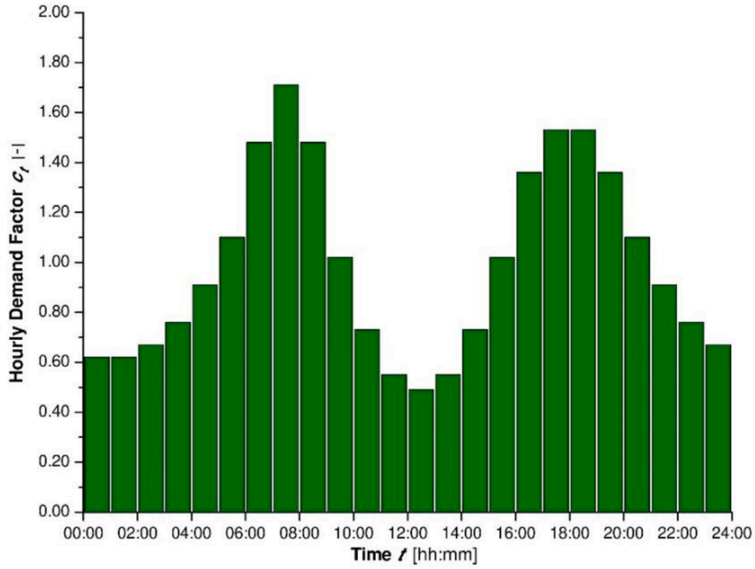


Fig. 10. c_t of van Zyl network.

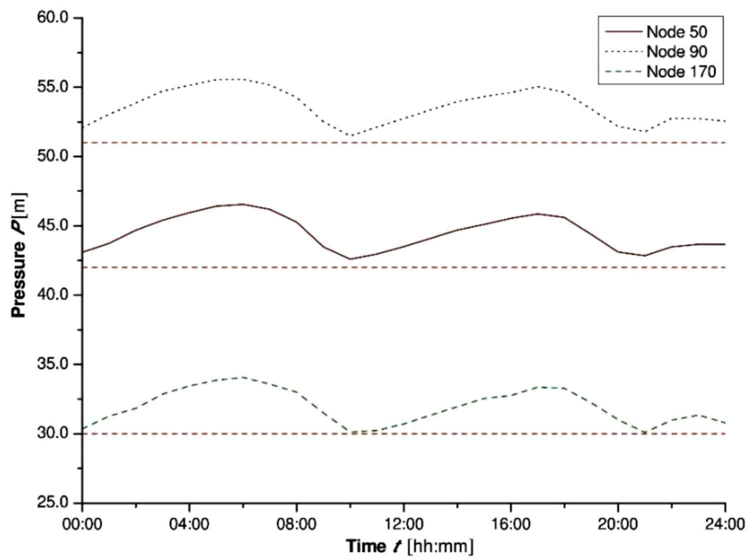


Fig. 11. P at nodes 50, 90, 170 - AT(M) network.

simulations were run, with $N_{SW\ max}$ equal to 2, 4 and 6, respectively. It worth noting that, in this work, regardless of the literature model, the switch was intended as each pump changing of state from switched on to switched off or vice versa.

Simulations were performed using a 64-bit, CPU Intel Core i7–2670QM CPU @ 2.20 GHz with 16 GB of RAM.

b) van Zyl (2004) network

The second network tested was useful to validate the results observed at the case study a). The network was the van Zyl (van Zyl et al. 2004) one, aimed to assessing the effectiveness of the novel approach on a small but, at the same time, complex water system. Reservoir R (total head of 20 m a.s.l.) feds two tanks TA and TB and a demand node through three pumps P1A, P2B and P3B. A check valve, on the parallel link of P3B prevents from water flowing backwards (Fig. 7). Pumps 1A and 2B are identical working in parallel according to the characteristic curve of Fig. 8a, whereas P3B boosts the flow to TB, following the characteristic curve of Fig. 8b. TB is located at an elevation of 85 m a.s.l., higher than that of TA (80 m a.s.l.), thus, entailing the operation by gravity from TB to TA through the links wherein the singular demand node of the system is located. The electricity cost shows a constant peak electricity tariff period from 7:00 to 24:00 and an off-peak tariff from 0:00 to 7:00 (Fig. 9), whereas the demand pattern of Fig. 10 has two peaks at 7:00 and at 18:00, respectively. For further details on the test instance please refer to van Zyl et al. (2004).

4. Results and discussion

a) Any Town Modified AT(M) network

Results showed the reliability of the implemented algorithm in satisfying the constraints of Eqs. (6-9). Eq. (10) was neglected according to Costa et al. (2016), instead.

Fig. 11 shows the pressure trend at the control nodes for simulations at $N_{SW\ max} = 6$. The constraint of Eq. (6) was satisfied at each time step, being the pressure not lower than 42 m, 51 m and 30 m at nodes 50, 90 and 170, respectively.

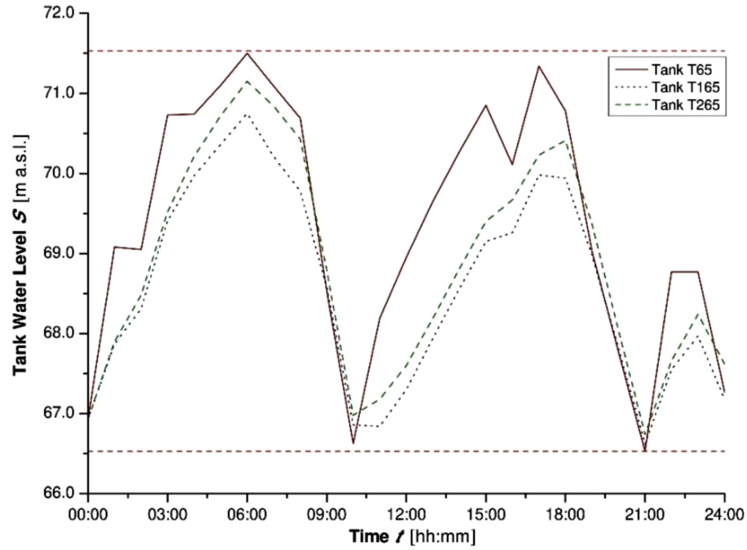


Fig. 12. Water level variation in tanks T65, T165, T265 - AT(M) network.

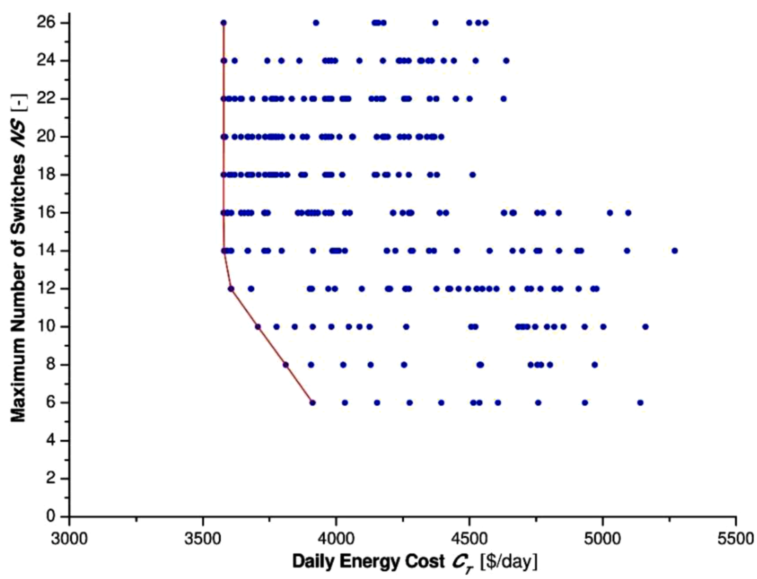


Fig. 13. C_T and NS plotting with Pareto front - AT(M) network.

Fig. 12 plots the water level of the tanks, showing its variability within the set range from 66.53 m and 71.53 m (Eq. (7)). Moreover, the water level at the end of the daily simulation was always not lower than the value at the beginning, consistently with the constraint of Eq. (8).

To limit the maintenance costs, the number of switches should be lowered. Notably, the maintenance costs increase when increasing the number of switches, due to pump wearing. Fig. 13 plots the set of observed solutions for the total number of switches within the network NS ≤ 26 and the Pareto Front, composed of the best economic solution for each NS calculated. NS was thus estimated as follows:

$$NS = \sum_{k=1}^{N_p} N_{swk} \tag{14}$$

Table 1 summarizes the results for $N_{SW\ max} = 6$, 4 and 2. C_T and the schedule of each pump are reported and compared with those of Costa et al. (2016) and Cimorelli et al. (2020).

For $N_{SW\ max} = 6$, Costa et al. (2016) got C_T of 3′578.67 $, against a computational effort of about 3 days (81.12 h). By reducing the number of switches, i.e. to $N_{SW\ max} = 2$, C_T was 3′916.98 $ with a calculation time of 425 s.

The proposed algorithm achieved slightly lower costs for three set $N_{SW\ max}$. Specifically, for $N_{SW\ max} = 6$, C_T was 3′577.4 $, for $N_{SW\ max} = 4$ $C_T = 3'605.53$ $ and for $N_{SW\ max} = 2$ $C_T = 3'911.52$ $. They reduced the Costa et al. (2016) costs by about 0.04 %, 0.34 % and 0.14 %, respectively. It is worth noting that, against a limited improvement of C_T, the proposed model assured shorter computational times, attaining to about 960 s, 904 s and 72 s for $N_{SW\ max} = 6$, 4 and 2, respectively. For the lowest $N_{SW\ max}$, the computational effort was thus significantly lower than both Costa et al. (2016) and that the authors achieved when setting as constraint the overall number of switches of the whole network.

Moreover, despite the statement by Costa et al. (2016), their B&B algorithm did not achieve the global optimum for the three tested configurations. The authors applied an enumerating approach, consisting of enumerating all solutions and identifying the feasible ones. It provided the reduction of the number of solutions to reach the global optimum. Nevertheless, it was aimed at determining the absolute minimum cost, thus implying longer computational times. To limit the computational efforts, the constraints may be relaxed when lowering $N_{SW\ max}$. Thus, the

Table 1
Comparison of schedules between the proposed model, Costa et al. (2016) and Cimorelli et al. (2020) - AT(M) network.

Maximum Allowable Number of Daily Switches per Pump $N_{SW\ max}$ [-]	Model	Energy Cost C_T [$/day]	Pump Id	Hour 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Number of Pump Switches TN_{SW} [-]	Number of Daily Switches NS [-]
6	Costa et al. (2016)	3578.67	P1	x	x	x	x	x	x	x	x			x	x	x	x	x	x	x	x				x	x		6	16
			P2		x		x							x	x	x	x	x										6	
			P3																	x					x			4	
	Cimorelli et al. (2020)	3575.54	P1	+	+	+	+	+	+	+	+			+	+	+		+	+	+					+	+		8	22
			P2	+			+							+	+	+		+	+	+								8	
			P3												+	+					+				+			6	
	Proposed Model	3577.40	P1	•	•	•	•	•	•	•	•			•	•	•	•	•	•	•	•				•	•		6	16
			P2	•		•								•	•	•	•	•										6	
			P3																	•					•			4	
4	Costa et al. (2016)	3618.59	P1	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x				x	x	x	4	12
			P2		x	x								x	x	x												4	
			P3															x		x								4	
	Cimorelli et al. (2020)	3580.11	P1	+		+	+	+	+	+	+								+	+								6	14
			P2											+	+	+	+								+	+		4	
			P3	+	+	+								+	+	+	+	+	+	+	+							4	
	Proposed Model	3606.22	P1	•	•	•	•	•	•	•	•			•	•	•	•	•	•	•	•				•	•	•	4	10
			P2		•	•								•	•	•	•	•										4	
			P3																	•								2	
2	Costa et al. (2016)	3916.98	P1	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x			x	x	x	2	6
			P2		x	x																						2	
			P3												x	x	x											2	
	Cimorelli et al. (2020)	3634.67	P1	+	+	+	+	+	+	+	+	+	+	+	+				+	+								4	10
			P2	+																					+	+	+	2	
			P3	+										+	+	+	+	+	+	+	+							4	
	Proposed Model	3911.52	P1				•																					2	6
			P2	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•			•	•	•	2	
			P3												•	•	•											2	

Table 2
Schedule of the proposed model getting the optimal cost solution, without the $N_{SW\ max}$ constraint.

Maximum Allowable Number of Daily Switches per Pump $N_{SW\ max}$ [-]	Model	Energy Cost C_T [$/day]	Pump Id	Hour 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Number of Pump Switches TN_{SW} [-]	Number of Daily Switches NS [-]
N.A.	Proposed Model	3574.90	P1	•	•	•		•	•	•	•			•	•	•		•	•	•	•				•	•		10	22
			P2	•		•	•								•	•		•	•	•								8	
			P3											•	•	•									•			4	

effectiveness of the approach from the literature depended on the number of constraints and switches.

Conversely, the proposed algorithm allowed gradually refining the constraints to reach the best solution quickly. Indeed, the evolutionary process assists the solution improvement at each step, rather than enumerating all the feasible ones.

Cimorelli et al. (2020) achieved on the same benchmark network better results in terms of C_T, resulting in a reduction of 0.09 %, 1.06 % and 7.21 % of Costa et al. (2016) results. Nevertheless, the comparison is actually unfair, given the different assumptions compared to those used by Costa et al. (2016). Indeed, Cimorelli et al. (2020) neglected the switch counting when changing the pump status between hour 24 and hour 1 of the simulation. Nevertheless, it is argued that if a pump is not activated by hour 24 and it works at hour 1, or conversely, the corresponding switch should be accounted for the overall TN_{SW} counting. This made $N_{SW\ max}$ constraint of Eq. (9) not satisfied, by achieving NS equal to 22, 14 and 10 for $N_{SW\ max} = 6$, 4 and 2, respectively (Table 1). As to Costa et al. (2016)'s assumptions, in the proposed model TN_{SW} increased when changing the status of the k-th pump between hours 24 and 1. TN_{SW} didn't raise when getting the same pump status at hours 24 and 1, instead. Conversely, in the Cimorelli et al. (2020) solutions of Table 1, at least one pump exceeded the set $N_{SW\ max}$, making these solutions infeasible and thus not consistently comparable.

Nevertheless, aimed to get the overall optimal cost solution, a further simulation was run, discarding the constraint of the maximum number of daily switches of each pump set by Eq. (9). The cost of 3′574.9 $/day was achieved with the same NS = 22 (after about 110 s of simulation), resulting in pump switches TN_{SW} of 10, 8 and 4, for P1, P2 and P3, respectively (Table 2). This led to the slight improvement of the daily energy cost achieved by Cimorelli et al. (2020) while supposing the same number of switches in the network.

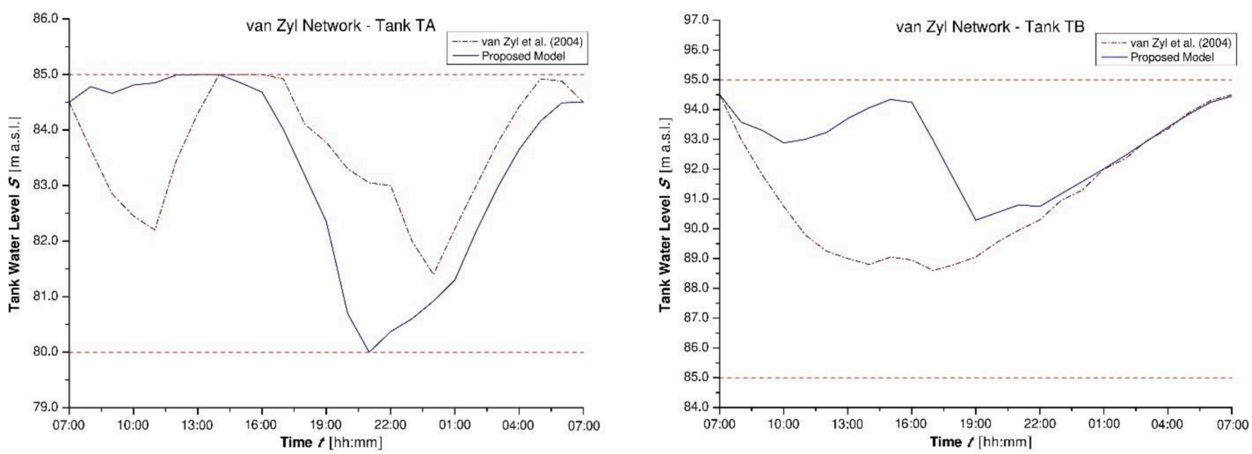
In terms of the overall daily average flow rate pumped within the network, the comparison between the proposed approach and Costa et al. (2016) showed that, for $N_{SW\ max} = 2$, the former returned an average value of 414.34 l/s, against the 418.73 l/s of the latter. Conversely for $N_{SW\ max} = 4$ and 6, Costa et al. (2016) provided a slightly lower average daily flow rate pump, equal to 413.27 l/s and 408.48 l/s, against 424.36 l/s and 420.41 l/s of the proposed approach, respectively, thus further remarking the need to optimally setting the time-steps when activating the pump systems, aiming at minimizing the overall management cost.

b) van Zyl (2004) network

Simulations were performed at $N_{SW\ max} = 2$, 3, 4, 5, 6, 7 and 8 and results were compared with the De Paola et al. (2017) ones, providing a benchmark for the model assessment. As for van Zyl et al. (2004), simulations started at 07:00 a.m. Moreover, consistent with the previous study of the authors (De Paola et al. 2017), the lowest C_T of 323.5 £/day was achieved for $N_{SW\ max} = 4$ with a computational time of about 2700 s, thus representing a key outcome of the study, serving as a reference point to compare the goodness of the proposed algorithm with further approaches available in the literature. Notably, the comparison with van Zyl et al. (2004)'s and López-Ibáñez (2009)'s criteria, in terms of both C_T and NS, shows the reliability of the proposed algorithm. Indeed, the minimum cost was lower than that got by van Zyl et al. (2004) and slightly higher than López-Ibáñez (2009) showing marginal discrepancies. The former achieved 344.2 £/day using Pure GA, whereas the

Table 3
Comparison of schedules between the proposed model and van Zyl et al. (2004) - van Zyl network.

Maximum Allowable Number of Daily Switches per Pump $N_{SW\ max}$ [-]	Model	Energy Cost C_T [£/day]	Pump Id	Hour																								Number of Pump Switches TN_{SW} [-]	Number of Daily Switches NS [-]
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24		
4	van Zyl et al. (2004)	344.19	P1A																		x	x	x	x	x		x	4	10
			P2B				x	x	x	x	x	x	x	x	x	x	x	x			x	x	x	x	x	x	x	4	
			P3B												x	x	x	x	x	x	x	x	x	x	x	x	x	2	
	Proposed Model	323.50	P1A	•	•	•	•	•	•	•	•	•																2	8
			P2B		•	•	•	•	•	•	•	•	•	•	•	•	•	•	•						•	•	•	4	
			P3B	•	•	•	•	•	•	•													•	•	•	•	•	2	



(a) **(b)**

Fig. 14. Comparison of tank water level between the proposed model and van Zyl et al. (2004) for (a) tank TA and (b) tank TB - van Zyl network.

latter got 322.5 £/day through SEA. The daily energy cost attained close to the López-Ibáñez (2009)'s benchmark, remarking the interesting potentiality of the method in minimizing energy consumption expenses. It is worth noting that, as stated by the authors, in López-Ibáñez (2009), the hydraulic simulations were performed using an EPANET toolkit different from the classic structuring of the hydraulic solver, thus making suitable the occurrence of slight discrepancies in the numerical calculations than those employed in the frame of the current work (e.g. for the approximation of the decimal digits).

Concerning the number of total switches of the network, NS = 8 is equal to the López-Ibáñez (2009) outcome, thus limiting the frequency of maintenance, wear and tear of pump systems equipment required when more starting and turning off activities occur. Thus, from a practical standpoint, the lower number of switches identified in the present work, in De Paola et al. (2017) and in López-Ibáñez (2009)'s work may present a more desirable solution for real-world applications, as it strikes a better balance between cost savings and system simplicity. van Zyl et al. (2004) achieved a higher number of 10, instead.

In the following Table 3 and Fig. 14 the comparison between the van Zyl et al. (2004)'s results and those of the proposed model is plotted in terms of the pump schedule and water level of tanks, respectively. López-Ibáñez (2009) data were not made available by the authors, instead.

Fig. 14 shows that, against van Zyl et al. (2004)'s outcomes, along with lower C_T and NS, for TA the proposed solution allowed better exploit the water level variation, also returning a slightly shorter time period when the maximum allowable water level of 85 m a.s.l. is achieved. The latter thus entailed more effective operations for both technical and environmental viewpoints, given the lower probability of tank overflow. Although not technically feasible, consistently with van Zyl et al. (2004), the maximum level of each tank in the optimization model was set equal to the maximum allowable level of the tank in the input file of the hydraulic solver. This is shown in Fig. 14 for both approaches when the water level in TA arrives at its maximum (between 14:00 and 16:00 in van Zyl et al. (2004) and in the time interval 13:00 – 14:00 in the proposed approach), while at least one pump is active, thus raising the water level of TB.

In the literature, multi-objected evolutionary algorithms were also tested on the van Zyl network, by coupling as objective function C_T and NS. They showed interesting results (Makaremi et al. 2017), however resulting in more consistent computational efforts, thus making them less suitable for real-time management of the network.

The comparison between the different optimization methodologies also shows the flexibility and robustness of the proposed approach. The ability to achieve results that are comparable to or better than established methods demonstrates that the proposed approach is not only effective but also suitable to different system configurations and constraints, making it reliable for the operational management of real water systems. This versatility is specifically valuable in the environment of energy management, where systems can vary significantly depending on factors such as load demand, infrastructure, and energy source availability.

5. Conclusions

The new Digital HS algorithm is a cutting-edge optimization method for improving pump scheduling in WDNs. Inspired by the improvisation process of musicians, it fine-tunes pump operations to reduce energy use and operational costs while ensuring efficient water delivery. In its digital form, HS leverages real-time data and digital simulations to enhance precision and responsiveness. By integrating these advanced capabilities, the algorithm can dynamically adjust to varying conditions in the network, resulting in smarter pump scheduling and improved system performance. This digital approach offers greater efficiency and adaptability in managing complex water systems operations. In this work, the novel version of the algorithm proposed, specifically, the use of a new function to set the HMCR parameter of the HS algorithm was implemented, as well as the aiding of restrictions on the solution space to enhance the algorithm performance.

Tests on the AT(M) benchmark demonstrated the algorithm's ability to deliver slightly better results than further approaches available in the literature (such as the B&B one), while significantly reducing computational time, resulting in the order of 900–960 s for $N_{SW\ max}$ of 6 and 4, and of about 72 s for $N_{SW\ max} = 2$.

Additionally, the van Zyl case study confirmed the reliability of the algorithm, achieving similar results with De Paola et al. (2017) and Costa et al. (2016), against competitive computational efforts.

The proposed approach aims to identify the technical minimum cost for each problem, rather than the global optimum. Given the complexity of pump scheduling, with numerous variables and influencing factors in real-life networks, the reduced computational time offers a valuable advantage when paired with effective technical solutions.

The next step of the research will then be focused on testing the proposed optimization approach to further benchmark and real water systems, aimed to prove its robustness when applied to more complex models.

CRediT authorship contribution statement

Francesco De Paola: Writing – review & editing, Methodology, Investigation, Formal analysis, Conceptualization. **Francesco Pugliese:** Writing – original draft, Validation, Data curation. **Nicola Fontana:** Writing – review & editing, Supervision, Methodology, Funding acquisition. **Maurizio Giugni:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Francesco De Paola, Francesco Pugliese, Nicola Fontana, Maurizio Giugni reports financial support was provided by Italian Ministry of University and Research. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The work was financed by Italian Ministry for Universities and Research under the PON ARS01_01080 Watergy - L'efficientamento energetico del Servizio Idrico Integrato (B52F20001180005) project.

Data availability

Data will be made available on request.

References

Beckwith, S.F., Wong, K.P., 1995. Genetic algorithm approach for electric pump scheduling in water supply systems. In: Proceedings of the IEEE Conference on Evolutionary Computation.

Brion L.M., Mays L.W. (1989) Methodology for optimal operation of pumps in water distribution systems.

Candelieri, A., Perego, R., Archetti, F., 2018. Bayesian optimization of pump operations in water distribution systems. J. Glob. Optim. https://doi.org/10.1007/s10898-018-0641-2.

Cimorelli, L., D'Aniello, A., Cozzolino, L., 2020. Boosting genetic algorithm performance in pump scheduling problems with a novel decision-variable representation. J. Water Resour. Plan. Manag. https://doi.org/10.1061/(asce)wr.1943-5452.0001198.

Costa, L.H.M., de Athayde Prata, B., Ramos, H.M., de Castro, M.A.H., 2016. A branch-and-bound algorithm for optimal pump scheduling in water distribution networks. Water Resour. Manag. https://doi.org/10.1007/s11269-015-1209-2.

Creaco, E., Pezzinga, G., 2015. Multiobjective optimization of pipe replacements and control valve installations for leakage attenuation in water distribution networks. J. Water Resour. Plan. Manag. https://doi.org/10.1061/(asce)wr.1943-5452.0000458.

De Paola, F., Fontana, N., Giugni, M., et al., 2017. Optimal solving of the pump scheduling problem by using a harmony search optimization algorithm. J. Hydroinformatics 19. https://doi.org/10.2166/hydro.2017.132.

Geem, Z.W., Kim, J.H., Loganathan, G.V., 2001. A new heuristic optimization algorithm: harmony search. Simulation. https://doi.org/10.1177/003754970107600201.

Hendy, M.D., Penny, D., 1982. Branch and bound algorithms to determine minimal evolutionary trees. Math. Biosci. https://doi.org/10.1016/0025-5564(82)90027-X.

Jowitt, P.W., Germanopoulos, G., 1992. Optimal pump scheduling in water-supply networks. J. Water Resour. Plan. Manag. https://doi.org/10.1061/(asce)0733-9496(1992)118:4(406).

López-Ibáñez, M., 2009. Operational Optimisation of Water Distribution Networks. Edinburgh Napier University.

López-Ibáñez, M., Prasad, T.D., Paechter, B., 2008. Ant colony optimization for optimal control of pumps in water distribution networks. J. Water Resour. Plan. Manag. https://doi.org/10.1061/(asce)0733-9496(2008)134:4(337).

Mackle, G., Savic, D.A., Walters, G.A., 1995. Application of genetic algorithms to pump scheduling for water supply. In: IEE Conference Publication.

Makaremi, Y., Haghighi, A., Ghafouri, H.R., 2017. Optimization of pump scheduling program in water supply systems using a self-adaptive NSGA-II; a review of theory to real application. Water Resour. Manag. https://doi.org/10.1007/s11269-017-1577-x.

Rao, Z., Salomons, E., 2007. Development of a real-time, near-optimal control process for water-distribution networks. J. Hydroinformatics. https://doi.org/10.2166/hydro.2006.015.

Rossman L.A. (2000) Epanet 2 User 's Manual. Natl. Risk Manag. Res. Lab. Off. Res. Dev. U.S. Environ. Prot. Agency Cincinnati.

Savic, D.A., Walters, G.A., Schwab, M., 1997. Multiobjective genetic algorithms for pump scheduling in water supply. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).

Shamir, U., Salomons, E., 2008. Optimal real-time operation of urban water distribution systems using reduced models. J. Water Resour. Plan. Manag. https://doi.org/10.1061/(asce)0733-9496(2008)134:2(181).

van Zyl, J.E., Savic, D.A., Walters, G.A., 2004. Operational optimization of water distribution systems using a hybrid genetic algorithm. J. Water Resour. Plan. Manag. 130, 160–170. https://doi.org/10.1061/(asce)0733-9496(2004)130:2(160).

Vieira, F., Ramos, H.M., 2008. Hybrid solution and pump-storage optimization in water supply system efficiency: a case study. Energy Policy. https://doi.org/10.1016/j.enpol.2008.07.040.

Walski, T.M., Brill, E.D., Gessler, J., et al., 1987. Battle of the network models: epilogue. J. Water Resour. Plan. Manag. https://doi.org/10.1061/(asce)0733-9496(1987)113:2(191).